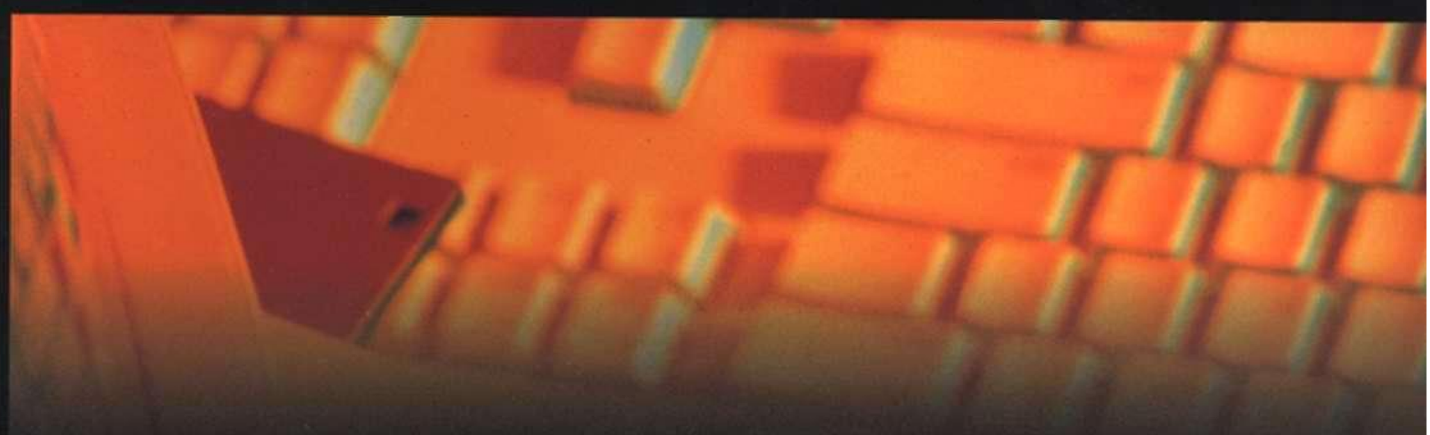
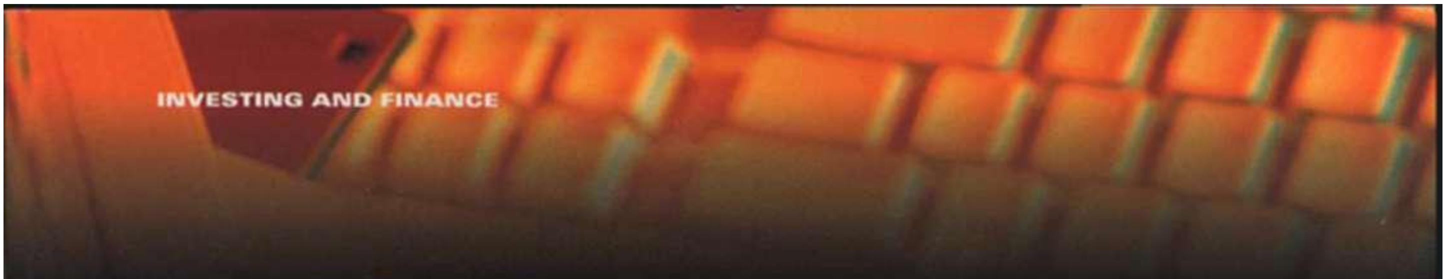
IRWIN TRADER'S EDGE

TRADING SYSTEMS THAT WORK

BUILDING AND EVALUATING EFFECTIVE TRADING SYSTEMS



THOMAS STRIDSMAN



GUIDELINES FOR DESIGNING AND BUILDING A UNIQUE, POWERFUL, AND PROFITABLE TRADING SYSTEM

Successful trading is more than just a series of single, isolated activities, each fighting its own battles in a dog-eat-dog marketplace. It is instead a **system** in which all components work together to ensure that each trade is well protected, easy to implement, and capable of generating a steady stream of low-risk trading returns.

Trading Systems That Work shows you how to combine today's best available information and techniques into a simple system that works for **you**—across all markets and market conditions. Look to this clear, step-by-step book for:

- Guidelines for implementing a consistent money management program
- Portfolio composition techniques to ensure maximum profit potential—while minimizing exposure to unnecessary risk
- Strategies to exercise proper risk management through stop losses, profit objectives, and more

Whether you are a multimillion-dollar institutional investor or an independent trader with a $10,000 account, your trading system—and your comfort with that system—will spell the difference between long-term success and failure. Let *Trading Systems That Work* help you design a strategic, well-thought-out trading system, one that puts you in complete charge of your trading fortunes.

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ISBN 0-07-135980-X

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McGraw-Hill

New York San Francisco Washington, D.C. Auckland Bogota
Caracas Lisbon London Madrid Mexico City Milan
Montreal New Delhi San Juan Singapore
Sydney Tokyo Toronto

Library of Congress Cataloging-in-Publication Data

Stridsman, Thomas.
Trading-systems that work : building and evaluating effective trading systems / by Thomas Stridsman.
p. cm.
1SBN0-O7-13598O-X
1. Investment analysis. 2. Portfolio management. I. Title.

HG4529.S77 2000
332.6—<lc21
00-055008

McGraw-Hill

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2 3 4 5 6 7 8 9 0 AGM/AGM 0 9 8 7 6 5 4 3 2 1

0-07-135980-X

This book was set in Times New Roman by Patricia Wallenburg.

Printed and bound by Quebecor World/Martinsburg.

This book is printed on recycled, acid-free paper containing a minimum of 50% recycled, de-inked fiber.

This book is dedicated to my mother, Britt-Marie Stridsman. Thank you for your support and always being there for all of us. There are not enough words in the world to describe how much I love you.

All my forthcoming proceeds from this book will be donated to Children's Wish List in Chicago, and similar voluntary organizations, dedicated to help kids with medical and other urgent needs, to help them grow up as healthy and happy individuals.

DISCLAIMER

Hypothetical performance results have many inherent limitations, some of which are described below. No representation is being made that any account will or is likely to achieve profits or losses similar to those shown. In fact, there are frequently sharp differences between hypothetical performance results and the actual results achieved by any particular trading program.

One of the limitations of hypothetical performance results is that they are generally prepared with the benefit of hindsight. In addition, hypothetical trading does not involve financial risk, and no hypothetical trading record can completely account for the impact of financial risk in actual trading. For example, the ability to withstand losses or to adhere to a particular trading program in spite of trading losses are material points which can also adversely affect actual trading results. There are numerous other factors related to the markets in general or to the implementation of any specific trading program which cannot be fully accounted for in the preparation of hypothetical performance results and all of which can adversely affect actual trading results.

All trading systems and strategies in this book are intended for educational purposes only, to provide a perspective of different market concepts. They are not meant to recommend or promote any trading system or approach. You are advised to do your own research and testing to determine the validity of a trading idea.

CONTENTS

INTRODUCTION

After I had been an editor, writer, and technical analysis expert for *Futures* magazine for two years it became apparent to me that the main mistake most people make in the trading industry is to believe that there is nothing to it; that it is a piece of cake to put together a trading strategy and then go out there and make the big bucks, knowing nothing about risk management, money management, why certain systems simply do not work when traded on certain markets, why your worst drawdown is still to come or why a system can work as it should but still break you. And horrifyingly enough, this attitude seems almost equally as common among long-time professionals as among wanna-be amateurs.

Another common mistake, made especially by smaller investors, is the thought that lesser money needs less efficient and less thoroughly researched trading methods. That there will be plenty of time to learn about more "sophisticated" strategies and market intricacies as their accounts grow. This is not so. Money is money; you are equally as likely to lose it, whether you are a long-time, multimillion dollar money manager or are new to the game with a $ 10,000 savings account, if the methods you are using won't allow you to succeed in the first place. Think about it; why would you be any more successful trading $10,000 in a basic moving average crossover system, with no money management attached (just because this is all you know about trading and all the money that you have), than if you were sitting on millions of dollars, knowing everything there is to know about trading?

If you think that you do not have enough money or knowledge to do it the right way from the very beginning, you should not trade. Period. Because if you do, you will find that there will in fact be plenty of time to learn about the more "sophisticated" methods, but not while trading. Ask me—I had the opportunity to experience this first hand.

Trading Systems That Work is for all of you traders out there, no matter what your level of experience is, who have come to realize that it is not as easy at it seems, but still haven't been able to pinpoint the missing pieces that will solve the whole puzzle. I would guess that what you believe is missing, or what is keeping you from succeeding as a trader, is the overall understanding of how it all ties together and what really constitutes a more sophisticated strategy with a higher likelihood for success. This book is my most sincere effort to try to provide you with this overall understanding, to help you solve the whole puzzle. Call me when you do.

Today, I am primarily an analyst and writer—not a trader, although I have traded in the past and currently have a few systems out there, traded by others. Many misinformed traders think that just because you are not a trader, you do not know anything about how the markets work. In my opinion, nothing could be further from the truth. Just as good math skill is no guarantee of good language skill, or good driving skill is no guarantee of good mechanical skill, good trading skill is no guarantee of good analytical skill—and vice versa for that matter. Furthermore, being an analyst and writer also is a matter of choice: I simply cannot resist sitting down in front of the computer and tinkering with something, then later trying to write about it in one form or another.

As an analyst and specializing in systems and mechanical trading, I believe it follows that I have the necessary trading skills—as long as I follow my own strategies. If you do not believe me, please continue reading and let me prove you wrong. As you turn the pages, I will provide you with a set of useful tools based on my personal and, I believe, highly innovative analysis techniques; all on a level of sophistication and market knowledge widely surpassing most of what you can find "out there" today.

Although I sometimes use scientific and academic jargon—words and phrases such as *standard deviation, kurtosis,* and *mathematical expectancy*—and sometimes even indulge in the mathematics and calculus behind it all, I do not purport to be a scientist, statistician, or psychiatrist, or to hold any other degree from which I might have stolen some of the techniques used throughout this book. In fact, I am convinced that several of you will identify several situations where I expose my ignorance in more topics than one. But that does not matter. The most important thing that I will show you is that you do not need to be a rocket scientist to analyze the markets successfully, but you must know a bit more than what you have been able to pick up from other books, and you must dare to think "outside of the box" a little. And for that I make no excuse.

When trying to explain something new, a teacher often finds himself in a dilemma. To explain subject C, he first must explain subjects A and B, but often these subjects interweave with each other. So to learn A we need to first understand B and C. For the purpose of this book I have tried hard to keep it all in some logical order and as simple as possible, but invariably there are instances where I must talk about and explain two new subjects at the same time. In other instances, I have simply left a certain topic unexplained and gotten back to it later, in a more thorough analysis and explanation. On a few occasions, I also cheated a bit by oversimplifying things. I apologize for this, with the explanation that I simply cannot give away the whole store in one book. I hope you will bear with me and find it worthwhile reading just the same.

Although I hope that you will perceive this as a practical book, it is not a book about a new set of ready-made technical analysis indicators, or a book about foolproof trading systems, because there is no such thing. Nor is it a book that will help you identify unique trading opportunities and show you how to exploit those opportunities with a swift decision and then go do something else. And although it might seem like it, it isn't even a book about new techniques or new ways to develop trading strategies.

Instead, this is a book about how to go about *reasoning* even before you start a development process that eventually and hopefully will allow you to put together a trading strategy that is exactly that—a strategy, a long-term work process, as opposed to a series of single, isolated decisions. With the risk of sounding way too pretentious right off the bat, this book is about *philosophy:* that is, the philosophy behind the work of putting together a good, working trading strategy; the philosophy behind what drives markets and what makes them behave as they do; and finally, the philosophy that allows us to understand why a strategy works, or why it doesn't.

The key point I hope to get across is that a trading strategy is a "process machine," where each decision made automatically and immediately leads to the next one, and next one, and next one... producing a long string of interacting decisions that form a never-ending process—almost a *perpetuum mobile.* And, just like a *perpetuum mobile,* the trading strategy is a very sensitive machine, consisting of a few parts that, by necessity, form a whole greater than those parts and can allow for no loss of energy. Ideally, for this to be possible, each part must be put together or constructed with all the other parts in mind but also be a part of all other parts. (This is the philosophical aspect of this book.) It is almost.. .No, in fact, *it is exactly* as if each part is both one of the parts that make a car work, and the car itself, made up of all the parts.

However, just as a *perpetuum mobile* is an impossibility, putting together a good trading strategy is very much like putting together, or buying, a good and well-balanced car. While doing all this work, you also must think about your own needs and current status in life, financially and otherwise. For instance, even if you can afford it, you do not go and buy yourself a NASCAR racer for your Sunday afternoon sightseeing drives with the family. Nor would you go and buy a road grader for the same purpose. Instead you probably try to find a car that fulfills its purpose for your everyday life, although you might think a station wagon or a mini van a little boring when you know you really are the Lamborghini type. The same goes with trading strategies. First, you must come to grips with who you are and what type of strategy is suitable for you, even if it is a little boring and leaves little room for fast "overtaking maneuvers" or any other cool improvisations "behind the wheel." In fact, my experience is that trading, at least systematic trading, is as boring as watching baseball without a beer in your hand and a few in your belly. But the same holds true for both the public roads and the trading rooms. They are no places for fun and games.

When putting together a trading strategy, this is how I look at it: the actual system with its buy and sell rules is the engine that could be anything from a fast intraday, market specific system (comparable to an 800 h.p., fast, NASCAR-type engine) to a slow, long-term, universal system (comparable to a slow but steady road grader engine). When this is done, I take a look at the money management, which is equal to the gearbox and the transmission. With the purpose of the system in mind, I now try to find a way to get its force down to the ground as efficiently and safely as possible. Continuing with the car analogy, you know it is a recipe for disaster if you try to fit the engine of a NASCAR racer with the transmission of a station wagon.

Once the engine (the system) and the transmission (the money management) seem to be working well in a balanced harmony with each other it's time to think about the coach and the chassis. In a trading strategy, this is comparable to the question of which markets to trade. In the case of a market-specific system, this is already done (and a case of when subject C comes before subject A). But whether a strategy is market specific or not, it still is a good idea to make sure that it works in as many markets as possible. In the case of a multimarket strategy, it is equally as important not to start curve-fitting the strategy by optimizing the markets in regard to the system, as it is not to curve-fit the system to the markets.

There is a vast difference between a good system and a profitable system. It is paramount to understand this difference. It also is very important to understand that a good system can always be turned into a profitable system, while the opposite does not necessarily hold true. This is because a well working system will usually work well on a multitude of markets, catching the same type of moves, measured in percentage terms or some other universal measurer. A profitable system, on the other hand, is a well working system that generates a surplus of dollars when applied in the context of a complete strategy to a specific market or portfolio of markets.

When you have put together the car (the overall strategy) with its engine (the system), the transmission (the money management), and the chassis (the portfolio of markets) there still are a few things missing: the fuel and the driver. The fuel is your time and money. The driver is you. But before you fill the baby up and jump into the driving seat, make sure that this really is the vehicle for you (even though you know in your heart that you really are the Lamborghini type).

Although *Trading Systems That Work* is not one of those 13-in-a-dozen books on day trading that seems to swamp the market these days, everything said here could be translated to day trading techniques as well. Neither is it a book specifically aimed toward any specific type of market, although I have made extensive use of the commodity futures markets in my examples. Instead, words such as *stocks, markets,* and *contracts* should be looked at as synonyms.

Part 1 takes a close look at how to measure the performance of a system using a set of basic and universal measurements and how to expand the analysis further by incorporating a spreadsheet program, such as MS Excel or Lotus 1-2-3. This part also takes a closer look at different types of data series and discusses when and how to use them. This is especially important to understand if you are a futures trader, but even if you have decided to stick to the stock market, this section should provide you with valuable insight on why so many of the systems you have built so far have ceased to work as soon as you have taken them live.

In Part 2,1 put together a set of basic long-term and short-term trading systems, using different types of data depending on what I am trying to achieve. Some of the systems are market specific, others are suitable for a basket of markets. A lot of the analysis is done in a spreadsheet program, and for this we need the code developed in Part 1. Other than the specific entry techniques that we will continue to use throughout the book, the most important things to learn from Part 2 are that a good working system does not necessarily have to be a profitable one and that some systems are doomed to fail when traded on specific markets.

In Part 3, we take the systems that we put together in Part 2 and examine them further for their statistical characteristics and how they can be improved upon, using John Sweeney's *maximum adverse excursion* (MAE) and *maximum favorable excursion* (MFE) analysis techniques and different ways of splicing up the drawdown. We also take a closer look at a few additional measurements, such as *kurtosis* and *skew.* In many ways, Part 3 is the most important part, thanks to the exits that we later attach to a fixed fractional money management regimen that boosts the results ten-fold—at least.

With the entries from Part 2 and the exits from Part 3, Part 4 takes a closer look at different ways of filtering out favorable market situations and set-ups. A lot of the work is done using random entries to generate as many trades as possible. Using random entries, we can take only a few years' worth of data to produce as many years of unique trading sequences as we deem necessary. (In fact, after writing this book, using the techniques described in this section, I tested a system on the last ten years of data for all the Dow-30 stocks, producing a total of more than 3,000,000 years of unique trading sequences. If that doesn't produce robust results, nothing will.) At the end of this part a more theoretically oriented chapter provides the framework for understanding for what makes a trend and why it is my conviction that systematic trading is likely to work in the first place.

In Part 5, we tie it all together by combining all the systems with different fixed fractional money management strategies. We also take a closer look at how to put together a portfolio consisting of several market/system combinations, which help each other produce results that would have been impossible to achieve without all systems working in tandem under a mutually shared money management regimen. To coin a new word, what we will do is to "optisize" rather than optimize the system. The main difference between "optisizing" and optimizing is that with optimizing we are fitting the system to the data; with "optisizing" we are fitting the bet size to the system. The less optimized your system is, the more "optisized" you can make the strategy. "Optisizing" will almost always do more for your bottom line than optimizing. Most of the work is with the help of a spreadsheet program, and there will be plenty of example formulas and code that you can copy and use in your own work. Before we round off the entire book, we also take a brief look at how to test a system for robustness to further increase our confidence in it before we start using it in real life trading.

A few people have asked me why I am giving away my ideas instead of making the most of them myself. Well, the truth is that I think I *am* making the most of them, because even if this book all of a sudden tops *The New York Times* best-seller list, these systems and strategies won't be widespread enough to arbitrage away what I will show you over the next few pages. Why? Because, first of all, not everyone who reads this will use it, because they won't feel comfortable with it or because they simply don't like working with other people's ideas, but like to come up with ideas of their own. Second, even if they do use them, many will still not be able to make any money out of them, because invariably they will come up with unthought-of ways of screwing things up anyway. And last but not least, because the markets are much bigger than any of us can fathom, these strategies will still only make up a mere fraction of all strategies out there—strategies that help make these work.

In fact, I hope that these strategies will be widespread enough to reinforce and feed on themselves, making them even more profitable. If you look at it from that perspective, you are not my enemy in this, but my best friend and accomplice. My only true enemy in this game is myself. As in almost any other situation in life there are a thousand-and-one ways I will be able to screw things up without your help. So, the bottom line is that even if I give this away to you, the danger that poses to my future wealth and well-being amounts to nothing, compared to the danger I pose to myself.

Last but not least, please read the following quotation by the renowned money manager Ralph Vince, then put *Trading Systems That Work* aside for awhile and contemplate it. Because if you do not understand, or do not agree with it, there is no need for you to continue:

> "The key to ensure that you have a positive mathematical expectation in the future is to not restrict your system's degrees of freedom... This is accomplished not only by eliminating, or at least minimizing, the number of optimizable parameters, but also by eliminating, or at least minimizing, as many of the system rules as possible. Every parameter you add, every rule you add, every little adjustment and qualification you add to your system diminishes its degrees of freedom. Ideally, you will have a system that is very

primitive and simple, and that continually grinds out marginal profits over time in almost all the different markets. Again, it is important that you realize that it really doesn't matter how profitable the system is [by itself], so long as it is profitable. The money you will make trading will be made by how effective the money management you employ is. The trading system is simply a vehicle to give you a positive mathematical expectation on which to use money management. Systems that work [show at least a marginal profit] on only one or a few markets, or have different rules or parameters for different markets, probably won't work real-time for very long..."

While you are reading through the rest of the book, please feel free to visit me at my Web site, at www.ThomasStridsman.com, for updates on how to order additional material, to help me help the kids at the Children's Memorial Medical Center, or to just leave me a comment or two.

Thomas Stridsman

I

ACKNOWLEDGMENTS

Never in my whole life did I think that I would get a chance to thank everybody who has meant so much to me, both professionally and personally. Inevitably, thanking everybody would result in a thank-you note longer than the rest of the book, so I just have to settle for a few very special and recent people. Thanks to Nelson Freeburg and his family, and to Dan and Maryanne Gramza, for believing in me and recommending me for the job as a technical analysis editor for *Futures* magazine.

Thanks to Ginger Szala and Jamey Holter and all the other editors at *Futures* magazine for hiring me and believing in me as an editor at *Futures,* despite my limited English. A special thank you to my friends Jim and Margie Kharouf for helping me get settled in Chicago.

Thanks also to Jonas Vikstrom and Johan Ljung at Vikstrom, Ljung & Partners, for providing me with a state-of-the-art computer, and to Max von Liechtenstein for contributing with the very important "What makes a trend" chapter in Part 4 and for helping me refresh my micro- and macroeconomics proficiencies.

A very warm "thank you" also to Melissa Lange for teaching me everything there is to know about what an open and honest relationship is all about. To all the rest of you that I have learned to know and learned from throughout the years, know that I am forever grateful.

A last minute thanks to Patty Wallenburg for being a great sport and of tremendous help during the final editorial stages of putting this book together.

PART ONE

Evaluating Performance

With the stock market in an unprecedented up-trend and with ever decreasing prices for state-of-the-art computers, more people than ever before are playing the markets, trying to make a living (and hopefully a fortune). More and more people also try to do this in a systematic fashion, using one or several mechanical trading strategies. In the backwater of this, several program vendors now offer programs with which you can build and test your own trading strategies, or even buy and plug in strategies made by others. A couple of the most popular programs for this are Omega Research's TradeStation and Equis' MetaStock. Other programs exist, but thanks to their built-in programming capabilities, these two programs are the most popular, aimed toward the retail customer.

Thanks to its PowerEditor and EasyLanguage, TradeStation probably provides the most professional way available today for coding and evaluating your own trading strategy. Most professional market analysts (myself included) probably have a strange love-hate relationship to TradeStation. On the one hand, it provides you with the most possibilities of any program, but on the other hand, its many possibilities also reveal a few embarrassing weaknesses, especially when it comes to the evaluation process—where it shares the same weaknesses found in many other programs.

This is very important, because before you can start to build and investigate any type of trading strategy you must know what type of information to look for, and if the information is not there, come up with a way to produce it yourself. In this first part, you will learn which measurements are most important. Some of them you will be able to derive directly from TradeStation or MetaStock's performance summaries. Others must be exported into a text file with the help of each program's built-in programming capabilities, for further analysis in Excel or any other spreadsheet program. For commodity futures traders, it also is very important to use the right type of data and to remember that not all time series should be treated the same.

CHAPTER 1

Performance Measures

Which system-testing measures are likely to work and which are not? By necessity all system testing and design must be made on historical data. The trick, then, is to make as good use as possible out of this data, and to make your evaluation measures as forward-looking as possible. This chapter presents a rundown of the most commonly used measures in TradeStation's performance summary and explains which have some value, which don't, and which can be modified with the help of a spreadsheet program. But before we go on, let us start with a little quiz.

If you can choose between buying two different stocks, one currently priced at $12.50 and the other at $20, and you know for sure that the one priced at $12.50 will rise by 1.75 points over the next couple of days, while the one priced at $20 will increase 2.60 points (almost a full point more) over the same period of time, which one would you choose? If you answer the $12.50 stock, you probably understand what I am hinting at and should have little trouble understanding this part of the book.

If however, you answered the $20 stock, you probably are a little too anxiously chasing that elusive dollar. Just do the math. In this case, 12.50 divided by 20 equals 0.625, or 5/8. This means that for every 500 $20 stocks you buy you can use the same amount of money to buy, 800 $12.50 stocks. 500 times 2.60 points equals 1,300 points (or 13%) in profits if you buy $10,000 worth of the $20 stock. 800 times 1.75 equals 1,400 points (or 14%) in profits if you buy $10,000 worth of the $12.50 stock.

If you think this difference isn't much to worry about, what if you could choose among 20 trades like this for the rest of the year, being able to use the profits from each trade in the next one? Then your initial $10,000 would grow to

$115,231 if you only bought the $20 stock, but to $137,435 if you only bought the $12.50 stock. And what if you could do this for three years straight? Then your initial $10,000 would grow to $15,300,534 if you only bought the $20 stock, but to $25,959,187 if you only bought the $12.50 stock. This is a difference of more than $10,000,000 after only 60 trades.

Although these numbers are idealized, they illustrate the point that it pays to take it easy and do the math before you jump into a trade. And it is exactly this type of math that no market analysis and trading software packages allow you to do.

TOTAL NET PROFIT

Probably the most frequently used optimization measure is *total net profit.* Often, it is used together with *maximum intraday drawdown.*[1] Unfortunately, however, the total net profit is of very little value when it comes to evaluating a trading strategy's estimated future performance, no matter how rigorous the testing or how robust the system. The reason for this is twofold and depends on whether you prefer to work with only one market at a time or with a basket of markets and/or systems to make up a portfolio. What applies to the one-market case also holds true for a portfolio.

In the one-market case, the total net profit tells you nothing about when your profits occurred and how large they were in relation to each other. This is especially important if the market you are interested in is prone to trending. For instance, if the market has been in a prolonged up-trend it is likely that the dollar value of each trade has increased with the increasing dollar value of the market. This, in turn, means that the total net profit is unevenly distributed through time and mostly influenced by the very latest market action. In a down-trend the opposite holds true. Notice however, that the trend of the market says nothing about whether the system has become more robust or not. In a market with several distinctive up-and-down trends, this matter is even more complex.

In the multimarket case, the total net profit tells you nothing about how well diversified your portfolio is. This is especially true if you stick to trading an equal amount of shares for all equities, or one contract per commodity in the commodity futures market. This is because what are considered huge dollar moves in some stocks or markets are only considered to be ripples on the surface in others. You cannot, for instance, diversify a one-contract trade in the S&P 500 futures markets with a one-contract trade in corn, no matter how well your system seems to work in each market. Simply stated, the larger the market value of the market, the larger the impact on the total net profit of the portfolio.

[1] Your maximum equity loss, or loss of capital, calculated over both open and closed out profits. The term intraday indicates that this drop in equity can start at any time, at any day, and end at any time, at any day.

In the stock market, to value a system by its total net profit can take on absurd consequences when a company decides to do a stock split. For instance, say that a stock currently is trading at $90, and a trading system that consistently buys and sells 100 stocks per trade shows a historical, hypothetically back-tested profit of $150,000. Tomorrow, after the stock has been split 3:1 and the stock is trading at $30, the historical, hypothetically back-tested profit has decreased to $50,000. Does this mean that the system all of a sudden is three times as bad as the day before? Of course not; it's exactly the same system, and from this example it is easy to see that after the split you must trade the stock in lots of 300 stocks per trade to make the new results comparable with old pre-split results. Many times, however, when we need to compare different markets, over different periods of time, and traded with different systems, it is not always this easy. The following chapters teach you how to work around this dilemma and build a well-diversified portfolio that is likely to hold up in the future and continue to provide good risk protection.

MAXIMUM INTRADAY DRAWDOWN

How many of us have not heard the old adage "your worst drawdown is still to come?" While this is likely to come true sooner or later, it does not have to happen first thing tomorrow, provided you have done your homework correctly. Unfortunately, the information most system testing software provides you will not be enough, because the number given is in dollars, without any relation to where and when this bad trade sequence struck. For instance, with a point value of $250 for a S&P 500 futures contract, there is a vast difference between a $20,000 drawdown when the market was trading around 500 and a $20,000 drawdown with the market trading at 1,350. In the latter case, a $20,000 drawdown is similar to being caught in a series of bad trades for about 5% of current market value, something that can happen to anybody. In the first case, however, an equally large drawdown in dollars would amount to approximately 16% of the market value at that point in time. With the market trading at 1,350 a 16% drawdown translates to $54,000. With only the information from your regular performance summary, however, there is no way for you to find that out. No wonder then, that so many traders blow out before they even have a chance to get started. To calculate the true expected drawdown, you must first find the largest drawdown—in percentage terms—in relation to the market value when it occurred and then translate that percentage into today's market value.

Also, when evaluating your drawdown, you must know exactly what you are looking at. In TradeStation's case, the drawdown is calculated as the closed trade drawdown (CTD), plus the open trade drawdown (OTD), making up the total equity drawdown (TED) at that point in time. But this is not necessarily the best way to look at the drawdown when it comes to building a robust system. (We will explore the reasons for this throughout this book). In Part 3 we also take a look at how to divide the OTD into start trade drawdown (STD) and end trade drawdown (ETD) and how to analyze them for better entries and exits. Not until this is done should you address the CTD for a better overall performance.

ACCOUNT SIZE REQUIRED AND RETURN ON ACCOUNT

The *account size required* and *return on account* are probably the most deceiving numbers of them all. As you can see by looking at Figure 1.1, which shows the performance summary for an early version of Black Jack/Meander system in TradeStation, the account size required is the same as the value for the max intraday drawdown. But this is a purely theoretical figure produced with the help of hindsight; there is no way for you to know that number before you start trading, and there certainly is no guarantee for this value to hold up in the future.

To calculate the return on account, TradeStation simply divides the total net profit by the account size required. The main thing wrong with this number is that

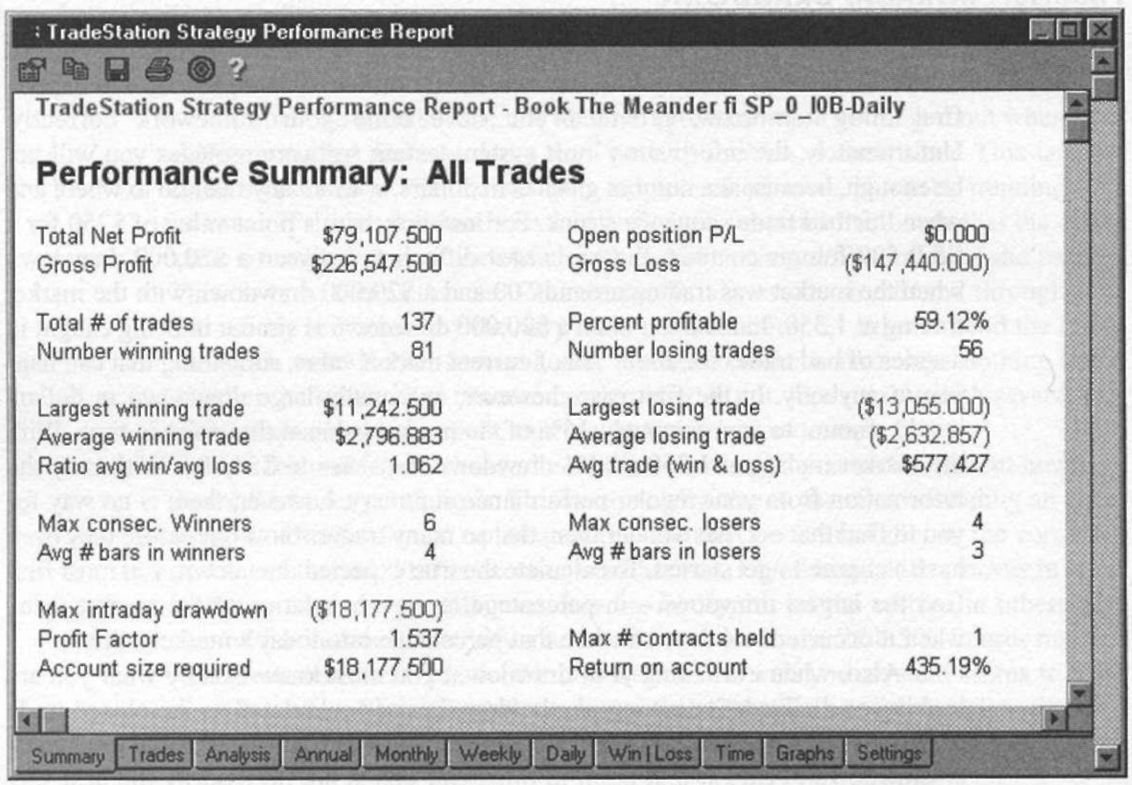


FIGURE 1.1

The performance summary for an early version of Black Jack/Meander system In TradeStation.

it is supposed to be calculated at one point in time (before you start trading) with the hindsight from two totally different points in time (during trading for the worst drawdown and when finished trading for total net profit). Perhaps even more important from a real-world point of view, no trader in his right mind would start out with a trading account that is only expected to cover his worst historical drawdown, especially because this drawdown figure has no connection to the future whatsoever and is very likely to be exceeded. Thus, because there is no way to know your exact largest future drawdown or ending equity, you have no idea about how large your trade account must be and consequently no way of estimating the return on your account either. Therefore, these two figures are completely unnecessary and provide you with no information whatsoever.

AVERAGE TRADE

One of the most important things to consider before starting to trade any system is the estimated average profit per trade in the future. Unfortunately, neither TradeStation's nor MetaStock's performance summaries give you any such forward-looking information. Basically, what can be said about the total net profit also can be said about the average profit per trade, at least as long as it is based solely on historical dollar measures. When it comes to the average profit per trade, however, the reasoning is that the trades that happened "way back when," when the market was trading at a completely different level, will impact the value of the average trade too much. For instance, if the market has traded from 1,000 points to 2,500 points, and you're trading a system based on three profitable trades, one for $100 when the markets was trading at 1,000; another for $200 when the markets was trading at 2,000; and most recently, one for $150 when the market was trading at 1,500, TradeStation will tell you that the average trade is $150. But this is not what you can expect the average trade to be now, when the market has rallied and is trading considerably higher. From this example it is not too difficult to figure out that with the market trading at the 2,500 level, the next trade is expected to show a profit of $250. A more disturbing example, however, can be seen in Figure 1.1. Here the average profit per trade is $577, while the true expected average profit per trade in today's market is $1,269 (as of October 1999).

LARGEST WINNING AND LOSING TRADES

Although the estimated largest drawdown holds information about how large your account size must be and can give you an indication of whether you have the psychological profile to trade the system in question, the information about the largest losing trade is much more important than the drawdown for money management purposes. As is the case with so many other of the most popular measures, however, the values for the largest winning trade and the largest losing trade essentially hold no value as long as you can't put them in relation to when they happened and where the market was trading at the time. Once this is known, the largest losing trade can be used to set up a fixed fractional money management strategy that most certainly will prove much more important for your bottom line than the system itself. (Fixed fractional money management is discussed in Part 5.)

GROSS PROFIT AND GROSS LOSS

If the total net profit is of little good as a performance evaluator, it should follow that so are the gross profit and the gross loss, right? Unfortunately, it is not that simple and the answer is "yes—and—no." Looked at separately, it is likely that the gross profit and the gross loss will be influenced in the very same way as the total net profit. That is, in a market prone to trending, the values of the winning and losing trades are likely to vary with the value of the market. And in a portfolio, the larger the market value of the market, the larger the impact on the gross profit and the gross loss of the portfolio. However, provided that the profits and the losses are evenly distributed through time and the relationship between them stays approximately the same over time, they can hold a wealth of information that is very useful in your initial performance evaluation. This information is derived via the profit factor.

The Profit Factor

To calculate the profit factor, simply divide the gross profit by the gross loss; the answer tells you how many dollars you are likely to win for every dollar you lose. For instance, say that you have $2 and place $1 in a bet, hoping to win $2 more, ending up with $4. The first time you try, you lose and your gross loss is $1. With your last $1, you take another chance. This time you win $2, ending up with a total of $3. Your gross profit is therefore $2. Two divided by one equals two, which is your profit factor.

Now, do the same betting sequence all over again, but this time multiply all values by 10. This time you first lose $10 and then win $20, ending up with $30. 20 divided by 10 also equals two. Hence, the profit factor is simply the relationship between dollars lost and dollars gained and, because it is a ratio, it is a way of normalizing your results to make them comparable between time frames and markets.

For the profit factor to work, it does not matter if the market has been trending or not as long as it is reasonable to assume that your profits and losses have fluctuated at an equal pace and are evenly distributed through time. For the same reason, it also is possible to use the profit factor as a comparison between different systems and markets. It is obvious that the higher the profit factor the better the system. It is even more important to determine how robust the profit factor is, than how high it is. That is, how likely is it that the profit factor will hold up in the future and in different market situations?

Many system vendors and trading experts believe that you should not trade a system with a hypothetically back-tested profit factor below three, because they know from experience that the profit factors for all their systems will decrease considerably when the system is traded live on unseen data. Probably the only reason for this recommendation is that they do not understand how to build a robust trading strategy in the first place. If nowhere else, this becomes evident when they continue to use the total net profit and drawdowns as their most important performance evaluators. To build a robust trading system that is likely to continue to perform in the future, make sure that the underlying logic is sound and simple, that the trading rules are as simple and as few as possible, and that the gross profit and the gross loss are evenly distributed through time and in relation to each other. If you manage to do all this, you will be surprised at how much you can expect to produce from a system with a profit factor as low as 1.5, or even lower.

AVERAGE WINNING AND LOSING TRADES

As is the case with gross profit and gross loss, the average winning and losing trades can hold some very valuable information if understood and treated correctly. Again, however, the trick is to measure them at today's market value. For instance, if you currently are in a drawdown and know the values of your average winner and loser and the frequency with which they are likely to occur, you can calculate the minimum estimated number of trades (and time) it should take to reach a new equity high. For instance, if you know that your average profit per trade equals $400, and you currently are in a $2,500 drawdown, the estimated number of trades to get you out of the drawdown is seven (INT(2,500 / 400) + 1).

NUMBER OF (WINNING/LOSING) TRADES AND AVERAGE NUMBER OF BARS PER TRADE

Many traders and analysts pay very little or no attention to the number of trades a system is likely to generate. But this is very important information that gives you the first clue to whether the system is suitable for you. The questions you must ask yourself are "does this system trade often enough" and "does it keep me in the market enough to satisfy my need for action?" These are seemingly silly questions at first glance, but the truth is that a specific system will not suit everybody, no matter how profitable it is. If it does not fit your personality or style of trading, you will not feel comfortable trading it.

What is even more important, however, is how much time the system is expected to stay in the market. This is because time spent in the market equals risk assumed. Therefore, the less time you can spend in the market to reach a certain profit, the better off you are. To calculate the relative time spent in the market, multiply the number of winning trades by the average number of bars[2] for the winners. Add this to the number of losing trades, multiplied by the average number of bars for the losers. Finally, divide by the total number of bars examined. Using the performance summary above, this equals approximately 0.4, which means that you will be in a trade only four days out of ten. Obviously, you also will be better off the fewer and shorter the losing trades are.

MAX CONSECUTIVE WINNERS AND LOSERS AND PERCENT OF PROFITABLE TRADES

You should try to keep the maximum numbers of consecutive winners and losers as low as possible and the percent of profitable trades as high as possible. The number of consecutive losers is especially important, if you like to feel comfortable with trading the system. For a correctly built system* however, with a relatively high number of profitable trades, these numbers hold very little value and should be looked upon more as freak occurrences than anything else. When you examine your system, it is very important to know whether the system has a tendency to produce strings of trades with similar outcomes. If it does, the system and the market are still holding valuable information that you haven't yet exploited. If you do not manage to get rid of this tendency, you need to keep this information in mind when you are designing the money management strategy to go with the system.

It also is a good idea, when monitoring your real-time performance, to keep track of how many consecutive winners it might take to bring you out of a drawdown. Continuing with the $2,500 drawdown example, it will take you four winning trades in a row to reach a new equity high if your average winning trade is worth $700 (INT(2,500 / 700) + 1). Once you know this, ask yourself how likely it is for this to happen. If the answer is it most likely happens once in a blue moon, that the most winning trades you can expect in a row are two, that it is highly likely that the losers will come in pairs, and that your average loser is for $300. Then you know that in the best of worlds, it can be expected to take at least ten trades before you are in the black again—provided that you experience two winners in a row, three times in a row, never experience more than two losers in a row, and start out with two winning trades. If you instead start out with two losing trades, taking the drawdown down to $3,100, everything else being equal, the estimated number of trades would be 16.

Together with the profit factor, the percent profitable trades is the only performance measure that can be derived immediately from the performance summary and has any value when it comes to estimating the system's future performance. Again, however, this assumes that the underlying logic is sound and

[2] A bar is a marker in a chart that shows the trader how the price of the market fluctuated over a specific time period. A bar usually shows the opening, high, low, and closing price. It can be specified to cover any time period, such as 1 minute, 1 hour, 1 day, 1 week, etc.

that the system can be considered robust. Obviously you should try to keep this number as high as possible to feel comfortable with the strategy, but, as is the case with the profit factor, a more robust number is better than a high one when it comes to the system's tradability and when picking the best money management strategy. In fact, sometimes it even is a good thing to keep this number down in favor of a higher number of profitable months for the overall strategy or portfolio. Nonetheless, with this number in hand, we now can put together a more generic formula to calculate the estimated number of trades, N, to get out of a drawdown:

N = INT(DDA / (X * AW - (1 - X) * AL)) + 1, where

DDA = Drawdown amount

X = Likelihood of a winner, between zero and one

AW = Average winner

AL = Average loser

For example: If the average winning trade is worth $700, the average losing trade $300, and the likelihood of a winner is 45%, then the estimated number of trades it will take to bring you out of a $2,500 drawdown is 17. Furthermore, if the average trade length is five days and the total amount of time spent in the market is 33%, then it will take you an estimated 250 trading days (17 5 + 0.33) to get out of the red again, not counting weekends and holidays. That is almost a full year's worth of trading to get out of a situation that, at a first glance, only seems to require "just a few good trades."

This equation shows that trading is a very deceptive business, and that we had better make sure that we know what we are doing. Note also that in this example we are working with dollar amounts and a fixed number of contracts traded on one market only. In upcoming sections, where we start working with percentages and an ever-changing number of contracts traded on a wide variety of both markets and systems, this matter becomes even more complex.

CODE

This chapter discussed which of TradeStation and MetaStock's performance summary measures are likely to work and which are not. The only two measures that you can put to immediate use are the profit factor and the percent profitable trades. With the code below, you can create a file that exports this information to a spreadsheet program, together with the time spent in the market. This can come in handy if you, for instance, want to compare the same system on a wide variety of markets, or several variations of the same system on one market during the initial steps of the building process. By interchanging the SysVer input with all your other inputs, you can keep track of which version of the system each row refers to.

In the next chapter we show how to use TradeStation's EasyLanguage to export more data into Excel for further analysis, and how to come up with a new set of forward-looking evaluation measures that are better suited to holding up in the future and helping you to build more robust and reliable trading strategies.

```
Inputs: SysVer(O);
Vars: PFactor(O), WTrades(O), TotBars(O), TradeStrl("");
If CurrentBar = 1 Then Begin
    TradeStrl = "Market" + "," + "Version" + "," + "P factor" + "," + "%
    Winners" + "," + "% in trade" + NewLine;
    FileAppend("C:\Temp\Chap 1 -1 .csv", TradeStrl);
End;
If LastBarOnChart Then Begin
    PFactor = GrossProfit / -GrossLoss;
    WTrades = NuraWinTrades * 100 / TotalTrades;
    TotBars = (TotalBarsLosTrades + TotalBarsWinTrades) * 100 / BarNumber;
    TradeStrl = LeftStr(GetSymbolName, 2) + "," + NumToStr(SysVer, 0) +
    "," +     NumToStr(PFactor, 2) + "," + NumToStr(WTrades, 2) + "," +
    NumToStr(TotBars, 0) + NewLine;
    FileAppend("C :\Temp\Chap 1-1 .csv", TradeStrl);
End;
```

CHAPTER 2

Better Measures

So far, most testing packages (and back-adjusted time series for the commodity futures markets) have only allowed you to back-test your strategies using dollar values. This is all fine and well if you are only interested in how much money you could have made had you been able to trade your strategy in the past. The main disadvantage with this way of testing, however, is that it tells you very little about how well your strategy is likely to hold up in the future. To achieve this, a whole new set of performance measures must be put together. In this chapter, we take a closer look at how to export the necessary data from your system trading software into a text file and how to calculate this new set of performance measures in a spreadsheet program.

In essence, what you must do is to calculate all the necessary values in percentage terms rather than in dollars or points. In this way, you will be able to perform more accurate comparisons of how a system is likely to work in different markets and time frames. For instance, say that a market (the S&P 500) currently is trading at 1,350 and that each point move is worth $250. If this market rises 1%, that move is worth $3,375 (1,350 X 0.01 X 250). But if the same percentage move happened "way back when," when the market was trading at 250, a 1% move was only worth $625 (250 X 0.01 X 250). If the market value increases, it is likely that the dollar moves increase as well, while the percentage moves are likely to remain approximately the same. (For proof of this, see Figures 2.1 through 2.3.) Thus, by using percentage-based calculations, you give each and every trade an opportunity to influence your strategy to an equal degree and you are able to build better and more reliable strategies, which are more likely to hold up in the future. The same reasoning can also be applied to a comparison of different markets with different market values. Once you are done with your percentage-based calculations, you can transform them into dollar values based on where the market is trading today.

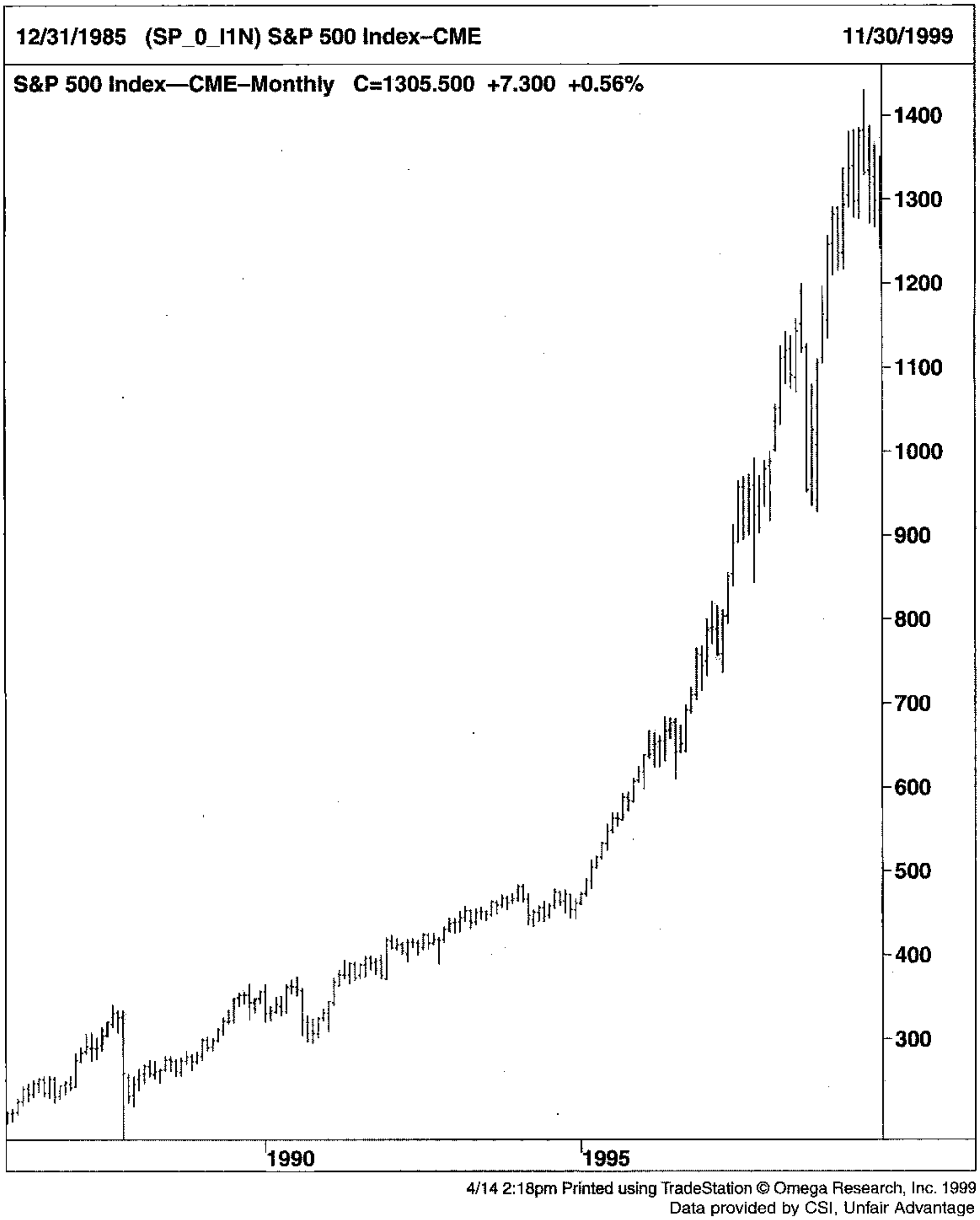


FIGURE 2.1

The higher the market value, the higher the point-based volatility.

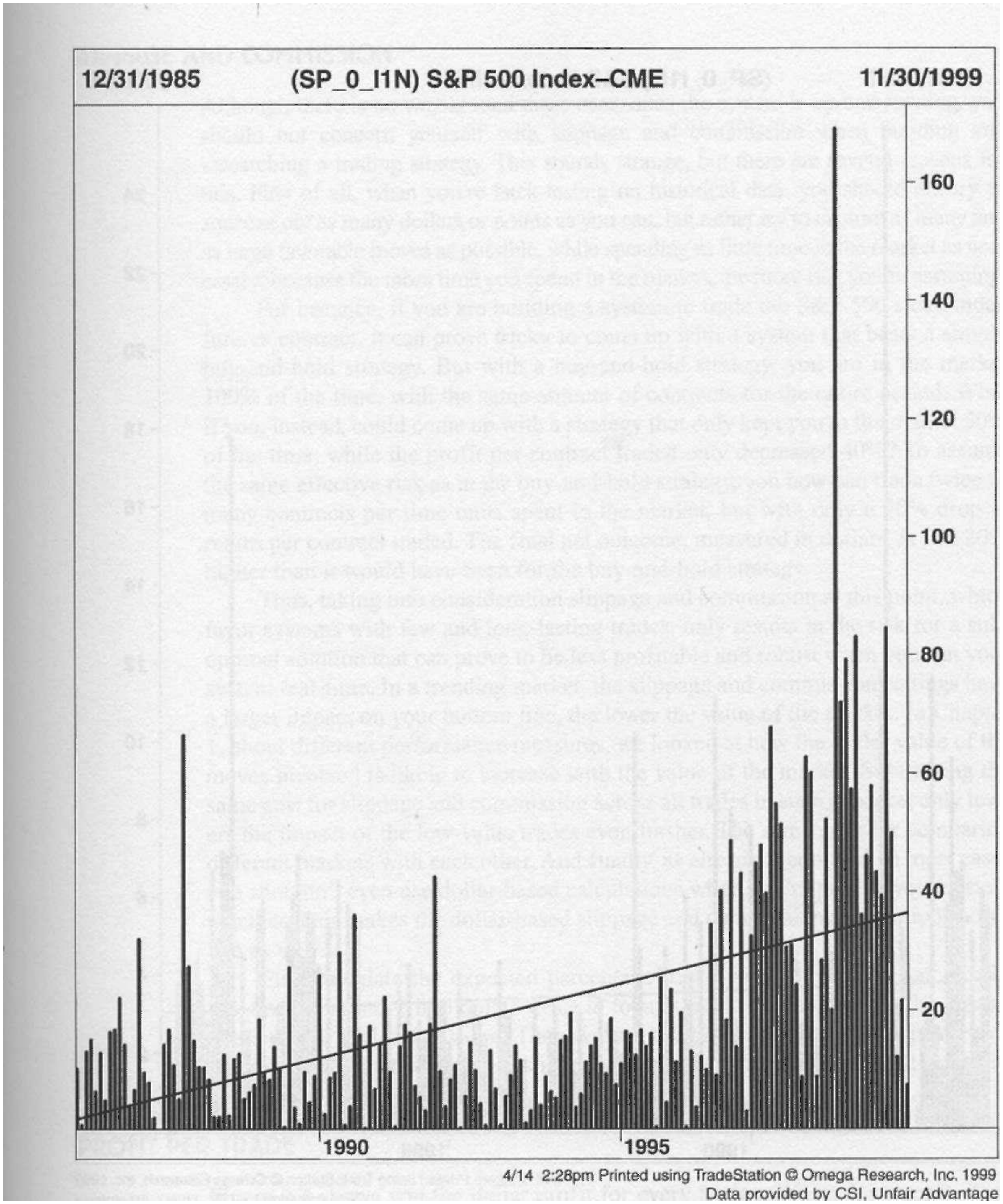


FIGURE 2.2

Least-square regression line of the point-based volatility.

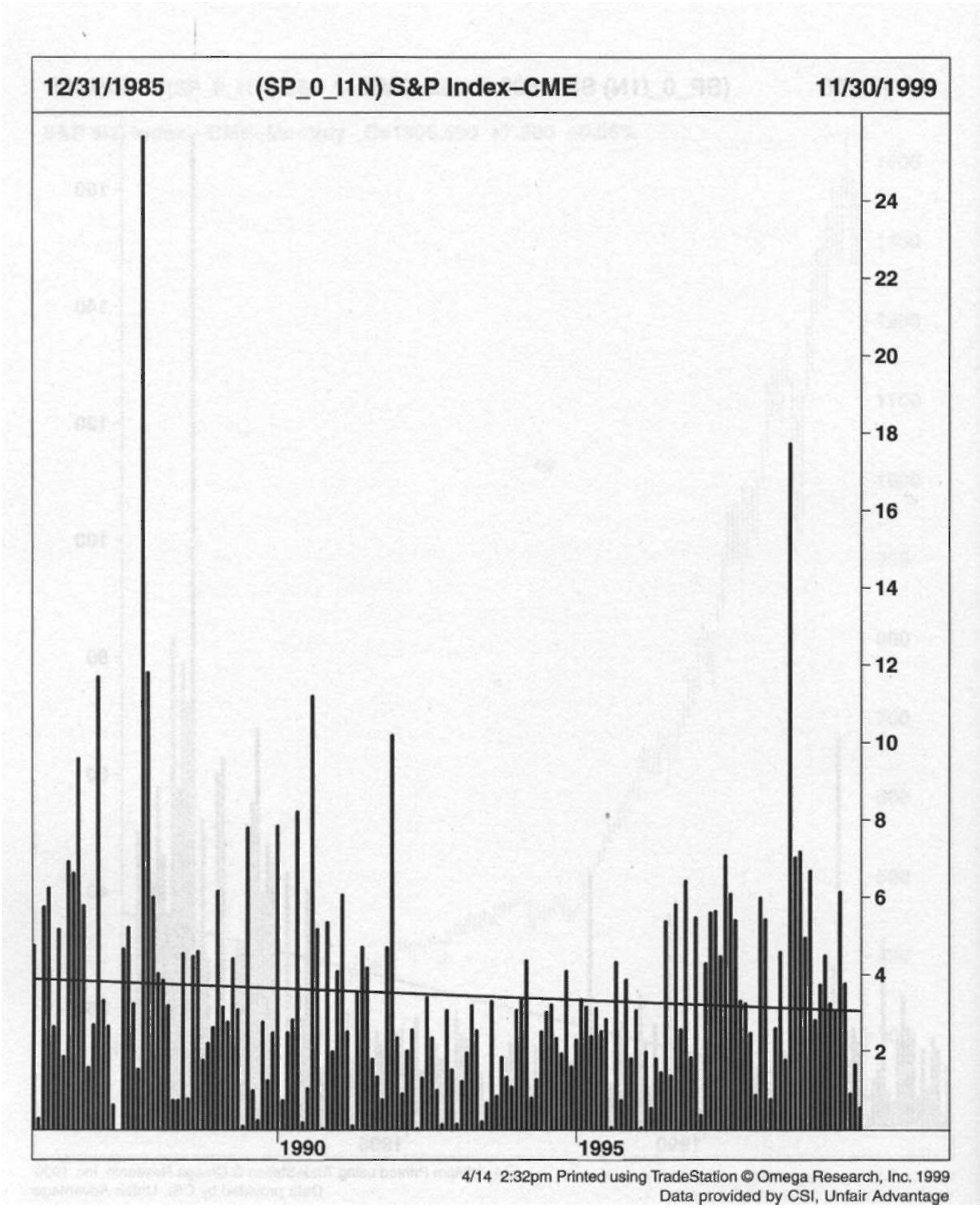


FIGURE 2.3

Least-square regression line of the percentage-based volatility.

SLIPPAGE AND COMMISSION

Although there is no way around these costs once the system is up and running, you should not concern yourself with slippage and commission when building and researching a trading strategy. This sounds strange, but there are several reasons for this. First of all, when you're back-testing on historical data, you should not try to squeeze out as many dollars or points as you can, but rather try to capture as many and as large favorable moves as possible, while spending as little time in the market as necessary, because the more time you spend in the market, the more risk you're assuming.

For instance, if you are building a system to trade the S&P 500 stock index futures contract, it can prove tricky to come up with a system that beats a simple buy-and-hold strategy. But with a buy-and-hold strategy, you are in the market 100% of the time, with the same amount of contracts for the entire period. What if you, instead, could come up with a strategy that only kept you in the market 50% of the time, while the profit per contract traded only decreased 40%? To assume the same effective risk as in the buy-and-hold strategy, you now can trade twice as many contracts per time units spent in the market, but with only a 40% drop in return per contract traded. The final net outcome, measured in dollars, is still 20% higher than it would have been for the buy-and-hold strategy.

Thus, taking into consideration slippage and commission at this point, which favor systems with few and long-lasting trades, only results in the risk for a suboptimal solution that can prove to be less profitable and robust when you run your system real-time. In a trending market, the slippage and commission settings have a larger impact on your bottom line, the lower the value of the market. In Chapter 1, about different performance measures, we looked at how the dollar value of the moves involved is likely to increase with the value of the market. Subtracting the same cost for slippage and commission across all trades in such a market only lowers the impact of the low-value trades even further. The same goes for comparing different markets with each other. And finally, as already mentioned, in most cases you shouldn't even use dollar-based calculations when you're putting your system together. This makes the dollar-based slippage and commission assumptions obsolete as well.

First calculate the expected percentage move you are likely to catch, then transform that move into dollar terms in today's market by multiplying by today's market level and point value. Then deduct the proper amount for slippage and commission. If this dollar value still looks good enough, you should take the trade.

PROFIT PER TRADE

Figure 2.4 shows you the dollar profit for every trade made with a simple stock index and bond system traded on historical data for the S&P 500 stock index future contract, using dollar-based calculations. Notice how the profits and loss-

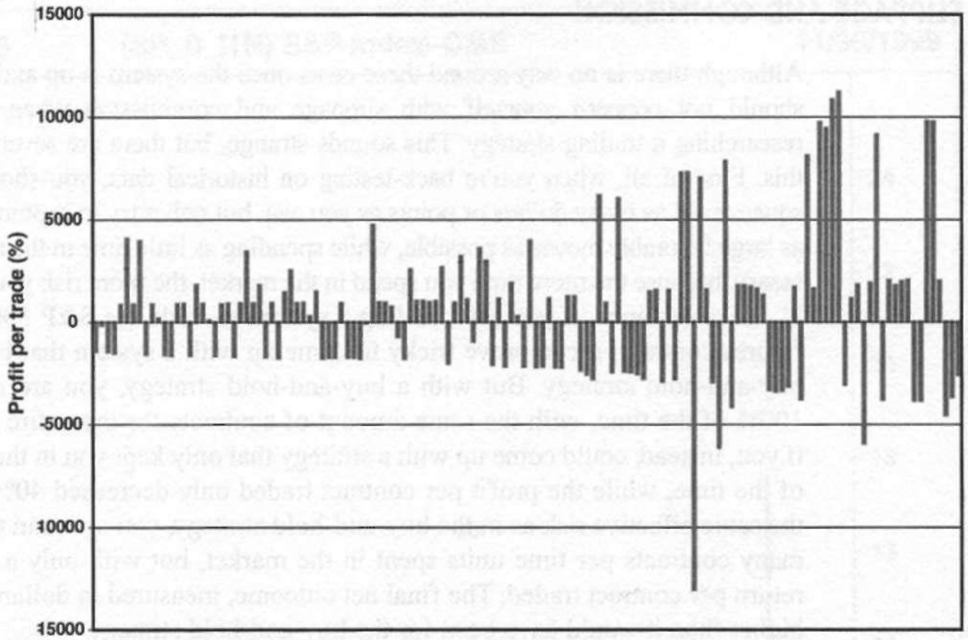


FIGURE 2.4

The dollar value of a series of Individual trades.

es per trade have increased dramatically for the last hundred trades or so. In this case, the average profit per trade comes out to $755, which also can be seen in Figure 1.1. Now, contrast this to Figure 2.5, which shows the same sequence of trades but this time with percentage-based calculations. Notice how the profits and losses per trade now are much more evenly distributed in time and come out to $1,269, based on a 0.38% average profit per trade and a market value, (in today's marketplace), of 337,500 (1,350 X 250). If you were to start using this system today (and provided that it is robust and your reasoning is sound), this is the average profit per trade that you could expect to make in the immediate future. Not $755, as implied by the performance summary. That is, by measuring the profit per trade in dollars, for a robust system, the value for both the profits and the losses increases (decreases) at the same rate at which the market trades higher (lower). This in turn gives more weight to the more distant results and consequently lowers (raises) the value of the average trade. Measuring the profit per trade in percentages, however, all trades are given an equal weighting. For a robust system, the percentage returns for both the profits and the losses stays the same no matter what the market is doing. Once the system building process is over, it is easy to transform the average percentage return into a dollar value applicable to today's market situation.

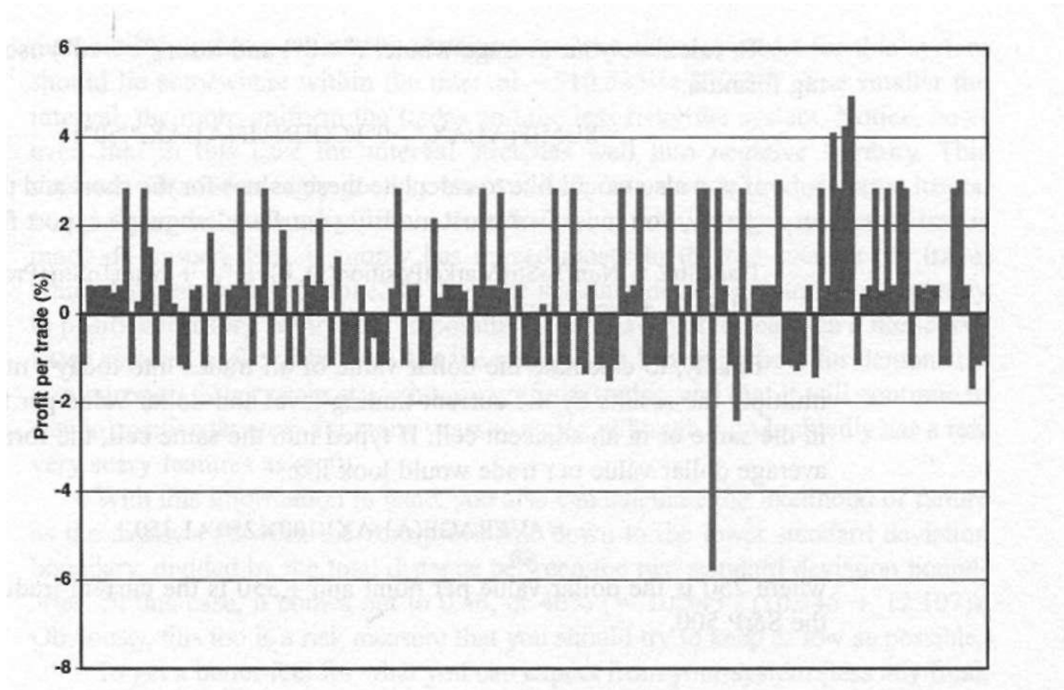


FIGURE 2.5

The same sequence of trades as in Figure 2.4 but with percentage-based calculations.

To calculate the percentage profit per trade in TradeStation you can use the following Easy Language code:

```
Vars: TotTr(O), Prof(0);
TotTr = TotalTrades;
If TotTr > TotTr[l] Then Begin
    Prof = 1 + PositionProfit(l)/(EntryPrice(l) X BigPointValue);
```

To export your data to a text file, the EasyLanguage code is as follows:

```
Vars: Prof(0), TradeStr2("");
TradeStr2 = NumToStr((Prof - 1) XI00, 2) + NewLine;
File Append("C:\Temp\Chap 1-2.csv", TradeStr2);
```

Once in Excel (or the spreadsheet program of your choice), type in the following formula at the bottom of the column where the data are stored:

=AVERAGE(A1 :AX)

where *A* denotes the column for data stored and *X* denotes the number of rows/trades.

To calculate your average winner (">0") and loser ("<=0") use the following formula:

=SUMIF(A1 :AX,">0")/COUNTIF(A1 :AX,">0")

If you also would like to calculate these values for the short and the long side respectively, you must first must modify your EasyLanguage export function to:

```
TradeStr2 = NumToStr(MarketPosition(l), 0) + "," + NumToStr((Prof - 1)
X100, 2) + NewLine;
```

Finally, to calculate the dollar value of all trades into today's market value, multiply the results by the current trading level and dollar value per trade, either in the same or in an adjacent cell. If typed into the same cell, the formula for the average dollar value per trade would look like:

=AVERAGE(A1: AX)/100 X 250 X1,350,

where 250 is the dollar value per point and 1,350 is the current trading level for the S&P 500.

LARGEST WINNING/LOSING TRADE

From a money management standpoint, it is much more important to know your largest losing trade than to know your drawdown. To calculate your largest winning trade, type in the following formula in the spreadsheet:

=MAX(A1:AX)

where *A* denotes the column for where the data is stored, and *X* denotes the number of rows/trades.

And for your largest losing trade, the formula is:

=MIN(A1:AX)

where *A* denotes the column for where the data are stored, and *X* denotes the number of rows/trades.

It also is very important, from a money management standpoint, to keep all trades as uniform as possible. Therefore, it is of importance to know your standard deviation intervals. To calculate the standard deviation interval for all trades, type in the following formula in Excel:

=STDEV(A1:AX)

To get the two standard deviation interval, simply multiply by two. In our case, with the system traded on the S&P 500 stock index futures contract, this interval comes out to 0.23% ± 3.36%, or $781 ± 11,326 in dollar terms in today's market. This means, with 95% certainty, the true average profit for this system should lie somewhere within the interval —$10,545 to $12,107. The smaller the interval, the more uniform the trades and the less risky the system. Notice, however, that in this case the interval stretches well into negative territory. This explains why a seemingly good system suddenly can start to produce large losers. Many times the system has not broken down, but with a large number of trades made on unseen data, it simply has moved closer to its true average per trade, which happens to be negative. To keep the standard deviation interval completely in positive territory is virtually impossible, and I have yet to see such a non-curve fitted system. In fact, I believe that the system that I'm using here for demonstration purposes is very robust, with very uniform trades, and that it will continue to stay in positive territory for many years to come, although it undoubtedly has a few very scary features as well.

With this information in hand, you also can calculate the likelihood of failure as the distance between the zero-profit line down to the lower standard deviation boundary, divided by the total distance between the two standard deviation boundaries. In this case, it comes out to 0.46, or 46% (= 10,545 / (10,545 + 12,107)). Obviously, this too is a risk measure that you should try to keep as low as possible.

To get a better feel for what you can expect from your system (less any freak occurrences) and depending on what type of system you're building/trading, it also may be a good idea to weed out all outlayer[1] trades before you continue to investigate it further. Remember, however, that some systems' sole purpose is to catch as many "outlayers" as possible, to make up for long strings of expected small losses. It also is questionable to weed out too many (if any at all) losers and, hence, fool yourself into believing that your system is better than it really is, especially considering that you cannot rule out that the true, future value of the average trade easily could be negative.

CUMULATIVE PROFIT AND EQUITY TOPS

The cumulative profit isn't really of any interest at this point, but is only needed to calculate other important measures such as drawdowns and *flat times* (the time spent between two equity highs). To calculate and export the cumulative profit and equity tops in TradeStation's EasyLanguage you can use the following formulas:

```
Vars: CumProf(l), ETop(0), TradeStr2("");
CumProf = CumProf x Prof;
ETop = MaxList(ETop, CumProf);
TradeStr2 = NumToStr((CumProf - 1) X 100, 2) + "," + NumToStr((ETop - 1)
```

[1] An outlayer trade is a trade that is judged to be so far away from the average trade that it can be considered a "freak occurrence". Usually trades that are more than three standard deviations away from the average trade are considered outlayers.

```
X 100,2) - NewLine;
FileAppend("C:\Temp\Chapl-2.csv",TradeStr2);
```

The plot in Figure 2.6 shows the cumulative, percentage-based equity curve for a version of the Black Jack system. The trick is to make all lines coincide with each other as much as possible and keep the "boxes" as small and as few as possible. The squiggly line is the cumulative profit, the upper straight line depicts the latest equity peak, and the lower straight line is the latest equity drawdown.

The reason the cumulative profit is of lesser interest at this point is that as long as the system is considered to be robust, with a stable profit factor and a constant relative amount of winners, and has a positive expectancy per trade based on today's market value and less expected costs for slippage and commission, the final equity growth is only a result of how aggressively you choose to trade it and/or what type of money management strategy you use.

Also, in the calculation above we are assuming that the entire equity, including previously made profits, is being reinvested each time. This is not all that correct, especially not in the futures markets, but could be so in the stock market, provided that you can buy fractions of a share. What it does allow you to do, however, is to compare different systems and markets with each other on an equal basis, or test how

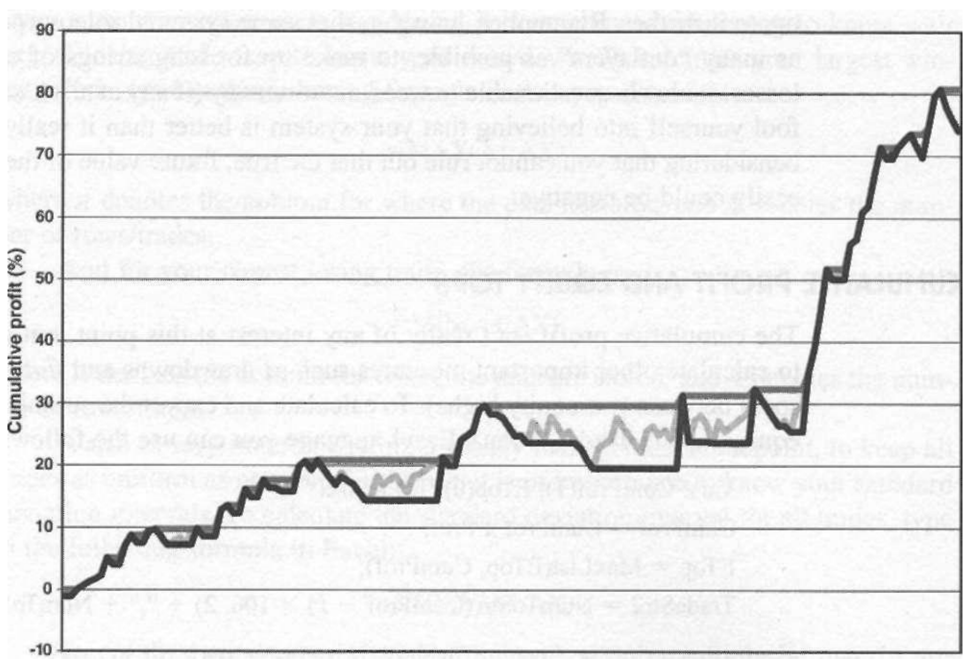


FIGURE 2.6

The cumulative, percentage-based equity curve for a version of the Black Jack system.

your strategy would have held up compared to a buy-and-hold strategy over the same time period.

DRAWDOWN

Many traders and analysts prefer to calculate the drawdown as the maximum intra-trade drawdown, or total equity drawdown (TED), including both closed trade drawdown (CTD) and open trade drawdown (OTD) in the same figure. To build a robust trading system, however (as already mentioned in Chapter 1), this is not the way to go about finding the optimal solution. The problem really consists of several parts. First, you must make each and every trade as efficient as possible, by dividing the OTD into the start trade drawdown (STD) and the end trade drawdown (ETD). This is achieved by a trade-by-trade efficiency analysis primarily using John Sweeney's maximum adverse excursion (MAE) and maximum favorable excursion (MFE) techniques *{Campaign Trading: Tactics and Strategies to Exploit the Markets* [Wiley Finance Editions, 1996] and *Maximum Adverse Excursion: Analyzing Price Fluctuations for Trading Management* [Wiley Trader's Advantage Series, 1997]).

Once this is done, you should have a trade management technique that will let you trade (at least marginally) profitably over a wide variety of markets, time frames, and market conditions, no matter what entry technique you use. Then, and only then, should you finalize your entry technique and start to look for a high probability filter technique to combine with your trade-by-trade management. The drawdown numbers you then come up with should be for closed out trades only.

As mentioned, the drawdown really isn't that interesting when it comes to deciding whether a system is robust and profitable enough to trade. But that doesn't free you from the responsibility to investigate it as thoroughly as you can to make sure that you're properly capitalized when you start trading. Take another look atTradeStation's performance summary in Figure 1.1. This system has a drawdown of $18,178. "Great," you think: "I can stomach a drawdown of less than $20,000, and if I start out with $60,000, the worst expected drawdown will only make up a third of my initial capital." But nowhere does it say when in time this drawdown happened or how large it was in relation to where the market was trading at the time (in this case it happened during mid-1998, when the market was trading around the 1,000 level).

A good way to get a feel for the drawdown for any trading strategy is to chart it as a so-called *underwater equity curve,* as in Figure 2.7, which shows the depth of the historical drawdown. From this chart you can see that the worst equity dip for this system is about 8%, which corresponds to approximately $27,000 in today's market value (1,350 X 250 X 0.08). This, in turn would have taken away close to 50% of your initial equity of $60,000, as mentioned above. If you do not want to experience a drawdown of, for instance, one-third of your equity right off the bat, you would need an initial trading capital of at least $81,000 were you to start trad-

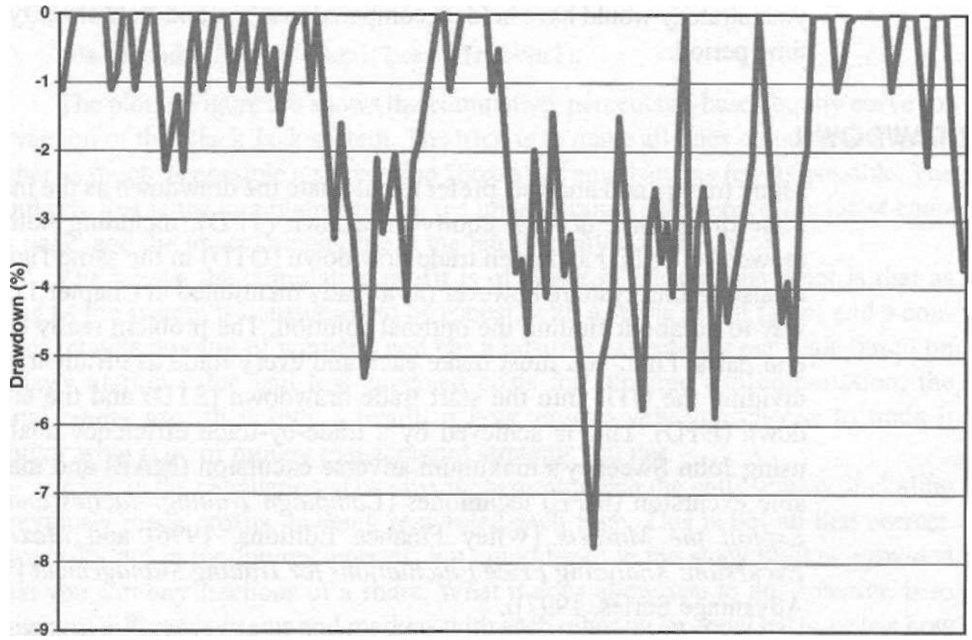


FIGURE 2.7

The underwater equity curve measures the depth of the historial drawdowns.

ing this system today. To come to the necessary conclusions, the drawdowns must be measured in percentages and then transformed into today's market value.

Only the most risk-seeking people, who thrive on stomach aches and sleepless nights, would trade a system with an expected drawdown closing in on 50% of their equity. That is in addition to all those who do not know that the expected drawdown of their system usually is much higher than what their system trading software's performance summary tells them. Remember also that your worst drawdown is always still to come. In fact, not only is your worst drawdown still to come—the truth is that you will eventually be completely wiped out. It is only a question of how long you stick around. If we all stick around long enough, the probabilities have it that we all will be wiped out sooner or later. It is just a matter of time. The trick then, is to do your homework as well as possible so that you can keep disaster in front of you and quit while you are still ahead. (Or, as in the case above, avoid getting started in the first place.)

This little piece of TradeStation code shows you how you can export the necessary drawdown information for your closed out trades to a text file for further analysis in Excel:

```
Vars: CumProf(l), EBot(O), EDraw(O), TradeStr2("");
EBot = MinList(EBot, CumProf);
```

```
EDraw = CumProf / ETop;
TradeStr2 = NumToStr((EBot - 1) X 100, 2) + '*," + NumToStr((EDraw - 1) X
100, 2) + NewLine;
FileAppend("C:\Temp\Chapl-2.csv",TradeStr2);
```

From Figure 2.7 it also is evident that this system will keep you in the red an awfully long time and only on occasion will you be able to get back to the surface and set a new equity high. Even the best of systems will spend most of their time in drawdowns.

FLAT TIME AND RUN UPS

Take a look at Figure 2.6 again. This looks like a pretty decent equity curve with a steady upward slope and tolerable drawdowns. But how long do you have to spend between two equity highs? This is revealed in Figure 2.8, which shows the so-called *flat time,* the time spent between two equity highs. (There is a risk of confusion of terms here. For many analyst and traders, flat time means the time spent in between trades, or in a directionally neutral position. In this book, however, this alternative interpretation only makes up a part of the total flat time, as

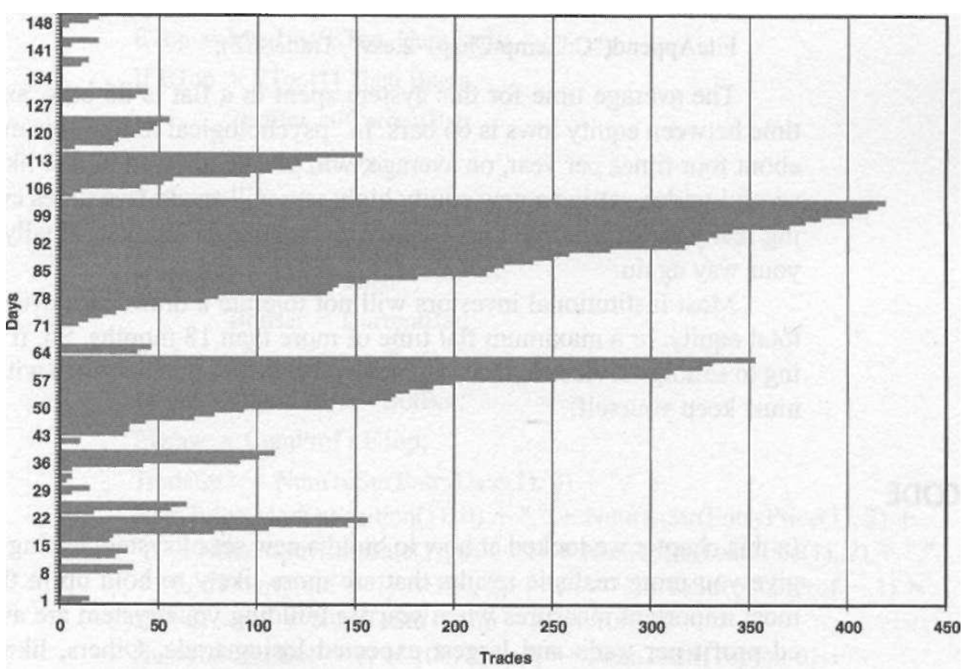


FIGURE 2.8

The flat time measured as the time spent between two equity highs.

we define it.) A good system should have a maximum flat time of no longer than 18 months. In this case, with a flat time of little more than 400 days, we come pretty close to what is tolerable.

If you started to trade this system just prior to this drawdown, you would have started out losing, stuck it out for approximately 1.5 years just to get your money back, and eventually broke even. But don't despair; drawdowns are simply something you have to learn to live with and the truth of the matter is that even the most robust and profitable trading strategies will keep you feeling on your way down more often than on your way up.

To chart the time spent between two equity highs and to calculate the average, you must add the following EasyLanguage code (which also allows you to calculate the time spent between equity lows) to the system:

```
Vars: Etop(0), TopBar(O), EBot(O), BotBar(O), TopInt(O), Botlnt(O);
IfETop > ETop[l]Then
	TopBar = CurrentBar;
IfEBot < EBot[l]Then
	BotBar = CurrentBar;
Toplnt = CurrentBar — TopBar;
Botlnt = CurrentBar - BotBar;
TradeStr2 = NumToStr(TopInt, 0) + "," + NumToStr(BotInt, 0) + NewLine;
FileAppend("C:\Temp\Chap 1 -2.csv", TradeStr2);
```

The average time for this system spent in a flat is 86 bars, and the average time between equity lows is 66 bars. In "psychological terms" this means that only about four times per year, on average, will you be allowed to feel like a really successful trader, setting a new equity high; you will spend five times every year feeling really rotten, setting a new equity low before the markets finally start to move your way again.

Most institutional investors will not tolerate a drawdown over 30 to 35% of total equity, or a maximum flat time of more than 18 months. So, if you are aspiring to selling services to the "big money," these are the measures within which you must keep yourself.

CODE

In this chapter we looked at how to build a new set of system testing measures that give you more realistic results that are more likely to hold up in the future. The most important measures when you are building your system are average expected profit per trade and largest expected losing trade. Others, like the expected drawdown and expected flat time, are only of interest from a psychological point of view, as long as you can keep them within tolerable levels. However, all variables must be examined equally thoroughly. If you do not feel comfortable with all of them, you probably are bound to lose, no matter what the market is doing or how well the same system seems to be working for others.

Below is all the code used in this chapter, put together into one piece:

```
Vars: FName(""), TotTr(O), Prof(0), CumProf(l), ETop(l), TopBar(O), Toplnt(O),
BotBar(O), Botlnt(O), EBot(l), EDraw(l), TradeStr2("");
If CurrentBar = 1 Then Begin
        FName = "C:\Temp\" + LeftStr(GetSymbolName, 2) + ".csv";
        FileDelete(FName);
TradeStr2 - "E Date" + "," + "Position" + "," + "E Price" + "," + "X Date" +
"," + "X Price" + "," + "Profit" + "," + "Cum. prof." + "," + "E-Top" + "," +
"E-Bottom" + "," + "Flat time" + "," + "Run up" + "," + "Drawdown" +
NewLine;
        FileAppend(FName, TradeStr2);
End;
TotTr = TotalTrades;
If TotTr > TotTr[l] Then Begin
        Prof = 1 + PositionProfit(l)/(EntryPrice(l) X BigPointValue);
        CumProf = CumProf X Prof;
        ETop = MaxList(ETop, CumProf);
        Tf ETop > ETop[l] Then Begin
                TopBar = CurrentBar;
                EBot = ETop;
        End;
        EBot = MinList(EBot, CumProf);
        IfEBot<EBot[l]Then
                BotBar = CurrentBar;
        Toplnt = CurrentBar - TopBar;
        Botlnt = CurrentBar - BotBar;
        EDraw = CumProf / ETop;
        TradeStr2 = NumToStr(EntryDate(l), 0) + "," +
        NumToStr(MarketPosition(l), 0) + "," + NumToStr(EntryPrice(l), 2) +
        "," + NumToStr(ExitDate(l), 0) + "," + NumToStr(ExitPrice(l), 2) + ","
        + NumToStr((Prof - 1) X 100, 2) + "," + NumToStr((CumProf - 1) X
        100, 2) + "," + NumToStr((ETop - 1) X 100, 2) + "," +
        NumToStr((EBot - 1) X 100, 2) + "," + NumToStr(TopInt, 0) +
        "," + NumToStr(BotInt, 0) + "," + NumToStr((EDraw - 1) X 100, 2) +
        NewLine;
```

```
    FileAppend(FName, TradeStr2);
End;
```

Once you have exported all the necessary data into Excel or any other spreadsheet program, you can use it to put together your own performance summary, which will be much more telling about your system than any other performance summary you are likely to find in any other program. From now on, we will work extensively with a type of performance summary that resembles that in Table 2.1.

To put together a performance summary like this, type the following formulas into your spreadsheet program:

For the average percentage profit, in cell C(X+4):

=AVERAGE(F$2: FX)/100

where *F* denotes the column where you have stored the profit from each individual trade, and *X* denotes the number of rows/trades.

For the standard deviation in percent, in cell C(X+5):

= STDEV(F$2:FX)/100

For the number of winners, in cell F(X+2):

=COUNTIF(F$2:FX,">0"),

For the largest (%) winner, in cell F(X+3):

=MAX(F$2:FX)/100

For the average (%) winner, in cell F(X+4):

=SUMIF(F$2:FX,">0")/COUNTIF(F$2:FX,">0")/100

For the cumulative (%) profit, in cell F(X+5):

=GX/100

where *G* denotes the column where you have stored the cumulative profit.

For the number of losers, in cell I(X+2):

TABLE 2.1

Example of performance summary.

Total trades		150	Winners	92	61.33%	Losers	58	38.67%
Profit factor		1.80	Lrg winner	4.88	16,470	Lrg loser	-5.74%	-19,373
Avg profit	0.38%	1,269	Avg winner	1.38	4,667	Avg loser	-1.22%	-4,121
St Dev	1.61%	5,421	Cum profit	74.12	250,155	Drawdown	-7.76%	-26,190

=COUNTIF(F$2:FX,"<=0")

For the largest (%) loser, in cell I(X+3):

MIN(F$2:FX)/100

For the average (%) loser, in cell I(X+4):

=SUMIF(F$2 :FX," <=0")/COUNTIF(F$2:FX," <=0")/100

For the largest (%) drawdown, in cell I(X+5):

=MIN(L$2:LX)/100

where *L* denotes the column for where you have stored the drawdown.

For today's dollar value of the average trade, in cell D(X+4):

=C(XX4)X 1350X250

where 1350 denotes today's index value, and 250 denotes dollar value per point.

For today's dollar value of the standard deviation, in cell D(X+5):

=C(X+5)X 1350X250

For the number of trades, in cell D(X+2):

=F(X+2)+I(X+2)

For the percentage of winners, in cell G(X+2):

=F(X+2)/D(X+2)

For today's dollar value of largest winner, in cell G(X+3):

=F(X+3)X 1350X250

For today's dollar value of average winner, in cell G(X+4):

=F(X+4)X 1350X250

For today's dollar value of the cumulative profit, in cell G(X+5):

=F(X+5)X 1350X250

For the percentage of losers, in cell J(X+2):

=I(X+2)/D(X+2)

For today's dollar value of largest loser, in cell J(X+3):

=I(X+3)X 1350X250

For today's dollar value of average loser, in cell J(X+4):

=I(X+4)X 1350X250

For today's dollar value of the largest drawdown, in cell J(X+5):

=I(X+5)X 1350X250

For the profit factor, in cell D(X+3):

=ABS((F(X+2) X G(G+4))/(I(X+2) X J(X+4)))

CHAPTER 3

Futures Contract Data

In Chapters 1 and 2 we looked at those performance measures that could be derived directly from TradeStation's performance summary, and those that we had to export into a spreadsheet program for further analysis to make them more forward looking. In Chapter 2 we also concluded that to achieve the latter, we had to base our calculations on percentages rather than dollars or points.

If you are a commodity futures trader, one of the main hurdles to overcome when testing trading strategies on historical futures data is the limited life span of a futures contract. To overcome this, various methods have been invented to splice several contracts together to form a longer time series. In this chapter, we take a closer look at these different methods, look at their pros and cons, and explore suggestions on when and how to use them. This is especially important when it comes to making your system reports as forward-looking as possible, using the percentage-based calculations described in the previous chapter.

There are three different methods to go about splicing contracts together. The *nonadjustment method,* the *back-adjustment method,* and the *perpetual-adjustment method.* The back-adjustment method can further be subdivided into *point-based adjusted* and *ratio-adjusted.*

NONADJUSTED DATA

With the nonadjustment method, you simply stop charting one contract when it expires or when you otherwise deem it justifiable to do so and continue to chart the next contract in line, which now is the new front contract. Usually, this coincides with when the market as a whole moves from one contract to the next, resulting in an increase of the open interest for the new front contract surpassing the open interest for the old contract. Many traders, however, prefer to roll over on a certain day of the month or when there are a certain number of days left on the life of the old contract. If there happens to be a difference in price between the new and the old contract, it is left unadjusted.

The main advantage of the nonadjusted time series is that, at each point in time, it shows you exactly how the front contract at that particular time was traded, with all trading levels and price relationships intact and exactly as they appeared in real life. Figure 3.1 illustrates what this looked like for the December contract on the S&P 500 index during the crash of 1987. From the high of 333 on October 2, the market fell a total of 152 points, or $38,000 (152 X 250) to the low of 181 on October 20. In percentage terms, this equals a drop of 45.6% (152 / 333) of the total market value (remember these numbers).

The main disadvantage of the nonadjustment method is the difference in price that frequently appears on the day of the roll, which will distort your back-testing results. Therefore, nonadjusted data is best for day traders or other commodity futures traders with very short trading horizons, who more often than not close out all their trades at the end of the day. With the TradeStation code provided in Chapter 1 and 2 it is easy to export all trading results from several different and separately tested contracts into the same spreadsheet for a combined analysis.

POINT-BASED BACK-ADJUSTED DATA

Most markets trade at cither a premium or a discount the longer in time you look. If we continue to use the S&P 500 as an example, it usually trades at a premium, meaning that the new front contract usually trades slightly higher than the old one on the day of the roll. Had you been in an open position at this time, during your historical profit testing, this difference would have been added or subtracted to the result of that particular trade. Over time, this error adds up. To overcome the distortions on the historical systems testing results induced by the nonadjustment method, the point-based back-adjusted contract was invented.

If the new front contract is trading at a premium compared to the old contract, the entire historical time series leading up to the roll is adjusted upward by that distance. For instance, if, on the day of the roll, the new contract closes at 1,309.5 and the old contract at 1,296.9, and the day before at 1,318.6, the entire time series up to that point of the roll is adjusted upward by 12.60 points (1,309.5 — 1,296.9), resulting in a new artificial value of 1,331.2 for the last close used from the old contract (12.6 + 1,318.6). A similar but opposite adjustment takes place each time the new contract is traded at a discount.

Figure 3.2 shows what the October 1987 market action looks like using a point-based back-adjusted contract, with the latest roll made in September 1999. In this chart, the high on October 2 is at 567.35 and the low on October 20 is at

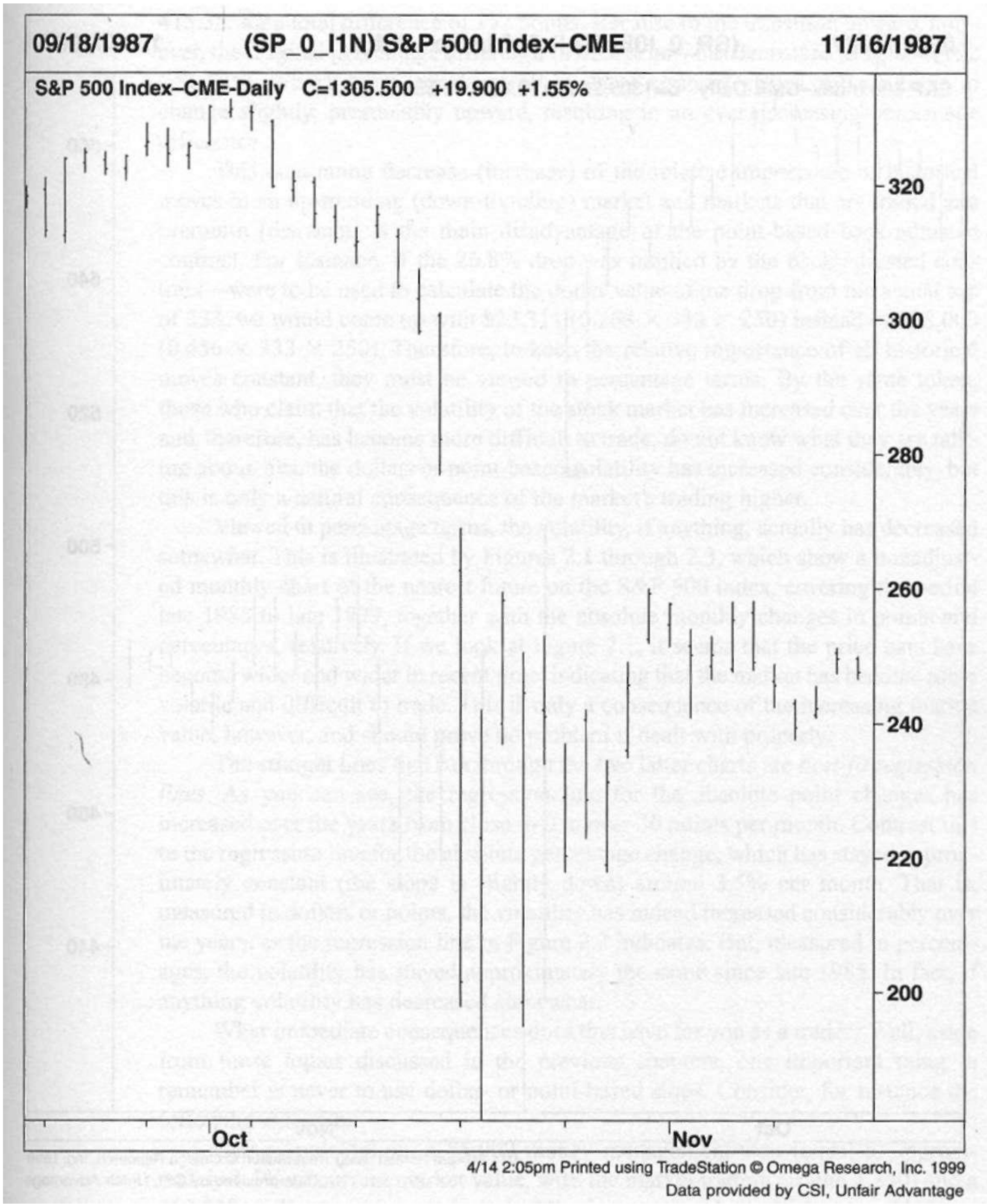


FIGURE 3.1

The crash of 1967 viewed through the nonadjusted contract

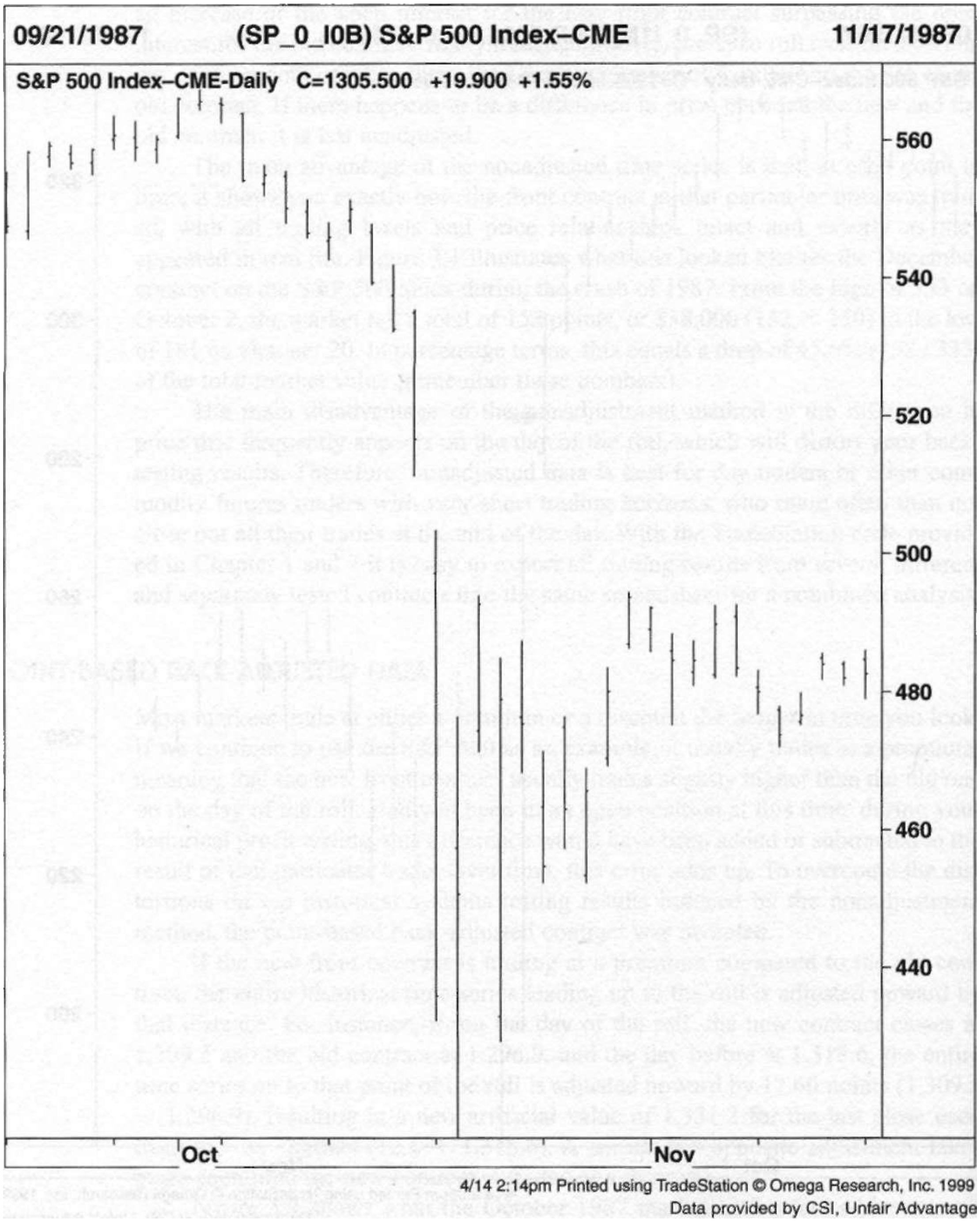


FIGURE 3.2

The crash of 1987 viewed through the point-based back-adjusted contract.

415.35, for a total difference of 152 points. Because of the transition upward, however, the original percentage difference of 45.6% now has decreased to 26.8% (152 / 567.35). What's more, for each roll all these contract values will continue to change slightly, presumably upward, resulting in an ever-decreasing percentage difference.

This continuing decrease (increase) of the relative importance of historical moves in an up-trending (down-trending) market and markets that are traded at a premium (discount) is the main disadvantage of the point-based back-adjusted contract. For instance, if the 26.8% drop—as implied by the back-adjusted contract—were to be used to calculate the dollar value of the drop from the actual top of 333, we would come up with $22,311 (0.268 X 333 X 250) instead of $38,000 (0.456 X 333 X 250). Therefore, to keep the relative importance of all historical moves constant, they must be viewed in percentage terms. By the same token, those who claim that the volatility of the stock market has increased over the years and, therefore, has become more difficult to trade, do not know what they are talking about. Yes, the dollar- or point-based volatility has increased considerably, but this is only a natural consequence of the market's trading higher.

Viewed in percentage terms, the volatility, if anything, actually has decreased somewhat. This is illustrated by Figures 2.1 through 2.3, which show a nonadjusted monthly chart of the nearest future on the S&P 500 index, covering the period late 1985 to late 1999, together with the absolute monthly changes in points and percentages, relatively. If we look at Figure 2.1, it seems that the price bars have become wider and wider in recent time, indicating that the market has become more volatile and difficult to trade. This is only a consequence of the increasing market value, however, and should prove no problem if dealt with properly.

The straight lines that run through the two latter charts are *best-fit regression lines.* As you can see, the regression line for the absolute point changes has increased over the years from close to 0 to over 30 points per month. Contrast this to the regression line for the absolute percentage change, which has stayed approximately constant (the slope is slightly down) around 3.5% per month. That is, measured in dollars or points, the volatility has indeed increased considerably over the years, as the regression line in Figure 2.2 indicates. But, measured in percentages, the volatility has stayed approximately the same since late 1985. In fact, if anything volatility has decreased somewhat.

What immediate consequences does this have for you as a trader? Well, aside from those topics discussed in the previous chapters, one important thing to remember is never to use dollar- or point-based stops. Consider, for instance the following example:

Using TradeStation, a $5,000 money management stop (equal to approximately 1.5% of current market value, with the market trading around 1,350) and a $10,000 trailing stop (approximately 3% of current market value) were added to a standard breakout system. In back-testing this system on nonadjusted S&P 500

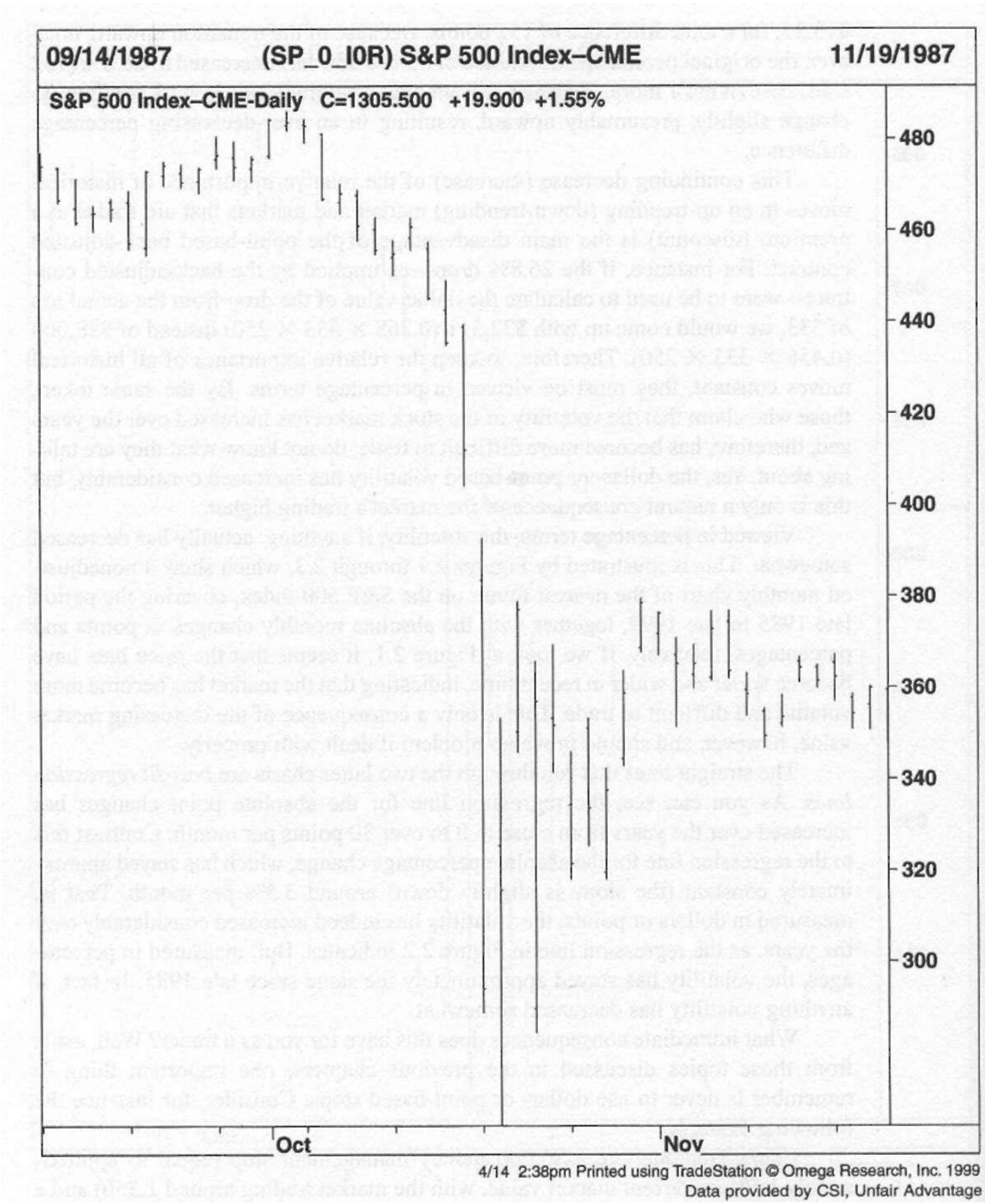


FIGURE 3.3

The crash of 1987 viewed through the RAD contract

data, covering the period January 1983 to April 1999, it took 55 trades (out of a total of 197 trades) before any of these stops got hit in October 1987. After this, it took another 35 trades before they were hit again in October 1990, only showing up again in March 1996. From then on, however, the hits became more frequent; for the period December 1996 to present, 25 out of 33 trades were stopped out, and from July 1998 to present, 13 out of 13 trades were stopped out this way.

RATIO-ADJUSTED DATA (RAD)

To overcome the dilemma induced by the point-based back-adjusted contract, I suggested in an article for *Futures* magazine ("Data Pros and Cons," *Futures* magazine, June 1998) and also later in a second article ("Truth Be Told," *Futures* magazine, January 1999) that a better way to adjust a spliced-together time series would be to use percentages rather than points or dollars. If we do so, this new time series will also vary in level as compared to when the true contract was traded, but instead of keeping the point- or dollar-based relationship between two points in time intact, the percentage relationship stays the same. This comparison is done with the help of the following formula:

$$C_{inew} = c_{iold} \times (1 + (C - c) / C)$$

Where:

c_{inew} = new price *i* bars ago.

c_{iold} = The old price *i* bars ago.

C — The close of the new contract on the day of the roll,

c = The close of the old contract on the day of the roll.

Figure 3.3 shows what the October 1987 crash looks like through the perspective of the ratio-adjusted data (RAD) contract, with the latest roll made in September 1999. This time the high of October 2 is at 486 and the low of October 20 at 264.15, for a point difference of 221.85 points, but with a percentage difference once again equal to 45.6% ((486 - 264.15) X 100 / 486). This increase in magnitude measured in points is due to the upward transition because of the many rolls. The important thing, however, is that the percentage-based move stays intact at 45.6%.

After the crash of 1987 it took close to 11 years before the S&P 500 experienced a larger drop measured in points. This happened in the autumn of 1998. This was announced as big news by the media, with some analysts and market writers even comparing it to the crash of 1987, implicitly suggesting that this was equally as bad or at least was soon to be. To get a better feel for the benefits of the RAD contract, let us take a closer look at this recent event and compare it to the crash of 1987 (see Figure 2.1). During October 1987, the market fell by 152 points, or $38,000, or 45.6%; this we know. During the autumn of 1998, the market fell from a July high of 1199.4 to an October low of 929, for a total drop of 270.4 points (as measured on the nonadjusted contract). In dollar terms, this equaled a drop of $67,600 (270.4 X 250). That is almost twice as much as the October 1987 drop. In percentage terms, however, the drop of 1998 only equaled 22.5% of total market value. That is, the drop in 1998 was not even half as bad as the crash of 1987. In fact, to equal the crash of 1987 in relative terms, the 1998 drop would have had to continue all the way down to the 652.5 level, for a total drop of 546.9 points, or $136,725.

Thus, the crash of 1987 is still the largest relative drop in equity in modern times, and if you, in your system building and analysis work, would like to treat it as such, to make your systems more robust and give them a better chance to hold up in the future, the only way to do that is to use the RAD contract in combination with the percentage-based performance measures described in the previous chapters. And while at it, do not forget to get rid of those dollar-based stops and profit targets as well.

Let's stop for a little quiz: Based on the information so far, what is the expected worst drop in equity for the S&P 500 if it were to equal the drop of 1987 and with the market trading at the 1,350-level? Is it

A. $38,000 (152 X 250)
B. $23,477 (0.282 X 333 X 250)
C. $54,625 (218 X 250)
D. None of the above

If you answer "none of the above," what is the correct answer?

The answer is: None of the above. Based on what we have learned so far the expected worst drop in equity, with the market trading at the 1,350 level is $153,900 (1,350 X 250 X 0.456). Furthermore, just because the drop in October 1987 stopped at 45.6%, there is no saying that there will be no larger drops coming. No wonder then that your software supplier, system vendor, or market guru of choice says that your worst drawdown is still to come—and they do not even know how to calculate it.

MULTIMARKET PORTFOLIOS

The benefits of the RAD contract also become evident when you want to put together a multimarket portfolio. We discuss multimarket portfolios and trading strategies in more detail in Part 5. For now we only state that the percentage-based calculations do not take into consideration how many contracts you're trading and, therefore, give each market an equal weighting in the portfolio. Let us look at the following example:

Using a regular 20-day breakout system that is always in the market, I hypothetically traded the Japanese yen and the S&P 500 over a period of 10 years, resulting in 71 trades for the Japanese yen and 79 trades for the S&P 500. Figure

3.4 shows what the individual and combined equity curves would have looked like had we been able to place all these trades for real, trading one contract. In short, the Japanese yen would have ended up with a profit of close to $60,000, and the S&P 500 with a profit of approximately $20,000, resulting in an overall profit for the portfolio of about $80,000. However, to make results comparable between the two markets and at the same time relevant to today's markets, we must look at how much a percentage move in each market is worth today. It turns out that a 1% move in the S&P 500, in today's market, is worth approximately $3,275, but only $1,200 in Japanese yen. Hence, had you been able to place all trades in today's markets, you would have had to trade approximately five Japanese yen contracts for every two S&P 500 contracts (3,275 / 1,200), which in turn would have resulted in an overall profit of approximately $240,000.

Now, wait a minute, you say, those results are purely hypothetical. How can I place all the trades in the same market at presumably the same point in time? Well, you can't, so that is a good and valid question; but let me ask you, can you place any of these trades for real, no matter how you do it? No, of course not. They all represent foregone opportunities. Isn't it better then to at least place them hypothetically in today's marketplace to get a feel for what might happen today, rather than in a ten-year-old market situation to get a feel for how the situation was back

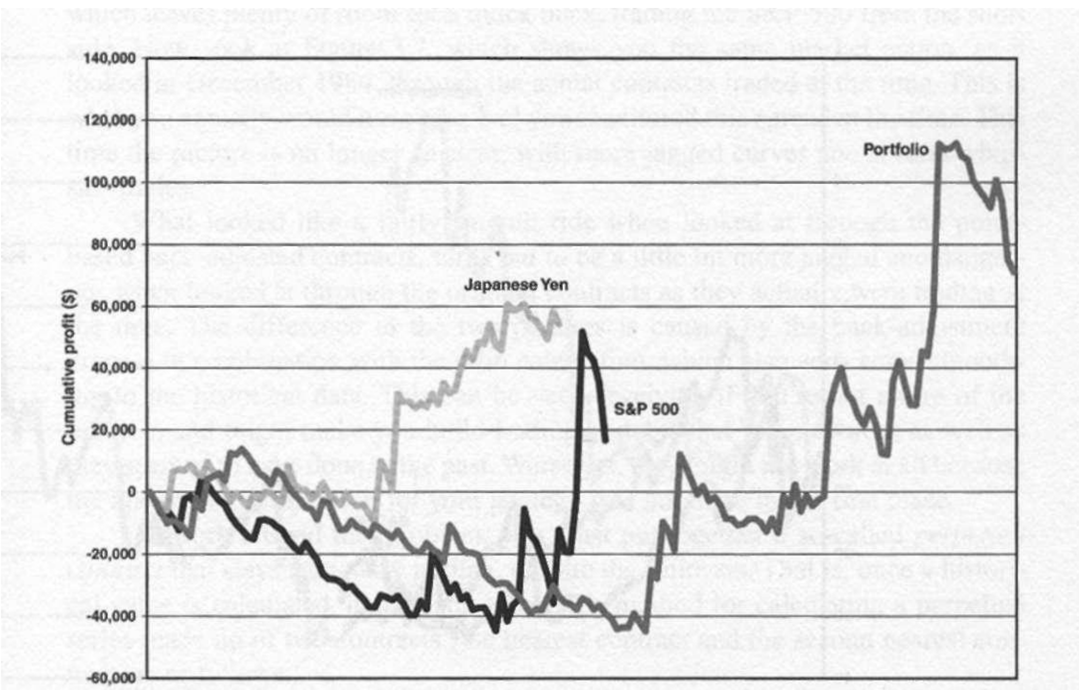


FIGURE 3.4

The results from a multi-market portfolio traded on a one-contract basis.

then? I think we all can agree that it is better to know what might happen today, rather than what happened ten years ago.

Nonetheless, this is looking good. By making the profits from the two markets more comparable to each other we have raised the total profit from $80,000 to $240,000. What we forget, however, is that this relationship changes with time, something we have not taken into consideration in the above example.

Furthermore, from the previous chapters we know that only looking at hypothetical dollars made is not the most efficient way to judge a trading strategy. And because both the dollar moves and the contract relationships between different markets are constantly changing, we must put together a chart based on the (cumulative) percentage moves we would have been able to catch. As you can see from Figure 3.5, this results in an approximately 40% combined move in the right direction (the market moved in favor of our position) for the Japanese yen, but in an almost 25% combined move in the wrong direction (the market moved against our position) for the S&P 500, resulting in an overall combined move that barely managed to reach a profit of 5%. (To understand how a 40% positive move and a 25% negative move can end up being close to zero, multiply 1 by 1.4 (1 + 0.4) and then by 0.75 (1 - 0.25), that is: 1 + 40% - 25% = 1 X 1.4 X 0.75 = 1.05 = 1 X (1 - 0.05) = 1 + 5%.)

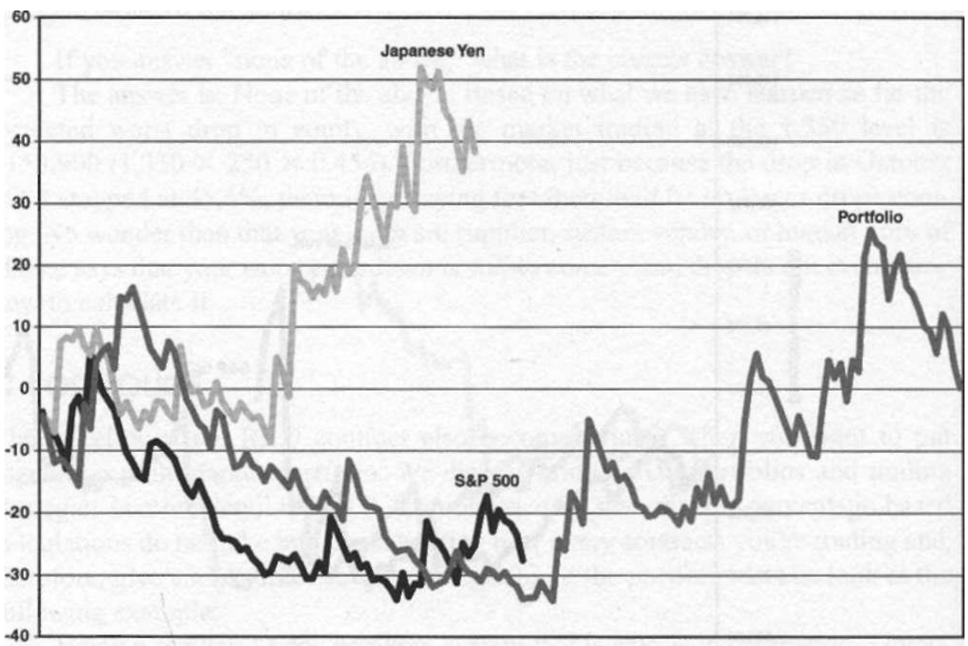


FIGURE 3.5

The results from a multi-market portfolio traded on a percentage basis with compounded returns.

Thus, what at a first glance seemed to be a profitable portfolio when tested on a one-contract basis in dollar terms, turns out to be a close-to-losing endeavor when giving both markets an equal percentage weighting and compounding the results.

PERPETUAL CONTRACTS

No matter how good the back-adjusted contracts are there is a certain situation when none of them should be used. That is when you must compare the development of two different markets, perhaps to find the one that seems to have the strongest relative strength. This is because none of these contracts stays stationary in time, but each is recalculated each time there is a roll from one contract to the next, which in turn can lead to perceptual changes in the historical relationship between the markets.

Figure 3.6 shows a ratio spread between the S&P 500 and the T-bill, as it is perceived to have looked in December 1984, using the point-based back-adjusted contract. When the squiggly line is below its fast and slow moving averages, the trend for the spread is down and the T-bill can be expected to outperform the stock market and, in this case, trigger a short position in the S&P 500 futures. Overall, this looks like a smooth ride with few erroneous signals and whipsaw trades, which leaves plenty of room for a quick buck, trading the S&P 500 from the short side. Now, look at Figure 3.7, which shows you the same market action, as it looked in December 1984, through the actual contracts traded at the time. This is what you actually would have seen had you monitored this spread at the time. This time the picture is no longer as clear, with more jagged curves and several whipsaw trades.

What looked like a fairly smooth ride when looked at through the point-based back-adjusted contracts, turns out to be a little bit more jagged and dangerous when looked at through the original contracts as they actually were trading at the time. The difference in the two pictures is caused by the back-adjustment process in combination with the ratio calculation, which also adds some smoothing to the historical data. This can be very deceiving if you're not aware of the problem and might make you build trading systems that will not work as well as they seemed to have done in the past. Worse yet, they might not work at all because the underlying assumption for your strategy was not there in the first place.

To work around this problem, you must put together a so-called *perpetual contract* that stays stationary in time, despite the rollovers. That is, once a historical value is calculated, it stays the same. The method for calculating a perpetual series made up of two contracts (the nearest contract and the second nearest contract) is as follows:

First set a forward quote day a certain number of days in the future and keep this number of days constant as time passes. Then calculate the number of days

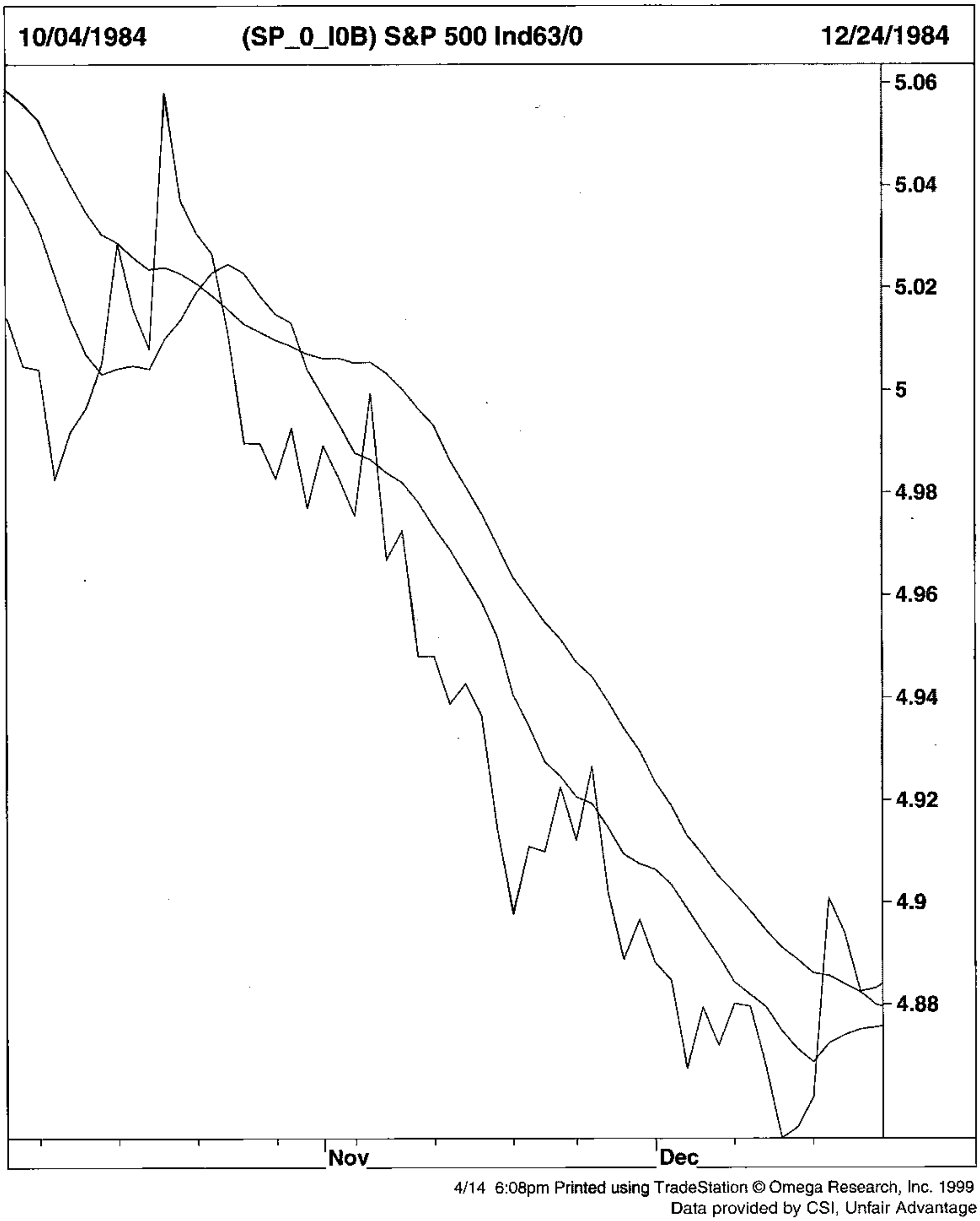


FIGURE 3.6

A spread between two markets put together using point-based back-adjusted contracts.

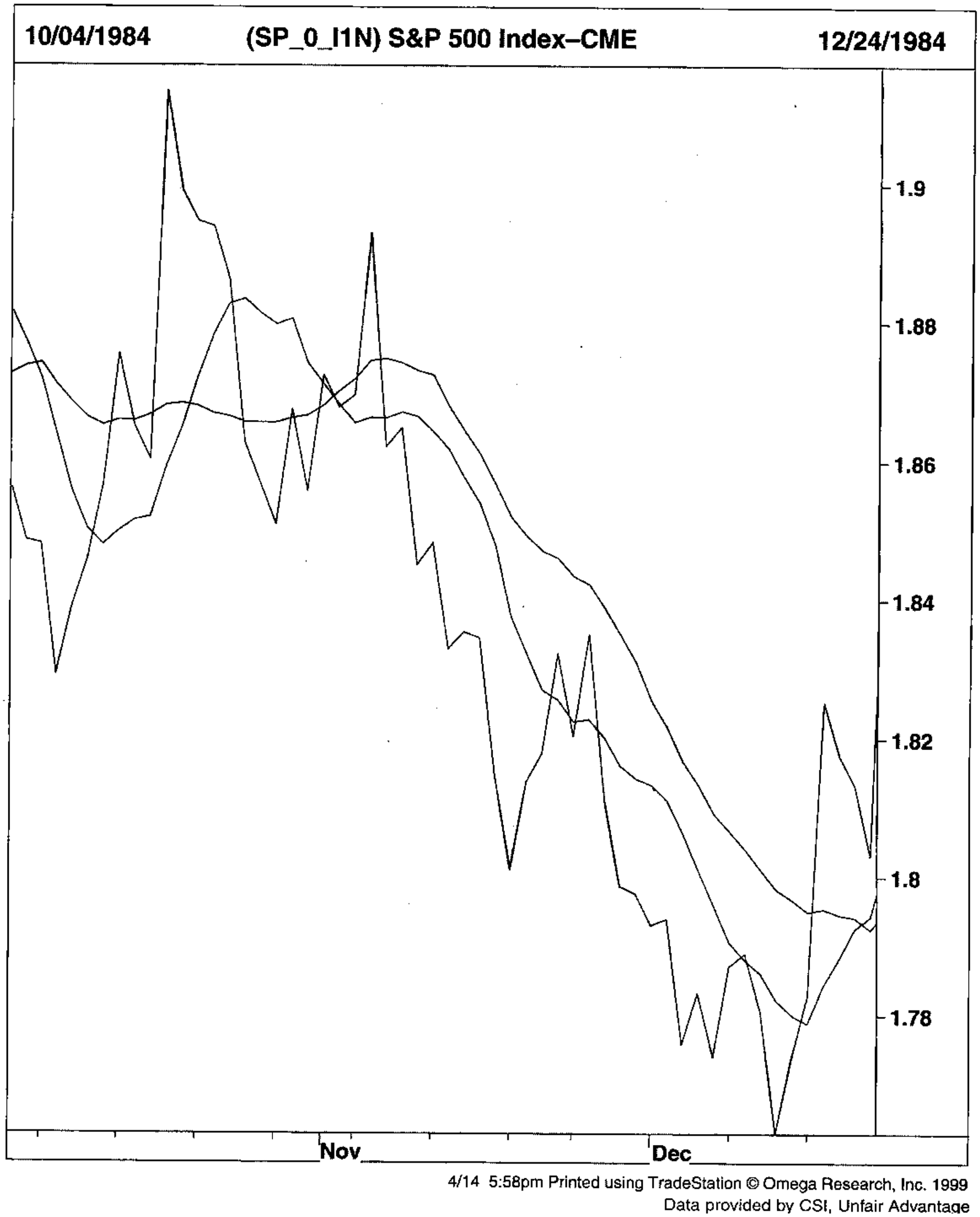


FIGURE 3.7

A spread between two markets put together using the actual contracts at the time.

between the expiration days for the two contracts and the forward quote day. When the distance to the forward quote day is kept constant (i.e. roll it forward one position for every new bar) the relative distance for the two contracts in relation to this day changes for each day. Finally, multiply the relative distance for both contracts by their respective prices and add them together, for today's perpetual price. The closer the nearest contract comes to expiration, the less weight it gets. When it expires it becomes 0; the second nearest contract is now the nearest contract, and the third nearest contract is the new second nearest contract.

PART ONE

A Few Final Thoughts About Part 1

This part started out by taking a closer look at which system testing measures are more useful than others, and why it could be a good idea to expand the analysis work a bit with the help of a spreadsheet program, like MS Excel or Lotus 1-2-3. To properly evaluate a trading system, it is of paramount importance to use a set of universal measures that give an equal weighting to all the trades, no matter where and when they are derived. To accomplish this, it also is important to use the right type of data. As we have seen, not all data can be used all the time; knowing when to use what is vital in building a robust and profitable trading system.

Later chapters take a closer look at how to evaluate a system or a strategy that is already up and running, to make sure that it stays on track and performs as it should. Before we go any further in the evaluation process, we need a couple of systems to trade. Building a system suited for a specific type of market action or trading perspective is the major topic in the next section.

PART TWO

System Concepts

In the first part, we discussed a few important concepts to understand and think about before the system building process can begin. Unfortunately, however, it does not stop there. There is more than one thing to think about when trying to put together a mechanical trading strategy. Aside from the psychological aspects—whether the system fits your style of trading, personality, trading budget—several other more technical questions must be answered as well. Before we can start designing and investigating any trading system, we must understand what it should try to accomplish.

We must know if the trading methodology should be long-term, short-term, or perhaps even intraday. Should the system be market specific or tradable over a wide variety of markets? If the system is a multimarket system, how should it be built and tested so that all the markets have an equal impact on the final result? Should we try to capture a certain type of trending move, or should we try to capture the shorter-term moves within a previously defined trend? Or are we trying to accomplish something completely different, like arbitraging one market or contract month against another, or buying or selling volatility with the help of options? Then there is the question of what type of money management strategy to use, and when this should be taken into consideration.

But even before these fundamental questions can be answered, there is a set of basic questions of a more philosophical character, which must be addressed and—if not answered—at least contemplated. What *is* long term and short term? Or what *is* high and low? There really are no generic, ready-made answers to these questions, because long term for me might be short term for you, and something completely different for someone else. Whatever your answer is, it is correct for you and not for anyone else to question.

Before you answer, however, here is some food for thought: what if, instead of measuring long-term or short-term market activity in regular time units, such as minutes, hours, or days, you were to measure it in number of bars (market time units) encapsulating as much time (regular time units) as you deem necessary? Or perhaps, long term and short term simply should be defined by the system, where a breakout-type system is always considered long term while a top-and-bottom picking system is always considered short term, no matter for how long the trade actually lasts, whether measured in regular time units or market time units?

Another important thing to consider before researching a trading system (and a commonly debated question among system builders) is whether it is a good idea to save some of the data for out-of-sample testing. The answer is that it depends on the system and its underlying assumptions; many times it shouldn't make any difference. In a correctly built system, you're interested in exploiting something that should, on average, work well in several different markets and over several different time periods, not with any specific type of anomaly that might or might not still exist in a particular market. By saving some of your data for out-of-sample testing, you can strengthen your trust in the model, but in doing so, you also use up valuable data that could have added even further to the robustness of the system. Only you can make that choice. That said, in many of these examples, we work with an out-of-sample period for comparative reasons. Whatever you choose, it is important to remember that by necessity all system testing and design must be made on historical data. The trick, then, is to make as good use as possible out of these data and make your evaluation measures as forward looking as possible.

Building systems is no easy matter, and you had better know the odds against you before you get started. For instance, if you only traded the S&P 500 index approximately every fifth day (I picked out all days randomly 20 times, calculated the compounded returns, and averaged the results), between May 1992, and October 1999, and if you could have been absolutely sure that all these days would have been down days, you would have made a whopping 71 times the index. If you instead had been able to pick the same amount of up moves, you would have made an incredibly 161 times the index. This tells us that we are much better at going with the underlying trend (as it undoubtedly has been up during the last few years), and if we can only temper ourselves and trade only on a few selected days, the rewards can be very good. No wonder day trading is such an alluring business. But rewards like this do not come without a price. The above examples assume that we can be 100% sure of the move, but what if we can only be 50% sure? Well, then the expected return sinks to only 0.25 times index, if going long only, or to a mere 0.11 times index, if going short only.

Similarly, if you're a long-term trader and prefer to compare yourself to a buy-and-hold strategy, you could have increased you return to 4.9 times the index, had you been able to stay out of the market every 20th day—if you also were absolutely sure that day also was a down day. But if you only were 50% sure about

CHAPTER 4

Picking Tops and Bottoms

When it comes to trying to trade shorter term, or *picking tops and bottoms,* many system traders usually start out trying to use any or all of the many oscillator-type indicators that have swamped the field of technical analysis in recent years. Examples of such indicators are *RSI, Stochastic, Momentum, Rate-of-change, MACD,* and *Plus and Minus DMI.* Many others exist, and the list can be made much longer, but those mentioned above are the most common and popular ones. These indicators are believed to be good top and bottom pickers because they're believed to be able to anticipate or even predict the market by moving in and out of overbought and oversold regions, or simply by not "confirming" the moves of the market. I believe, however, that one main reason you have picked up this book in the first place is that you have come to realize that many of these indicators simply do not work nearly as well in real-time as they seem to do when looked at on a historical price chart.

If all these indicators do not work, how then should one go about finding profitable short-term trading opportunities? Well, probably the most important task for you as a trader, especially if you prefer to trade fairly short term, is to mine the data from which you hope to make a living. If, for nothing else, it must be done to get an in-depth feel for the markets you are trading, which in turn should help you to better interpret the current market situation and the indicators you are using to gauge it. But before you can go about doing this, you must know exactly what it is you should look for and how to measure it.

To build a system that works equally well in all markets, you must decide what type of data to use. With the ordinary point-based back-adjusted contract, you can estimate how much profit your system would have made historically in each market, but because of the way it is constructed you cannot channel any information from one market to another. To give all moves an equal importance, and to derive the necessary input for your calculations, it is of paramount importance that you only use percentage-based calculations—and if you are a futures trader, also use the newly invented RAD contract (see "Data Pros and Cons," *Futures* magazine, June 1998, and "Truth Be Told," *Futures* magazine, January 1999). In a trending market, the dollar value of the magnitude of the moves changes with the market value, so that if the market is in an up trend, with a steadily increasing market value, the dollar- or point-based move is likely to increase as well. The relationship between the moves and the market value stays the same, resulting in a average percentage move that is more likely to stay the same, no matter at what level the market is trading. This is also the contract you need as soon as you start to work with any type of percentage-based decisions, such as rate-of-change analysis or percentage-based stops.

Notice that the key words here are "equally well" instead of "equally profitable." To build a trading system that continues to work equally well in the future as it did during the building process, when it was hypothetically traded on historical data, it also is important to understand the difference between a good working system and a profitable system. Furthermore, once this is fully comprehended, it is even more important to understand why a good working system is not necessarily a profitable system, but why a profitable system always must be a good system. These key concepts that will be stressed continuously throughout this book.

Whether a good working system will be profitable or not has nothing to do with the system, but rather with the level at which the market is currently trading and the dollar value of that level. For instance, suppose the dollar value of the S&P 500 futures contract were to be lowered from today's $250 per point to $2.50 per point. How many S&P 500 systems would still be profitable in the future, or even test profitable in hypothetical back-testing? Probably not many. The point is that the actual value of the market and its move is a technicality decided by the exchange, which has nothing to do with whether the system is good at capturing the moves of the market.

During the building process, the actual dollar values are of no concern. Instead, we focus on the universal measures: the profit factor, the percentage move, and the number profitable trades. To make sure the results do not differ too much between markets, we also look at the standard deviations of all these measures. Thus, a well-working system—a good system—is a system that captures as many and as large moves as possible in any and all market environments, as measured with a universal method like those mentioned. For a system to be profitable, however, it must be traded in a market where the moves it is designed to catch also are worth taking. This has nothing to do with the system, but rather with the level at which the market currently is trading and the dollar value of that level.

Once you know what to look for in terms of the data and the different measurements, you also must figure out exactly what it is you would like to do. That is, should you only take trades that go in the same direction as the longer-term underlying trend, or should you also look for counter-trend moves? Whatever your answer, you then must ask yourself whether you should try to anticipate the turning point with an early limit-order entry; or play it a little safer and look for proof that the preceding move has run its course, and then enter with a stop? Furthermore, once you're in the trade, should you then try to ride it for as long as possible, or should you only go with the short-term thrust and perhaps exit many of the winners with a limit order at a specific price or after a move of a certain magnitude?

In this chapter, we took a closer look at a few different system ideas that all have a high likelihood of producing a large number of profitable trades for a decent overall profit. The first two are a couple of market-specific data mining systems, where we only are interested in the specific characteristics of that particular market, or group of related markets, although it is fully possible and realistic to apply both the research technique and the systems to any market. The next is based on a proprietary indicator perhaps best described as a mix between percentage-based analysis, Bollinger bands, and pivot-points. The last system, which really is only a demonstration of how to come up with a good set of exit rules, I have given the name Black Jack, because of its ability to make use of small statistical advantages, which are the same for all markets, in an attempt to produce long-term profits out of several smaller and sometimes just barely profitable trades. It is especially designed to work well together with more advanced money management strategies, such as Ralph Vince's Optimal f, or fixed fractional investing. (In Part 3, we will continue to work with different ways of deriving exits, which we then apply to all our systems.)

CHAPTER 5

Data Mining

What will the market do today? Each day we ask our fellow trader friends and ourselves the same old question, and each day the market answers us at the end of the day. One would think that after having asked the question and observed the answer, say, a couple of thousand times or so, we either would learn the answer or stop wasting time pondering the question. Yet, we keep on asking and each day the market baffles us, by always behaving more or less out of sync with what we had expected.

One day the stock market is behaving exactly as anticipated, except for that little dip after lunch that had us stopped out with a loss. Which, by the way, reminded almost everybody about how the T-bond used to behave a couple of years ago, when the typical characteristics of the European currency crisis were casting their shadow over the financial world. Then, the next day, the very same market behaves in a way never seen before. Except for your buddy Joel that is, who traded the grain and meat markets back in the 1970s and therefore recognizes the similarities to how the corn market used to behave back then.

The point I am trying to make here is that it's very difficult to distinguish the behavior of one market from that of another, and the very same second that we think we've nailed it, it all changes and the experience gained loses almost all its value. Let's face it: can you really say that the stock market today behaved exactly as the stock market usually does, or was it more like the recent coffee market or the lumber market in the 1980s? And, if it behaved like the coffee market, is the recent behavior for the coffee market really typical for coffee at this time, and on and on and on? Is there really a specific, consistent behavior for each and every market, and, if so, can it be traded profitably? To find out you must examine each and every market very carefully and ask yourself an abundance of questions:

For how long does a typical trend last? What are the typical characteristics of any corrections? When can a move be considered to have gone too far? What is the likelihood for a certain amount of days in a row in the same direction? And most important: how can you benefit from this information and implement it in your arsenal of existing trading tools? Those are only some of the questions to ask when you start mining your data to come up with high-probability trading opportunities; or at least, in trying to avoid the most obvious bad ones.

For example, if the market has been in a down trend for four months straight but you know that a typical down trend should last for only two months, it probably isn't too good an idea to add to your position when your breakout system signals that you once again should go short. Granted, the market might have changed from what is typical for one market to what is typical for another, but at least you still have the long-term statistics on your side. Alternatively, if you already are short, perhaps it is a good idea to start scaling back, no matter what your system is telling you. Or, if you know that only 22% of all down moves, measured on daily data, last for more than two days, you could speculate on the high statistical likelihood for a short up trend to follow, set up a contrarian trading system, and probe the market with a small position whenever the market has fallen for two days or more. Similarly, if you know that only 9% of all down moves result in a decline of 8% or more, measured on monthly data, you could take a long position, betting on an extended up move to follow, as soon as the market has declined that amount.

To get a feel for relationships like these, it is a good idea to put together a set of tables like Table 5.1 through Table 5.3, which serve as good starting points for experimentation. All tables have been put together using the RAD contract for the S&P 500 futures market, with data expanding from January 1985, to December 1994, and January 1995 to October 1999. (The most up-to-date data, from January 1995 to October 1999, were used for out-of-sample testing, and are placed within parentheses.) From Table 5.1 you can see that during the period January 1, 1985, to December 31, 1994, the average up move for the S&P 500, measured on weekly data, went on for 2.29 weeks, for an average total gain of 3.3%, while the average down move, measured on monthly data, went on for 1.35 months with an average total decline of 4.82%. From Table 5.2 you can see that measured with daily data, 25% of all up moves lasted for longer than two weeks, while only 6% of all down moves could be expected to last for three weeks or more. In Table 5.3 the monthly amplitudes are within the parentheses in the headers. Measured with weekly data, 42% of all up moves resulted in an increase of the market value of more than 3%. Measured with monthly data, 46% of all up moves resulted in an increase of the market value of more than 6%.

To put together Tables 5.1 through 5.3 you must be able to export your data into a text file, which can be opened with the help of MS Excel or any other spreadsheet program. Once in Excel, you first must calculate the percentage change of the closing price with the following formula:

TABLE 5.1

Data mining summary.

	Move per period	Periods in move	Amplitude
		Daily data	
All moves	0.68%	1.95	1.34%
Up moves	0.69% (0.77%)	2.04 (2.17)	1.41% (1.68%)
Down moves	0.68% (0.71%)	1.86 (1.93)	1.26% (1.36%)
		Weekly data	
All moves	1.52%	1.97	2.99%
Up moves	1.44% (1.78%)	2.29 (2.21)	3.30% (3.98%)
Down moves	1.64% (1.67%)	1.65 (1.52)	2.70% (2.52%)
		Monthly data	
All moves	3.32%	1.72	5.73%
Up moves	3.22% (3.47%)	2.09 (3.31)	6.72% (11.93%)
Down moves	3.56% (3.50%)	1.35 (1.25)	4.82% (4.36%)

TABLE 5.2

Periods of moves of certain length.

	1	>1	>2	>3
		Daily data		
All moves	50%	50%	23%	11%
Up moves	46% (43%)	54% (57%)	25% (33%)	13% (15%)
Down moves	53% (53%)	47% (47%)	22% (25%)	10% (12%)
		Weekly data		
All moves	50%	50%	25%	11%
Up moves	41% (43%)	59% (57%)	33% (28%)	17% (15%)
Down moves	60% (67%)	40% (33%)	17% (13%)	6% (4%)
		Monthly data		
All moves	57%	43%	16%	6%
Up moves	37% (38%)	63% (61%)	23% (46%)	9% (46%)
Down moves	76% (83%)	24% (17%)	9% (8%)	3% (0%)

TABLE 5.3

Percentage of moves of certain amplitude.

	1(2)%	>1(2)%	>2(4)%	>3(6)%	>4(8)%	>5(10)%
			Daily data			
All moves	55%	45%	20%	9%	4%	2%
Up moves	51% (42%)	49% (58%)	22% (28%)	11% (18%)	4% (11%)	2% (4%)
Down moves	59% (57%)	41% (43%)	18% (25%)	8% (11%)	4% (6%)	2% (3%)
			Weekly data			
All moves	26%	74%	53%	36%	25%	16%
Up moves	23% (10%)	77% (90%)	61% (75%)	42% (59%)	28% (41%)	18% (24%)
Down moves	28% (28%)	72% (72%)	45% (43%)	31% (27%)	22% (21%)	14% (18%)
			Monthly data			
All moves	25%	75%	45%	35%	19%	12%
Up moves	26% (0%)	74% (100%)	57% (92%)	46% (62%)	29% (46%)	17% (46%)
Down moves	24% (25%)	76% (75%)	32% (33%)	24% (17%)	9% (8%)	6% (8%)

```
=E3/E2
```

where *E* denotes the column where the data is stored.

To calculate how many periods in a row a certain move lasts, first use the following formula in the adjacent column:

```
=IF(OR(AND(F3>1;F2<1); AND(F3<1;F2>1)); 1;G2+1)
```

Then, continue the calculation in the next column:

```
=IF(G3>=G4;SIGN(F3-1)XG3;"")
```

Finally, in the last column, use the following formula to calculate the percentage move:

```
=IF(H3<>M";PRODUCT(INDEX(F:F;ROW()-ABS(H3)+l;l):
INDEX(F:F;ROW();l))-1;"")
```

After you have filled in all the calculations, type in the following sets of formulae at the bottom of the spreadsheet to derive the necessary numbers for the tables. (For the down moves, simply change " > " to " <= ".)

To calculate the total number of periods up:

```
=ABS(SUMIF(H$3:H4429;">0"))
```

To calculate the total number of moves up:

```
=ABS(COUNTIF(H$3:H4429;">0"))
```

To calculate the average number of periods in an up move:

=H4431/H4432

To calculate the average percentage amplitude for an up move:

=SUMIF(I$3:I4429;">0")/COTJNTIF(I$3:I4429;">0")

To calculate the average percentage amplitude for each period within the up move:

=((H4434+1)^(1/H4433)-1)

To calculate the likelihood for an up move to last for two periods or more:

=COUNTIF(H$3:H4429;">1")/H4432

To calculate the likelihood for the amplitude of an up move to be greater than 1%:

=COUNTIF(I$3:I4429;">0.01")/H4432

To test a simple trading system that makes use of information like this, you can, for instance, set up a system that only goes long as soon as you have a down day that follows a down week that follows a down month. Because of the natural upward drift in the stock market and because of what the data mining has shown about up moves going on for a longer period of time, the requirements for a short position could be two up days, two up weeks, and two up months. The TradeStation code for this simple system, Gold Digger I, looks something like this:

```
Condition1 = CloseM(l) > C and CloseW(l) > C and C[l] > C;
Condition2 = CloseM(2) < CloseM(l) and CloseM(l) < C and
CloseW(2) < CloseW(l) and CloseW(l) < C and C[2] < C[l] and C[l] < C;
If Condition1 = True and MarketPosition = 0 Then
    Buy ("Go long") at open;
If C[2] < C[l] and C[l] < C Then
    ExitLong ("Exit long") at close;
If Condition2 = True and MarketPosition = 0 Then
    Sell ("Go short") at open;
IfC[l] > CThen
    ExitShort ("Exit short") at close;
```

Using the trade-by-trade export function from Part 1, together with the RAD contract for exporting the results into a spreadsheet program, and then using the Excel formulae we also derived in Part 1, you can put together a performance summary table like those in Tables 5.4 and 5.5.

TABLE 5.4

Performance summary for Gold Digger I, January 1985-December 1994.

Total trades		251	Winners	15	63.35%	Losers	9	36.65%
Profit factor		1.34	Lrg winner	7.76	26,190	Lrg loser	-19.12	-64,530
Avg profit	0.18%	597	Avg winner	1.09	3,684	Avg loser	-1.40	-4,739
St Dev	2.01%	6,799	Cum profit	47.74	161,123	Drawdown	-26.71	-90,146

Over the period January 1, 1985, to December 31, 1994, Gold Digger I produced 251 trades, among which close to 64% were profitable, for an average gain per trade of 0.18% (or $597 in today's market value, with the S&P 500 trading around 1,350). A fairly low drawdown and standard deviation also make us want to continue the research.

When tested on out-of-sample data, the average profit had increased to $1,467, while the largest loss had decreased to 4.20% (or $14.175 in today's market value). An ever-low standard deviation and a high percentage profitable trades keep us interested. No money was deducted for slippage and commission, but with an expected $75 in slippage and commission, you can expect this system to generate approximately $1,392 per contract traded ($1,467 — $75) in the immediate future. Table 5.5 also shows that the drawdown decreased substantially from close to 27%, for the in-sample period, to 7% for the out-of-sample period. For drawdown and cumulative profit values to be correct, however, we are assuming that the entire equity, including previously made profits, was reinvested at each new trade. As mentioned in Part 1, this is seldom possible, especially not in the futures markets, but it could be so in the stock market, provided that you can buy fractions of a share. What this does allow you to do, however, is to compare different systems and markets with each other on an equal basis, or compare how your system would have held up against a buy-and-hold strategy over the same time period.

Despite the not too bad results, it is important to remember that Gold Digger I is put together merely to illustrate a simple system for taking advantage of a market's statistical characteristics. This particular system is not a good system to trade if you compare the statistical characteristics in Tables 5.1 to 5.3 for the market dur-

TABLE 5.5

Performance summary for Gold Digger I, January 1995-October 1999.

Total trades		105	Winners	7	66.67%	Losers	3	33.33%
Profit factor		2.27	Lrg winner	3.45	11,644	Lrg loser	-4.20	-14,175
Avg profit	0.43%	1,467	Avg winner	1.16	3,928	Avg loser	-1.02	-3,456
St Dev	1.40%	4,719	Cum profit	56.10	189,338	Drawdown	-7.20	-24,300

ing the first 10-year period, with the characteristics for the latest four years. Comparing the in- and out-of-sample periods with each other shows that ever-so-small differences between the daily and weekly data soon add up to quite large differences in the monthly time perspective. For instance, when looking at the monthly data, you notice the average magnitude of an up move, measured on monthly data, has grown from 2.09 months and 6.72% to 3.31 months and 11.93%. Also, in the table describing the likelihood for periods of moves of certain length, for the period up until 1994 there was only a 9% chance for an up move to last for more than three months, but for the period spanning January 1995 to October 1999, there was a 46% chance for the same type of move.

In the same table, the most recent study suggests that 57% of up moves measured on weekly data go on for more than one week. This is two percentage points less than what could be expected looking at the period ending in 1994. Hence, while the number of persistent up trends measured on weekly data has decreased, the number of persistent up trends measured on monthly data has skyrocketed. The same phenomenon also can be seen in the table for percentage of moves of certain amplitude, where the percentage of up moves with an amplitude of more than 5%, measured on weekly data, has only increased by 33% (from 18% to 24%), while the number of up moves with an amplitude of more than 10%, measured on monthly data, has skyrocketed by 170% (from 17% to 46%).

This suggests that when the market changes its characteristics or mode, these changes can be very hard to detect when looking at a shorter time frame within the bigger picture. Or, put differently: no matter what long-term mode the market is in, the short-term statistical characteristics are likely to still look the same and be close to stationary in nature. This is a very important conclusion, because if this is true, the only way to build a mechanical trading system that holds up and behaves the same way in the future as it does during testing—no matter what the longer-term underlying trend looks like—is to focus on the shorter time perspective, with trades lasting for no longer than approximately a week and using as little historical data for the signals as possible.

To test if this could be true, a modified version of the original system considers only daily and weekly data, as suggested by the following TradeStation code, which also does not differentiate between up trends and down trends:

```
Conditionl = CloseW(2) > CloseW(l) and CloseW(l) > C and C[2] > C[l] and
C[l] > C;
Condition = CloseW(2) < CloseW(l) and CloseW(l) < C and C[2] < C[l] and
C[l] < C;
If Conditionl =True and MarketPosition = 0 Then
    Buy ("Go long") at open;
IfC[2] < C[l] and C[l] < CThen
    ExitLong ("Exit long") at close;
```

```
If Condition2 = True and MarketPosition = 0 Then
        Sell ("Go short") at open;
IfC[l] > CThen
        ExitShort ("Exit short") at close;
```

The results for this version of the system can be seen in Table 5.6. Tested on the out-of-sample period this system had 107 trades, with 63% profitable trades and an average profit of 0.31% (or $1,045 in today's market value). No money was deducted for slippage and commission, but this is easily accounted for, for trades in the immediate future, by deducting an appropriate amount from the expected value of the average trade. Because Gold Digger II is a simpler system (less curve-fitted) than Gold Digger I, its performance is not quite as good, as judged by a slightly lower profit factor and percentage profitable trades and a much lower cumulative profit. It does, however, seem to be a little more robust, as judged by a lower standard deviation. Although the average profit and profit factor are slightly lower for Gold Digger II when compared to Gold Digger I, the lower standard deviation, in combination with Gold Digger IPs being more symmetrical in nature (less curve-fitted), makes it clear that Gold Digger II is the preferable system.

From the TradeStation code, however, you can see that the only exit criteria we have on the long side is two up closes in a row, while we will exit a short trade as soon as we have a down day. Because the market does not always behave as we want it to, the losses can be quite severe before we are allowed to exit the trade. This can, for instance, happen if the market immediately takes off in the wrong direction, or if in a long position, every other day is an up day and every other day is a down day, but with down days of greater magnitude than up days. Therefore, the lack of properly developed stops still makes this a dangerous system, as can be seen from the values for the largest and average losing trades. (We will talk more about stops and exits in Part 3.)

BETTER USE OF YOUR DATA

If you are better off using as few bars as possible in your system, it should follow that you should make as good use of those bars as possible. For instance, a moving average usually only looks at one particular price within a time series, not tak-

TABLE 5.6

Performance summary for Gold Digger II, January 1995-October 1999.

Total trades		107	Winners	6	62.62%	Losers	4	37.38%
Profit factor		1.98	Lrg winner	7.31	24,671	Lrg loser	-4.06	-13,703
Avg profit	0.31%	1,045	Avg winner	1.00	3,364	Avg loser	-0.84	-2,840
St Dev	1.38%	4,666	Cum profit	37.84	127,710	Drawdown	-7.26	-24,503

ing into account that each bar actually holds three other important price levels. That is, when calculating a moving average of closing prices, all open, high, and low prices usually are ignored. Using regular moving averages and Bollinger-band-type indicators to identify trading opportunities also present a problem in that the readings are not always comparable over time. For example, a value of 1,350 for the S&P 500 index may very well be below its moving average and standard deviation bands today, but may not be so a couple of years from now, if and when the market trades at the same level again. It all depends on where the market is coming from at that point in time.

Wouldn't it be great to come up with an indicator that can make use of all four of these price extremes, shorten the lookback period by 75%, and at the same time make it possible to make all of the indicator observations comparable with each other, regardless of when they happened or at what level the market was trading at the time?

Contrast the above with a statistical examination, where you are measuring the height of a random sample of men that you meet throughout the day. At the end of the day you write down the height of the first man, the tallest man, the shortest man, and the last man you have measured that day. It does not matter in what order you write them down. After five days you have 20 observations, which is the minimum amount required to make any statistical conclusions. (This number varies; some say 20, others say 30, while still others say 100 or more. In the medical field, it is close to 1,000. Aside from the fact that you will not always have that much data to experiment with, there is no reason why you shouldn't treat your money any less seriously.)

Let us say that the average for all 20 men was 6 feet and the standard deviation was 3 inches. The one standard deviation boundaries and the two standard deviation boundaries hold approximately 68% and 95%, respectively, of the men measured and the expected height of all men to be measured in the future. With this information at hand you now can classify all men that you met as, for instance, average height (between 5 feet 9 inches to 6 feet 3 inches), short (between 5 feet 6 inches to 5 feet 9 inches), very short (below 5 feet 6 inches), tall (between 6 feet 3 inches to 6 feet 6 inches), and very tall (above 6 feet 6 inches). For each and every investigation done this way, and depending on where they are done, these levels will vary slightly. But for each investigation, at least some of the previous information will be useful in estimating the future outcome or what can be expected for the next day. For instance, because the chances of meeting a tall or very tall man are approximately 16% ((1 — 0.68) X 100 / 2), you also know that the chance of meeting two such men in a row is a mere 2.5% (0.16 X 0.16 X 100).

To develop and use the same type of research in the markets, it is important to note not at what level the markets are trading, but the amplitude of the moves. To make each move comparable to all others, both in time and between different markets, we must use the RAD contract, which keeps the percentage changes constant instead of using the actual point or dollar values. To calculate the move rather than the level, it also is necessary to relate each move to a base or ground level. Continuing the comparison with measuring men on the street, it makes little or no sense to measure each man's height from sea level instead of from the ground where he is standing. That is, for a comparison to be meaningful, it is necessary to *normalize* the data; the obvious level from which to normalize a person's height is the ground on which he stands.

In market research, there are a few levels to which each move can be normalized, like the previous bar's close or the average price of the previous bar. Here each move has been normalized to the previous bar's closing price. Another difference between measuring men and market action is the use of *absolute* and *percentage* values. If you are 6 feet tall, you will be 6 feet tall whether you are standing on a pair of skis in Vail or lying down on a beach towel in Hawaii. It would make little or no sense to compare your height in percentage terms to how high you are from the ocean. But in the market there is a huge difference between a move worth $20,000 if the market is trading at the 1,350 level, compared to the same dollar move if the market is trading at 250. In the first case, a $20,000 move equals only a 6% move, while in the latter the same dollar move amounts to over 30%. Thus, it is of paramount importance to measure market moves in percentages rather than point or dollar values so that you can compare different types of moves, no matter where and when they happened.

In our measuring-men example, four observations were kept each day. This can be done for the markets as well with what I call the Meander indicator. The following TradeStation code sets up an array containing all the opening moves, moves to the highs, moves to the lows, and moves to the close, for a total of 20 data points for the last five bars:

```
Input: VSStd(l);
Vars: SumVS(O), AvgVS(O), DiffVS(O), StdVS(O), SetArr(O), SumArr(O),
DiffArr(O), VSLow(O), VSMid(O), VSHigh(O), FNameC*"), TradeStrl("");
Array: VS[20](0);
For SetArr = 0 To 4 Begin
    VS[SetArr * 4 + 0] = (0[SetArr] - C[SetArr + 1]) / C[SetArr + 1];
    VS[SetArr * 4 + 1] = (H[SetArr] - C[SetArr + 1]) / C[SetArr + 1];
    VS[SetArr * 4 + 2] = (LfSetArr] - C[SetArr + 1]) / C[SetArr + 1];
    VS[SetArr * 4 + 3] = (C[SetArr] - C[SetArr + 1]) / C[SetArr + I];
End;
For SumArr = 0 To 19 Begin
    If SumArr = 0 Then
        SumVS = 0;
    SumVS = SumVS + VS[SumArr];
    If SumArr = 19 Then
```

```
            AvgVS = SumVS / 20;
        For DiffArr = 0 To 19 Begin
            If DiffArr = OThen
                DiffVS = 0;
            DiffVS = DiffVS + Square(VS[DiffArr] - AvgVS);
            If DiffArr = 19 Then
                StdVS = SquareRoot(DiffVS / 20);
        End;
    End;
    VSLow = C * (1 + (AvgVS - StdVS * VSStd));
    VSMid = C * (1 + AvgVS);
    VSHigh = C * (1 + (AvgVS + StdVS * VSStd));
    Plotl(VSLow, "VS Low");
    Plot2(VSMid, "VS Mid");
    Plot3(VSHigh, "VS High");
    If CurrentBar = 1 Then Begin
        FName = "C:\Temp\" + LeftStr(GetSymbolName, 2) + ".csv";
        FileDelete(FName);
        TradeStrl = "Date" + "," + "Open" + "," + "High" + "," + "Low" + ","
        + "Close" + "," + "VS Low" + "," + "VS Mid" + "," + "VS High" +
        NewLine;
        FileAppend(FName, TradeStrl);
    End;
    If CurrentBar > 5 then Begin
        TradeStrl = NumToStr(Date, 0) + "," + NumToStr(Open, 2) + "," +
        NumToStr(High, 2) + "," + NumToStr(Low, 2) + "," +
        NumToStr(Close, 2) + "," + NumToStr(VSLow[l], 2) + "," +
        NumToStr(VSMid[l], 2) + "," + NumToStr(VSHigh[l], 2) + NewLine;
        FileAppend(FName, TradeStrl);
    End;
```

All moves are measured with the previous bar's close as a base. Once the data are collected, the code calculates the average move and the standard deviation before the data are denormalized to fit with the latest price action. When the calculation is completed, you have an indicator that makes the most out of each bar's price action and allows you to trade intraday using only end-of-day data or intraweek, using a mix of weekly and daily data. The last part of the code holds the necessary instructions for exporting all the data into a text file for further analysis in a spreadsheet program, such as Excel. Figure 5.1 shows what this pivot-point-type indicator looks like when charted together with the latest price action for the S&P 500 futures contract. As you can see, the *Meander indicator* consists of three lines, among which the upper (VS High) and lower (VS Low) lines can be chartered one or two standard deviations away from the middle (VS Mid) line. The Meander indicator works exactly the same for all markets.

With the necessary data imported into Excel, you can type in the following formula in adjacent columns to calculate the long entry level, the long risk level (stop loss), the long exit level, and the result of the trade. (Reverse the calculations in the next four columns for the short side.)

```
= IF(B2<F2;B2;IF(D2<F2;F2;"")),
```

Column *B* denotes the opening price, column *F* denotes the VS Low level, and column *D* the Low.

```
=IF(I2<>"";I2*(1-H$1212/100);"")
```

Column *I* denotes the long entry level and cell *HI212* refers to the cell where you have typed in your percentage risk.

```
=IF(I2<>"**;IF(D2<J2;J2;IF(AND(C2>H2;E2<H2);H2;E2));"")
```

Column *J* denotes the long risk level, column *C* denotes the High, column *H* the VS High level, and column *E* the closing price.

```
= IF(I2<>"'*;(K2 - I2)/I2;n - ")
```

Column *K* denotes the long exit level.

At the bottom of the spreadsheet type in the following formulas to calculate the total number of trades, percent winning trades, average percentage profit per trade and average dollar profit per trade. (Again, reverse the calculations for the short side.)

```
=COUNT1F(L2:L1208;"<>-")
```

Column *L* denotes the percentage result for each trade.

```
=COUNTIF(L2:L1208;">0")/L1210

=SUMIF(L2:L1207;"<>-")/L1210

=L1212*1350*250
```

The percentage risk that you are willing to take is, in this case, typed into cell H1212.

This simple system puts on a long (short) trade immediately at the open if the opening price is below (above) the VS Low (VS High) level, or at the VS Low

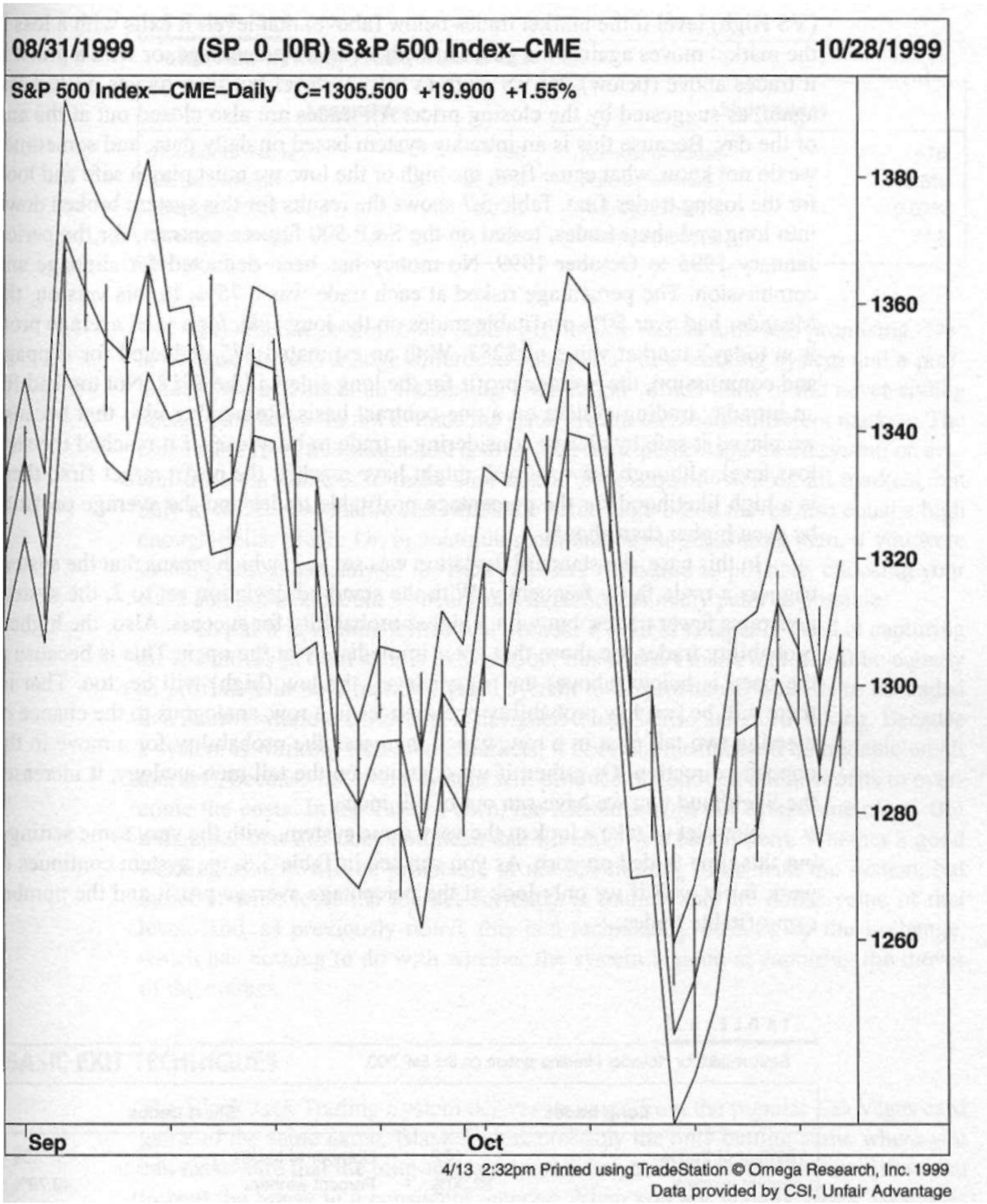


FIGURE 5.1

The Meander indicator makes the most out of your data.

(VS High) level if the market trades below (above) that level. It exits with a loss if the market moves against the position with a certain percentage, or with a profit if it trades above (below) the VS High (VS Low) level but then moves back down again, as suggested by the closing price. All trades are also closed out at the end of the day. Because this is an intraday system based on daily data, and sometimes we do not know what came first, the high or the low, we must play it safe and look for the losing trades first. Table 5.7 shows the results for this system broken down into long and short trades, tested on the S&P 500 futures contract, for the period January 1995 to October 1999. No money has been deducted for slippage and commission. The percentage risked at each trade was 0.75%. In this version, the Meander had over 50% profitable trades on the long side, for a total average profit in today's market value of $287. With an estimated $75 deducted for slippage and commission, the average profit for the long side will be $212. Not too bad for an intraday trading system on a one-contract basis. Remember also that because we played it safe by always considering a trade to be a loser if it reached the stop loss level, although we very well might have reached the profit target first, there is a high likelihood for the percentage profitable trades and the average profit to be even higher than shown.

In this case, the standard deviation was set to 1, which means that the system triggers a trade fairly frequently. With the standard deviation set to 2, the system generates fewer trades, but with a higher probability for success. Also, the highest probability trades are those that enter immediately at the open. This is because if the open is below (above) the trigger level, the low (high) will be, too. That is, there will be two low probability occurrences in a row, analogous to the chance of meeting two tall men in a row, which increases the probability for a move in the opposite direction. Or rather, if we continue on the tall men analogy, it increases the likelihood that we have run out of tall men.

Now, let us take a look at the very same system, with the very same settings, but this time traded on corn. As you can see in Table 5.8, the system continues to work fairly well if we only look at the percentage average profit and the number of profitable trades.

TABLE 5.7

Basic results for Meander I trading system on the S&P 500.

Long trades		Short trades	
Number of trades	522	Number of trades	459
Percent winners	52.30%	Percent winners	43.79%
Average profit (%)	0.09%	Average profit (%)	0.03%
Average profit ($)	287.16	Average profit ($)	112.81

TABLE 5.8

Basic results for Meander I trading system on com.

Long trades		Short trades	
Number of trades	439	Number of trades	476
Percent winners	48.97%	Percent winners	44.75%
Average profit (%)	0.07%	Average profit (%)	0.07%
Average profit ($)	6.88	Average profit ($)	7.02

But when it comes to the dollar profits, the results look less promising. This is because there is a huge difference between a good working system and a profitable system. This is an interesting observation, which adds to the never-ending debate on whether or not to trade the same system on several different markets. The conclusion from this simple test is to test the same percentage-based system on several different markets to make sure that it works equally well on all markets, but only to trade those markets in which the percentage-based moves also equal a high enough dollar profit. Or, in continuing our analogy to measuring men, if you were to sell pants to as many of the men you have measured as possible, choosing your sizes and markets would be beneficial in selling as many pairs as possible.

To put it in trading terms: just because a system is equally good at capturing all 2% moves in corn as it is in S&P 500, this doesn't mean that it will be equally as profitable in both markets. For a system to be profitable, it needs to be traded in a market where the moves it is designed to catch also are worth taking. Because a system is working well on all markets, it does not mean it will be tradable on all markets, because not every system will produce big enough dollar profits to overcome the costs. In the case of corn, the Meander does not even come close. But remember that this does not mean that Meander is a bad system. Whether a good working system will be profitable or not has nothing to do with the system, but rather at what level the market currently is trading and the dollar value of that level. And, as previously noted, this is a technicality decided by the exchange, which has nothing to do with whether the system is good at capturing the moves of the market.

BASIC EXIT TECHNIQUES

The Black Jack Trading System derives its name from the popular Las Vegas card game of the same name. Black Jack is probably the only betting game where you can make sure that the long-term odds work in your favor and therefore allow you to beat the house in a consistent manner. When you are playing Black Jack, it is essential to know when to hold, when to ask to be hit with yet another card, and when to bet more or less aggressively (if at all). To accomplish this you must know the current composition of the deck and how to analyze your odds correctly as compared to the dealer's. The basic rules are to bet more aggressively, but hold at a lower number if there are more high cards left in the deck, especially if the dealer's card is high as well. If you know how to do this, in the long run it will not matter what cards you are being dealt, you will end up being a winner anyway.

In the trading system Black Jack, all this is comparable to being able to trade profitably, no matter what the entry rule looks like, as long as you only take trades in the direction of the underlying trend, and know exactly when to exit and why. You are trying to keep your average trade (hand) in positive territory with just enough money to make it worthwhile. If you can accomplish this, the rest is just a matter of trading as frequently (playing as many hands) as possible in as short a time as possible. Therefore, it is not only essential that your entry rule allows you to take as many trades as possible, but even more important that your trades don't last too long.

When exiting a trade, you can do so under four different assumptions. In the best of worlds, exit technique number one is the *profit target,* which lets you exit the market with a limit order at the maximum open profit. Exit technique number two is the *trailing stop,* which comes into play when the market is starting to move against you after you have accumulated an open profit. Number three is the *stop loss* for those occurrences when the trade goes against you right off the bat. Finally, you also can exit with a *time-based stop,* possibly in combination with any of exit techniques one to three.

When it comes to the entries and trade triggers, there are probably as many ways to go about designing them as there are traders (and then some), so instead of delving any deeper into this matter, and because of the reasoning above, this version of Black Jack was put together with a very simple top-and-bottom-picking entry technique paired with a short-term breakout system in case the retracement wasn't deep enough to trigger an entry. In Part 3, where we focus more explicitly on efficient exits and overall trade efficiency, we will substitute these entries with random entries. That said, for a set of good short-term entry ideas, look into the work of Linda Bradford Raschke or Tom DeMark.

Finally, there is the *trend filter.* In the academic community and among fundamental analysts who pay homage to the efficient market hypothesis, for the longest time there was no such thing as a trend. However, in recent years even these people have had to cave in and admit that there is something that they call "a random walk with a drift." For decades, this *drift* has been measured by technical analysts with the help of moving averages of various lengths. Probably the most simple trend filter, which also has withstood the test of time, is the *200-days moving average.* To continue to keep it as simple as possible, this is also what we use for Black Jack. If you would like to look into more sophisticated long-term techniques, don't overlook the work of Nelson Freeburg.

Before we can put together the system, we also need to understand what it is we are trying to achieve, and consequently, how to go about doing it. Picture yourself as a quality controller standing at the end of an assembly line. Your pay (final estimated profit) for this job is dependent on how many units (number of trades) you and your machine (system) can produce, but also on how little you can make the look of all these units deviate from each other or from the average look (a low standard deviation). Obviously, you would like the assembly line to run as fast as possible, but only after you have examined one unit can the next unit be placed on the line, so the longer the time spent examining a single unit, the lower your payoff will be.

Along comes an obviously defective unit that is bound to lower your results. Without wasting any time, you toss it behind your back right away, freeing up the line for another unit to be placed upon it. The next unit looks pretty average, but to be sure, you examine it for a while longer than you did the previous one. In fact, without knowing it, with this average unit you spent an average amount of time.

But the third unit that comes along is much trickier. This one shows all the right features for being a real money maker, and while you're watching it, these features grow even bigger, promising to make this unit at least three times as valuable as the average unit. What to do? Should you let it grow even bigger or should you free up the line for more units? But then, all of a sudden its value-added features start to diminish. You freeze in panic, and not until its value has sunk back to twice the value of the average unit do you take it off the line. The problem is that in the time you spent processing this unit you could have processed three average units. What was it that happened here? By trying to increase your profits from an individual unit you put yourself in unfamiliar territory, which made you panic, increased the standard deviation of the outcome, and lowered the number of units produced, which in the end resulted in less overall profits.

But wait a minute, you say. What about the big winners? Doesn't the old adage say that you should let your profits run? Yes, it does, and it is probably good advice to listen to every now and then, but in trading it also has its price. The price is that you lose track of what is average. The really big winners are usually few and far between; the rest are just a bunch of look-alikes there to confuse you. By staying away from all of them, you are freeing both your mind and capital to milk that big winner several times over in a sequence of average trades, while at the same time allowing yourself to step in and out of other markets as well.

Translated into trading terms, for a trading system to be both as robust and as profitable as possible you should strive to make each trade as similar to all other trades as possible, even if it means that you have to cut your profits short every now and then. By doing this, you are freeing up time and money that can be spent on other average trades—trades with which you are familiar and know how to handle without panicking, which in the end should prove itself more profitable.

Now what exactly does this mean? It means that to come up with a reliable system with a positive average trade and a standard deviation that is as low as possible, and with as many profitable trades as possible, it is of paramount importance that the system work, on average, equally well on several different markets over several different time periods. This holds true even if you only are going to trade it on one market, because you never know when the characteristics of this market will change to resemble more closely those of another market. Therefore, if and when this happens, you must have taken this into consideration beforehand by making sure that the system (at the least) will not go berserk in this new market environment.

Hence, if the underlying assumption isn't market specific, always make sure that your system runs at least marginally profitably, if ever so slightly, in percentage terms, on as many markets as possible. If you wish, this could be comparable to making sure that your Black Jack card playing skills stay independent from any external factors, such as how many other people are playing, how the deck is shuffled, who the dealer is, or the name of the hotel.

For this system we use data covering the period January 1985 to October 1999, from 14 different markets. These are: coffee, copper, corn, cotton, CRB-index, D-mark, Eurodollar, Japanese yen, crude oil, live cattle, natural gas, orange juice, T-bond, and the T-bill.

We know that we should look for as many profitable trades as possible to generate an as high as possible average profitable trade in percentage terms, but with am as low as possible standard deviation. We can modify the code from Part 1 before we attach it to the bottom of the system, so that we can export the right data into a text file for further analysis in Excel. The TradeStation code for the Black Jack I trading system follows:

```
Inputs: BarNo(O), SL(0), PT(0), MP(0);
Vars: Trigger(O), BSLevel(O), TotTr(O), ExpVar(O), Prof(0), TotProf(0),
TradeStrl ("");
      Filters *****}
Trigger = Average(C, 200);
I ***** Retracement Entry *****}
If C > Trigger and MarketPosition = 0 and (L < XAverage(L, 6) or
L Crosses above XAverage(L, 6)) and C Crosses above XAverage(C, 6) and
H < XAverage(H, 6) Then Begin
    Buy ("Buy Support") at C;
    BSLevel = C;
End;
If C < Trigger and MarketPosition = 0 and (H > XAverage(H, 6) or
H Crosses below XAverage(H, 6)) and C Crosses below XAverage(C, 6) and
L > XAverage(L, 6) Then Begin
    Sell ("Sell Resist.") at C;
    BSLevel = C;
End;
```

```
{***** Breakout Entry *****}
If C > Trigger and MarketPosition = 0 and H Crosses above XAverage(H, 6) and
C Crosses above XAverage(C, 6) Then Begin
    Buy ("Buy Break") at C;
    BSLevel = C;
End;
If C < Trigger and MarketPosition = 0 and L Crosses below XAverage(L, 6) and
C Crosses below XAverage(C, 6) Then Begin
    Sell ("Sell Break") at C;
    BSLevel = C;
End;
{***** Exit techniques *****}
If BarsSinceEntry >= BarNo and BarNo <> 0 Then Begin
    ExitLong ("Long time") at C;
    ExitShort ("Short time") at C;
End;
If SL <> OThen Begin
    ExitLong ("Long loss") tomorrow at BSLevel * (1 + SL*0.01) Stop;
    ExitShort ("Short loss") tomorrow at BSLevel * (1 - SL*0.01) Stop;
End;
IfPT <> OThen Begin
    ExitLong ("Long profit") tomorrow at BSLevel * (1 + PT*0.01) Limit;
    ExitShort ("Short profit") tomorrow at BSLevel * (1 - PT*0.01) Limit;
End;
IfTS <> OThen Begin
    If C > BSLevel * (1 + MP*0.01)Then
        ExitLong ("Long stop") tomorrow at BSLevel * (1 + MP*0.01) Stop;
    If C < BSLevel * (1 - MP*0.01)Then
        ExitShort ("Short stop") tomorrow at BSLevel * (1 - MP*0.01) Stop;
End;
```

As you can see from the code, so far all input values are denoted by zeros. This is because we would like to activate them one at a time. The first thing we must do is find the optimal length of our trades. Therefore, we start by adding the following piece of code to the bottom of the system:

```
TotTr = TotalTrades;
If TotTr > TotTr[l] Then Begin
    Prof = PositionProfit(l) / (EntryPrice(l) * BigPointValue);
```

```
        TotProf = TotProf + Prof;
    End;
    If LastBarOnChart Then Begin
        ExpVar = BarNo;
        TotProf = TotProf / TotalTrades;
        TradeStrl = LeftStr(GetSymbolName, 2) + "," + NumToStr(ExpVar, 2) +
        "," + NumToStr(TotProf * 100, 2) + "," + NumToStr(Percentprofit, 2) +
        NewLine;
        FileAppend("D:\Temp\B J.cvs", TradeStrl);
    End;
```

Once this is done, we can run an optimization process in TradeStation. For each time TradeStation runs a test, it also exports the data we need into a text file for further analysis in Excel. Never mind the optimization report in TradeStation. In Excel, start by sorting and separating the data by numbers of days in trade, then type in the following formulae at the bottom of each group.

To calculate the average percentage profit for a specific trade length for all markets:

=AVERAGE(C1:C14)

where column *C* denotes the average profit for a specific market and trade length.

To calculate the standard deviation of the percentage profit for a specific trade length for all markets:

=STDEV(C1:C14)

To calculate the ratio between the average profit and standard deviation of outcomes:

=E14/E15

where cell *El4* denotes the average profit and cell *El5* denotes the standard deviation.

To calculate the percentage profitable trades for a specific trade length for all markets:

=AVERAGE(D1:D14)

where column *D* denotes the percentage profitable trades for a specific market and trade length.

To calculate the standard deviation of the percentage profitable trades for a specific trade length for all markets:

= STDEV(D1:D14)

To calculate the ratio between the percentage profitable trades and its standard deviation:

=F147F15

where cell *F14* denotes the percentage profitable trades and cell *F15* denotes the standard deviation.

Summed up in a table for easier interpretation, the results resemble those in Table 5.9, which shows the data for the time-based stop, which is triggered at a certain number of days, no matter what. In this case, we are looking for a high average profit and a high percentage of profitable trades. The higher the ratio between the critical variable and its standard deviation, the more robust the system.

From Table 5.9 we can see that the ratio between the average profit and its standard deviation is at its highest with a trade length of 14 days. A trade length of ten to 11 days, however, also seems to have a decent risk/reward relationship, especially considering that the ratio between the percentage profitable trades and its standard deviation also is slightly higher for these trade lengths than for the 14-day alternative. If we were to set a maximum trade length of either 10 or 11 days, however, the actual average trade length is slightly shorter when the other stops are added. Therefore, we will change the time-based stop slightly and turn it into a very tight trailing stop that will be triggered if the trade lasts for 11 days or more.

TABLE 5.9

Summary tradelength statistics for Black Jack I trading system.

	Days in trade						
	2	3	4	5	6	7	8
Average profit	0.05	0.04	0.01	0.04	0.00	0.03	0.05
Standard deviation	0.10	0.13	0.16	0.18	0.21	0.26	0.25
Ratio	0.51	0.32	0.08	0.22	-0.01	0.13	0.21
Percent profitable	52.99	51.64	52.30	53.30	53.12	52.91	52.82
Standard deviation	4.32	4.08	3.91	3.70	4.28	4.37	4.23
Ratio	12.27	12.64	13.38	14.39	12.40	12.12	12.49
	9	10	11	12	13	14	15
Average profit	0.08	0.20	0.17	0.10	0.11	0.14	0.15
Standard deviation	0.38	0.36	0.35	0.35	0.30	0.24	0.32
Ratio	0.21	0.56	0.50	0.29	0.36	0.58	0.45
Percent profitable	54.04	53.96	54.12	53.61	53.32	53.21	53.54
Standard deviation	3.89	4.79	4.78	5.01	5.96	5.15	5.05
Ratio	13.91	11.28	11.31	10.70	8.94	10.34	10.60

If the trade runs on for too long, our profit target eventually stops it out instead. The TradeStation code for the time-based trailing stop is :

```
If BarsSinceEntry >= BarNo Then Begin
    ExitLong ("Long time") tomorrow at C Stop;
    ExitShort ("Short time") tomorrow at C Stop;
End;
```

With a time-based trailing stop that kicks in after 11 days in place, it is time to set a profit target. In the TradeStation code for the export function simply change the line "ExpVar = BarNo" to "ExpVar = PT". Remember that the profit target is only there to catch the most extreme trades, but because the entire idea behind Black Jack is to keep all trades as uniform as possible, we don't want our profits to run for too long either. In this case, we aim for the 5 to 10% region. Table 5.10 shows what our results look like.

From Table 5.10 we can see that the ratio between the average profit and its standard deviation is at its highest with a profit target of 9.5%. This value also seems to be surrounded by other fairly high values, which indicates that this is a robust level, likely to produce good results in the future, even though the optimal level might move around slightly. Therefore, we decide that we will add a profit target of 9.5% to the system.

TABLE 5.10

Summary profit target statistics for Black Jack I trading system

	Percentage profit target					
	5	5.5	6	6.5	7	7.5
Average profit	0.10	0.09	0.10	0.08	0.10	0.13
Standard deviation	0.48	0.45	0.45	0.49	0.47	0.46
Ratio	0.20	0.21	0.23	0.17	0.21	0.27
Percent profitable	55.91	55.41	55.10	54.41	54.21	54.14
Standard deviation	4.06	3.97	4.07	4.32	4.55	4.63
Ratio	13.77	13.97	13.54	12.59	11.92	11.69
	8	8.5	9	9.5	10	10.5
Average profit	0.13	0.13	0.13	0.15	0.13	0.13
Standard deviation	0.43	0.43	0.45	0.43	0.41	0.42
Ratio	0.30	0.31	0.29	0.36	0.33	0.32
Percent profitable	54.05	53.90	53.72	53.64	53.55	53.47
Standard deviation	4.69	4.71	4.90	4.99	4.91	4.99
Ratio	11.52	11.44	10.96	10.75	10.91	10.72

With a time-based trailing stop and a profit target in place, the same maneuvers are repeated for the minimum profit stop and the stop loss. The minimum profit stop we try to place somewhere between zero profits and halfway up to the profit target, which means that we must look in the 0 to 5% region. Table 5.11 shows the result for these levels.

From Table 5.11 we can see that the higher the minimum accepted profit, the lower the average trade, but also that the *uncertainty,* as measured by the ratio between the average profit and its standard deviation, is increasing. To be sure, it seems as if we should go with a fairly low accepted minimum profit. In doing so we also can expect a high percentage of profitable trades even though the insecurity about this number decreases with a lower minimum accepted profit. For this system, we decide to aim for a minimum accepted profit of 1%.

The stop loss, finally, we would like to keep as tight as possible, but at the same time make sure that we give the trade some initial slack. Let us see what we can find in the 0.5 to 2.5 percent region. Table 5.12 shows our findings.

In looking at Table 5.12, we immediately can make one very important observation. The ratio between the average profit and its standard deviation now is above 1 in most instances. (Remember, the higher the ratio between the critical variable and its standard deviation, the more robust the system.)

TABLE 5.11

Summary minimum profit level statistics for Black Jack I trading system.

	Percentage minimum target				
	0.5	1	1.5	2	2.5
Average profit	0.16	0.17	0.14	0.16	0.11
Standard deviation	0.23	0.26	0.25	0.25	0.33
Ratio	0.69	0.65	0.54	0.61	0.33
Percent profitable	69.39	65.47	62.35	60.58	58.86
Standard deviation	5.73	5.84	5.81	5.02	4.21
Ratio	12.10	11.20	10.73	12.07	13.98
	3	3.5	4	4.5	5
Average profit	0.12	0.11	0.14	0.13	0.12
Standard deviation	0.35	0.40	0.41	0.43	0.40
Ratio	0.33	0.28	0.33	0.30	0.30
Percent profitable	57.21	56.43	55.52	55.17	54.69
Standard deviation	3.86	3.83	3.98	4.04	4.18
Ratio	14.83	14.72	13.93	13.66	13.08

TABLE 5.12

Summary stop loss statistics for Black Jack I trading system.

	Percentage stop loss				
	0.50	0.75	1.00	1.25	1.50
Average profit	0.17	0.18	0.18	0.17	0.15
Standard deviation	0.14	0.14	0.16	0.16	0.15
Ratio	1.27	1.24	1.18	1.08	1.00
Percent profitable	33.40	38.93	43.57	46.88	49.25
Standard deviation	11.04	9.35	7.92	6.93	6.73
Ratio	3.02	4.16	5.50	6.76	7.32
	1.75	2.00	2.25	2.50	2.75
Average profit	0.13	0.13	0.14	0.16	0.16
Standard deviation	0.12	0.15	0.15	0.17	0.16
Ratio	1.03	0.84	0.95	0.94	1.01
Percent profitable	51.37	53.35	55.24	56.79	57.97
Standard deviation	6.50	5.99	5.53	5.54	4.93
Ratio	7.90	8.90	9.99	10.25	11.77

With 68% certainty, we can say that the average profit will be positive. For instance, with the stop loss at 0.5%, the average profit is 0.17% and the standard deviation 0.14%. This means that with 68% certainty, we can say that the true value for the average profit will lie somewhere in the interval 0.03 to 0.31%. Table 5.12 also reveals that, after adding the stops, the uncertainty (as measured by the standard deviation) about the outcome has decreased at the same time as the average expected profit has increased somewhat for the tightest stops. The price for this is a lower percentage of profitable trades, however. By the same token, we can see that the percentage of profitable trades seems to increase somewhat the further away we place the stop, but that this comes at the price of a deteriorating profit factor. A good compromise between these two phenomena, therefore, seems to be to place the stop in the middle of the interval, at the 1.5% level. That this is a compromise is emphasized by the fact that none of the markets tested actually had the 1.5% level as its best alternative.

With all exit levels in place, it is now time to look at what performance can be expected from each of the individual markets. Table 5.13 shows the average percentage profit for each market, together with its current dollar value.

As you can see, for most of our 15 markets, the average percentage profitable trade is not big enough to generate a big enough dollar profit to be worthwhile trading. Although Black Jack I works well on almost all markets, this does not mean it will be tradable on all markets, because not every system produces big

TABLE 5.13

Market summary for Black Jack I trading system.

Market	Average profit	Dollar value	Percent profitable
Orange Juice	0.21	28.69	46.20
Copper	0.18	36.24	44.26
Live cattle	0.30	80.78	55.64
Japanese yen	0.01	13.97	48.50
Corn	0.13	13.48	48.17
T-bond	0.22	243.93	58.48
Eurodollar	0.04	82.52	60.13
Natural gas	0.37	119.40	37.13
D-mark	-0.13	-88.68	49.38
Coffee	0.28	99.89	40.97
CRB-index	-0.01	-7.73	52.02
Cotton	0.11	29.74	47.96
T-bill	0.02	51.70	56.71
Crude oil	0.33	76.55	43.93
All markets	0.15	—	49.25
S&P 500	0.18	579.14	52.86

enough dollar profits to overcome the costs. This does not mean that Black Jack I is a bad system. In fact, of all the markets tested, the only market that might be worthwhile trading is T-bonds and even this market is a border case. Other markets that, while not ruining you, but at the same time only feed your broker—are natural gas, coffee, live cattle, Eurodollar, and crude oil. This does not mean, however, that the model is not working for these markets, but simply that these markets, at this particular point in time, are not trading at the appropriate price levels and with a high enough point value to generate a profit after slippage and commission. Hence, a good working model is not the same as a profitable model.

The S&P 500 was not among the markets chosen for the testing process, because I wanted to save this, perhaps the most popular of all markets, for some out-of-sample testing. The bottom row in Table 5.13 shows the initial findings for how our model would have fared on the S&P 500 futures contract. And as you can see, it would have done fairly well, with an average percentage profit of 0.18%, equal to an average dollar profit of $579, not counting slippage and commission, in today's market value. This is very interesting information, because the way TradeStation and several other testing packages calculate this number, it would have come out to approximately $387. Again, this is because all of these packages look at how many dollars you could have made, not how many dollars you can expect to make; in an up-trending market, the historical value will almost always (providing a steady working model) be lower than the actual value for today's market.

On a separate note, it is once again worthwhile mentioning that the reason you don't want to adjust your results for slippage and commission while you're building the system is that you would like to find a solution that can trade as efficiently as possible (squeeze out the most of the move) with as few constraints (rules) as possible. Applying slippage and commission at this point will result in a suboptimal solution and make the system more unreliable when traded on real-time data. Ideally, you should not bother with slippage and commission until it is time to trade the system with real-time data and then decide if the expected profit is worth the expected cost.

Let us use our detailed export function from Part 1 to take a closer look at how Black Jack would have fared trading the S&P 500, as presented by Table 5.14. Tested on the S&P 500 with data from January 1985 to October 1999, Black Jack I produced 280 trades, with an average profit of $581 in today's market value. However, with a drawdown of more than $102,000, Black Jack can hardly be considered a tradable model—at this point.

Note, however, that in TradeStation this drawdown figure would only have come out to $43,695 on a one-contract basis. Why is this? It's because when this drawdown happened, the market was trading at a much lower level than today, and consequently the dollar moves were smaller as well. But because the percentage moves stay approximately constant, you can take this sequence of trades, measured in percentages, and transfer them to today's market level for an estimate of what the dollar value would be today. No wonder they say, "your largest drawdown is still to come." Remember, however, that this value assumed that all trades would have been taken from today's market value and provided that all profits and losses could have been reinvested. Therefore, you cannot use this value when comparing your system with other ready-made systems or the results from a CTA, whom you might contemplate giving your money to instead. Instead, it should only be used for your own research during the building process. As such, is it much better than any value any technical analysis or system-trading package will give you.

Now, you probably are thinking, "Yeah, but even so, how likely is it that all trades would be repeated from today?" Well, it's just as likely (or shall we say unlikely) that the market will repeat itself level for level, move for move, price for price, which is what you're assuming when you're doing it the old-fashioned way. If neither of these two assumptions is likely to happen again, ask yourself, "am I

TABLE 5.14

Performance summary for Black Jack traded on the S&P 500, January 1985-October 1999.

Total trades		280	Winners	148	52.86%	Losers	132	47.14%
Profit factor		1.25	Lrg winner	9.50%	30,991	Lrg loser	-2.23%	-7,275
Avg profit	0.18%	581	Avg winner	1.69%	5,521	Avg loser	-1.52%	-4,958
St Dev	2.02%	6,594	Cum profit	55.38%	180,662	Drawdown	-31.47%	-102,662

more interested in knowing what profits or losses I could have made historically, or am I more interested in getting to know how I can make my results as forward-looking as possible, to get a feel for how much I might be making today?"

Nonetheless, in its current version Black Jack would be very difficult to trade. But do not despair. As we will see in later chapters, there are much better ways of building a system like Black Jack than this example.

CHAPTER 6

Trade or Not to Trade

If a specific system is not worth trading on a specific market, although it works as well on that market as on any other markets, then it becomes interesting to know how much the market in which you are interested really is worth, and if the risks are worth taking considering the volatility of the market and other viable trading alternatives. This is especially interesting if it is a short-term system, with trades lasting no longer than a week or two. As it turns out, the weekly moves of most agricultural markets have too small dollar values, as compared to many other markets, such as currencies, indexes, and interest rates.

Table 6.1 shows how much half the average percentage weekly true range is worth in today's market value in several different markets. For instance, for coffee half the average weekly true range for the last ten years and for the last year are worth $1,343 and $1,453, respectively. At the same time, a 1% move is worth $359. For coffee a $1,459 move equals a 4.05% move. Hence, the higher the number in the rightmost comparative volatility column, the more volatile the market, on a percentage basis, as compared to the other markets.

Let us take a closer look at some markets in this table. It is interesting to see that basically all weather-sensitive markets (like the American agricultural markets), such as corn, wheat and soybeans, have fairly high comparative volatility. Even more weather-sensitive markets (and perhaps traditional gambling hot spots), such as coffee, natural gas, and orange juice, have even higher volatility.

On the other hand, the macroeconomic-oriented markets, such as the currencies and interest rates, all have very low comparative volatility, many times below 1, which means that these markets seldom produce a half-weekly average true range of above 1%. With true ranges this low it is doubtful that one can trade a market like this profitably with a short-term system if the current market level and price value aren't high enough. Fortunately, most macro-markets are still viable trading alternatives.

TABLE 6.1

Dollar value of half average weekly true range (AWTRO, 1% move, and their comparative volatility (AWTR/% move)

Market	10 years	5 years	1 year	1%	Comp. Vol.
Bean oil	203	206	272	98	2.78
Cacao	231	200	278	87	3.20
Canada dollar	345	369	447	680	0.66
Coffee	1,343	1,512	1,453	359	4.05
Copper	452	490	492	199	2.47
Corn	187	208	218	100	2.18
Cotton	502	499	570	267	2.13
CRB index	825	828	1,063	1,020	1.04
Crude oil	703	708	859	229	3.75
Dollar index	866	781	825	992	0.83
Eurodollar	204	173	139	2,347	0.06
Feeder cattle	473	573	526	398	1.32
Gold	339	310	393	294	1.34
Heating oil	776	763	941	257	3.66
Japanese yen	1,425	1,617	1,825	1,206	1.51
Lean hogs	413	478	780	186	4.19
Live cattle	345	391	385	272	1.42
Lumber	714	756	650	251	2.59
Municipal bonds	840	884	745	1,087	0.69
Natural gas	—	1,628	1,542	322	4.79
Nikkei	—	1,723	1,645	874	1.88
Oats	148	149	135	55	2.45
Orange juice	409	428	476	134	3.55
Pork bellies	982	1,045	1,311	248	5.29
S&P 500	4,767	5,387	6,390	3,264	1.96
Silver	614	641	616	261	2.36
Soy beans	444	477	574	241	2.38
Soy meal	299	347	406	147	2.76
Sugar	213	209	325	77	4.22
T-bills	192	171	162	2,374	0.07
T-bonds	1,037	1,046	1,030	1,115	0.92
T-notes	680	676	659	1,084	0.61
Unleaded gas	818	836	979	268	3.65
Wheat	280	316	321	128	2.51

But even many highly volatile markets can be difficult to trade if the dollar values of their moves are not high enough. For instance, say that you have a short-term system with a profit factor as high as 2.2 that is expected to produce 55% profitable trades. In the best of worlds, you can expect the average winning trade to be half the average true range of that market. So far, you have only traded it on T-bonds, which is a very liquid and modestly volatile market for an average profit per trade of $294 (with $75 deducted for slippage and commission). Now you would like to trade this system on a more volatile market, like orange juice. With a profit factor of 2.2 and an average winning trade of $476 (see Table 6.1), the average losing trade is $216 ($476 / 2.2). With 55% profitable trades, a sequence of 20 trades will, on average, produce a profit of $3,292 (11 X $476 - 9 x $216), which in turn breaks down to an average profit of $165 per trade ($3,292 / 20). Deduct from that another $75 to cover slippage and commission, and you are down to $90 per contract traded, or less than one third of what you are making in the T-bonds. Considering that you only get one or two chances like this per week, making only a little over a $100 a week simply is not worth sticking your neck out and running the risk of losing it all.

CHAPTER 7

Following the Trend

From the previous chapters we have seen that short-term trading can be incredibly rewarding, but also very risky, especially if the market you are trading simply does not produce the moves you seek. Because not every market can produce a short-term average profit big enough in dollar terms, the only way to trade these markets is to go with less frequent trading and longer trades that raise the value of the average trade to a level worth trading.

In the previous chapters we discussed how to classify trades and what might constitute long term and short term. It might be a good idea to always try to be as short term as you can when it comes to market time units (bars). When you're designing a long-term system, measured in regular time units (days), you should use weekly (or perhaps even monthly) data during the building and research process so that you can work with as few market time units (bars) as possible. After an optimal number of time units for the system in question, the further away from the signal you move, the less profitable and reliable your results will be, as can be seen from Table 7.1.

Table 7.1 shows the average profit per trade from a 20-day (four-week) breakout system, traded on the long side only on the S&P 500 stock index futures contract over the period June 1983 to August 1999, and with all trades lasting for a certain amount of days (weeks) no matter what. From the top half of this table you can see that, in this case, the longer the holding period, the higher the average profit. But with a higher average profit comes a higher standard deviation of the individual outcomes, indicating that the uncertainty about the results also is increasing. This can be measured by the ratio between the average profit and the standard deviation. As long as the ratio is increasing as well, however, the average profit is growing faster

TABLE 7.1

Trade/time reliability comparison.

	Days in trade					
	10	20	30	40	50	60
Avg. perc. profit	0.152	0.462	0.854	0.886	1.293	1.304
St. Dev.	2.033	2.822	3.368	3.842	4.913	4.982
Ratio	0.075	0.164	0.254	0.231	0.263	0.262
Profit/day	0.015	0.023	0.028	0.022	0.026	0.022
	Weeks in trade					
	2	4	6	8	10	12
Avg. perc. profit	0.366	0.818	1.086	1.205	1.468	1.780
St. Dev.	2.136	2.651	3.433	3.559	4.571	4.746
Ratio	0.171	0.309	0.316	0.339	0.321	0.375
Profit/week	0.183	0.205	0.181	0.151	0.147	0.148
Profit/day	0.037	0.041	0.036	0.030	0.029	0.030

than the standard deviation, indicating a decreasing relative risk. In this case, the ratio seems to level off after about 50 days, indicating that there is little to be gained by staying any longer in the trade. This is confirmed by the average profit made per day, which starts to decrease after 30 days. Similar observations also can be made from the bottom, weekly part of the table. What is even more important is that by comparing the weekly data with the corresponding daily data, we can see that the weekly data produce both more profitable and less risky results, as measured by the average profit and the standard deviation. That said, in the following long-term systems we work both with weekly and daily data.

MOVING AVERAGES

More than one book or article has been written on the topic of moving averages, most of them focusing on the *basic crossover signal.* The crossover signal is produced either by the price crossing one or several averages, or that of a faster moving average crossing a slower one. (A fast moving average is an average that is calculated with fewer data points, or a shorter lookback period, than a slow moving average, and vice versa.) With a basic system like this, most of us probably have produced fantastic results on historical back-testing, only to discover that reality looks less glamorous when the model is traded live or tested on previously unseen data. To cure this, many try to filter out the actual buy/sell signals, either by adding additional requirements like only taking the trade after a retracement and/or on the second crossover, or by adding additional moving averages or other indicators of various lengths.

Another strategy that looks good on paper is to avoid the moving average model completely when the market is in a trading range, and consequently only use it when the market is trending. The problem is that the only way to classify the market as either trending or nontrending, using this method, is by hindsight, which is a luxury that few of us are granted in actual real-time trading. Therefore, for a long-term system to be stable over time it must be constructed in such a way that it leaves you with enough slack, so you are not stopped out time and time again during less advantageous times.

When it comes to moving averages, the *directional slope* method is a better choice than the basic crossover method. As an example, we can apply a 100-day moving average to the CRB index, which is a notoriously choppy market. From its inception in May 1986 to October 1999, there have been 214 occurrences where the closing price has crossed over the average, but only 160 occurrences where the average has changed its direction from one day to another. On a trendier market, like the Japanese yen, there have been 184 crossovers and 127 directional changes from May 1972 to October 1999. With a 200-days average, the same numbers come out to 122 and 82 for the CRB index, and 170 and 92 for the Japanese yen. What does this mean? If it is reasonable to assume that in a prolonged trend, the trend of the moving average will follow, you should be able to reduce the number of wrong signals considerably by using the slope of the average as a trigger for your trade, instead of the actual crossover.

But that is not all. Notice that for the Japanese yen, with the 200-day moving average the number of crossovers is still larger than the number of directional changes for the 100-day average. With the directional slope method, you also can build a system that uses less and more up-to-date data, and still achieve the same effect. For instance, for the CRB index the percentage profitable trades went from 16% for the crossover method to 33% for the directional slope, with the 200-day moving average, and from 10 to 32% with the 100-day moving average. For the Japanese yen the same numbers went from 17 to 36% with the 200-day moving average, and from 31 to 40% with the 100-day moving average.

Another common trading technique, when it comes to moving averages, is to use two moving averages and to require the fast moving average to cross over the slow one before entering a trade, but only to require the price to cross the fast average to exit. When it comes to the directional slope technique, the same effect can be achieved by using the slope of a slower moving average for the entry (Entry MA), but the slope of a faster moving average for the exit (Exit MA). When the two contradict each other, you stay out. Yet another way of doing this is to use one moving average (or one set of averages) for the long side and another average (or set of averages) for the short side. This could be a good idea for markets with a natural upward drift, such as the stock market. When you test such a combination, remember to treat each side as two different markets, traded with two different systems; when the systems contradict each other, you can either choose to stay out or trade in smaller positions.

Let's put together a model using the directional slope method, consisting of two moving averages that will be the same for both the long and the short side and that will work equally as well on as many markets as possible. Also, in accordance with our finding that we will be better off using as few bars as possible when examining the system, we will put it together using weekly data substituting a 200-day moving average with a 40-bar moving average. At the end of the code we attach our export function for the profit factor, percentage profitable trades, and time-in-market, and tailor it so that it also exports the current moving average combination. The TradeStation code for this system follows:

```
Input: EntryMA(lO), ExitMA(5);
Vars: EntryVal(O), ExitVal(O), PFactor(O), WTrades(O), TotBars(O), TradeStrl("");
EntryVal = Average(Close, EntryMA);
ExitVal = Average(Close, ExitMA);
Conditionl = EntryVal > EntryVal[1];
Condition2 = ExitVal > ExitVal[l];
If Conditionl = True and Condition2 = True Then
	Buy at Close;
If Conditionl = False and Condition2 = False Then
	Sell at Close;
If Condition2 = False Then
	ExitLong at Close;
If Condition2 = True Then
	ExitShort at Close;
If LastBarOnChart Then Begin
	PFactor = GrossProfit / — GrossLoss;
	WTrades = NumWinTrades * 100 / TotalTrades;
	TotBars = (TotalBarsLosTrades + TotalBarsWinTrades) * 100 / BarNumber;
	TradeStrl = LeftStr(GetSymbolName, 2) + "," +
	NumToStr(EntryMA, 0)+ "," + NumToStr(ExitMA, 0) + ",'* +
	NumToStr(PFactor, 2) + "," + NumToStr(WTrades, 2) + "," +
	NumToStr(TotBars, 0) + NewLine;
	FileAppend('"D:\Temp\MaDirect.txt", TradeStrl);
End;
```

The model was tested on all moving average combinations on 16 different markets over the period from January 1979 to October 1994. The rest of the data were saved for some out-of-sample testing. The 16 markets tested were: T-bonds, live cattle, Japanese yen, corn, Canada dollar, crude oil, dollar index, lumber, orange juice, S&P 500, copper, Eurodollar, CRB index, cotton, gold, and coffee. No money was deducted for slippage and commission. The data was put together using the ordinary point-based back-adjustment method.

With all the data exported into Excel, we build a matrix as a base for a surface chart. This lets us graphically examine our data and look for robust and stable moving average combinations, which are likely to continue to hold up in the future.

Start by using the data-sort function to sort first by the Entry MA and then by the Exit MA. Then type in the following formulae in two adjacent columns, and fill down to the bottom of the spreadsheet.

To calculate the average profit factor for each moving average combination:

=IF(C17<>C18;AVERAGE(D2:D17);"")

where column C denotes the Exit MA and column *D* the profit factor for each moving average combination and market.

To calculate the ratio between the profit factor and its standard deviation:

=IF(G2<>"";G2/STDEV(D2:D17);"")

where column *G* denotes the previously calculated average profit factor.

=INDEX(B:B;2+((ROW()-2)*16))

where column *B* denotes the Entry MA. The value 16 stems from the fact that we are testing on 16 markets.

=INDEX(C:C;2+((ROW()-2)*16)),

= INDEX(G:G;2+((ROW()-2)* 16))

=INDEX(H:H;2+((ROW()-2)* 16))

where column *H* denotes the ratio between the profit factor and its standard deviation.

When this is done, in an adjacent column, leave the top cell blank and fill in the values 0 to 11 in the following rows. Starting at the top row in the next column, fill in the values 0 to 11 in the following columns. Figure 7.1 shows what this can look like.

Figure 7.1 shows a sample matrix created in a spreadsheet program after we exported the necessary data from TradeStation and applied the suggested formulas. In cell Q2 fill in the following formula and carry it out all the way to cell AA2:

=INDEX($K:$K;2+(P1*1))

where column *K* denotes the Exit MA and cell PI denotes the value zero.

O	P	Q	R	S	T	U	V	W	X	Y	Z	AA
	0	1	2	3	4	5	6	7	8	9	10	11
0		5	6	7	8	9	10	11	12	13	14	15
1	10	1.65	1.60	1.78	1.76	1.67	1.60	1.63	1.76	1.75	1.75	1.82
2	11	1.68	1.66	1.77	1.77	1.67	1.67	1.57	1.76	1.77	1.72	1.80
3	12	1.66	1.66	1.82	1.83	1.69	1.69	1.78	1.72	1.82	1.72	1.77
4	13	1.70	1.67	1.86	1.85	1.70	1.71	1.77	1.88	1.70	1.75	1.75
5	14	1.66	1.65	1.81	1.85	1.72	1.77	1.73	1.80	1.81	1.67	1.79
6	15	1.67	1.67	1.85	1.87	1.70	1.77	1.76	1.83	1.81	1.78	1.69
7	16	1.67	1.68	1.85	1.93	1.79	1.85	1.83	1.93	1.85	1.79	1.78
8	17	1.70	1.70	1.85	1.89	1.77	1.84	1.85	1.95	1.88	1.85	1.83
9	18	1.72	1.68	1.88	1.91	1.75	1.83	1.84	1.93	1.86	1.82	1.80
10	19	1.63	1.72	1.90	1.95	1.76	1.87	1.86	1.96	1.85	1.84	1.90
11	20	1.62	1.68	1.90	1.91	1.70	1.80	1.80	1.85	1.76	1.74	1.75

FIGURE 7.1

The average profit factor for different MA combinations.

In cell P3 fill in following formula, down to cell PI3:

=INDEX(J:J;2+(02*11))

where column *J* denotes the Entry MA and cell 02 denotes the value zero.

Finally, in cell Q3 fill in the following formula, out and down, all the way to cell AA13 to complete the matrix in Figure 7.1:

=OFFSET(L1;($02*$AA$1)+Q$1;0)

where column *L* denotes the average profit factor.

With the matrix ready, it is now easy to create a surface chart similar to that in Figure 7.2, which shows how the average profit factor for all markets varies with the length of the moving averages that make up the system. The higher the profit factor, the better the system. Similar charts also can be made for the number of profitable trades or the time spent in the market, or even of the standard deviation of any of the above, as yet another measure over the robustness of the system.

From Figure 7.2, we can see that an Entry MA in the 16- to 20-bar region seems to produce very high profit factors with almost any Exit MA from 10 bars and up, but also with an Exit MA in the 7- to 8-bar region. The most profitable Exit MAs seem to be the 8-bars and 12-bar Exit MAs. However, from Figure 7.3, we also can see that the ratio between the profit factor and its standard deviation seems to be the highest for the 8-bar Exit MA, either together with an Entry MA around 12 bars or with an Entry MA around 18 bars. The ratio between the profit factor and its standard deviation measures the robustness of the system. The higher the ratio, the more robust the system. The most robust combinations seem to be with an 8-bar Exit MA, together with a 12- or 18-bar Entry MA. Therefore, the two charts in conjunction tell us to go with an 18-bar Entry MA and an 8-bar Exit MA.

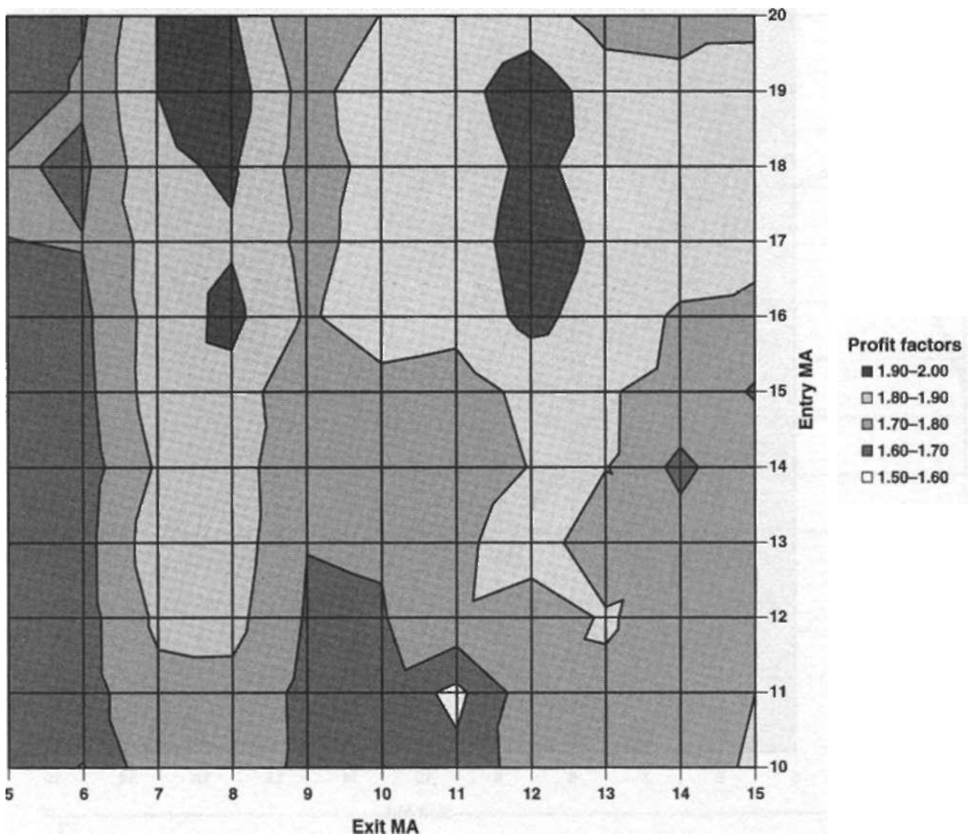
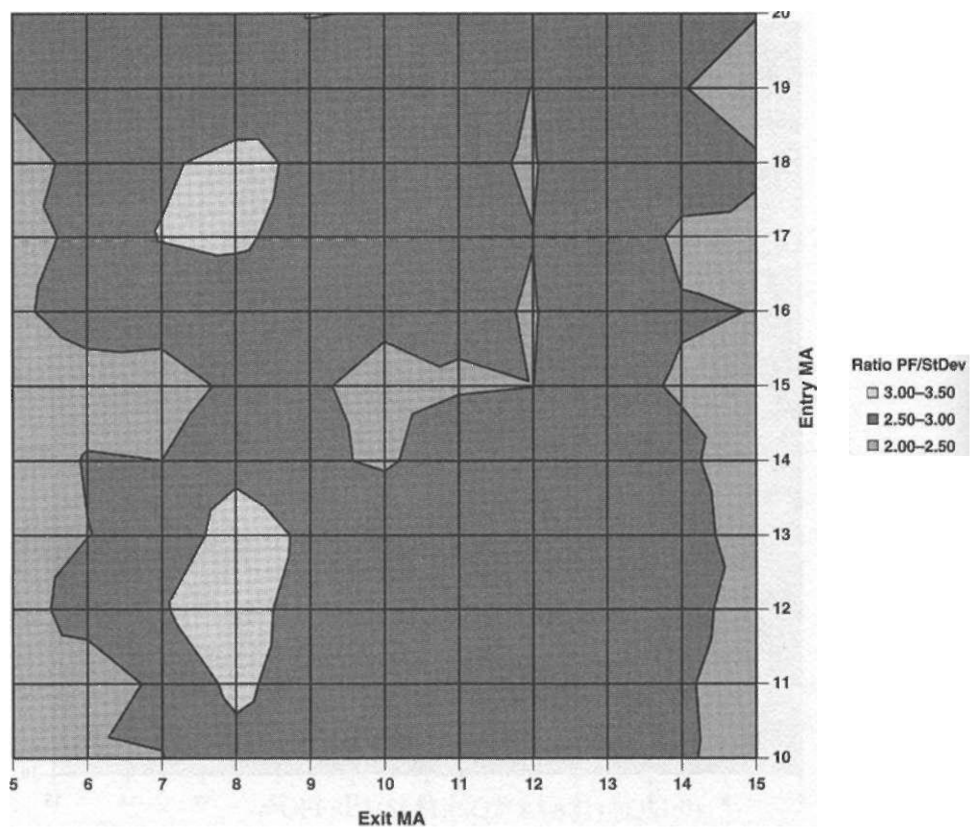


FIGURE 7.2

The average profit factor for different MA combinations.

Another method is to calculate how often a specific moving average combination happens to be among, for instance, the top 10 combinations for each market or among, for instance, the top 200 for all markets. Using our Entry MA as an example, in Figure 7.4 we can see that all Entry MAs between 14 and 20 bars were among the best 200 combinations at least 15 times each, with the 16-bar MA topping the crowd with a total of 27 occurrences. This strengthens our conclusion that an Entry MA of 18 bars will be a robust and stable choice that is likely to hold up in the future.

Figure 7.5 shows yet another example of this technique, but this time we have sorted on the percent profitable trades column and for how many times we could find any Exit MAs among the best 200 combinations. As you can see, if you're looking to boost the number of profitable trades, you should go for an Exit MA in the 6- to 10-bar region. The jewel of the crown is the 8-bar MA, with 27 occurrences.



Exit MA

FIGURE 7.3

The ratio between the average profit factor and the standard deviation shows the robustness of the system.

Tables 7.2 and 7.3 show how the directional slope system, with an 18-bar Entry MA and an 8-bar Exit MA, would have performed on the individual markets on both the in-sample data and the out-of-sample data. For the in-sample period, the average profit factor was 1.91. With the ratio between the profit factor and its standard deviation equal to 3.13, the standard deviation comes out to 0.61 (1.91 / 3.13), which means that we can be 68% sure that the true average profit factor will be no lower than 1.30 (1.91 - 0.61). During the out-of-sample period, the average profit factor was 2.09. With the ratio between the profit factor and its standard deviation equal to 0.73, the standard deviation comes out to 2.86 (2.09 / 0.73), which means that we no longer can be 68% sure that the true average profit factor will be above 1. Hence, the profit factor was slightly higher for the out-of-sample data than for the in-sample data, but the price for this came in the form of a smaller ratio between the profit factor and its standard deviation, which means that the system has become less robust.

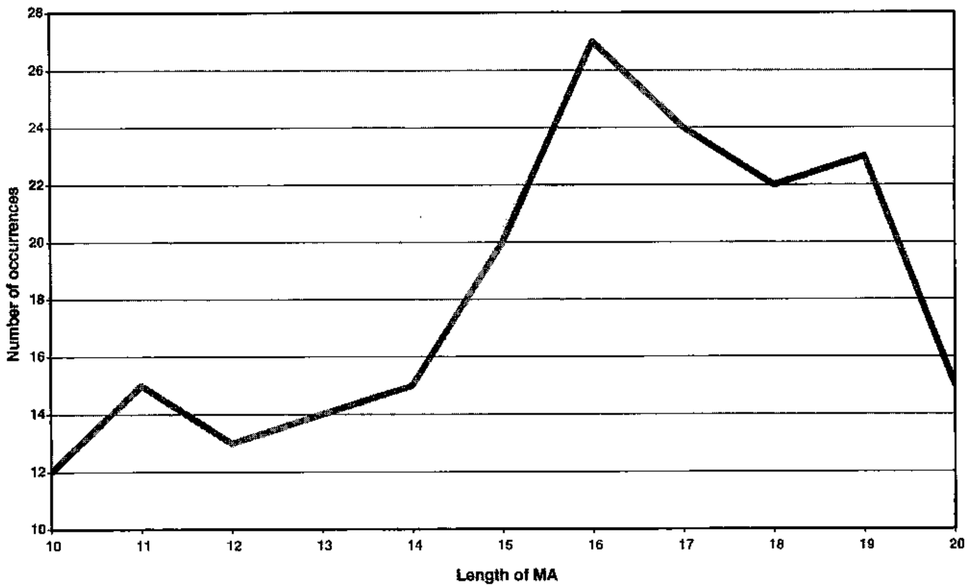


FIGURE 7.4

Number of top 200 profit factor occurrences for different entry MAs.

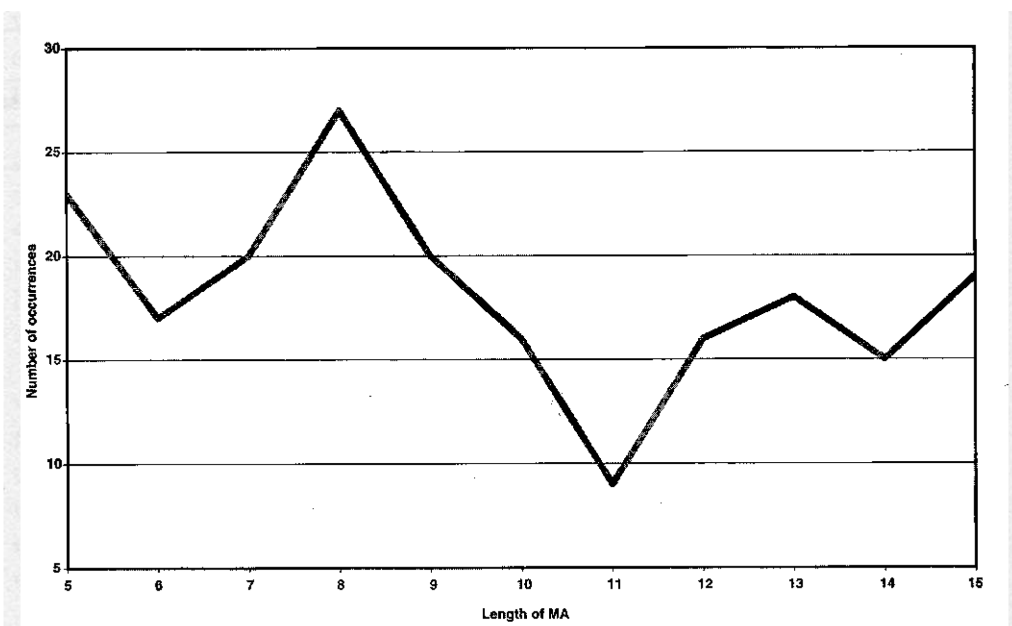


FIGURE 7.5

Number of top 200 percentage winners for different exit MAs.

TABLE 7.2

Performance summary I for the directional slope system.

	Data from January 1979 to October 1994, with 18/8 setting				
Market	Entry MA	Exit MA	P factor	% Winners	% In trade
Corn	18	8	2.06	36.99	77.00
Canada dollar	18	8	1.29	46.25	77.00
Crude oil	18	8	2.73	54.35	77.00
CRB index	18	8	1.02	33.33	72.00
Cotton	18	8	2.28	45.71	81.00
Dollar index	18	8	2.07	42.86	76.00
Eurodollar	18	8	2.94	48.00	76.00
Gold	18	8	1.85	42.11	76.00
Copper	18	8	1.70	35.29	77.00
Japanese yen	18	8	2.28	54.84	78.00
Coffee	18	8	2.59	41.03	77.00
Lumber	18	8	1.99	42.86	76.00
Live cattle	18	8	1.48	35.71	79.00
Orange juice	18	8	1.96	44.16	78.00
S&P 500	18	8	0.63	33.33	81.00
T-bonds	18	8	1.73	45.83	77.00
Average			1.91	42.67	77.19
Ratio			3.13	6.43	36.68

TABLE 7.3

Performance summary II for the directional slope system.

	Data from October 1994 to October 1999, with 18/8 setting				
Market	Entry MA	Exit MA	P factor	% Winners	% In trade
Corn	18	8	12.16	69.23	75
Canada dollar	18	8	1.19	40	76
Crude oil	18	8	2.61	52.17	80
CRB index	18	8	2.5	40	71
Cotton	18	8	0.79	25.93	80
Dollar index	18	8	0.87	28.57	73
Eurodollar	18	8	0.58	37.5	74
Gold	18	8	1.72	47.62	80
Copper	18	8	0.85	26.92	85
Japanese yen	18	8	4.37	66.67	76
Coffee	18	8	0.92	25	83
Lumber	18	8	1.36	52.38	76
Live cattle	18	8	1.13	45.45	74
Orange juice	18	8	0.38	24.14	83
S&P 500	18	8	0.72	40.91	82
T-bonds	18	8	1.23	41.67	78
Average			2.09	41.51	77.88
Ratio			0.73	2.98	18.93

Just because the system has become less robust, however, does not have to mean that it is no longer working as well. It could be that it is still just as good in catching the right types of moves, but there simply have been no such moves to catch. One way to find out is to look at the overall average profit factor and its standard deviation ratio for all markets and moving average combinations, for both the in-sample period and the out-of-sample period. This is not shown, so you just have to take my word for it, but as it turns out the profit factor for the in-sample period was 1.77, as compared to 1.73 for the out-of-sample period. Not much of a difference, but what is interesting is that the ratio between the profit factor and the standard deviation has decreased from 2.63 for the in-sample period, to a mere 1.07 for the out-of-sample period, which means that not only has the 18/8 combination become less robust, but so has the entire logic for this trend-following method (and perhaps all trend-following methods).

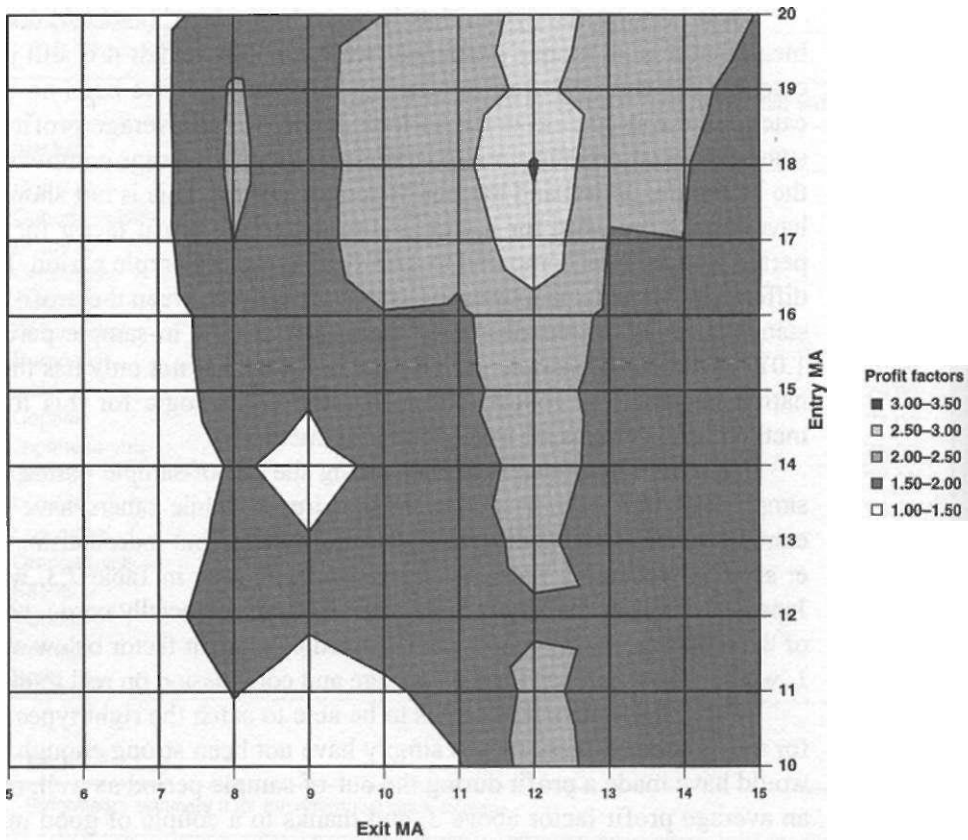
Another interpretation is that during the out-of-sample period, most markets simply have not been in strong enough trends, while others have been trending extremely well. This results in a higher profit factor, but indeed also in a much higher standard deviation. This can, for instance, be seen in Table 7.3, where corn and Japanese yen have extremely high profit factors—especially corn—while almost all of the others are losing money, as indicated by a profit factor below or very close to 1, which won't make up for the slippage and commission on real trading.

Thus, the system still seems to be able to catch the right types of moves, but for most markets, these moves simply have not been strong enough. Even so, you would have made a profit during the out-of-sample period as well, as indicated by an average profit factor above 2, and thanks to a couple of good moves in a few markets. The ride would just have been a little choppier.

Notice also that Figure 7.3 indicates that the trends have not been strong enough, not that they have disappeared all together. This information can be derived from the fact that the percentage of profitable trades only decreased from 43% for the in-sample period to 42% for the out-of-sample period, and the 18/8 setting; and from 40% to 39% for the entire methodology (not shown). Again, however, there is a higher standard deviation for the out-of-sample period, which again confirms the fact that a few markets have made up for all the others.

This also can be seen from Figures 7.6 and 7.7, which are derived the same way as Figures 7.2 and 7.3, except this time with data for the period October 1994 to October 1999. The main difference between Figure 7.2 and 7.6 is that during the out-of-sample period, the profit factor has become more heterogeneous, with a few markets making bigger profits than previously and making up for many small losses and below previously expected average profits made by other markets. This is also confirmed by the differences between Figures 7.3 and 7.7.

One other interesting observation that can be made from comparing the in-sample charts and the out-of-sample charts is how well a 12-bar Exit MA holds up in both periods. Therefore, it can be interesting to look a little closer at the 18/12



5 6 7 8 9 10 11 12 13 14 15
Exit MA

The average profit factor for different MA combinations for the out-of-sample period.
FIGURE 7.6

combination as well. As it turns out, these findings are the same as those for the 18/8 combination. That is, a few very profitable markets keep the overall average profit factor very high, but with all the other markets showing very low or no profits at all, resulting in a very low stability (high standard deviation).

But this is not the most interesting observation that can be made when studying all four charts. Yet another very interesting finding is the relative robustness surrounding the area of the 6-bar Exit MA. Figures 7.2 and 7.3 show that this entire area has a profit factor ranging from approximately 1.6 to 1.9, with a ratio ranging from 2.0 to 3.0. Not top values by any means, but good enough, especially considering that these values do not change that much in Figures 7.6 and 7.7, where the same values range from approximately 1.0 to 2.0, and from 1.5 to 2.5, respectively. These values are perhaps a little lower than for the 18/8 and 18/12 combinations, but the relative robustness over time makes this an interesting area to consider.

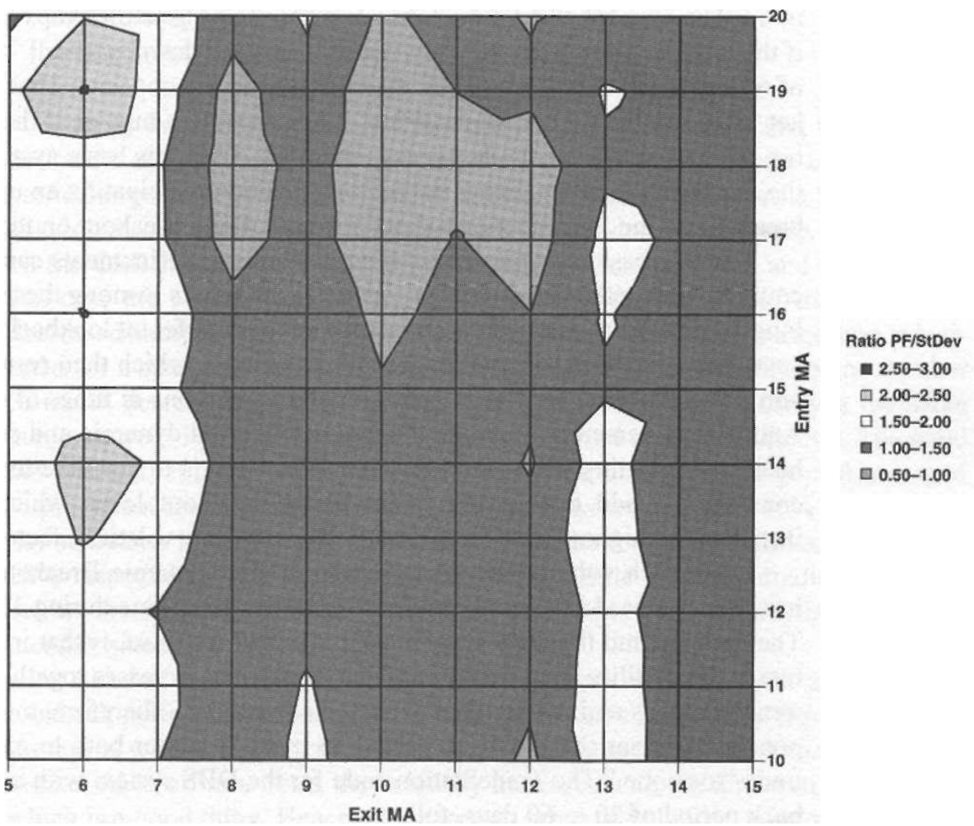


FIGURE 7.7

The ratio between the average profit factor and the standard deviation for the out-of-sample period.

As for the 18/8 and 18/12 combinations: Just because they have not worked as well nor been as stable on the out-of-sample data does not mean that they don't work in the long run, but simply that they haven't worked that well on that many markets recently. Remember also that the sole purpose of many trend-following systems is to catch the few winners that will make up for many of the losers that occur when trends aren't strong enough to generate decent profits. This is exactly the situation we have had during our out-of-sample period.

DYNAMIC BREAKOUT SYSTEMS

Ever since the mid-eighties when Richard Dennis and Bill Eckhardt made a huge success with their *turtle traders,*[1] breakout systems have been on everybody's

[1] A group of aspiring young traders trained by Richard Dennis. Dennis named the group "turtles" after having visited turtle farms in Singapore and having decided to grow traders as the farms grew turtles.

mind. The concept is easy enough: never mind trying to pick tops and bottoms—if the market is going up, you buy, and if it is going down, you sell. In fact, instead of trying to sell the tops and buy the bottoms, do the opposite. That is, if the market takes out the highest high for the last *n* days then buy, or if the market takes out the lowest low for the last *n* days then sell. With this basic system, you are in the market all the time, either with a long position anticipating an up-trend after a breakout on the long side, or a short position after a breakout on the short side.

To this basic system several improvements or refinements can be made that could be used either separately or together with others. Among these is to treat the long and the short side separately, assigning them different lookback periods, or to have a separate lookback period handling the exits, which then results in the system's also allowing for flat or neutral market situations in times of consolidation. Another refinement is to make the lookback period dynamic and sensitive to the historical volatility of the market. Yet another way is to keep the lookback period constant but add a volatility factor to the breakout level, which can be, for instance, the highest high for the last *n* days, times a volatility factor.

One such volatility-sensitive system is the Dynamic Breakout System that has been featured in several articles for *Futures* magazine during 1996 and 1998. The logic behind the DBS system, as it is called for short, is that in times of relative high volatility the number of "false" breakouts increases together with "false" trend reversals and deeper than expected corrections. Therefore, a volatility component increases the lookback period, to make it harder both to enter and exit a trade "too soon." The TradeStation code for the DBS system with a variable lookback period of 20 to 60 days, follows:

```
Inputs: MaxLB(60), MinLB(20);
Vars: HistVol(O), YestHistVol(O), DeltaHistVol(O), EntryLB(O), ExitLB(O),
YestEntryLB(O);
YestHistVol = HistVol;
HistVol = StdDev(C, 30);
DeltaHistVol = (HistVol - YestHistVol) / HistVol;
If CurrentBar = 1 Then
    EntryLB = 20;
YestEntryLB = EntryLB;
EntryLB = YestEntryLB * (1 + DeltaHistVol);
EntryLB = MaxList(EntryLB, MinLB);
EntryLB = MinList(EntryLB, MaxLB);
ExitLB = EntryLB * 0.5;
Buy Tomorrow at Highest(High, EntryLB) Stop;
Sell Tomorrow at Lowest(Low, EntryLB) Stop;
```

```
ExitLong Tomorrow at Lowest(Low, ExitLB) Stop;
ExitShort Tomorrow at Highest(High, ExitLB) Stop;
```

From the code (we will call this version la), you can see that the lookback period for the exits will always be half the lookback period for the entries at that particular point in time. The problem with this version, however, is that the variable lookback period does not always work as intended. For instance, when traded on the CRB index over the period June 1986 to October 1999, and the Japanese yen over the period May 1972 to October 1999, the number of trades actually decreased somewhat for both markets, if the variable lookback period was substituted for a stationary lookback period of 20 days. For the CRB index the number of trades decreased from 125 to 112 trades, and for the Japanese yen the same numbers were 191 with the variable lookback period and 181 without it. The good news is that, at least for the Japanese yen, the variable lookback period managed to produce a few more profitable trades—52% as compared to 46% with the 20-day stationary lookback period. The same numbers for the CRB index were 26 and 28% respectively. Hence, the first part of this little study contradicts the logic behind the system, while the results from the second part can only be considered inconclusive.

Another less desirable feature with this system is that with an increasing lookback period you run the risk of having the stops move away from the market instead of with it, if the market takes off in either direction. Also, usually when the market takes off in a trend, the volatility increases with the direction of the trend, which is a good thing. Hence, there are two types of volatility, *good volatility* that works for your position and *bad volatility* that works against it. One example of this phenomenon occurred October 7, 1998, when the Japanese yen took off with a move worth almost $10,000, and continued higher over the next few days for a total move worth $14,500. Figure 7.8 shows how this affected the breakout and exit levels for the DBS system when viewed with the ordinary point-based back-adjusted contract. When the market took off on October 7, the system gave a buy signal at 0.822 (the solid upper line), with a stop loss placed at 0.781 (the dotted lower line), for a total value at stake of $5,125 on a one-contract basis. During the next couple of days, the volatility of the market increased the lookback period to its maximum 60 days, which in turn resulted in a lowering of the stop loss to 0.764, for a total value at stake from the entry point of $7,250, or $15,875 from the close of 0.891 at October 13.

One way to change the stop-loss dilemma is to apply the same logic to the exits as to the entries. That is, if higher volatility—a sign of increasing insecurity and higher risk—makes it more difficult to enter the market (or easier to stay out, if you so wish), shouldn't the same reasoning then make it easier to exit the market (or more difficult to stay in) as well? If you adhere to that theory, the TradeStation code for the DBS system can be rewritten as follows:

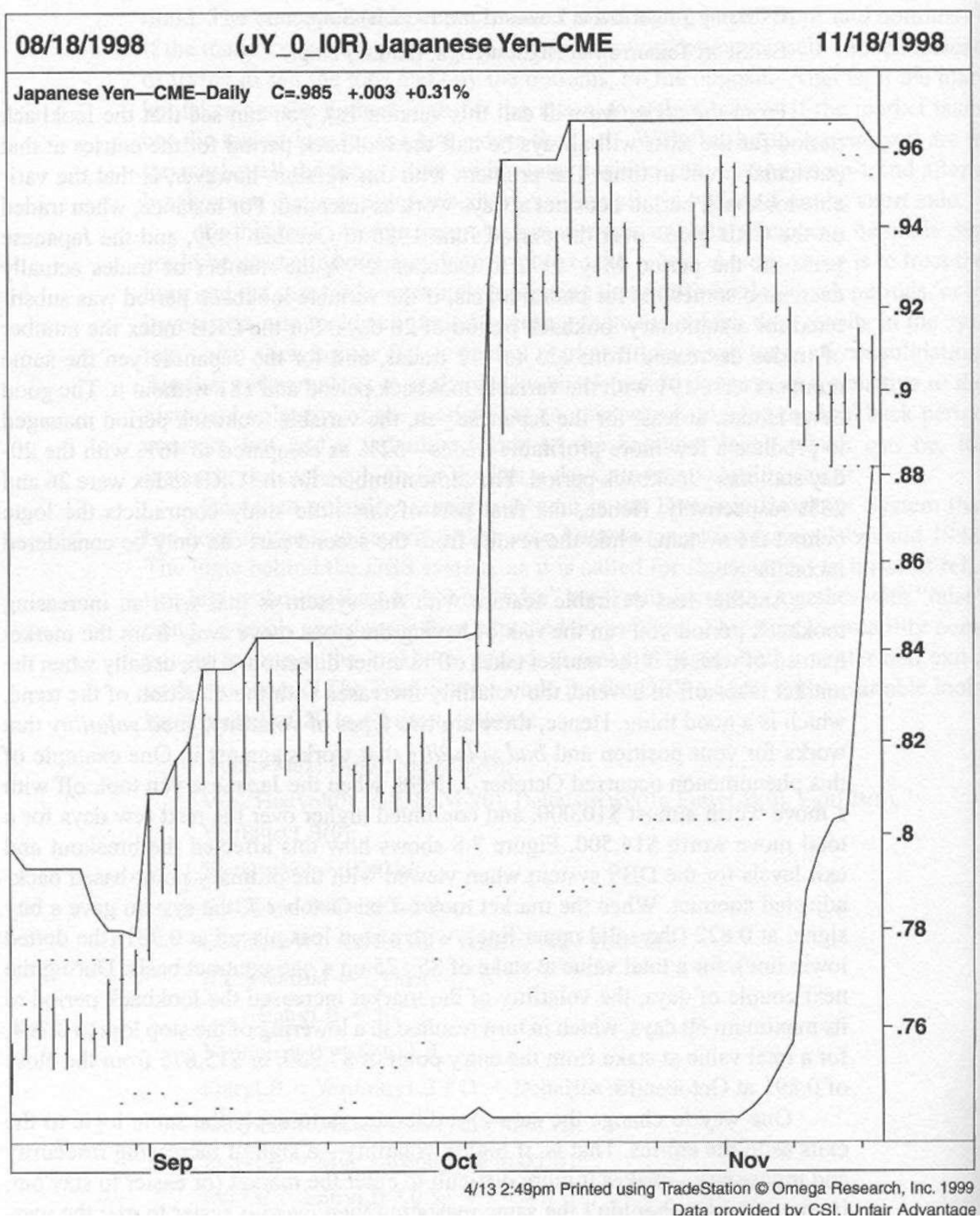


FIGURE 7.8

The DBS system applied on the Japanese yen.

```
Inputs: MaxEntryLB(60), MinEntryLB(20), MaxExitLB(30), MinExitLB(lO);
Vars: HistVol(O), YestHistVol(O), DeltaHistVol(O), EntryLB(O), ExitLB(O),
YestEntryLB(O), YestExitLB(O);
YestHistVol = HistVol;
HistVol = StdDev(C, 30);
DeltaHistVol = (HistVol - YestHistVol) / HistVol;
If CurrentBar = 1 Then
    EntryLB = 20;
YestEntryLB = EntryLB;
EntryLB = YestEntryLB * (1 + DeltaHistVol);
EntryLB = MaxList(EntryLB, MinEntryLB);
EntryLB = MinList(EntryLB, MaxEntryLB);
YestExitLB = ExitLB;
ExitLB = YestExitLB * (1 - DeltaHistVol);
ExitLB = MinList(ExitLB, MaxExitLB);
ExitLB = MaxList(ExitLB, MinExitLB);
Buy Tomorrow at Highest(High, EntryLB) Stop;
Sell Tomorrow at Lowest(Low, EntryLB) Stop;
ExitLong Tomorrow at Lowest(Low, ExitLB) Stop;
ExitShort Tomorrow at Highest(High, ExitLB) Stop;
```

In this version of the code (version lb), there also are situations when the lookback period for the entry is shorter than for the exit, which means that there also will be several stop-and-reversal situations, as well as plain exits into a neutral position. Perhaps this could be considered slightly more "dynamic" than the original system, where the lookback period for the entry always is longer than for the exit. In this case, the number of trades when traded on the Japanese yen over the period May 1972 to October 1999 was 201, among which 53% were profitable. For the CRB index, the same numbers over the period June 1986 to October 1999 were 31% profitable trades out of a total of 114 trades. To be sure, however, some of these extra trades can be explained by the fact that a faster exit also allows the system to enter the market a second time in the same direction. Nonetheless, because these results are inconclusive, as compared to what would be desirable, the question still remains: is there a way to use the historical volatility both to decrease the number of trades and increase the number of winners?

By letting the volatility alter the lookback period, we only implicitly alter the actual level at which a trade is triggered. A more direct way to do this is to let the volatility explicitly alter the level that triggers the trade. An attempt at such a system coded in TradeStation (version 2a) can look something like this:

```
Inputs: VolMethod(l), VolFactor(0.5);
Vars: HistVol(O), HalfHistVol(O), LongEntry(O), ShortEntry(O), LongExit(O),
ShortExit(O);
If VolMethod > 0 Then
      HistVol = StdDev(C, 30) * VolFactor
Else
      HistVol = AvgTrueRange(30) * VolFactor;
HalfHistVol = HistVol * 0.5;
LongEntry = Highest(High, 20) + HistVol;
ShortEntry = Lowest(Low, 20) - HistVol;
LongExit = Lowest(Low, 20) - HalfHistVol;
ShortExit = Highest(High, 20) + HalfHistVol;
Buy Tomorrow at LongEntry Stop;
Sell Tomorrow at ShortEntry Stop;
ExitLong Tomorrow at LongExit Stop;
ExitShort Tomorrow at ShortExit Stop;
```

With this system, we add half the 30-day historical volatility to the breakout level, but only a quarter to the exit level, making it relatively harder to get in than to get out. In this way, we still leave the system with some slack so as not to be stopped out too soon, but also allow for neutral, or flat, positions in case the volatility gets too rough. Another way to achieve essentially the same thing is to substitute all the historical volatility factors, as measured with the standard deviation, with the average true range for the period. You can do this in the code by changing the VolMethod input to zero.

To make it easier for the system to exit in times of high volatility, simply change the plus sign to a minus sign when calculating the long exit, and the minus sign to a plus sign when calculating the short exit (this will be version 2b). In doing so, however, the system exits a trade before the market reaches down (up) to the lowest low (highest high) of the lookback period, which is assumed to be a pivotal support (resistance) level.

Let us see how all these systems would have performed on a portfolio of 16 markets over the period from January 1980 to October 1999. The 16 markets we will use are S&P 500, copper, crude oil, live cattle, cotton, Eurodollar, Canada dollar, Japanese yen, gold, lumber, orange juice, corn, coffee, dollar index, CRB index, and T-bonds. Because we are not interested in any percentage-based calculations or relationships, we use the ordinary point-based back-adjusted contract. No money has been deducted for slippage and commission to avoid coming up with any suboptimal solutions. We do this by using our export function for the profit factor, percent profitable trades, and time in market, from Part 1.

Table 7.4 shows that the original system (version la) indeed had the highest profit factor, but that this also comes at the expense of a higher standard deviation, as compared to version lb. This is illustrated by the first ratio column, which depicts the ratio between the profit factor and its standard deviation. The higher the ratio, the more homogenous the behavior between the markets. For instance, with a profit factor of 1.46 and a ratio of 2.74, DBS system version la cannot be expected, with 68% certainty, to produce a profit factor above 1 (1.46 — 1.46 / 2.74 = 0.93). This also holds true for version lb (1.36 - 1.36 / 3.52 = 0.97), but in choosing between the two, version lb comes out on top because of its higher stability. Interestingly enough, all version b systems have higher ratios than their version A counterparts, except for the time spent in the market. In addition, when it comes to the two most important readings, the profit factor and the percentage profitable trades, all version 2b systems also show better results. That is, in most instances, not only do the version b systems show results that are more profitable, they also seem to be more robust when compared between different markets.

Let us take a closer look at version lb in Tables 7.5 and 7.6, and see how it performed on all the individual markets. For this we also use a variation of our trade-by-trade export function, which we also developed in Part 1. To do so, we also must switch over to the RAD contract. The code for this version of the export function follows:

```
Vars: FileName("™), TotTr(O), Prof(0), TradeStr2("");
If CurrentBar = 1 Then Begin
     FileName = "DATempV + LeftStr(GetSymbolName, 2) + ".txt";
     FileDelete(FileName);
     TradeStr2 = "Position" + "," + "Profit" + NewLine;
     FileAppend(FileName, TradeStr2);
End;
TotTr = TotalTrades;
```

TABLE 7.4

Trade statistics summary for different DBS systems.

Version	P Factor	Ratio	Trades	Ratio	% Prof.	Ratio %	In market	Ratio
VeMa	1.46	2.74	145	7.39	37.24	5.64	79	28.29
VeMb	1.36	3.52	140	7.89	40.90	8.16	80	33.65
Ver 2a (HV)	1.36	2.64	100	7.10	39.21	5.72	88	27.67
Ver 2b (HV)	1.38	2.65	116	7.48	40.02	6.54	76	15.95
Ver 2a (ATR)	1.35	2.71	107	6.78	39.24	5.73	90	42.50
Ver 2b (ATR)	1.36	2.92	119	7.49	39.36	.39	81	21.58

```
If TotTr > TotTr[l] Then Begin.
    Prof = 1 + PositionProfit(l) / (EntryPrice(l) * BigPointValue);
    TradeStr2 = NumToStr(MarketPosition(l), 0) + "," +
    NumToStr((Prof - 1) * 100, 2) + NewLine;
    FileAppend(FileName, TradeStr2);
End;
If LastBarOnChart Then Begin
    TradeStr2 = NumToStr(Close, 4) + "," + NumToStr(BigPointValue, 2) +
    NewLine;
    FileAppend(FileName, TradeStr2);
End;
```

Table 7.5 shows that, as is the case with many trend-following breakout-type systems, this version of the DBS system works very well on a handful of markets, while others barely break even or lose money, even if at a not-too-alarming rate. The question is, are these markets still worthy of being traded in a portfolio? Table 7.6 gives a more detailed picture of the same phenomenon. From this table we can see that the average losses for most markets are quite substantial in percentage terms. Copper, for instance, will on average allow for a 4.25% move against the trade before it allows you to exit.

TABLE 7.5

Trade statistics summary for DBS system, version Ib.

Market	P Factor	Trades	% Prof.	% In market
Canada dollar	1.03	152	38.82	78
Coffee	1.47	155	39.35	79
Copper	0.90	158	39.87	80
Corn	1.72	144	42.36	81
Cotton	1.27	148	35.14	84
CRB index	0.65	114	30.70	78
Crude oil	1.56	117	47.01	82
Dollar index	1.60	95	44.21	83
Eurodollar	1.78	127	46.46	83
Gold	1.53	141	43.26	80
Japanese yen	2.05	144	50.00	78
Live cattle	0.83	157	35.03	79
Lumber	1.38	147	40.14	78
Orange juice	1.62	152	41.45	79
S&P 500	1.00	139	36.69	78
T-bonds	1.33	146	43.84	85

TABLE 7.6

Trade statistics summary for DBS system, version lb.

	Avg. Trade		Avg. Profit		Avg. Loss	
Market	(%)	($)	(%)	($)	(%)	($)
Canada dollar	0.04	26	1.61	1,092	-0.80	-545
Coffee	1.51	541	13.46	4,830	-5.76	-2,065
Copper	-0.34	-67	5.91	1,178	-4.25	-848
Corn	1.00	100	7.47	749	-3.48	-349
Cotton	0.72	194	8.76	,340	-3.81	-1,017
CRB index	-0.52	-532	2.74	2,793	-1.78	-1,814
Crude oil	2.38	545	10.74	2,463	-5.40	-1,239
Dollar index	0.67	663	3.13	3,100	-1.44	-1,427
Eurodollar	0.09	208	0.59	1,378	-0.29	-677
Gold	0.59	175	5.53	1,628	-2.98	-876
Japanese yen	1.02	1,225	4.30	5,188	-1.90	-2,294
Live cattle	0.01	3	3.89	1,057	-2.64	-716
Lumber	0.37	93	9.43	2,368	-5.09	-1,277
Orange juice	1.21	162	8.64	1,156	-4.43	-592
S&P 500	-0.33	-1,093	3.94	12,848	-2.78	-9,060
T-bonds	0.23	255	3.81	4,250	-2.24	-2,499

Let us also investigate how version lb would have performed over two different time periods and see if we can add to or confirm any of the conclusions we made about our directional slope system in the previous chapter. In this case, we will look at the periods January 1980 to October 1989 (Table 7.7) and January 1990 to October 1999 (Table 7.8). Table 7.7 shows that, although this version of the DBS system trades profitably in most markets, the profit factor is somewhat on the low side. Note also that the profit factor differs somewhat from our original findings, due to the different contracts used. Here I used the ratio-adjusted contract and calculated the profit factor with the help of the average weighted values of the winners and losers. As shown in Table 7.8, for the last ten years, the results look even less promising.

As was the case with the directional slope system, we can say that this version of the DBS system has not performed as well recently as in the past. This can be seen, for instance, from the average profit factor for the two periods, which not only is slightly lower for the later period, but also has a higher standard deviation than in the earlier period. As for all other numbers, they too are not as good for the later period. The number of profitable trades, for example, has decreased ever so slightly; but another indication that there are less profitable trades can be derived from the time in market column and the number of trades column. Usually, the

Performance summary for version Ib, January 1980-October 1989.

Market	P factor	Trades	% Winners	% In trade
Canada dollar	1.01	78	37.18	79
Coffee	1.66	76	39.47	79
Copper	0.71	80	37.5	82
Corn	1.65	71	42.25	84
Cotton	1.32	68	36.76	86
CRB index	0.84	25	28	74
Crude oil	2.31	40	55	84
Dollar index	1.04	28	35.71	82
Eurodollar	1.91	41	51.22	82
Gold	1.48	68	42.65	77
Japanese yen	2.44	71	56.34	78
Live cattle	0.97	70	40	77
Lumber	1.38	70	40	81
Orange juice	2.41	69	49.28	81
S&P 500	1.25	56	39.29	75
T-bonds	1.35	73	42.47	85
Average	1.48	61.50	42.07	80.38
Ratio	2.71	3.44	5.62	22.60

TABLE 7.8

Performance summary for version Ib, January 1990-October 1999.

Market	P factor	Trades	% Winners	% In trade
Canada dollar	0.95	72	38.89	75
Coffee	1.33	76	39.47	78
Copper	1.11	74	41.89	76
Corn	1.9	68	45.59	76
Cotton	1.16	75	36	83
CRB index	0.57	83	33.73	78
Crude oil	1.24	74	43.24	80
Dollar index	2.37	58	51.72	80
Eurodollar	3.12	38	60.53	85
Gold	1.53	70	44.29	81
Japanese yen	1.83	69	43.48	77
Live cattle	0.62	81	32.1	80
Lumber	1.39	73	39.73	75
Orange juice	0.85	80	33.75	76
S&P 500	0.92	79	34.18	79
T-bonds	1.44	66	46.97	83
Average	1.40	71.00	41.60	78.88
Ratio	2.11	6.57	5.58	25.84

higher the profit factor, the fewer the trades and, simultaneously, the more time spent in the market. It will be interesting to see if we can improve on these numbers in the upcoming sections.

Compared to the directional slope system, the profit factor also is considerably lower, while the percentage of profitable trades is approximately the same, albeit with a lower standard deviation. This is an interesting observation that suggests that whatever system you chose, there always is a price to pay, and you have to compromise on one performance measure in favor of another.

Roth the DBS system and the directional slope system have in common the fact that they do not have any fixed stop levels. Although the directional slope system lacks a natural stop level completely, the DBS system at least has a dynamic level. Even in version lb, however, this level is running the risk of moving away from the market, which makes it difficult to trade this system with a fixed fractional money management strategy.

This takes us back to the beginning of this section where we talked about the *turtles-,* because what is even more important for a turtle than when or what to trade, is how much to trade. For a turtle it is vital to cut back in size during times of high volatility and drawdown to preserve as much capital as possible in expectation of the next major move, which can come in any market.

STANDARD DEVIATION BREAKOUT

The *Bollinger bands indicator* is one of the most versatile indicators there is. It can be used both in short-term oscillator-type systems, looking for overbought/oversold situations or in a long-term breakout-type system. To calculate the indicator, first calculate an appropriate-length moving average, and then add the number of standard deviations for the same time period to that average for the upper band or deduct the number of standard deviations for the lower band. For a long-term breakout system, experience has shown that you should look for a lookback period for the moving average and the standard deviation calculations somewhere between 50 and 100 days. For a shorter-term system, you should aim for about 20 to 40 days. Usually the Bollinger bands indicator is charted together with the price, as shown in Figure 7.9. When you look at Figure 7.9 it is important to remember that just because the price penetrates the bands, it doesn't have to come back from there. Equally as often it will be the band that catches up with the price. In fact, the Bollinger bands indicator often makes up the foundation for some excellent breakout systems. The TradeStation code for this is as follows:

```
Inputs: BandLen(60), NoStDev(2);
Vars: BandDevi(O), MidBand(O), UpBand(O), LoBand(O);
BandDevi = StdDev(Close, BandLen) * NoStDev;
MidBand = Average(Close, BandLen);
```

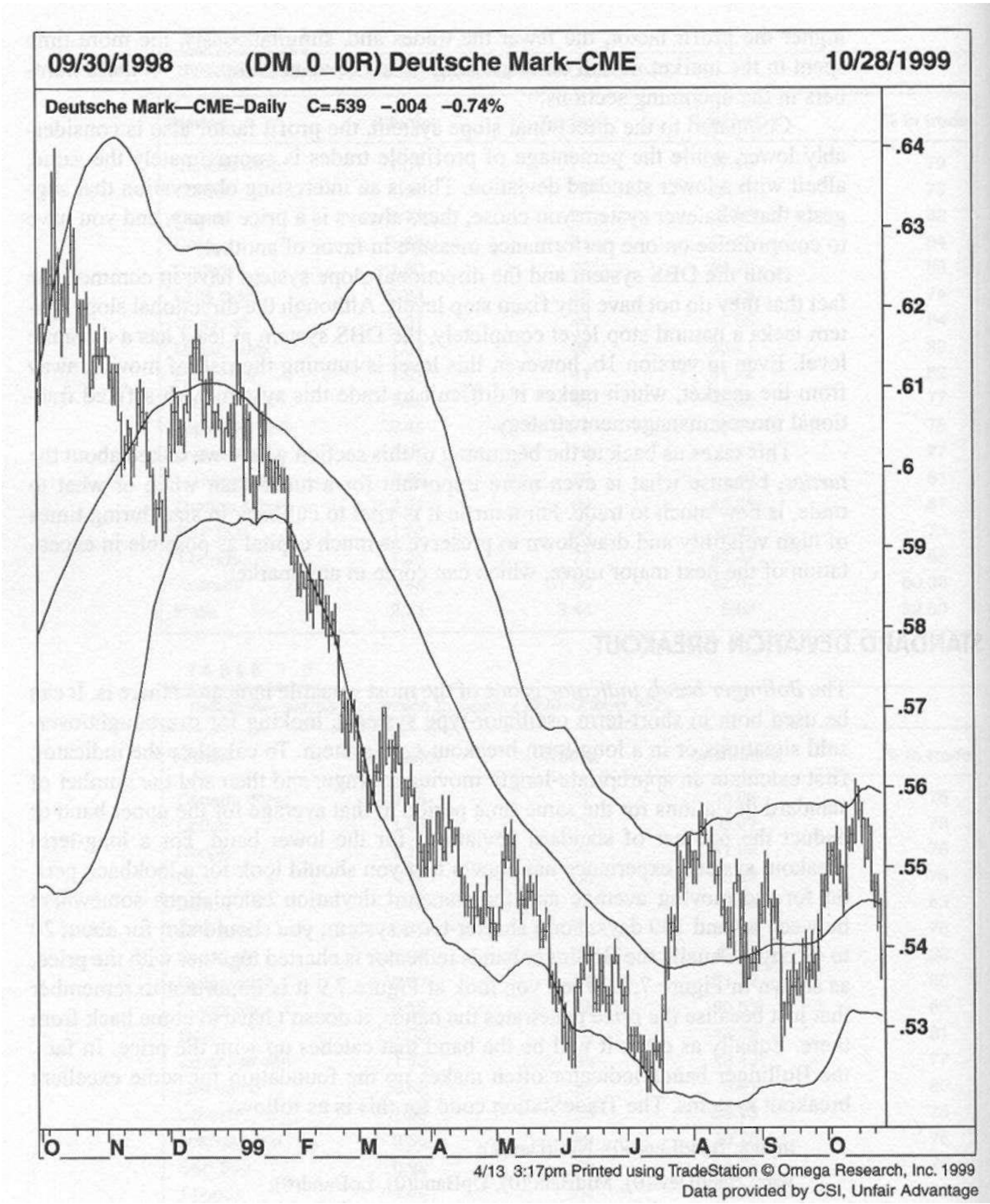


FIGURE 7.9

The Bollinger bands indicator applied on the Deutsche Mark.

```
UpBand = MidBand + BandDevi;
LoBand = MidBand - BandDevi;
Plotl (MidBand, "MidBand");
Plot2(UpBand, "UpBand");
Plot3(LoBand, "LoBand");
```

Many times it can be difficult to see what is actually happening when the price reaches one of the bands and then starts to hug the band in a trending motion. In this case it might be better to chart the indicator as a normalized oscillator instead, where you keep the upper and lower bands stationary at, for instance, 100 and 0, respectively. This is especially useful if you are primarily interested in catching the short-term move against the underlying trend. This is shown in Figure 7.10, which uses the same chart as in Figure 7.9, but this time with the Bollinger bands oscillator added at the bottom. The code for the oscillator follows:

```
Inputs: BandLen(60), NoStDev(2);
Vars: BandDevi(O), MidBand(O), UpBand(O), LoBand(O), BandPos(O);
BandDevi = StdDev(Close, BandLen) * NoStDev;
MidBand = Average(Close, BandLen);
UpBand = MidBand + BandDevi;
LoBand = MidBand - BandDevi;
BandPos = (AvgPrice - LoBand) * 100/ (UpBand - LoBand);
Plotl (BandPos, "Position");
Plot2(100, "UpBand");
Plot3(0, "LoBand");
```

One interesting phenomenon of the Bollinger bands indicator when used as an oscillator is how fast it catches the most recent moves despite a relatively long lookback period. This means that you will be able to take much more data into consideration but still achieve the same effect as, for instance, with an ordinary RSI or stochastic indicator. Or, alternatively, use the same amount of data for a faster reacting indicator. Figure 7.11 shows a 20-day Bollinger oscillator together with a 10-day RSI, charted on top of each other, depicting the same price activity on the same market. This time the upper and lower boundaries for the Bollinger bands oscillator are set to 70 and 30, respectively. As you can see, although the Bollinger bands indicator takes twice as much data into consideration, it still moves much faster between the overbought and oversold regions than the RSI indicator.

Although the Bollinger bands indicator has several advantages compared to most other indicators, it also shares several of their disadvantages. One of them we stressed when we discussed the Meander indicator: you can make no comparative assumptions between two different readings, whether you look at the same market at two different points in time or at two different markets at the same point in time.

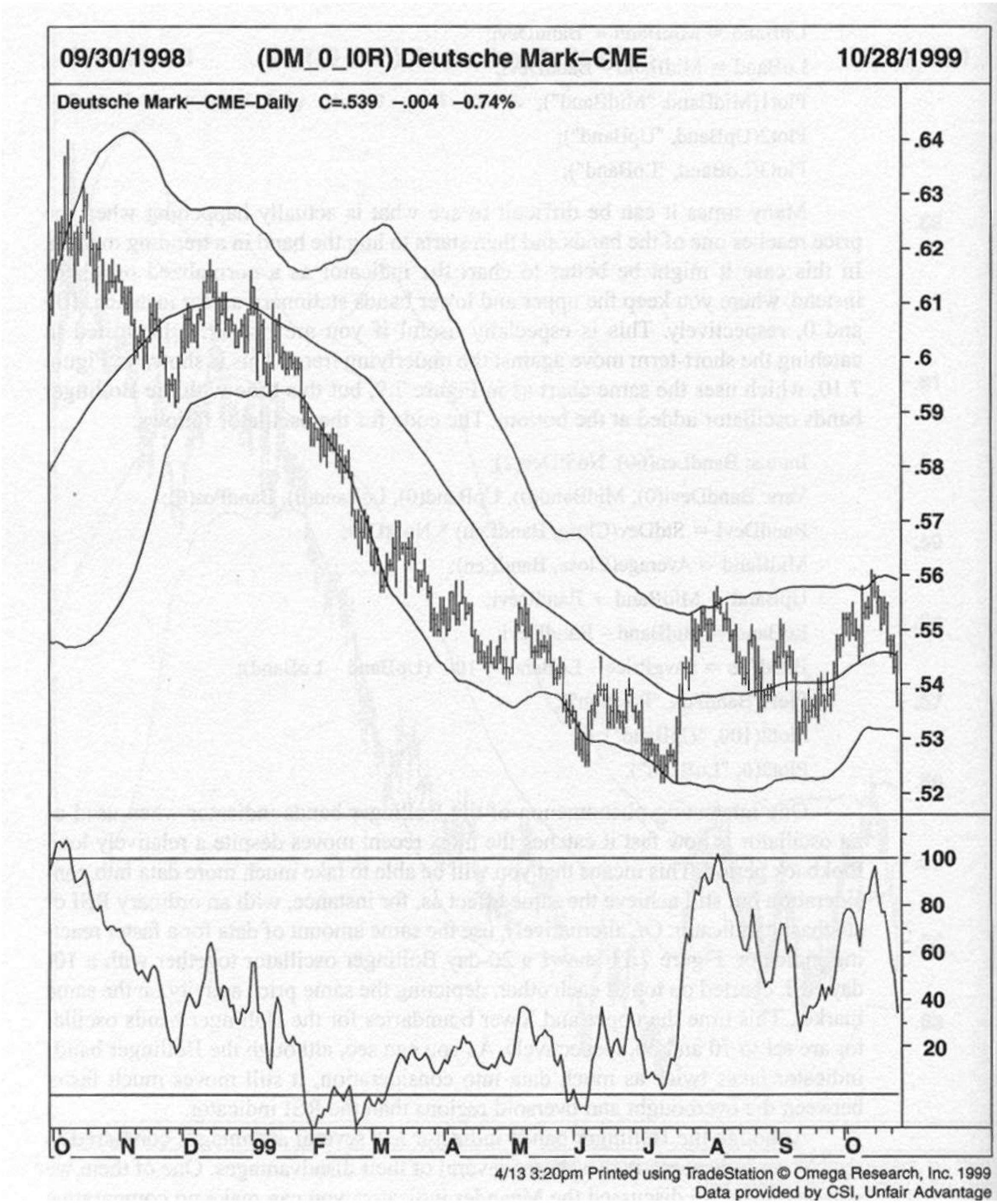
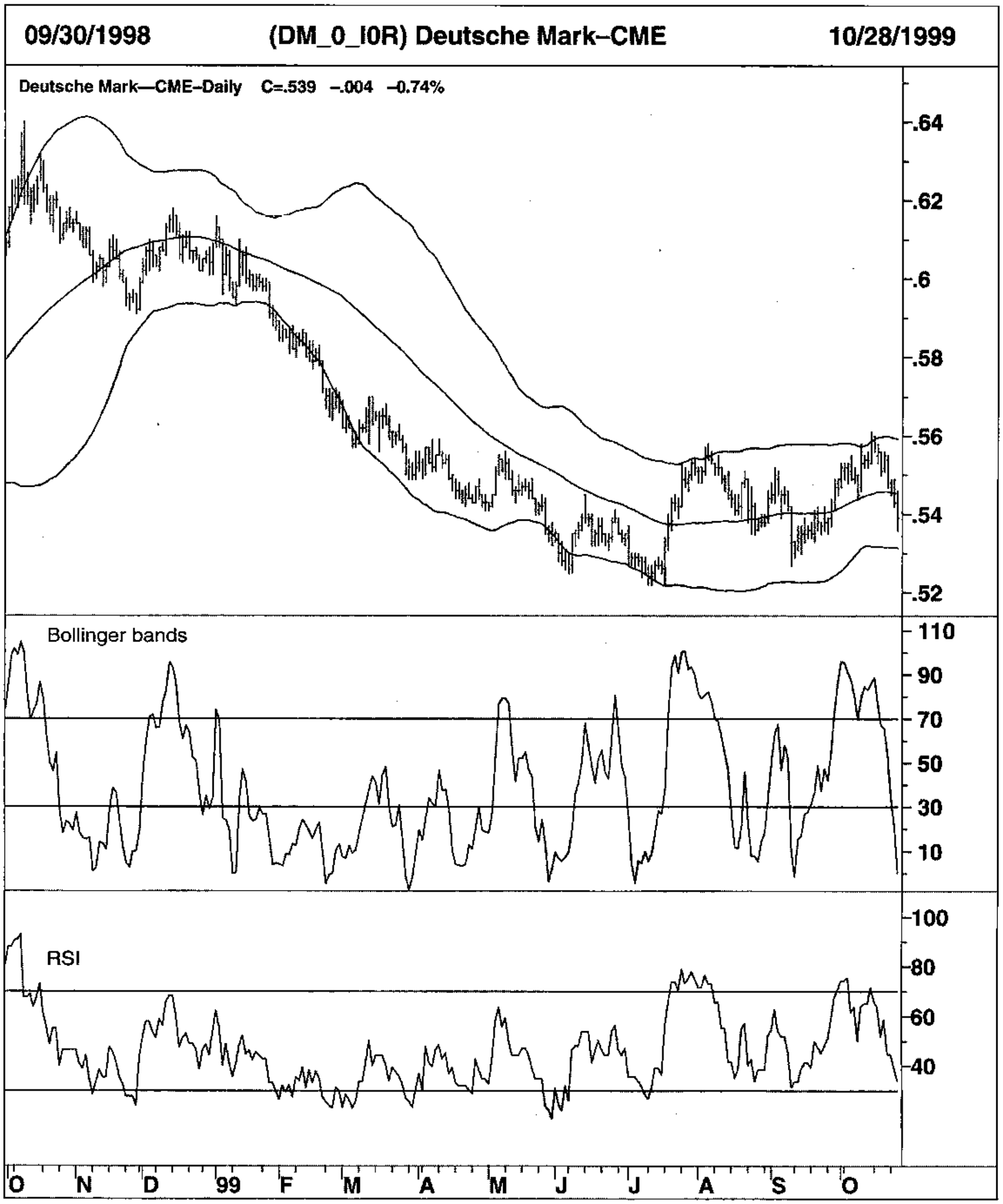


FIGURE 7.10

The Bollinger bands indicator also can be charted as an oscillator.



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Data provided by CSI, Unfair Advantage

FIGURE 7.11

The Bollinger bands indicator reacts much faster than RSI.

When it comes to using the Bollinger bands in a trading system, another disadvantage is that you will take the volatility into consideration twice, as compared to what happens in a basic breakout system. For instance, if you currently do not have a position on and the market is in a relatively wide trading range, with relatively high historical volatility readings, it already is relatively difficult for an ordinary highest high/lowest low breakout system to enter the market, because of the large distance between these entry levels. But to a Bollinger band-type system you also have to add the distance to the upper and lower bands which, because of the volatility, could be placed at a considerable distance away from the highest high and lowest low. Also, as is the case with many breakout-type systems, most Bollinger bands systems only seem to take the volatility into consideration when entering the market but not when exiting. Instead the exit usually is governed only by a crossover of the mid-band, which most of the time is a standard moving average.

Nonetheless, here is an alternative long-term system, where we make it even harder than usual to enter. The TradeStation code follows:

```
Inputs: BandLen(60);
Vars: UpBand(O), LoBand(O);
UpBand = XAverage(High, BandLen) + 2* StdDev(High, BandLen);
LoBand = XAverage(Low, BandLen) - 2 * StdDev(Low, BandLen);
Buy tomorrow at UpBand Stop;
Sell tomorrow at LoBand Stop;
ExitLong tomorrow at XAverage(Low, BandLen) Stop;
ExitShort tomorrow at XAverage(High, BandLen) Stop;
```

As you can see from the code, for the upper band, we have substituted the closing price with the high, and for the lower band, we have substituted the closing price with the low. We also have made it a little more difficult to exit by substituting the closing price with the low, for the long exit, and the high, for the short exit. To compensate somewhat for both the slower/delayed entries and exits, we also substituted the standard moving average for an exponential one. All in all, we hope that these slight changes to the original setup will weed out a few trades that were bound to go nowhere and only catch those signals that have a high enough momentum to follow through and develop into a profitable trade. The lookback period is set to 60 days and has not been optimized in any way. To find an optimal, robust setting you could use the same technique as we did for the directional slope system, where we exported the different moving average combinations and then put together a couple of so-called surface charts.

The model was tested on data from January 1980 to December 1992. The period January 1993 to October 1999 was saved for some out-of-sample testing, after we added a few additional stops and some sort of filter, in section three and four, respectively. The 16 markets tested were D-mark, crude oil, lumber, copper, gold, dollar index, live cattle, T-bonds, cotton, Japanese yen, natural gas, wheat, Nikkei, coffee, T-bills, and rough rice. Because we used the ordinary point-based back-adjusted contract, we added the export function for the profit factor, days in trade, and percentage profitable trades to the code above, for further analysis in a spreadsheet program. Table 7.9 shows the results. No money has been deducted for slippage and commission.

As you can see from Table 7.9, this version of the Bollinger bands system seems to have several desirable features, such as a high profit factor in most markets, a high percentage of profitable trades, and a fairly low percentage of the time spent in the market. In fact, as Table 7.9 shows, all markets traded profitably, with profit factors well above 1 in many cases and with the average profit factor as high as 3.82, attributable to the slight changes we made to the original system. For a long-term system, most markets also had a very high percentage of profitable trades, with an average of 51.74% profitable trades per market.

TABLE 7.9

Long-term Bollinger bands system, January 1980-December 1992.

Market	P factor	Trades	% Winners	% In trade
Deutsche mark	3.62	34	61.76	59
Crude oil	5.41	23	73.91	61
Lumber	1.21	46	32.61	53
Copper	2.29	37	40.54	52
Gold	1.67	43	41.86	55
Dollar index	3.92	17	64.71	54
Live cattle	1.32	34	38.24	44
T-bonds	1.94	33	45.45	52
Cotton	2.32	39	43.59	59
Japanese yen	3.01	40	60	62
Natural gas	10.28	6	66.67	82
Wheat	2.37	38	34.21	53
Rough rice	12.65	15	66.67	59
Timber	3.41	33	60.61	62
Coffee	3.3	34	47.06	50
Nikkei index	2.42	6	50	63

PART TWO

A Few Final Thoughts About Part 2

In this part, we created a few basic trading systems to take with us to the upcoming sections, where we will continue to develop and examine them further. Although all the systems have been very basic, with as few rules as possible, we have shown that it is possible to exploit different types of market behavior and create a trading system that is likely to continue to work well in the future and on several different markets—sometimes even on markets the system has not been tested on previously.

In fact, the whole key to making a system robust is to keep it as simple as possible, while at the same time making sure it works well on several different markets. Notice once again that the key words here are "work well," not "be profitable." For a well-working system to be profitable it needs to be applied to a market that can exhibit a high enough dollar value in relation to the moves the system is designed to catch. This does not always have to be the case, but this does not mean that the system is a bad system.

Before we go on to Part 3,1 would like to leave you with a few questions and a little food for thought. Is there a way of measuring curve fitting? Is it as easy as saying that the better the result, the more curve-fitted the system; or the more rules, the more curve-fitted the system? For instance, say that you just have finished building a system with thousands of rules, which will capture every historical daily move in the S&P 500 futures contract perfectly. No doubt this system is curve fitted, but what if you reverse all the rules? In other words, for every rule you had, you will add one rule, ending up with twice as many. What will the historical results from this system be? They will be disastrous. So is this second system more or less curve fitted that the first one?

Here is a suggestion on how to measure the degree of curve fittedness: take the market or markets on which you would like to trade, manually pick out all those market segments you would like for your system to catch, and string them together in a fantasy equity curve or several curves. Then start building your system, adding and deducting rules in an effort to mimic the fantasy results. For every change you make, measure the difference between the fantasy curves and those on which you are working by looking at the correlation between them. If you have to add a rule to increase the correlation, that is a bad thing, but if you manage to increase the correlation by deducting a rule, that is a good thing.

Have I done this myself? Nope. It just came to me, but nonetheless, here is what I consider to be a rule: every time I need to use any equal to (=), more than (>), or less than (<) signs I am, in fact, formulating a rule. For me, the trick then is to keep all these signs down to a minimum, preferably below five for the entire strategy. As you will discover, if you are being honest about what constitutes a sign, it is very difficult.

In the next part, we will see if we can improve each system's performance further by adding a few stops to protect us from too severe losses and lock in profits. Although it is true that every rule you add to the system means that you probably are curve fitting it more, adding stops and exits is a necessary evil and should be looked upon more as a commonsense proceeding than actual curve fitting. Look at it this way: if you are long in the market and it goes against you, you lose money, and losing money is not a bright thing to do. At least not in a systematic fashion, and that is what this is all about.

PART THREE

Getting Out

Once you have a basic idea about what you would like to achieve with your system and which type of moves you would like it to catch, it is time to start experimenting with different types of stops and exits. If you wish, you can look at any basic system, like those in the previous section, as a set of entry rules only. That is, the basic system tells you when it is time to enter into a long, short, or neutral position. Of course, entering into a short position usually also means exiting a long position. But in essence, a basic system is a set of entry rules, which we hope signals a high-probability trading opportunity, no more no less. But as so many successful traders have said, "anyone can enter the market, but to be successful in the long run, the trick is to consistently exit with profits that are bigger than the losses."

From this it follows that most of the time the exits are much more important than the entries. Therefore, starting out with the entry is not always the best way to go. Of course, you might already have come up with a set of excellent entry techniques without giving the exits any second thoughts. In that case, it should "only" be a question of examining or adding a set of exits to improve performance even further.

Sometimes, however, it is an even better idea to start out with the stops and exits, and work backward to come up with a simple entry technique that matches your exit criteria and the underlying assumptions for the trade. Notice, however, that this does not by any means mean that the work you do looking into different entries is a waste of time, because many times it will turn out that there will be a better entry technique than the one with which you started. But to know about it you need to have examined and tested it on a previous occasion.

In Part 4, we continue the development process by adding some sort of *filter* technique. A filter efficiently keeps you away from the markets as much as possible, only letting you place a trade according to your original or modified triggers after you have examined and constructed the exit techniques. By necessity (and whether you like it or not), filters and entries always to some extent try to forecast the market. Exits, on the other hand never try to forecast the market, but only tell you whether this position, as it looks so far, keeps up with what could be expected and that it doesn't run amok with your account. A good exit should also let you use your entry and filter techniques as often as possible without letting such use affect the bottom line. The normal order of work then, is as follows:

- Start out with a basic, stable, and robust set of entries, and let the entry for one position (long, short, or neutral) also signal the exit for any other type of position.
- Add a set of appropriate, standalone exits that form a good compromise between risk and reward.
- If necessary, change the entry technique and/or add a filter to sift out low-probability trades.

CHAPTER 8

Efficient Trades

The idea is to try to maximize the efficiency of each trade as much as possible. This is a concept popularized by RINA systems. With the highly improved systems performance summary in TradeStation 2000i, you can now get a feel for both the entry and exit efficiencies, as well as the overall efficiency of your trades as RINA systems and Omega Research define them.

As an initial measure and starting point, TradeStation's efficiency calculations work very well, but if you would like to expand your research and try to optimize the possibilities these techniques offer, the TradeStation performance summary will no longer be enough. TradeStation again makes the mistake of calculating all moves in dollar terms, rather than in percentages. In the case of efficiency analysis, this is OK when looking at the numbers, but not if you would like to do something about them. Let us take a look at how TradeStation does it.

For Long Trades

Total efficiency = (Exit price — Entry price) / (Highest price - Lowest price)

Entry efficiency = (Highest price - Entry price) / (Highest price - Lowest price)

Exit efficiency = (Exit price - Lowest price) / (Highest price - Lowest price)

For Short Trades

Total efficiency = (Entry price — Exit price) / (Highest price - Lowest price)

Entry efficiency = (Entry price - Lowest price) / (Highest price - Lowest price)

Exit efficiency = (Highest price — Exit price) / (Highest price — Lowest price)

For All Trades

Average total efficiency = Sum of total efficiencies / Number of trades

Average entry efficiency = Sum of entry efficiencies / Number of trades

Average exit efficiency = Sum of exit efficiencies / Number of trades

Figure 8.1 shows an individual long trade. In this case we enter the market at 1,350, reach a low at 1,330, and then a high at 1,390, before we exit at 1,380. Inserting these numbers in the above formula, we get an entry efficiency of 67%, an exit efficiency of 83%, and a total efficiency of 50%. Had this instead been a short trade, the entry efficiency would have been 33%, the exit efficiency 17%, and the total efficiency —50%.

Note, however, that in the case of a short trade, we would have started out with a profit, then moved into a substantial loss, before we recaptured some of that open position loss. What really happened then, was that both the entry and the exit were quite good. It was the middle part of the trade that failed. This, however, does not show up in the performance summary and, therefore illustrates the importance of dividing the trade and especially the drawdown into several subcategories, as

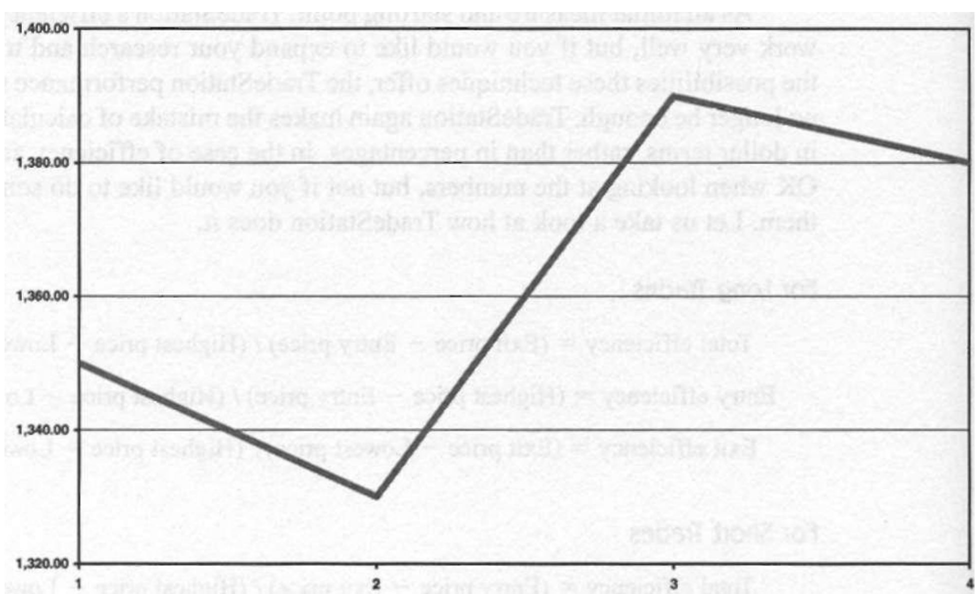


FIGURE 8.1

An Individual long trade.

already touched upon in Part 1: the start trade drawdown (STD), the end trade drawdown (ETD), the closed trade drawdown (CTD), and the total equity drawdown (TED). Almost every trade can be divided into three distinct parts. First, there is the STD, leading down to the low. Then there is the actual money-making phase, leading up to the high. Finally, there is the ETD, leading down to the exit level and the final profit.

Although this last conclusion is very important, however, it is not the main reason why these efficiency calculations are good to look at but not to tinker with. As you can see, all values are expressed as percentages or ratios of the distance between the low and high values for the trade. Because they are ratios, they work well as comparison measures, between both different markets and different time frames. But if you would like to do something about them, like adding different exit techniques or add-on entries, you must look at all the price changes and relationships in percentages as well.

For instance, if you would like to add a stop loss to this system, you cannot calculate that stop in dollar terms, but have to do it in percentage terms. As we discussed, this is because we want all our trades to be affected in the same way, whether the stop is applied to a market that has been trending heavily or to several different markets that trade at different levels and point values. With this also comes the necessity of using the RAD contract that is put together using percentage differences rather than point differences, on the day for the roll from one contract to the next.

DRAWDOWNS

Ah, drawdowns! There is plenty that can be said about this intriguing subject. But what many traders do not know, is that the drawdown is highly overrated as a system testing decision variable. True, the drawdown should be neither neglected completely nor investigated less than thoroughly, but you must know what you are doing and what you are investigating. For one thing, the estimated largest drawdown holds valuable information about how large your account size must be and can give you an indication about whether you have the psychological profile to trade the system in question. Unfortunately, however, the information that can be derived from most system-testing packages will not be enough, because the number is given in dollars without any relation to where and when this bad sequence of trades struck you.

Aside from not placing the drawdown in relation to the market situation at the time, another major error most system designers make when they are building and evaluating systems is only to look at the overall total equity drawdown (TED). This is calculated using both the open equity and the already closed out equity on your account. For instance, say that you, at a specific point in time, don't have any positions and that your last trade was a $3,000 winner that also took your account to a new total equity high at, let's say, $9,000. But before you managed to exit the position, it gave back $1,000 of its open equity.

According to most analysis packages, this means that even though you managed to add $3,000 to your closed out equity, you now are $1,000 in the hole as compared to your latest total equity high. Furthermore, if your next trade turns out to be a loser that immediately had you stopped out with a $4,500 loss before, your closed out equity now is $4,500, and your drawdown is $5,500. Then you have a $5,000 winner which, before it took off, started out going the wrong way with an additional $1,000, leaving you $6,500 in the hole. Then it gave back $1,500 of the open profit, and your total equity drawdown would now be a $1,500. Figure 8.2 shows what this sequence of trades could have looked like.

However, if you look closely at these numbers, they consist of three different types of drawdowns. At point 3, we are dealing with the end trade drawdown (ETD) that tells us how much of the open profit we had to give back before we were allowed to exit a specific trade. At point 4, we are looking at the closed trade drawdown (CTD) that measures the distance between the entry and exit points without taking into consideration what is going on within the trade. At point 5, we are dealing with the start trade drawdown (STD) that measures how much the trade went against us after the entry and before it started to go our way. And at point 7, finally, we again have to do with the ETD.

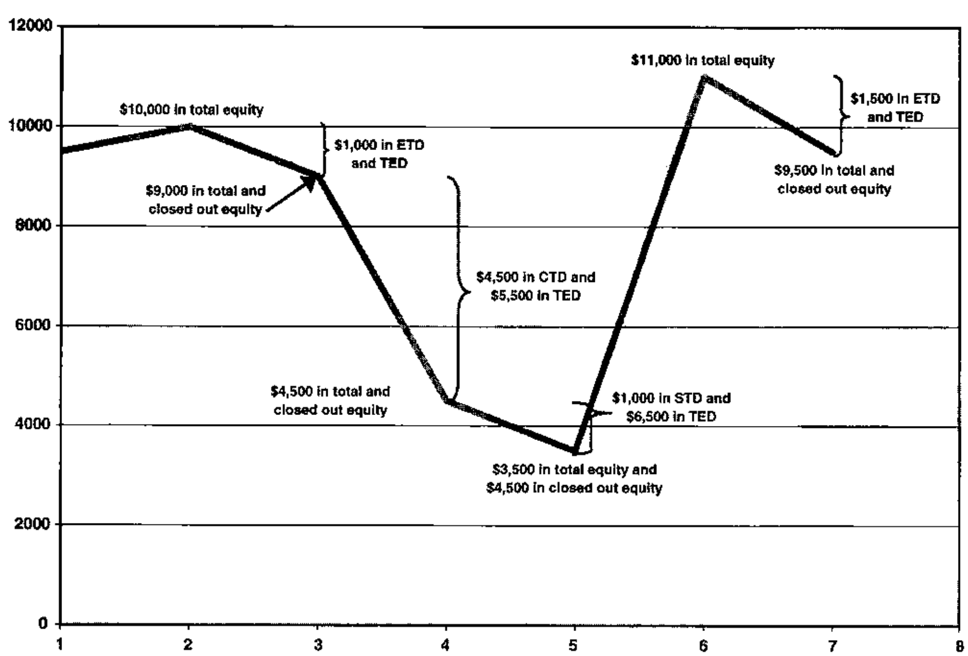


FIGURE 8.2

A look at different types of drawdown.

Of course we would like to keep all these drawdown numbers as small as possible. But when only examining the overall drawdown number (the TED) and blindly trying to do something about it leaves us with no way of knowing what it is we're really doing and what is actually changing within the system when we're making any changes to the input parameters.

To be sure, in recent years a few system developers and market analysts have addressed this issue in various ways, but as far as I know nobody has really nailed it down when it comes to how one must go about examining the markets and the systems in an appropriate and scientific fashion. One of these analysts is John Sweeney, technical analysis editor at Technical Analysis of Stocks and Commodities, who, in his two books *Campaign Trading* (Wiley Finance Editions, 1996) and *Maximum Adverse Excursion* (Wiley Trader's Advantage Series, 1997) came up with the concepts of *maximum adverse excursion* (MAE) and *maximum favorable excursion* (MFE). More recently, David Stendahl at RINA Systems has taken this a little further and developed a method to calculate the efficiency of a trade.

With version 2000i of Omega Research's TradeStation, the efficient trade analysis also has been implemented in the systems and optimization report. But the question still seems to remain open about whether this analysis is necessary and how one can gain from it. Furthermore, if it is necessary, there still remains the question of how to go about making the most out of it.

At any given moment, the TED is made up of the STD, ETD, and CTD. This means that to come to grips with the TED, you must come to grips with the STD, ETD, and CTD.

Depending on what type of entry technique you are using, many of your trades will experience a start trade drawdown (STD) before they start going your way. This is especially true for short-term top and bottom picking systems, where you enter with a limit order. In this case, the only way to avoid an STD is to enter at the absolute low or absolute high, and how often will that happen?

For instance, let's simplify the code for our intraday Meander system slightly to go long on the open. If we open below the VS Mid level and then stay in the trade all the way to the close the same day, our STD will be the distance between the entry point (the open) and the low of the day. Figure 8.3 shows this, with the STD charted on the horizontal x-axis and the result of the trade on the vertical y-axis. From this chart we can see that only one trade with an STD/MAE of more than or equal to 3% managed to produce a slight profit. Most of the trades that produced an STD/MAE over 2% also ended up as losers, while most of the trades with an STD/MAE less than 1% turned around and produced a profit. Note, however, that in this particular case we are assuming that the low comes before the high, which is not always the case for a system like this.

Longer-term breakout systems often also experience an STD, when they enter with a stop order on the highest high or lowest low over the lookback period. Usually, this level coincides with a pivotal resistance or support level in the

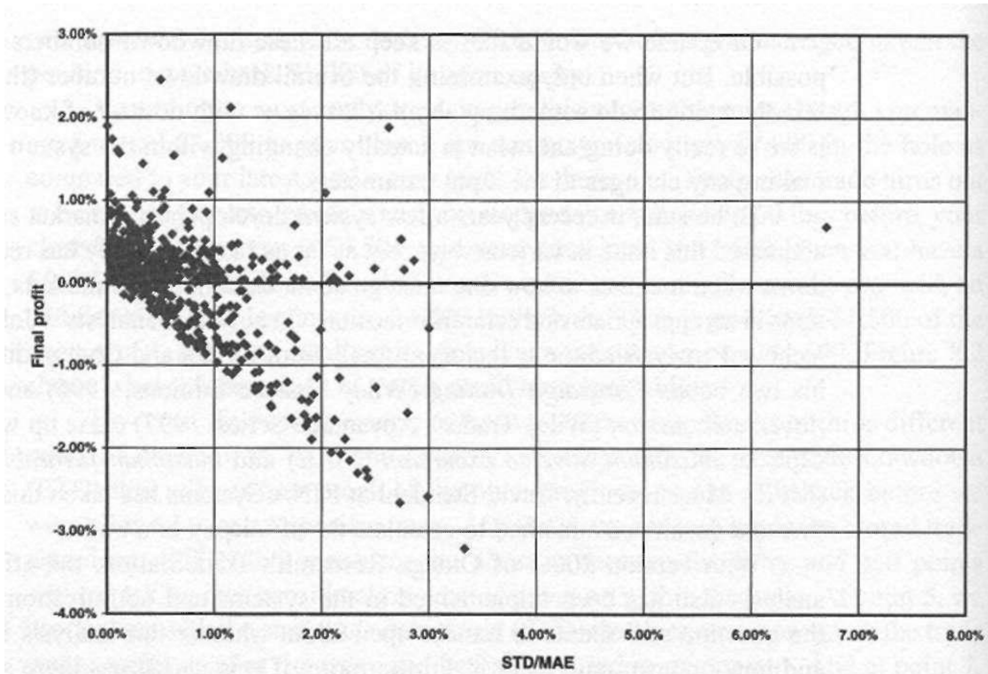


FIGURE 8.3

The final profit In relation to the STD/MAE for the intraday Meander system.

market, from which, after this level has been tested and you've entered the trade, the market usually makes yet another correction before the final penetration and follow-through takes us away (we hope) in a major trending move. Yet, other systems might completely lack any specific levels around which to place any natural orders. In our directional slope system, for instance (which based its entries on the slope of the moving average rather than the crossover), getting a feel for the STD is crucial, because this system, as it is constructed so far, operates not only completely without any actual levels for when a trade gets triggered, but also completely without any exit rules as we define them. Figure 8.4 shows that there is no connection between the level of the price or the moving average, and the reason why the trade is triggered. (Note that in this section we work with an 18-bar Entry MA and a 12-bar Exit MA.)

To start looking for the STD/MAE and ETD/MFE levels that should work well on several different markets and time periods, we must do all our research with the RAD contract. To export the necessary data for the directional slope system into a spreadsheet program, use the following TradeStation code:

```
Input: EntryMA(18), ExitMA(12);
Vars: EntryAvg(O), ExitAvg(O), LongEntry(O), ShortEntry(O), LongExit(O),
ShortExit(O), LongEntryDate(O), ShortEntryDate(O), LongExitDate(O),
```

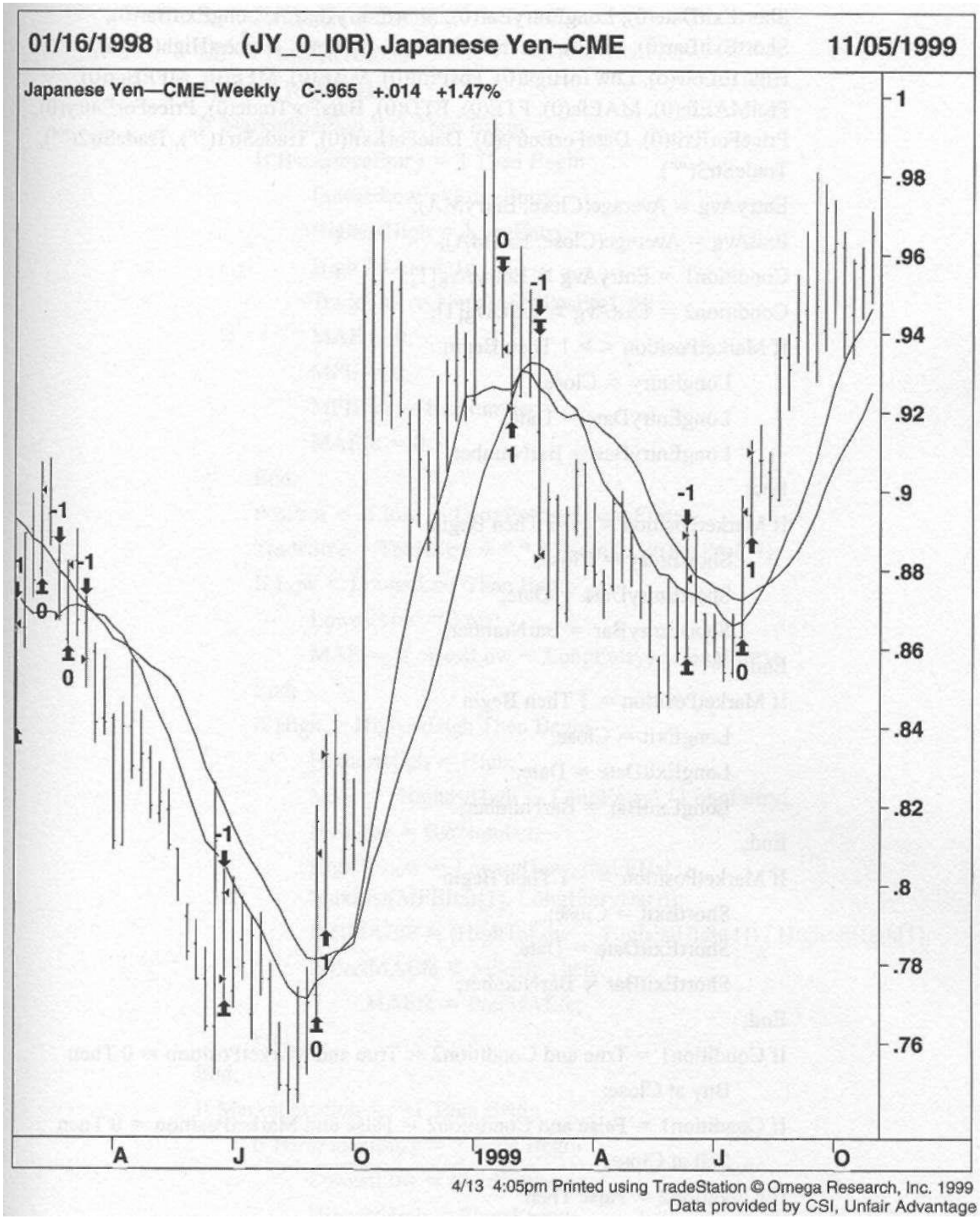


FIGURE 8.4

The directional slope system applied to the Japanese yen.

```
ShortExitDate(O), LongEntryBar(O), ShortEntryBar(O), LongExitBar(O),
ShortExitBar(O), MP(0), TotTr(O), LowestLow(Low), HighestHigh(High),
HighToLow(O), LowToHigh(O), PosProf(0), MAE(O), MFE(O), MFEBar(O),
PrelMAEfe(O), MAEfe(O), FTE(O), ETD(O), BarsForTrade(O), PriceForEntry(O),
PriceForExit(O), DateForEntry(O), DateForExit(O), TradeStrl (""), TradeStr2(""),
TradeStr3("");
Entry Avg = Average(Close, EntryMA);
ExitAvg = Average(Close, ExitMA);
Conditionl = EntryAvg > EntryAvg[l];
Condition2 = ExitAvg > ExitAvg[l];
If MarketPosition <> 1 Then Begin
	LongEntry = Close;
	LongEntryDate = Date;
	LongEntryBar = BarNumber;
End;
If MarketPosition <> — 1 Then Begin
	ShortEntry = Close;
	ShortEntryDate = Date;
	ShortEntryBar = BarNumber;
End;
If MarketPosition = 1 Then Begin
	LongExit = Close;
	LongExitDate = Date;
	LongExitBar = BarNumber;
End;
If MarketPosition = — 1 Then Begin
	ShortExit = Close;
	ShortExitDate = Date;
	ShortExitBar = BarNumber;
End;
If Conditionl = True and Condition2 = True and MarketPosition = 0 Then
	Buy at Close;
If Conditionl = False and Condition2 = False and MarketPosition = 0 Then
	Sell at Close;
If Condition2 = False Then
	ExitLong at Close;
If Condition2 = True Then
```

```
        ExitShort at Close;
MP = MarketPosition;
TotTr = TotalTrades;
If MarketPosition = 1 Then Begin
        If BarsSinceEntry = 1 Then Begin
                LowestLow = LongEntry;
                HighestHigh = LongEntry;
                HighToLow = 0;
                TradeStr2 = NumToStr(PosProf, 4);
                MAE = 0;
                MFE = 0;
                MFEBar = BarNumber;
                MAEfe = 0;
        End;
        PosProf = (Close — LongEntry) / LongEntry;
        TradeStr2 = TradeStr2 + "*," + NumToStr(PosProf, 4);
        If Low < LowestLow Then Begin
                LowestLow = Low;
                MAE = (LowestLow — LongEntry) / LongEntry;
        End;
        If High > HighestHigh Then Begin
                HighestHigh = High;
                MFE = (HighestHigh — LongEntry) / LongEntry;
                MFEBar = BarNumber;
                HighToLow = Lowest(Low, (MFEBar -
                MaxList(MFEBar[ 1 ], LongEntryBar)));
                PrelMAEfe = (HighToLow - HighestHighfl]) / HighestHighfl];
                If PrelMAEfe < MAEfe Then
                        MAEfe = PrelMAEfe;
        End;
End;
If MarketPosition = —1 Then Begin
        If BarsSinceEntry = 1 Then Begin
                LowestLow = ShortEntry;
                HighestHigh = ShortEntry;
                LowToHigh = 0;
                TradeStr2 = NumToStr(PosProf, 4);
```

```
            MAE = 0;
            MFE = 0;
            MFEBar = BarNumber;
            MAEfe = 0;
        End;
        PosProf = (ShortEntry - Close) / ShortEntry;
        TradeStr2 = TradeStr2 + "," + NumToStr(PosProf, 4);
        If High > HighestHigh Then Begin
            HighestHigh = High;
            MAE = (ShortEntry - HighestHigh) / ShortEntry;
        End;
        If Low < LowestLow Then Begin
            LowestLow = Low;
            MFE = (ShortEntry - LowestLow) / ShortEntry;
            MFEBar = BarNumber;
            LowToHigh = Highest(High, (MFEBar -
            MaxList(MFEBar[ 1 ], ShortEntryBar)));
            PrelMAEfe = (LowestLow[l] — LowToHigh) / LowestLow[l];
            If PrelMAEfe < MAEfe Then
                MAEfe = PrelMAEfe;
        End;
End;
If TotTr > TotTrfl] Then Begin
        IfMP[l] = 1 Then Begin
            PriceForEntry = LongEntryfl];
            PriceForExit = LongExit[l];
            FTE = (PriceForExit - PriceForEntry) / PriceForEntry;
            ETD = (PriceForExit - HighestHigh[ll) / Highesthigh[l];
            DateForEntry = LongEntryDatefl];
            DateForExit = LongExitDate[l];
            BarsForTrade = LongExitBar[ 1 ] - LongEntryBar[l];
            If MAEfe[l] > (PriceForExit - HighestHigh[l]) / HighestHigh[l]
Then
                MAEfe = (PriceForExit - HighestHigh[l]) / HighestHighfl];
        End;
        IfMP[l] = -1 Then Begin
            PriceForEntry = ShortEntry[1];
```

```
            PriceForExit = ShortExit[l];
            FTE = (PriceForEntry - PriceForExit) / PriceForEntry;
            ETD = (LowestLowfl] — PriceForExit) / LowestLow [1];
            DateForEntry = ShortEntryDatefl];
            DateForExit = ShortExitDate[l];
            BarsForTrade = ShortExitBarfl] - ShortEntryBar[l];
            If MAEfe[l] > (LowestLow[l] - PriceForExit) / LowestLow[l] Then
                  MAEfe = (LowestLow[l] — PriceForExit) / LowestLow[l];
      End;
      If FTE < MAE[1] Then
            MAE = FTE Else MAE = MAE[1];
      If FTE > MFE[1] Then
            MFE = FTE Else MFE = MFE[1];
      TradeStrl = LeftStr(GetSymbolName, 2) + "," + NumToStr(MP[l], 0) +
      ","    + NumToStr(DateForEntry, 0) + "," + NumToStr(PriceForEntry, 4) +
      "," + NumToStr(DateForExit, 0) + "," + NumToStr(PriceForExit, 4) +
      "," + NumToStr(MAE, 4)+ "," + NumToStr(MFE, 4) +      +
      NumToStr(FTE, 4) + "," + NumToStr(ETD, 4) + "," +
      NumToStr(MAEfe, 4) + "," + NumToStr(BarsForTrade, 0);
      TradeStr3 = TradeStrl + "," + TradeStr2[l] + NewLine;
      FileAppend("D:\Temp\DSS.csv",TradeStr3);
End;
```

Unfortunately, I am not the best programmer around, which is probably revealed by the code above. However, its length is also because of one of the stupidest features in TradeStation—the way the program registers an open trade and its entry price and counts the number of bars in trade. TradeStation does not note that a trade is open until after the first full bar in the trade and, consequently, does not calculate the number of bars in the trade correctly. For instance, apply the following code to any market:

```
Buy at Close;
ExitLong ("Loss") tomorrow at EntryPrice * 0.98 stop;
ExitLong ("Profit") tomorrow at EntryPrice * 1.02 limit;
```

The result is that TradeStation will exit each trade at the open of the next bar, no matter what. But if you change the code to the following:

```
Buy at Open;
ExitLong ("Loss") tomorrow at EntryPrice * 0.98 stop;
ExitLong ("Profit") tomorrow at EntryPrice * 1.02 limit;
```

The result is that TradeStation enters and exits each trade on the very same open, leaving you with a bunch of zero-bar, zero-profit trades. These, by the way, are all counted as winners in the performance summary. I do not know about you, but to me a winner is a trade that ends up with a profit; everything else is a loss. One way to work around this is to rewrite the code to:

```
Buy at close;
If BarsSinceEntry >= 1 Then Begin
	ExitLong ("Loss") tomorrow at EntryPrice * 0.98 stop;
	ExitLong ("Profit") tomorrow at EntryPrice * 1.02 limit;
End;
```

But then TradeStation simply skips a bar before it starts to track the trade and does not let you exit the trade until bar three (counting the bar for the entry as bar one), which won't change even if you decide to enter at the open instead of the close. And setting the BarsSinceEntry function equal to or greater than zero does not work either.

Another example of the same flaw is when you, for instance, enter a trade intrabar on a breakout. You will not be able to exit on the close, or intrabar of that same bar, no matter how much the market moves against you, as suggested by the closing price of that same bar. (That is why I have chosen to do all the research for the intraday version of the Meander system within Excel, rather than in TradeStation.)

To me, this is the equivalent of Excel's purporting to calculate everything in a spreadsheet correctly, without Microsoft's letting you know that sometimes, when the formula get too complicated, it loses track and simply makes up an answer. After all, it is my (your) money we are dealing with here and we should all expect things to work properly. Unfortunately, for that to happen we simply must find a way around the problem. Hence, we end up with a large chunk of extra spaghetti code, which obviously increases the risk for other types of errors and logical blunders. Enough said, let us work with what we have.

Once we are in the spreadsheet program it is easy to create a scatter chart like Figures 8.3 and 8.5 that compare the STD to the final profit. Although we might be using the same techniques to derive the necessary data for the STD as for the MAE, it is important to understand that the two are not the same. Nor is either one of them the same as RINA Systems' entry efficiency. The difference is that the STD should primarily be adjusted with the entry technique, while the MAE should primarily be adjusted with a specific exit technique, such as a stop loss. Together, the MAE and STD make up the entry efficiency.

Notice also the word "primarily," because in a good working system all parts should and will intervene to form a whole larger than the parts. Many times, it can be difficult to distinguish between the two. The point is that you should at least be aware of the differences and exactly what it is you are trying to achieve. It is still your money we are talking about here.

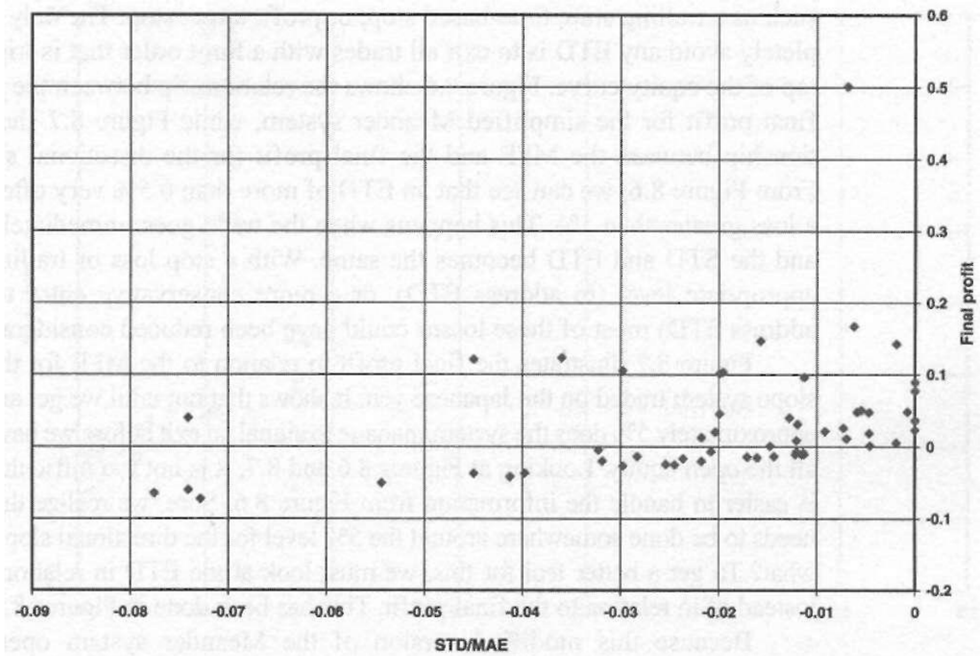


FIGURE 8.5

The final profit in relation to STD/MAE for the directional slope system.

Figure 8.5 shows the STD/MAE for the directional slope system traded on the Japanese yen. This chart shows that of all trades with an STD/MAE of more than or equal to 4% only two did not end up as losers, while most of the trades with an STD/MAE of 2% or less ended up as winners.

In the case of the Meander system, after you have made sure that you have optimized your exit techniques and taken every other step necessary, perhaps all that must be done to the entry is to wait a couple of ticks before you enter, or at least not enter immediately at the open when the volatility can be high. In the case of the directional slope system, one solution could be to wait for a pullback and then enter on a break through the price level that causes the Entry MA to change its direction.

Just as the STD is not the same as the MAE, the end trade drawdown (ETD) is not the same as the maximum favorable excursion (MFE), although we might be using essentially the same techniques to derive the necessary information. MFE is the maximum open profit of the position. ETD is the difference between the MFE and the exit point, and the amount you are giving back to the market before the system signals the time to exit. The MFE and the final profit should therefore be maximized with the amount invested and the numbers of contracts traded. The ETD, on the other hand, should be managed with different types of exit techniques and stops, such as a trailing stop, time-based stop, or profit target stop. The only way to completely avoid any ETD is to exit all trades with a limit order that is triggered at the top of the equity curve. Figure 8.6 shows the relationship between the ETD and the final profit for the simplified Meander system, while Figure 8.7 shows the relationship between the MFE and the final profit for the directional slope system. From Figure 8.6, we can see that an ETD of more than 0.5% very often resulted in a loss greater than 1%. This happens when the trade goes immediately against us, and the STD and ETD becomes the same. With a stop loss or trailing stop at an appropriate level (to address ETD), or a more conservative entry technique (to address STD) most of these losses could have been reduced considerably.

Figure 8.7 illustrates the final profit in relation to the MFE for the directional slope system traded on the Japanese yen. It shows that not until we get an MFE above approximately 5% does the system manage to signal an exit before we have given away all the open equity. Looking at Figures 8.6 and 8.7, it is not too difficult to see that it is easier to handle the information from Figure 8.6. Sure, we realize that something needs to be done somewhere around the 5% level for the directional slope system, but what? To get a better feel for this, we must look at the ETD in relation to the MFE instead of in relation to the final profit. This has been done in Figures 8.8 and 8.9.

Because this modified version of the Meander system operates with a dynamic profit target that triggers an exit with a limit order, the higher the MFE, the lower the ETD. Figure 8.8 shows that for all trades with an MFE above 0.5%,

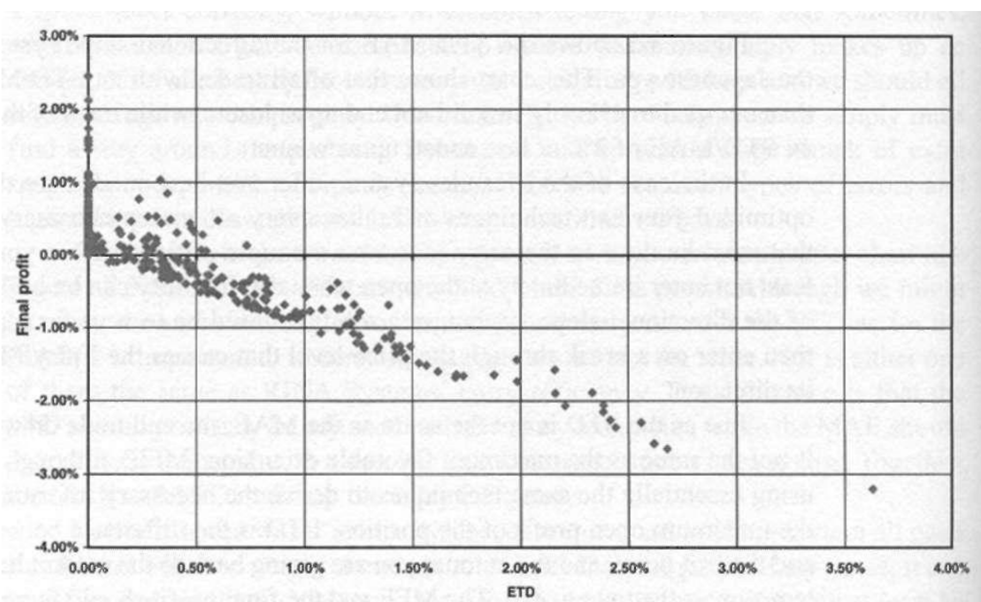


FIGURE 8.6

The final profit in relation to ETD for the Meander system.

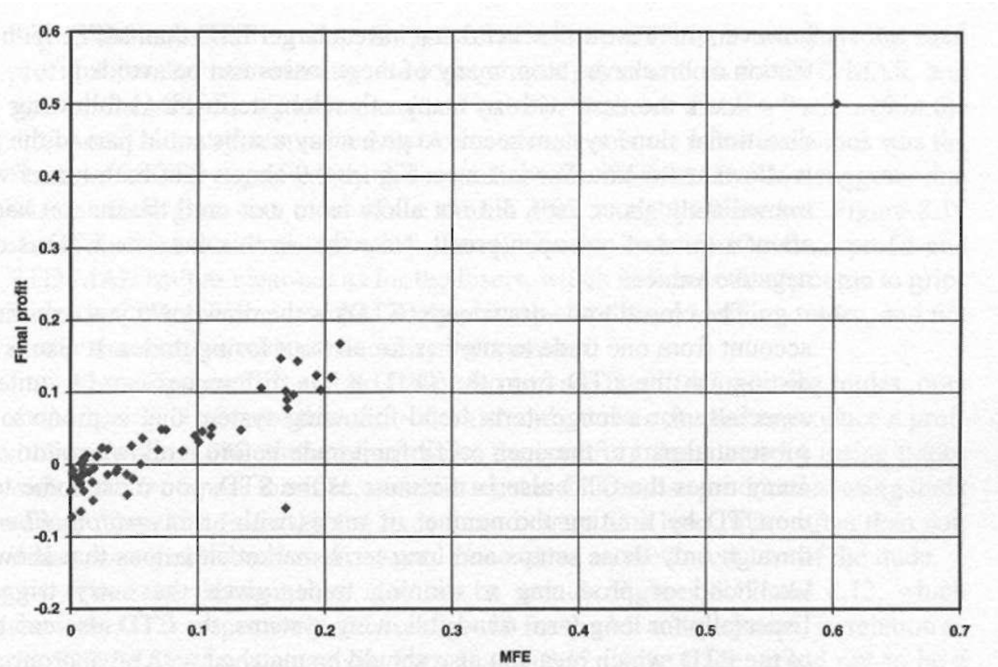


FIGURE 8.7

The final profit in relation to the MFE for the directional slope system.

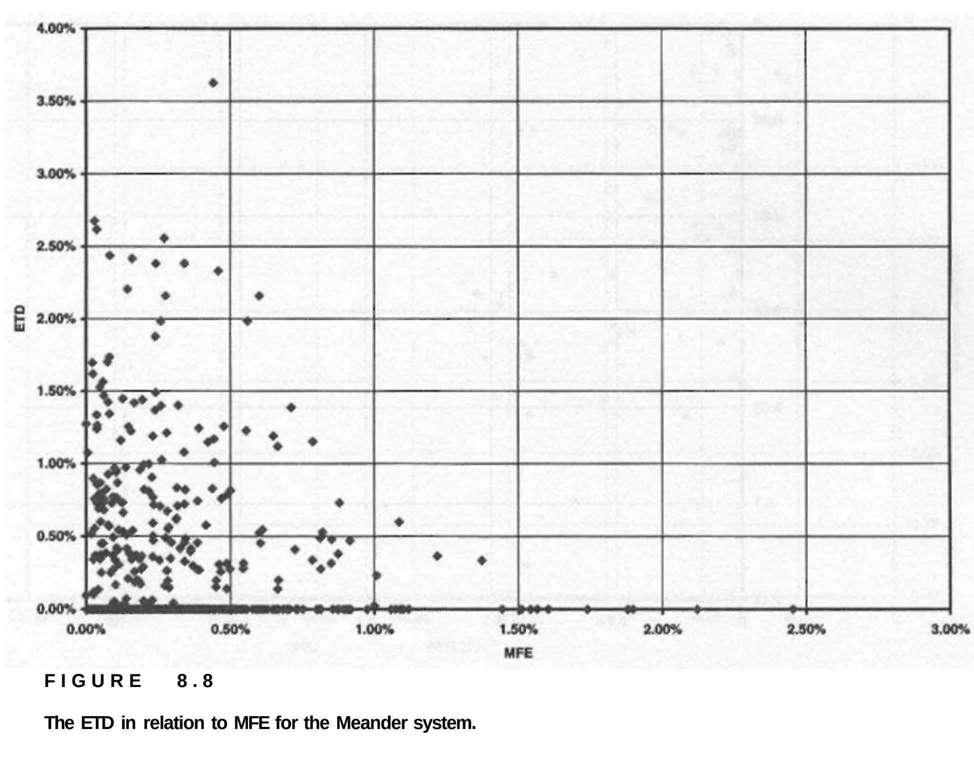


FIGURE 8.8

The ETD in relation to MFE for the Meander system.

however, there are still several that have a larger ETD than MFE. With a profit protection or breakeven stop, many of these losses can be avoided.

As is the case with so many other long-term trend-following systems, the directional slope system seems to give away a substantial part of the profit before it allows us to exit. For instance, Figure 8.9 shows that both trades with an MFE immediately above 20% did not allow us to exit until the market had taken back about a third of our open profit. Note that in this case the ETD is denoted with negative values.

The closed trade drawdown (CTD) is the drawdown you experience on your account from one trade to another for all your losing trades. It also is important to distinguish the CTD from the TED, as the differences can be quite substantial, especially for a longer-term trend-following system that is prone to give back a substantial part of the open profit for a trade before it allows you to exit. Because many times the CTD also is the same as the STD, you must come to terms with the CTD by limiting the number of trades with an *overriding filter,* which lets through only those setups and long-term market situations that show the highest likelihood of producing a winning trade, given the entry trigger you use. Especially for long-term trend-following systems, the CTD also can be a function of the ETD, which means it also should be matched with an appropriate exit tech-

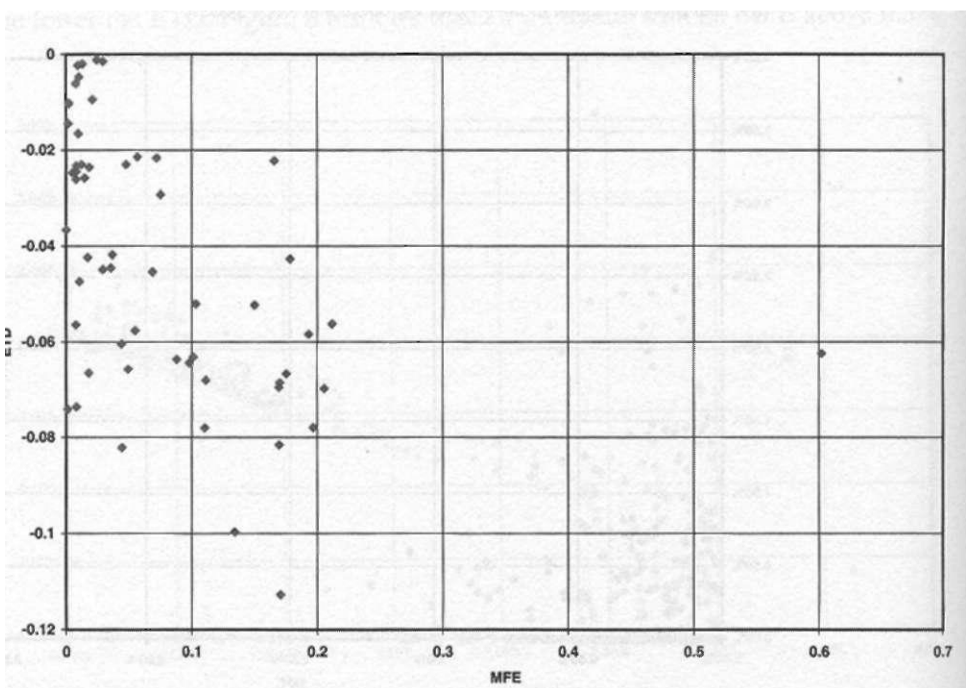


FIGURE 8.9

The ETD in relation to MFE for the directional slope system.

nique, such as a trailing stop. To get a feel for the CTD, you can chart the final profit, separated into winning and losing trades, against both the STD/MAE, and against the MFE for all losing trades. Figure 8.10 shows that if a trade within the directional slope system turned out to be a loser, only on a few occasions was the final profit/CTD significantly different from the STD/MAE. This suggests that when a trade goes bad, most of the time it does so right off the bat. Figure 8.11 shows that for the winning trades, the relationship between the final profit and STD/MAE isn't as clear-cut as for the losers, which indicates that to come to grips with the CTD, it is important to analyze it separated from winning trades, and not clutter the analysis with unnecessary information.

From Figures 8.10 and 8.11, we also can see that of all winning trades, only six had an STD of more than 2%, of which only three managed to produce a profit of more than 10%. At the other end of the spectrum there were 16 losing trades with an STD of more than 2%, which in most instances also produced a losing trade of more than 2%. In fact, if the trade turned out to be a loser, more often than not, it also managed to be closed out very close to, or at, the lowest low of the trade.

The same phenomenon also can be seen in Figures 8.12 and 8.13, which show the CTD respectively, the final profit for the Meander system, in relation to the STD/MAE. As you can see from Figure 8.12, if the trade turned out to be a loser, only on a few occasions was the final profit/CTD significantly different

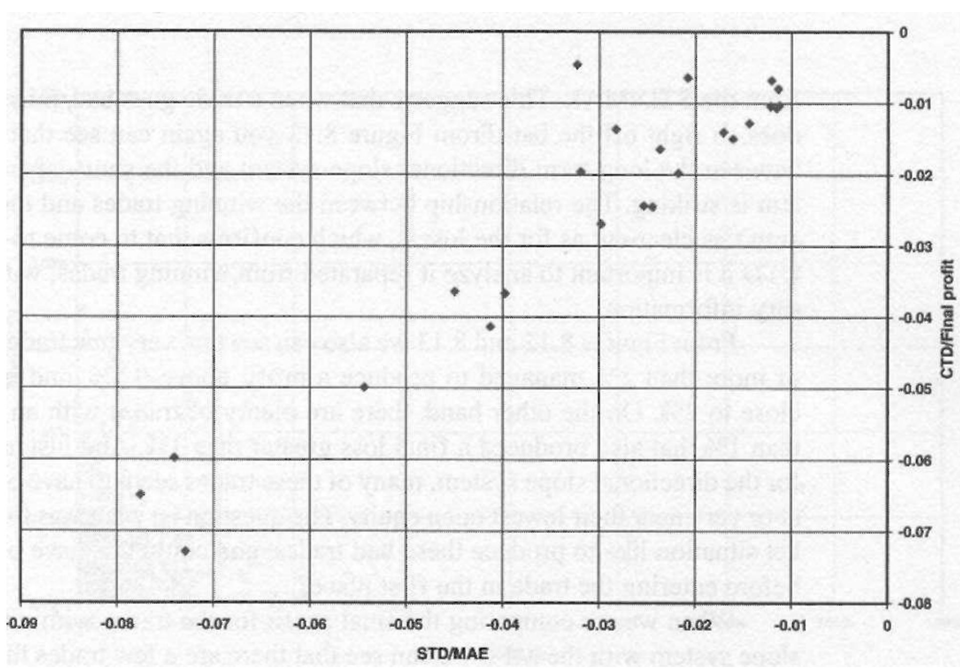


FIGURE 8.10

The final profit for all losing trades in relation to STD/MAE for the directional slope system.

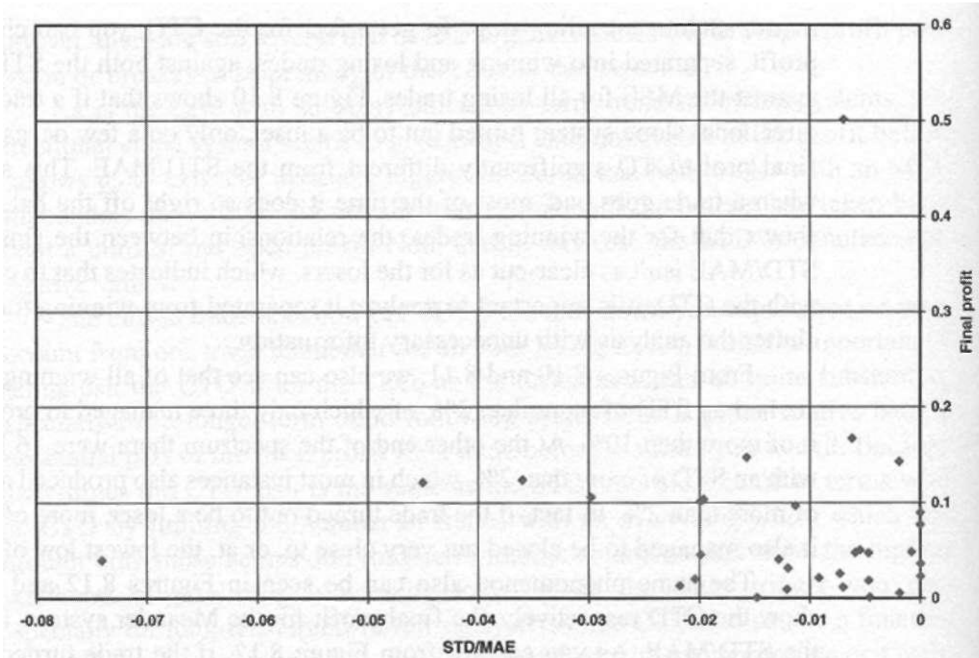


FIGURE 8.11

The final profit for all winning trades In relation to STD/MAE for the directional slope system.

from the STD/MAE. This suggests that when a trade goes bad, most of the time it does so right off the bat. From Figure 8.13 you again can see that the similarity between the long-term directional slope system and the short-term Meander system is striking. The relationship between the winning trades and their STD/MAE aren't as clear-cut as for the losers, which confirms that to come to grips with the CTD it is important to analyze it separated from winning trades, with no unnecessary information.

From Figures 8.12 and 8.13 we also can see that very few trades with an STD of more than 2% managed to produce a profit above 0.5%, and only one came close to 2%. On the other hand, there are plenty of trades with an STD of more than 1% that also produced a final loss greater than 1%. And just as was the case for the directional slope system, many of these trades seem to have been closed out at or very near their lowest open equity. The question is, what was the current market situation like to produce these bad trades, and could this have been dealt with before entering the trade in the first place?

When we are comparing the final profit for the trades within the directional slope system with the MFE we can see that there are a few trades that seem not to be stopped out until there has been an adverse move in the neighborhood of 5% or more. Obviously, this is too much to give back, which makes it a good idea to

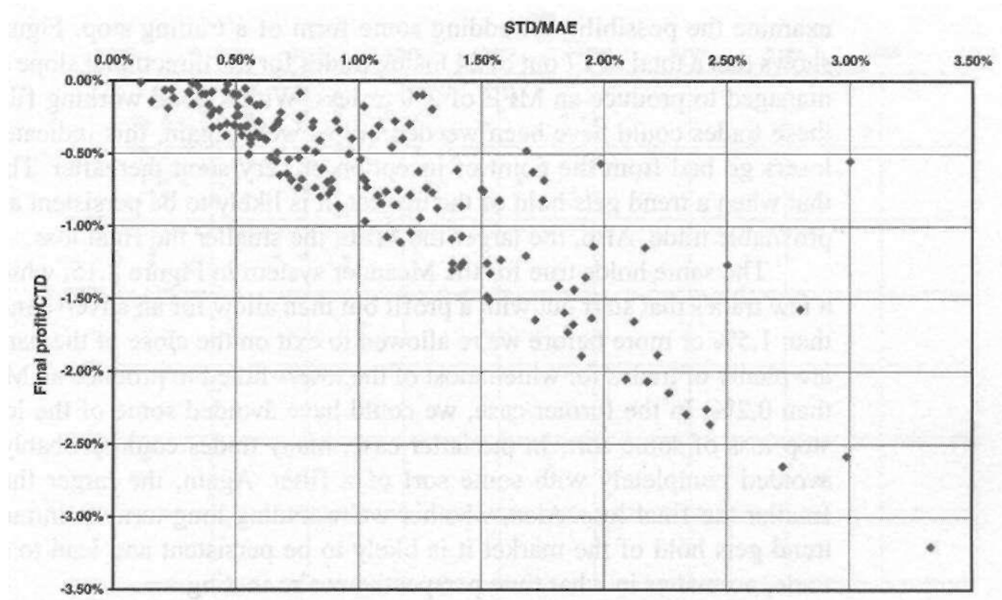


FIGURE 8.12

The CTD in relation to STD/MAE for the Meander system.

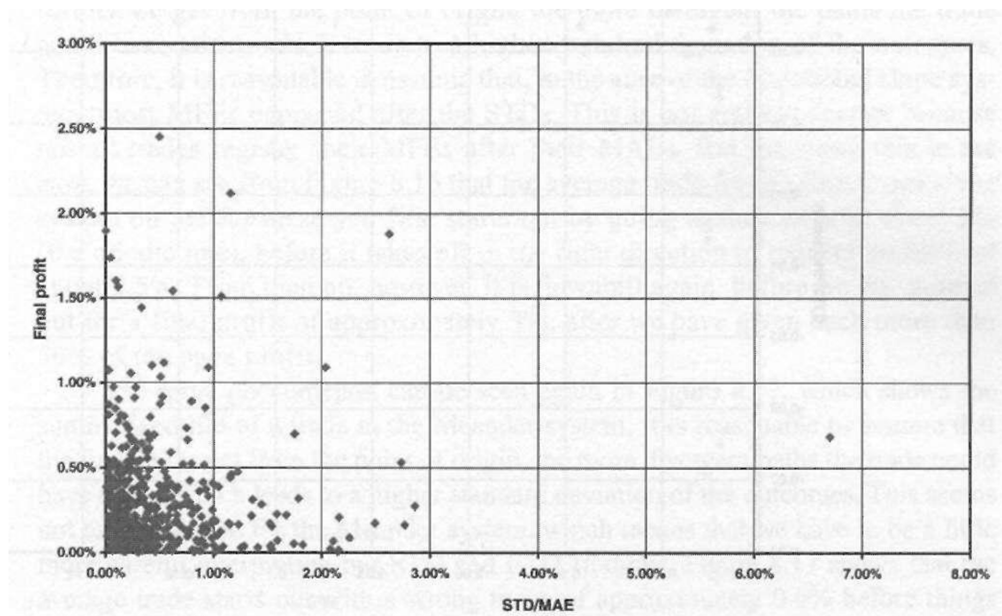


FIGURE 8.13

The final profit for all winning trades in relation to STD/MAE for the Meander system.

examine the possibility of adding some form of a trailing stop. Figure 8.14 also shows that a total of 17 out of 24 losing trades for the directional slope system only managed to produce an MFE of 2% or less. With a good working filter many of these trades could have been weeded out as well. Again, this indicates that most losers go bad from the point of inception or very soon thereafter. This indicates that when a trend gets hold of the market, it is likely to be persistent and lead to a profitable trade. Also, the larger the MFE, the smaller the final loss.

The same holds true for the Meander system in Figure 8.15, which has quite a few trades that start out with a profit but then allow for an adverse move of more than 1.5% or more before we're allowed to exit on the close of the bar. There also are plenty of trades for which most of the losers failed to produce an MFE of more than 0.2%). In the former case, we could have avoided some of the losses with a stop loss of some sort. In the latter case, many trades could probably have been avoided completely with some sort of a filter. Again, the larger the MFE, the smaller the final loss. Also, whether we're trading long term or intraday, when a trend gets hold of the market it is likely to be persistent and lead to a profitable trade, no matter in what time perspective we're trading.

Another way to summarize the entire life span of a trade is to chart the STD/MAE, the MFE, and the ETD/final profit in one sequence, as they are assumed to have taken place. Figure 8.16 attempts to show the summarized life

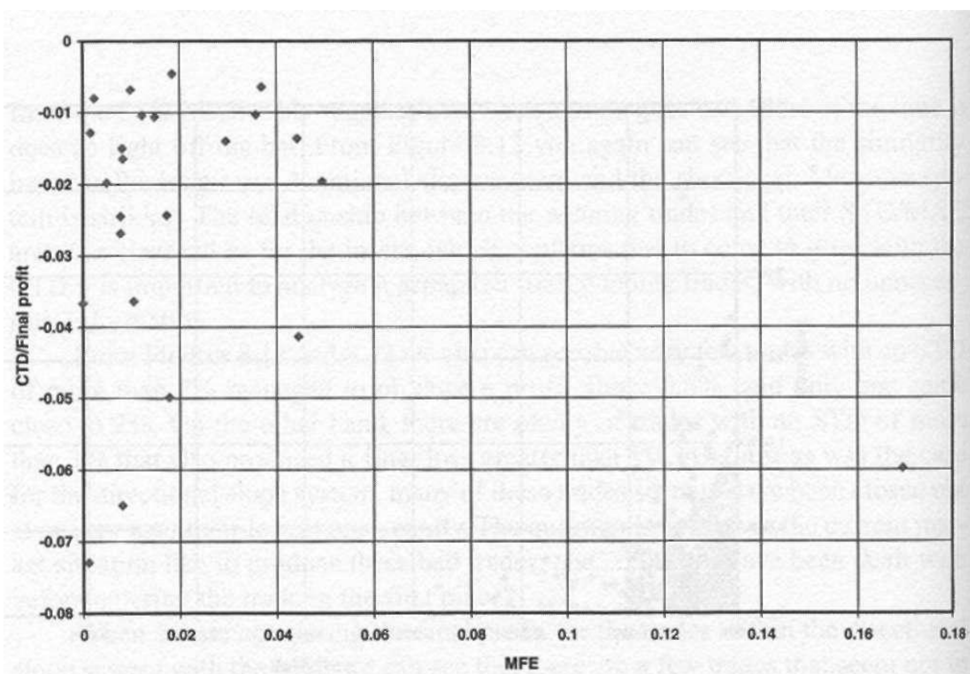


FIGURE 8.14

The CTD in relation to MFE for the directional slope system.

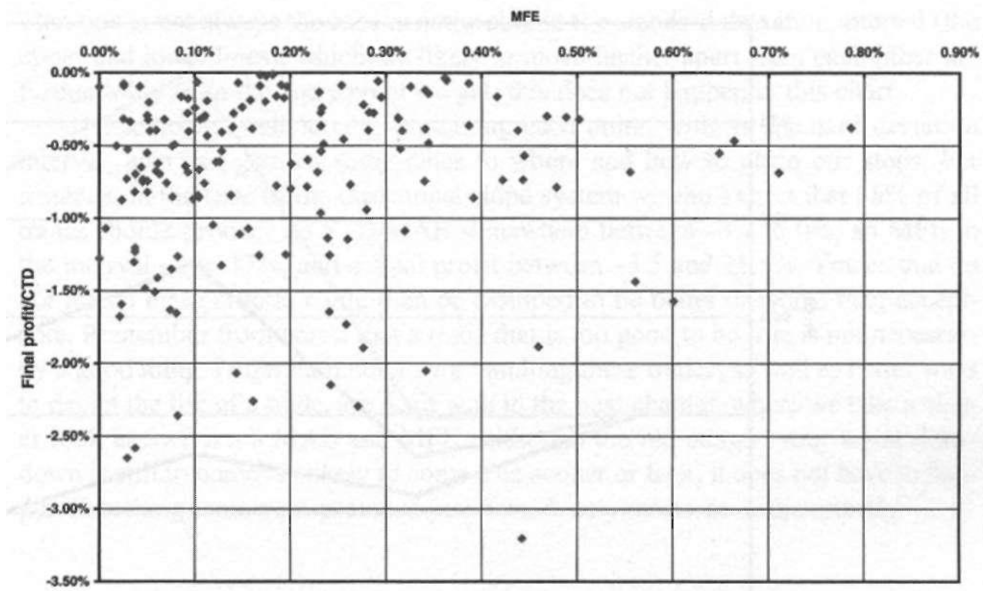


FIGURE 8.15

The CTD in relation to MFE for the Meander system.

for a trade in the directional slope system. The assumption we make is that the further we get from the point of origin, the more divergent the paths the trade could have taken, which leads to a higher standard deviation of the outcomes. Therefore, it is reasonable to assume that, in the case of the directional slope system, most MFEs happened after the STDs. This is not entirely correct because not all trades register their MFEs after their MAEs. But assuming this is the case, we can see from Figure 8.16 that the average trade for the directional slope system on the Japanese yen first starts out by going against us with about 2% (the middle line), before it takes off in the right direction to register an MFE of about 7.5%. From then on, however, it is downhill again, before we are stopped out for a final profit of approximately 3%, after we have given back more than 50% of the open profit.

The same phenomenon can be seen again in Figure 8.17, which shows the summarized life of a trade in the Meander system. It is reasonable to assume that the further we get from the point of origin, the more divergent paths the trade could have taken, which leads to a higher standard deviation of the outcomes. This seems not to be the case for the Meander system, which means that we have to be a little more careful interpreting our STD and ETD findings. Figure 8.17 shows that the average trade starts out with a wrong move of approximately 0.6% before things start to go our way, and we can register an MFE of about 0.6% and a final profit of about 0.1%. Again, however, this assumes that the course of events is as outlined.

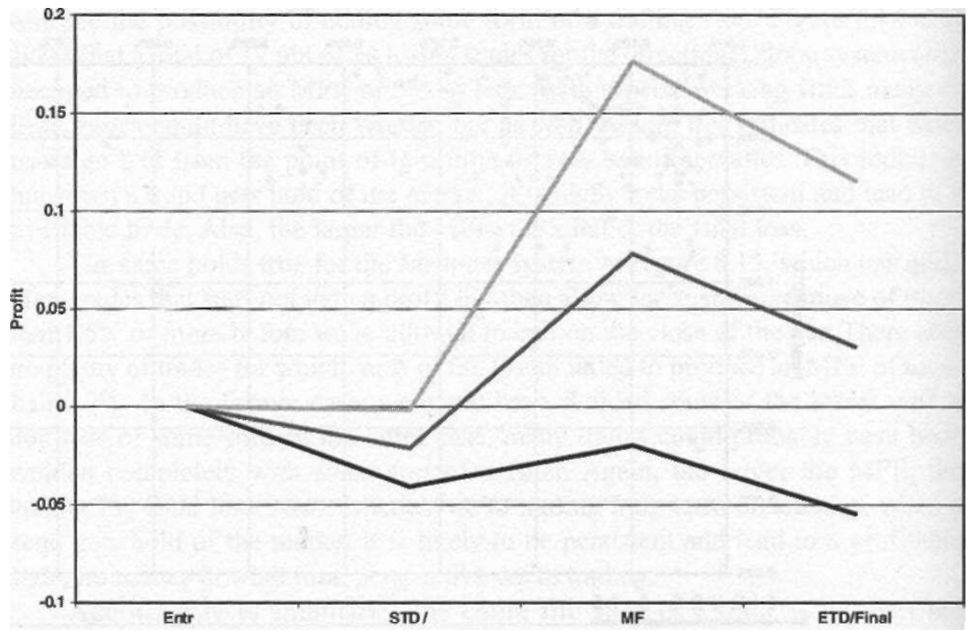


FIGURE 8.16

The summarized life for a trade in the directional slope system.

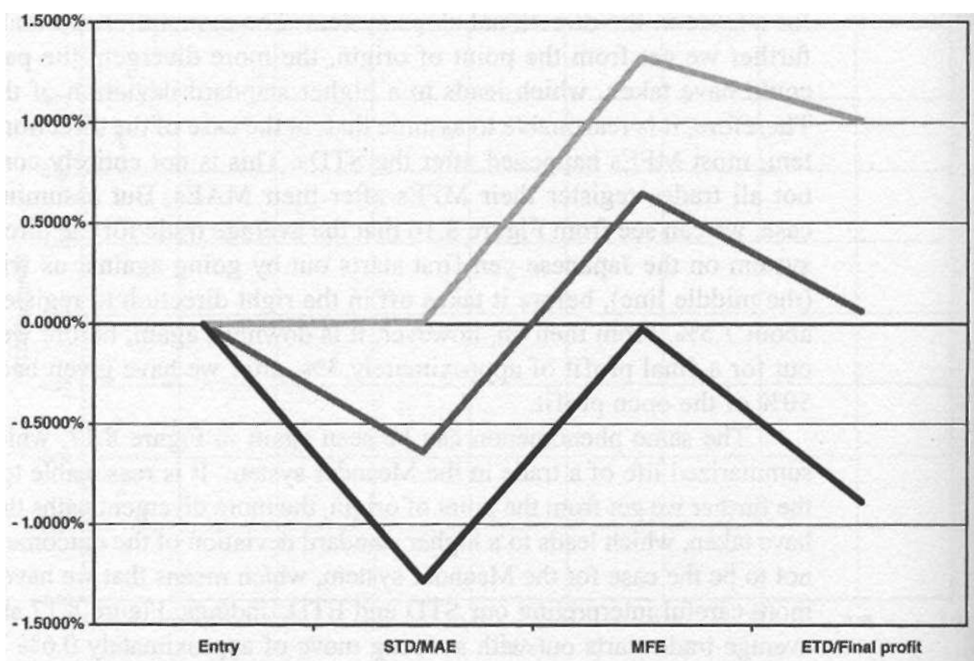


FIGURE 8.17

The summarized life for a trade in the Meander system.

That this is not always the case is noticeable in the standard deviation interval (the upper and lower lines), which are likely to move further apart from each other the further away from the entry point we get; this does not happen in this chart.

Nonetheless, individually examining each point, with its standard deviation interval, also can give us some clues to where and how to place our stops. For instance, in the case of the directional slope system we can expect that 68% of all trades should produce an STD/MAE somewhere between -3.7 to 0%, an MFE in the interval -2 to 17%, and a final profit between -5.5 and 11.5%. Trades that do not match these criteria could then be assumed to be better or worse than acceptable. Remember from Part 2 that a trade that is too good to be true is not necessarily a good thing. Different methods for handling these trades, as well as better ways to depict the life of a trade, are dealt with in the next chapter, where we take a closer look at Sweeney's MAE and MFE. Although the old adage "your worst drawdown is still to come" is likely to come true sooner or later, it does not have to happen first thing tomorrow, provided you have done your homework correctly.

CHAPTER 9

Sweeney's MAE/MFE

Look at it this way: Whether your trading style resembles a gunslinger shooting from the hip or a well-aimed sniper lying in ambush, knowing where your trades are heading could mean the difference between riding into the sunset or lying fatally wounded on a dusty street at high noon. To stay alive you must know when to draw and when to run.

For a gunslinger or a sniper, the ultimate advantage comes from being able to calculate the trajectory of the bullet. Although this hardly is possible in a shootout that demands split second decisions, it can be done in the financial markets where you can estimate the trajectory of your trades in relation to their targets.

The first thing you must do, is find where your targets have been and how you have performed in the past. To do this you must take a deep look into your population of trades and examine each individual trade closely. When you do, you will discover that there are several similarities between them, but that every trade also has a unique set of characteristics and traits that distinguish the winners from the losers. All of these characteristics often can be spotted when you trade using John Sweeney's MAE and MFE techniques, as illustrated in Figure 9.1. This chapter illustrates one way of interpreting and making better use of Mr. Sweeney's excellent work.

The MAE is defined as the most negative intraday price movement against your position, which corresponds to the lowest open equity during the lifespan of the trade. The MAE does not take into consideration whether this happens immediately at the inception of the trade, or just before exiting, after the trade might have lost all its open profit and turned into a loser. The MFE is defined as the most positive price movement for your position, which corresponds to the highest open equity, during the lifespan of

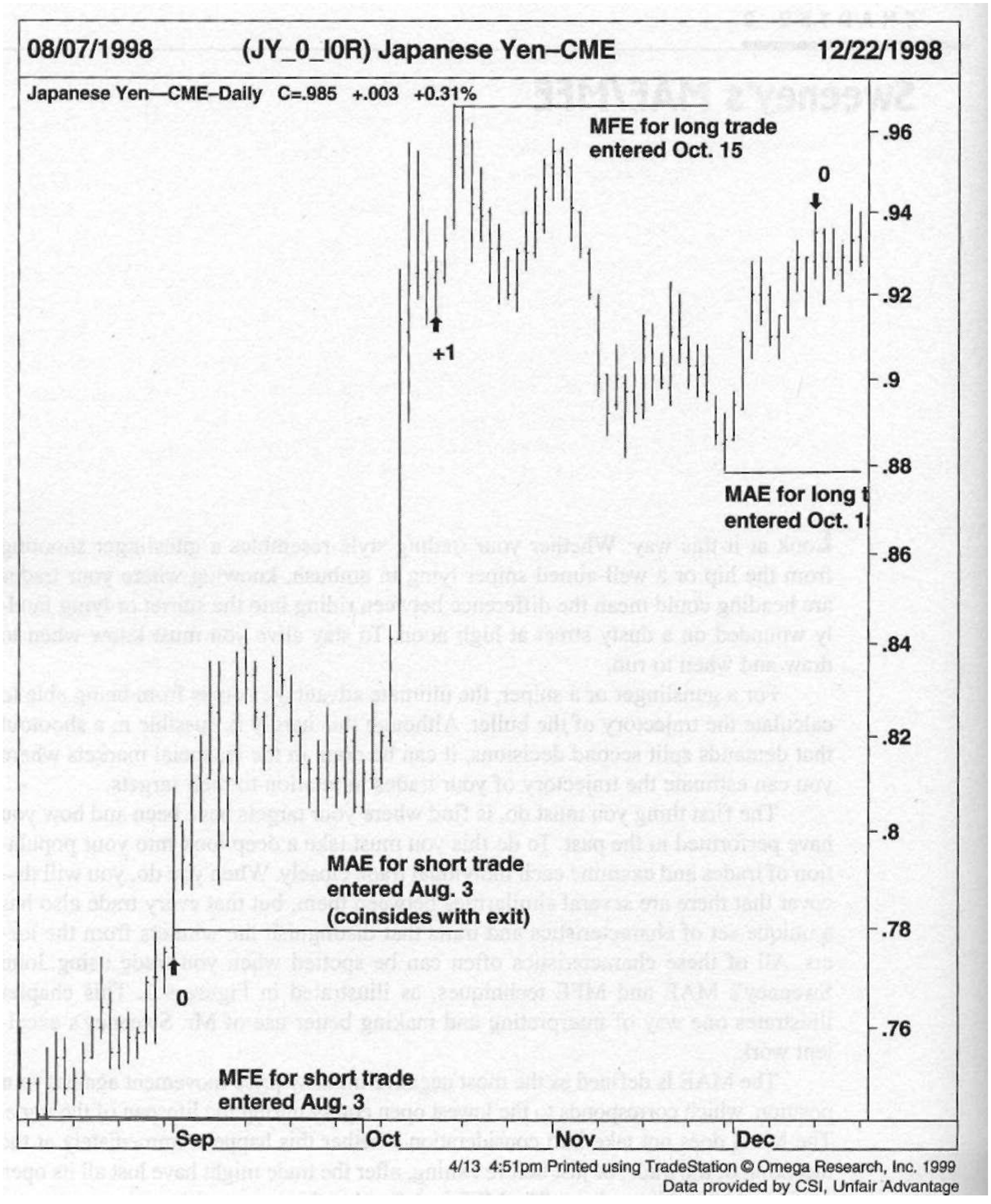


FIGURE 9.1

MAE and MFE levels for two trades in the Japanese yen.

the trade. The MFE does not take into consideration whether this happens early on in the trade or just before exiting with or without a profit. Notice, for instance, that in Figure 9.1, both MAEs occurred after the MFEs, and for the short trade also in conjunction with the exit of the trade. If we look at the long trade and refer back to the different drawdowns just discussed, the distance between the entry and the MAE level would in fact make up the STD and as such should preferably have been avoided completely with the help of some sort of a filter. But once in the trade anyway, the adverse move following the MFE should have been limited by a trailing stop or a stop loss. With the MAE and MFE techniques, we can examine our systems for high-probability exit techniques and even for situations when it could be a good idea to add to a trade, or even fade (to trade against the trend) a previously given signal.

As a complement and a starting point to the MAE/MFE analysis we also take a closer look at the entire lifespan and development of a trade. (A sort of trajectory analysis if you like.) This helps us examine our systems for additional trading rules, depending on whether the trade stays within the boundaries set by the MAE/MFE analysis. As an analogy, albeit with a little backwards reasoning, compare the MAE/MFE values with the pop-up targets at a shooting range. In this case, the MFE targets are the bad guys to be aimed at, while the MAE targets are the "innocent people" who should be avoided.

The trajectory analysis helps us determine if we should "freeze" the bullet (the trade) mid-air if we mistakenly shoot at one of the good guys (or even take a shot in the completely opposite direction), or if it could be a good idea to throw away a couple of additional shots in the same direction when we have one of the bad guys in our sights. Additionally, with the trajectory analysis, each curve of the open equity is a mirror image of the price development of the market, which makes it possible to compare each trade's ongoing price action with what actually happened during similar situations in the past. If technical analysis is the study of the price action from the past on the assumption that it will repeat itself in the future, isn't this the ultimate, practical, and beneficial form by which this can be done? To export the entire necessary data into a spreadsheet, we continue to use the code from the previous chapter.

Let us apply this code to all markets, over the time period January 1980 to October 1999, in our directional slope system from Part 2. The markets tested are T-bonds, live cattle, Japanese yen, corn, Canada dollar, crude oil, dollar index, lumber, orange juice, S&P 500, copper, Eurodollar, CRB index, cotton, gold, and coffee. If you have this workspace saved already, do not forget to change from the ordinary point-based back-adjusted contract to the RAD contract. And, as before, do not deduct any money for slippage and commission, because this will only result in a suboptimal solution.

In this case, we start by looking at all trades (winners and losers, longs and shorts) for all markets, and then divide our analysis into winners and losers, respectively. Once in your spreadsheet program, make three copies of the spreadsheet. If you also would like to examine short and long trades separate from each other, it is recommended that you make separate copies for this as well. With the data from the spreadsheet, we can create a chart similar to Figure 9.2, which shows the development for a set of trades.

Although just charting all trades on top of each other makes little sense and looks more like the inside of a magpie's nest, already at this point we can distinguish a few differences between the winners and the losers. For one thing, it is fairly easy to see that the life span for several of the losers is fairly short, while the winners seem to live on for much longer. There also seem to be a bias (trend) to the upside, the longer the trade lasts. To emphasize and make it easier to see this tendency we can channel in the entire bouquet, as in Figure 9.3. Although we already can see some tendencies and form some basic guidelines, like "a winner should be in positive territory, approximately by bar 18" or "around bar 30, most trades should show a profit between 10 to 30%," this is not enough to formulate any systematic and mechanical rules that move us away from "trading with the gut."

To be able to do this, we must simplify things. The first thing to do is calculate the average percentage move for each bar, together with its standard deviation boundaries. At the bottom of the spreadsheet, type in the following formula and fill them out to the right for as long as you have any open trades:

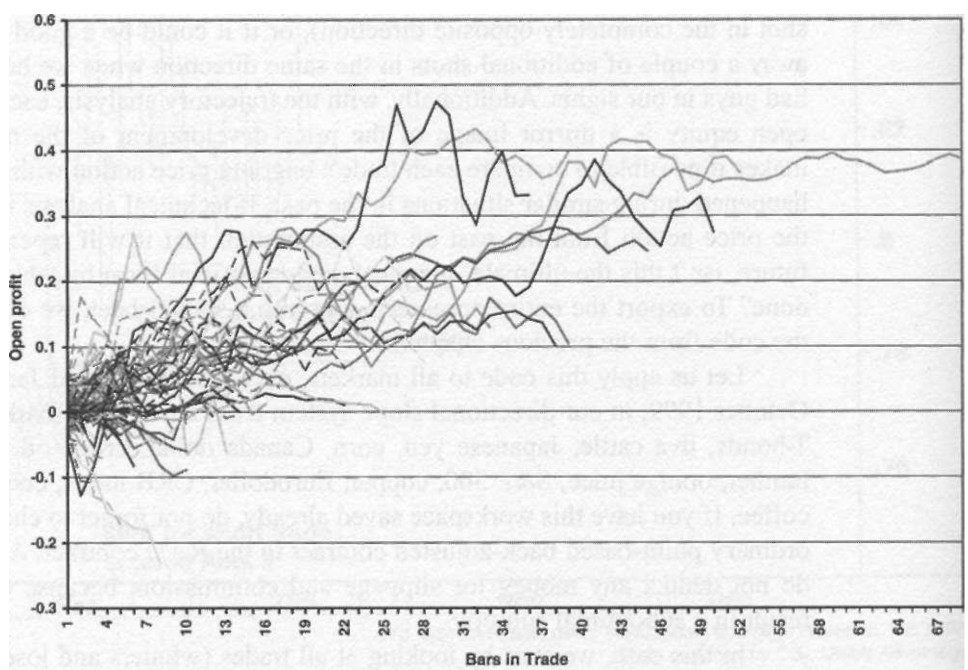


FIGURE 9.2

The development for a set of trades for the directional slope system.

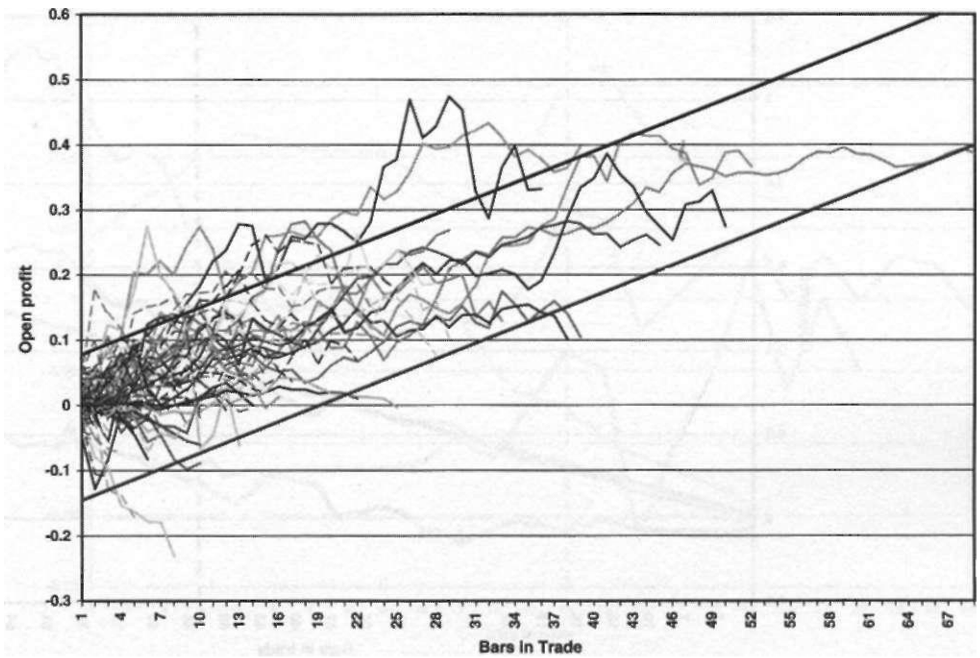


FIGURE 9.3

The development for a set of trades with manually added trend lines.

=AVERAGE(H1:H1240)

where *H* denotes the column where we stored the percentage move for bar one.

=H1246+STDEV(H1:H1240)

=H1246 - STDEV(H1:H1240)

When done, you should be able to produce a chart like Figure 9.4, which shows the development of the average trade (the middle squiggly line) together with the plus (upper line) and minus (lower line) standard deviation boundaries. The standard deviation boundaries denote the area in which 68% of all trades can be expected to fall. To this you also could add a least square regression line for the average trade. Instead of looking at hundreds of lines that make little sense, we are now down to four, making for much easier interpretation and rule making.

The further away from the entry point we get, more and the more trades are closed out. However, the fewer the trades, the less reliable our results. The vertical dashed line marks out the point where we have fewer than 20 open trades. In this case, this happens at bar 48. To this chart, I also have added the regression line (middle straight line) for the average trade. The regression equation for this line is

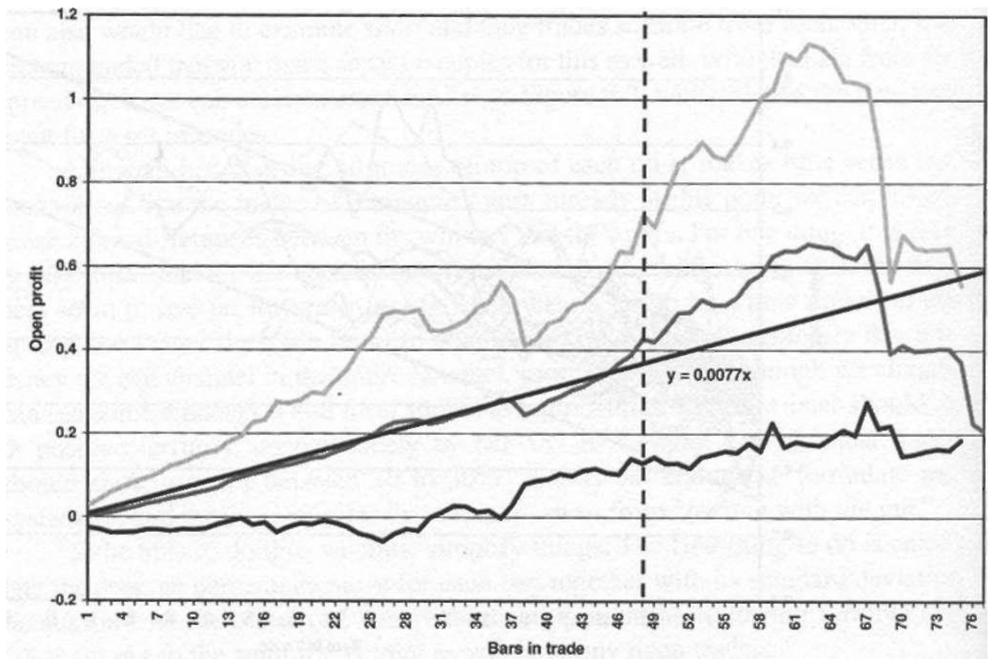


FIGURE 9.4

The development of the average trade (the middle squiggly line) together with the plus (upper line) and minus (lower line) standard deviation boundaries.

0.0074X, which means that the average trade increases in value by approximately 0.74% per day.

With a chart like this we can start to set up some more definite guidelines like "if we cross the average line from below, the trade is about to become better than average and can be worth adding to" or "if we cross the upper standard deviation line from below the trade is too good to be true and we had better take some profit." If we also divide all the trades into groups of winners and losers, we get an even better feel for our rule making. Figure 9.5 shows the development of the average losing trade, which seems to go nowhere fast. The dashed line at bar 14 marks out the day after which we have less than 20 trades still alive. This is too few to be able to make any statistical conclusions. If a trade is not at least marginally profitable at this time, your money is probably better used elsewhere.

As you can see, the average loser hardly manages to produce an open profit of more than 2%, and no more than an estimated 16% of all losers ((1 - 0.68)/2) manage to produce an open profit of more than approximately 7%, as indicated by the upper 1 standard deviation line around bar 16. Together, Figures 9.4 and 9.5 can give rise to guidelines such as "if we're not profitable by bar 14, the trade is probably a loser and should be ditched."

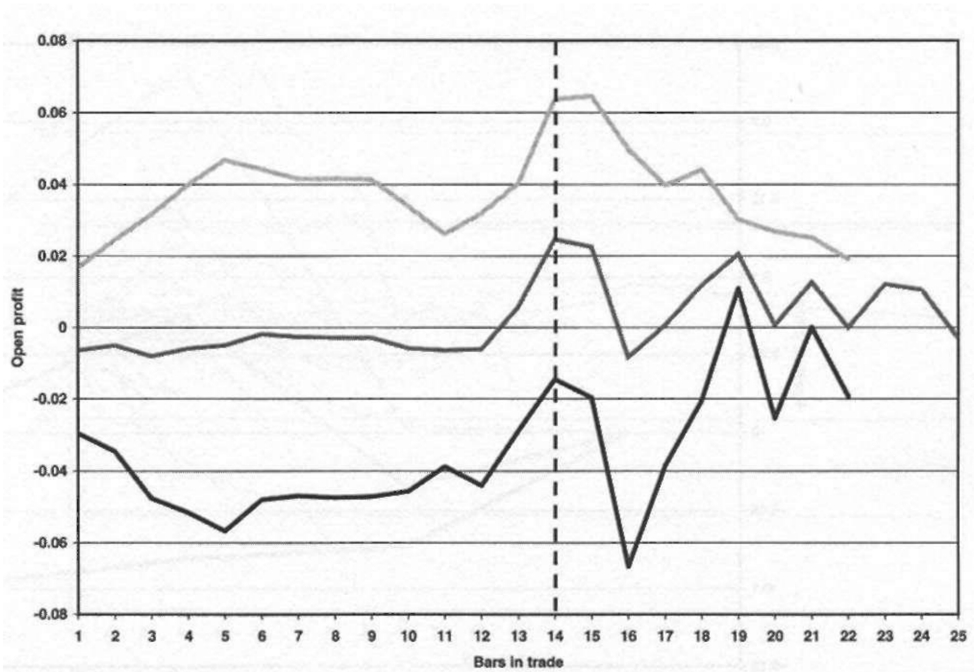


FIGURE 9.5

The development of the average losing trade.

By the way, Figure 9.4 also supports our assumption from the previous chapter about the typical look of a trade, with the MAE occurring before the MFE. What this looks like for all of our 1,240 trades in the directional slope system can be seen in Figure 9.6, which also gives us some additional insight into the system, like "a trade that quotes an MAE below 7.5% (which is the lower 1 standard deviation boundary for the MAE) is too far away from the average trade and therefore bound to be a loser." The standard deviation interval is narrower for the exit than for the point of the MFE because the exit for many losers happens much sooner after the entry than the time it takes for most winners to produce an MFE reading in the first place. Because of the short distance traveled from the entry for many of these trades, the dispersion of the outcomes has not yet had a chance to become that large. By narrowing down our analysis as much as this, we now can summarize the life of our trades using only three lines with only four data points each.

That there definitely is a difference between winners and losers can be seen from Figures 9.7 and 9.8, which show the same thing as Figure 9.3, but this time with the winners and the losers separate from each other. The most obvious thing when comparing these charts is how difficult it is for the losers to take off in any direction, while the winners, on the other hand, clearly have a upward bias; there

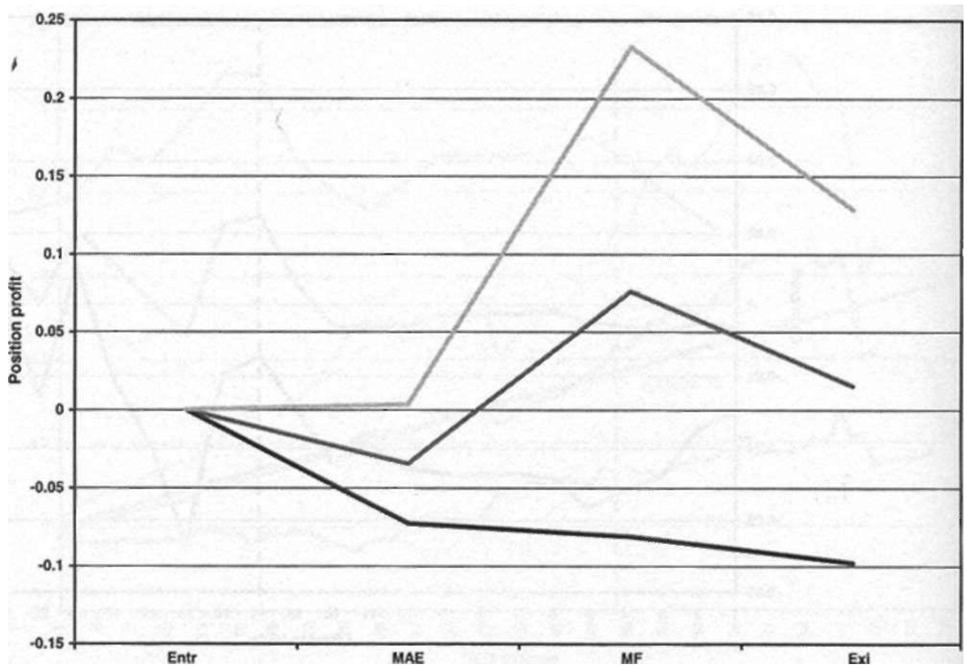


FIGURE 9.6

The summarized life for the average trade in the directional slope system.

are plenty more winners taking off to higher grounds than there are losers taking the express elevator to the basement. In fact, very few of the losers really take off in any direction, and those that manage to move into positive territory quickly end their lives with a swift move in the wrong direction. As for the winners, we can see that more often than not, they quickly take off with a bold move in the right direction. Too often, however, they give back way too much of the open profit before the system allows us to exit with some of the profits. Another compelling difference is the lengths of the trades. Although most winners last well above 30 bars, most losers do not last half that long. In essence, a winning trade usually starts out very well right off the bat and continues to develop favorably for quite some time, while most losers usually go nowhere fast.

The purpose of the MAE/MFE analysis is to find those points in the trade where, with the highest likelihood based on previous experience, we can estimate the outcome of the trade, if we just let it run without any stops or exits. To do this we must perform the same type of analysis as we did in the previous chapter about different types of drawdowns. For the directional slope system this may resemble the charts in Figures 9.9 and 9.10 which show the final profit from all trades in all 16 markets (1,240 trades in total) in relation to each trade's MAE and MFE readings, respectively. Figure 9.9 shows that the least square regression line for this MAE

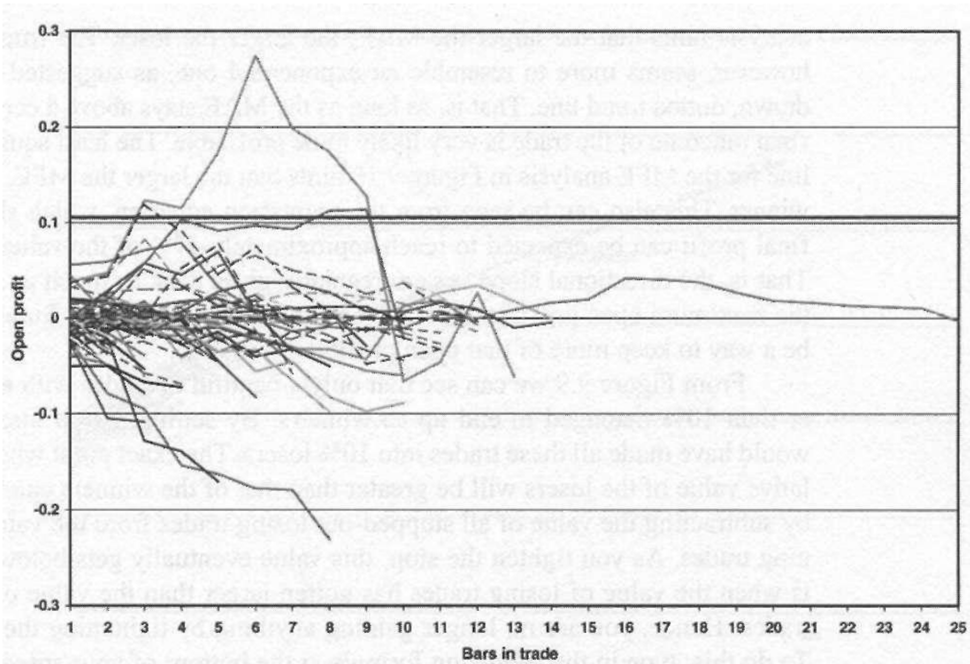


FIGURE 9.7

The development for a set of losing trades.

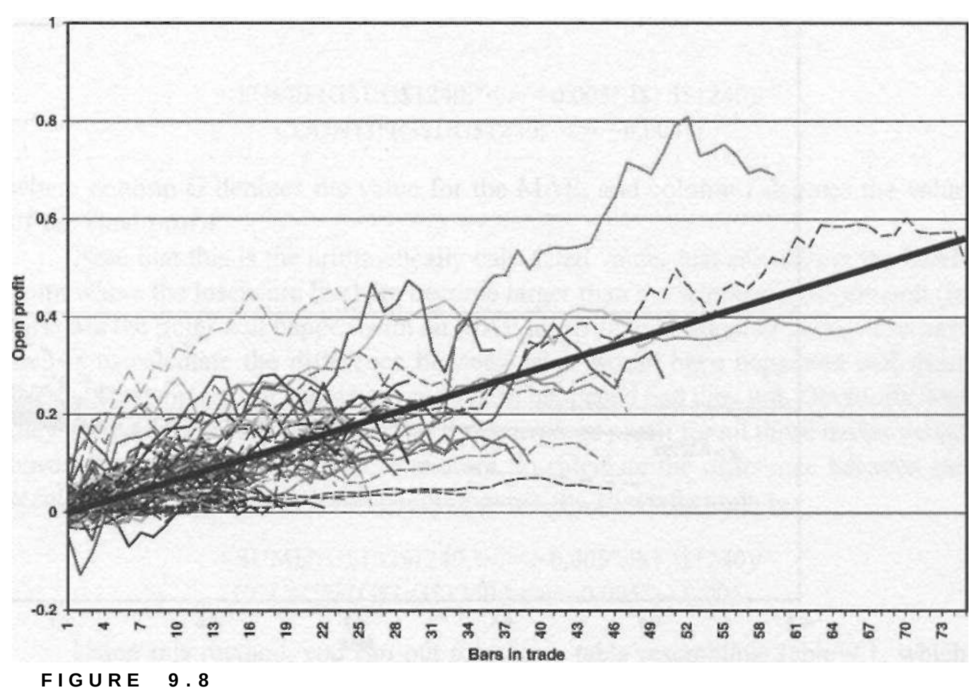


FIGURE 9.8

The development for a set of winning trades.

analysis hints that the larger the MAE, the larger the loser. The true relationship, however, seems more to resemble an exponential one, as suggested by the hand-drawn, dotted trend line. That is, as long as the MAE stays above a certain level, the final outcome of the trade is very likely to be profitable. The least square regression line for the MFE analysis in Figure 9.10 hints that the larger the MFE, the larger the winner. This also can be seen from the regression equation, which shows that the final profit can be expected to reach approximately 57% of the value of the MFE. That is, the directional slope system regularly gives back as much as 40 to 50% of the maximum open profit in the trade before it allows us to exit. Surely, there must be a way to keep more of that open profit?

From Figure 9.9 we can see that only a handful of trades with an MAE larger than 10% managed to end up as winners. By setting a stop loss at 10%, we would have made all these trades into 10% losers. The exact point where the cumulative value of the losers will be greater than that of the winners can be calculated by subtracting the value of all stopped-out losing trades from the value of all winning trades. As you tighten the stop, this value eventually gets below zero, which is when the value of losing trades has gotten larger than the value of all winning trades. Hence, you are no longer gaining anything by tightening the stop further. To do this, type in the following formula at the bottom of your spreadsheet:

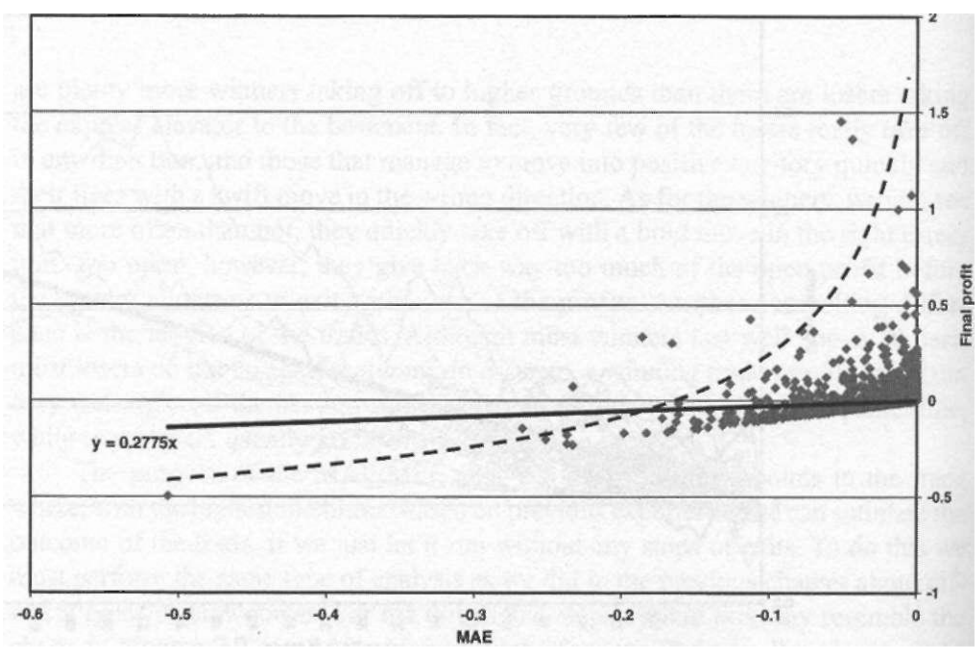


FIGURE 9.9

The final profit in relation to MAE for 16 markets in the directional slope system.

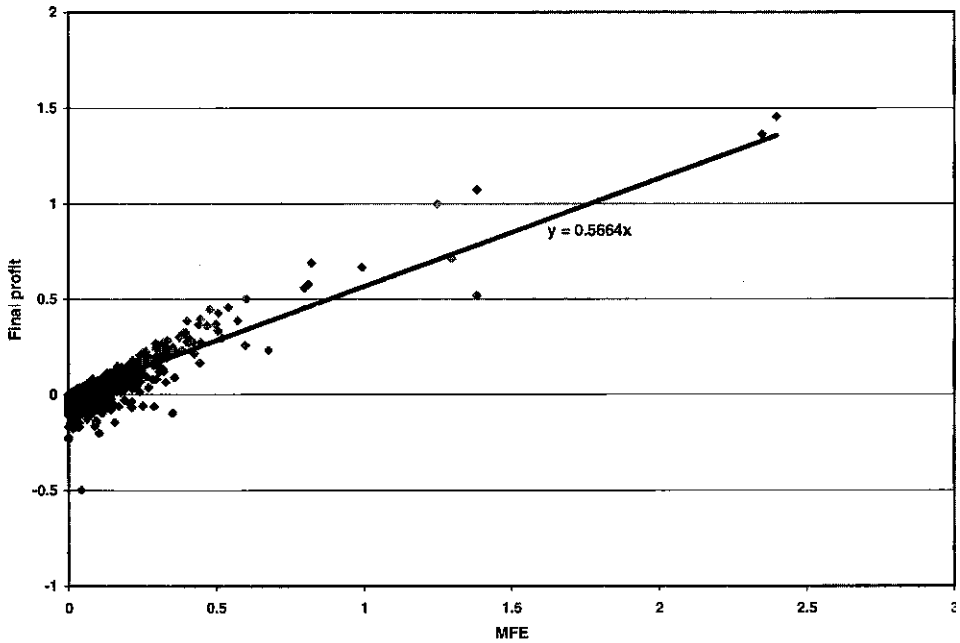


FIGURE 9.10

The final profit in relation to MFE for 16 markets in the directional slope system.

=SUMIF(G$1:G$1240;"< = -0.005";I$1:I$1240)/
COUNTIF(G$ 1 :G$ 1240;" < = - 0.005")

where column *G* denotes the value for the MAE, and column *I* denotes the value of the final profit.

Note that this is the arithmetically calculated value. Just calculating the MAE point where the losers are likely to become larger than the winners is not enough (in this case the point will happen with an MAE larger than or equal to 1.5%). The next step is to calculate the difference between what would have happened had these trades been stopped out and what would have happened had they not. Obviously, had they been stopped out at the MAE level, the average profit for all those trades would have equaled that level as well. Therefore, to calculate the difference between the results at a specific MAE level, simply rewrite the above formula to:

=SUMIF(G$ 1 :G$ 1240;" < = - 0.005 ";I$ 1 :I$ 1240)/
COUNTIF(G$ 1 :G$ 1240;" < = - 0.005")+0.005

Using this method, you can put together a table resembling Table 9.1, which shows the differences in the average profits from all trades corresponding to a certain MAE, depending on whether or not you have assumed the trades to be stopped out.

TABLE 9.1

MAE levels, original profits and differences in outcome for 16 markets in the directional slope system.

MAE	Original profit	Difference
-0.50%	0.84%	1.34 points
-1.00%	0.25%	1.25 points
-1.50%	-0.24%	1.26 points
-2.00%	-0.56%	1.44 points
-2.50%	-0.95%	1.55 points
-3.00%	-1.05%	1.95 points
-3.50%	-1.54%	1.96 points
-4.00%	-1.66%	2.34 points
-4.50%	-2.47%	2.03 points
-5.00%	-3.07%	1.93 points
-5.50%	-3.75%	1.75 points
-6.00%	-3.94%	2.06 points
-6.50%	-4.08%	2.42 points
-7.00%	^1.16%	2.84 points
-7.50%	-4.65%	2.85 points
-8.00%	-5.29%	2.71 points
-8.50%	-6.12%	2.38 points
-9.00%	-6.53%	2.47 points
-9.50%	-6.69%	2.81 points
-10.00%	-6.74%	3.26 points

With these values in place, we now can compare the original final profits for all trades corresponding to a certain MAE level to the same set of trades as if they had been stopped out at that level. For instance, for all trades with an MAE of at least 3% the arithmetically calculated average profit for all trades would have been —1.05%, but with the stop it obviously would have been —3.0%. Hence, we would have done worse with a 3% stop loss than without. But, as can be seen from Table 9.1, in this case, no matter where you place the stop you are worse off than had you not used a stop at all. An interesting observation is that generally the larger the MAE, the larger the percentage point difference among the results from using the stop when compared to not using the stop.

Such is the nature of this game. By making sure that you know exactly how much you are expected to lose in a worst-case scenario you decrease the standard deviation of outcomes for the system and increase your feeling of certainty and well-being for that particular trade. The price you pay for this is the higher likelihood for a lower accumulated result over a longer sequence of trades.

As Table 9.2 shows you, this holds true at the other end of the spectrum as well. That is, by taking profits when a trade has reached a certain level we once again lower the standard deviation of outcomes, making the system "less risky." The price we pay is a lower accumulated profit over a longer sequence of trades, no matter where we place the profit target level.

"So what is the point with all this?" you might ask. The point is, by keeping the standard deviation of the outcomes lower, while at the same time also decreasing the ratio between the open and closed out profits, we can be more aggressive when it comes to the number of contracts traded in our portfolio, according to an optimal/or fixed fractional trading strategy.

So, where to place the stops, if we even should have any? That is pretty much a question only you can answer depending on how you evaluate the risk/reward relationships between different stop or profit target levels for the particular system on which you currently are working. In this case, we make things as "backwards" as possible and place a stop loss at 4% and a profit target at 60%, simply because those are the levels (within reason) where we lose the most in the long run, as suggested by Tables 9.1 and 9.2. This should also mean that these levels will help us gain the most when we apply the system to a fixed fractional money management strategy.

TABLE 9.2

MFE levels, original profits, and differences for 16 markets In the directional slope system.

MFE	Original profit	Difference
0.05	8.08%	3.08 points
0.10	12.93%	2.93 points
0.15	18.72%	3.72 points
0.20	23.98%	3.98 points
0.25	30.93%	5.93 points
0.30	36.45%	6.45 points
0.35	43.62%	8.62 points
0.40	50.34%	10.34 points
0.45	60.44%	15.44 points
0.50	63.98%	13.98 points
0.55	71.44%	16.44 points
0.60	77.94%	17.94 points
0.65	80.47%	15.47 points
0.70	86.19%	16.19 points
0.75	86.19%	11.19 points
0.80	89.53%	9.53 points
0.85	97.00%	12.00 points
0.90	97.00%	7.00 points
0.95	97.00%	2.00 points
1.00	102.05%	2.05 points

BEYOND MAE/MFE

With a stop loss and a profit target in place, we now turn our attention to the trailing stop. We would like to find the maximum adverse excursion (MAE) from the latest favorable excursion (FE) within each trade. Note that this does not have to be the maximum favorable excursion point, which is likely to be the very last favorable excursion, leading into the end trade drawdown, but rather any of the previous maximum favorable excursions preceding the largest retracement in the opposite direction that did or did not result in an exit. We call this point MAEfe.

The difficulty with the MAEfe is that we do not know where the market was trading before the MAEfe (at least not in this analysis). Therefore to come up with some meaningful results we must proceed differently from the way we work the profit target and the stop loss analysis. In this case, we compare the MAEfe with the average corresponding MFE for all trades and then calculate the theoretical result as if the MAEfe had been the end trade drawdown. The basic Excel formulae are the same as for the stop loss and the profit target. The results can be seen in Table 9.3.

TABLE 9.3

MAEfe levels, average MFE levels, and theoretical profits for 16 markets In the directional slope system.

MAEfe	Avg. MFE	Profits
-2.50%	9.78%	7.04%
-3.00%	10.28%	6.98%
-3.50%	10.85%	6.97%
-4.00%	11.39%	6.94%
^.50%	12.02%	6.98%
-5.00%	12.66%	7.03%
-5.50%	13.34%	7.10%
-6.00%	13.71%	6.89%
-6.50%	14.31%	6.88%
-7.00%	14.86%	6.82%
-7.50%	15.33%	6.68%
-8.00%	16.02%	6.74%
-8.50%	16.96%	7.02%
-9.00%	17.24%	6.69%
-9.50%	18.06%	6.84%
-10.00%	19.24%	7.32%
-10.50%	20.14%	7.53%
-11.00%	20.92%	7.62%
-11.50%	21.51%	7.54%
-12.00%	22.08%	7.43%

From Table 9.3 we can see that when the MAEfe is at 4%, there is a bottom for the theoretical profits. With a trailing stop at this level, and assuming our reasoning makes sense, the average profit from all stopped out trades should now be slightly below 7%. All trades that did not produce a retracement of 4% will continue to produce the same total profit as they would have before.

A trailing stop of 4% from the latest favorable excursion also makes sense from a symmetrical point of view when compared to the stop loss and what could be a general market behavior, if we assume that the breakout and initial entry usually coincides with a test of a previous high (low) that acts as a pivotal resistance (support) level. Note also that for both the stop loss and the trailing stop, the next worse level seems to be very close to 8%, which further confirms the theory that there seems to be some kind of symmetrical behavior that results in, on average, 4% retracements (or multiples thereof) after the market has set a new high/low in the direction of the underlying trend.

Another way of lowering the standard deviation of the outcome is to work with time-based stops as a complement to any of the stops discussed so far. If it is reasonable to assume that a market that first takes out the latest resistance/support level signals that it is ready to take off in one direction, and then goes nowhere from there, is a likely reversal candidate (perhaps after a prolonged move in the same direction), it could be a good idea to complement the initial stop loss with a time-based stop, which is triggered if the trade hasn't reached a certain profit within the stipulated number of bars.

Table 9.4 shows that if we would like to take the expected end trade drawdown (ETD) into consideration to calculate the estimated final profit for a trade, it will take an average open profit of 8.59% before we can expect the average trade to end with a small profit at some bar in the future. For the average trade, this open profit will, on average, be reached on bar 14.

This finding, in conjunction with what we already have discussed, makes it seem a good idea to put a time-based stop loss at this bar. That is, if a trade stays or turns negative after this bar, we exit with a market order at the close. Note that it is the final profit in which we are interested, which should be positive after bar 14. This means that although the average open profit for bar 14 is 8.58, we let the trade live on if it is below this level, as long as it does not move into negative territory.

At the other end of the trade, a time-based stop also could work as a complement to the profit target, to streamline the entire group of trades and lower even further the standard deviation of the outcomes of all trades. Also, if we let a trade go on for too long, we only start giving back large parts of the open profit before we're allowed to exit in accordance with the original system. To investigate this, we employ a strategy similar to that we used for the stop loss and profit target and put together a table like Table 9.5.

From Table 9.5 we can see that all trades that last for 40 bars or longer have an average open profit of 25.74%, but produce an average final profit of 31.96%)

TABLE 9.4

Bars in trade, open profits, ETD, and differences for 16 markets in the directional slope system.

Bars in Trade	Open profit	ETD	Difference
2	0.17%	-5.74%	-5.58 points
4	1.16%	-7.20%	-6.04 points
6	2.43%	-7.78%	-5.34 points
8	3.75%	-7.94%	-4.18 points
10	5.07%	-8.11%	-3.04 points
12	6.31%	-8.22%	-1.91 points
14	8.59%	-8.24%	0.35 points
16	10.36%	-8.20%	2.16 points
18	11.98%	-7.90%	4.08 points
20	13.25%	-7.96%	5.29 points
22	14.42%	-8.06%	6.35 points
24	16.66%	-8.20%	8.46 points
26	19.37%	-8.59%	10.79 points
28	22.67%	-8.91%	13.76 points
30	23.16%	-8.66%	14.50 points
32	22.90%	-9.04%	13.86 points
34	24.83%	-9.28%	15.55 points
36	26.66%	-9.55%	17.10 points
38	27.78%	-8.60%	19.18 points
40	25.74%	-8.11%	17.63 points

at some future date. As we can see, there is no such thing as a free lunch at the markets. Cutting all trades short lowers the total result over a longer string of trades. What is gained in increased certainty regarding the individual outcome and lower standard deviation, is lost in a lower expected final profit.

Finally, the time-based stop also could be implemented into the trailing stop technique. One way of doing this is to make use of the findings from a chart resembling Figure 9.4. For instance, if the current trade is doing better than what could be expected, as suggested by the least square regression line, then the regression line from the basic system with no stops added could work as a trailing stop level. For a trade that currently is not doing as well as the average trade, but has not yet been stopped out for any other reasons, we could use the regular trailing stop. Alternatively, a combination of several techniques could be used that, for instance, stops out all trades that retrace more than what is allowed by the trailing stop, but only if the retracement also means that the trade has moved below the regression line, as suggested by the original unadjusted trade. If you also are using a stop loss, or a time-based stop, as we do at bar 14, then you must think about giving these stops ample leeway as well. If you do not, the trailing stop will probably

TABLE 9.5

Bars in trade, final profit open profits, and differences for 16 markets in the directional slope system.

Bars in Trade	Final profit	Open profit	Difference
12	8.84%	6.31%	-2.53 points
14	11.35%	8.59%	-2.76 points
16	12.69%	0.36%	-2.33 points
18	14.30%	11.98%	-2.32 points
20	15.94%	13.25%	-2.69 points
22	17.67%	14.42%	-3.25 points
24	19.94%	16.66%	-3.28 points
26	22.73%	19.37%	-3.35 points
28	24.70%	22.67%	-2.03 points
30	25.18%	23.16%	-2.02 points
32	27.69%	22.90%	-4.79 points
34	28.63%	24.83%	-3.79 points
36	31.08%	26.66%	-4.43 points
38	27.97%	26.66%	-1.31 points
40	31.96%	25.74%	-6.22 points
42	33.96%	28.90%	-5.06 points
44	35.84%	31.37%	-4.47 points
46	37.50%	34.26%	-3.24 points
48	42.98%	38.81%	-4.18 points
50	44.33%	42.00%	-2.33 points

have you stopped out too soon during the initial stage of the trade, when it is the most vulnerable.

Let us compare the results for the original directional slope system with some of the findings we have made in this section. The rules for the modified system and the corresponding TradeStation code are:

- Enter long/short when the 18-bar average turns up/down.
- Exit with a loss if the market moves the wrong way by 4%.
- Exit with a small loss/breakeven if the market moves into (stays in) negative territory at or after bar 14.
- Exit with a trailing stop, after bar 14, if the market moves the wrong way by 4% or more and ends up below the regression line for the original average trade.
- Exit with a profit target if the market moves by 60% or more.
- Exit with a profit if the trade lasts for 40 bars or more.
- Enter into a neutral position if the 12-bar average changes direction.

The TradeStation code for our additional exit techniques is:

```
If MarketPosition = 1 Then Begin
    ExitLong at EntryPrice * 1.60 Limit;
    If BarsSinceEntry >= 40 Then
        ExitLong at Close;
    If BarsSinceEntry >= 14 Then Begin
If Highest(High, BarsSinceEntry) * 0.96 < EntryPrice * ( 1 + 0.0074 *
BarsSinceEntry) Then
            ExitLong at Highest(High, BarsSinceEntry) * 0.96 Stop;
        ExitLong at EntryPrice Stop;
    End;
    ExitLong at EntryPrice * 0.96 Stop;
End;
If MarketPosition = — 1 Then Begin
    ExitShort at EntryPrice * 0.40 Limit;
    If BarsSinceEntry >= 40 Then
        ExitShort at Close;
    If BarsSinceEntry >= 14 Then Begin
If Lowest(Low, BarsSinceEntry) * 1.04 > EntryPrice * ( 1 - 0.0074 *
BarsSinceEntry) Then
            ExitShort at Lowest(Low, BarsSinceEntry) * 1.04 Stop;
        ExitShort at EntryPrice Stop;
    End;
    ExitShort at EntryPrice * 1.04 Stop;
End;
```

To this code, we also must attach the trade-by-trade export function from Part 1. We must use the trade-by-trade function because we are now dealing with ratio adjusted data and can, therefore, no longer rely on the performance summary from TradeStation.

Finally (because of another little TradeStation feature), there will be a few trades that we must adjust manually within the spreadsheet program. This happens when the trade moves immediately and swiftly against us and, therefore, should have been stopped out sooner than TradeStation allows. We also run the risk of inadvertently changing the results to the better for a few trades, which truly did have a loss greater than 4% because of legitimate opening gaps. We also must recalculate the cumulative profit, latest equity high, and drawdown. In this case, we have assumed that all losses larger than 5% are erroneous and consequently adjusted them down to 4%. Obviously, I am cheating a little bit here and obviously, you will need to be more careful in your own research, but there's not room enough here to go into details.

To recalculate the cumulative profit in Excel, type in the following formula on top of the values in the cumulative profits column:

In cell G2:

=M2

In cell G3:

=((1+G2/100)*(1+F3/100)-1)*100

then drag down to the bottom of the sheet, to fill all the cells in the column.

To recalculate the equity top, type:

In cell H2:

=MAX(G2,0)

In cell H3:

=MAX(H2,G3)

then drag down to the bottom of the sheet, to fill all the cells in the column.

To recalculate the drawdown, type into cell L2:

=((1 + G2/100)/(1 + H2/100) -1)* 100

then drag down to the bottom of the sheet, to fill all the cells in the column.

When you are done exporting and calculating in Excel, you can put together a set of tables resembling Tables 9.6 and 9.7 for all of the individual markets, and Tables 9.8 and 9.9 with a composite of the most important measurements. In Table 9.10, we summarize the differences for each market.

Table 9.6 shows that with the original system, copper had a profit factor of 1.60. The largest winner would have been 71.4%, or $13,692 in today's market value. The largest loser would have been 16.8%, or —$3,231 in today's market value. Table 9.7 shows that with the modified system, copper had a profit factor of 2.01, calculated on the average percentage winner and loser, and then trans-

TABLE 9.6

Example of performance summary.

Copper, before exits (original system)									
Total trades		96	Winners	37	38.54%	Losers	59	61.46%
Profit factor		1.60	Lrg winner	71.36%	13,692.20	Lrg loser	-16.84%	-3,231.18
Avg profit	1.49%	286.05	Avg winner	10.32%	1,980.46	Avg loser	-4.05%	-776.54
St Dev	12.67%	2,429.91	Cum profit	128.72%	24,698.15	Drawdown	-43.02%	-8,254.46

TABLE 9.7

Individual market performance summary.

Copper, after exits (modified system)								
Total trades		113	Winners	46	40.71%	Losers	67	59.29%
Profit factor		2.01	Lrg winner	60.00%	11,512.50	Lrg loser	-4.69%	-899.89
Avg profit	1.76%	337.90	Avg winner	8.62%	1,653.17	Avg loser	-2.95%	-565.11
St Dev	9.96%	1,944.14	Cum profit	363.64%	69,772.90	Drawdown	-40.88%	-7,843.57

formed into today's market value. The largest winner would have been 60% (thanks to the profit target), or $11,513 in today's market value. The largest loser would have been 4.7% (thanks to the stop loss), or —$900 in today's market value.

From Table 9.8 we can see that all markets but one had a profit factor above 1 in the original system. A high profit factor, however, does not necessarily mean that the market in question is worth trading. For this conclusion, we must also look at the value of the average trade, in today's market, and deduct a proper amount for slippage and commission. A rule of thumb could be that the remaining value of the average trade should be at least two times the estimated slippage and commission,

TABLE 9.8

Performance measurements for all markets with the original system.

	Before exits (original system)			
Market	P. factor	Avg. trade	2 St. dev.	Drawdown
Corn	2.43	285.7	62,254.95	-3,604.93
S&P 500	1.01	31.63	37,680.83	-136,839.38
Orange juice	1.58	218.63	3,126.66	-6,671.28
Live cattle	1.34	149.33	3,285.72	-8,007.16
Lumber	2.20	816.09	7,019.19	-14,383.49
Coffee	2.00	1,443.41	19,797.92	-22,991.64
Japanese yen	3.88	3,462.79	19,158.31	-11,891.25
Copper	1.60	286.05	4,859.82	-8,254.46
Gold	1.51	243.21	4,174.29	-9,413.32
Eurodollar	1.74	239.40	3,375.29	-5,953.72
Dollar index	2.22	1,004.14	7,502.97	-7,436.68
Cotton	2.47	681.00	5,227.15	-4,309.28
CRB index	0.70	-390.33	7,135.96	-38,390.04
Crude oil	2.46	584.00	5,540.84	-6,996.26
Canada dollar	1.59	194.31	2,617.40	-^,331.60
T-bonds	1.34	521.24	10,826.72	-37,845.11

TABLE 9.9

Performance measurements for all markets.

	After exits (modified system)			
Market	P. factor	Avg. trade	2 St. dev.	Drawdown
Corn	2.62	266.72	2,036.38	-2,384.17
S&P 500	0.67	-1,947.59	26,215.82	-177,550.12
Orange juice	2.04	234.21	2,346.97	-3,544.32
Live cattle	1.23	93.94	2,707.90	-6,913.48
Lumber	2.38	758.44	6,289.95	-11,438.38
Coffee	2.08	917.67	10,271.95	-15,742.83
Japanese yen	2.72	2,000.98	11,427.63	-8,938.80
Copper	2.01	337.90	3,822.28	-7,843.57
Gold	1.54	248.07	3,882.21	-10,208.43
Eurodollar	1.74	238.78	3,373.71	-6,416.68
Dollar index	2.00	829.42	7,282.08	-8,200.28
Cotton	2.02	462.77	4,669.08	-6,965.14
CRB index	0.78	-258.75	5,991.32	-33,982.87
Crude oil	4.21	1,363.21	7,898.06	-5,875.78
Canada dollar	1.36	116.00	2,204.25	-5,551.04
T-bonds	1.28	399.42	9,802.15	-28,461.80

to make room for a decrease in performance and so that the system will continue to be profitable in case the market declines and, consequently, the value of the average trade becomes lower as well. With a slippage and commission of $75, Tables 9.8 and 9.9 contain 11 and 12 markets, respectively, that are worth trading. The five markets not worth trading, in Table 9.8, are S&P 500, orange juice, live cattle, CRB index, and Canada dollar. Of these five markets, three also had a lower profit factor and average trade, after the exits were implemented. Most remarkable is that orange juice goes from being a non-tradable market to a tradable one.

Of the remaining 11 markets that were tradable with the original system, six had a better profit factor with the modified system, but only three had a better average trade. In essence, this means that we will not make as much money per contract traded with the modified system as with the original system, but at the same time, the cost of doing business will also be much less. Also, just to look at the average trade by itself is not always that useful. Instead, it should be compared to the standard deviation of the outcome; in this case, 15 out of 16 markets had a lower standard deviation, which suggests that the system has become more stable and less risky to trade. In most cases the drawdown also has decreased dramatically.

From Table 9.10 we also can see that out of the 12 tradable markets with the modified system (including orange juice), seven (corn, orange juice, lumber, copper,

TABLE 9.10

Summarized differences, before/after exits.

	Differences				
Market	**P. factor**	**Avg. trade**	**2 St. dev.**	**Drawdown**	**Better**
Corn	7.92%	-6.66%	-9.69%	-33.86%	3
S&P 500	-33.35%	-6257.25%	-30.43%	29.75%	1
Orange juice	29.11%	7.13%	-24.94%	-46.87%	4
Live cattle	-8.70%	-37.09%	-17.59%	-13.66%	2
Lumber	8.59%	-7.06%	-10.39%	-20.48%	3
Coffee	4.03%	-36.42%	-48.12%	-31.53%	3
Japanese yen	-29.99%	-42.21%	-40.35%	-24.83%	2
Copper	25.58%	18.13%	-21.35%	-4.98%	4
Gold	1.68%	2.00%	-7.00%	8.45%	3
Eurodollar	0.47%	-0.26%	-0.05%	7.78%	2
Dollar index	-10.11%	-17.40%	-2.94%	10.27%	1
Cotton	-18.19%	-32.05%	-10.68%	61.63%	1
CRB index	11.48%	-33.71%	-16.04%	-11.48%	3
Crude oil	71.19%	133.43%	42.54%	-16.02%	3
Canada dollar	-14.68%	-40.30%	-15.78%	28.15%	1
T-bonds	-4.11%	-23.37%	-9.46%	-24.79%	2
Better	9	4	15	10	—

Eurodollar, crude oil and T-bonds) also show a positive relationship when it comes to how much the average trade has changed in relation to the standard deviation. The drawdown, finally, has decreased for eight (corn, orange juice, lumber, coffee, Japanese yen, copper, crude oil, T-bonds) out of the 12 worth trading. That is, with the modified system the cost of doing business has decreased, while at the same time we can feel more sure about the outcome and sleep better thanks to a lower expected drawdown. The drawback is that the value of the average trade has decreased; but because of all the benefits, we still should be able to make more money over any given period of time. This is thanks to the fact that a more stable system allows us to trade more aggressively with more contracts, in accordance with a fixed fractional money management strategy.

Finally, please remember that this is a sample system only and that we used all the exit techniques previously discussed. This might not be the most optimal solution, and it might be better, excluding one or several of the exits. In this case (and all the following), I added all the exits directly on top of the results from the original system. Because the statistical traits for the system will change with every change we make, this is not necessarily the best way to do it. Instead, a better way could be to examine only one exit technique at a time and then rerun the system before each new implementation. Or, set up the modified system as we have done here and work backwards from there, modifying or excluding one exit type at a time. Also, in this and the other long-term systems to follow, because of a variety of unwanted TradeStation "features" I have had to make a few modifications to the TradeStation code and simplifications in the Excel spreadsheet that might have diluted the results somewhat.

CHAPTER 10

Adding Long-term Exits

There are probably several ways of locking in a profit or taking a loss, but one technique that has great scientific value is John Sweeney's maximum adverse (MAE) and maximum favorable excursion (MFE). Even this method can produce catastrophic results if not understood and implemented properly. As I have stressed throughout this book, one of the most important things you must do is make sure that you understand exactly what it is you are measuring and how to go about doing it. In the following chapters, I will run down what we have learned and implement it on the other two long-term systems with which we have worked so far. In doing so, I am painfully aware that this might not be the optimal solution, and you might be better off excluding one or several of the exits we discuss here. The important thing to remember is what it is you want your system to do. If for instance, you want it to be a long-term trend-following system, you must treat it as such and allow proper leeway for each trade, so that you do not inadvertently change it into a shorter-term system.

With the MAE/MFE technique it also is possible to add to trades that show tendencies of being better than what could be expected. However, call me a bad systems developer, if you like, but I have yet to come across such a system that is capable of delivering results and is thoroughly robust and stable. Therefore, I have chosen not to look into this technique in this book.

Another possibility I have not explored is to *fade* the original system if the trade moves against us by a certain amount. I believe that such a technique, although it has its merits, starts to come awfully close to curve fitting. This becomes apparent if you formulate the rules in plain English. For instance, first we want the system to trigger a trade in one direction, which is a very specific request in the first place. Then we want the market to move against us by a certain amount within a limited time frame, which are two other very specific requests. Furthermore, to take all the other exits and risk levels into consideration, we might even add another criterion or two that might stipulate that the market is allowed or not allowed to behave in a certain fashion. A little too many rules, ifs, ands, and buts for my comfort.

THE DYNAMIC BREAKOUT SYSTEM

In Part 2 we discussed several different versions of the Dynamic Breakout System (the DBS system) before we settled for version lb, which had a "reversed" volatility relationship for the exits. That is, when the historical volatility increased, the lookback period for the exit decreased. The underlying reasoning was that if a higher volatility, as an indication of higher risk, makes it more difficult to enter the market, then a higher volatility also should make it more difficult to stay in (or easier to get out, if you so wish).

In this chapter we apply that system (version lb) to the same 16 markets as in Part 2, to examine the possibility of increasing its performance by adding a few stops and exits in accordance with our findings regarding John Sweeney's MAE/MFE methods. The time period covered is from January 1980 to October 1999. Another reason I chose to work with this system is simply that the original system is closer in resemblance to the standard deviation breakout system that follows. The export function from TradeStation into Excel is essentially the same for the DBS system as for the directional slope system.

Figure 10.1 shows the average open profit for all trades in relation to the number of bars in trade. Instead of looking at hundreds of lines that make little sense, we are now down to four, for much easier interpretation and rule making. From this chart we can see that the average profit is expected to increase with about 0.23% per bar. To the right of the dotted line we have fewer than 20 trades that remain open, which is too few to make any meaningful statistical conclusions.

The first things we will examine are the stop loss in accordance with the MAE, the trailing stop in accordance with the MAEfe, and the least square regression line from Figure 10.1. To find the most logical level for where to place a stop loss or trailing stop you can put together a set of tables resembling Tables 10.1 and 10.2. As you can see from Table 10.1, for this version of the DBS system, we would have benefited from placing a stop loss at just about any level. In fact, the greater the MAE, the more we would gain had we decided to place a stop at a specific level. Because there seem to be no local minima, indicating some kind of market inefficiency that we could have tried to exploit, we simply must place the stop where it makes most sense.

Table 10.3 shows that, basically the same reasoning goes for the trailing stop as for the stop loss. In this case, the greater the MAEfe value, the less we benefit

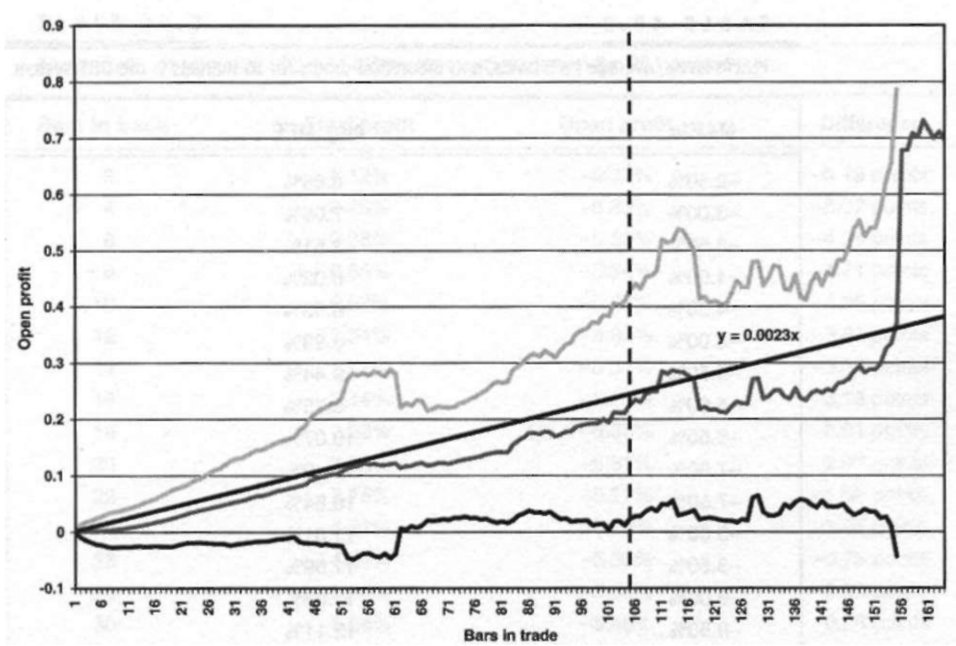


FIGURE 10.1

Tthe average open profit for all trades in relation to the number of bars In trade.

TABLE 10.1

MAE levels, original profits, and differences in outcome for 16 markets in the DBS system.

MAE	Original profit	Difference
-0.50%	-0.92%	-0.42 points
-1.00%	-1.35%	-0.35 points
-1.50%	-1.98%	-0.48 points
-2.00%	-2.64%	-0.64 points
-2.50%	-3.43%	-0.93 points
-3.00%	^.20%	-1.20 points
-3.50%	^.67%	-1.17 points
^1.00%	-5.29%	-1.29 points
-4.50%	-5.89%	-1.39 points
-5.00%	-6.58%	-1.58 points.
-5.50%	-7.27%	-1.77 points
-6.00%	-7.76%	-1.76 points
-6.50%	-8.46%	-1.96 points
-7.00%	-9.00%	-2.00 points
-7.50%	-9.65%	-2.15 points
-8.00%	-10.08%	-2.08 points
-8.50%	-10.39%	-1.89 points
-9.00%	-11.08%	-2.08 points
-9.50%	-11.71%	-2.21 points
-10.00%	-12.56%	-2.56 points

TABLE 10.2

MAEfe levels, average MFE levels, and theoretical profits for 16 markets in the DBS system.

MAEfe	Avg. MFE	Profits
-2.50%	6.68%	4.02%
-3.00%	7.08%	3.87%
-3.50%	7.51%	3.75%
-4.00%	8.02%	3.70%
-4.50%	8.53%	3.65%
-5.00%	8.98%	3.54%
-5.50%	9.44%	3.42%
-6.00%	9.75%	3.17%
-6.50%	10.07%	2.91%
-7.00%	10.49%	2.75%
-7.50%	10.84%	2.52%
-8.00%	11.01%	2.13%
-8.50%	11.59%	2.11%
-9.00%	11.83%	1.76%
-9.50%	12.11%	1.46%
-10.00%	12.49%	1.24%
-10.50%	12.49%	0.68%
-11.00%	13.13%	0.69%
-11.50%	13.53%	0.47%
-12.00%	14.29%	0.58%

from a stop at a specific level. No local maxima indicate any market inefficiency that we could have tried to exploit, so again, you simply must place the stop where it makes the most sense to you. For the sake of simplicity, then, we place a stop loss and a trailing stop at 4%. The trailing stop comes into play at the same time as the time-based breakeven stop and only kicks in if the decrease in open profit also takes us below the regression line from Figure 10.1. Exactly how deep this retracement must be before we exit we don't know, but we do know that as long as the retracement does not bring us below the regression line, the trade is still doing better than average and could be worth staying in.

Another way of analyzing the expected profits is to look at the average open profit at a specific bar and then deduct the expected ETD for trades lasting longer. This is shown in Table 10.3, which shows that final profit is not expected to turn positive until after bar 30. With the information from Figure 10.1 and Table 10.3, we can formulate our third exit rule, which says that if the open profit for a trade stays or turns negative at or after bar 30, we exit with a market order at the close.

Table 10.4 shows that we would not have benefited from placing a profit target anywhere. However, using the same backwards reasoning as we did for the stop

TABLE 10.3

Bars in trade, open profits, ETD, and differences for 16 markets in the DBS system.

Bars in trade	Final profit	Open profit	Difference
2	0.12%	-5.31%	-5.19 points
4	0.26%	-5.33%	-5.07 points
6	0.38%	-5.33%	-4.94 points
8	0.65%	-5.36%	-4.71 points
10	0.97%	-5.32%	-4.35 points
12	1.34%	-5.30%	-3.97 points
14	1.72%	-5.31%	-3.59 points
16	2.14%	-5.28%	-3.13 points
18	2.69%	-5.30%	-2.61 points
20	3.25%	-5.31%	-2.07 points
22	3.75%	-5.27%	-1.52 points
24	4.21%	-5.28%	-1.08 points
26	4.61%	-5.36%	-0.75 points
28	5.15%	-5.38%	-0.23 points
30	5.54%	-5.48%	0.06 points
32	6.13%	-5.52%	0.61 points
34	6.48%	-5.58%	0.90 points
36	7.02%	-5.59%	1.44 points
38	7.50%	-5.67%	1.83 points
40	7.92%	-5.61%	2.31 points

loss and profit target in the directional slope system, the "best" result seems to be around the 35 to 40% area. Because this seems to be a little too close to the entry, we will instead choose to go with the second "best" level at around 70%. That is, as soon we reach an open profit of 70% or more, we exit with a limit order. The purpose of this is to streamline all trades as much as possible and keep the standard deviation as low as possible. By keeping the standard deviation down, we are decreasing the overall risk of the system and should be able to trade it more aggressively with more contracts within a fixed fractional money management strategy. Therefore, what we lose with the profit target stop, we hope to regain from more aggressive trading.

Another way to achieve parts of the same effect is to apply a time-based stop. Just as was the case for the profit target, Table 10.5 shows that the DBS system seems to have two different trade lengths at which this would be the least opportune moment. The first one comes after about 50 bars and the second after about 100 bars, which, by the way, again indicates that there is some sort of symmetry in how the markets behave. Using the same reasoning as for the profit target, and not to place the stop too close to the entry point, we place it at bar 100. Remember,

TABLE 10.4

MFE levels, original profits, and differences for 16 markets in the DBS system.

WIFE	Original profit	Difference
5.00%	6.14%	1.14 points
10.00%	11.61%	1.61" points
15.00%	16.27%	1.27 points
20.00%	22.86%	2.86 points
25.00%	28.20%	3.20 points
30.00%	35.08%	5.08 points
35.00%	44.54%	9.54 points
40.00%	48.30%	8.30 points
45.00%	51.77%	6.77 points
50.00%	53.96%	3.96 points
55.00%	55.96%	0.96 points
60.00%	61.49%	1.49 points
65.00%	70.85%	5.85 points
70.00%	78.62%	8.62 points
75.00%	81.24%	6.24 points
80.00%	81.24%	1.24 points
85.00%	95.07%	10.07 points
90.00%	95.07%	5.07 points
95.00%	95.07%	0.07 points
100.00%	150.62%	50.62 points

however, that this is very backward reasoning and for demonstration purposes only, just to come up with some motivation to use these stops at all.

Hence, the suggested exit levels for the DBS system are as follows:

- Exit with a loss if the market moves the wrong way by 4%.
- Exit with a small loss/breakeven if the market moves into (stays in) negative territory at or after bar 30.
- Exit with a trailing stop, after bar 30, if the market moves the wrong way by 4% or more and ends up below the regression line for the original average trade.
- Exit with a limit order if the open profit exceeds 70%.
- Exit with a profit if the trade lasts for more than 100 bars.

When you are done exporting and calculating in Excel, you can put together a set of tables like Tables 10.6 and 10.7 for all of the individual markets, and Tables 10.8 and 10.9 with a composite of the most important measurements. In Table 10.10, finally we summarize the differences for each market. Tabic 10.6 shows that with the

TABLE 10.5

Bars in trade, final profit, open profits, and differences for 16 markets in the DBS system.

Bars in trade	Final profit	Open profit	Difference
30	5.56%	5.54%	-0.02 points
35	6.70%	6.74%	0.03 points
40	7.97%	7.92%	-0.05 points
45	9.62%	9.73%	0.10 points
50	10.74%	11.32%	0.58 points
55	11.72%	12.12%	0.41 points
60	12.43%	11.38%	-1.05 points
65	12.56%	11.84%	-0.73 points
70	12.91%	12.36%	-0.55 points
75	13.91%	13.42%	-0.49 points
80	14.43%	14.12%	-0.31 points
85	16.95%	17.56%	0.61 points
90	16.66%	17.29%	0.63 points
95	18.52%	19.12%	0.60 points
100	18.35%	21.25%	2.90 points
105	22.76%	23.05%	0.29 points
110	27.06%	28.14%	1.07 points
115	28.67%	26.91%	-1.75 points
120	24.36%	21.29%	-3.07 points
125	24.36%	22.70%	-1.66 points

original system, Japanese yen had a profit factor of 2.00. The largest winner would have been 21.5%, or $25,263 at today's market value. The largest loser would have been 5.71%, or -$6,709 at today's market value. Table 10.7 shows that with the modified system, Japanese yen had a profit factor of 2.21, calculated on the average percentage winner and loser, and then transformed into today's market value. The largest winner would have been 17.6%, or $20,668 at today's market value. The largest loser would have been 4.20%, or —$4,935 at today's market value.

TABLE 10.6

Individual market performance summary.

Japanese yen, before exits (original system)								
Total trades		140	Winners	65	46.43%	Losers	75	53.57%
Profit factor		2.00	Lrg winner	21.50%	25,262.50	Lrg loser	-5.71%	-6,709.25
Avg profit	1.00%	1,173.83	Avg winner	4.31%	5,060.09	Avg loser	-1.87%	-2,194.27
St Dev	4.41%	5,178.98	Cum profit	254.60%	299,155.00	Drawdown	-12.04%	-14,147.00

TABLE 10.7

Individual market performance summary.

Japanese yen, after exits (modified system)									
Total trades		143	Winners	66	46.15%	Losers	77	53.85%
Profit factor		2.21	Lrg winner	17.59%	20,668	Lrg loser	-4.20%	-4,935
Avg profit	1.05%	1,236	Avg winner	4.17%	4,898	Avg loser	-1.62%	-1,902
St Dev	4.13%	4,848	Cum profit	298.86%	351,159	Drawdown	-11.66%	-13,701

From Table 10.8 we can see that compared to the directional slope system, the DBS system has several markets with considerably lower profit factors and several markets with an average trade too low to make it worthwhile trading after we have deducted the necessary amount for slippage and commission. Of all 16 markets traded with the original system, all but three (S&P 500, copper, and CRB index) had a profit factor above one. For a system to be profitable on a specific market, however, the value of the average trade also must be high enough. To stay on the safe side and to make room for future changes in the value of the average trade, which is dependent on the current level at which the market is trading and

TABLE 10.8

Performance measurements for all markets.

Before exits (original system)				
Market	P. factor	Avg. trade	2 St. dev.	Drawdown
Corn	1.51	113.34	1,549.46	-2,865.10
S&P 500	0.80	-1,220.96	29,455.57	-166,159.78
Orange juice	1.50	173.24	2,808.58	-9,319.17
Live cattle	1.06	26.23	2,388.86	-9,217.80
Lumber	1.07	55.70	5,022.72	-16,904.45
Coffee	1.44	509.15	11,095.92	-16,446.50
Japanese yen	2.00	1,173.83	10,357.98	-14,147.00
Copper	0.91	-46.29	2,705.02	-12,075.74
Gold	1.34	174.87	3,470.76	-9,157.20
Eurodollar	1.61	226.78	3,057.64	-8,576.59
Dollar index	2.04	737.82	5,972.58	-9,281.08
Cotton	1.27	178.81	5,137.79	-14,027.04
CRB index	0.59	-517.88	5,032.53	-56,549.59
Crude oil	1.84	569.80	5,974.32	-10,282.72
Canada dollar	1.09	28.86	1,931.03	-7,990.00
T-bonds	1.11	161.90	8,898.80	-30,230.08

the point value of the market, a rule of thumb is that the value of the average trade, net after expected costs, should be two times the expected costs. For instance, if you expect slippage and commissions to be $75, the gross value of the average trade should be $225. Using this rule of thumb, this version of the DBS system holds five markets that are worth trading both with the original system and with the modified version.

Table 10.9 shows that after we have added the stops, the changes in the system are not that large in the profit factor and average trade. However, when looking at the standard deviation of the trades and the drawdown, we can see that the improvements for the portfolio as a whole are quite dramatic.

On a separate note, it is worth mentioning that just because a market seems not to be profitable in itself, it still could be worth trading in a portfolio of markets, with a proper money management strategy: it might be uncorrelated enough with all or some of the other markets to perform satisfactorily when the other markets are performing badly, thus, keeping the equity level up, as well as smoother, for the future when the other markets start to perform better. When tested on historical commodity futures data, such tendencies can many times be found in such markets as short-term interest rates, lumber, live cattle, and precious metals.

TABLE 10.9

Performance measurements for all markets.

	After exits (modified system)			
Market	P. factor	Avg. trade	2 St. dev.	Drawdown
Corn	1.38	82.76	1,431.65	-3,203.35
S&P 500	0.83	-886.14	26,848.42	-167,873.90
Orange juice	1.49	141.62	2,442.96	-8,684.48
Live cattle	1.02	7.54	2,289.34	-10,738.53
Lumber	1.13	74.29	3,581.20	-12,035.95
Coffee	1.01	10.65	4,635.90	-23,150.08
Japanese yen	2.21	1,236.13	9,696.50	-13,700.98
Copper	0.94	-25.61	2,249.53	-10,131.14
Gold	1.45	194.71	2,964.58	-8,556.81
Eurodollar	1.69	248.93	3,018.58	-8,578.04
Dollar index	2.10	702.19	5,733.17	-7,862.49
Cotton	1.24	131.13	3,843.48	-10,841.46
CRB index	0.60	-502.97	5,123.84	-56,819.25
Crude oil	2.23	544.72	4,662.18	-7,504.91
Canada dollar	1.12	40.08	1,938.18	-7,202.11
T- bonds	1.24	332.91	8,688.05	-25,087.24

TABLE 10.10

Summarized differences, before/after exits.

	Differences				
Market	**P. factor**	**Avg. trade**	**2 St. dev.**	**Drawdown**	**Better**
Corn	-8.31%	-26.98%	-7.60%	11.81%	1
S&P 500	4.47%	-27.42%	-8.85%	1.03%	2
Orange juice	-0.04%	-18.25%	-13.02%	-6.81%	2
Live cattle	-4.29%	-71.23%	-4.17%	16.50%	1
Lumber	5.79%	33.38%	-28.70%	-28.80%	4
Coffee	-29.65%	-97.91%	-58.22%	40.76%	1
Japanese yen	10.41%	5.31%	-6.39%	-3.15%	4
Copper	3.46%	-44.68%	-16.84%	-16.10%	3
Gold	7.61%	11.34%	-14.58%	-6.56%	4
Eurodollar	5.14%	9.77%	-1.28%	0.02%	3
Dollar index	2.81%	-4.83%	-4.01%	-15.28%	3
Cotton	-2.33%	-26.67%	-25.19%	-22.71%	2
CRB index	0.90%	-2.88%	1.81%	0.48%	1
Crude oil	21.16%	-4.40%	-21.96%	-27.01%	3
Canada dollar	3.34%	38.90%	0.37%	-9.86%	3
T-bonds	11.90%	105.63%	-2.37%	-17.01%	4
Better	11	6	14	10	—

Table 10.10 shows that of all 16 markets examined, we managed to lower the drawdown for 10 and lower the standard deviation of the trades for 14. Also, of all markets, only four increased their performance in only one category, while as many as nine managed to improve at least three categories. Of all markets tested, 6 ended up with a higher average trade after the exits were added, while a total of 14 also managed to end up with lower standard deviations. This is all good news, indicating that the system has become more stable and easier to trade. This is further confirmed by the profit factor, which has increased for a total of 11 markets after the exits have been added. This means that the cost of doing business has decreased considerably.

Although this system overall seems to be less profitable than the directional slope system, and although the average trade did not improve as much as we would have liked, we can see that the exits are still doing their job when it comes to streamlining the trades, which should make it possible to trade it more aggressively with the proper money management. Other things that could increase performance might be to change back to the original DBS system (version la), which should give the individual trades a little more leeway, and/or continue to experiment with different types of stops other than the profit target stop and the time-based stop.

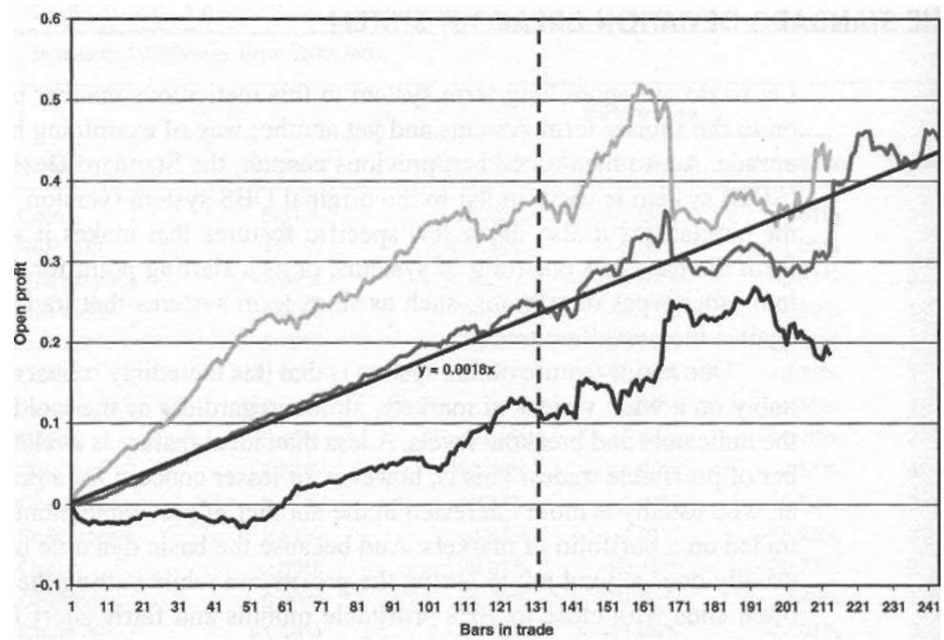
THE STANDARD DEVIATION BREAKOUT SYSTEM

Let us do one more long-term system in this meticulous manner before we move on to the shorter-term systems and yet another way of examining how best to exit a trade. As we mentioned in a previous chapter, the Standard Deviation Breakout (SDB) system is very similar to the original DBS system (version la), but despite the similarities it also has a few specific features that makes it very suitable to form the base in a portfolio of systems, or as a starting point for diversifying out into other types of systems, such as short-term systems that trade both with and against the prevailing trend.

One major feature of this system is that it is incredibly robust and trades profitably on a wide variety of markets, almost regardless of the lookback period for the indicators and breakout levels. A less than ideal feature is a relatively low number of profitable trades. This is, however, of lesser concern for a professional trader, who usually is more interested in the number of profitable months for a system traded on a portfolio of markets. And because the basic dynamic breakout system usually does a good job in letting the profits run while cutting the losses short, it often ends with close to 70% profitable months and fairly short flat times (time spent between two equity highs). For our purposes, I settled for a system with a lookback period of 60 bars. This was for no particular reason other than that I know it works fairly well. There was no optimization influencing this decision.

When traded on 16 different markets, using the RAD contract, on data from January 1980 to October 1992, it traded profitably on all 16 markets. The 16 markets traded were crude oil, T-bonds, T-bills, rough rice, Nikkei index, natural gas, live cattle, lumber, coffee, copper, gold, dollar index, Japanese yen, D mark (as a proxy for the Euro), cotton, and wheat. The export function from TradeStation into Excel is essentially the same for the SDB system as for the directional slope system. The data for the period November 1992 to October 1999 were saved for some out-of-sample testing in later sections. Figure 10.2 shows that the open equity for the average trade is exceptionally smooth all the way up to over 150 bars, and that we can expect the average trade to increase its open profit with about 0.18% per bar. We will make use of this finding later, when we put together a trailing stop. The dotted line denotes the number of bars from which point on there are fewer than 20 open trades. This happens at bar 132. As you can see, there are a few trades that go on for much longer than that.

One disadvantage with this system is that it bases its exits on a moving average, which might start moving away from the market somewhat before you are allowed to exit. This is especially important to remember at the time of the entry, because the maximum loss, as indicated by the system at that point, might not be the same as after a few days; you never can be completely sure about how much to risk and how many contracts to trade in a fixed fractional money management strategy.



rluURc 10.2

The average profit for all open trades in relation to the number of bars in trade.

Therefore, it is very important to examine the system for any natural stop loss levels based on percentage data. Table 10.11 shows that all trades with an MAE equal to or greater than 5.5% would have ended with an average profit of — 1.90%. Obviously, had we decided to put a stop in at this level, the average profit would have been —5.5%, which would have resulted in an overall decrease of performance of 3.60%) points. For all trades with an MAE of 2%, the overall decrease in performance would have been 0.99% points for these trades. It also seems that the 2% MAE forms some sort of local minimium, with higher values on each side of it. The 5.5% MAE level, on the other hand, seems to form a local maximium, with lower values on each side of it. The natural choice, and definitely one that should be investigated further, would then be to place the stop at 2%. However, in accordance with our previous discussion about everything in trading being a trade-off between good and bad, wanted and unwanted features, we decide to go with the 5.5% stop, simply because this seems to be the most obvious place for where *not* place a stop, hoping that what we might lose in a few individual trades on a one-contract basis we will win back with the proper money management. Furthermore, the most obvious solution doesn't necessarily have to be the best one in the long run; what we lose on the swings, we might make up on the merry-go-round.

Table 10.12 shows that the larger the MAEfe, the larger the expected profit, assuming that the MAEfe corresponds to the ETD, which is the last retrace-

TABLE 10.11

MAE levels, original profits, and differences in outcome for 16 markets in the SDB system.

MAE	Original profit	Difference
-0.50%	-1.00%	1.50 points
-1.00%	-0.52%	1.52 points
-1.50%	-0.23%	1.27 points
-2.00%	-1.01%	0.99 points
-2.50%	-1.17%	1.33 points
-3.00%	-1.52%	1.48 points
-3.50%	-1.89%	1.61 points
-4.00%	-2.40%	1.60 points
-4.50%	-2.45%	2.05 points
-5.00%	-2.24%	2.77 points
-5.50%	-1.90%	3.60 points
-6.00%	-3.38%	2.62 points
-6.50%	-2.64%	3.86 points
-7.00%	-4.16%	2.84 points
-7.50%	-4.73%	2.77 points
-8.00%	-4.15%	3.85 points
-8.50%	-3.53%	4.97 points
-9.00%	-8.02%	0.98 points
-9.50%	-7.65%	1.85 points
-10.00%	-12.57%	-2.57 points

ment down from the MFE level. Because of this we probably would be better off without a trailing stop, but because we want to make use of our techniques, we decide to place one anyway at the 5.5% level, provided that a retracement this large also results in a downside breakthrough of the regression line for the average trade.

Because of the expected ETD, a trade must accumulate a certain open profit before it can be expected to close with a profit. When it comes to the time-based stop, Table 10.13 shows that the average profit on bar 40, for all trades that go on for more than 40 bars, is 7.74%, but before a trade that goes on for this long is allowed to exit it will, on average, give back 7.63. Thus not until this bar can we expect the average trade to end with a profit. Therefore, we will cut all trades that are not profitable at this point on the assumption that they will only turn even worse because of the ETD that is still likely to come.

At the other end of the spectrum, we do not want our trades to go on for too long either, because the larger the open profit, the larger the resulting retracement is likely to be as well, resulting in a less-than-stellar final profit. It just so happens that one unsatisfactory feature of the SDB system is its tendency to give back a

TABLE 10.12

MAEfe levels, average MFE levels, and theoretical profits for 16 markets in the SDB system.

MAEfe	Avg. MFE	Profits
-2.50%	9.96%	7.21%
-3.00%	10.47%	7.15%
-3.50%	11.11%	7.22%
-4.00%	11.79%	7.32%
-4.50%	12.68%	7.61%
-5.00%	13.44%	7.77%
-5.50%	14.07%	7.80%
-6.00%	14.65%	7.77%
-6.50%	15.52%	8.01%
-7.00%	16.42%	8.27%
-7.50%	17.35%	8.55%
-8.00%	18.65%	9.16%
-8.50%	20.06%	9.85%
-9.00%	20.81%	9.94%
-9.50%	21.50%	9.96%
-10.00%	22.86%	10.58%
-10.50%	23.15%	10.22%
-11.00%	24.39%	10.71%
-11.50%	26.12%	11.62%
-12.00%	27.05%	11.80%

substantial part of the open profit before it signals time to exit. This can be seen from Table 10.14 which, for instance, shows that all trades with an MFE of 60% or more, are likely to produce only an average profit of 45.63%. For the SDB system, we seem to be better off no matter where we place a profit target. There seems to be no local maxima or minima on which to base our reasoning (backwards or otherwise), so just for the heck of it we place it at 75%, which should result in a performance increase of about 25.58 percentage points. (Remember that these systems are for demonstration purposes only.)

Also, notice the differences between this system and the not too different DBS system in the previous chapter. With the SDB system, we seemingly do worse using a stop loss and a trailing stop, but do better with a profit target—the exact opposite of what we found for the DBS system, although we are dealing with two trend-following strategies, which, one would think, would act pretty much the same. When you put together your own systems, you must think about all these subtleties and make sure that they work the way you want them to and in a way that make sense to you. Nobody else can make these decisions for you. I am merely pointing them out and using them as examples for you to learn from.

TABLE 10.13

Bars in trade, open profits, ETD, and differences for 16 markets in the SDB system.

Bars in trade	Open profit	ETD	Difference
12	1.56%	-6.91%	-5.35 points
14	2.01%	-6.92%	—4.91 points
16	2.42%	-6.97%	-4.55 points
18	2.64%	-7.02%	-4.38 points
20	3.23%	-7.10%	-3.87 points
22	3.81%	-7.21%	-3.41 points
24	4.29%	-7.28%	-2.98 points
26	4.49%	-7.44%	-2.95 points
28	4.89%	-7.47%	-2.59 points
30	5.26%	-7.53%	-2.27 points
32	5.72%	-7.60%	-1.88 points
34	6.30%	-7.61%	-1.30 points
36	6.88%	-7.60%	-0.72 points
38	7.24%	-7.63%	-0.40 points
40	7.74%	-7.63%	0.11 points
42	7.86%	-7.62%	0.24 points
44	8.25%	-7.69%	0.55 points
46	8.83%	-7.76%	1.07 points
48	9.13%	-7.83%	1.30 points
50	9.68%	-7.70%	1.98 points

When it comes to not letting a winning trade go one for too long we also could decide to cut all winners at a certain bar, no matter what. A trade that goes on for too long not only increases the standard deviation of outcomes for the entire system, but also builds up an open profit that it is likely to give back a substantial part of before the system signals an exit. Therefore, it could be a good idea to cut all profitable trades that go on past a certain number of bars. To come to a conclusion for this we can compare the average open profit for a specific bar with the average final profit for all trades that last longer. In this case, Table 10.15 shows that there seems to be some kind of local maximum surrounding the 105-day region, so we decide to go with a maximum trade length of 105 days.

With all the suggested exit levels in place, the exit techniques for the SDB system are as follows:

- Exit with a loss if the market moves the wrong way by 5.5%.
- Exit with a small loss/breakeven if the market moves into (stays in) negative territory at or after bar 40.

TABLE 10.14

MFE levels, original profits, and differences for 16 markets in the SDB system.

MFE	Original profit	Difference
5.00%	7.34%	2.34 points
10.00%	12.03%	2.03 points
15.00%	16.16%	1.16 points
20.00%	20.02%	0.02 points
25.00%	24.88%	-0.12 points
30.00%	32.25%	2.25 points
35.00%	34.60%	-0.40 points
40.00%	37.65%	-2.35 points
45.00%	41.65%	-3.35 points
50.00%	42.97%	-7.03 points
55.00%	45.63%	-9.37 points
60.00%	45.63%	-14.37 points
65.00%	47.10%	-17.90 points
70.00%	47.52%	-22.48 points
75.00%	49.42%	-25.58 points
80.00%	49.42%	-30.58 points
85.00%	45.69%	-39.31 points
90.00%	45.69%	-44.31 points
95.00%	49.41%	-45.59 points
100.00%	49.41%	-50.59 points

- Exit with a trailing stop, after bar 40, if the market moves the wrong way by 5.5% or more and ends up below the regression line for the original average trade.
- Exit with a limit order if the open profit exceeds 75%.
- Exit with a profit if the trade lasts for more than 105 bars.

Tables 10.16 and 10.17 show the hypothetical results for wheat traded with and without the exits. Without the exits, wheat had a profit factor of 1.66 and an average profit per trade of 1.27%, equal to $277 in today's marketplace. With the exits, wheat had a profit factor of 1.85 and an average profit of 1.48%, equal to $307 in today's marketplace. Tables 10.16 and 10.17 also show that the added exits have decreased both the drawdown and the standard deviation, which is good news. For the modified system, the largest winner would have been 32.13%, or $6,665 at today's market value. The largest loser would have been 5.50% (thanks to the stop loss), or —$1,141 at today's market value.

That the SDB system is very robust can be seen from Table 10.18, which shows that no market ended up with a profit factor below 1 or an average trade less

TABLE 10.15

Bars in trade, final profit, open profits, and differences.

Bars in trade	Final profit	Open profit	Difference
55	10.92%	10.93%	0.02 points
60	11.90%	11.51%	-0.39 points
65	12.36%	12.62%	0.26 points
70	13.00%	13.44%	0.43 points
75	13.87%	14.49%	0.62 points
80	14.21%	14.85%	0.64 points
85	15.35%	16.12%	0.77 points
90	16.50%	17.57%	1.07 points
95	17.71%	18.76%	1.04 points
100	18.10%	19.75%	1.65 points
105	18.71%	20.05%	1.34 points
110	20.41%	21.93%	1.52 points
115	20.37%	21.34%	0.97 points
120	22.78%	23.00%	0.22 points
125	23.09%	24.46%	1.37 points
130	23.81%	24.69%	0.88 points
135	23.47%	23.71%	0.24 points
140	23.43%	23.16%	-0.27 points
145	27.17%	28.02%	0.85 points
150	27.17%	28.99%	1.82 points

than three times the expected costs of $75 per trade. Some markets, like rough rice and natural gas, even showed amazingly good results with profit factors well above 10.

Table 10.19 shows that with the exits added, all markets still have a profit factor above 1, but unfortunately the increased security about each trade's individual outcome also results in a lower average trade for most markets. However, because of no disaster markets, the overall result confirms the stability of the SDB

TABLE 10.16

Individual market performance summary.

Wheat, before exits (original system)								
Total trades		3	Winners	15	39.47%	Losers	23	60.53%
Profit factor		1.6	Lrg winner	31.11%	6,762.54	Lrg loser	-7.59%	-1,649.88
Avg profit	1.27%	276.5	Avg winner	8.09%	1,759.29	Avg loser	-3.18%	-690.40
St Dev	7.73%	1,678.7	Cum profit	46.50%	10,107.94	Drawdown	-25.76%	-5,599.58

TABLE 10.17

Individual market performance summary.

Wheat, after exits (modified system)								
Total trades		3	Winners	16	41.03%	Losers	23	58.97%
Profit factor		1.8	Lrg winner	32.13%	6,665.05	Lrg loser	-5.50%	-1,140.92
Avg profit	1.48%	307.3	Avg winner	7.84%	1,626.46	Avg loser	-2.94%	-610.23
St Dev	7.52%	1,559.5	Cum profit	61.39%	12,734.93	Drawdown	-23.06%	-4,784.24

system, even after we have "polluted" it with all the exits. Interestingly enough, the markets that did get a higher average trade and profit factor were markets that usually do well in almost any trend-following system. These markets were T-bonds, Nikkei index, Japanese yen, and wheat; dollar index and D mark only managed to increase their average trades, and crude oil and cotton their profit factors.

From Table 10.20 we can see that a total of six markets managed to increase their performance in at least three categories, but also that as many as seven only managed to increase one category or less. The one market that did not improve its performance at all was natural gas, but even so, it was highly profitable, both with

TABLE 10.18

Performance measurements for all markets.

	Before exits (original system)			
Market	P. factor	Avg. trade	2 St. dev.	Drawdown
Crude oil	3.08	987.94	5,524.19	-4,275.06
T-bonds	1.23	378.11	10,932.67	-28,771.85
T-bills	2.65	917.62	6,513.73	-5,750.25
Rough rice	10.07	1,678.34	6,042.87	-2,181.27
Nikkei index	2.16	2,847.55	20,787.00	-6,747.19
Natural gas	17.11	2,200.72	4,964.46	-546.27
Live cattle	1.45	228.30	3,596.36	-7,212.76
Lumber	1.49	333.37	5,089.97	-6,816.53
Coffee	2.95	639.42	3,918.96	-3,958.94
Japanese yen	2.29	1,675.54	14,463.96	-11,781.00
Copper	1.89	535.64	5,825.51	-6,583.29
Gold	1.85	662.89	5,732.22	-7,241.86
Dollar index	2.51	1,444.03	7,693.95	-4,357.46
D mark (Euro)	3.11	1,818.71	9,699.02	-8,303.75
Cotton	2.35	755.11	5,557.00	-4,430.03
Wheat	1.66	276.58	3,357.54	-5,599.58

and without the exits. Of all 16 markets tested, we managed to decrease the standard deviation for 13 and the drawdown for 8. Unfortunately, we did not manage to increase the profit factor and the average trade for as many as we wanted.

In conclusion, for the SDB system, we could come to the same conclusion as we did for the DBS system. That is, although the average trade did not improve as much as we would have liked, we can see that the exits are still doing their job when it comes to streamlining the trades, which is indicated by the fact that we managed to lower the drawdown for eight markets and the standard deviation for 13 markets. This should make it possible to trade it more aggressively with proper money management; to possibly increase performance, optimize the lookback and breakout period, and/or continue to experiment with different types of stops and exit levels.

TABLE 10.19

Performance measurements for all markets.

	After exits (modified system)			
Market	P. factor	Avg. trade	2 St. dev.	Drawdown
Crude oil	3.44	747.03	4,182.98	-1,803.36
T-bonds	1.29	440.87	10,925.97	-19,886.70
T-bills	2.15	676.68	6,451.11	-5,626.32
Rough rice	1.26	125.77	3,042.76	-5,176.72
Nikkei index	4.09	6,118.78	24,009.93	-4,904.47
Natural gas	6.98	1,557.54	6,441.10	-1,041.45
Live cattle	1.09	48.38	3,018.49	-8,610.89
Lumber	1.42	267.40	4,768.68	-5,572.99
Coffee	1.25	87.68	2,458.44	-4,157.51
Japanese yen	2.41	1,711.84	12,882.49	-10,575.98
Copper	1.15	96.01	4,049.64	-6,919.10
Gold	1.27	248.28	5,376.98	-8,558.86
Dollar index	2.43	1,447.94	8,019.24	^1,357.46
D mark (Euro)	2.96	1,829.22	9,472.23	-12,074.73
Cotton	2.72	670.49	4,529.95	-3,890.78
Wheat	1.85	307.38	3,119.04	-4,784.24

Summarized differences, before/after exits.

	Differences				
Market	P. factor	Avg. trade	2 St. dev.	Drawdown	Better
Crude oil	11.49%	-24.39%	-24.28%	-57.82%	3
T-bonds	4.68%	16.60%	-0.06%	-30.88%	4
T-bills	-18.76%	-26.26%	-0.96%	-2.16%	2
Rough rice	-87.45%	-92.51%	-49.65%	137.33%	1
Nikkei index	89.12%	114.88%	15.50%	-27.31%	3
Natural gas	-59.20%	-29.23%	29.74%	90.65%	0
Live cattle	-24.96%	-78.81%	-16.07%	19.38%	1
Lumber	-4.77%	-19.79%	6.31%	-18.24%	2
Coffee	-57.55%	-86.29%	-37.27%	5.02%	1
Japanese yen	4.95%	2.17%	-10.93%	-10.23%	4
Copper	-39.40%	-82.08%	-30.48%	5.10%	1
Gold	-31.25%	-62.55%	-6.20%	18.19%	1
Dollar index	-3.24%	0.27%	4.23%	0.00%	1
D mark (Euro)	-4.80%	0.58%	-2.34%	45.41%	2
Cotton	15.70%	-11.21%	-18.48%	-12.17%	3
Wheat	11.57%	11.14%	-7.10%	-14.56%	4
Better	6	4	13	8	—

CHAPTER 11

Working with Random Entries

For our shorter-term systems, we take a slightly different approach. We look more closely into the world of descriptive statistics and learn about a few new measurers that can come in handy, not only when building systems but also when analyzing markets in general.

With descriptive statistics, we can estimate and make use of the likelihood of a certain occurrence, as we did by measuring men's height for the Meander system in Part 2. That is, we can start saying things like "under normal circumstances, and assuming the height of men is normally distributed; there is only a 2.27% chance that the next man I bump into will be very tall and only a 0.05% chance that I will bump into two such men in a row." When doing so, we are relating the random variable directly to its mean and standard deviation.

So far, when we have used several of our statistical measurements, such as the average profit and the standard deviation of the outcomes, we have assumed that all our variables, such as the percentage profit per trade, have been normally distributed and statistically independent, continuous random variables. The beauty of this assumption is that the familiar bell-shaped normal distribution is both easy to understand and, at the same time, lends itself to approximate other, close to normally distributed variables as well. Figure 11.1 shows what such a distribution can look like.

Note, however, that for a variable to be random it does not have to be normally distributed, as Figure 11.2 shows. This chart is simply created with the help of the random function in Excel. Figure 11.1, in turn, is created by taking a 10-period average of the random variable in Figure 11.2. More often than not, a random variable (like that in Figure 11.2) that is an average of another random variable (like

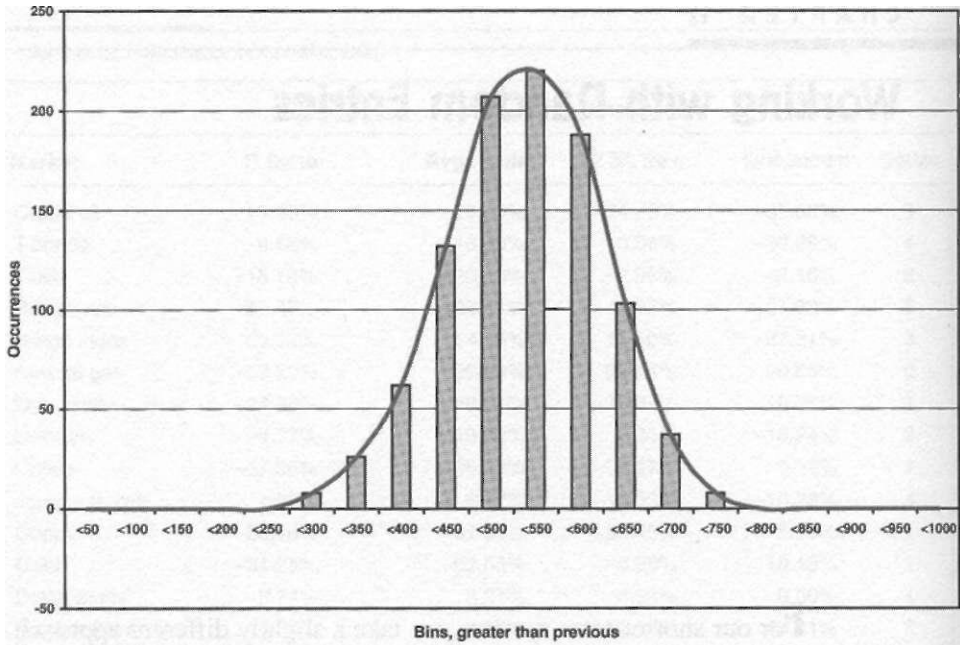


FIGURE 11.1

The bell-shaped curve of a normal distribution.

that in Figure 11.1) is distributed approximately as a normal random variable, regardless of the distribution of the original variable.

However, a normal distribution can very well be both higher and narrower, or lower and fatter, than that in Figure 11.1. Most important, it has a single mode (one value that appears more frequently than the others) and is symmetrical, with equally as many observations to the left as to the right of the mean. For any normally distributed variable, it holds that 68.27% of all values lie within 1 standard deviation of the mean; 95.46% of the values lie within 2 standard deviations; and 99.73% of the values lie within 3 standard deviations of the mean. To calculate the standard deviation of a sample you can use the standard deviation formula in Excel.

For the longest time, the normal distribution has been the statistical distribution most analysts used to calculate market returns, although it has long been evident that the market does not follow a normal distribution. This can be seen from Figure 11.3, which shows the daily percentage returns for the S&P 500 index over the period April 1982 to October 1999.

As you can see from Figure 11.3, this curve is not entirely symmetrical, and it seems to have much fatter tails than the normal distribution curve in Figure 11.1. If a distribution has a relatively peaked and narrow body and fatter tails than a normal distribution, it is said to be *leptokurtic*. If the opposite hold true, it is said to

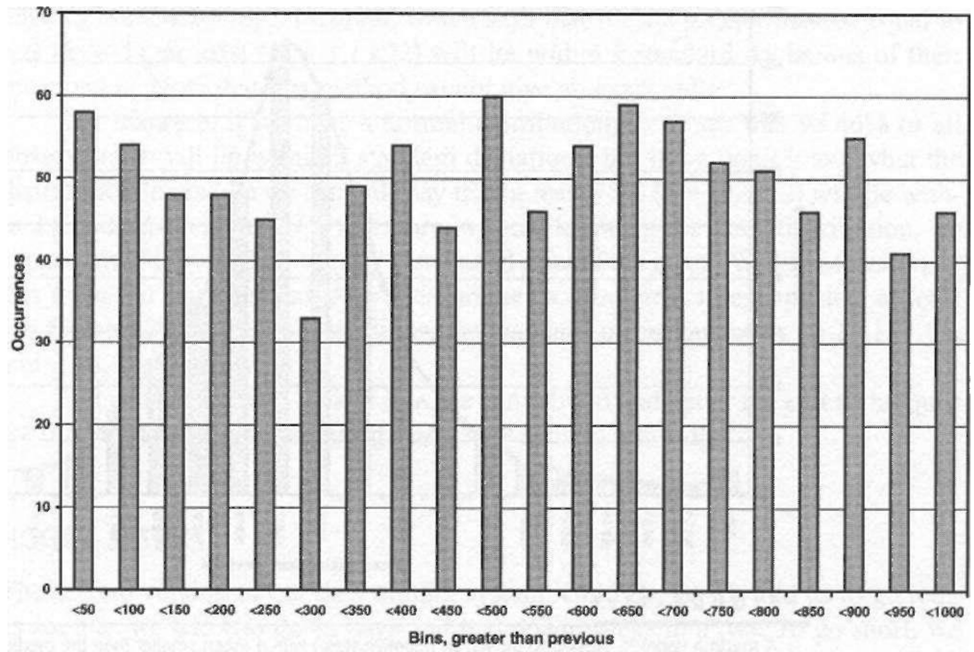


FIGURE 11.2

A random variable, not normally distributed.

be *platykurtic.* To calculate the *kurtosis* of a variable you can use the kurt function in Excel. In the case of the daily distributions of returns for the S&P 500 index, kurtosis equals 56. A positive value means that the distribution is leptokurtic; a negative value means that it is platykurtic. When building a trading system we would prefer for the distribution of returns to be platykurtic, so that we make sure that the system does not stand or fall with any large out Iyer trades. This is a two-edged sword, however, in that a positive value for the kurtosis also might indicate that we are doing a good job of keeping all our trades as similar as possible to the average trade. If that is the case, the kurtosis should increase with the number of trades from which we can draw any statistical conclusions, while the dispersion of these trades stays the same. That is, we are not changing the levels at which we take our profits and losses.

What probably cannot be seen from Figure 11.3 is that it also is slightly *skewed* to the left (a negative skew) with a mean smaller than the median (the middle value, if all values are sorted from the smallest to the largest). The tail to the left of the body stretches out further than the tail to the right. To calculate the degree of skew of the distribution you can use the skew function in Excel. In this case, the skew equals -2.01, with the average return per day equal to 0.0296% and the median equal to 0.0311%. When building a trading system we would prefer for

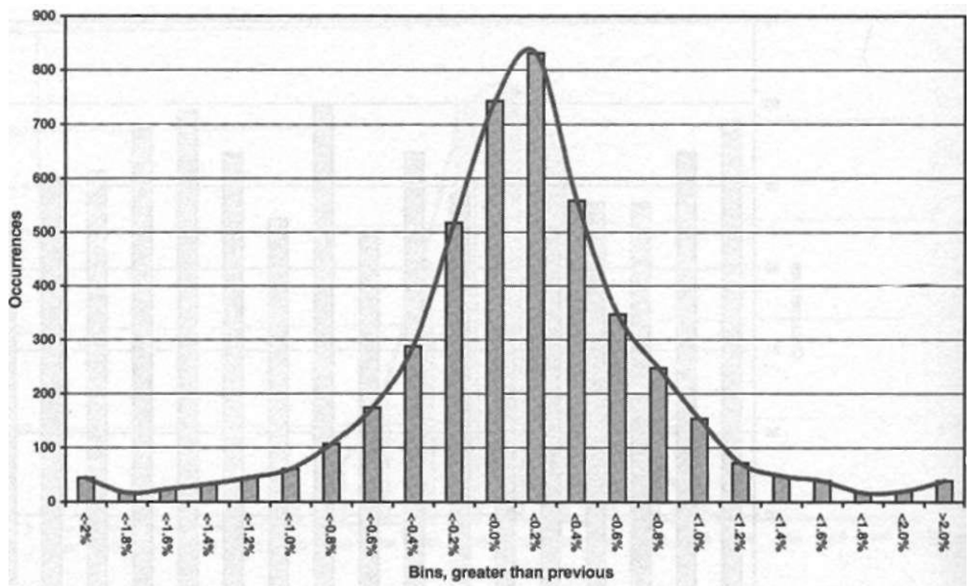


FIGURE 11.3

A random variable skewed to the left (a negative skew) with a mean smaller than the median.

the returns to be positively skewed (to the right) with the tail to the right stretching out further from the body than the tail to the left, so that we make sure that we're cutting our losses short and letting our profits run.

Another way to make sure that a system is not too dependent on any out-lyers is to exclude them when calculating the average return. You can do this in Excel with the trimmean function, which excludes a certain percentage of observations from each end of the distribution. Ideally, when building a trading system we would prefer for the trimmean to remain above zero, so that we make sure that the bulk of our trades are behaving as they should. If the trimmean is larger than the average return, it means that historically the positive out-lyers have been smaller than the negative out-lyers. If the trimmean is smaller than the average return, it means that historically the positive out-lyers have been larger than the negative out-lyers. In this case, whatever you think is best depends on what you expect and how you would like the system to perform in the future. After a few bad trades, it could be comforting to know that the positive out-lyers historically have a tendency to be larger than the negative ones; but on the other hand, having to rely on a set of not-yet-seen out-Iyer trades to find your way out of a drawdown, seems to be awfully close to gambling with your life and the need to rely on Lady Luck.

If we don't know for sure whether the distribution is normal, we cannot use our normal distribution measurements that, for instance, say that 68.27% percent of all observations will be within 1 standard deviation of the mean. Instead we have to use *Chebychef's theorem,* which says that for a *k* greater than or equal to one (k 2= 1), at least (1 - 1 / k^2) will lie within *k* standard deviations of their mean value. Note that this method cannot give an exact value.

For instance, if we have a normal distribution, we know that 95.46% of all observations will lie within 2 standard deviations, but if we don't know what the distribution looks like we can only say that at least 75% (1 — 1 / 2^2) will lie within 2 standard deviations. Furthermore, without knowing the exact distribution, we cannot say if they will be equally distributed around the mean. We have to estimate this from our kurtosis and skew measurements. Similarly, to encapsulate at least 50, 67, and 90% of all observations, the standard deviations must be 1.41, 1.74, and 3.16, respectively.

Let us take a closer look at how we can rebuild and better the exit techniques for our short-term systems using this newly found knowledge.

THE GOLD DIGGER SYSTEM

The second version of our data mining system, Gold Digger II, told us to go long as soon as we had two down days and two down weeks in a row. To go short, we needed two up days and two up weeks. The reasoning behind this strategy was that a move in a certain direction cannot go on forever and that a short-term rebound is likely to happen sooner or later. The exit techniques also were very simple. If the market proved us right by going our way for two consecutive days, we would exit a long position, or if we were short, we would exit at the first close that went our way. The danger with this strategy is, however, that it lacks any type of stops other than the entry in the opposite direction, which can be quite a substantial amount of time and money away.

The advantage with this system, as compared to Gold Digger I, is that Gold Digger II is more symmetrical in nature, but because of the different exit techniques, not completely so. Let us see if we can make it *completely* symmetric and at the same time examine the possibility of adding some sort of stop-loss techniques as well. For a system to be completely symmetrical in both the long and short entries, the long and short exit should be mirror images of each other. A partly symmetrical system, such as Gold Digger II, from Part 2, has either symmetrical entries or exits. You will find the original TradeStation code for this system in Part 2. Because we want this to continue to be a short-term strategy, we also start out with the assumption that no trade will be allowed to go on for longer than five days. The first step is to modify the TradeStation code to the following:

```
Conditionl = CloseW(2) > CloseW(l) and CloseW(l) > C and C[2] > C[l] and
C[l] > C;
Condition = CloseW(2) < CloseW(l) and CloseW(l) < C and C[2] < C[l] and
C[1]<C;
```

```
If Conditionl = True and MarketPosition = 0 Then
    Buy ("Go long") at open;
If Condition2 = True and MarketPosition = 0 Then
    Sell ("Go short") at open;
If BarsSinceEntry 5= 5 Then Begin
    ExitLong ("Exit long") at close;
    ExitShort ("Exit short") at close;
End;
```

Of course, we might have decided on a different maximum trade length and, for instance, looked for an optimal value in the same manner as we did with the Black Jack system in Part 2. If that had been the case, we also could have used the measures for skew and kurtosis that seemed to be producing the most stable results. But for now, let us settle for the five-day limit to a trade. As was the case with the original system, we will test this strategy on the RAD contract for the S&P 500 index futures contract, covering the period January 1995 to October 1999.

Using the trade-by-trade export function from Part 1 produced the results in Table 11.1, If we compare this system to the original version of Gold Digger II, we can see that the standard deviation for this version is much higher, while the average profit is much lower, which means that this version is much riskier to trade. A lower profit factor also indicates that the cost of doing business has increased. The drawdown also has increased considerably. In all, this new version of Gold Digger is not as good as the original version. Overall, this totally symmetrical version of Gold Digger does not look as good as its predecessor, although it has its benefits and perhaps also a few strengths that can be improved upon even further using the right analysis tools.

As can be deduced from Table 11.2 and Figure 11.4, these results are not normally distributed at all. Instead, we have a median that is smaller than the mean and a positive skew, suggesting that the right-hand tail stretches out further than the one on the left-hand side. This is good, because despite the fact that we are cutting all trades at day five the system by itself is still letting the profits run while cutting losses short. One not so good thing, however, is the positive value

TABLE 11.1

Performance summary for the modified version of Gold Digger II, January 1995-October 1999.

Total trades		80	Winners	4	53.75%	Losers	3	46.25%
Profit factor		1.18	Lrg winner	8.54	28,823	Lrg loser	-4.33	-14,614
Avg profit	0.13%	453	Avg winner	1.65	5,559	Avg loser	-1.62	-5,480
StDev	2.22%	7,483	Cum profit	9.18	30,983	Drawdown	-17.47	-58,961

TABLE 11.2

Descriptive statistics for Gold Digger II (modified version).

Mean	0.13
Median	0.21
Kurtosis	2.49
Skew	0.83
Trimmean (20%)	0.04

for the kurtosis, which suggests that so far the system is leptokurtic and, hence, does not produce stable returns. However, with the proper set of exit techniques we should be able to lower the kurtosis into negative territory while keeping a positive skew.

The trick then is to see if we can improve on the results somewhat, while also making the distribution of the outcomes less leptokurtic and perhaps slightly more skewed to the right. That this should be possible is suggested by the 20% trimmean, which is smaller than the mean, indicating that, historically, the positive outlyers have been larger than the negative ones. From Figure 11.4, we also can see

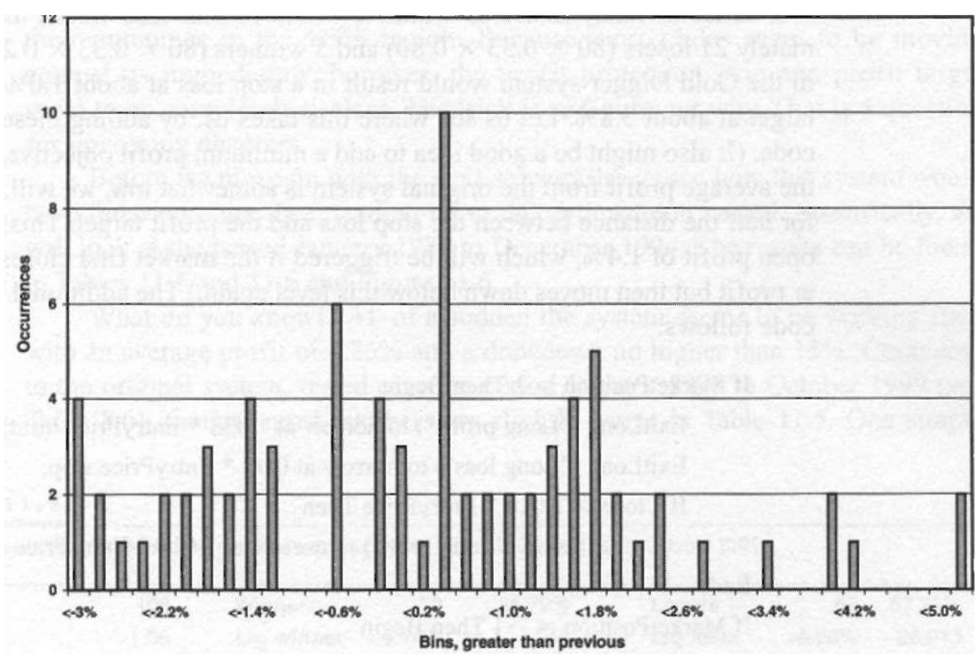


FIGURE 11.4

The distribution of returns for the modified Gold Digger II system.

that the distribution of returns indicates that the right-hand tail is stretching out further than the left-hand side. This is generally good and an indication that we are letting the profits run. The positive kurtosis, however, suggests that the results also are a little too toppy, which indicates instability.

Let us say that we would like to cut all trades that go against us with more than two standard deviations. Because we know that the returns from this version of Gold Digger are not normally distributed, we cannot simply cut off all trades that go against us by a certain value, as suggested by the regular standard deviation formula. Instead, we have to use Chebychev's theorem that says that the two standard deviation boundaries will hold for at least 75% of all observations. But because we do not know the exact distribution, we also do not know how many of the remaining 25% will be located in the right-hand tail or the left-hand tail, respectively. This we can only estimate with the help of the other measures. The reasoning, then, is that because of the positive skew, a larger quantity of the 25% remaining trades should be located to the left of the mean. For argument's sake then we could say that 20 percentage points should be located in the right tail with the remaining 5 percentage points in the left tail.

An alternative method could be to look for a different amount of trades that the standard deviation boundaries should encapsulate. For instance, if we would like to encapsulate 68% of all trades, we should leave out about 16% of all trades on each side. Just for argument's sake, let us say that among these we should cut four times as many losers as winners, which in this case would mean approximately 21 losers (80 X 0.33 X 0.80) and 5 winners (80 X 0.33 X 0.20). Doing so in the Gold Digger system would result in a stop loss at about 1.0% and a profit target at about 3.8%. Let us see where this takes us, by adding these stops to the code. (It also might be a good idea to add a minimum profit objective, but because the average profit from the original system is somewhat low, we will, instead, aim for half the distance between the stop loss and the profit target. This will be at an open profit of 1.4%, which will be triggered if the market first closes with a larger profit but then moves down below this level again.) The additional TradeStation code follows:

```
If MarketPosition = 1 Then Begin
    ExitLong ("Long profit") tomorrow at 1.038 * EntryPrice limit;
    ExitLong ("Long loss") tomorrow at 0.99 * EntryPrice stop;
    If Close > 1.014 * EntryPrice Then
        ExitLong ("Long prot") tomorrow at 1.014 * EntryPrice stop;
End;
If MarketPosition = -1 Then Begin
    ExitShort ("Short profit") tomorrow at 0.962 * EntryPrice limit;
    ExitShort ("Short loss") tomorrow at 1.01 * EntryPrice stop;
```

```
        If Close < 0.986 * EntryPrice Then
            ExitShort ("Short prot.") tomorrow at 0.986 * EntryPrice stop;
End;
```

Table 11.3 shows the result with these stops in place. As you can see, these stops most certainly did not improve results. This looks really bad, with an average profit of a mere 0.07% and a cumulative profit of *4.72%* after five years of trading. The only positive thing is that we managed to decrease the drawdown quite a bit, although the standard deviation stayed approximately the same. But because we believe in the original concept (please say "yes") we will not give up. Perhaps we might be able in the end to increase the profits somewhat by substituting these exits with more generic and less curve-fitted ones, and perhaps the entry criteria might even be too strict? Let's take a look.

From Table 11.4 and Figure 11.5 we also can see that the bad news continues when we look at the statistical measures. Not only did the stops, exits, and profit targets help to completely screw up the actual results, they also helped to worsen the statistical measures, most notably when it comes to the still-positive kurtosis and the just barely positive skew. As we can see from Figure 11.5 it is obvious that most trades move against us right off the bat, a fact more evident because of the way we have split the final profit into fewer possible outcomes. As things are right now, most trades will be stopped out by the stop loss. A profit protection exit also makes sure that more trades will have their outcomes in the 1.5% region. Because most trades seem to be moving against us immediately, however, the profit protection stop and profit target seem to be completely useless. The trick is to figure out why. That is a question for upcoming chapters.

Before we move on with the next strategy, let us see how this system would have fared on older data, leading up to the optimization period. Specifically, we will look at the period January 1985 to December 1994. The results can be found in Tables 11.5 and 11.6 and Figure 11.6.

What do you know!? All of a sudden the system seems to be working fine, with an average profit of 0.25% and a drawdown no higher than 15%. Compared to the original system, tested over the period January 1995 to October 1999 (see Table 5.6), though, most numbers are slightly worse in Table 11.5. One simple

TABLE 11.3

Performance summary for the second modified version of Gold Digger II, January 1995-October 1999.

Total trades		106	Winners	39	36.79%	Losers	67	63.21%
Profit factor		1.08	Lrg winner	5.14%	17,348	Lrg loser	-8.30%	-28,013
Avg profit	0.07%	229	Avg winner	2.51%	8,462	Avg loser	-1.35%	-4,564
StDev	2.21%	7,446	Cum profit	4.72%	15,930	Drawdown	-12.01%	-40,534

TABLE 11.4

Descriptive statistics for Gold Digger II (second modified version).

Mean	0.07
Median	-1.00
Kurtosis	1.14
Skew	0.15
Trimmean	0.00

reason for this is the test period, which is more than twice as long and consequently leaves a lot more room for bad things to happen.

A positive value for the kurtosis, as compared to Table 11.4, is a positive because it means that most outcomes now are centered around the mean. That is, the system is doing a good job doing the same thing over and over again. It is just not profitable enough. Another negative reflection is that the skew is now negative, indicating that the system is doing a good job catching those situations when the market is poised to take off in a swift move—only thing, these moves seem to be in the wrong direction. This also is the conclusion to be made from studying the distribution of returns chart in Figure 11.6.

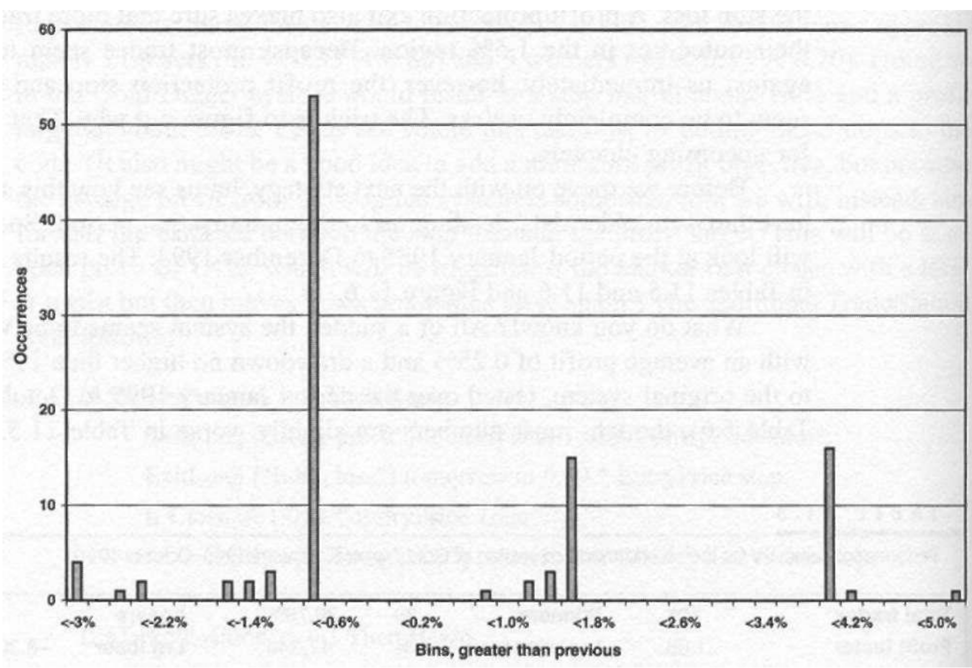


FIGURE 11.5

The distribution of returns for the second modified version of Gold Digger II system.

TABLE 11.5

Performance summary for the second modified version of Gold Digger II, January 1985-December 1994.

Total trades		270	Winners	11	42.96%	Losers	15	57.04%
Profit factor		1.38	Lrg winner	7.62	25,718	Lrg loser	-12.61	^42,559
Avg profit	0.25%	859	Avg winner	2.16	7,283	Avg loser	-1.18	-3,981
St Dev	2.00%	6,745	Cum profit	87.86	296,528	Drawdown	-15.11	-50,996

Looking at the distribution of trades, we can make two interesting observations. First, most losers are stopped out by the stop loss, and only on occasion does a trade end up as a loser otherwise. Second, very few trades are stopped out by the profit limit. The big discrepancy in number of trades, when looking at trades stopped out with a loss and trades stopped out at the maximum profit, indicates that the momentum, when the trade was taken, simply wasn't working in favor of the trade. We will try to do something about that later. For simplicity's sake, from now on I simply refer to this system as the Gold Digger.

THE MEANDER SYSTEM (WEEKLY DATA)

So far, with the Meander system we have only looked at daily data. Now we take a closer look at the same system using a combination of weekly and daily data. That is, we will build the indicator and its trigger levels using weekly data and then try to trade and monitor it using daily data. The best way to go about achieving this is to use the weekly data series as data 2 in TradeStation. Assuming we are once again trying to pick.the tops and bottoms, stay with the trade for five days (no matter what), and with the trigger levels set to two standard deviations away from the mean, the TradeStation code looks as follows:

```
Input: VSStd(2);
Vars: SumVS(O), AvgVS(O), DifrYS(O), StdVS(O), SetArr(O), SumArr(O),
DifTArr(O), VSLow(O), VSMid(O), VSHigh(O);
Array: VS[20](0);
```

TABLE 11.6

Descriptive statistics for Gold Digger II, January 1985-December 1994 (second modified version).

Mean	0.25
Median	-1.00
Kurtosis	6.00
Skew	-.019
Trimmean	0.06

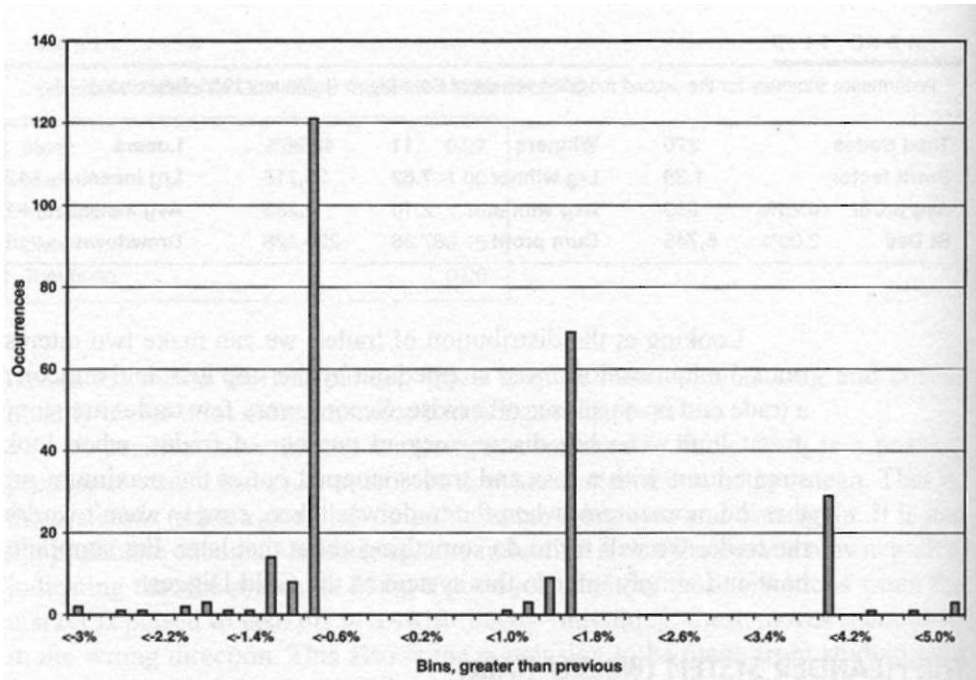


FIGURE 11.6

The distribution of returns for the second modified version of Gold Digger II, between January 1985-December 1994.

```
For SetArr = 0 To 4 Begin
    VSfSetArr * 4 + 0] = (OfSetArr] Data2 - CfSetArr + 1] Data2) /
CfSetArr + 1] Data2;
    VSfSetArr * 4 + 1] = (H[SetArr] Data2 - CfSetArr + 1] Data2) /
C[SetArr + 1] Data2;
    VS[SetArr * 4 + 2] = (L[SetArr] Data2 - CfSetArr + 1] Data2) /
CfSetArr + 1] Data2;
    VSfSetArr * 4 + 3] = (CfSetArr] Data2 - CfSetArr + 1] Data2) /
CfSetArr + 1] Data2;
End;
For SumArr = 0 To 19 Begin
    If SumArr = 0 Then
        SumVS = 0;
    SumVS = SumVS + VSfSumArr];
    If SumArr = 19 Then
        AvgVS = SumVS / 20;
    For DiffArr = 0 To 19 Begin
        If DiffArr = OThen
```

```
                DifTVS = 0;
            DiffVS = DiffVS + Square(VS[DiffArr] - AvgVS);
            IfDiffArr = 19 Then
                StdVS = SquareRoot(DiffVS / 20);
        End;
    End;
    VSLow = C Data2 * (1 + (AvgVS - StdVS * VSStd));
    VSMid = C Data2 * (1 + AvgVS);
    VSHigh = C Data2 * (1 + (AvgVS + StdVS * VSStd));
    If MarketPosition = 0 Then Begin
        Buy ("Go long") tomorrow at VSLow limit;
        Sell ("Go short") tomorrow at VSHigh limit;
    End;
    If BarsSinceEntry >= 5 Then Begin
        ExitLong ("Long time") at close;
        ExitShort ("Short time") at close;
    End;
```

Tables 11.7 and 11.8 and Figure 11.7 show the results for this version of the Meander, when tested on data for the period January 1995 to October 1999, and with the trade-by-trade export function from Part 1 attached to the code.

From Table 11.7 we see that this is not a bad start at all, compared to Gold Digger at the same stage. A high profit factor is complemented by a high average trade. The standard deviation is somewhat high, but a slightly higher ratio between the average profit and the standard deviation shows that the Meander, at this stage, manages to produce a higher risk-adjusted return than Gold Digger. The drawdown is a little too high, but could probably be worked on with a well-working stop loss and some type of filtering technique (to be added later). Another positive factor is the positive value for the skew, in Table 11.8, which means that the Meander, too lets its profits run while cutting the losses short. The very high positive value for the kurtosis is, however, a negative factor at this point, indicating that the individual outcomes are a little too centered around the mean.

TABLE 11.7

Performance summary for the modified version of Meander, January 1995-October 1999.

Total trades		55	Winners	29	52.73%	Losers	26	47.27%
Profit factor		1.90	Lrg winner	13.93%	47,014	Lrg loser	-4.65%	-15,694
Avg profit	0.67%	2,270	Avg winner	2.70%	9,116	Avg loser	-1.59%	-5,365
St Dev	3.13%	10,569	Cum profit	41.02%	138,443	Drawdown	-15.33%	-51,739

TABLE 11.8

Descriptive statistics for Meander (modified version).

Mean	0.67
Median	0.10
Kurtosis	5.55
Skew	1.78
Trimmean	0.37

The clustering of individual outcomes around, or just below, the mean also can be seen in Figure 11.7, which shows the distribution of trades. Trades ending up in this area are likely not to be stopped out by a stop loss or a profit target. The only way to limit these losses even further is to either exit the trade with a small profit (if and when that happens), or to use a time-based stop that forces us to exit before profits turn even worse. Hopefully, a profit protection stop will do it, as the high number of very profitable trades, at the 3.4 and 5% levels, indicates that the Meander is doing a good job of working with the momentum of the market.

Using the same reasoning as for Gold Digger, but this time assuming that all outcomes are evenly distributed around the mean, we place a stop loss approxi-

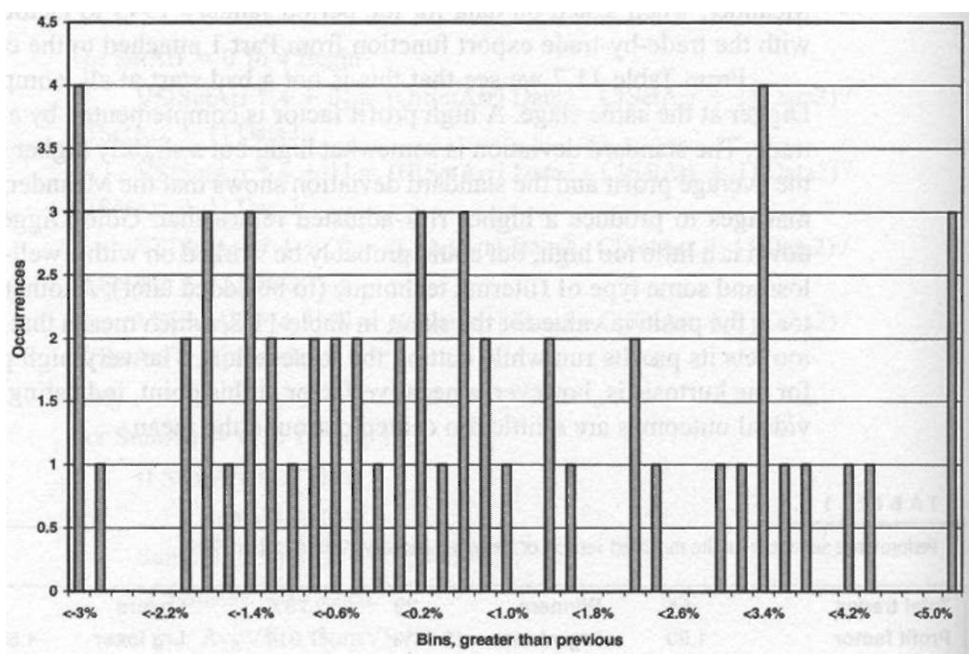


FIGURE 11.7

The distribution of returns for the modified version of Meander.

mately 12 trades in both on the left-hand tail and on the right-hand tail. This means that we place a stop loss (using the same type of code and principles as for Gold Digger) at about 1.8% and a profit target at about 3.2%. Furthermore, using the profit for the average trade as a guide we also add a minimum profit level at 0.64%. Tables 11.9 and 11.10, and Figure 11.8 show the results of using these stops and exits in accordance with the following TradeStation code:

```
If MarketPosition = 1 Then Begin
    ExitLong ("Long profit") tomorrow at 1.032 * EntryPrice limit;
    ExitLong ("Long loss") tomorrow at 0.982 * EntryPrice stop;
    If Close > 1.0064 * EntryPrice Then
        ExitLong ("Long prot") tomorrow at 1.0064 * EntryPrice stop;
End;
If MarketPosition = -1 Then Begin
    ExitShort ("Short profit") tomorrow at 0.968 * EntryPrice limit;
    ExitShort ("Short loss") tomorrow at 1.018 * EntryPrice stop;
    If Close < 0.9936 * EntryPrice Then
        ExitShort ("Short prot.") tomorrow at 0.9936 * EntryPrice stop;
End;
```

Are we good, or what? As can be seen from Table 11.9, although the average trade and profit factor declined somewhat, we still managed to lower the standard deviation to 2.19% and the drawdown to 10.81%. The number of profitable trades also increased dramatically to 65.75%. The good news continues with a negative kurtosis. A negative kurtosis means that we have spread out (or perhaps "plateaued out" is a better expression) the individual outcomes a little more, which could be interpreted as our target area has grown and, therefore, should be easier to hit. With the skew in negative territory, however, we are no longer cutting our losses as short as we probably should. From Figure 11.8, we see that we have transformed the distribution of returns to resemble Gold Digger. Although this system is even more distinct, with three very different and clear-cut scenarios that have crystallized: one highly profitable, one modestly profitable, and one with a negative return, and with only a few trades scattered around. Either the trade becomes a 1.8% loser, or a 0.64 or 3.2% winner.

TABLE 11.9

Performance summary for the second modified version of Meander, January 1995-October 1999.

Total trades		73	Winners	48	65.75%	Losers	25	34.25%
Profit factor		1.78	Lrg winner	4.88%	16,470	Lrg loser	-5.74%	-19,373
Avg profit	0.52%	1,764	Avg winner	1.81%	6,113	Avg loser	-1.95%	-6,587
St Dev	2.19%	7,388	Cum profit	43.78%	147,758	Drawdown	-10.81%	-36,484

TABLE 11.10

Descriptive statistics for Meander (second modified version).

Mean	0.52
Median	0.64
Kurtosis	-0.56
Skew	-0.03
Trimmean	0.49

The interesting thing is that these different scenarios are so distinctly separate from each other that we almost can start calculating the likelihood for a certain scenario to happen. For instance, from Figure 11.8, we can see that there are a total of 21 out of 73 trades (or 28.8 %) that ended up with a profit of 3.2% or more, 28.8% that ended up with a profit of 0.64%, 32.9% that ended up as 1.8% losers or worse, and only 9.5% that ended up somewhere in between. That is, we know that on close to every third trade, or at least every fourth trade, we should end up with a 3.2% winner, on average. With the average trade being a 0.52% winner, we also can calculate the expected average return for all the trades that fall outside of the three major scenarios, which will come out to approximately

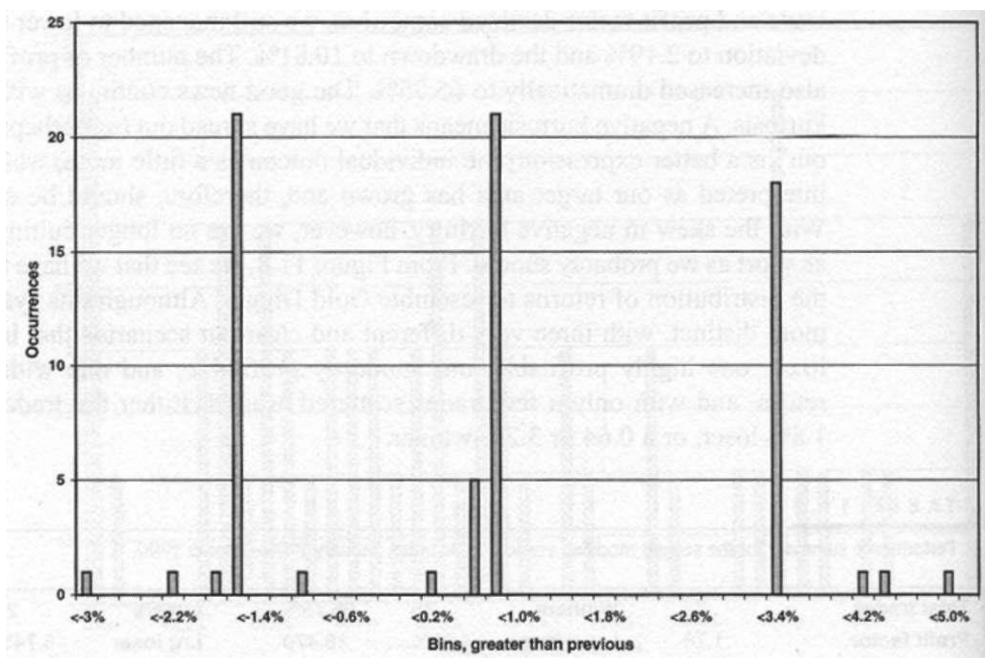


FIGURE 11.8

The distribution of returns for the second modified version of Meander.

0.048% (or approximately $161 in today's market value). Not, too bad for what is falling through the net.

Before we move on with the next system, let us see how this strategy would have performed on data covering the period January 1985 to December 1994, as shown in Table 11.11. Compared to the optimization period, we did not do quite as well, but even so, we definitely did well enough, with an average profit of *0.52%* and a standard deviation of 3.03%. Nonetheless, although the out-of-sample data did not completely stand up against those for the optimization period, they did come in remarkably close. This indicates that the system is very robust and therefore very likely to hold up in the future as well.

The good news also continues when we look at Table 11.12 which once again shows that the skew has moved into positive territory, indicating that we are once more letting our profits run while cutting the losses short. The high value for the kurtosis, as compared to Table 11.12, also is positive in that it indicates that the system is doing a very good job in producing a very similar set of trades. The mean and median values for the out-of-sample data are exactly the same as for the in-sample data, which indicates that the system is working basically the same over different time periods.

This can also be seen from Figure 11.9, which shows the distribution of returns. When tested on out-of-sample data, the minimum profit trades now make up the majority of all trades, while not quite as many trades manage to be closed out with a limit order at the profit target level. It is obvious the market has changed its behavior somewhat, but because the basic characteristics are still there, the results look very robust and promising. That there are plenty more 1.8% losers than there are 3.2% winners does not matter as long as the winners are worth so much more in dollar terms.

What do the Meander and Gold Digger experiences teach us? It is very possible to come up with a profitable trading system that is likely to work equally as well on both the optimization period and the out-of-sample data, as long as we do not aim for the stars. Also, that if something seems to be too good to be true during optimization, it likely is. But even with such a modest system as Gold Digger, we still can work wonders after we improve it by adding a filter that helps us weed out the most obvious losers. And there is plenty of hope for the Meander as well.

TABLE 11.11

Performance summary for the second modified version of Meander, January 1985-December 1994.

Total trades		121	Winners	78	64.46%	Losers	43	35.54%
Profit factor		1.71	Lrg winner	21.92%	73,980	Lrg loser	-11.21%	-37,834
Avg profit	0.52%	1,745	Avg winner	1.93%	6,507	Avg loser	-2.04%	-6,894
St Dev	3.03%	10,232	Cum profit	69.28%	233,820	Drawdown	-13.28%	-44,820

TABLE 11.12

Descriptive statistics for Meander.

Mean	0.52
Median	0.64
Kurtosis	21.27
Skew	2.62
Trimmean	0.33

THE BLACK JACK SYSTEM

In Part 2 we built a system, which we called Black Jack, the name implying that the system should be able to exploit minute market discrepancies and that if we only stay at it long enough we should be able to make a profit—not much from each trade, but slowly and surely build up a stake worth retiring on. We started with a couple of preset entry and filter criteria, based upon common sense and market knowledge.

This time, we will reverse our procedure and start with no such criteria at all, but instead enter each trade randomly, using TradeStation's random number generator. By entering randomly, we can test all markets several times and each

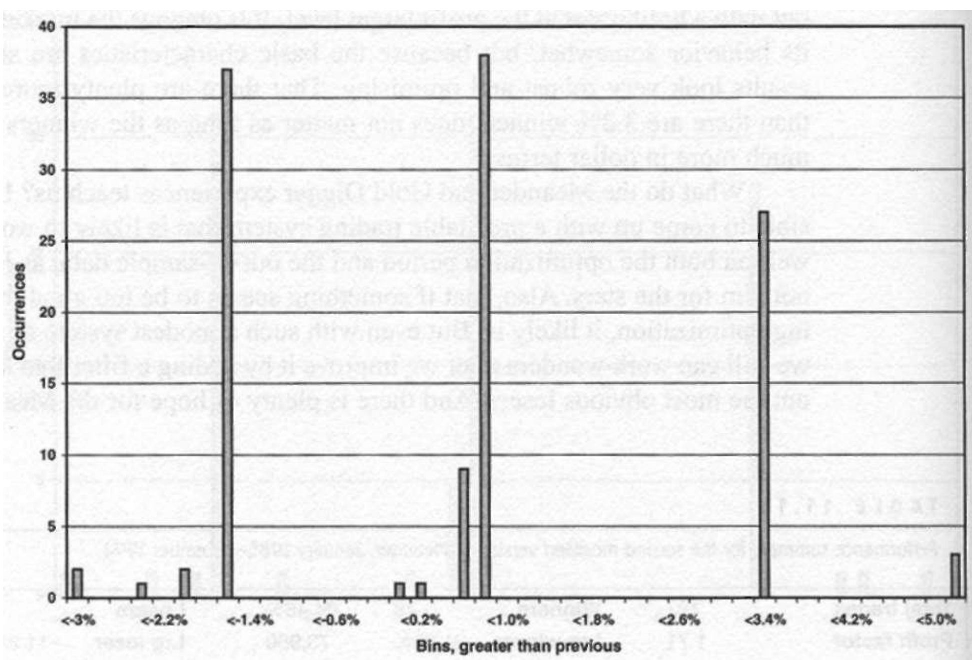


FIGURE 11.9

The distribution of returns for the second modified version of Meander between January 1985-December 1994.

time come up with a new and unique sequence of trades. For this version of the Black Jack system, we use the same 16 markets as we did for the Standard Deviation Breakout (SDB) system, covering the time period January 1980 to December 1992. To mimic approximate general market conditions that keep the market in a trading range approximately 60% of the time, and in an up- or down-trend approximately 20% of the time in each direction, we set the random number generator to signal a long or short position approximately every fifth day, if we're not in a position already.

Basically, there are two slightly different ways to go about building a system like this. You could examine for one type of exit at a time, starting out with the time-based stop, which later could be removed. (With all trades entered randomly there invariably will be situations when we need some type of exit to take us out of the market no matter what the underlying market conditions look like at the time.) Or you could examine all exits in pairs, starting out with the time-based stop and the stop loss. This is what we do in this example. To do this, we must know the value of the average trade for each market and each stop loss/trade length combination, for every time we run that particular combination on that particular market. Remember, thanks to the fact that each trade will be taken randomly, we can run the same test on the same market as many times as we wish and always come up with a new and different result.

It is a good idea to start out with the stop loss/trade length combination because if it happens that we enter exactly when the market takes off in one direction and we happen to be right, the maximum trade length shows us for how many bars (days, hours, etc.) the market remembers a certain event or whatever external factor that triggered the move. This is the amount of time we would like to stay with the trade, no more, no less. When the market starts to discount other factors as more important, we want to exit and wait for the next move that might come our way, because at the point of exit, the reason for our entry is no longer there. The stop loss is obviously necessary to tell us when we are most likely to be wrong, whatever the reason for entering in the first place.

Because we want this to be a short-term system, we restrict our search to the area between two to ten days. I chose to go with two days instead of one day because of the same TradeStation bug I already have described and will rant further about below. As for the stop loss, we know from experience that we probably are best off looking in the 0.5 to 2% region, so this is what we will do.

The quickest way to do the search is to declare both the trade length and the stop loss as inputs, run them through the optimization procedure and, for each run through the data, export the necessary information into a spreadsheet program for further analysis. Do not bother using the optimization report in TradeStation, because it is tailored to run on point-based back-adjusted contracts only. In the optimization dialog boxes we tell TradeStation to run through every combination of our input variables, from two to ten, in steps of one, for the maximum trade length, and from 0.5 to two, in steps of 0.1, for the stop loss.

We also declare a third input variable, which we can use to run the same stop loss/trade length combination as many times as we wish. I run each combination ten times. This results in 1,440 loops for each market. With 16 markets to test, each one holding about ten years' worth of data, this produces something like 230,000 unique yearly trading sequences. I have not bothered to count how many trades we will do, but hopefully this will be enough to form some solid statistical conclusions. *Note:* This takes a hell of a lot of time, even on the fastest of computers. I work on a dual processor, 500MHz Pentium III, 256Mb memory, and I still have a few hours to go do other things when I do runs like this.

If you perform the analysis by exporting the result for each trade separately, the testing becomes extremely slow (now we're talking days), but you also generate so many data that a single Excel spreadsheet won't be large enough to hold it all. (One Excel spreadsheet has close to 17 million cells [65,536 rows X 256 columns].) The TradeStation code for this and all other runs follows:

```
Inputs: Counter(O), TradeLength(7), StopLoss(l.l),TrailingStop(O.l),
ProfitTarget(2);
Vars: PositionGenerator(O), TotTr(O), MP(0), LowestLow(O), HighestHigh(O),
MAE(0), MFE(0), FTE(0), ETD(0), SumMAE(O), SumMFE(O), SumFTE(O),
SumETD(O), FName(""), TradeStrl("");
PositionGenerator = IntPortion(Random(5));
If MarketPosition = 0 Then Begin
    If PositionGenerator = 3 Then
        Buy at Close;
    If PositionGenerator = 4 Then
        Sell at Close;
End;
If BarsSinceEntry >= 1 Then Begin
{ ExitLong ("Long Target") at Entry Price * (1 + (ProfitTarget * 0.01)) limit;
    ExitShort ("Short Target") at EntryPrice * (1 - (ProfitTarget * 0.01)) limit;
    If Close > EntryPrice * (1 + (TrailingStop * 0.01)) Then
        ExitLong ("Long Trailing") at EntryPrice * (1 + (TrailingStop * 0.01))
        stop;
    If Close < EntryPrice * (1 - (TrailingStop * 0.01)) Then
        ExitShort ("Short Trailing") at EntryPrice * (1 - (TrailingStop * 0.01))
        stop;}
    ExitLong ("Long Loss") at EntryPrice * (1 - (StopLoss * 0.01)) stop;
    ExitShort ("Short Loss") at EntryPrice * (1 + (StopLoss * 0.01)) stop;
End;
```

```
If BarsSinceEntry >= TradeLength Then Begin
    ExitLong ("Long Time") at Close;
    ExitShort ("Short Time") at Close;
End;
TotTr = TotalTrades;
MP = MarketPosition;
If MarketPosition = 1 Then Begin
    If BarsSinceEntry = 1 Then Begin
        LowestLow = EntryPrice;
        HighestHigh = EntryPrice;
        MAE = 0;
        MFE = 0;
    End;
    If Low < LowestLow Then Begin
        LowestLow = Low;
        MAE = (LowestLow — EntryPrice) / EntryPrice;
    End;
    If High > HighestHigh Then Begin
        HighestHigh = High;
        MFE = (HighestHigh - EntryPrice) / EntryPrice;
    End;
End;
If MarketPosition = — 1 Then Begin
    If BarsSinceEntry = 1 Then Begin
        LowestLow = EntryPrice;
        HighestHigh = EntryPrice;
        MAE = 0;
        MFE = 0;
    End;
    If High > HighestHigh Then Begin
        HighestHigh = High;
        MAE = (EntryPrice — HighestHigh) / EntryPrice;
    End;
    If Low < LowestLow Then Begin
        LowestLow = Low;
        MFE = (EntryPrice — LowestLow) / EntryPrice;
```

```
        End;
End;
If CurrentBar = 1 Then Begin
        FName = "D:\Temp\BJS.csv";
End;
If TotTr > TotTr[l] Then Begin
        IfMP[l] = IThen Begin
                FTE - (ExitPrice(l) - EntryPrice(l)) / EntryPrice(l);
                ETD = (ExitPrice(l) - HighestHigh[l]) / Highesthigh[l];
        End;
        IfMP[l] = -1 Then Begin
                FTE = (EntryPrice(l) - ExitPrice(l)) / EntryPrice(l);
                ETD = (LowestLc-wfl] - ExitPrice(l)) / LowestLowfl];
        End;
        If FTE < MAE[1] Then
                MAE = FTE Else MAE = MAE[1];
        If FTE > MFE[1] Then
                MFE = FTE Else MFE = MFE[1];
        SumFTE = SumFTE + FTE;
        SumETD = SumETD + ETD;
        SumMFE = SumMFE + MFE;
        SumMAE = SumMAE + MAE;
End;
If LastBarOnChart Then Begin
        FTE = SumFTE / TotalTrades;
        ETD = SumETD / TotalTrades;
        MFE = SumMFE / TotalTrades;
        MAE = SumMAE/TotalTrades;
        TradeStrl = LeftStr(GetSymbolName, 2) + "," + NumToStr(MAE, 4)+
        V + NumToStr(MFE, 4) + "," + NumToStr(FTE, 4) + "," +
        NumToStr(ETD, 4) + "," + NumToStr(TradeLength, 2) + "," +
        NumToStr(StopLoss, 2) + "," + NumToStr(TrailingStop, 2) + "," +
        NumToStr(ProfitTarget, 2) + NewLine;
        FileAppend(FName, TradeStrl);
End;
```

This code exports the MAE, MFE, and CTD values, together with the average profit, and the value of the input parameters for that particular run, each time the program loops through the market. For our purposes, we only need the average profit and the value for the inputs to keep track of all combinations. The others are there for other, but similar, analysis techniques, such as when exporting each individual trade or examining one exit technique at a time. Once we are done testing, we substitute for the random trade generator a high probability entry technique, knowing that we now should have a system that lets us trade marginally profitably or at least does not force us into too large disasters, no matter what the underlying market conditions look like.

The code above also illustrates another TradeStation feature. As you can see, for the stop loss we use the criteria If BarsSinceEntry 3= 1. This really should not be necessary, but without this line TradeStation sometimes exits the long on the first open following the entry, whether the trade is (or might have been) a winner or loser.

Because of this extra piece of code, we encounter another problem, which I already ranted about. That is, on the day you wait for this condition to come true (the first whole day in the trade, if you entered at the close the day before) the system does not recognize that you have a trade going. One way to work around this is to declare your own entry price variables, but that causes you a multitude of other problems further down in the code, like in the export function and on, and on, and on....

Okay, we must move on. After you have exported all the necessary data for the trade length and the stop loss into your spreadsheet program, you can use the same charting technique as we did in Part 2, when we examined different moving average length combinations. A *surface chart* is an excellent way to get a feel for how the output variable reacts to two different input variables and how the inputs are interacting with each other. The first chart, Figure 11.10, shows the average percentage profit as a function of the stop loss in percent and the trade length in days. For instance, with a stop loss of 1.3% and a trade length of eight days, the average profit comes out to somewhere between —0.1 and 0%. The trick is to try to find a squared area that is as large as possible, with a value for the profitable trade that is as high as possible. In Figure 11.10 there are two areas that look particularly promising. The first one is around the 0.7% stop loss and the other one around the 1.1 to 1.2% stop loss. The area surrounding the eight-day trade length and the 1.1% stop loss looks very interesting.

Figure 11.11 shows the standard deviation of the returns. In this chart we would like to find an area that is as large as possible, but has a value that is as low as possible. In this case we can see that, generally, the longer the trade length and the wider the stop loss, the higher the standard deviation. Obviously, we also need the standard deviation that we choose to coincide with an area of positive returns in Figure 11.10. The two charts in combination tell us that if we have two similar alternatives to choose from when it comes to the average profit, we should select the one with the narrowest stop and shortest trade length.

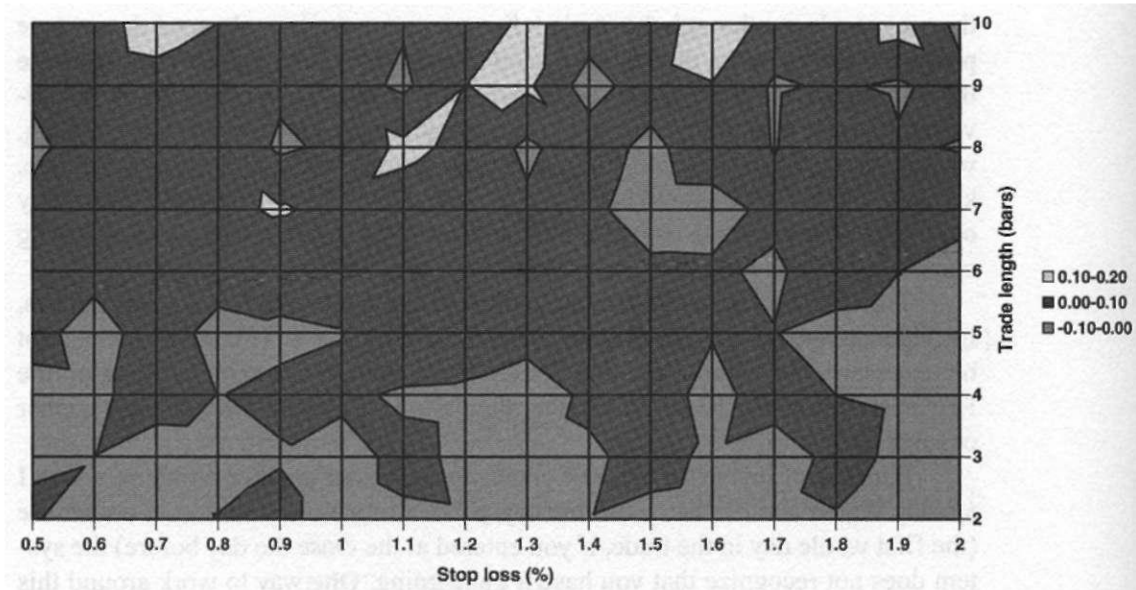


FIGURE 11.10

The percentage return from random entries as a function of the trade length and stop loss level.

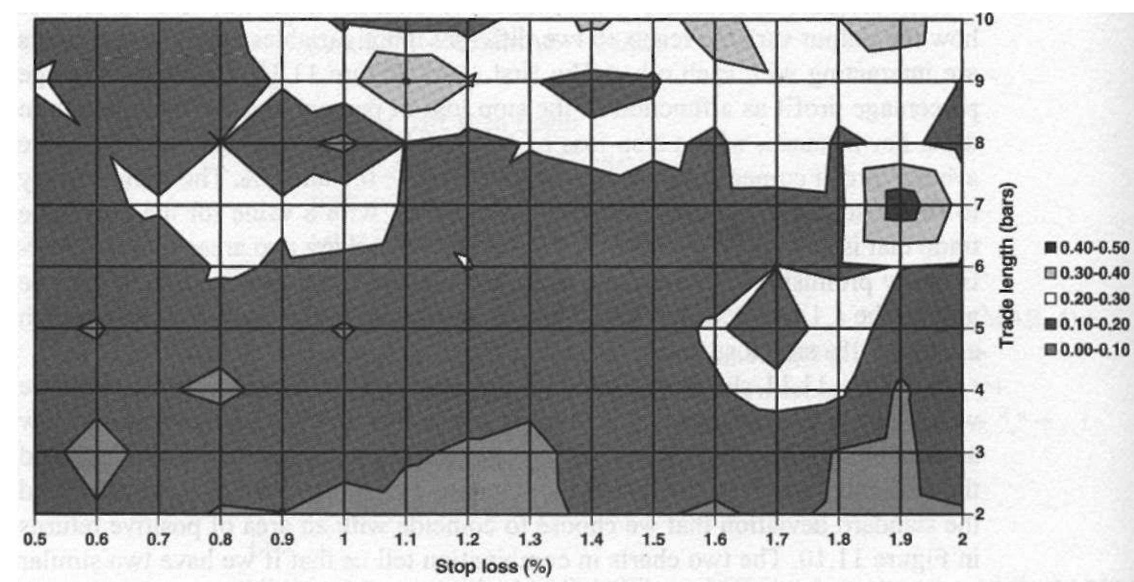


FIGURE 11.11

The standard deviation of the percentage returns as a function of the trade length and stop loss level.

Figure 11.12 shows the kurtosis for each stop loss/trade length combination. Here we also would like to find an area as large as possible with a value as low as possible and preferably also in negative territory. In this case too, we can see that, generally, the longer the trade length and the wider the stop loss, the higher the kurtosis. Finally, Figure 11.13 shows the skew, which should be as high as possible. In this case, it once again seems that the streak around the 1.2% stop loss looks most promising. In this case, it becomes difficult to keep it negative. It also seems that the kurtosis generally behaves the opposite way from the standard deviation. My rule-of-thumb is to give a higher consideration to the standard deviation and give the kurtosis the absolute lowest consideration.

To find the individual stop loss or trade length that is likely to be the most robust input parameter, no matter what happens with all the other input combinations, we also can look at separate kurtosis and skew tables for each input. Tables 11.13 and 11.14 show what these measures look like for each trade length applied to all the different stop loss values, and each stop loss value applied to every trade length, respectively. From Table 11.13 we can see that the skew increases with the trade length, which means that the longer the trade, the better off we seem to be. A similar relationship does not to exist for the kurtosis. When it comes to the stop loss both the kurtosis and the skew peak around the 1.2% level. This is good when it comes to the skew, but bad from a kurtosis point of view.

From Figures 11.10 through 11.13 and Tables 11.13 and 11.14 it seems as though a stop loss/trade length combination of 1.1 to 1.2% and seven to eight days

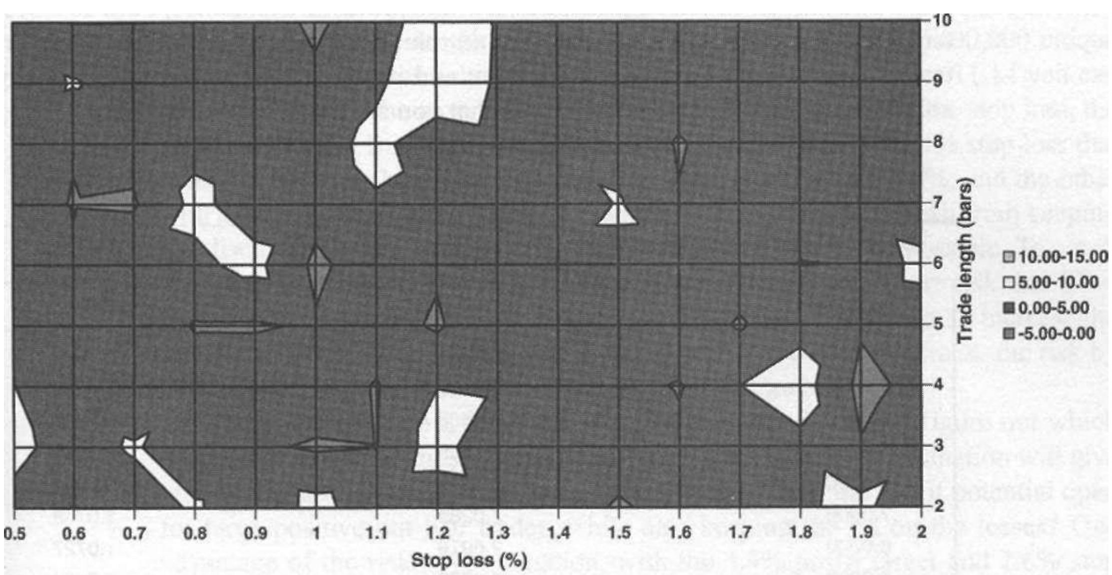


FIGURE 11.12

The kurtosis of the returns as a function of the trade length and stop loss level.

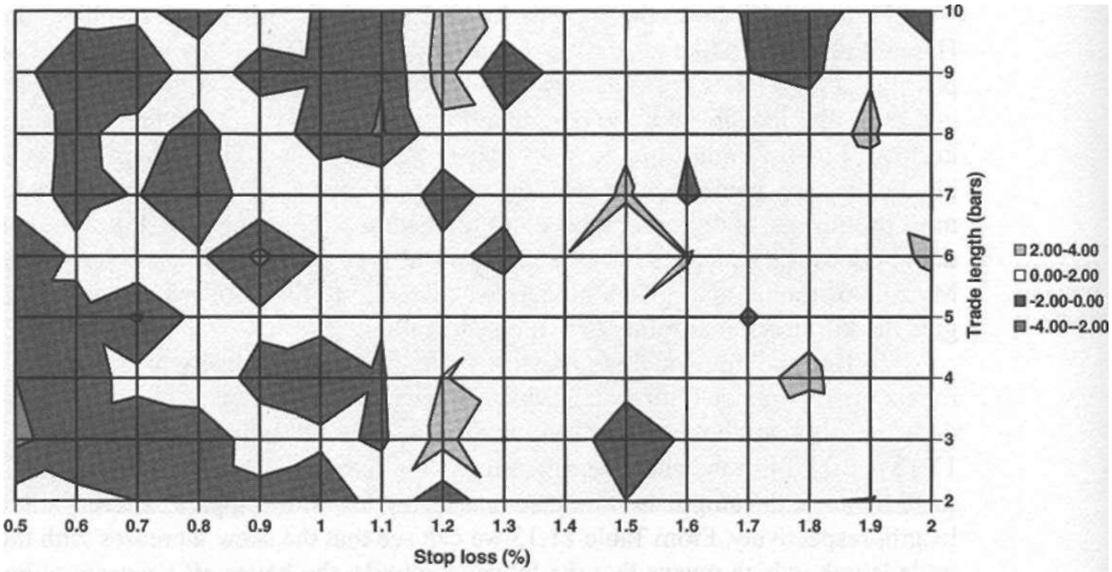


FIGURE 11.13

The skew of the returns as a function of the trade length and stop loss level.

has a lot going for itself. Remember these values when we move on to compare the stop loss in relation to the profit target. Note that despite all the fancy techniques and statistical measurements, this is where the system-building profession still is more of an art form than a science and where previous experience, both as a systems designer and as a trader, plays a vital role for the end result. It also is important to always keep in mind who you are and if you actually are psychologically able to trade and cope with the system that you are about to put together.

TABLE 11.13

Kurtosis and skew for the trade length.

Trade length	Kurtosis	Skew
2.0000	3.5569	-0.7034
3.0000	3.8781	-0.7326
4.0000	4.8803	-0.3035
5.0000	4.3825	-0.3015
6.0000	3.1974	0.6934
7.0000	7.0289	1.0748
8.0000	2.6979	1.0727
9.0000	4.4220	0.7154
10.0000	3.8914	1.2584

TABLE 11.14

kurtosis and skew for the stop loss.

Stop loss	Kurtosis	Skew
0.5000	4.0508	1.0517
0.6000	3.8028	1.1058
0.7000	2.7710	0.9926
0.8000	3.7190	1.1055
0.9000	5.0752	1.0647
1.0000	7.9998	2.0985
1.1000	10.0930	0.3240
1.2000	11.6853	2.4169
1.3000	4.2248	1.0409
1.4000	3.1491	0.8757
1.5000	2.1659	0.9603
1.6000	9.7810	2.0154
1.7000	2.9646	0.5511
1.8000	4.1007	-0.4604
1.9000	8.6028	1.2669
2.0000	4.8537	0.4595

Figure 11.14 shows the average return as a function of the profit target and the stop loss. As you can see, the profit target was tested for all values between 1 and 4% in increments of 0.2%. The profit target/stop loss tests were made the same way as the stop loss/trade length tests, but this time for a total of over 400,000 unique yearly trade sequences, which took forever and a day. From Figure 11.14 you can see that generally, the more distant the profit target and the wider the stop loss, the better the results. But there also are two smaller areas around the 1% stop loss that could be worth looking into: one with a profit target of about 2.8%, and the other with a profit target around 3.4%. The average return seems to benefit from keeping the distance between the stop and the profit target as wide as possible. To reach these returns, however, we must take on proportionally much more risk that if we choose to keep the profit target down to around 2.8%. For instance, to increase the return for the profit target by 21%, from 2.8 to 3.4%, we must increase the risk by 60%, from 1 to 1.6%>, which is not such a desirable trade-off.

With several alternatives like this, you must sit down and figure out which one will give you the most bang for the buck. That is, which combination will give you the highest average profit and at the same time keep the profit potential open for large positive out Iyer trades, while also keeping the lid on the losses? One advantage of the riskier combination, with the 3.4% profit target and 1.6% stop loss, is that it is surrounded by several other high-value areas, which means that it probably will continue to produce good results even if the true best values happen

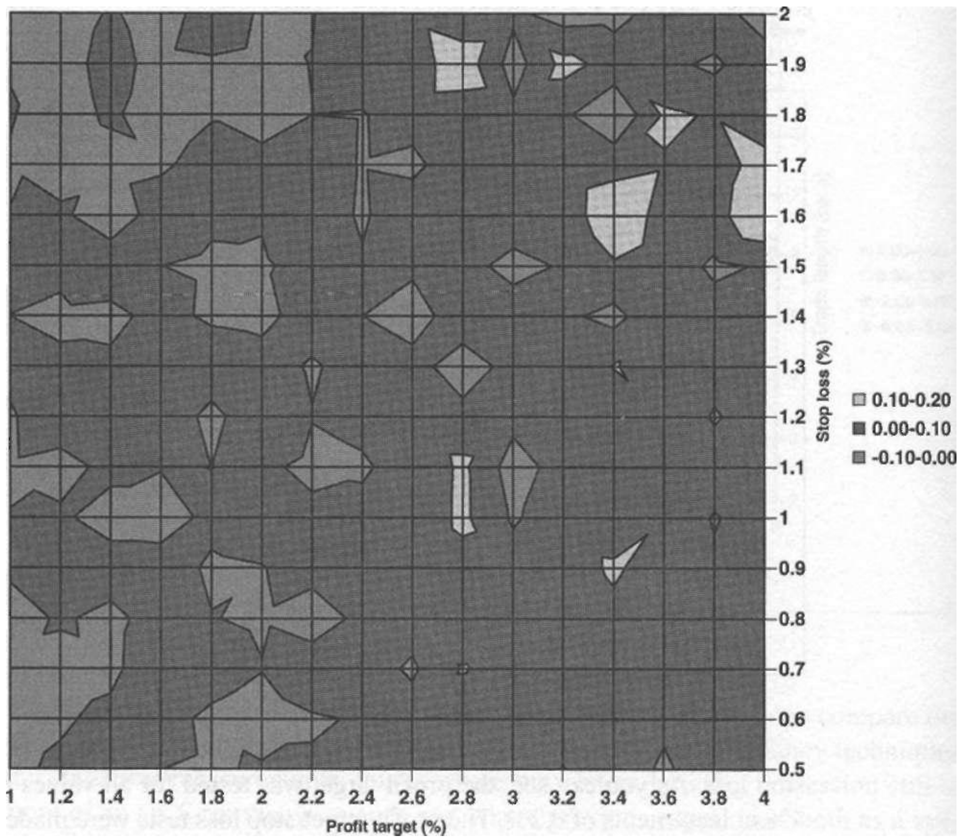


FIGURE 11.14

The percentage return from random entries as a function of the profit target and stop loss levels.

to move away from where we think they are. But, as noted, there is a price to everything in the market and only you can make the choices most suitable for you.

To make a choice like this, it also could be a good idea to look at the standard deviation chart which, in this case, shows that the standard deviation also increases the wider the stop loss and the more distant the profit target (chart not shown). Other charts and tables, such as those for kurtosis and skew also indicate that we probably would be better off with a stop loss somewhere in the 0.9 to 1.1% region, which also confirms our findings from the stop loss/trend length examination. Let us go with a stop loss of 1.1% and a profit target of 2.8%.

To come up with a trailing stop or minimum profit level we will run it against the time-based stop, testing all values between 0.2 and 1% in increments of 0.1%. This results in more than 125,000 unique yearly trade sequences. Parts of the result from this run can be seen in Figure 11.15, which shows the average profit in relation to different minimum profit levels and time-based stops. When testing for the minimum profit level, the criterion is that the market must have closed above a certain open profit and then moved below this level on a later bar for a trade to be closed out. A minimum profit of 0.6% produces fairly robust results, no matter what the maximum trade length happens to be. However, a maximum trade length of seven to nine days seems to be the most robust time window. This confirms what we already suspected when we analyzed Figure 11.10.

When it comes to the minimum profit level, you might also say that the market must close with a low above the desired level for all long trades or the high below the desired level for all short trades. This generally gives the system slightly more slack and results in fewer trades getting closed out at the minimum profit level, slightly more trades getting closed out at the maximum profit target, and a bunch of trades somewhere in between because of the time-based stop. There also will be a bunch of trades closed out with a loss, because they never managed to fulfill the more stringent criterion for the profit protection stop to kick in.

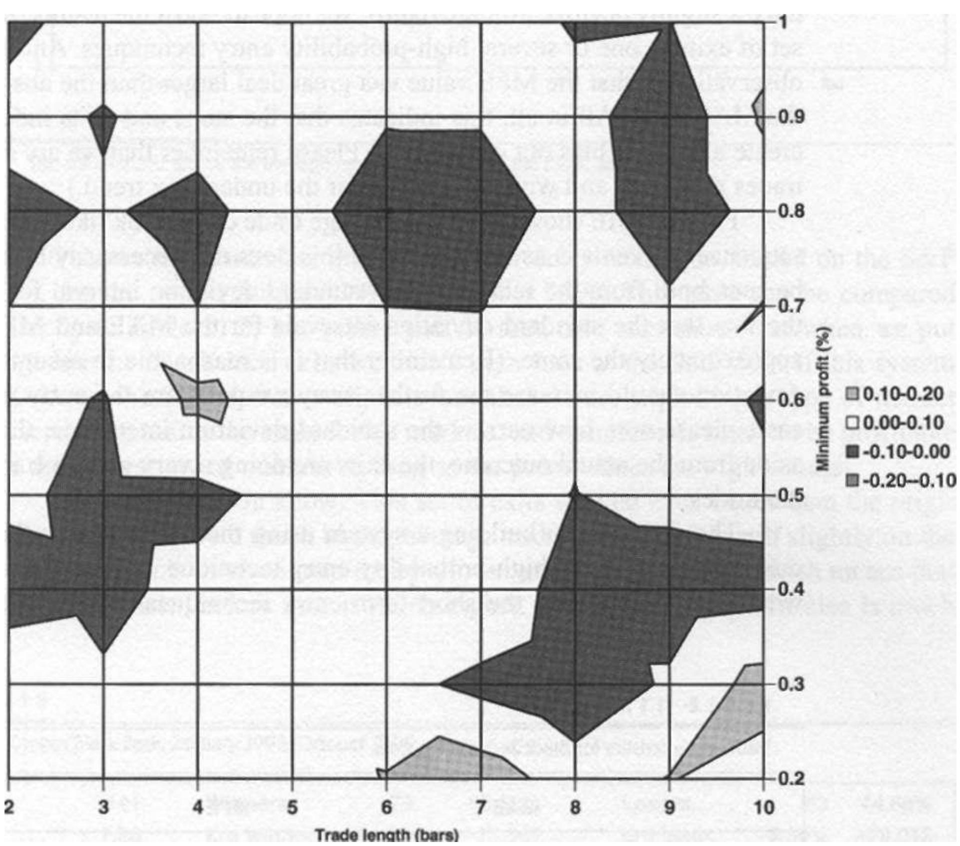


FIGURE 11.15

The percentage returns from random entries as a function of the trade length and minimum profit level.

As you can see from Figure 11.15, it seems that our best alternative is a minimum profit level of 0.6% together with a trade length between seven to nine days. This confirms our previous findings about an eight-day maximum trading horizon. Thus, the final system has the following exit rules:

- Exit with a loss if the market moves the wrong way by 1.1%
- Exit with a profit if the market closes with a 0.6% open profit and then moves below this level.
- Exit with a limit order if the open profit exceeds 2.8%).
- Always exit at the close at the eighth day of the trade.

The summarized results from adding these exits to the system, together with the export function for the RAD contract, can be seen in Table 11.15. As you can see, the average final profit is only one hundredth of a percent. It isn't much, but at least it's there. Of course, an expected return this small is not tradable, but the point is that just by using a set of logical exits and stop techniques, we managed to produce a slightly positive average return. We hope to boost the results by applying this set of exits to one or several high-probability entry techniques. Another interesting observation is that the MFE value is a great deal larger than the absolute value for the MAE level. All in all, this indicates that the stops and exits indeed manage to create a positive bias out of nothing. (Please remember that we are still placing all trades randomly and with no concern for the underlying trend.)

Figure 11.16 shows what the average trade could look like, assuming that the sequence of events is as outlined. That this does not necessarily have to be so can be seen both from the relatively low standard deviation interval for the close and the fact that the standard deviation intervals for the MAE and MFE seem to be approximately the same. (Remember that it is reasonable to assume the standard deviation should increase the further away we get from the entry.) Whatever the case, please note how narrow the standard deviation interval is; that means that, aside from the actual outcome, the exits are doing a very good job in streamlining the trades.

The next step in building a system using the Black Jack technique is obviously to attach it to a high-probability entry technique. Let us see how these exits would have fared with the short-term entry techniques already discussed. Table

TABLE 11.15

Trade characteristics for Black Jack system exits.

	MAE	MFE	Final profit
Average	-1.0841	1.3200	0.0140
St Dev	0.3192	0.3652	0.1203

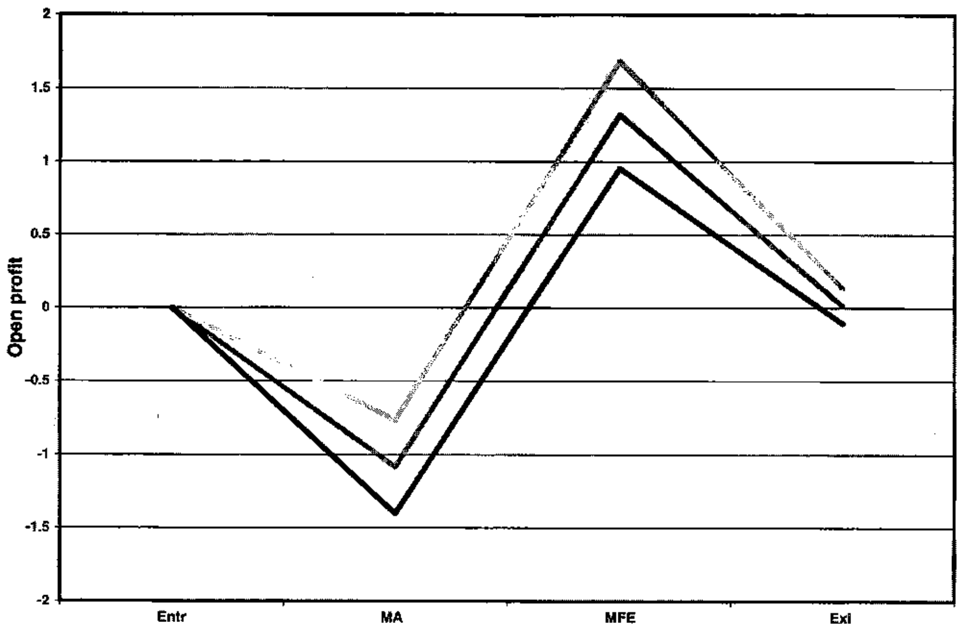


FIGURE 11.16

The summarized life for the average random trade, using the Black Jack exits.

11.16 shows the results for the Gold Digger entry technique, traded on the S&P 500, for the period January 1995 to October 1999. This table can be compared directly to Table 11.3, but before you do that, also remember that when we put together the Black Jack exits we didn't even look at the S&P 500. If this system works on the S&P 500 as well, it means that we are exploiting a type of market discrepancy that is the same for all markets, and therefore, is likely to be profitable on a wide variety of markets as long as the point values are high enough.

And what do you know! This set of exits worked even better than the originals. First, we have a much higher average trade, although it is still slightly on the low side. This is compensated for by a lower standard deviation, which means that the risk-adjusted return now is much higher. The cumulative profit also is much

TABLE 11.16

Results for Gold Digger/Black Jack, January 1995-October 1999.

Total trades		141	Winners	78	55.32%	Losers	63	44.68%
Profit factor		1.26	Lrg winner	5.14%	17,348	Lrg loser	-8.30%	-28,013
Avg profit	0.17%	569	Avg winner	1.49%	5,031	Avg loser	-1.47%	-4,955
St Dev	1.88%	6,348	Cum profit	23.68%	79,920	Drawdown	-15.66%	-52,853

higher, as is the percentage of winning trades. On the negative side, we see that the drawdown is slightly higher as well.

When we built the Gold Digger system, we used the period January 1985 to December 1994 for some out-of-sample testing, which naturally put the lid on the results when compared to the optimization period. The out-of-sample period was, furthermore, much larger in size, which meant that it should hold more unfavorable market conditions. Therefore, it is likely that a comparison with that period will come closer to the truth regarding what the Gold Digger/Black Jack combination really is worth. Compare Tables 11.17 and 11.5.

The truth is that if you have built a system exactly right, any market condition that does not exactly parallel the conditions under which you built the system will be unfavorable. Because if you have built a system exactly right, you will have squeezed out every ounce of information the market holds and the system will therefore have a positive bias, but behave as if the individual results were dropping in randomly. The reason for this is, as long as the system does not behave in this random fashion, the outcome is predictable, and if something is predictable there is more information to squeeze out. If the conditions have changed from one time to another that means that there is more and newer information to squeeze out, and the system will now perform on a suboptimal level—even if it temporarily might produce better-than-expected results.

The above reasoning also puts a twist to another interesting question. Is there such a thing as a system that (seemingly) could be doing too well? For instance, say that you have put together a system that is expected to produce an average profit of 1%. But after you have traded the system for a while you realize that the average profit, in fact, has been closer to 2%. What to do? The answer is, examine the system closely and try to find out what is causing these excess returns and adjust the system to take these causes into consideration. Because the truth is that when the system is not working as intended, you do not know what you are doing; what might cause excess returns might also be the reason why you have to sell your house tomorrow.

Tested over the period January 1985 to December 1994, the Gold Digger/ Black Jack combination has a lower profit factor and average trade than the Gold Digger system alone. When it comes to the percentage profitable trades and standard deviation, on the other hand, Gold Digger/Black Jack excels. It also is interesting to

TABLE 11.17

Results for Gold Digger/Black Jack, January 1985-December 1994.

Total trades		292	Winners	159	54.45%	Losers	133	45.55%
Profit factor		1.20	Lrg winner	7.62%	25,718	Lrg loser	-12.61%	-42,559
Avg profit	0.12%	407	Avg winner	1.31%	4,412	Avg loser	-1.30%	-4,381
St Dev	1.74%	5,864	Cum profit	35.80%	120,825	Drawdown	-15.88%	-53,595

note that the results for the out-of-sample period no longer differ that much from those of the in-sample period, which means that, although the profit potential is somewhat low, at least the results are very robust over time.

For the Meander/Black Jack combination, the results are a little more inconclusive. Table 11.18 shows how this system would have performed during the optimization period, and is directly comparable to Tabic 11.9. As you can see, this system has a slightly lower profit factor and average profit per trade. The percentage of profitable trades also is lower. On the positive side, however, there is a quite dramatic decrease of maximum drawdown, from an already low 10.8% to a very low 7.8%.

When it is tested on the out-of-sample period, two sad things happen with the Meander/Black Jack combination. The most obvious thing, when we compare Tables 11.19 and 11.11, is that it continues to be outperformed by the original Meander system. What is even worse is that the results for the out-of-sample period are no longer similar to those from the in-sample period. As you can see, the average profit now has decreased to 0.22%, while the profit factor is down to 1.32. The drawdown also has increased to 15.8%. One positive thing is the slightly lower standard deviation, as compared to the original system, but because the ratio between the average profit and the standard deviation still comes out much lower, this does not help much.

The Black Jack exits are not as good together with the Meander system as those developed specifically for this system. The question we then must ask ourselves is if we should stick to the original exits because we know they work well with this particular system, or switch to the Black Jack exits, because they should work well, on average, with any type of entry technique?

To answer this question, we must go back and look at the differences between the two sets of exits. In doing so, we can see that there are three major differences. First, the profit target is much further away from the entry in the original set of exits. Second, the original set of exits also operates without a time-based stop. This means that we are letting the profits run "more fluently," so to speak, with the original set of exits, making the most of what seems to be a very strong entry technique. Finally, the stop loss is also further away from the entry in the original set of exits, which means that we are putting more trust into the entry signal. This confirms the reasoning behind points number one and two, because the better the

TABLE 11.18

Results for Meander/Black Jack, January 1995-October 1999.

Total trades		79	Winners	44	55.70%	Losers	35	44.30%
Profit factor		1.67	Lrg winner	4.88%	16,470	Lrg loser	-5.74%	-19,373
Avg profit	0.39%	1,321	Avg winner	1.75%	5,902	Avg loser	-1.32%	-4,440
St Dev	1.90%	6,379	Cum profit	34.24%	115,560	Drawdown	-7.76%	-26,190

TABLE 11.19

Results for Meander/Black Jack, January 1985-December 1994.

Total trades		136	Winners	7	52.21%	Losers	6	47.79%
Profit factor		1.32	Lrg winner	21.92%	73,980	Lrg loser	-11.21%	-37.834
Avg profit	0.22%	731	Avg winner	1.72%	5,793	Avg loser	-1.42%	-4,799
St Dev	2.76%	9,299	Cum profit	25.64%	86,535	Drawdown	-15.79%	-53,291

entry signal, the more trust we should give it and not worry so much if the market does not happen to take off in the right direction immediately.

The answer then, seems to be to stick to the original set of exits. This is also a matter of personal choice. Personally I really like the reasoning behind the Black Jack exits. Therefore, that's the set I will stick with, under the assumptions that these things will even out over time and if there is one thing that the version with the Black Jack exits is not, that's curve fitted. (By the way, there is nothing keeping you from trading each entry technique with several sets of exit techniques, anyway.)

Finally, let us compare this new set of exits with those that we created for the original Black Jack system in Part 2. Table 11.20 shows what this Black Jack/Black Jack combination looks like when traded on the S&P 500 over the period January 1995 to October 1999, while Table 11.21 shows the results for the period January 1985 to December 1994. Note that neither table is directly comparable to Table 5.14 which shows the results for both these periods combined.

However, just by comparing Tables 11.20 and 11.21 we can come to a few interesting conclusions, the most obvious being that what worked during one time period did most definitely not work in the other. This is very interesting and becomes even more so if we also mix in what we discovered about the original Gold Digger system in Tables 11.3 and 11.5, where the scenario was exactly the opposite.

Obviously, had we put together an entry/exit combination like Black Jack/Black Jack, with a profit factor of 1.03 and an average profit per trade of —0.08% in early 1995, we would not have traded it. Instead, it is quite reasonable to assume that we would have started to trade the Gold Digger/Black Jack combi-

TABLE 11.20

Results for Black Jack/Black Jack, January 1995-October 1999.

Total trades		87	Winners	59	67.82%	Losers	28	32.18%
Profit factor		2.16	Lrg winner	3.09%	10,429	Lrg loser	-2.90%	-9,788
Avg profit	0.50%	1,695	Avg winner	1.38%	4,654	Avg loser	-1.35%	-4,541
St Dev	1.59%	5,352	Cum profit	53.00%	178,875	Drawdown	-4.01%	-13,534

TABLE 11.21

Results for Black Jack/Black Jack, January 1985-December 1994.

Total trades		202	Winners	9	48.02%	Losers	10	51.98%
Profit factor		0.89	Lrg winner	4.12%	13,905	Lrg loser	-6.29%	-21,229
Avg profit	-0.08%	-257	Avg winner	1.24%	4,199	Avg loser	-1.30%	-4,373
St Dev	1.54%	5,197	Cum profit	-16.35%	-55,181	Drawdown	-26.05%	-87,919

nation. But with the help of hindsight, we now know that we in fact should have thrown away the Gold Digger/Black Jack combination and started to trade the Black Jack/Black Jack combination.

So what does this teach us? It teaches us that it is paramount to make sure that the system works, on average, equally as well over several time periods and markets, and that the input parameters we are using are robust enough to be trusted. From just looking at the results for the period leading up to December 1994, we had no way of coming to that conclusion. It also tells us that even a market/system combination that we trust completely will go through dry spells and that we never should place all our eggs in one basket (more about that in Part 5). Because—as already pointed out—whether a system works better or worse than expected, in both cases you are taking a walk on the wild side, and exactly the same environment that seems to be so friendly this very moment will eat you alive in five minutes if you haven't made sure that you have other alternative routes of action when danger strikes.

PART THREE

A Few Final Thoughts About Part 3

In this part, we discussed the various forms of drawdown with which you must be familiar, or at the very least be aware of, when you are examining your trading systems. If you are not aware of where and when the drawdown happens, you do not know what means you must use to come to grips with it. Then it does not matter how much you might think you know about other, related topics such as trade efficiency, maximum adverse excursion, and maximum favorable excursion.

After we explored those topics as well, we set out to better the systems developed in Part 2 by adding a set of tailor-made stops and exits to each system, basing a lot of our findings on random entries, derived with the help of TradeStation's random number generator. (By the way, if you are using an older version of TradeStation, you should be able to download a random number generator, courtesy of Dave DeLuca at Trade Works Software, at the following Internet site: www.mechtrading.com/tradestation/random.html.)

In Part 3, we also introduced a set of new statistical measures to help us evaluate a system's performance quickly and efficiently. In particular, we made use of kurtosis and skew. These two measurements will continue to be used in Part 4, where we take a closer look at different ways of filtering out favorable, long-term market situations.

I hope you also have noticed how almost every single system has been applied to a broad selection of markets, and that I have used almost no market-specific parameter settings whatsoever. True, most of the short-term systems have only been applied to the S&P 500, but the reason for that is simply that the S&P 500 is one of the few markets that is worth trading short-term.

Remember—a well-working system does not have to be a profitable system, but a profitable system also is a well-working system. The difference lies in how we define well-working and profitable. By well-working, we mean a system that does a good job catching a specific type of move in several different markets, ending up with a positive return measured in percentage terms. We use percentage terms, because that is a universal measure that allows us to ignore other market technicalities such as the point value or the current trading level.

By a profitable system, on the other hand, we mean a well-working system that achieves a positive return in dollar terms, as well as in percentage terms. Because all markets are trading at different levels and with different point values, however, not all well-working systems will be profitable on all markets. As far as the system goes, it all comes down to what type of move we want it to catch. But perhaps even more important, no system will trade profitably if the necessary prerequisites are not there, namely a high enough dollar value per point in relation to where the market is trading and low enough costs in relation to this level.

PART FOUR

High-probability Filters

To continue to trust your trading strategy after a long dry spell, especially if at the same time, the market is breaking out to record highs or lows, is very difficult and probably the first reason why so many of us fail as traders. If only there was a way to tell when to take the signal, when not to take the signal or, heaven forbid, perhaps even when to fade the signal. Basically, there are two ways of filtering out high-probability trading opportunities and the question you should ask yourself is, "Is it better to trade with the long-term trend and can the short-term volatility help to determine the outcome of the trade?" This is an important question that all traders should ask themselves, and the only way to find out is to do the necessary research.

CHAPTER 12

Filtering

Besides filtering, *indicator piling* is especially popular among new traders and a horrifying number of broker-type salespeople who, in one way or another, make their living explicitly out of you instead of out of the markets. Indicator piling is executed by piling several similar indicators and "expert commentaries" on top of each other in the high hopes that one day, when they all move in unison, you will have a sure winner. Never mind that they all give different answers, and with 10 indicators on your screen and only one being the "right one," you actually have a 90% chance of coming to the wrong conclusion if you look at each one at a time; not to mention what the odds are if you combine them all.

Nonetheless, this inefficient and risky method is favored by most trading program vendors. Aren't these guys pros, you might ask, shouldn't they know better? Well, they might or might not know better, but the only way they can make money out of the wanna-be trader is to sell him their trading program. And the fastest way they can do that is to show him the fancy looking indicator-piling technique. (At least this is my experience from more than three years of watching these guys and their marketing tactics from a very close distance.) If you still are fairly new to this game, please do not buy into this method. You do not need all those indicators—even though vendors compete with each other to develop the program that has the most.

Once you're past the piling stage (which you probably are, since you've read this far), the most obvious thing to test for first is to see if there is anything to be gained from only going with the longer-term trend. The longer-term trend can be determined in several different ways, the simplest (but certainly not the easiest) being your own fundamental and discretionary judgment about where the economy in general, and your markets or stocks in particular, are heading. Then stick to that prognosis over a prolonged period of time. (Presented later is a more thorough discussion of what makes a trend and how this knowledge might add a more theoretical, or even philosophical, aspect to the way you might perceive your role as a market participant and what it is you are trying to achieve.)

Alternatively, you could simply only trade in the same direction as a long-term moving average. In a series of articles for *Futures* magazine, "Skimming the Trend" and "Fading Away," (February 1999), and "In the Pudding," (March 1999), and in the April 2000 issue of *Active Trader Magazine,* I concluded that trading only in the direction of a 200-day moving average does, indeed, increase results significantly. This holds true even if you enter the markets randomly, as long as you take trades only in the direction of the underlying trend and stick to the same exit strategy for all trades.

Table 12.1 shows the result of entering 16 different markets randomly in any direction over the time period January 1980 to October 1999, as compared to entering randomly but only in the same direction as a 200-day moving average. Each market was traded 12 times, creating a total of close to 3,500 unique yearly trading sequences per strategy. In both strategies, I stayed in each trade for five days, come rain or come shine. The 16 markets traded were D mark, crude oil, lumber, copper, gold, dollar index, live cattle, T-bonds, cotton, Japanese yen, natural gas, wheat, Nikkei index, coffee, T-bills, and rough rice.

Without the trend filter, only seven markets had an average profit factor above one, but for none of them can we say with 68% certainty that the true profit factor is above 1. For instance, with an average profit factor of 1 and a standard deviation of 0.19, we cannot say with 68% certainty that the true profit factor for rough rice is above 1. For all markets combined, the true profit factor is with 68% certainty likely to be found somewhere within the interval 0.88 to 1.12.

With the trend filter, however, all markets but one (natural gas) had an average profit factor above 1 and for a total of nine we also can say that we can be 68% sure the true profit factor will be above 1. For all markets combined, the average profit factor comes out to 1.16, with a standard deviation of 0.13. This means that we can be 68% sure that the true profit factor for all market will lie somewhere in the interval 1.03 to 1.29. (Similar observations that support the findings regarding the profit factor also can be made for the percentage of profitable trades.) Thus, with a simple test like this we prove the benefits of always trading with the long-term trend, even when we enter randomly and with such a simple exit technique as always exiting after five days. Imagine what we could do if we were to optimize a trend-monitoring strategy with a set of well-researched entry and exit techniques.

TREND FILTERS FOR SHORT-TERM SYSTEMS

A basic moving average filter should form the base of any filter testing procedure, in which you test which lookback period works best together with the original entry technique on a wide variety of markets.

TABLE 12.1

A simple 200-day moving average trend filter.

	Without trend filter				With trend filter			
Market	Profit factor	St Dev	% profitable	St Dev	Profit factor	St Dev	% profitable	St Dev
D-mark	0.98	0.07	52.45	1.90	1.21	0.11	56.08	2.24
Crude oil	0.94	0.16	50.10	2.01	1.15	0.15	56.21	1.83
Lumber	0.98	0.11	50.68	1.79	1.23	0.09	53.56	1.64
Copper	0.97	0.06	50.11	1.59	1.25	0.10	51.43	1.96
Gold	1.04	0.18	50.98	1.82	1.11	0.13	52.23	1.52
Dollar index	1.02	0.09	50.26	2.63	1.18	0.13	52.65	2.23
Live cattle	1.04	0.09	50.43	1.96	1.06	0.11	52.42	1.76
T-bonds	1.04	0.11	50.14	2.21	1.22	0.09	54.81	1.75
Cotton	0.97	0.11	50.09	1.76	1.22	0.11	54.05	1.94
Japanese yen	0.99	0.11	52.24	1.88	1.22	0.08	56.56	1.52
Natural gas	1.03	0.12	49.76	3.46	0.99	0.11	49.26	1.86
Wheat	1.03	0.10	51.15	1.64	1.11	0.11	53.03	1.57
Nikkei index	0.97	0.15	50.60	3.51	1.09	0.11	54.26	1.99
Coffee	1.00	0.13	49.87	2.40	1.06	0.09	51.60	1.65
T-bills	1.01	0.14	51.53	1.95	1.20	0.16	55.32	1.78
Rough rice	1.00	0.19	50.19	2.62	1.26	0.13	55.26	2.25
All markets	1.00	0.12	50.66	2.32	1.16	0.13	53.67	2.65

Alternatively, you could incorporate the on-balance-volume (OBV) indicator that weights each day's price action with its volume, creating a new time series that holds both price and volume information. In this way, the time series increases/decreases more in value the more volume there is behind the move of the price, the interpretation being the same as for the moving average of price. That is, when the OBV indicator is above its long-term moving average the trend is up and when it is below, the trend is down. Personally, I think this is one of the best and most versatile indicators there is, because of its ability to in one single and simple calculation, cover everything there is to know and monitor in the field of technical analysis, namely, the psychology of the masses. Figure 12.1 shows what this can look like for the S&P 500, when charted together with the OBV indicator and its 200-day moving average.

One important thing to remember when looking at Figure 12.1 is that the trend, as you decide to define it, does not necessarily have to coincide with the actual trend of the price chart. For instance, according to this indicator, which also takes the volume behind the move into consideration, the trend for the stock market has been down since July 1998, although we all know that the prices have not fallen much (if any). In this case, however, the OBV indicator tells us that the volume on

FIGURE 12.1

The S&P 500 futures contract charted together with a 200-day moving average and the OBV indicator.

the down side has increased, while there has been a diminishing volume on the up side, making it increasingly harder to trade any rallies successfully. Also, there is nothing keeping you from having several different strategies, based on several different trend filters. It is important to stay consistent with your beliefs and trust what your research has shown you for that particular system.

If you like to take a more fundamental approach, you instead could calculate a ratio between the market of your interest and the short-term interest rate, such as that of the T-bill. The reasoning behind this indicator is that when the price for T-bills is increasing faster than the price for "your market," many market participants prefer the safe haven of interest rates instead of taking the chance of investing in a market that they deem to have a very low profit potential. This could present a good opportunity to go short, especially if "your market" starts to decline as well. If the opposite holds true, however, and your market is increasing faster in price than the T-bills, more and more investors now prefer to buy the market instead of staying in interest rates. This could present a good opportunity to go long. Again, the method is the same as for the basic moving average filter. With the help of a long-term moving average we can decide whether or not the money is flowing into or out of the market in which we are interested.

Finally, I use another method that sort of turns the entire reasoning around. With the three methods above, we strive to trade in the direction of the underlying trend, but because many short-term systems try to enter with limit orders, there might be plenty of contradicting signals—short-term entry signals saying "buy" and long-term trend filters saying "sell." To work around this, you might formulate a rule that says, "as long as the trend is *not* down, I can go long, and as long as the trend is *not* up, I can go short." One way of doing this is to use a basic highest high/lowest low breakout indicator, which says that as soon as we make a new high (low) the long-term trend is up (down) and, as long as the short-term limit order, sell (buy) signal does not collide with a new high (low), we can take the trade.

In this chapter we test a few versions and different lengths of these trend filters, together with all our short-term systems, on a portfolio of different markets to see if there is anything to be gained from adding filters to the systems as they function so far.

For the basic price filter, the OBV filter, and the T-bill ratio filter we test if it is better to go with the slope or the crossover of their respective moving averages. This counts for a total of six different filter techniques. For each moving average filter, 10 different lengths of the moving average will be tested, ranging from 50 to 250 days, in steps of 20 days. For the breakout filter, the lookback period will vary from 20 to 120 days, in steps of 10 days. Each trade is entered randomly, but only in the same direction as the underlying trend, as indicated by the filter, and each market is traded 10 times for God knows how many trades and unique yearly trading sequences—certainly enough to let us come up with some meaningful conclusions anyway. The exit strategy for all markets and filters is the generic exits and stops combination we derived in Part 3. The 16 markets tested over the period January 1980 to October 1992 are D mark, crude oil, lumber, copper, gold, dollar index, live cattle, T-bonds, cotton, Japanese yen, natural gas, wheat, Nikkei index, coffee, S&P 500, and rough rice.

In TradeStation, the code for taking a short position with any of these filters, together with a simple export function that exports the value of the average trade for each time the system runs through the market, looks something like this:

```
Inputs: Counter(O), SystemSwitch(O), OBVLen(O), MALen(O), RaLen(O),
BOLen(O);
Vars: TotTr(O), MP(0), FTE(O), Firstlnput(O), TradeStrl("");
If (SystemSwitch =3 and OBV < Average(OBV, OBVLen)) Or
(SystemSwitch =4 and Average(OBV, OBVLen) < Average(OBV, OBVLen)[l]) Or
(SystemSwitch =5 and Close < Average(Close, MALen)) Or
(SystemSwitch =6 and Average(Close, MALen) < Average(Close, MALen)[l]) Or
(SystemSwitch =7 and Ratio < Average(Ratio, RaLen)) Or
(SystemSwitch =8 and Average(Ratio, RaLen) < Average(Ratio, RaLen)[l]) Or
(SystemSwitch =9 and Close < Highest(Close, BOLen)) Then
    Sell at Close;
If TotTr > TotTrfl] Then Begin
    If MP[1] =1 Then
        FTE =(ExitPrice(l) - EntryPrice(l)) / EntryPrice(l);
    IfMP[l] =-1 Then
        FTE =(EntryPrice(l) - ExitPrice(l)) / EntryPrice(l);
    SumFTE = SumFTE + FTE;
End;
If LastBarOnChart Then Begin
    If SystemSwitch =3 or SystemSwitch =4 Then
        Firstlnput = OBVLen;
    If SystemSwitch =5 or SystemSwitch =6 Then
        Firstlnput = MALen;
    If SystemSwitch =7 or SystemSwitch =8 Then
        Firstlnput = RaLen;
    If SystemSwitch =9 Then
        Firstlnput = BOLen;
    FTE = SumFTE / TotalTrades;
    TradeStrl =LeftStr(GetSymbolName, 2) + "," + NumToStr(FTE, 4) +
    "," + NumToStr(FirstInput, 2) + NewLine;
    FileAppend("D:\Temp\LT-Filter.csv", TradeStrl);
End;
```

With this code you can set up a workgroup containing all the markets you would like to test, and run the system optimizer on all markets at once. While the computer is chewing away, go do something else for a change, because this can take a while. By the way, be careful when you are exporting data from TradeStation while using the optimizer. For some reason, when the optimization is done, the program once again runs through and exports the results for the "best" input variable combination, not once, but twice, and sometimes even three times! Weed out these extra runs from your spreadsheets manually before you do any further analysis.

When it comes to volatility, in any market, higher volatility also means higher risk because of the greater likelihood that the market can move against you. Obviously then, from a safety point of view, the lower the volatility the better. The problem is that especially for shorter-term trading, high volatility also means a higher profit potential. The trick is to find those short-term situations when the volatility is high enough to make it worthwhile to trade but not so high that only a fool would enter the market. But because there is more than one way to measure volatility, how do you know which method will give the most accurate reading?

The truth is, nobody knows, and your guess is as good as mine. Probably the most common way is to calculate the standard deviation of the closes, which is basically what you do if you are an options trader and, therefore, work with different option pricing formulas, such as *Black and Scholes* or *Black-76.* However, over the last couple of years there seems to be at least one method that has emerged as the most popular among technical analysts. This is the *true range* or *average true range method* that states that when the true range of today's price action is below the average true range for a specified lookback period (sometimes multiplied by a chosen factor) the most recent volatility is lower than expected, and hence, the market is about to calm down and become less risky to trade, no matter the direction of the potential trade. The true range is defined as the distance between today's high (low), and today's low (high) or yesterday's close, whichever produces the largest distance.

To test if there is any validity to this commonly used technique, I set out to test this technique over several different lookback periods, ranging from 10 to 40 days, in steps of three days, using the same markets and set up as for the long-term filters. The rule was not to take a trade in any direction if the most recent volatility (true range) was higher than the average volatility (average true range) over the lookback period.

The main disadvantage, however, with both the standard deviation method and the average true range method is that none takes the direction of the volatility into consideration. For instance, in a strongly up-trending market that only climbs higher and higher, it is obvious that most, if not all, of the volatility is to the up side. This, in turn, is of course very good if you are long in the market but not so good if you are short. Therefore, it also could be a good idea to try to use some sort of volatility measure that can tell the difference between up volatility and down volatility, or better yet, when the market is about to shift from a higher down volatility to a higher up volatility, and vice versa.

Fortunately, there are a few methods that readily lend themselves to this purpose. If you have studied the math behind many of the most commonly used oscillators that you can find in most technical analysis programs, you will realize that two of these indicators are your regular everyday technical analysis tools, the *RSI indicator* and the *ADX indicator.*

In the RSI indicator, the reasoning is simple enough. When the indicator reading is above 50, the upward volatility is stronger than the downward volatility, and vice versa. For the ADX indicator, however, it is slightly more complicated, because a high ADX reading could mean either a strong upside volatility or a strong downside volatility. Therefore, instead of using the ADX indicator, it is better to use two of the components upon which it is built, the *DMI-plus* and *DMI-minus lines.* With the DMI-plus line above the DMI-minus line, the upward volatility is greater than the downward volatility, and vice versa. For the RSI indicator you also can experiment with different trigger levels and, for example, only allow long trades if the RSI reading is above 60 and short trades if the RSI reading is below 40, leaving the area in between as a neutral zone. You also could add to that the usual overbought/oversold technique and not go long (short) if you consider the RSI to be too high (low).

To test if these two indicators could serve as filters for our short-term trading models, I set out to test them with lookback periods ranging from 10 to 40 days in steps of three days. The rule was only to take a trade in a specific direction if the volatility reading suggested that the volatility was stronger in that direction as well. For this I used the same markets and general setup as for the long-term filters and for the average true range filters. The TradeStation code for all the volatility filters basically looked the same as for the trend filters.

The results for all filters were then summarized in separate tables, as shown in Tables 12.2 and 12.3, which show the results for the basic moving average crossover filter and the breakout filter, respectively. For instance, for the 50-day MA cross filter the average profit per trade was 0.12%, from trading all 16 markets 10 times, using random entries and the Black Jack exits were derived in Part 3. The most robust results seem to be around the 110- to 170-day area, with the absolute best risk-reward alternative being the 110-day average. Because the true best average might move around, I decided to go with the 130-day alternative. This is how you must reason in any type of optimization procedure.

If the results look promising for the regular moving average filter, the opposite holds true for the breakout filter. For instance, with a 60-day lookback period and the exact same set up as for the moving average filter, the breakout filter only managed to produce an average profit per trade of 0.05%, which also seems to be the best alternative after we have measured in all the other variables, such as the

TABLE 12.2

MA cross filter, January 1980-October 1992.

Length	Average	St Dev	Ratio	Kurtosis	Skew
50	0.1201	0.2071	0.5799	6.2312	2.0777
70	0.1186	0.2116	0.5606	6.1378	1.3598
90	0.0821	0.1400	0.5863	4.5955	0.2875
110	0.1252	0.1766	0.7088	8.2450	1.3125
130	0.1131	0.1722	0.6568	4.6584	0.8590
150	0.1058	0.1718	0.6157	4.5265	0.1703
170	0.1139	0.1715	0.6641	10.4910	-0.9180
190	0.0818	0.1578	0.5181	4.6071	-0.5006
210	0.1001	0.1525	0.6563	18.6751	-2.9483
230	0.1023	0.1538	0.6654	8.3662	0.6040
250	0.1202	0.2020	0.5950	13.4122	0.2106

standard deviation, the kurtosis, and the skew. As we will see, however, just because one filter seems to be inferior to another at this stage of the testing procedure it does not mean that it will not work in the end.

For all different lookback periods for all different filters I picked out one lookback period from each filter, which I set out to test together with the complete system. The different filter/lookback periods I decided to test further can be seen in Table 12.4. For instance, the DMI indicator proved most useful with a lookback period of 34 days, which generated an average profit of almost 0.13% per trade.

TABLE 12.3

Breakout filter, January 1980-October 1992.

Length	Average	St Dev	Ratio	Kurtosis	Skew
20	0.0460	0.1478	0.3112	5.3691	0.3835
30	0.0408	0.1385	0.2946	3.7634	1.2145
40	0.0309	0.1267	0.2437	6.0328	-0.7399
50	0.0456	0.1475	0.3088	4.5719	0.7597
60	0.0511	0.1461	0.3499	7.2699	1.7590
70	0.0401	0.1578	0.2543	5.0591	-0.1657
80	0.0317	0.1196	0.2649	7.2570	1.5680
90	0.0318	0.1486	0.2141	5.0252	-1.1230
100	0.0293	0.1438	0.2034	10.8615	-1.7311
110	0.0474	0.1597	0.2966	5.2053	-0.4098
120	0.0419	0.1318	0.3182	4.0369	0.5033

TABLE 12.4

Chosen input parameters for different filters.

Filter	Length	Average	St Dev	Ratio	Kurtosis	Skew
DMI	34	0.1287	0.1860	0.6920	4.9766	1.8047
True range	37	0.0467	0.1807	0.2583	6.1131	-0.1240
RSI	28	0.1128	0.2165	0.5210	4.0422	0.1418
OBV-cross	70	0.1019	0.1686	0.6045	3.6123	1.0086
OBV-slope	70	0.1026	0.1767	0.5805	5.9592	1.4997
MA-cross	130	0.1131	0.1722	0.6568	4.6584	0.8590
MA-slope	70	0.1261	0.1679	0.7510	6.9234	1.7958
Ratio cross	70	0.1117	0.1984	0.5629	4.3042	1.6645
Ratio slope	90	0.0776	0.2137	0.3633	9.8603	-0.9665
Breakout	60	0.0511	0.1461	0.3499	7.2699	1.7590

Those that did not work at all were the true range method, the T-bill ratio slope indicator, and the breakout method.

A few things worth mentioning from this test can come in handy for your own testing: the OBV and ratio indicators probably would have done better had they been tested with shorter lookback periods. The not-so-tantalizing results for the breakout filter probably are because of the backwards reasoning you must use for a filter like this, in combination with the random entries, which, as things are right now, allow for a lot of trades with the market in no trend at all, or in consolidation mode. The same holds true for the true range method, when compared to the results for the DMI and RSI indicators. Finally, it is interesting to note that the moving average crossover method does not seem to work quite as well as the slope method of half the length. This confirms our findings from Part 2, where we put together our weekly directional slope system.

THE GOLD DIGGER SYSTEM

When each filter was tested on the S&P 500 together with the Gold Digger system, over the two time periods January 1985 to December 1994 and January 1995 to October 1999, the ratio cross filter produced the best results. These can be seen in Tables 12.5 and 12.6 and directly compared to Tables 11.16 and 11.17.

Perhaps it worked a little too well: high profit factors and low drawdowns count for very little if the trades are too few to make it possible to come to any meaningful conclusions. The reason for the very few trades is to be found in the original composition of the entry technique, which needs to be modified to make it worthwhile trading it together with a filter.

TABLE 12.5

Gold Digger (original)/ratio cross filter, January 1985-December 1994.

Total trades		30	Winners	16	55.33%	Losers	14	46.67%
Profit factor		1.32	Lrg winner	2.80%	9,450	Lrg loser	-2.07%	-6,986
Avg profit	0.18%	593	Avg winner	1.37%	4,613	Avg loser	-1.19%	-4,002
St Dev	1.51%	5,093	Cum profit	5.06%	17,078	Drawdown	-4.16%	-14,040

This is largely because the original entry trigger demands two weeks in a row in the same direction, which comes awfully close to a complete change of trend, before we are allowed to enter with a limit order in the opposite direction. To make it a little easier to enter a trade we can loosen the original entry somewhat and only look at the latest week's market action. If we do that, it turns out that the breakout filter produces the best results for the period covering January 1985 to December 1994, which is shown in Table 12.7.

After we modified the original entry technique, the breakout filter was the most profitable for the period January 1985 to December 1994, with a profit factor of 1.30 and an average profit per trade of 0.17%. The drawdown is a tolerable 7.94%. For the period January 1995 to October 1999, the profit factor also came out to 1.30, while the average profit increased somewhat to 0.20% per trade. This is shown in Table 12.8. However, the increase for the average profit also was accompanied by a slightly higher increase of the standard deviation, which meant that the risk-adjusted return also decreased somewhat. The drawdown also increased to approximately 12%. If you compare this version of the Gold Digger—with its slightly loosened entry trigger and the attached filter—with the version depicted by Tables 11.16 and 11.17, you see that this latest version beats its predecessor in almost every single category, not the least of which is the drawdown, which is an indication of how well the system will let you sleep at night.

Now all that needs to be done is to make sure that this new filter/entry combination indeed betters the results as compared to the new entry technique alone. If it does not, there is little use adding the filter. The results for trading the new entry technique only, without the filter, can be seen in Tables 12.9 and 12.10, and as you can see these results are not as good as those with the filter, especially when

TABLE 12.6

Gold Digger (original)/ratio cross filter, January 1995-October 1999.

Total trades		9	Winners	7	77.78%	Losers	2	22.22%
Profit factor		5.91	Lrg winner	2.80%	9,450	Lrg loser	-1.10%	-3,713
Avg profit	1.20%	4,050	Avg winner	1.86%	6,268	Avg loser	-1.10%	-3,713
St Dev	1.65%	5,584	Cum profit	11.21%	37,834	Drawdown	-1.10%	-3,713

TABLE 12.7

Gold Digger (modlfied)/break filter, January 1985-December 1994.

Total trades		367	Winners	193	52.59%	Losers	174	47.41%
Profit factor		1.30	Lrg winner	5.03%	16,976	Lrg loser	-4.48%	-15,120
Avg profit	0.17%	569	Avg winner	1.38%	4,642	Avg loser	-1.17%	-3,949
St Dev	1.52%	5,135	Cum profit	77.58%	261,833	Drawdown	-7.94%	-26,798

TABLE 12.8

Gold Digger (modified)/break filter, January 1995-October 1999.

Total trades		188	Winners	101	53.72%	Losers	87	46.28%
Profit factor		1.30	Lrg winner	5.14%	17,348	Lrg loser	-8.30%	-28,013
Avg profit	0.20%	685	Avg winner	1.62%	5,464	Avg loser	-1.44%	-4,862
St Dev	1.88%	6,329	Cum profit	41.68%	140,670	Drawdown	-12.11%	-40,871

it comes to the drawdown and percentage of profitable trades. The profit factors and average trades, too, are not as good without the filter. The lower cumulative profit, with the filter attached, does not matter at this point, because this will be dealt with later by attaching the proper money management during the "optisizing" process.

Thus, by following the system building sequence outlined in Part 3, we have not only managed to consistently improve the original system from Part 2, which really was nothing more than a very simple entry technique, but we also have managed to do so without stacking indicators on top of each other and curve fitting the final version to a specific market. In fact, even though this is a system specifically designed for the S&P 500, most of the time we haven't even used the S&P 500 index in our testing and when we have, we have traded it randomly, summarizing the results together with 15 other markets. Furthermore, as a final step we even took away some of the original components, ending up with a model that trades far more often than its predecessor.

TABLE 12.9

Gold Digger (modified)/no filter, January 1985-December 1994.

Total trades		454	Winners	242	53.30%	Losers	212	46.70%
Profit factor		1.26	Lrg winner	7.62%	25,718	Lrg loser	-12.61%	-42,559
Avg profit	0.15%	513	Avg winner	1.36%	4,595	Avg loser	-1.23%	-4,147
St Dev	1.68%	5,654	Cum profit	86.55%	292,106	Drawdown	-18.29%	-61,729

TABLE 12.10

Gold Digger (modified)/no filter, January 1995-October 1999.

Total trades		236	Winners	120	50.85%	Losers	116	49.15%
Profit factor		1.23	Lrg winner	5.14%	17,348	Lrg loser	-8.30%	-28,013
Avg profit	0.15%	520	Avg winner	1.60%	5,401	Avg loser	-1.34%	-4,529
St Dev	1.81%	6,095	Cum profit	38.37%	129,499	Drawdown	-13.48%	-45,495

THE MEANDER SYSTEM

For the Meander, it turned out to be very difficult to find a filter that could produce consistent results. In fact, the best filter was the moving average slope filter, which produced a very high profit factor for the latter of our two testing periods, but still failed miserably during the period January 1985 to December 1994. Tables 12.11 and 12.12 show the results, which are comparable to Tables 11.18 and 11.19.

The reason for this can probably be found in the composition of the original entry technique, which is already taking the trend into consideration by looking at the last five weekly bars to calculate the entry levels. This was very difficult to work around by, for instance, altering the entry level by changing the number of standard deviations away from the mean needed to signal an entry. Nor did it help to switch away from the Black Jack exits, back to the original exits, also developed in Part 3. Therefore, we will keep the Meander system, together with the Black Jack exits, as it is.

At this point, it also could be worthwhile pointing out the importance of trying to come up with a logical reasoning and a way to understand why a specific

TABLE 12.11

The Meander/MA slope filter, January 1985-December 1994.

Total trades		60	Winners	32	55.33%	Losers	28	46.67%
Profit factor		0.89	Lrg winner	2.80%	9,450	Lrg loser	-8.05%	-27,169
Avg profit	--0.07%	-250	Avg winner	1.09%	3,672	Avg loser	-1.40%	-4,732
St Dev	1.68%	5,685	Cum profit	-4.13%	-13,939	Drawdown	-13.19%	-44,516

TABLE 12.12

The Meander/NA slope filter, January 1995-October 1999.

Total trades		29	Winners	21	72.41%	Losers	8	27.59%
Profit factor		3.36	Lrg winner	4.21%	14,209	Lrg loser	-1.64%	-5,535
Avg profit	0.77%	2,609	Avg winner	1.52%	5,127	Avg loser	-1.19%	-3,999
St Dev	1.63%	5,498	Cum profit	24.56%	82,890	Drawdown	-3.41%	-11,509

filter/system combination does not work. Remember that there is no such thing as a failed experiment, as long as we can learn something and come to some conclusion about how or what to do to improve results in future experiments.

THE BLACK JACK SYSTEM

When we built the Black Jack entries in Part 2, we had already added a 200-day moving average filter. With this filter, the system worked very well during the latter of our two testing periods but not at all during the former. To see if any of our other filter techniques would work any better and be more consistent, I substituted the original filter for each one derived in this section. As a result, the system started to produce fairly consistent results together with the OBV slope filter.

The results for the time period January 1985 to December 1999 can be seen in Table 12.13 and directly compared to those in Table 11.21. As you can see, we have taken a negative average profit per trade and turned it into a positive one of 0.19%. Other positive signs are a low standard deviation and a tolerable drawdown. The percentage of winning trades also is very high.

For the period January 1995 to December 1999, the results are not quite as good as with the original system, as can be seen if you compare Tables 12.14 and 11.20. However, in the larger scheme of things, this matters very little, because the system now is much more robust and reliable, and hence much more likely to hold up in the future as well.

TABLE 12.13

Black Jack (modified)/OBV slope filter, January 1985-December 1994.

Total trades		202	Winners	117	57.92%	Losers	85	42.08%
Profit factor		1.38	Lrg winner	4.12%	13,905	Lrg loser	-3.09%	-10,429
Avg profit	0.19%	641	Avg winner	1.20%	4,038	Avg loser	-1.20%	-4,036
St Dev	1.43%	4,838	Cum profit	43.35%	146,981	Drawdown	-10.88%	-36,720

TABLE 12.14

Black Jack (modified)/OBV slope filter, January 1995-October 1999.

Total trades		92	Winners	60	65.22%	Losers	32	34.78%
Profit factor		2.00	Lrg winner	4.04%	13,635	Lrg loser	-2.90%	-9.788
Avg profit	0.46%	1,556	Avg winner	1.41%	4,775	Avg loser	-1.33%	-4,478
St Dev	1.63%	5,485	Cum profit	50.02%	168,818	Drawdown	-5.03%	-16,976

CHAPTER 13

Long-term Volatility Filters

For long-term systems, we must think a little differently. For short-term systems, the purpose of the filter was to identify the type of trend that holds as many and as favorable short-term moves as possible. For the longer-term system the trend is, per definition, already defined. Instead, we must find the most opportune, short-term entry point as early as possible within this trend. For one thing, this means that we no longer can trade the system randomly. In theory, the best way to achieve this is to look for either low-volatility situations in general, or situations where the direction of the volatility coincides with the anticipated move of the market. Hence, the paradox is that for the long-term system filter we must work with shorter-term data, and vice versa.

A good indicator to use for the former method is the average true range indicator, as we did for the short-term systems. This time, however, we will do it a little differently and change the range multiplier as well as the lookback period. A two-variable test also means that we once again can make use of the surface chart method that we developed for the directional slope system in Part 2. For the lookback period we varied the length from 5 to 25 days, in steps of 2 days. The range multiplier we varied from 0.5 to 2.5, in steps of 0.2. The added trading rule was not to take the trade if the true range for the day of the breakout surpassed the average true range times its multiplier.

For long-term systems, with the direction of the trend already defined, we also can use the ADX indicator, which could not be used in a short-term system, because, as a standalone indicator, it says nothing about the direction of the volatility. But if we use it together with any other long-term indicators, we can assume that a high ADX reading means a high volatility in the direction of the trend, as indicated by the second indicator, which for our purposes is also the original entry strategy—or this is the theory many system vendors seem to adhere to, because as the ADX indicator is their first choice when it comes to measuring the strength of the trend. The ADX test also was done as a two-variable test, where we tested different lengths for the lookback period together with several different trigger levels. For the lookback period we varied the length from 10 to 20 days, in steps of 1 day. The trigger level we varied from 15 to 35, in steps of 2. The added trading rule was not to take the trade if the ADX reading for the day if the breakout was below the required trigger level. Both system/filter combinations also make use of the stops and exits for each respective system we developed in Part 3.

Another important difference between the long-term and short-term testing procedures is that for the long-term systems we cannot look at the final profit for the trade, because this would weed out far too many trades and make the results less meaningful. To do that would also contradict the reason we added the filter to the system in the first place, which was to find the most opportune moment to enter in a trend that was already defined. Therefore, the best way is to try to minimize the STD, described in detail in Part 3, in relation to the final profit of the trade. However, just examine the STD wouldn't make much sense either, because we still would like the trade to go on for as long as possible within the confines of the original system. In essence, this means that we must examine the entry efficiency of the trade.

In Part 3 we concluded that, for a long-term system, it is reasonable to assume that the STD will be the same as the maximum adverse excursion (MAE) and therefore can be derived the same way, although the interpretations and treatments of the two are not the same. The MAE should primarily be dealt with by adjusting the stops, which we did in Part 3, where we also took care of all the other types of drawdowns and excursions. The STD, on the other hand, should primarily be dealt with by filtering out the most opportune trading situations, which is what we are about to do now.

Although we might be using the same techniques to derive the necessary data for the STD as for the MAE, it is important to understand that the two are not the same. Nor does either one of them equal RINA Systems' entry efficiency. The difference is that the STD should primarily be adjusted with the entry technique, although the MAE should primarily be adjusted with a specific exit technique, such as a stop loss. Together, the MAE and STD make up the entry efficiency.

The markets used for testing were D mark, crude oil, lumber, copper, gold, dollar index, live cattle, T-bonds, cotton, Japanese yen, natural gas, wheat, Nikkei index, coffee, T-bills, and rough rice. The time period covered was January 1980, to October 1992.

Figure 13.1 shows that the Dynamic Breakout System (DBS system) produced the highest entry efficiency in combination with the average true range filter with a seven-day lookback period and a multiplier of 0.5. Because this is not a

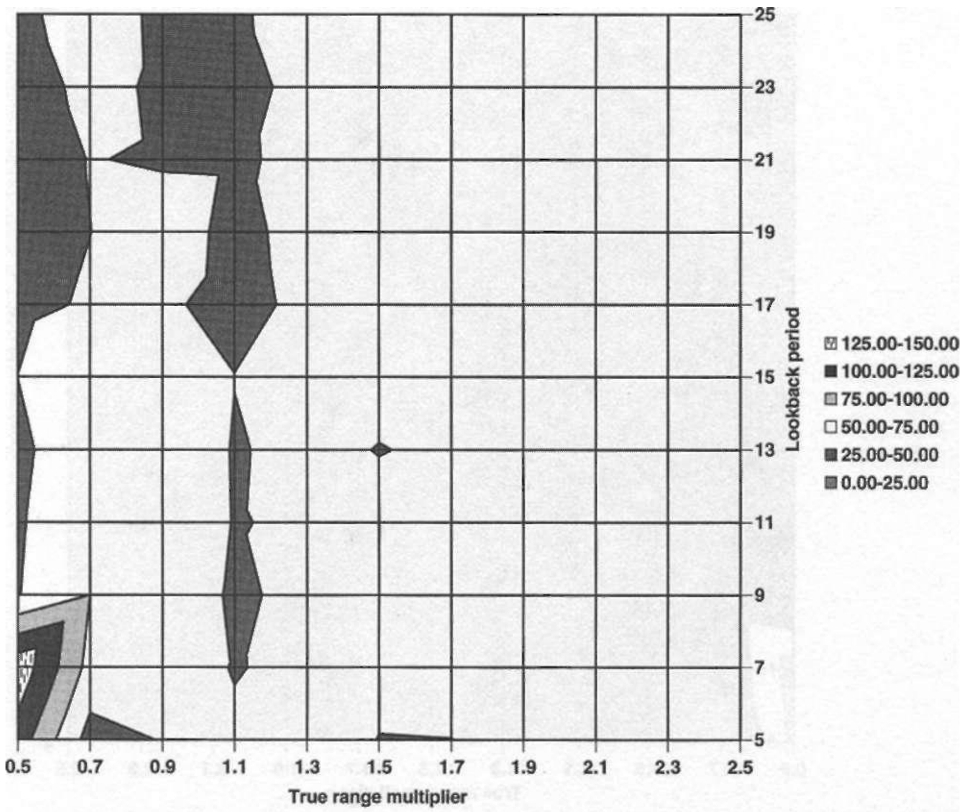


FIGURE 13.1

The entry efficiency for the DBS system in relation to the true range multiplier and its lookback period.

particularly robust solution, it cannot be our preferred choice. Instead, we should strive to place ourselves somewhere in the area around a lookback period of nine days and a multiplier around 1.5. In this way, we avoid any of the areas of lower efficiency around, for instance, the 1.1 multiplier, if it just so happens that the true best combination might shift around a little in the future.

Support for this also can be found in Figure 13.2, which depicts the standard deviation of the efficiency. In Figure 13.2 it seems that, as far as the standard deviation goes, we should be able to go with a multiplier of 1.5, without getting too close to the higher standard deviation areas. Which means we will settle for a 9/1.5 lookback/multiplier combination.

Figure 13.3 shows that the DBS system produced the highest entry efficiency in combination with the ADX filter with a 20-day lookback period and a trigger level of 33. Because this too is not a particularly robust solution, however, it cannot be our preferred choice. Instead, we should strive to place ourselves somewhere in the area around a lookback period of 12 days and a trigger level at or above 25. In

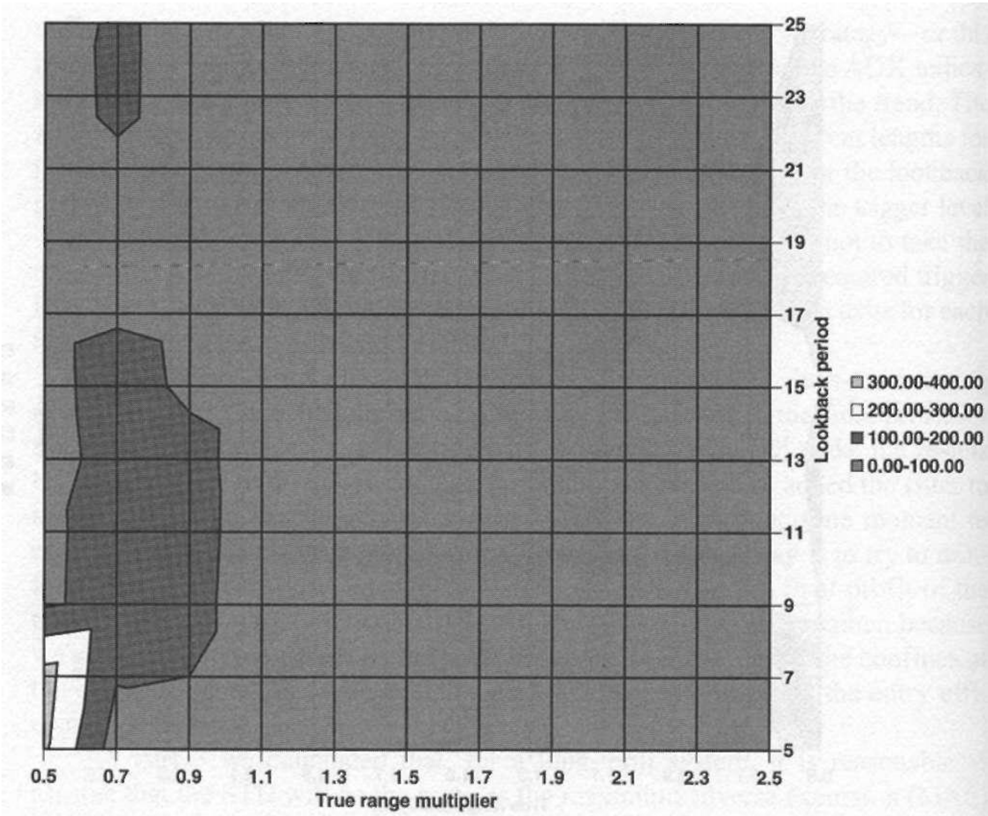


FIGURE 13.2

The standard deviation of the entry efficiency for the DBS system and the true range filter.

this way, we avoid any of the areas of lower efficiency around, for instance, a trigger level of 21 and a lookback period of 11 days, if it happens that the true best combination might shift slightly in the future

This is confirmed by Figure 13.4, which depicts the standard deviation of the efficiency. In Figure 13.4, it seems that, as far as the standard deviation goes, we should go with a trigger level of 25 and a lookback period of 11 days, without increasing the standard deviation too much; because this seems to be possible without running the risk of lowering the efficiency, this is our preferred choice.

Table 13.1 summarizes all the preferred choices for our three long-term systems and filters. The time period covered is from January 1980, for all systems, to October 1999 for the DBS and directional slope systems, and to October 1992 for the standard deviation breakout system. The trade-by-trade export function from Part 1 is used to export the results into an Excel spreadsheet for further evaluation and comparison with earlier, pre-filter results.

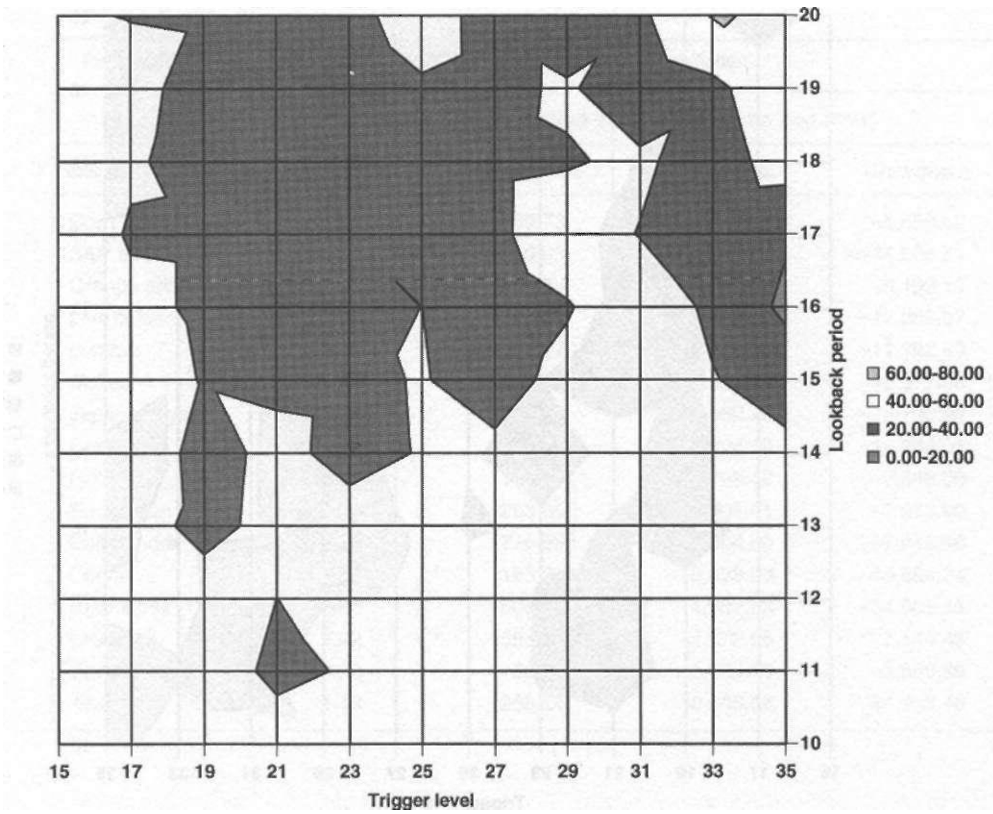


FIGURE 13.3

The entry efficiency for the DBS system in relation to the ADX trigger level and its lookback period.

TABLE 13.1

Preferred system/filter combinations.

	ADX filter		True range filter	
System	LB period	Trigger	LB period	Multiplier
Dynamic Breakout	11	25	9	1.5
Standard Deviation Breakout	14	21	17	0.9
Directional Slope	11	25	11	1.7

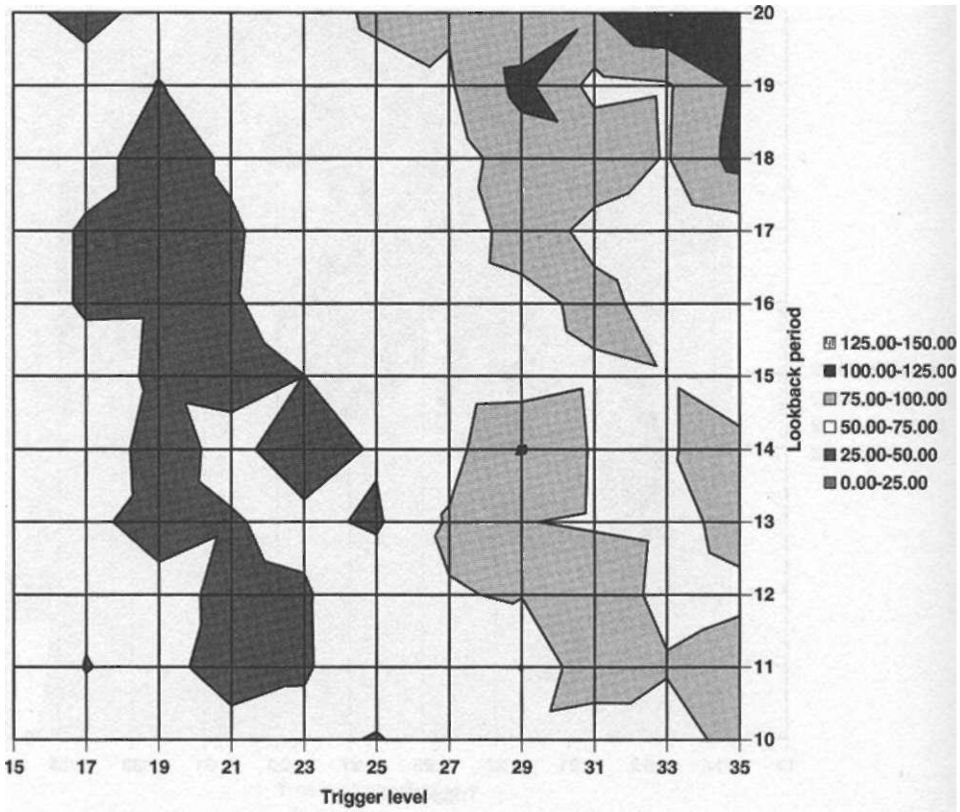


FIGURE 13.4

The standard deviation of the entry efficiency for the DBS system and the ADX filter.

THE DBS SYSTEM

Tables 13.2 and 13.3 show the result for the DBS/true range combination, as outlined in Table 13.1. These tables can be directly compared to Tables 10.9 and 10.10. Table 13.2 shows that of all 16 markets, only five are worth trading (if we use our mle of thumb that says that the gross average profit should be at least three times the expected slippage and commission, which we estimated at $75). This is no different from Table 10.9, so the filter did not help any in this regard, even though it did increase the value of the average trade in nine markets.

When it comes to the profit factor, the filter left us with a profit factor above 1 in twelve markets. This, too, is the same as without the filter, but because the filter only managed to increase the profit factor in seven markets and, hence, decrease it in nine, it is obvious that this system does not benefit from this filter. It does not matter that the filter managed to lower the drawdown for nine markets.

TABLE 13.2

Performance measurements for all markets for the DBS/true range combination.

	After filter (modified system with exits and filter)			
Market	P. factor	Avg. trade	2 St. dev.	Drawdown
Corn	1.31	69.73	1,425.07	-3,556.69
S&P 500	0.94	-289.83	27,234.52	-144,606.61
Orange juice	1.35	104.50	2,407.67	-9,192.10
Live cattle	0.98	-6.81	2,293.99	-12,059.97
Lumber	1.20	114.27	3,630.98	-11,792.83
Coffee	1.19	153.91	5,558.24	-19,517.05
Japanese yen	2.13	1,207.82	9,862.45	-13,700.98
Copper	0.87	-52.83	2,224.48	-11,294.01
Gold	1.23	107.37	2,799.42	-9,348.00
Eurodollar	1.77	263.05	3,001.01	-7,073.90
Dollar index	2.23	776.99	6,054.09	-7,816.56
Cotton	1.32	165.24	3,923.99	-10,654.24
CRB index	0.59	-505.79	4,982.93	-54,603.45
Crude oil	2.22	555.04	4,772.65	-7,144.46
Canada dollar	1.20	62.68	2,055.76	-7,899.86
T-bonds	1.18	258.24	8,695.56	-24,953.48

Unfortunately, the depressing results continue when we look at the DBS/ADX combination, as illustrated by Tables 13.4 and 13.5. The only thing positive thai can be said about this combination is that it did manage to make one more market (gold) worth trading, but other than that it only managed to increase the value of the average trade and the profit factor for five markets (lowering them for 11) and decrease the drawdown and standard deviation for five and eight markets, respectively.

These are not very impressive numbers at all and certainly not impressive enough to warrant the extra set of rules that we would have to add to the original system. The conclusion that can be made from these tests is, therefore, that this version of the DBS system, when it comes down to measuring pure profits or robustness of the results, does not benefit from being traded together with either of the two filter techniques discussed.

THE SDB SYSTEM

For the Standard Deviation Breakout (SDB) system combined with the true range filter, the results are, however, more encouraging. Of all 16 markets tested, a total of 12 and 11 resulted in higher profit factors and average profits per trade. Tables 13.6 and 13.7 show the results for this system/filter combination, which also are

TABLE 13.3

Summarized differences, before/after filter for the DBS/true range combination.

	Differences				
Market	P. factor	Avg. trade	2 St. dev.	Drawdown	Better
Corn	-5.02%	-15.74%	-0.46%	11.03%	1
S&P 500	12.99%	-67.29%	1.44%	-13.86%	2
Orange juice	-10.02%	-26.22%	-1.44%	5.85%	1
Live cattle	-3.47%	-190.30%	0.20%	12.31%	0
Lumber	6.61%	53.80%	1.39%	-2.02%	3
Coffee	17.98%	1344.93%	19.90%	-15.69%	3
Japanese yen	-3.59%	-2.29%	1.71%	0.00%	0
Copper	-6.72%	106.33%	-1.11%	11.48%	2
Gold	-15.00%	-44.85%	-5.57%	9.25%	1
Eurodollar	4.77%	5.67%	-0.58%	-17.53%	4
Dollar index	6.45%	10.65%	5.60%	-0.58%	3
Cotton	5.82%	26.01%	2.09%	-1.73%	3
CRB index	-1.00%	0.56%	-2.75%	-3.90%	3
Crude oil	-0.47%	1.90%	2.37%	-4.80%	2
Canada dollar	6.67%	56.39%	6.07%	9.69%	2
T-bonds	-4.43%	-22.43%	0.09%	-0.53%	1
Better	7	9	6	9	—

TABLE 13.4

Performance measurements for all markets for the DBS/ADX combination.

	After filter (modified system with exits and filter)			
Market	P. factor	Avg. trade	2 St. dev.	Drawdown
Corn	1.26	58.29	1,396.50	-3,355.61
S&P 500	0.86	-732.10	27,240.46	-170,608.33
Orange juice	1.42	127.51	2,562.59	-10,495.37
Live cattle	0.99	-4.31	2,293.65	-11,805.89
Lumber	1.12	68.83	3,572.99	-13,732.89
Coffee	1.10	79.02	4,792.56	-19,299.50
Japanese yen	2.14	1,205.34	9,841.21	-16,746.74
Copper	0.87	-54.77	2,166.07	-11,078.56
Gold	1.58	237.19	2,916.27	-6,728.37
Eurodollar	1.68	238.06	2,992.40	-8,849.74
Dollar index	1.71	525.55	5,854.09	-10,174.83
Cotton	1.25	131.08	3,910.42	-11,709.41
CRB index	0.50	-647.78	4,884.03	-55,666.35
Crude oil	2.36	600.54	4,868.78	-7,508.33
Canada dollar	1.11	37.30	1,929.15	-6,386.36
T-bonds	1.19	264.28	8,514.21	-25,036.36

TABLE 13.5

Summarized differences, before/after filter for the DBS/ADX combination.

	Differences				
Market	P. factor	Avg. trade	2 St. dev.	Drawdown	Better
Corn	-8.80%	-29.57%	-2.46%	4.75%	1
S&P 500	3.28%	-17.38%	1.46%	1.63%	1
Orange juice	-5.06%	-9.97%	4.90%	20.85%	0
Live cattle	-2.88%	-157.13%	0.19%	9.94%	0
Lumber	-0.72%	-7.36%	-0.23%	14.10%	1
Coffee	8.14%	641.83%	3.38%	-16.63%	3
Japanese yen	-3.04%	-2.49%	1.49%	22.23%	0
Copper	-7.71%	113.89%	-3.71%	9.35%	2
Gold	9.14%	21.81%	-1.63%	-21.37%	4
Eurodollar	-0.97%	-4.37%	-0.87%	3.17%	1
Dollar index	-18,38%	-25.16%	2.11%	29.41%	0
Cotton	0.07%	-0.04%	1.74%	8.01%	1
CRB index	-16.57%	28.79%	-4.68%	-2.03%	3
Crude oil	5.58%	10.25%	4.43%	0.05%	2
Canada dollar	-0.74%	-6.92%	-0.47%	-11.33%	2
T-bonds	-4.06%	-20.62%	-2.00%	-0.20%	2
Better	5	5	8	5	___

TABLE 13.6

Performance measurements for all markets for the SDB/true range combination.

	After filter (modified system with exits and filter)			
Market	P. factor	Avg. trade	2 St. dev.	Drawdown
Crude oil	4.22	808.63	4,276.38	-2,192.25
T-bonds	1.34	517.60	11,124.55	-19,518.81
T-bills	2.54	865.65	6,978.05	-5,794.19
Rough rice	3.57	1,266.12	9,152.78	-3,587.94
Nikkei index	1.21	770.16	22,715.90	-9,832.09
Natural gas		8,817.78	21,619.06	0.00
Live cattle	1.28	160.80	3,353.59	-9,101.18
Lumber	1.50	376.28	5,895.38	-4,591.37
Coffee	1.73	274.34	4,278.94	-4,998.12
Japanese yen	1.64	966.81	12,290.12	-13,073.75
Copper	2.29	765.87	7,659.45	-5,704.59
Gold	1.92	693.90	5,423.84	-5,592.07
Dollar index	2.89	1,418.88	7,538.99	-4,611.68
D mark (Euro)	2.93	1,693.64	9,198.07	-11,567.57
Cotton	4.03	948.52	4,829.12	-2,639.46
Wheat	1.42	202.91	3,382.67	-6,670.94

TABLE 13.7

Summarized differences, before/after filter for the SDB/true range combination.

	Differences				
Market	P. factor	Avg. trade	2 St. dev.	Drawdown	Better
Crude oil	22.73%	8.25%	2.23%	21.56%	2
T-bonds	3.77%	17.41%	1.82%	-1.85%	3
T-bills	18.00%	27.93%	8.17%	2.98%	2
Rough rice	182.47%	906.66%	200.80%	-30.69%	3
Nikkei index	-70.47%	-87.41%	-5.39%	100.47%	1
Natural gas		466.14%	235.64%	-100.00%	3
Live cattle	17.43%	232.39%	11.10%	5.69%	2
Lumber	5.31%	40.72%	23.63%	-17.61%	3
Coffee	38.21%	212.89%	74.05%	20.22%	2
Japanese yen	-31.83%	-43.52%	-4.60%	23.62%	1
Copper	99.84%	697.70%	89.14%	-17.55%	3
Gold	50.94%	179.49%	0.87%	-34.66%	3
Dollar index	18.80%	-2.01%	-5.99%	5.83%	2
D mark (Euro)	-1.15%	-7.41%	-2.89%	-4.20%	2
Cotton	48.15%	41.47%	6.60%	-32.16%	3
Wheat	-23.62%	-33.99%'	8.45%	39.44%	0
Better	12	11	4	8	—

comparable to Tables 10.19 and 10.20. Another positive factor is that the number of tradable markets, as measured by the value of the average trade, also has increased from 12 to 14.

Less optimistic is the fact that the risk, as measured by the standard deviation, has increased for a total of 12 markets. But as long as the risk does not increase at a faster rate than the value of the average trade, the risk-adjusted return still increases, in 11 out of 12 instances. The only market that really does not like this filter strategy is the wheat market, which does not manage to improve by one single measure.

Given the good performance of the SDB system together with the true range filter and the popularity of the ADX filter among the elite system builders, one would think that the SDB system/ADX filter combination is bound to be a success. Wrong! As Tables 13.8 and 13.9 show, the ADX filter did not work this time either, improving the profit factor for only seven and the value of the average trade for only eight, out of 16 markets. Compared to Tables 10.19 and 10.20, this system/filter combination also made a total of four markets untradable, as measured by the profit factor, by lowering it to 1.0 or lower.

Among the markets that really were hit by this combination are rough rice and Nikkei index. For the Nikkei index, for instance, the profit factor decreased

TABLE 13.8

Performance measurements for all markets for the SDB/ADX combination.

	After filter (modified system with exits and filter)			
Market	P. factor	Avg. trade	2 St. dev.	Drawdown
Crude oil	2.91	685.61	4,302.23	-1,738.02
T-bonds	2.36	1,633.85	13,332.82	-8,787.06
T-bills	2.09	692.96	7,150.36	-7,690.38
Rough rice	0.90	-64.51	3,130.25	-6,798.88
Nikkei index	0.11	-3,477.53	6,978.33	-13,336.11
Natural gas	25.96	6,892.23	20,012.22	-1,104.33
Live cattle	1.00	0.27	3,378.56	-8,096.56
Lumber	1.27	191.77	5,353.82	-6,417.54
Coffee	0.90	-34.70	2,004.95	-4,677.28
Japanese yen	2.47	2,000.98	13,937.97	-13,918.76
Copper	2.59	920.57	8,005.03	-5,594.21
Gold	1.52	416.74	5,333.78	-7,406.50
Dollar index	2.47	1,427.69	7,923.35	-4,357.46
D mark (Euro)	2.51	1,502.94	8,893.76	-8,294.33
Cotton	3.38	877.76	5,145.42	-3,821.89
Wheat	1.84	332.38	3,119.55	-5,114.78

TABLE 13.9

Summarized differences, before/after filter for the SDB/ADX combination.

	Differences				
Market	P. factor	Avg. trade	2 St. dev.	Drawdown	Better
Crude oil	-15.41%	-8.22%	2.85%	-3.62%	1
T-bonds	83.31%	270.60%	22.03%	-55.81%	3
T-bills	-2.59%	2.41%	10.84%	36.69%	1
Rough rice	-28.76%	-151.29%	2.88%	31.34%	0
Nikkei index	-97.38%	-156.83%	-70.94%	171.92%	1
Natural gas	271.87%	342.51%	210.70%	6.04%	2
Live cattle	-8.07%	-99.44%	11.93%	-5.97%	1
Lumber	-10.39%	-28.29%	12.27%	15.15%	0
Coffee	-27.89%	-139.58%	-18.45%	12.50%	1
Japanese yen	2.70%	16.89%	8.19%	31.61%	2
Copper	125.63%	858.83%	97.67%	-19.15%	3
Gold	19.66%	67.85%	-0.80%	-13.46%	4
Dollar index	1.38%	-1.40%	-1.20%	0.00%	2
D mark (Euro)	-15.17%	-17.84%	-6.11%	-31.31%	2
Cotton	24.14%	30.91%	13.59%	-1.77%	3
Wheat	-0.83%	8.13%	0.02%	6.91%	1
Better	7	8	5	7	—

from 4.09 without the filter, to 0.11 with the filter. With too few markets benefiting in the form of lower standard deviation of the outcome of the returns and the maximum drawdown, it does not matter that other markets, like natural gas, really excel. The conclusion must be that the ADX filter does not do its job together with this system and, therefore, must be put aside in favor of the true range filter.

THE DIRECTIONAL SLOPE SYSTEM

For the directional slope system I decided to show only those tables depicting the summarized differences, simply because neither of the two filters managed to add to the performance. Table 13.10 shows the differences between trading with and without the true range filter. Table 13.11 shows the differences between trading with and without the ADX filter. These tables are directly comparable to Table 9.10.

The use of the ADX indicator as a filter in systems like these always is questionable, at best. However, the above results do not rule out that the ADX indicator might work very well together with other systems, some of the time and/or traded on some other markets. But to me, a test like this shows that this indicator

TABLE 13.10

Summarized differences, before/after filter.

	Differences				
Market	P. factor	Avg. trade	2 St. dev.	Drawdown	Better
Corn	-13.45%	-23.14%	-7.08%	36.24%	1
S&P 500	-3.29%	2.66%	-6.85%	4.38%	2
Orange juice	-10.60%	-19.86%	-8.11%	10.49%	1
Live cattle	-10.81%	-58.90%	-7.21%	17.61%	1
Lumber	-23.44%	-35.52%	-6.53%	24.08%	1
Coffee	-10.44%	-16.48%	-2.38%	-9.31%	2
Japanese yen	-3.00%	-8.86%	-4.06%	6.74%	1
Copper	-27.55%	-48.55%	-1.50%	2.39%	1
Gold	-28.93%	-81.58%	-4.25%	59.60%	1
Eurodollar	14.57%	22.10%	0.47%	-9.70%	3
Dollar index	9.29%	18.43%	3.66%	-8.42%	3
Cotton	4.16%	2.51%	-1.36%	-23.55%	4
CRB index	-35.98%	154.00%	-17.92%	26.24%	2
Crude oil	-21.23%	-19.88%	-6.81%	-10.99%	2
Canada dollar	-6.42%	-25.23%	-1.04%	9.01%	1
T-bonds	-5.02%	-19.99%	0.40%	12.35%	0
Better	3	5	13	5	—

TABLE 13.11

Summarized differences, before/after filter.

	Differences				
Market	**P. factor**	**Avg. trade**	**2 St. dev.**	**Drawdown**	**Better**
Corn	-38.94%	-37.13%	4.30%	155.44%	0
S&P 500	-10.60%	46.20%	4.39%	-15.70%	2
Orange juice	-20.65%	-19.25%	16.06%	86.99%	0
Live cattle	-11.90%	-62.62%	-11.03%	28.56%	1
Lumber	^13.84%	-67.32%	-2.69%	17.19%	1
Coffee	-12.38%	-14.32%	3.05%	8.34%	0
Japanese yen	-18.72%	-30.38%	-15.31%	67.02%	1
Copper	-18.09%	-18.57%	21.57%.	-11.58%	1
Gold	-8.18%	-12.10%	13.98%	-23.63%	1
Eurodollar	-2.30%	19.91%	12.07%	-18.51%	2
Dollar index	-36.89%	-65.45%	-13.76%	28.87%	1
Cotton	34.31%	60.46%	7.93%	^5.17%	3
CRB index	-58.62%	295.44%	-25.85%	-9.55%	3
Crude oil	-25.59%	-22.13%	-1.74%	47.38%	1
Canada dollar	-17.99%	-60.76%	12.89%	48.30%	0
T-bonds	6.22%	42.15%	8.42%	12.07%	2
Better	2	5	6	6	—

is not robust and reliable enough for me to allow it to make its way into any of my systems. In fact, as soon as I see a system developer speaking at a seminar about filtering with the ADX indicator, I start to wonder if this guy really knows what he is doing.

Because I had a pretty good idea beforehand about the results of the long-term filters, I debated even bringing up the topic. What finally made me decide to do it was my belief that there is no such thing as a "failed" experiment, and that even when the hypothesis leading up to the test cannot be proved, the results are still worth mentioning so that others won't spend their time on unnecessary work.

CHAPTER 14

What Makes a Trend

This chapter was cowritten with Max von Liechtenstein, graduate student majoring in economics at Uppsala University, Sweden, and influenced by the ideas of Richard Werner, chief economist, Profit Research Center, Tokyo, Japan; Edgar Peters, chief investment strategist, Panagora Asset Management, Boston; Dr. Henry Pruden, Professor, Golden Gate University, San Francisco; and Dr. Bruno Latour, Professor, Ecole Nationale Superieure des Mines, Paris, France and Dr. Knut Wicksell (d. 1926), Professor, Lund University, Sweden.

Popular histories from LaSalle and Wall Street tell the story of tycoons and market operators like Nathan Rotschild, Jesse Livermore, and George Soros. But underneath these colorful stories there also runs a more serious history of the development of the financial system as the heart of capitalist society. These stories also provide insights into why technical analysis and rule-based trading in general are profitable if understood and treated correctly.

One lesson we learn from the tycoons and market operators is that failure in the financial markets is based on lack of discipline and knowledge, and that trading is a business and a craft carried out in a work process rather than as a set of individual and isolated decisions. For those who do not want to understand the markets, calling them "random" is an easy way out, but without knowledge, the individual's chances of meaningful profits are greatly reduced. Granted, there always will be a few uninformed traders who will make incredible profits. However, these results are usually not based on knowledge, but on luck. That is, trading limited to the act of isolated decisions is plain gambling with or without a favorable outcome, while truly skillful trading is a work process, which interweaves tasks like analysis and money and portfolio management.

To trade mechanical trading systems, we must understand that our work process contains much more than the actual decision to buy or sell something as signaled by the system. A general problem with today's finance is the preoccupation with assuming and studying the separate decisions of individuals made at a fixed point in time. A better perspective is to assume and study individual work processes, where each decision is not only a decision by itself, but also part of a larger plan that might take a certain amount of time to work through.

We deliberately use the word "work," because when today's general knowledge of finance only focuses on the single decision and the allocation of wealth, the part missing in the equation is how this wealth is created in the first place. One consequence of this is the widespread belief that market fluctuations are a source of wealth and that fortunes are made or destroyed by prices going up and down. That is not so. Prices are a product and not a cause of wealth. Prices and volumes are therefore just materialized wealth, which is caused and created by the aggregated work processes of individuals in the economy. Therefore, you must put in effort, and work and compete to get wealthy from price changes, or else just gamble and lose.

We believe the concept of work to be a better starting point for discussing profitable rule-based trading. The advantage with the concept of work, in comparison with decision, is that trading can be understood as a form of problem solving. Thus, work is what we do by carrying out different tasks in a working role. If an individual wants to learn the work of rule-based trading, he must develop an ability to solve the problem of making money in financial markets by using the four P's of speculation: philosophy, principles, procedures, and performance.

The emphasis in this chapter is on philosophy, whereas the rest of the book is about principles, procedures, and performance. Philosophy answers the question why, and explains the value of the suggested principles and procedures in the book. However, it is hard to discuss a philosophy without points of reference. It is, therefore, essential to understand the development of general knowledge in the field of finance and where we stand today. We try to do this as it relates to how to isolate the underlying long- and short-term trends.

The development of general knowledge of the financial markets has taken a curious route since the 1950s. While the academic world has been searching for general and abstract theories that could be derived and proven mathematically, practitioners have concentrated on relevant principles that have proven practical to use in their own working environments. Before the 1950s, both practitioners and academicians participated in the creation of general knowledge. This meant that practitioners, especially within the subgroup of financial analysts, influenced what was taught in higher learning institutions. After the 1950s, however, the academic world alone to a large extent created the general knowledge of the financial markets; important knowledge regarding the financial market from traders and technical analyst simply was overlooked. The problem with the dominance of the scholars is the lack of relevant practical principles adapted to the "real-world" restrictions in the practitioners' everyday work processes.

The scholars' dominance in defining the general knowledge of the financial markets started in the area of portfolio theory. In the early 1950s, Harry Markowitz showed how a stock portfolio, with a certain objective of expected return, could be optimized to have the lowest possible variability in periodic return. In the early 1960s, the academic society strengthened its dominance over financial theory through William Sharpe's *Capital Asset Pricing Model (CAPM)* and Eugene Fama's *Efficient Market Hypothesis (EMH).* CAPM states that an asset price, with a certain expected return, depends on its risk relative to the market. EMH states that, on average, competition will cause new information regarding intrinsic values to be reflected instantaneously in actual prices. The scholars' dominance of general knowledge consolidated in the 1970s with a set of option pricing models by Fisher Black, Robert Merton, and Myron Scholes.

The cornerstones of modern finance are the *arbitrage principle,* formed by Merton Miller and Franco Modigliani, and the *random walk hypothesis (RWH).* In modern finance, arbitrage is always possible, because investors can borrow freely. Furthermore, in an informationally efficient market, price changes must be unpredictable and random. The randomness is achieved through competition between active rational investors seeking greater wealth. Arbitrage between competitors eliminates all profit opportunities by incorporating available information instantaneously into market prices. Therefore, according to the scholars, a truly efficient market is one where price changes are completely random and unpredictable. The implication is that investors should use probability theory to make rational investment decisions in random real and financial markets.

In the past few years some scholars, within the field of behavioral finance, have attacked modern finance and received strong support from traders and technical analysts in the Wall Street community. The attackers believe that financial asset prices change in a predictable, biased, random process rather than in an unpredictable random walk and that the persistence in behavior of prices and the way they change are explained by social factors like ideas and human bias. Because of this, price changes in financial markets are likely to and will trend from time to time. But even if behavioral finance is a good step forward, it is limited to the concept of decision making by only looking at social factors, such as individual wants or needs at specific points in time.

If changes in asset prices follow a biased random walk, then they are to some degree predictable. Thus, fundamental analysis can be used to beat the market. Small firms and value strategies have shown this. Another insight from practitioners is the value of rule-based trading. It has been shown that asset prices tend to overreact and that, for instance, relative strength strategies, therefore, can be profitable. This, too, contradicts modern finance, which considers price changes to be essentially unpredictable.

However, social factors only explain half the story and must be complemented by more material factors, forming a global structure that explains the creation and flow of the necessary funds for materializing these "wants" and "needs." Together, the social factors (the wants) and the global structure (the funds, or flow of funds) create the necessary demand to create different markets for all types of goods and services, other factors of production, and financial assets. But that is not all. Together they also form a complex process of at least partially predictable trends in several different markets intervening with each other. This stresses the need to look at any type of trading as a rational work process rather than a quest for a set of optimal decisions at different fixed points in time. This way of looking at trading also emphasizes the need for money management and portfolio management, which, outside of the world of rational investors, becomes something completely different from just buying and holding the most efficient portfolio in accordance with CAPM and EMH.

The rule-based approach to trading is essentially a reflection of the idea that prices move in at least partially predictable trends and by following the same strategy, or work process, you end up being right more often than not and/or make more money than you lose. The following example illustrates what we mean by a trend being partially predictable.

In his book, *Patterns in the Dark* (Wiley, 1999), Edgar Peters describes a judge who goes mad. The judge's madness stems from a simple observation: every day, bad people cause bad things to happen. Could so many tragedies simply be a string of random events? No, according to the judge, they must be the result of a conspiracy. This story captures our ability and desire to impose a stable order and on specific explanations for what is happening around us in our everyday life, even when there are none. The observation that bad people cause bad things to happen, however, implies that there exists a stable and certain structure. What the judge missed is that most victims are still singled out by more or less purely random events. Thus, good people become victims due to local randomness in joint action with a global structure.

In nature, there are many complex processes (for example the weather) that consist of several elements acting as an entity, forming local randomness in joint action with global structure. This is also true in technological and financial (techno-financial) systems. On the one hand, individuals act together, forming a global structure based on similar material prerequisites and conditions. But because of different social factors, such as individual preferences and willingness to change, they also create local randomness. The complexity of it all causes the evolving entity to look like a conspiracy, although no mastermind is behind it.

In his book, *Aramis or the Love of Technology* (Harvard University Press, 1996) Bruno Latour points out that if we want to understand material changes like price and volume changes in traded assests, we need to define and integrate social and material factors in the same model. In other words, in the economy, the joint action between local randomness and global structure forms an at least partially certain and stable change of events within a complex process. This joint action forms a trend of some sort in something we try to predict or explain. This implies that economic trends are partly created by us as we interact and take part in forming these changes with our predictions and explanations.

Up until recently, standard neoclassic economics and modern finance have been occupied with explaining economic fluctuations and growth in the gross domestic product (GDP) only as a result of social factors, such as investors' allocation of purchasing power, neglecting how this purchasing power is created in the first place. This logic depends on the assumption that market prices and quantities always equal the value they offer the individual. This assumption also applies to the markets, where the net present value (NPV) equals the intrinsic value of an asset, because arbitrage otherwise would be possible. In both cases, the reasoning is justified by an assumption that individuals always can borrow freely. As a consequence, change in GDP is explained only by social factors such as individual preferences, because this is the only variable left that can explain the portfolio allocation decisions in the economy. This implies that intrinsic values command or determine prices and quantities in the markets.

But, as we all know, we cannot borrow freely, and this makes the inclusion of individuals' budget or income constraints in absolute terms a great fallacy, in neoclassic economics and modern finance because even Mr. Joe Sixpack acknowledges the problem with allocating a nonexistent purchasing power. This problem stems from the neoclassic economics' definition of purchasing power and money as savings and deposit aggregates like M1, M2, etc., which, in turn, has its origin in a too-simple model based on a barter economy instead of a credit-driven capitalist economy. Because the savings themselves are a result of the creation and allocation of purchasing power, this has led to difficulties in explaining financial crisis, growth, and fluctuations in both GDP and asset prices and why these processes to some degree are predictable.

To solve this problem some scholars inspired by Knut Wicksell's book, *Interest and Prices* (A.M. Kelley, 1965) have instead started to explain the creation of purchasing power as a creation of credit and banks' willingness to lend. With an emphasis on the material constraints in society, changes in both transaction flows and GDP can now not only be explained by individuals' portfolio allocation alone, but also by the banks' credit creation process as an underlying force inducing the wants and needs of individuals. The distinction between social and material factors also is important, because financial crisis and bubbles otherwise tend to be explained only by irrational decision-making by individuals rather than by a market failure within the system. Two such important material factors that affect the allocation of purchasing power are demographics and fiscal policies. These factors also create trends in the markets, because they determine the supply (allocation) of funds.

By means of credit, machines are created, managed, and fed with raw materials. By means of credit, products are consumed—house and cars are bought, and money is spent abroad by foreign customers. Thanks to the credit creation process, single individuals and the economy as a whole can obtain the necessary funds needed to materialize all our "wants." All our "wants," as explained by behavioral finance, will not cause the market to trend by itself. Instead, the ability of a market to trend is dependent on how much and what type of credit it can attract. That is, short- and long-term trends are separated by whether the purchasing power is created inside the market, as investors speculate on margin, or come from outside flows.

The importance of credit in understanding markets can be illustrated by comparing our capitalist society with the barter economy of ancient Egypt. The economic world of Pharaoh was very simple. He just needed to use his whip and power to command labor and material to build pyramids. The pyramid of Cheops consumed 600,000,000 days of human labor and all that was created after a period of 20 years was a frozen asset.

In our economy, there is no solitary pharaoh with the power to command labor and material by word alone. In our economy, labor and material is commanded by money. In a barter economy, money is viewed as a tangible, "immortal" asset, the quantity of which will only change as more gold or other precious material can be dug up from the ground. In a modern, capitalist society, however, the life cycle of money and credit is such that it is born when a bank issues a loan and is put to death as the person who borrows it pays it back. There is neither value nor power in money itself, only in what it represents—command of labor and material.

In place of Egypt's single pharaoh, we have several pharaohs seeking command of labor and material by means of credit. At first, it does not really matter how this money, or credit, is used, because it creates demand and transactions in the economy. Thus, at first, credit, or money, is a fabulous agent both for borrowers and others in the society. However, if credit commands labor and material into something unproductive—for example, to build a pyramid—then this capital loss is really lost labor. Further, credit that cannot be repaid hurts society, because it discourages banks' creation of new credit—the command of labor and material for upcoming periods.

The price borrowers have to pay to command labor and material is annual interest. To increase the likelihood for the debt to be amortized (or put to death), banks often require collateral for their lending. These restrictions have a functional significance because they force borrowers to make sure that their command of labor and material will be productive enough to generate income that pays for interest, repayment, and some profit. Thus, credit constraints restrain pyramid building. Nevertheless, our modern world is filled with thousands of "pyramids," and the invisible ones are the most dangerous, because they can survive only by new loans.

In his article, "Towards a New Monetary Paradigm" (Kredit und Kapital, 1997) Richard Werner points out that there is a fundamental difference in outcome between transactions in the real and financial markets. Transactions in real markets for goods, services, and factors of production, involve income or production flows. Financial market transactions involve asset stocks. Transactions in real markets are an economic activity measured as GDP. Transactions in financial markets are a noncreative activity that is not a part of GDP. Thus, when changes in asset prices or GDP are explained or forecast, total credit creation must be subdivided into a real and a financial part. Quantities of stocks are more fixed in comparison with production flows. Therefore, in the real market, an increase in demand is mainly met by an enlarged quantity supplied, whereas in the financial market, where the supply is more limited, an increase in demand will, by necessity, result in an increase of price.

A stock-exchange speculation with ever-increasing prices, such as that before the crash of 1929, is an invisible pyramid. Its stones are the supply of funds and human sentiment. The "1929 pyramid" consumed credit in an uncontrollable manner. In two years, brokers' loans on the New York Stock Exchange alone increased by $5 billion, which only served to inflate stock prices. The pyramid caused a great number of problems. For one thing, credit could have been used for more productive purposes, but was not. But even more seriously, it caused the lenders substantial losses, which decreased production and employment (i.e. command for labor and material) during the period that followed.

Today, we once again speak of the "new economy" as we experience a period of high growth in GDP, a booming stock market, and a low growth in consumer prices. This is because new and improved technology has made it possible to meet the increased demand for goods and services with increases in productivity, thus increasing GDP without increasing inflation. At the same time, there has been a sharp shift in demographics, resulting in a dramatic increase in the ratio of savers to spenders. A lot of these savers have invested their savings in mutual funds, which means a long trend of money flowing out of the real markets and into (allocated to) the financial markets.

Add to this that several governments throughout the world have both lowered their taxes and started to buy back huge amounts of bonds issued in the 1980s (the United States is supposed to have bought back all its debt by 2013). This also transfers money that would have been spent in the real markets to the financial markets. All in all, this has created a situation of high economic growth, coupled with a very low inflation in the real markets, but with highly inflated financial markets. Once again, as during the margin lending of the 1920s, the booming markets have made banks lend heavily for speculative purposes. Normally, this would result in higher interest rates, as central banks fight expected inflation and private banks demand a higher risk premium for money lent for speculative purposes. However, the interest rates are being hampered by competition among the banks, governments decreasing outstanding stock of bonds, and the fact that there is no inflation to fight in the real economy.

In times when banks lend heavily for speculative purposes, such as the margin lending of the 1920s or as is seen today, asset price inflation occurs, although consumer prices may hardly rise at all. Banks tend to extend loans with real or financial assets as collateral, where an increase in collateral values alleviates credit constraints. If banks extend loans with real or financial assets as collateral, then an increase in collateral values alleviates credit constraints. Thus, invisible pyramids of extreme changes in asset prices always depend on increasing asset-related lending from the banks. The paradox is, however, that while individual banks assume asset prices to be independent of their actions, rising asset prices cause extended asset-related loans, which lead to a continued increased demand for financial assets.

Technical analysis is increasingly recognized for explaining price predictability based on a study of investors' actions by charting the development of traded volume and price of a financial asset. This school of thought in general, and rule-based trading in particular, perceive market behavior to be both deterministic and random. Technical analysis can be broken down into four essential areas: creation-of-funds, flow-of-funds, sentiment, and market microstructure indicators. The creation-of-funds and flow-of-funds analyses represent the more stable trends that are reflected in the sentiment and market microstructure analysis. The creation-of-funds indicators include central banks' open market operations and private banks' loans to the total economy, subdivided into financial and real sectors. Flow-of-funds indicators analyze the financial position of various investor groups in an attempt to measure their financial capacity for buying or selling stocks. Flow-of-funds analysis is concerned with trends in mutual fund cash positions and other major institutions such as pension funds and insurance companies. Other flow-of-funds indicators are new equity offerings, secondary offerings, and customers' free balances, which are normally a source of cash on the buy side. The use of margin (or leverage) borders is both a long-term creation-of-funds indicator, as the use of margin is a form of borrowing, and a shorter-term sentiment indicator, as the current use of margin by larger market participants oftentimes can reflect a more short-term use of what normally is deemed stable or more long-term money.

The sentiment indicators monitor the different market participants such as mutual funds and floor specialists. They monitor the emotions or expectations of investors moving from one extreme at a market bottom to another at a market top. It is assumed that different groups of investors are consistent in their actions at major market turning points. Advisory services and newspapers, for example, are two groups that are considered to be wrong more often than not at or just prior to major turning points. A very good sentiment indicator in the commodity futures markets is Commodity Futures Trading Commission's (CFTC) Commitment of Traders Report that monitors the positions of commercial and noncommercial traders.

We perceive the material factors to be captured by the creation-of-funds and flow-of-funds indicators, while the social factors are captured by the sentiment indicators. However, because of the difficulty to measure, quantify, and rank these indicators' relative importance and how they affect different markets at different points in time, we often must use what we call *market microstructure indicators.* In essence, all technical analysis indicators that are based on price, volume, time, breadth, and volatility are market microstructure indicators.

In his article, "Life Cycle Model of Crowd Behavior" *{Technical Analysis of Stocks and Commodities,* January 1999), Henry Pruden describes how an adoption-diffusion model, based on behavioral finance, can be used to explain the rise and fall of financial asset prices. Dr. Pruden argues that the adoption-diffusion model captures how innovations over time are adopted in a techno-financial system, as illustrated by the familiar bell-shaped normal distribution curve. We have expanded Dr. Pruden's thoughts to encompass more material factors when we explain the existence of long- and short-term trends of changing supply/demand relationship in the specific market.

An idealized market cycle begins with a consolidating phase, known as either a *distribution* or *accumulation area.* The S-shaped cumulative normal distribution curve in Figure 14.1 illustrates what this may look like. In a consolidating phase, the demand and supply of assets are in a relative equilibrium. In an accumulation (distribution) phase, assets pass from weaker (stronger) to stronger (weaker) hands. But asset prices can only advance if investors have the purchasing power and courage to buy. That is, the credit creation process together with other material factors, such as demographics and fiscal policies, induce the necessary funds, while at the same time the social factors, such as all our wants and needs, are strong enough to entice buying.

Short-term trends are caused by investors' speculation on margin, which forces the market prices beyond what the economy can afford in the long run. Therefore, a highly leveraged trader has a weak hand. Whenever the value of the leveraged trader's holdings shrinks, he must sell a portion of his holdings. When the proportion of stocks in strong hands is abnormally high, the market is in a strong position. Therefore, the longer the period of accumulation, the greater the amount of strong hands and the larger the base from which prices can rise. In real life this can be approximated with the help of a long-term moving average, applied either directly on price or to the now familiar OBV indicator, as in Figure 12.1. The benefit of applying this type of analysis to the OBV indicator, rather than directly to the price, is that the OBV indicator, as suggested by its name, weights each day's price action with its trading volume and by doing so becomes a better measure of the relative amount of participation behind the trend.

It also is possible, with the trend creation process still in mind, to approximate a society's short-term willingness to allocate money (flow of funds) toward

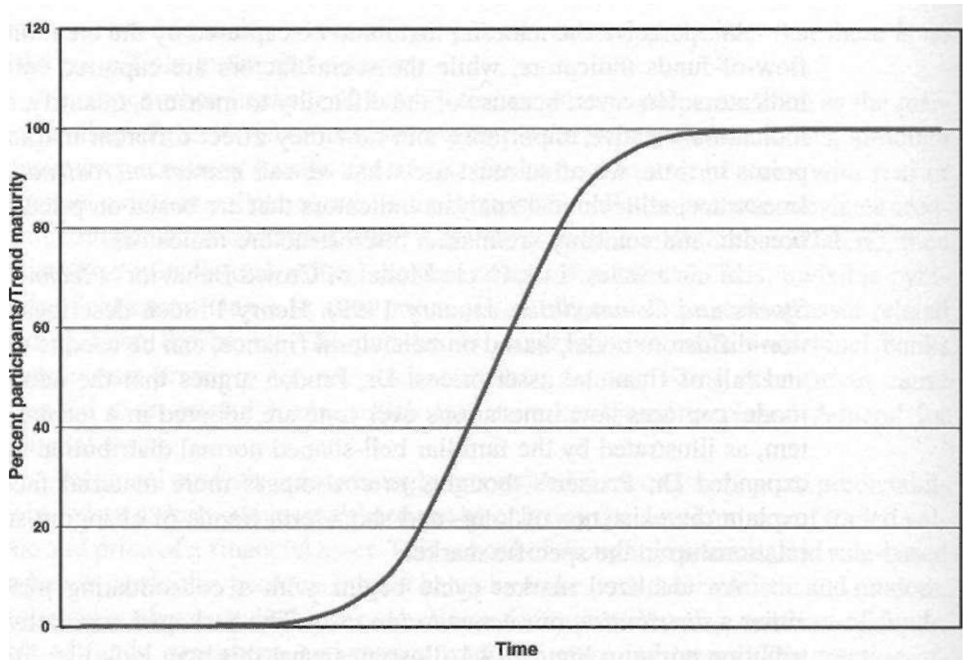


FIGURE 14.1

The cummulative normal distribution of a dependent variable.

a certain type of investment vehicle by looking at the relative performance of the investment alternative in question as compared to the interest rate. Whether the interest rate is currently increasing or decreasing does not matter in this analysis as long as it does so at a rate different than that of the alternative investment. For example, if the interest rate is decreasing more slowly (bond prices move up) than, for instance, the price of com is increasing, but faster than the increase in the price for wheat, it is reasonable to assume that investors prefer to invest in bonds rather than wheat, but also that they favor corn over interest rates. This means that, in this particular case, you should look for situations to short the wheat and go long the com.

For you as a trader, this means that as long as you can keep a rate of increase in your investment or trading account that is higher than a combination of the interest rate at which the invested money is assumed to have been borrowed, the rate of inflation, and a reasonable premium for the risk you are assuming, you are doing OK. But to do better than just OK—to be competitive—you also must do better than you would have done using any other investment alternative or method. That is what the rest of this book is all about.

Returning to the analysis of a trend, unfortunately, it is seldom as simple as just isolating one trend from all the others and then riding that wave. When several different ideas, preferences, and norms interweave, a larger trend naturally consists of several smaller ones, making life difficult for any trader. The theoretical explanation behind these shorter-term trend and momentum changes is illustrated by Figures 14.2 and 14.3. In Figure 14.3, we can see how this long-term trend really consists of two distinctly different states of market behavior. In this case they also are separated by a transition phase, forming the well-known *halfway flag* of technical analysts.

To come to grips with this, many technical analysts try to isolate different trends from each other using, for instance, different moving averages applied directly to the price, again on the assumption that the longer the average, the more stable and long-term the trend. In this case, however, we do not concern ourselves with whether the trend is driven mainly by material or social factors, although there also is the underlying assumption that the material factors are more long term than the social factors.

To isolate both the long-term and short-term shifts in the trend caused by, for instance, sentiment shifts and the amount of trading taking place on margin, many analysts also use one or several oscillator-type indicators that could be applied either directly to the price or to any other indicator that attempts to capture the material or social factors more explicitly. In this case, the longer the lookback

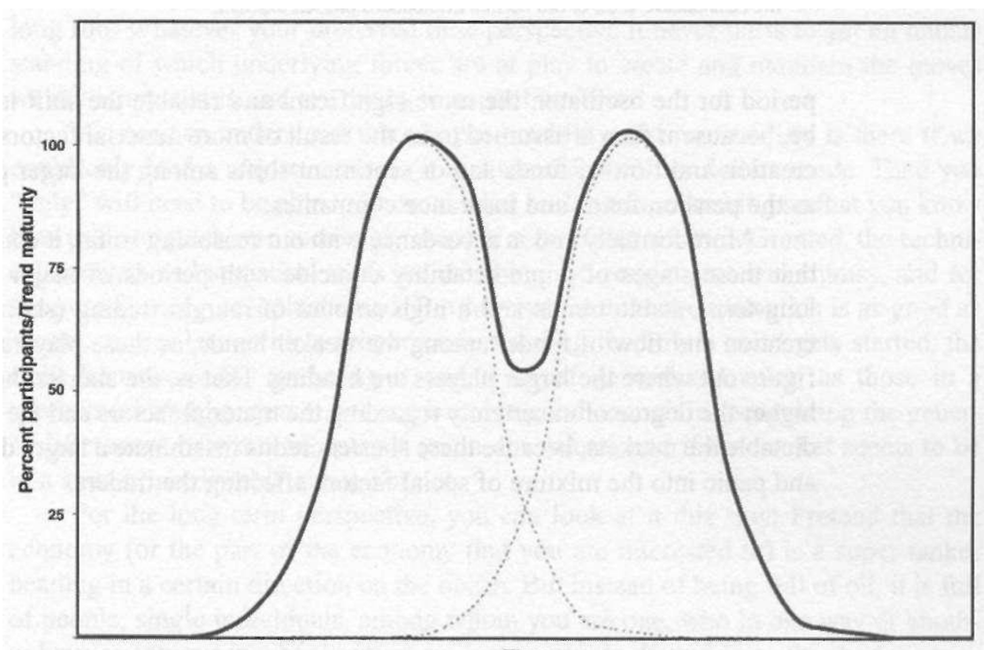


FIGURE 14.2

Two normal distributions intervening with each other.

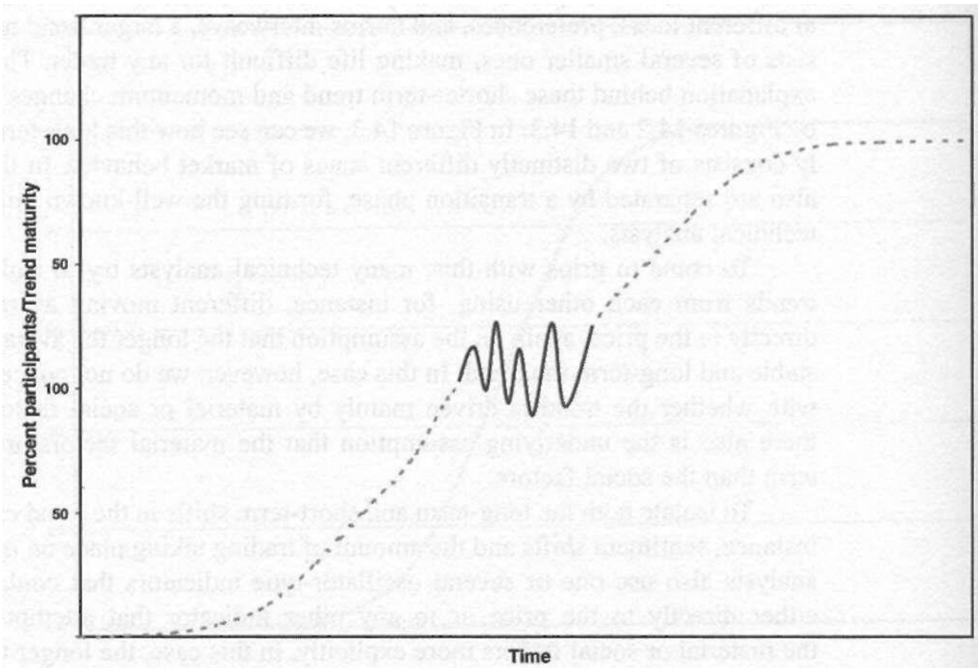


FIGURE 14.3

The cummulative effect of two normal distributions phased together.

period for the oscillator, the more significant and reliable the shift is assumed to be, because it then is assumed to be the result of more material factors, such as the creation and flow of funds and/or sentiment shifts among the larger players, such as the pension funds and insurance companies.

More formally and in accordance with our reasoning so far, it could be argued that these stages of unpredictability coincide with periods of major shifts in the long-term, stable trends and a high amount of margin trading (short-term credit creation and flow of funds) among the weaker hands, as these players scramble to figure out where the larger players are heading. That is, the shorter the credits, the higher the degree of uncertainty regarding the material factors and the more unpredictable the markets, because these shorter credits inseminate a larger degree of fear and panic into the mixture of social factors affecting the traders.

PART FOUR

A Few Final Thoughts About Part 4

This section started out by taking a closer look at how to filter out those situations when the markets seem to greet us with a particularly friendly environment, suitable for the entry/exit triggers we currently are working with. What it all comes down to is to increase your chances to place a winning bet, both in the short and the long run. Whatever your preferred time perspective it never hurts to get an understanding of which underlying forces are at play to create and maintain the moves we are interested in and are trying to capitalize from.

We need to understand that the predictability and profitability is there if we could only find a way to measure it and transform it into dollars made. Then you "only" will need to be able to know at what scale you are looking so that you know how to distinguish one seemingly random move from another. Granted, the technical analysis and statistical tools we are using are very coarse and clumsy, and for the purpose very unsophisticated. But however clumsy the tools, this is as good as it gets, and at least with a proper understanding for how a trend gets started, the right framework for analyzing it and a set of generalized rules, as those in a mechanical trading system, we can become good enough in recognizing the general differences between an uptrend and a downtrend, and if the market seems to be in a state of predictable change or not.

For the long-term perspective, you can look at it this way: Pretend that the economy (or the part of the economy that you are interested in) is a super tanker heading in a certain direction on the ocean. But instead of being full of oil, it is full of people, single individuals, among whom you are one, who in one way or another have an interest in what is going on, just as you do. It could be other traders, brokers, analysts, farmers, regular workers, and all these people's families, relatives, and friends.

Pretend further that the person in charge of this ship, for instance Alan Greenspan, has decided that the ship is heading in the wrong direction, or that he can see trouble ahead, and decides to change course. Even if he puts the engines into full reverse, the sheer mass and momentum of the ship force it to continue in the original direction for many miles to come. Not even if everybody on the ship agrees with his decision and wishes to turn around right away will the ship be able to turn around any sooner. Wishful thinking has nothing to do with where the markets are heading or the outcome of your trading.

Now, pretend that you, as a trader, instead are standing on the shore, looking at this ship on the horizon, holding exactly the same information as everybody on board. What would you bet on: that it will continue in the same direction for another couple of miles, or minutes, or days, or that the next thing you know, it will have turned around? Of course, you are better off betting it will continue in the same direction. You do not mm a super tanker on a dime; not even if you close your eyes hard and wish. And the same goes for the economy, or even any specific smaller part of it, like an individual stock.

To be sure, in the short run strange things happen every now and then—exceptions to the rule bring short-lived fame and fortune to a lucky few. But they are just that—exceptions to the rule. Generally speaking, you are much better off going with the current flow of events. On the financial markets, this means placing your trades in the same direction as the trend is heading. Place a long-term bet that tries to catch the beginning of the move, but be prepared to get out as soon as it is clear it is not heading where you expected or where the situation is less clear, as indicated by high short-term volatility levels.

Or to continue the analogy, when you can see bad weather approaching or when mist or fog makes it difficult to assess the situation, that is when your filters should signal to stay out. To do that, you must know what to look for, how to measure it and how to make the most of it, which sums up the purpose of this book and all the hard work we've done leading up to and including the "optisizing" process in Part 5.

PART FIVE

Money Management and Portfolio Composition

Now that we have finished building the engines, let us move over to the intricate subject of putting together a gearbox and a chassis to get our babies going. But first I need to point out that there is no way I would have been able to come up with the math and the logical reasoning behind this section myself. For this I rely solely on Ralph Vince, who also coined most of the terminology I use in this section, in his books *Portfolio Management Formulas* (John Wiley & Sons, 1990) and *The Mathematics of Money Management* (John Wiley & Sons, 1992). I have merely taken what is in these books and tweaked it around a little bit to suit my needs. If you are interested in learning more about what is covered in the following section, don't ask me—go buy Mr. Vince's books.

When it comes to the gearbox (the money management), it is quite simple really. Because in a well-working system you really have no idea about whether your next trade will be a winner or a loser, you will be best off, in the long run, always and for each trade, to risk the same fraction of your account. That is, if your account size going into a particular trade is $100,000 and you have decided that if the trade goes wrong, you can stand to lose 2% of that amount, you will be willing to lose $2,000. But if your account size is only $50,000, a 2% loss equals only $1,000, whereas a $2,000 loss equals a fraction of 4%.

CHAPTER 15

Money Management

The whole idea of money management is to always invest that fraction, or percentage, of your account going into each trade, most suitable to you, considering such factors as account size, expected worst-case trades, drawdowns, flat times, growth rates, and dependency among trades. To be able to do this—to "optisize" your trading—you must start to think in fractions and percentages, rather than in flat dollar rates. Otherwise, you will not be able to practice the very same techniques that already are in practice with professional money managers.

Another important point is that although these techniques add more to your bottom line than your actual systems, or entry and exit triggers, they do not perform miracles. For these techniques to work, your systems must have positive mathematical expectations in the first place. That is, they must have a profit factor above 1 and a positive value for the average trade to be worthwhile. If they just have that, if they are only marginally positive, with the proper money management you can work wonders.

On a separate note, however, it is worth mentioning that this only holds true for the special case of one market-one system. As soon as you trade a portfolio of markets and/or systems, it is fully possible to have individual market/system combinations that have a negative mathematical expectancy (a profit factor below 1 and a negative value for the average trade), which may raise the positive expectancy for the trading strategy as a whole. The trick is to put together a portfolio of systems and/or markets with correlations as low as possible to each other, where a few markets still zig when others zag, but with the zigging greater than the zagging, generating a small but steady profit in the long run. The negative expectancy markets/systems help to hold up the bottom line while you wait for the positive expectancy markets/systems to move back in line and start performing again.

Before we go on there are a few things you must fully understand:

- Price does not behave in a rational manner.
- Potential gain is not a straight-line function of potential risk; it is not true that the more you risk, the more you are likely to gain.
- The amount of risk you assume has nothing to do with which type of vehicle you are trading.
- Diversification does not necessarily have to reduce drawdown.

Of these four things, we immediately must address the fact, that for money management purposes, when price does not behave in a rational manner it means that if it goes from, for instance 1,350 to 1,000, it does not have to stop at every tick in between. If you are caught on the wrong side of such a move you will suffer a severe, if not totally devastating, loss, because there will be no way out even if you had a stop loss at 1,345. Furthermore, because these moves happen, the only thing that is certain in trading is that we all will be blown out of the markets sooner or later. It is just a matter of time. Or to use a simple analogy: if you can only die by from being hit by a truck, eventually you will die from being hit by a truck. It is as simple as that.

In the world of trading, however, what might be devastating for some may only be a freak occurrence but still a fully expected outcome for others. From this it follows that to fit as many outcomes as possible into the boundaries of what could be considered expected, you must have considered and treated the whole subject of trading very defensively. Or, to use the old start-a-new-business cliche, money management (making a business plan) is to hope for the best but prepare for the worst. Still, for some the catastrophe might come first thing tomorrow, no matter how much they have tried to protect themselves. If it happens to you, I'm sorry, but that's just the name of the game.

Now, let us consider the next point in the list above. "Potential gain is not a straight-line function of potential risk." If it is not, then what is it? To answer that question we first must define a few terms.

We need to understand the term holding period return (HPR). The HPR is the percentage gained or lost for each specific trade, plus one. For example, if a trade ends up with a 5% profit, the HPR is 1.05 (1 + 5% = 1 + 0.05 = 1.05). On the other hand, if a trade ends up with a 5% loss, the HPR is 0.95 (1 + (-5%) = 1 + (-0.05) = 0.95).

The second term we must understand is terminal wealth relative (TWR). The TWR is the geometrically compounded HPR for all trades, which means that we are using multiplication rather than addition. For example, if you have two winning trades, with HPRs of 1.05 and 1.10, respectively, the TWR is 1.155 (1.05 X 1.10 = 1.155). A TWR of 1.155 means that after the two trades, you have 1.155 times your original equity, or your total profit is 15.5% (1.155 - 1 = 0.155 = 15.5%).

Note that a profit of 5% and a profit of 10% do not add up to a profit of 15%, but slightly more. This is because you were able to use the extra money you made in trade one going into trade two. You were able to reinvest your winnings. This clearly demonstrates the importance of always risking the same fraction of your account, as represented by your expected worst-case scenario for that particular trade. To understand this better, consider instead if the two trades above tumed out to be two losers of 5% each—which was the fraction you were willing to risk. Then your TWR would be 0.9025, your equity would have decreased to 0.9025 times the original equity and your total loss is 9.75% (0.9025 — 1 = —0.0975 = —9.75%). Thus, two 5% losses in a row don't equal a total loss of 10%, but slightly less than that.

Two major benefits of working with a fixed fractional money management strategy, where you always reinvest your profits and losses, is that your account measured in dollars grows geometrically, and at the same time it keeps you in the game for much longer during drawdown periods, because the strategy forces you to scale back and trade fewer and fewer units (contracts, stocks, etc.). (By the way, if you can make your account grow geometrically, it will take you, on average, the same amount of time [trades] to take it from $10,000 to $100,000, as it will to take it from $100,000 to $1,000,000, or from $1,000,000 to $10,000,000.)

As your account grows, you should trade more and more units, to keep the relative amount risked at a constant level. It has always amazed me how most traders simply do not concern themselves with this, but instead put all their attention in whether or not they managed to call the right direction of the move. For most traders, being right about the direction of the move seems to be more important than actually making any money out of it, not to mention making the optimal amount of money. But, because we have no control over whether the next trade will be profitable or not, but do have control over the quantity we can put on, wouldn't it be better to focus our attention on "optisizing" that amount, once we have a system that we can trust and with a positive expectation in the long run?

The third term we must understand is the variable f which is simply the fraction of account size. The variable f can be optimized in several different ways: what might be optimal for you might not be optimal for me. If we only decide to optimize in relation to the speed with which we wish to make the account grow, it is called the *optimal* f. With this value for f in our hand, we then calculate the "optisized" number of units (stocks or contracts) we can put on for any given trade, given our expected worst-case scenario and current account status. For instance, suppose we already have calculated f to be 0.5 (we will see how to find the optimal f value shortly), that we currently have $100,000 in our account, and that the worst-case scenario is a 10% loss (which in this case happens to equal $10,000 per unit traded). In this case, we can put on 5 units (100,000 X 0.5 / 10,000 = 5). Had f instead been 0.6, we could have put on six units (100,000 X 0.6 / 10,000 = 6). Thus, the higher the f the more units we can trade.

To be sure, there are other ways of coming up with an optimal number of units to trade. For instance, examine if there are any type of serial correlations or dependencies among the outcomes of your trade. One way of examining for dependency is to do a *runs test,* which tells you if your system has more or fewer streaks of consecutive wins or losses than what could have been expected if the trades had been randomly distributed. Another way is to look at the linear correlation coefficient.

As we learned in Part 3, if a system has any dependencies or correlations among the outcomes of the trades, there is information there that we are failing to exploit at the system building stage. That is, we should have formulated our entry and exit rules in such a way that the information the market was giving us, by signaling dependency, would have been dealt with at that time. This illustrates the paradox that with a system working optimally, there is no way to know if the next trade will be a winner or a loser.

Furthermore, even if your systems seem to exhibit some serial correlation or dependency, you probably still are much better off ignoring it as long as the evidence is not truly and really overwhelming "beyond any reasonable doubt." This is because the evidence is just that—evidence, not proof—and for a money management strategy based on dependency and correlations to prove itself more profitable than any other type of money management regimen (or even just profitable), the dependency needs in fact to be there. If it is not, your money management strategy will be suboptimal. To understand this, consider the following example: suppose you consider trading a system that shows evidence of dependency among the outcomes of the historical trades. You form a hypothesis that states that the dependency is in fact there and, therefore, the system should be traded with this in mind.

But what if it turns out that the dependency were not there? Then you will have committed a *type II error* (statistical jargon for accepting a hypothesis that in fact should have been rejected) and will lose money from trading the system either too aggressively or not aggressively enough. Had you done it the other way around, rejected the hypothesis when you in fact should have accepted it (a *type I error),* and traded it according to a fixed fractional money management strategy, although in hindsight you would have been better off trading it according to some dependency strategy, you still would have made money, albeit at a slower rate. Thus, the penalty for making a type II error would be a complete wipe out, while for a type I error it would only be a slower growth of equity. The above reasoning also applies to the special case of scaling back faster in times of drawdown than what is dictated by the fixed fractional strategy.

This also relates to what we learned about the system building process and the importance of keeping it as simple as possible, based on as few rules as possible. This method results in a system that not only trades profitably on historical data, but also continues to do so in the future as well. By adding rules to build away the (presumed) dependency, we are curve fitting the system and making it less likely to work in the future. Therefore, my recommendation is not to bother with the dependency or serial correlation at all. Whether it's there or not, build your system with as few rules as possible that make sense to you, then trade it with a fixed fractional money management strategy. The price of not doing so is simply too high.

Now, suppose that the trade in the previous example ended up in a profitable move of 5%, equal to a profit of $5,000 per contract, or a total profit of $25,000 or 25%. The following formula tells us that the HPR is 1.25:

$$HPR = 1 + f \times (-PFIT / WCS)$$

where *f* = the value we are using for f = 0.5; —PFIT = the profit or loss, per contract, on the trade, with the sign reversed = $5,000; and WCS = the worst-case scenario (always a negative number) = —$10,000.

Notice that the only difference between this and the previous formula for the HPR is that we now multiply the percentage made on the trade with the factor *f* and the worst-case amount is the amount risked. In the previous example we really didn't state how much we risked or lost in dollar terms, but just stated the percentage value as a result of the formula -PFIT X 100 / WCS. To do this in Excel, type in the following formulas and values into an empty spreadsheet:

In cell B3: 100,000
In cell C3: -10,000
In cell D3: 0.5
In cell B5: 5,000

Type in the following number sequence (one below the other) into cells B6 to B14: 2,000, 7,000, -4,000, -2,000, 6,000, 2,000, -10,000, -7,000 and -3,000.

In cell C5: =1+D$3*(-B5/C$3) (then drag down to fill all the cells C5 to C14)
In cell D5: =C5
In cell D6: =D5*C6 (then drag down to fill all the cells D6 to D14)
In cell E3: =COUNTIF(B5:B14, "<>0")
In cell E5: =D5*B$3 (then drag down to fill all the cells E5 to E14)
In cell F3: =D14^(1/E3)
In cell F5: =B3/(C$3/-D$3)
In cell F6: =E5/(C$3/-D$3) (then drag down to fill all the cells F6 to F14)

When you are done, your spreadsheet will resemble that in Figure 15.1.

To the example above, I also have added another very useful variable, the *geometric mean,* which is akin to the average HPR or growth factor per play. To arrive at any final TWR, you could either multiply all the HPRs, or you could take the geometric mean raised by the number of trades (more about this shortly).

B	C	D	E	F	G
Initial eq.	**Worst case**	**f**	**Trades**	**Geo. mean**	
100,000	-10,000	0.50	10	1.0093	
Profit	**HPR**	**TWR**	**Current eq.**	**Units**	
5,000	1.2500	1.2500	125,000	5	
2,000	1.1000	1.3750	137,500	6	
7,000	1.3500	1.8563	185,625	7	
-4,000	0.8000	1.4850	148,500	9	
-2,000	0.9000	1.3365	133,650	7	
6,000	1.3000	1.7375	173,745	7	
2,000	1.1000	1.9112	191,120	9	
-10,000	0.5000	0.9556	95,560	10	
7,000	1.3500	1.2901	129,006	5	
-3,000	0.8500	1.0965	109,655	6	

FIGURE 15.1

How to use Excel to calculate your holding period returns and terminal wealth relative.

You can manually change the value in cell D3 between 0 and 1 to try to find the highest value for TWR in cell D14. For instance, if you change the value in cell D3 to 0.1, the value in cell D14 changes to 1.0889 (if you're displaying four decimals). The value in cell D3 that correspond to the highest value in cell D14 is the optimal f for the system. Another and quicker way is to use the Solver Add-in function in Excel, under the Tools menu (Figure 15.2).

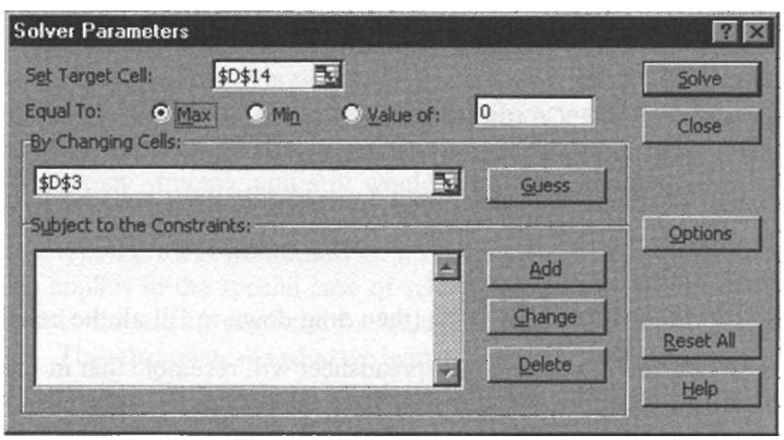


FIGURE 15.2

Use the solver add-in function in Excel to calculate your optimal f.

Note also that in this particular case we assumed the worst case to be constant and equal to the worst case in our sequence of trades. There are several other ways to do this, including calculating the standard deviation of all outcomes and setting the worst trade to equal a certain distance from the average trade, or letting the stops of your system (as they pertain to each individual trade) determine an individual worst-case scenario for each trade. This is how I prefer to do it. Figure 15.2 also hints at the fact that you could perform more complex optimizations by adding a few other constraints, such as not letting the maximum drawdown or the standard deviations of the individual outcomes grow past specific values.

In this case, the optimal *f* equals approximately 0.31, with a final TWR of approximately 1.18. This means that for any particular trade, you should not risk more than 31% of your total equity going into the trade. This is the optimal *f* for this system when we work under no other constraints than trying to maximize the growth rate, not taking into consideration any costs or the fact that we cannot trade fractions of contracts. And just as we do not take slippage and commission into consideration when we are looking for the optimal variable setting for a system (so we do not come up with a suboptimal solution), this is also how you should look for your system's optimal *f* Remember that we first and foremost want the system to be well working rather than profitable—we want it to catch a certain type of market move as efficiently as possible. As long as we do that, eventually we also will be able to apply it to a market where it will be profitable as well. Besides, when it comes to trading with a fixed fractional money management, seldom will you be able to trade your system at its optimal *f* level anyway, as will become evident shortly.

Consider the following expectancies for a system you are thinking about trading real-time:

- The percentage of winning trades are over 72%.
- For every winning trade you win, on average, 1.52%.
- For every losing trade you lose, on average, 1.19%.
- The profit factor is 3.36.

This is a fantasy system similar to that depicted by the performance summary in Table 12.12. With a system like this, what could go wrong? The losers are considerably smaller than the winners and with plenty more winners than losers, at first glance it looks like you should bet almost your entire equity each time, just saving a little in case you happen to get into a drawdown, which you should make up for easily considering the high percentage winning trades.

Because the data that is exported into Excel has all outcomes measured in percentages rather than dollars, as is the case in the example above, the calculations look a little different. In this case, I have used the trade-by-trade export function from Part 1, which you can use for single market/system combinations. (We will learn how to build a bar-by-bar export function for multiple market /system combinations and bar-by-bar portfolio analysis later.) In this case, you must insert a few empty rows at the top of the spreadsheet and a few empty columns directly to the right of the "Profit" column, as shown in Figure 15.3. If your spreadsheet looks like that in Figure 15.3 (remember, this is a fantasy system that you can substitute for any system of your choice), you can then type in the following formulas or values:

In cell F3:

=MIN(F5:F219)/100,

where F219 denotes the last data row.

In cell G5:

= 1 +G$3*(-(F5/100)/F$3) (then drag down to fill all the cells G5 to G219)

In cell H3:

=H219^(1/COUNTIF(F5:F219,"<>0"))

In cell H5:

=G5

In cell H6:

=G6*H5 (then drag down to fill all the cells H6 to H219)

Then manually enter into cell G3 all values for f between 0 and 1, in steps of 0.05, and copy each value into a separate column. When done, you should have no problem creating a chart like that in Figure 15.4.

Sure enough, the optimal *f* for this system turns out to be as high as 0.90, which generates a TWR of 3,325. That is, had you been able to trade this system at its optimal *f* level, you would have made a whopping 3,325 times your original equity, corresponding to a total profit of equally whopping 332,400% ((3,325 - 1) * 100). Figure 15.4 shows the TWR you would have been able to achieve depending on what *f* level you traded.

	A	B	C	D	E	F	G	H	I
1									
2						W. case	f	G. mean	
3						-0.0929	0.898522739	1.038437992	
4	E Date	Position	E Price	X Date	X Price	Profit	HPR	TWR	
5	880115	-1	381.7	880119	371.01	2.8	1.270814173	1.270814173	
6	880122	1	365.6	880125	375.84	2.8	1.270814173	1.614968662	
7	880129	-1	382.5	880205	372.26	2.68	1.259207851	2.033581219	
8	880205	1	372.26	880210	382.69	2.8	1.270814173	2.584303836	

FIGURE 15.3

Using Excel to calculate TWR as a function of f.

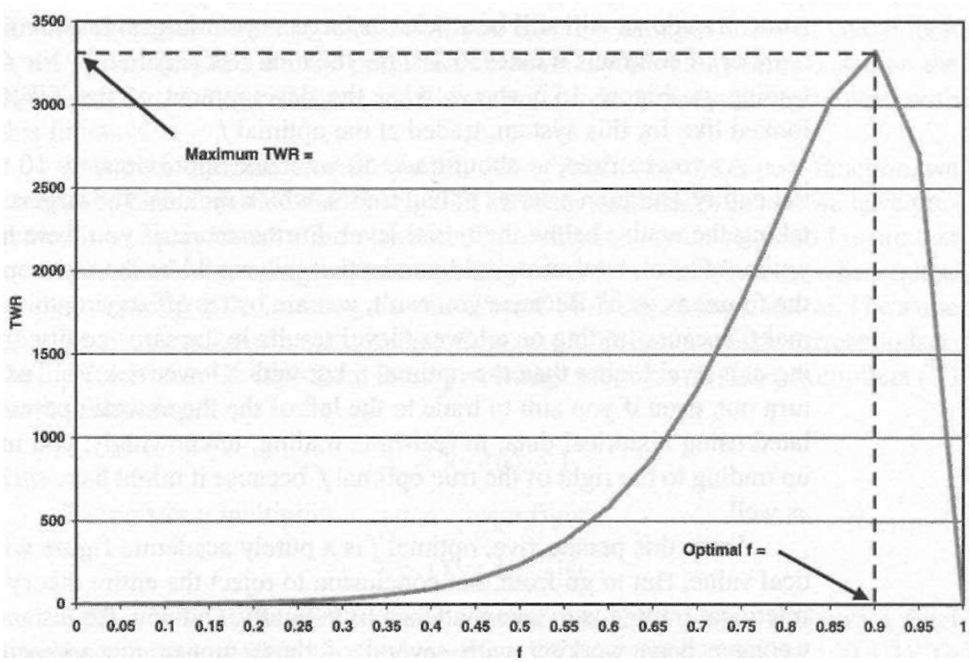


FIGURE 15.4

The TWR of a fantasy system in relation to the fraction of your capital risked per trade.

As you can see, trading at an *f* level higher than the optimal *f* does not make your account grow any faster. Instead you are assuming more risk than necessary to accomplish the same growth rate as you could have done trading at a lower *f* and you are also taking on a higher likelihood for going broke the more trades you place. (See point two in the list at the beginning of this section.) But there is more to it than that. If you cut your risk (your *f)* in half, you will cut the expected profits by much more than that. In fact, if you change your *f* arithmetically, profits change geometrically.

The paradox is that the better the system and the higher the optimal *f* the larger the drawdowns you suffer. This is because the optimal *f* is the percentage amount you are willing to lose on one trade, based on how large you expect the largest loser to be. When that loser hits you, you lose that percentage amount of your equity, as suggested by the *f* level that you are using. And this is for one trade only. If the next couple of trades turn out to be losers as well, the drawdown is even more severe than that.

This relates to points three and four in the list at the beginning of this chapter, because this has nothing to do with how many markets or what type of markets you trade (i.e. how well diversified you think you are, or how you think that you can keep a lower risk by only trading stocks and/or not selling short). Your worst drawdown will still be at least as large as your largest loser multiplied by the number of contracts it takes to assume the total risk required by the *f* level you are trading at. Figure 15.5 shows what the development of the TWR would have looked like for this system, traded at the optimal *f*

As you can see, at about trade 50 we made approximately 10 times our initial equity. But then a series of bad trades, which includes the largest loser, hits us, taking the equity below the initial level. Furthermore, if you were to trade at the optimal *f* level, how sure could you be that this would be the most optimal level in the future as well? Because you can't, you are better off staying to the left of optimal *f* because trading on a lower *f* level results in the same equity growth as trading at a level higher than the optimal *f* but with a lower risk. And as things might turn out, even if you aim to trade to the left of the theoretical optimal *f* you calculated using historical data, in real-time trading, unknowingly, you might still end up trading to the right of the true optimal *f* because it might have shifted to the left as well.

From this perspective, optimal *f* is a purely academic figure with little practical value. But to go from that conclusion to reject the entire theory behind fixed fractional trading is to take matters a little lightly. Did you, for instance, know that we have been working with several of these money management parameters

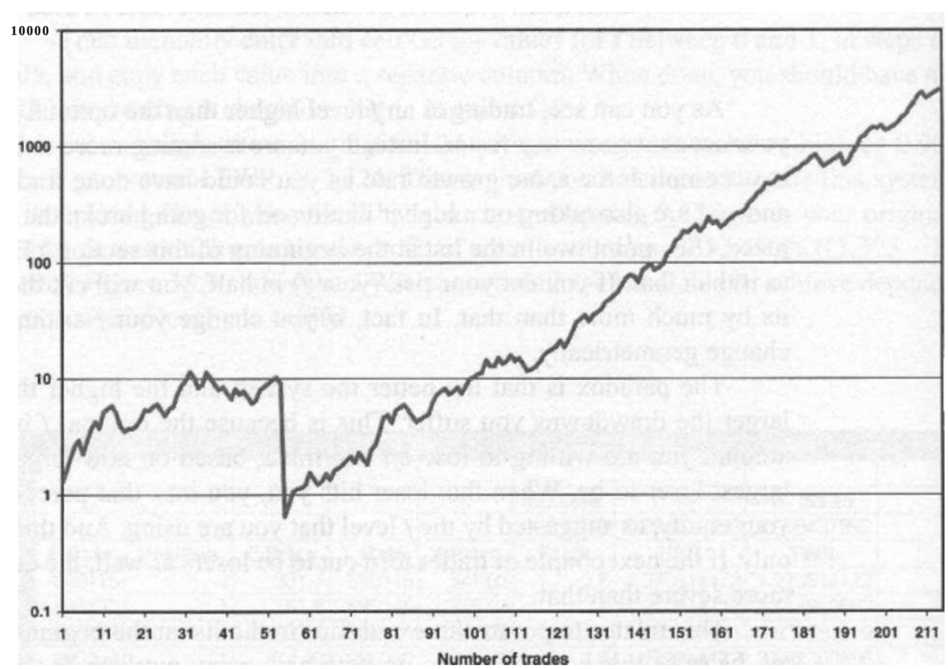


FIGURE 15.5

The growth in equity for a fantasy system traded with an f of 0.9.

already throughout the entire book? If you have not thought about it, take a look at the export function for the performance summary for all systems based on the RAD contract and any of the spreadsheets you might already have produced with this function.

Into the individual profits column, titled "Profit" by the export function, we essentially have exported the unweighted HPR for each trade, except we have presented it as a percentage figure instead of a multiplier. By unweighted I mean that we have not taken the largest loser and the *f* level into consideration when calculating it, as we did, for instance, in cells C5 to C14 in the example above. The same goes for the cumulative profit, in the "Cum. prof." column, which corresponds to the TWR variable. To transform these percentage numbers (X) into multipliers (Y) do the following:

$$Y = X / 100 + 1$$

To transfer a multiplier to a percentage figure:

$$X = (Y - 1) * 100$$

Take a look at the performance summary in Table 12.14. It shows a final cumulative profit of 50.02%, which equals a TWR of 1.5002 (50.02 / 100 + 1). To calculate the geometric mean, raise it by 1 divided by the number of trades for the system and you will get 1.00442 (1.5002 ^ (1 / 92)). This translates to approximately 0.44% ((1.00442 - 1) * 100). This is the return per trade you could expect to make had you been able to reinvest all previous profits.

We also can estimate the geometric mean by taking the average profit (0.46%) and transforming it into a multiplier (1.0046). Let us call this multiplier APM and the estimated geometric mean EGM. Then raise that by 2, before we deduct the standard deviation (SD), also raised by 2. Finally, raise everything by 1 divided by 2. Hence, in this case we calculate EGM to be 1.00447 ((1.0046^2 - 0.0163^2)^(l/2)), or approximately 0.45%. From here, we can continue to estimate the TWR by raising everything by the number of trades (please bear with me). Let us call the estimated TWR *ETWR* and the number of trades *N*. That is:

ETWR = EGM^N, where

EGM = (APM^2 - SD^2)^(l/2), then

ETWR = (APM^2 - SD^2)^(1/2)^N = (APM^2 - SD^2)^(N/2)

This final equation is so important that Ralph Vince dubbed it the fundamental equation of trading. It is *The Equation,* if you wish, the one that explains everything. Perhaps not, but it does explain a lot. For instance, if the first parenthesis does not end up with a number greater than 1, the system will not make any money. The only way for this to happen is for APM to be sufficiently larger than

SD. Of course, the larger the APM in relation to the SD, the better, but what really matters is how sure you can be that this relationship will hold up in the future. Because as long as you can be sure of that, the only thing that will affect your bottom line is how frequently you can trade. That is, make N as large as possible. You do that by making sure that the system works well and/or trades profitably on as many markets as possible. And how do you do that?

Once again, this relates to what we learned about the system-building process and the importance of keeping it as simple as possible, based on as few rules as possible. This is the only way to come close to a system that not only trades profitably on historical data, but continues to do so in the future. By adding rules to build away individual market discrepancies, we curve fit the system and make it less likely to work in the future. But by working with techniques such as random entries and percentage-based stops and exits, we make sure that the system will work well in any market, in any time frame, and almost at any time.

The fundamental equation of trading also relates to what we discussed earlier about drawdown. Although diversification does not necessarily reduce drawdown, a fixed fractional trading strategy will dampen it by forcing you to cut back on the number of contracts traded, while a larger number of markets traded will help you to recover from drawdown at a faster rate, simply because of the additional number of trades each new market brings to the portfolio.

PRACTICAL APPLICATIONS FOR MONEY MANAGEMENT

All that we have discussed so far leaves us at a crossroads. Because the same system traded at different markets will come up with a different optimal *f* for each market, it seems we should trade each market individually on a separate account, or at least trade each market on a separate level of aggressiveness, as suggested by each market/system combination's optimal *f* Furthermore, if we blend in the Capital Asset Pricing Model (CAPM) and the Efficient Market Hypothesis (EMH) we also should weigh each market/system combination against all others so that each market/system combination is delivering the same risk-adjusted return as all others and so that the entire portfolio of market/system combinations balances on the *efficient frontier.*

However, after we have gone to great lengths not to treat any of the markets any differently from all the others, why should we start doing it now? Because if we did, once again we would be curve fitting. This time we wouldn't be curve fitting a specific system to a specific market, but instead a specific blend of separately weighted market/system combinations to the overall result of our portfolio.

If we decide to do this, it seriously contradicts what we have done so far. That is, to make sure that each and every one of our systems, on average and over a long period of time, works equally well on all markets, and that we have treated each and every market the same as all the others, basically stating that a time series is a time series is a time series.... Note that the key words here are "equally as well," not "equally as profitably." If we only wanted to optimize historical profits, we would have curve fitted a system to a specific market, calculated the optimal *f* level to 0.99 or higher, then traded it real-time and gone broke tomorrow. Remember that we are not solely interested in optimizing our equity, but to optisize our betting size in accordance with a number of constraints, among which a desired ending equity is one.

Another key phrase in the paragraph above is "over a long period of time." Of course we will end up with different optimal *fs* for different market/systems combinations within a limited time frame, say the last 20 years or so, which is basically how far back we have tested the systems in this book. But that is just pure coincidence. Over the next 20 years there might be other market/system combinations with higher *fs* than those that seem to be doing the best right now, while the average for the entire portfolio of all market/system combinations will still be approximately the same.

It also is possible to do the same type of logical reasoning as we did when we decided not to make the amount invested dependent on any serial correlations among the trades. In this case the hypothesis, based on historical observations, will be, "that each market has its own specific features and statistical traits, and, therefore, should be traded at its own/" If this turns out to be false, then we are making a type II error by accepting a hypothesis that in fact should have been rejected. We will trade the system too aggressively when we shouldn't and not aggressively enough when wc should. In the long run, we will lose money and increase the likelihood of going bust. Had we, on the other hand rejected the hypothesis when we shouldn't have (a type I error) by trading all the market/system combinations with the same *f* as suggested by, for instance, the lowest *f* or the *f* for the portfolio as a whole, we still would have made money, only at a slower rate.

To keep it simple, I therefore suggest that for each portfolio of markets to which you apply the same system, you should treat each trade the same way, no matter in which market that particular trade happens to be, and trade it at a fixed fractional level that makes the most sense to you, in regards to expected equity growth, drawdowns, flat times, and worst-case scenarios. Exactly the same goes for a situation where you have several systems applied to one market. Finally, if you would like to combine all your portfolios into one, continue to do the same. If your systems are thoroughly researched and you "know" they will continue to work, you still will make tons more money trading at a fixed fractional level as low 0.015, not risking more than 1.5% of your total equity per trade, than you would on a fixed contract basis, depending on how you choose to define the constraints against which you are maximizing your utility.

For instance, using the fantasy system above, if we were to risk only 3%, the new TWR would equal 1.4478, which means a total equity growth of a mere 45%. Not too good, because the original system without optimal *f* managed to produce a total of more than 216%. But what if instead we change the expected worst-case scenario to equal the stop loss for the system at 1.1%, by typing "—0.011" into cell F3. For each new trade I put on, this is as bad as I expect things to go. Now, I know that sometimes things will go worse than that, but that is as bad as I expect them to go. The fact is that I know if I do this long enough there will come along one trade that will blow me away completely. So from that point of view, whether I choose to go with the largest loser (as suggested by the historical data) or with what I expect to lose the most in any particular trade (as suggested by the stop loss in the system) makes little difference.

Doesn't it make sense then to go with what I expect to lose in this particular trade, not what I might have lost in the past? Besides, if you trade the same system on a portfolio of markets you wouldn't be able to trade it at the optimal *f* level anyway, as the following example shows.

If you trade 10 markets and it happens that they all signal entry the same day, you won't be able to allocate more than 10% of your total capital, on average, to each market, no matter what the optimal/might be for each individual market/system combination. And by allocating the maximum 10% per market you will go broke if all trades go against you. Not to risk going broke you must allocate less than that, say 2% per market, which will give you a total risk of 20%. Granted, rarely will you enter all markets at once and rarely will they all go against you, but on the other hand, trading only 10 markets isn't much either.

Anyway, with the worst-case scenario set to equal the stop loss, the new optimal/for this overall strategy comes out to 0.10, with the relationship between different *f*s and the TWR resembling Figure 15.6. As you can see, now it becomes even more important that you do not overtrade, because already at an *f* equal to 0.15, the likelihood for going broke is 100%.

By risking only 3% instead of 10% of total equity I believe I have given myself all the slack I need. In that case, the new TWR equals 19.44, which equals a total equity growth of 1,844%. That is about 35% per year, continuously compounded, over the last 10 years. As a comparison, the best CTAs average around 20% to 25% per year, while the average return from the stock market over the last 15 to 20 years is no more than 12% or so. Figure 15.7 shows you what the equity growth for this strategy would look like. Now, I will not be making 332,400%, as suggested by the original optimal *f* but this fantasy figure describes the power of this method. In Figure 15.7, notice especially that the drawdown around trade 50 (although the scales are different) is no worse than any of the others.

We can do a statistical type I/type II error analysis to confirm the importance of trading at an *f* lower than the optimal *f* This time the hypothesis is "the true *f* for the future will be higher or the same as the optimal *f* of the past; therefore we should not use an *f* lower than that *f*" If we accept this hypothesis and it turns out to be false, then we again commit a type II error. We will trade at an *f* that is too high, making it likely that we will go bust sooner rather than later. Had we instead

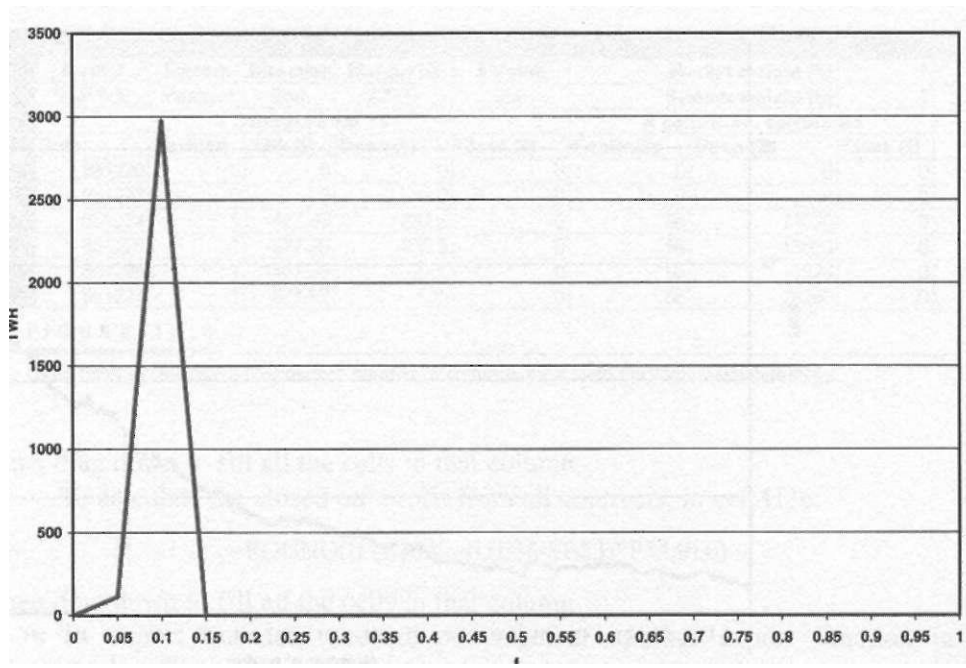


FIGURE 15.6

The TWR of a fantasy system using an individual worst-case scenario for each trade.

rejected the hypothesis by trading at an *f* sufficiently lower than the historical optimal *f*, when it turned out that we shouldn't have, well, then we wouldn't have made as much money as we could have, but we also would have increased the likelihood of still being in the game.

Next, we must decide the "optisized" amount of contracts or shares we should feasibly trade. And we will look at actual dollar figures instead of theoretical percentage numbers.

SHORT-TERM SYSTEMS

For each market/system combination, we have put together a spreadsheet like that shown in Figure 15.8, which contains a daily summary for that particular market/system combination. For example, Figure 15.8 shows that on December 24, 1985, the system signaled to go long with a maximum risk of $578 per contract. The fixed fractional money management strategy attached to this system told us to put on 56 contracts. On the close of that day, this market/system combination was down $232.50, on a one-contract basis and -$13,020 for the overall portfolio. The position was closed out on December 30, with a $315 profit per contract, for a total profit of $13,440.

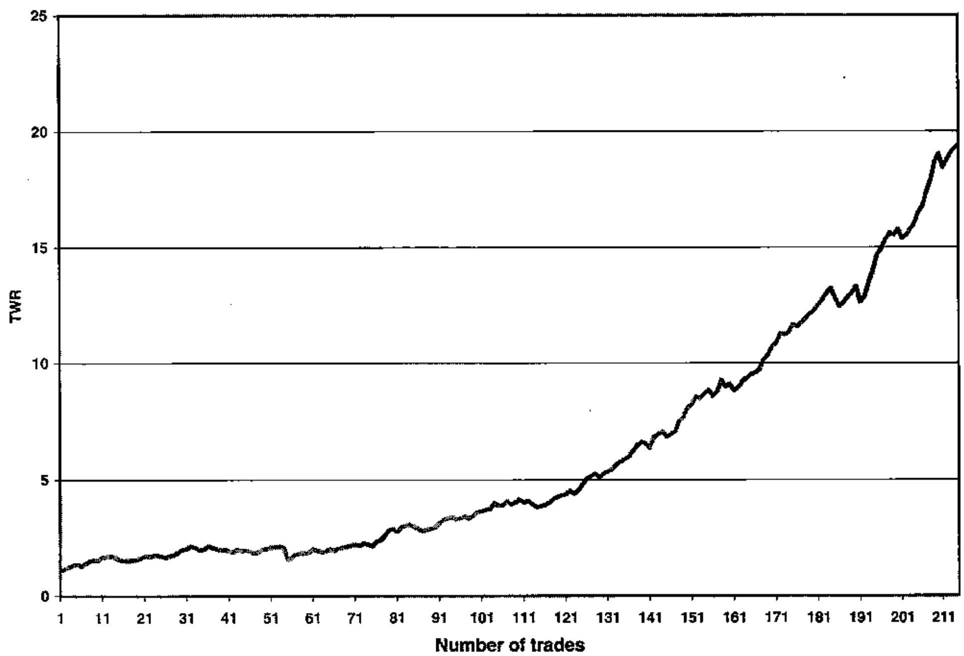


FIGURE 15.7

The growth equity for a fantasy system with an individual worst-case scenario for each trade.

In Figure 15.8, the data in the five columns under the "1 Contract from TS" header are imported directly from Trade Station, while the data in the three columns under the "N contracts—calculated" are calculated in Excel. All other cells also are imported directly from TradeStation, but can be altered within Excel as well. To perform the necessary calculations in columns F to H, type in the following formulas (disregard that some formulas hold references to other cells, outside of Figure 15.8):

In cell F36:

0

In cell F37:

=IF(AND(C37<>C36,C37<0),H$32*H$33*MAX(INT($AN36*
(B47100)/C37), 1),IF(E37=0,F36,0))

then drag down to fill all the cells in that column.

To calculate the open profit of all contracts:

In cell G36:

=ROUND(D36*F36,0)

	A	B	C	D	E	F	G	H
32	Market	System	Direction	Margin ($)	$ Value		Market weight (%)	1
33	S&P 500	Meander	Both	22000	250		System weight (%)	1
34		1 Contract from TS				N contracts - calculated		
35	Date	Position	Risk ($)	Open ($)	Close ($)	Contracts	Open ($)	Close ($)
36	851220	0	0	0	0	0	0	0
37	851223	0	0	0	0	0	0	0
38	851224	1	-577.99	-232.5	0	56	-13020	0
39	851225	1	-577.99	-232.5	0	56	-13020	0
40	851226	1	-577.99	-32.5	0	56	-1820	0
41	851227	1	-577.99	505	0	56	28280	0

FIGURE 15.8

Using Excel to calculate an "optisized" number of contracts for a fixed fractional trading strategy.

then drag down to fill all the cells in that column.

To calculate the closed out profit from all contracts; in cell H36:

=ROUND(IF(E36<>0,(E36-B3)*F35,0),0)

then drag down to fill all the cells in that column.

To export the data needed, put together another export function in TradeStation. We use the Meander system as an example:

```
Inputs: MarketName("MaxlOChar."), SystemName("MaxlOChar."),
Direction("Both"), MarginReq(l), DollarValue(l), MarketWeight(l),
SystemWeight(l);
Vars: VSStd(2), SumVS(O), AvgVS(O), DiffVS(O), StdVS(O), SetArr(O),
SumArr(O), DiffArr(O), VSLow(O), VSMid(O), VSHigh(O), TrueEntry(O),
FName(""), TradeStr2(""), Vacuum(O), Missing(O), FillDay(O), RiskValue(O),
PosProfit(O), ClosedProfit(O), MP(0), TotTr(O);
Array: VS[20](0);
For SetArr = 0 To 4 Begin
    VS[SetArr * 4 + 0] = (0[SetArr] Data2 - C[SetArr + 1] Data2) /
C[SetArr + 1] Data2;
    VS[SetArr * 4 + 1] = (H[SetArr] Data2 - QSetArr + 1] Data2) /
C[SetArr + 1] Data2;
    VS[SetArr * 4 + 2] = (L[SetArr] Data2 - C[SetArr + 1] Data2) /
C[SetArr + 1] Data2;
    VS[SetArr * 4 + 3] = (C[SetArr] Data2 - C[SetArr + 1] Data2) /
C[SetArr + 1] Data2;
End;
For SumArr = 0 To 19 Begin
    IfSumArr = OThen
        SumVS = 0;
```

```
        SumVS = SumVS + VS[SumArr];
        If SumArr = 19 Then
            AvgVS = SumVS / 20;
        For DiffArr = 0 To 19 Begin
            If DiffArr = OThen
                DiffVS = 0;
            DiffVS = DiffVS + Square(VS[DiffArr] - AvgVS);
            If DiffArr = 19 Then
                StdVS = SquareRoot(DiffVS / 20);
        End;
End;
VSLow = C Data2 * (1 + (AvgVS - StdVS * VSStd));
VSMid = C Data2 * (1 + AvgVS);
VSHigh = C Data2 * (1 + (AvgVS + StdVS * VSStd));
If MarketPosition = 0 Then Begin
        Buy ("Go long") tomorrow at VSLow limit;
        Sell ("Go short") tomorrow at VSHigh limit;
End;
If MarketPosition = 1 Then Begin
        ExitLong ("Long Target") at EntryPrice * (1 + (2.8 * 0.01)) limit;
        If Close > EntryPrice * (1 + (0.6 * 0.01)) Then
            ExitLong ("Long Trailing") at EntryPrice * (1 + (0.6 * 0.01)) stop;
        ExitLong ("Long Loss") at EntryPrice * (1 - (1.1 * 0.01)) stop;
End;
If MarketPosition = -1 Then Begin
        ExitShort ("Short Target") at EntryPrice * (1 - (2.8 * 0.01)) limit;
        If Close < EntryPrice * (1 - (0.6 * 0.01)) Then
            ExitShort ("Short Trailing") at EntryPrice * (1 - (0.6 * 0.01)) stop;
        ExitShort ("Short Loss") at EntryPrice * (1 + (1.1 * 0.01)) stop;
End;
If BarsSinceEntry >= 8 Then Begin
        ExitLong ("Long Time") at Close;
        ExitShort ("Short Time") at Close;
End;
{***** Export function starts here *****}
MP = MarketPosition;
TotTr = TotalTrades;
```

```
If CurrentBar = 1 Then Begin
    FName = "D:\Temp\MM-TM-" + LeftStr(GetSymbolName, 2) + ".csv";
    FileDelete(FName);
    TradeStr2 = "Market" + "," + "System" + "," + "Direction" + "," +
    "Margin ($)" + "," + "$ Value" + "," + "," + "Market weight (%)" +
    "," + NumToStr(MarketWeight, 2) + NewLine;
    FileAppend(FName, TradeStr2);
    TradeStr2 = LeftStr(MarketName, 10) + "," + LeftStr(SystemName, 10) +
    "," + LeftStr(Direction, 10) + "," + NumToStr(MarginReq, 0) + "," +
    NumToStr(DollarValue, 0) + "," + "," + "System weight (%)" + "," +
    NumToStr(SystemWeight, 2) + NewLine;
    FileAppend(FName, TradeStr2);
    TradeStr2 = "1 Contract fromTS" + "," + "," + "," + "," + "," +
    "N contracts - calculated" + NewLine;
    FileAppend(FName, TradeStr2);
    TradeStr2 = "Date" + "," + "Position" + "," + "Risk ($)" + "," +
    "Open ($)" + "," + "Close ($)" + "," + "Contracts" + "," + "Open ($)" +
    "," + "Close ($)" + NewLine;
    FileAppend(FName, TradeStr2);
End;
Vacuum = DateToJulian(Date) - DateToJulian(Date[l]);
For Missing = 2 To Vacuum Begin
    FillDay = JulianToDate(DateToJulian(Date[l]) + (Missing-1));
    If DayOfWeek(FillDay) > 0 and DayOfWeek(FillDay) < 6 Then Begin
        TradeStr2 = NumToStr(FillDay, 0) + "," +
        NumToStr(MarketPosition, 0) + "," + NumToStr(RiskValue, 2) +
        "," + NumToStr(PosProfit[l], 2) + "," + "0" + NewLine;
        FileAppend(FName, TradeStr2);
    End;
End;
RiskValue = 0;
PosProfit = 0;
ClosedProfit = 0;
If MP <> MP[1] and MarketPosition <> 0 Then Begin
    TrueEntry = C Data3 * (EntryPrice / C);
    RiskValue = TrueEntry * (1.1 * 0.01) * BigPointValue;
End;
If MarketPosition = 1 Then
```

```
        PosProfit = ((C / EntryPrice) - 1) * TrueEntry * BigPointValue;
    If MarketPosition = -1 Then
        PosProfit = -((C / EntryPrice) - 1) * TrueEntry * BigPoint Value;
    If TotTr <> TotTrfl] Then Begin
        If MarketPosition(l) = 1 Then
            ClosedProfit = ((ExitPrice(l) / EntryPrice(l)) - 1) * TrueEntry[l] *
            BigPointValue;
        If MarketPosition(l) = -1 Then
            ClosedProfit = -((ExitPrice(l) / EntryPrice(l)) - 1) * TrueEntry[l] *
            BigPointValue;
    End;
    TradeStr2 = NumToStr(Date, 0) + "," + NumToStr(MarketPosition, 0) + "," +
    NumToStr(-RiskValue, 2) + "," + NumToStr(PosProfit, 2) + "," +
    NumToStr(ClosedProfit, 2) + NewLine;
    FileAppend(FName, TradeStr2);
```

We will work with dollar values now, because we would like to build hypothetical track records that can be compared to similar track records from different CTAs, fund managers, and/or other system builders like ourselves.

Remember from Part 1 that we learned we cannot make any percentage-based calculations on the point-based back-adjusted contract and no dollar-based calculations on the RAD contract. This causes a problem now, when we would like to have our results in dollars, but still are dependent on a set of percentage-based exit techniques to maintain them. Therefore, to transfer our system's results back to the dollar-based world, we must use some ingenuity and incorporate the unadjusted time series, where all individual front months are attached to the time series one after the other. In this example, we have added the daily data for the unadjusted time series as *data 3.*

With this time series in place, we can use percentage values to calculate the number of points at risk and the open and closed-out profits in dollars for the unadjusted time series, and then export that value into the spreadsheet program. In the code above you can see that this has been done in a variable called "TrueEntry," which is calculated at the same time as the open and closed-out profits.

Another important feature of this code is the loop function, which makes sure that you also export data for all days missing in your database or during holidays (except weekends). When you start to put together portfolios, all the data from all different markets must be in sync.

Now that we know how to export the data, look again at Figure 15.8. As you can see, row 33 holds information on which market and system this export stems, as well as information about point value and margin requirements. This information can be typed into the spreadsheet directly, or as inputs to the code. I also have prepared both the export function and the spreadsheet for the possibility of experimenting with different systems and market weights. To give all market/system combinations an equal weighting keep the setting at 1, if you don't want to turn off that particular market/system combination completely, in which case you can set either one of the weights to 0.

Once you have typed in the necessary information and formulae in columns F to H, following Figure 15.8, you can either continue to add more markets in adjacent columns before you finish with the portfolio summary calculations or, if you only are interested in this particular market, move on directly to the portfolio summary in columns J to Q, as shown in Figure 15.9.

To build the portfolio summary type in the following formulas:

In cell J36:

=A36

then drag down to fill all the cells in that column.

In cell K36:

=SUM(G36)

then drag down to fill all the cells in that column.

In cell L36:

=SUM(H36)

then drag down to fill all the cells in that column.

In cell M36:

=B2

In cell M37:

=M36+L37+(K37-K36)

then drag down to fill all the cells in that column.

	J	K	L	M	N	O	P	Q
34					Portfolio			
35	Date	Open ($)	Close ($)	Total ($)	OE Ratio (%)	EqTop ($)	Drawdown (%)	Flat time (d)
36	851220	0	0	1,000,000	0	1,000,000	0	0
37	851223	0	0	1,000,000	0	1,000,000	0	0
38	851224	-13020	0	986,980	-1.32	1,000,000	-1.3	1
39	851225	-13020	0	986,980	-1.32	1,000,000	-1.3	2
40	851226	-1820	0	998,180	-0.18	1,000,000	-0.18	3
41	851227	28280	0	1,028,280	2.75	1,028,280	0	0
42	851230	0	13440	1,013,440	0	1,028,280	-1.44	1

FIGURE 15.9

Using Excel to calculate the aggregate results from trading several markets In a portfolio.

In cell N36:

=ROUND(K36* 100/M36,2)

then drag down to fill all the cells in that column.

In cell 036:

=M36

In cell 037:

=MAX(M37,036)

then drag down to fill all the cells in that column.

In cell P36:

=ROUND((M36-036)* 100/036,2)

then drag down to fill all the cells in that column.

In cell Q36:

=IF(P36=0,0,Q35+1)

then drag down to fill all the cells in that column.

Notice especially the use of the sum function in columns K and L. This is because had you also added data from other markets, that data would have been added to the overall portfolio results.

In several of the above Excel formulae there are references to a set of cells in the B column, because this is where I stored the initial parameter settings, like the initial account balance, the dollar value to be deducted for slippage and commission, and the percentage risked per trade. This can be seen in Figure 15.10. In this case, we start out with $1,000,000 in initial equity, of which we will risk 3.25% per trade. Before we add the closed-out profit to the overall equity of the portfolio, we deduct $75 per contract for slippage and commission.

Now, with the data and all the formulas in place it is time to build a performance summary that resembles that in Figure 15.11. In this particular case it shows the results from trading the Meander system on the S&P 500, over the period March 1996 to October 1999, with $75 deducted for slippage and commission per contract traded. The fixed fraction of the total equity risked per trade was set to 5% and the initial capital was $1,000,000.

As you can see, in this particular case we took the initial capital to an ending capital of $3,203,971, which equals a yearly percentage return of approximately 36.4%. The "price" for doing this came in the form of having to spend approximately 16 out of every 100 days in the market, a maximum drawdown of close to 28%, and a longest flat time of 317 days.

Before we go on, let us take a closer look at how each performance figure is calculated and what you need to type into each cell.

I11 =

	A	B	C
1	Change these		
2	Initial Eq ($)	1,000,000	
3	S&C ($)	75	
4	Risk (%)	3.25	
5	No. years	13.8	
6	Days / year	260	
7			

FIGURE 15.10

Example of initial parameter setting for all Excel calculations.

In cell E3:

=ROUND(AN(X),0),

where column *AN* refers to the column for where the portfolio equity is calculated (column M, in Figure 15.9, above) and *X* refers to the last row of data.

In cell E4:

=ROUND((E3/B2-1)*100,0)

In cell E5:

=ROUND(((E3/B2)^(1/B5)-1)*100,2)

	D	E	F	G	H
1	Strategy summaries				
2	Profitability			Trade statistics	
3	End Eq ($)	3,203,971		No Trades	73
4	Total (%)	220		Avg Tr ($)	30,191
5	Year (%)	36.41		Tr / Mark / Year	4.9
6	P factor	1.82		Tr / Month	0.4
7					
8	Risk measurers			Time statistics	
9	Max DD (%)	-27.76		Lng Flat (d)	317
10	Lrg Loss ($)	-289,260		TIM (%)	16.35
11	Winners (%)	57.53		Avg Days	4.00
12					

FIGURE 15.11

Strategy summary for a portfolio during the "optisizing" process in Excel.

In cell E6:

=ROUND(SUM(SUMIF(H36:H989,">0"),SUMIF(Q36:Q989,">0"),
SUMIF(Z36:Z989,">0"),SUMIF(AI36:AI989,">0"))/ABS(SUM(SUMIF
(H36:H989,"<=0"),SUMIF(Q36:Q989,"<=0"),SUMIF(Z36:Z989,"<=0"),
SUMIF(AI36:AI989,"<=0"))),2),

where columns *H, Q, Z,* and *AI* refers to the closed out profit for each market/ system in the portfolio (in this case I prepared the fixed fractional portfolio calculations for four markets/systems, but temporarily turned off the other three).

In cell E9:

=ROUND(MIN(AQ36:AQ989),2),

where column *AQ* refers to the portfolio drawdown (column *P,* in Figure 15.9, above).

In cell E10:

=ROUND(MIN(AM36:AM989),0),

where column *AM* refers to the closed out equity for the portfolio (column *L,* in Figure 15.9, above).

In cell E11:

=ROUND(SUM(COUNTIF(H36:H989,">0"),COUNTIF(Q36:Q989,">0"),
COUNTIF(Z36:Z989,">0"),COUNTIF(AI36:AI989,">0"))*100/H3,2)

In cell H3:

=SUM(COUNTIF(H36:H989,"<>0"),COUNTIF(Q36:Q989,"<>0"),
COUNTIF(Z36:Z989,"<>0"),COUNTIF(AI36:AI989,"<>0"))

In cell H4:

=ROUND(SUM(SUM(H36:H989),SUM(Q36:Q989),SUM(Z36:Z989),
SUM(AI36:AI989))/H3,0)

In cell H5:

=ROUND(H3/B5/B7,1)

In cell H6:

=ROUND(H5/12,1)

In cell H9:

=MAX(AR36:AR989),

where column *AR* refers to the flat time for the portfolio (column *Q,* in Figure 15.9, above).

In cell H10:

=COUNTIF(AL36:AL989,"<>0")*100/COUNT(AL36:AL989),

where column *AL* refers to the total open equity for all open trades in the portfolio (column *K*, in Figure 15.9, above).

In cell HI 1:

=ROUND(COUNTIF(AL36:AL989,"<>0")/COUNTIF(AM36:AM989,">0"),0)

With all the formulae in place, it is easy to put together a set of charts like those in Figure 15.12 through 15.14, which show the total equity, the drawdown, and the open profit, respectively. Figure 15.12 shows the equity curve for a portfolio consisting of only one market/system combination. It corresponds to the performance summary in Figure 15.11. Because of the very long initial flat period, it is not difficult to see that this equity curve is no good, despite the fact that the overall growth rate is as high as 36.5% per year. At this point, it also is important to understand that the percentage moves of the market are not the same as the percentage increase or decrease of our account. That the system will have us stopped out if the market moves against the position by 1.1%, is not the same as if we are risking only 1.1% of our capital at that trade. No matter how much the market

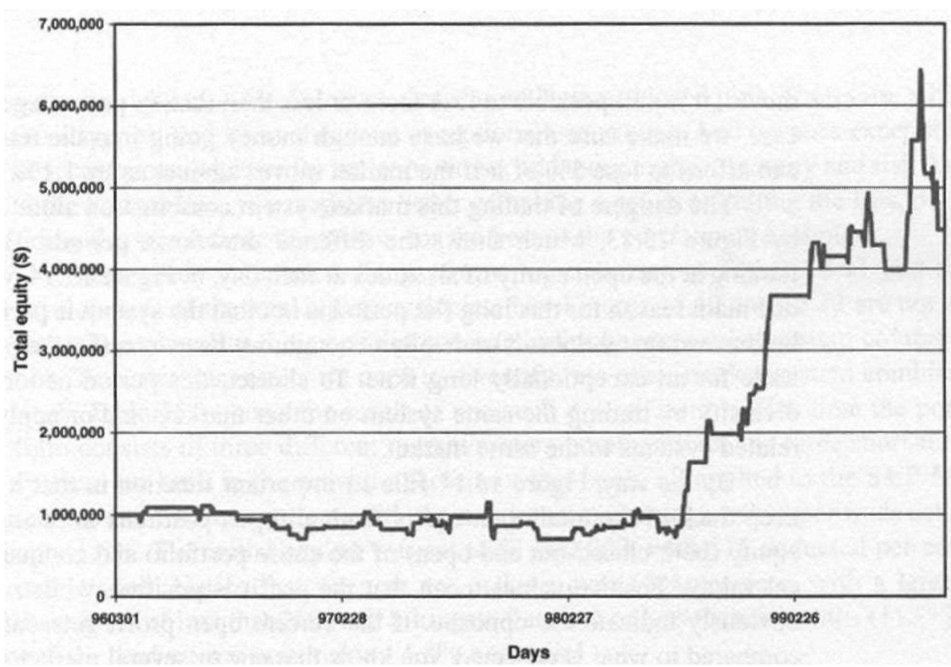


FIGURE 15.12

The equity curve from trading Meander on the S&P 500 with a 5% fixed fractional setting.

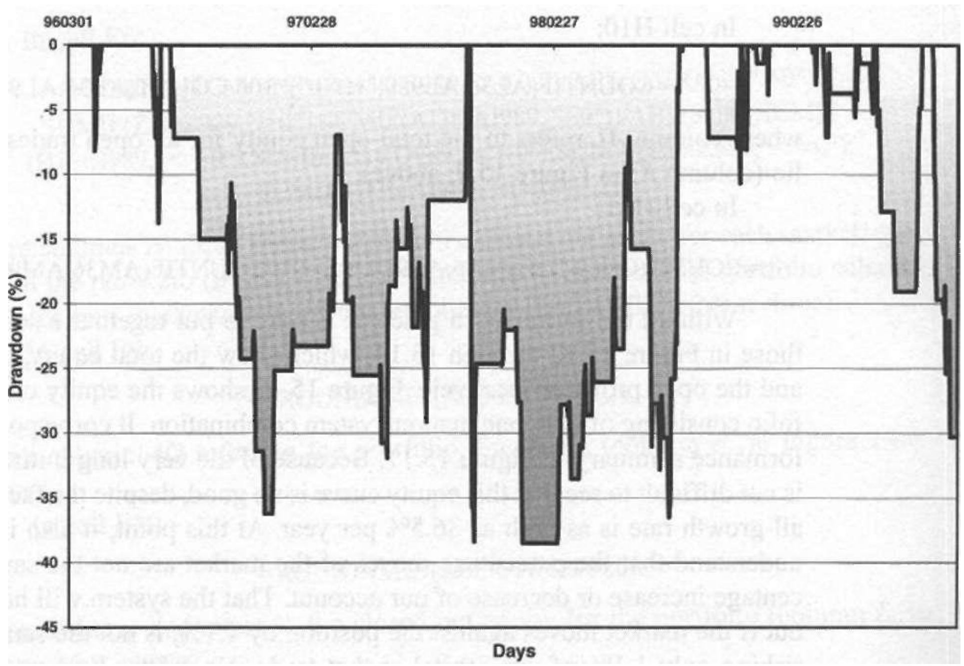


FIGURE 15.13

The drawdown curve from trading Meander on the S&P 500 with a 5% fixed fractional setting.

moves, it is still possible to lose more or less than that, in percentage terms. In this case, we make sure that we have enough money going into the trades so that we can afford to lose 5% of it if the market moves against us by 1.1%.

The dangers of trading this market/system combination alone are confirmed by Figure 15.13, which shows the different drawdown periods. However, when looking at the open equity of all trades at each day, in Figure 15.14, we can see that one main reason for this long flat period is not that the system is performing badly, but instead that it doesn't trade often enough; we have to suffer the pain of one bad trade for an exceptionally long time. To shorten this period of torture, we must diversify by trading the same system on other markets and/or apply other uncorrected systems to the same market.

By the way, Figure 15.14 fills an important function in that it allows you to keep track of the total open equity from all open positions in relation to the total equity (both closed-out and open) of the entire portfolio and compare it to historical values. Positive values mean that the profit is positive, while negative values obviously indicate the opposite. If the current open profit gets out of line when compared to what is expected, you know that one or several market/system combinations have developed in such a way that you now are steering the entire portfolio into unfamiliar territory. In this case, very seldom will the profit exceed 10%, or

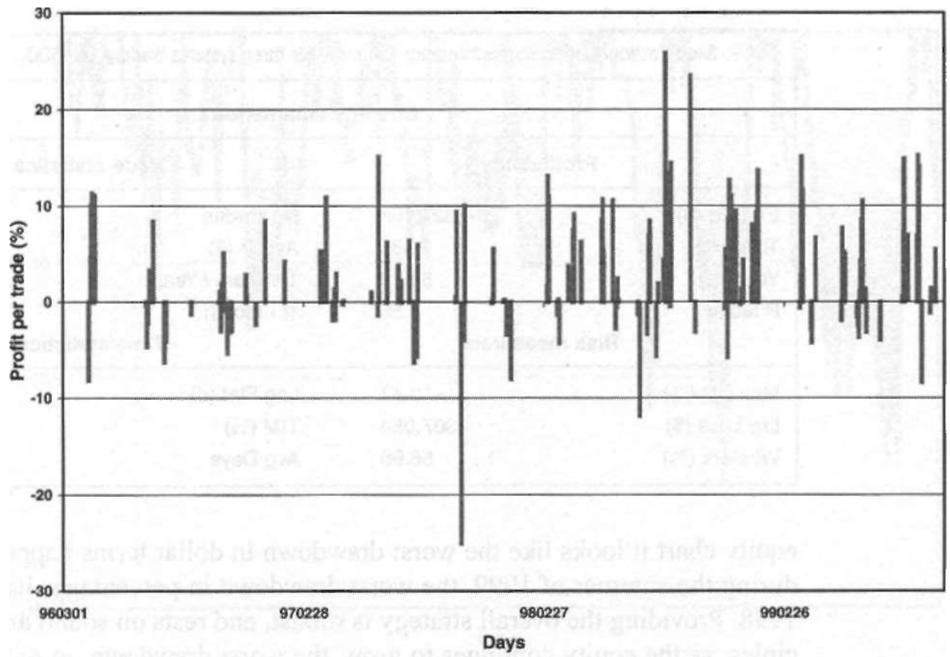


FIGURE 15.14

Profits per trade for Meander traded on the S&P 500 with a 5% fixed fractional setting.

surpass a loss of —5% (because that should have us closed out). Therefore, when this happens, you know this is an exceptional occurrence. And because exceptional occurrences, whether for better or worse, add more to the insecurity and risk than to the bottom line, you might be better off taking a profit or cutting the loss, overriding the signal from the system for the best of the portfolio as a whole.

As already concluded, the performance summary in Figure 15.11 and the development of the total equity as depicted by Figures 15.12 and 15.13 are not all that impressive. But this portfolio consisted of only one market/system combination. To better our results we need to diversify into other market/system combinations. Table 15.1 shows the result of one such diversification. This time the portfolio consists of three different market/system combinations, the three short-term systems we built in the previous section of this book, all applied to the S&P 500 commodity futures contract, with the maximum percentage risked per trade set to only 1.5%. The initial capital was set to $1,000,000, with $75 deducted per contract traded. Notice that we now are making over 50% per year, with a largest drawdown of less that 20% and a longest flat time of less than 6 months (113/21 = 5.4). And we are only risking 1.5% per trade!

Figures 15.15 and 15.16 show the accompanying equity curve and historical drawdown for this short-term strategy. As you can see, although from the total

TABLE 15.1

1.5% fixed fractional portfolio performance summary for three systems trading S&P 500.

Strategy summaries			
Profitability		**Trade statistics**	
End Eq ($)	4,827,166	No Trades	316
Total (%)	383	Avg Tr ($)	12,773
Year(%)	52.17	Tr/ Mark /Year	28.1
P factor	1.56	Tr / Month	2.3
Risk measurers		**Time statistics**	
Max DD (%)	-19.47	Lng Flat (d)	113
Lrg Loss ($)	-307,050	TIM (%)	54.82
Winners (%)	56.96	Avg Days	3.00

equity chart it looks like the worst drawdown in dollar terms happened sometime during the summer of 1999, the worst drawdown in percentages happened late in 1998. Providing the overall strategy is robust, and rests on sound and simple principles, as the equity continues to grow, the worst drawdown, in dollar terms, will

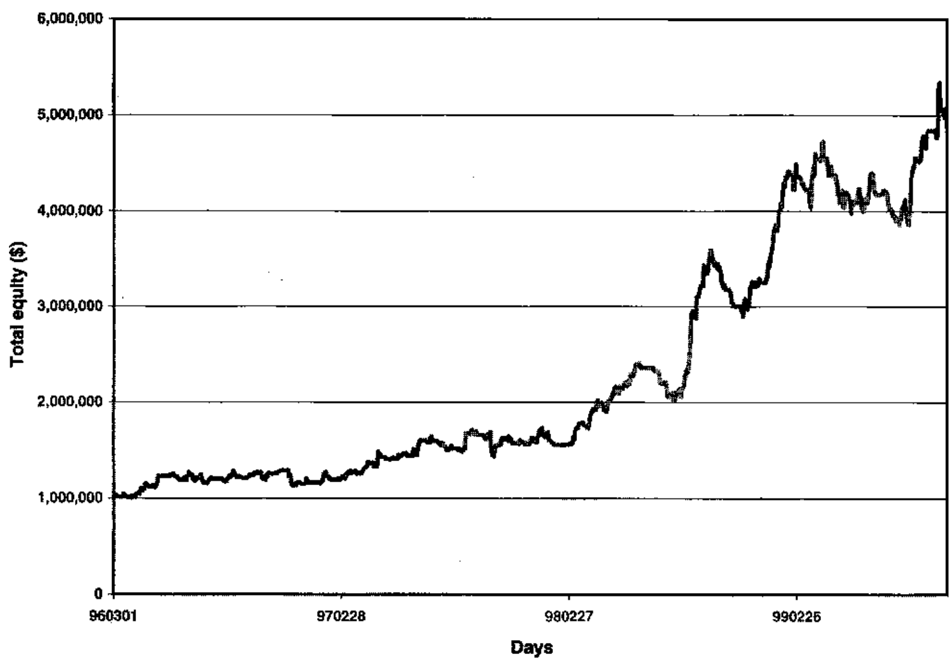


FIGURE 15.15

The combined equity curve from trading three different market/system combinations.

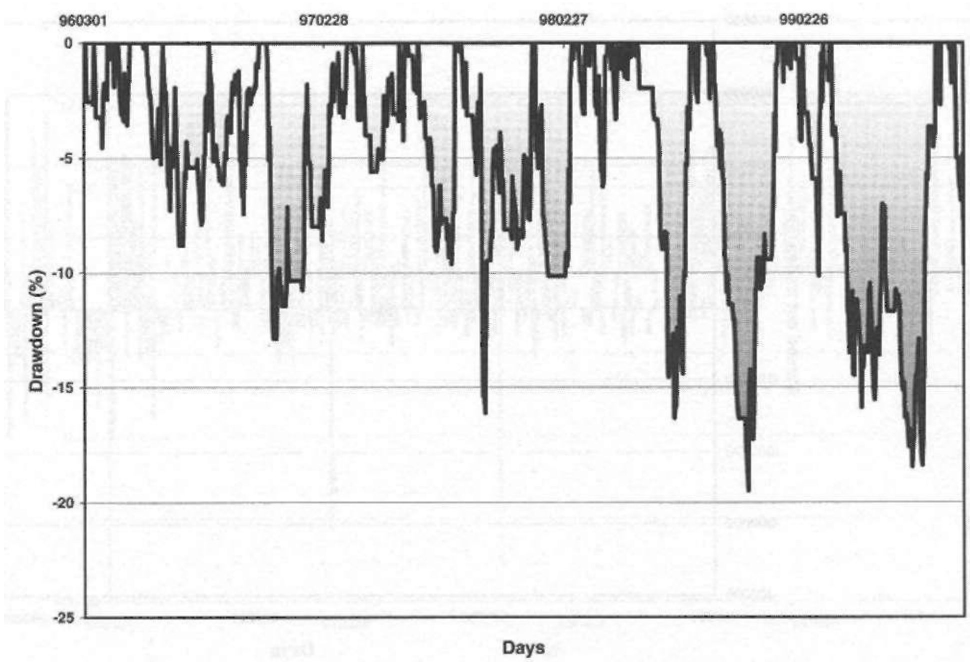


FIGURE 15.16

The combined drawdowns from trading three different market/system combinations.

continue to grow as well, while the drawdown as a percentage of your equity is likely to stay the same. If it happens to increase, this will have nothing to do with the level the market currently is trading, if the market trend is up or down, the size of your account, or any other reason. This is not the case when using any of the commercially available system testing packages. With the technique illustrated here, you know that the only reason why you suddenly get a higher drawdown figure is that your strategy is no longer working as it should (or at least is behaving in an unexpected manner). If and when this happens, you no longer need to worry, because having read the previous sections, you know exactly how to go back and correct what is wrong. You may even choose to build a new system, especially suited to trade with a portfolio of other systems and markets, all of which are developed solely to work well together under a fixed fractional money management regimen, thus forming an overall trading strategy where the whole is greater than the sum of its parts.

With the above paragraph in mind, look at Figures 15.17 and 15.18, which show two different ways of measuring the performance of the individual trades. Compare them to Figures 2.4 and 2.5. In Figure 2.5 and 15.18 there seem to be an upper and lower limit to how big each bar is likely to be. This is because in both charts the magnitude of the bars is expressed in percentage terms. In Figure 2.5,

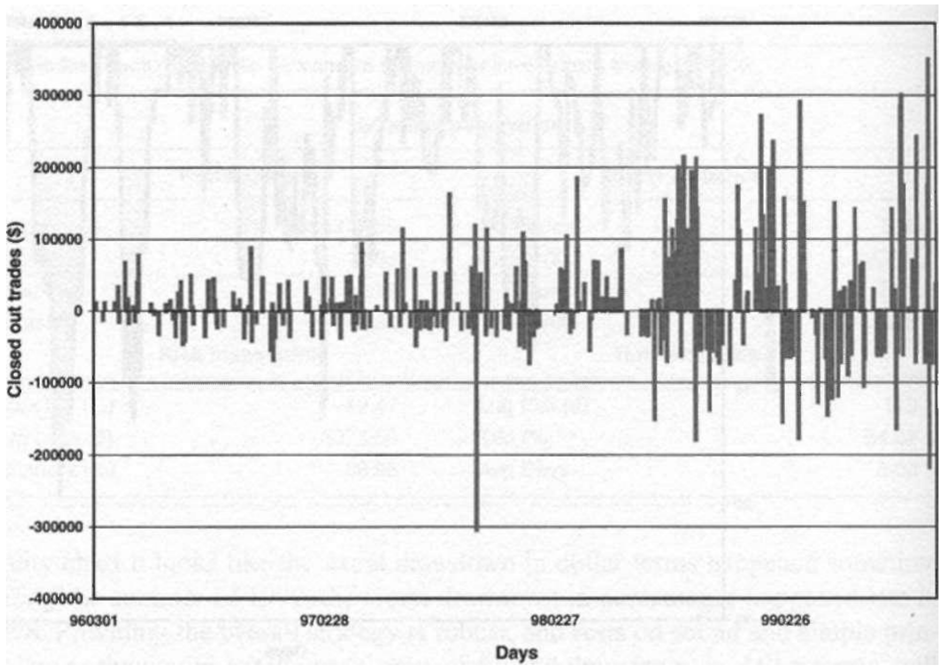


FIGURE 15.17

The dollar value for each trade from three different market/system combinations.

the percentage is calculated as the value of a specific move in relation to where the market currently is trading. In Figure 15.18, it is calculated as the value of a specific trade in relation to the total equity of the portfolio.

Figures 2.4 and 15.17, on the other hand, do not use these relative comparisons, but chart the dollar values directly. In Figure 2.4, we are looking at the dollar value from trading each move with one contract. In Figure 15.17, we are looking at the dollar value from trading each move with an increasing number of contracts. The main difference between Figures 2.4 and 15.17 is that in Figure 2.4 the dollar value per trade is increasing because the market is trading higher, while in Figure 15.17 the dollar value is increasing because our equity is increasing. However, whether our equity is increasing or not has nothing to do with whether the market(s) are trending up, down, or sideways, but rather with the fact that our strategy is working as it should, catching whatever type of trend or move happens. We know this now, but there was no way of knowing this from just looking at Figure 2.4, when we started out putting our strategies together.

Although Figure 15.17 can be fun to look at as long as everything is going the right way, the most important chart to keep track of is Figure 15.18, for exactly the same reasons as those for Figure 15.14, above. That is, if the closed-out profits seem to get out of line when compared to what could be expected, you know

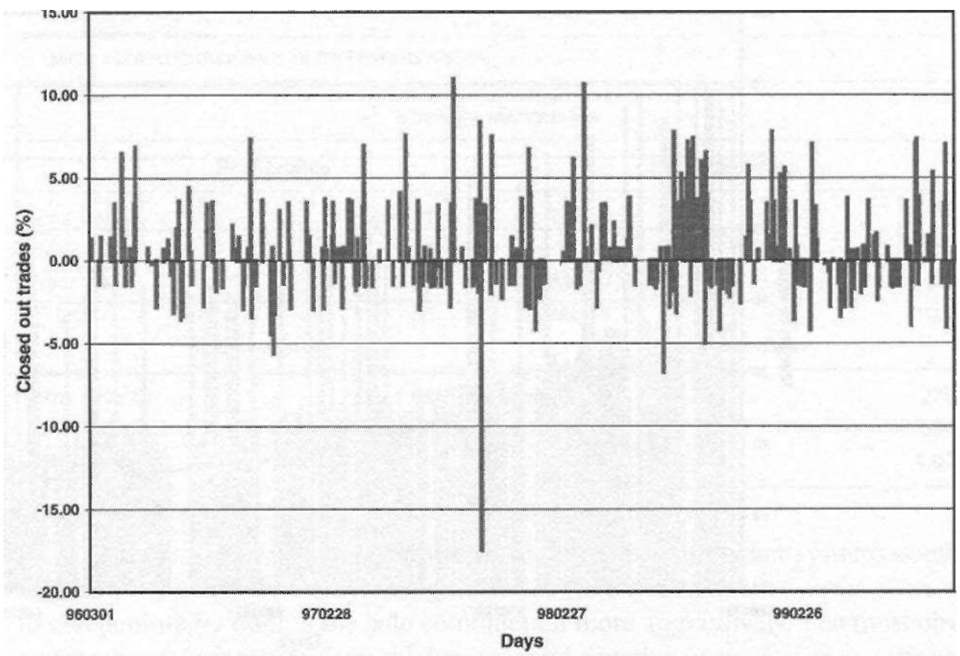


FIGURE 15.18

The percentage return for each trade from three different market/system combinations.

that one or several market/system combinations have developed in such a way that you now are steering the entire portfolio into unfamiliar territory. In this case, very seldom will the closed-out losses be any worse than just a few percentage points. Therefore, if this starts to happen more and more often, you know that one or several of your market/system combinations have started to behave in ways not in line with what could be expected and perhaps even against the logic of the system.

When working with the daily and bar-by-bar data there is one more important chart to consider. That is the *margin to equity ratio,* which is shown in Figure 15.19. This chart shows how much of your total equity you actually need to keep on account with your broker to do the necessary trades. In the case of the S&P 500 portfolio we have been working with so far, I have assumed a margin of $22,000 per contract. In this case, as time moves on, the average margin to equity ratio should probably even out just below 20%, with an expected maximum around 35%. This means that of the total equity we have at stake, we only need to keep, say 50% just in case, on account with our broker. The rest of it we can have elsewhere, where we hope it can generate a higher return than the interest rate our broker can offer. It is important to realize, though, that you must have this money readily available and committed to your strategy as well. Otherwise, it would be as if you were trading your portfolio with only half the equity, but twice the *f* a recipe for disaster, indeed.

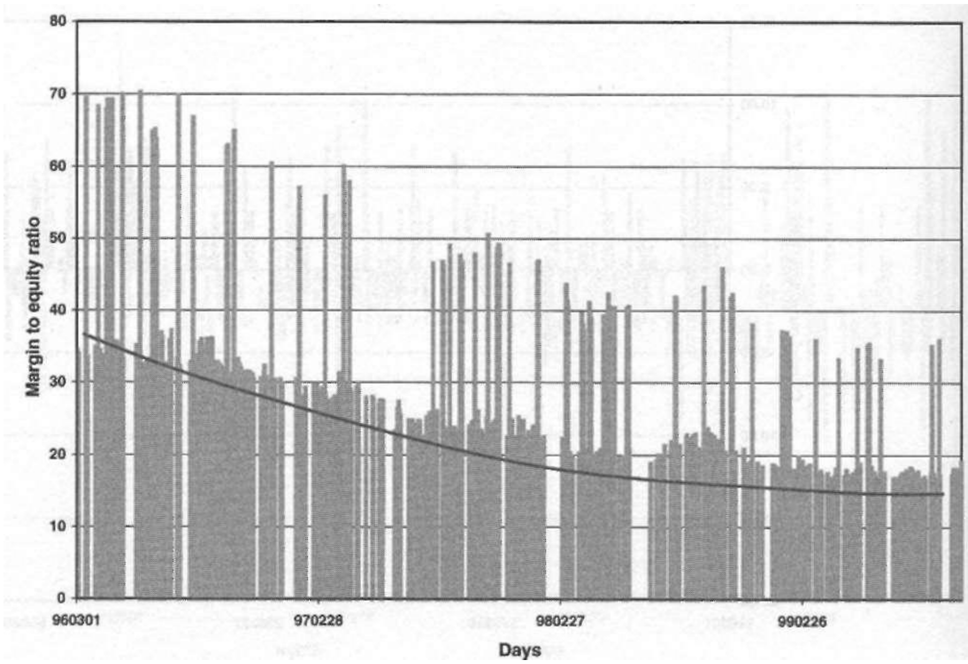


FIGURE 15.19

The margin to equity ratio for a portfolio.

Before we move on to the long-term systems, let us compare the performance summaries in Figure 15.11 and Table 15.1 with Tables 15.2 and 15.3 which show the results from trading both these portfolios on a one-contract basis. If a fixed fractional trading strategy is not doing any better than a one-contract, then what is the point? But we do not have to worry. Table 15.2 shows that the single market/system portfolio would only have made $88,500 on a one-contract basis, while the three-market/system portfolio would have made $331,000, or approximately 8% per year on an initial equity of $1,000,000. That is quite a difference compared to the 52% per year we could have made only risking 1.5% of total equity per trade.

Other interesting observations are that the profit factor, the value of the average trade, the percentage profitable trades, and the drawdown all are better in Figure 15.11 and Table 15.2 than they are in Tables 15.1 and 15.3. For the average system builder, these are all important figures. Had we not known what we now know, chances are that we might have ditched the three-market/system portfolio for the benefit of the single-market/system combination, and then traded that one more aggressively instead, if we had derived these numbers directly from TradeStation's or any other commercially available program's performance summary.

TABLE 15.2

Single contract performance for the Meander system.

Strategy summaries			
Profitability		**Trade statistics**	
End Eq ($)	1,088,541	No Trades	73
Total (%)	9	AvgTr($)	1,213
Year (%)	2.29	Tr/Mark/Year	6.5
P factor	1.86	Tr / Month	0.5
Risk measurers		**Time statistics**	
Max DD (%)	-1.68	Lng Flat (d)	275
Lrg Loss ($)	-13,148	TIM (%)	16.35
Winners (%)	57.53	Avg Days	4.00

There are several reasons why a portfolio of several market/systems combinations does better than only a single market/sy stem combination, even if we try to compensate by trading the sole combination more aggressively. The most obvious reason, as we learned from the fundamental equation of trading, is that the best way to speed up the equity growth rate for a trading strategy with a positive expectancy is to trade it as frequently as possible. And no matter how aggressively we trade a single market/system combination, the actual number of trades will not increase, as it will if we trade several market/system combinations simultaneously. Furthermore, by letting two or several market/system combinations with positive expectancies share the same account, there is a positive expectancy that there will be more money to play with, going into each individual trade.

TABLE 15.3

Single contract portfolio performance summary.

Strategy summaries			
Profitability		**Trade statistics**	
End Eq ($)	1,331,013	No Trades	316
Total (%)	33	Avg Tr($)	1,079
Year(%)	7.92	Tr/Mark/Year	28.1
P factor	1.59	Tr/Month	2.3
Risk measurers		**Time statistics**	
Max DD (%)	-3.85	Lng Flat (d)	112
Lrg Loss ($)	-32,656	TIM (%)	54.82
Winners (%)	56.96	Avg Days	3.00

This is true as long as the different market/system combinations are not perfectly (100%) correlated and with each one having a positive expectancy. It could also be true even if one or several of the market/system combinations have a negative expectancy, as long as they are uncorrelated enough with the rest of the combinations and the portfolio as a whole. There is a price for doing this, however, and that is that the overall efficiency of the portfolio diminishes the more market/system combinations you add. For instance, trading two market/system combinations that are not perfectly correlated, with an optimal *f* of 0.5 each, results in an optimal *f* of less than 0.5 for the strategy as a whole. This means that there also is a limit to how many market/system combinations it is meaningful to trade.

But, to take the reasoning through yet another circle, the decrease in efficiency as a result of trading several uncorrelated market/system combinations also has a major benefit. The lower the optimal *f* or the fixed fractional trading level, the lower the risk and the shallower the expected drawdowns. Consider, for instance, two perfectly correlated market/system combinations. When one of them has a losing trade, so has the other, which means that all losing trades leading into a new drawdown from a recent equity high hit you full force, whereas a drawdown for an uncorrelated portfolio of market/system combinations is likely to be dampened because the combinations are low correlated, but also because they don't trade at the same time. This means that each losing trade decreases the number of contracts that can be traded going into each consecutive trade.

All the above leads to one important conclusion: the optimal *f* is not a measure of how high a certain portfolio's return is likely to be, but instead of how risky it is. To get an indication of how high the return will be, we must look at the estimated growth rate, as measured by the estimated geometric mean (EGM), given the assumed risk as dictated by the largest expected amount to lose per contract and the largest expected amount to lose per trade (the fixed fractional trading level).

Finally, just for the heck if it, it could be fun to know how much we could have made had we traded the three-market/system portfolio at or near its optimal *f* Table 15.4 and Figure 15.20 reveal that we would have taken the initial million to $114,148,000, which corresponds to an average percentage return of 254% per year. However, the price for this would have been to suffer through a drawdown of more than 75% of account equity and a largest single loss of close to $37,000,000. (By the way, which one of all the drawdowns in Figure 15.20 do you think is the worst, as a percentage of total equity?) These are clearly not tolerable or tradable numbers, which also is illustrated by the fact that the maximum number of contracts traded at one time would have been more than 10,000 and that the average margin-to-equity ratio would have been close to 200%. We would have had to borrow the same amount as we had on the account, just to cover margin. And who in his right mind would have lent us that kind of money with a track record showing drawdowns upwards of 80%? No, although the theory surrounding optimal *f* is beautiful, to trade at an unconstrained optimal *f* level simply is not feasible. (The

TABLE 15.4

7% fixed fractional (optiomal f) performance summary for a three market/system combination.

Strategy summaries			
Profitability		Trade statistics	
End Eq ($)	114,147,973	No Trades	316
Total (%)	11,315	Avg Tr ($)	451,612
Year(%)	253.72	Tr/Mark/Year	28.1
P factor	1.33	Tr / Month	2.3
Risk measurers		Time statistics	
Max DD (%)	-75.67	Lng Flat (d)	160
Lrg Loss ($)	-36,724,875	TIM (%)	54.93
Winners (%)	56.96	Avg Days	3.00

worst drawdown as a percentage of total equity happened during the fall of 1997, and shows up as a little blip about halfway through the time series in Figure 15.20.)

THE LONG-TERM STRATEGIES

When it comes to fixed fractional investing, the long-term systems have one major disadvantage compared to their short-term siblings: their lower frequency of trades, which, as we have learned from the fundamental equation of trading, is a key factor in the success of a fixed fractional trading strategy. To overcome this we, therefore should use the system together with as many markets as possible to speed up the trading frequency. However, in doing so it is vital that the system be robust and likely to trade profitably on as many markets as possible. As we have seen, to achieve this the system must work the same, no matter what the current market conditions are like or what market we are trading. To be consistent, this also means that we assume no significant statistical differences between the markets and that they are all treated identically and traded with the same *f* even though there might be significant differences between the *fs* when we compare different market/sy stem combination with each other.

The SDB Strategy

During the entire testing procedure for the SDB system we only used data up until October 1992. The rest of the data we saved for some out-of-sample testing. Table 15.5 shows the result of trading the entire portfolio on the in-sample data, using the same fixed fractional money management for all markets, and risking no more than 1.5% of total portfolio equity per trade, going into the trade. The starting balance

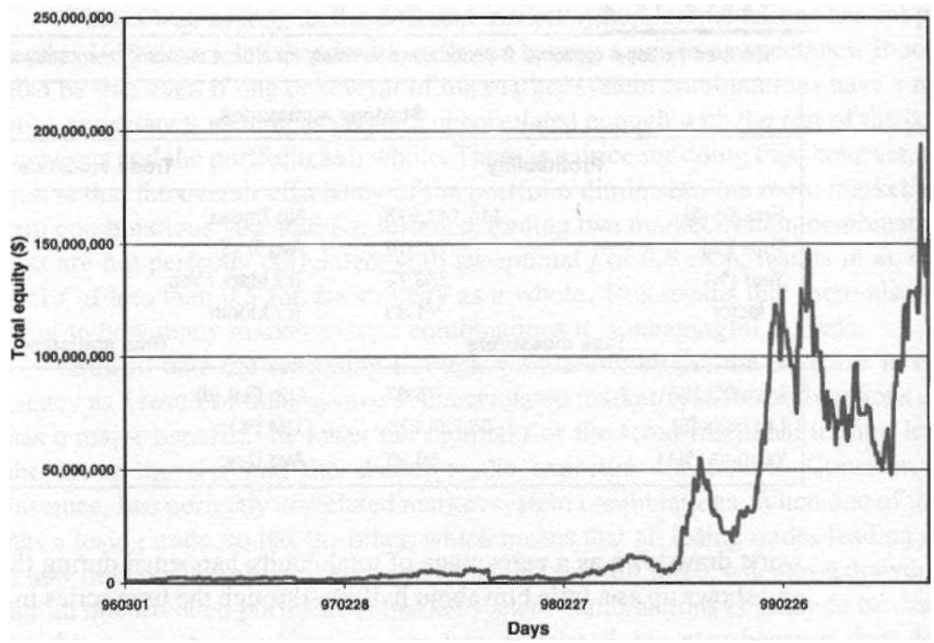


FIGURE 15.20

The equity curve from trading three different market/system combinations at their optimal f.

was set to $1,000,000, with $75 deducted for slippage and commission per contract traded.

Just to make sure that it is indeed beneficial to use a fixed fractional trading strategy, even if we keep the/as low as 0.015, you can compare the results in Table

TABLE 15.5

1.5% fixed fractional trading with the SDB strategy (in-sample period).

Strategy summaries			
Profitability		**Trade statistics**	
End Eq ($)	7,462,552	No Trades	424
Total (%)	646	AvgTr($)	14,614
Year(%)	17.6	Tr/Mark/Year	2.1
P factor	2.04	Tr / Month	2.8
Risk measurers		**Time statistics**	
Max DD'(%)	-17.17	Lng Flat (m)	25.9
Lrg Loss ($)	-148,124	TIM (%)	99.81
Winners (%)	41.75	Avg Days	20.00

15.5 with those in Table 15.6, which shows how much you would have made trading one contract only. The only major drawback with the statistics in Table 15.5 is a little too long flat period. However, research and experimentation show that it is more a result of bad portfolio composition than of the system itself, although at this stage all three variables—the system, the money management, and the portfolio composition—interfere and influence each other, making all three parts equally responsible for results. Nonetheless, in this case the longest flat period remains the same even if *f* is increased to 2.5% or lowered to 1%. The only thing that happens is that with a higher *f* comes a higher drawdown and a higher return, and vice versa.

By the way, the optimal *f* for this portfolio can be found around 14%, which produces a final profit of more than $21.5 billion, corresponding to a yearly rate of return close to 125%, but also a drawdown close to 95%, a largest loss close to $4.5 billion, and a longest flat time of more than 40 months. As should be clear by now, the final return is only a function of how well you would like to sleep at night. In this case we would be making something like $1.75 billion a year, on average—if you believe that is worth sleepless nights, be my guest.

Now that we know the SDB system works fine within a more complete trading strategy incorporating consistent money management on a whole portfolio of market/system combinations, perhaps it is time to look at how the same strategy would have performed on previously unseen data. That we will do, but first we will add another few analysis techniques to our portfolio summary spreadsheet.

We will put together a set of formulae that produce monthly results, resembling those in Figure 15.21, which we will use for further input into a new set of formulae that produce results like those in Tables 15.7 and 15.8.

TABLE 15.6

Single-contract trading with the SDB strategy (in-sample period).

Strategy summaries			
Profitability		**Trade statistics**	
End Eq ($)	1,329,060	No Trades	424
Total (%)	33	AvgTr($)	765
Year(%)	2.32	Tr/ Mark /Year	2.1
P factor	1.99	Tr / Month	2.8
Risk measurers		**Time statistics**	
Max DD (%)	-2.53	Lng Flat (m)	20.81
Lrg Loss ($)	-6,726	TIM (%)	99.81
Winners (%)	41.75	Avg Days	20.00

	EZ	FA	FB	FC	FD	FE
29	Date	Equity	Top	DD	1	3
30	800602	1,000,000	1,000,000	0.00		
31	800630	1002547	1,002,547	0.00	0.25	
32	800731	1054785	1,054,785	0.00	5.21	
33	800829	1095614	1,095,614	0.00	3.87	9.56
34	800930	1095839	1,095,839	0.00	0.02	9.31

FIGURE 15.21

Using Excel to calculate monthly returns.

To start, highlight the cell in the column, one column away from your portfolio calculations and at the same row for where you start the portfolio calculations. In Figure 15.21, that is cell EZ30.

In cell EZ30:

=EO30

where column EO denotes the daily updated dates.

In cellEZ31:

=IF(INT(E031/100)<INT(EO32/l 00),EO31,"")

then drag down to fill all the cells in that column.

In cell FA30:

=ER30,

where column ER the daily updated total equity.

In cellFA31:

=IF(INT(EO31/100)<INT(EO32/100),ER31,"")

TABLE 15.7

Cumulative percentage period returns, n months rolling window (in-sample period).

Cumulative	1	3	6	12	24	36	48	60
Most recent	-0.94	3.95	26.37	39.14	54.52	79.46	119.78	159.88
Average	1.43	4.41	8.77	17.65	39.97	69.48	110.03	159.17
Best	13.25	27.13	49.21	62.70	116.21	162.76	228.11	256.53
Worst	-9.09	-12.34	-10.97	-6.54	-11.42	-1.67	8.71	25.23
St. dev.	3.92	7.21	11.26	15.42	29.05	44.40	60.53	69.04
EGM	1.35	4.16	8.19	16.64	36.92	63.56	101.12	149.81
Sharpe ratio	0.36	0.61	0.78	1.14	1.38	1.56	1.82	2.31
Avg. winning	3.57	7.48	12.17	20.80	44.63	70.11	110.03	159.17
Avg. losing	-2.33	-3.52	-3.63	-3.35	-4.26	-1.67	N/A	N/A

TABLE 15.8

Annualized percentage period returns, n months rolling window (in-sample period).

Annualized	1	3	6	12	24	36	48	60
Most recent	-10.71	16.76	59.69	39.14	24.31	21.52	21.76	21.05
Average	18.58	18.84	18.31	17.65	18.31	19.23	20.38	20.98
Best	345.1	161.21	122.64	62.7	47.04	37.99	34.59	28.95
Worst	-68.13	-40.95	-20.74	-6.54	-5.88	-0.56	2.11	4.6
St. dev.	58.63	32.11	23.79	15.42	13.6	13.03	12.56	11.07
Sharpe	0.32	0.59	0.77	1.14	1.35	1.48	1.62	1.9
% winners	63.76	72.11	78.47	86.96	90.48	99.12	100.00	100.00

then drag down to fill all the cells in that column.

You must delete all the blank cells in columns EZ and FA and line up all the other cells containing information underneath each other so that the end result will look like Figure 15.21. This can be done either manually or with the help of a macro. When you are done, continue to calculate the latest equity high and drawdown.

In cell FB30:

=FA30

In cell FB31:

=MAX(FA31,FB30)

then drag down to fill all the cells in that column.

In cell FC30:

=(FA30-FB30)*100/FB30

then drag down to fill all the cells in that column.

In columns FD and FE, we calculate the rolling monthly and quarterly returns. In cell FD31:

=(FA31/FA30-1)*100

then drag down to fill all the cells in that column.

In cell FE33:

=(FA33/FA30-1)*100

then drag down to fill all the cells in that column.

In columns FF to FK (not shown in Figure 15.21) continue to calculate the rolling 6-, 12-, 24-, 36-, 48-, and 60-month rolling returns. With the above formulae and all other formulae we have used throughout the book, it should be no problem to go on and produce a table like Table 15.7.

To transform the cumulatively compounded values in Table 15.7 to annualized dittos in Table 15.8, simply raise each value by (12/PL), where *PL* equals the length of the period. For instance, if the most recent monthly return is stored in cell K3, to transfer it into an annualized figure in cell K13, use the following formula in cell K13:

=ROUND(((K3/100+1)^(12/K2)-1)*100,2),

where cell K2 denotes the length in months of the original period.

From Tables 15.7 and 15.8 we can, for instance, see that during no 12-month period did we lose any more than 6.54% and never did we produce a losing period lasting longer than 3 years. We also can see that although the percentage of profitable trades was less than 42%, the percentage of profitable months was as high as 64%.

This is such an important finding that it must be explained further for a deeper understanding. Because we have constructed the system to cut our losses short, using such techniques as time-based stops we accomplish two things. First, a single loss won't go on forever, weighting down the results for several months in a row. Second, other trades to come will have an easier time making up for the recently produced loss. In the end, this might mean that a lower percentage of profitable trades will produce a higher percentage of profitable months. Once you have taken your analysis to this point, I think you will agree when I say that it is far more important to have a high percentage of profitable months than it is to have profitable trades. To make sure that the number of winning months will be high, you must have taken that into consideration at step one of your system-building process.

This is the same type of trade-off we must do when we compare the average trade to the standard deviation. The trick is not to have as high as possible an average trade, but only to make sure that it is sufficiently larger than the standard deviation; every change we make to the system that decreases the average trade is all right, as long it decreases the standard deviation even more. (Within reason that is—the mathematical expectancy still must be positive and the average trade large enough to make it worthwhile trading the system.) The positive side effect from all this is that we also are likely to increase the number of trades, which boosts our profits even further according to the fundamental equation of trading.

Another way to illustrate several of the numbers in Tables 15.7 and 15.8 is to create charts like those in Figures 15.22 and 15.23.

Let's take a look at how the SDB strategy would have fared both during the in-sample period from January 1980 to October 1992, and the out-of-sample period from October 1992 to October 1999. As before, the starting equity was set to $1,000,000, and $75 was deducted for slippage and commission per contract traded. Table 15.9 reveals that the ending equity now would have been close to $20,000,000, corresponding to a yearly return of 16.68%. The fact that this is slightly lower than for the in-sample period alone indicates that the strategy has

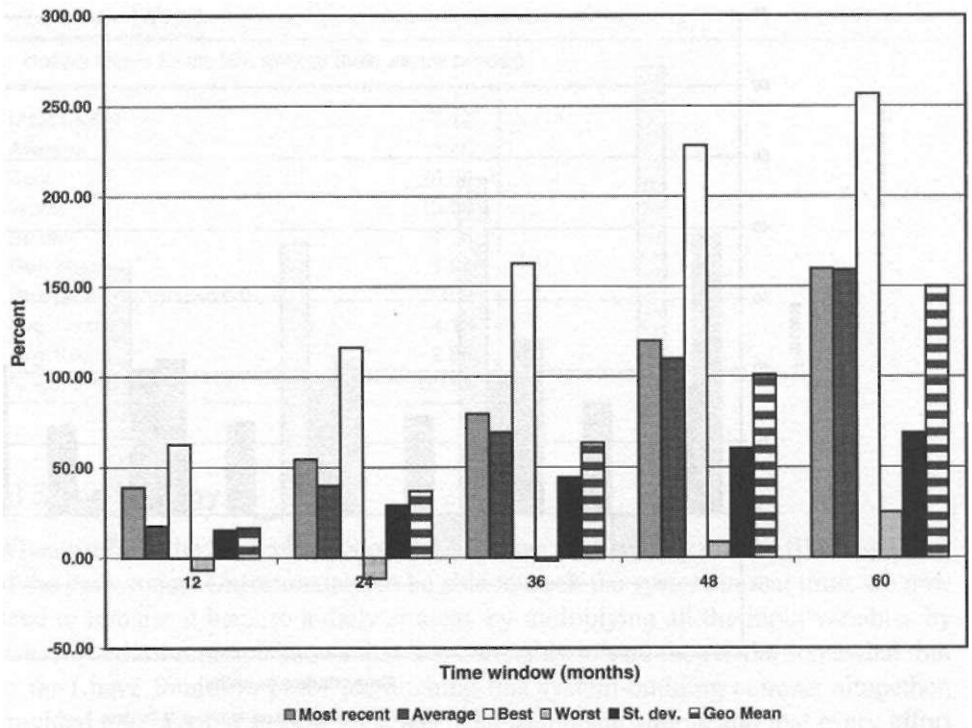


FIGURE 15.22

A graphical presentation of cumulative monthly returns (in-sample period).

TABLE 15.9

1.5% fixed fractional trading with the SDB strategy (both sample periods).

Strategy summaries			
Profitability		**Trade statistics**	
End Eq ($)	19,949,789	No Trades	730
Total (%)	1,895	AvgTr($)	25,184
Year(%)	16.68	Tr/Mark/Year	2.4
P factor	1.52	Tr/ Month	3.1
Risk measurers		**Time statistics**	
Max DD (%)	-27.3	Lng Flat (m)	25.9
Lrg Loss ($)	-568,453	TIM (%)	99.88
Winners (%)	39.59	Avg Days	19.00

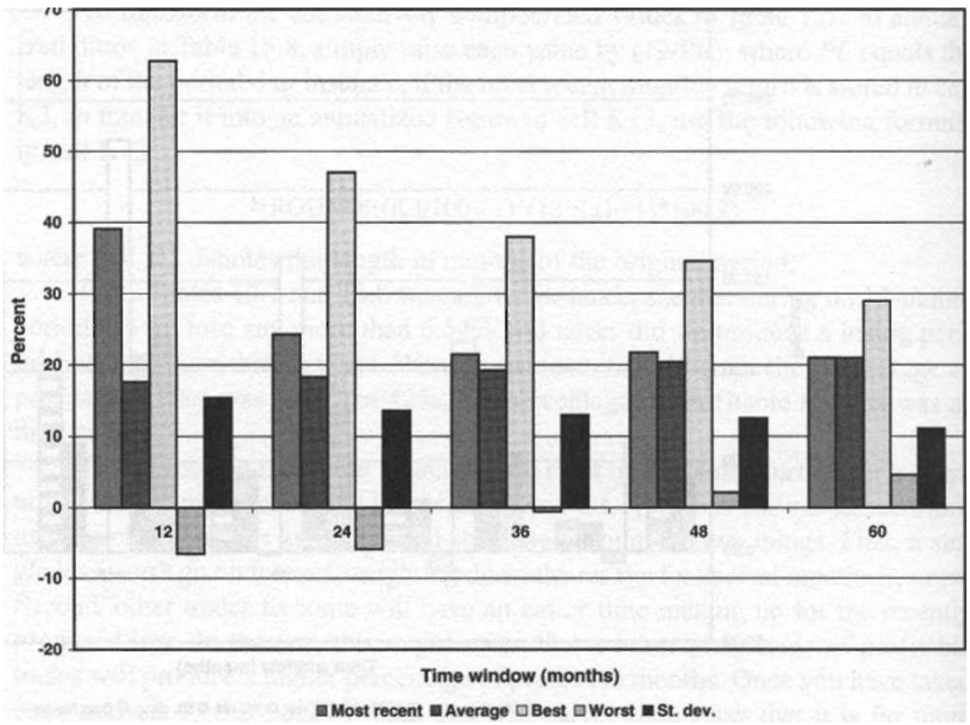


FIGURE 15.23

A graphical presentation of annualized monthly returns (in-sample period).

not worked as well during recent years. This is further confirmed by a lower profit factor, a larger maximum drawdown, and a lower percentage profitable trades. As you can see, the average trade measured in dollars is much higher in Table 15.9 than in Table 15.5, but, as should be clear by now, this has nothing to do with the strategy's performing any better, but simply because the available equity is so much higher—we can have more money at stake at each individual trade.

From Table 15.10 we also can see that the average trade, measured in percentage terms, has decreased while at the same time the standard deviation has increased. This is not a good sign, because it implies that not only has the strategy turned less profitable, but also it has turned more risky. The percentage of winning months also has decreased somewhat. All in all this is a decrease in performance, but still not too far away from what could be considered tolerable for a professional money manager. In fact, the only thing that most definitely is not tolerable is the longest flat time, although it has stayed intact during the out-of-sample period. Figures 15.24 and 15.25 give you essentially the same type of information as Tables 15.7 and 15.8, and figures 15.22 and 15.23.

TABLE 15.10

Monthly returns for the SDB strategy (both sample periods).

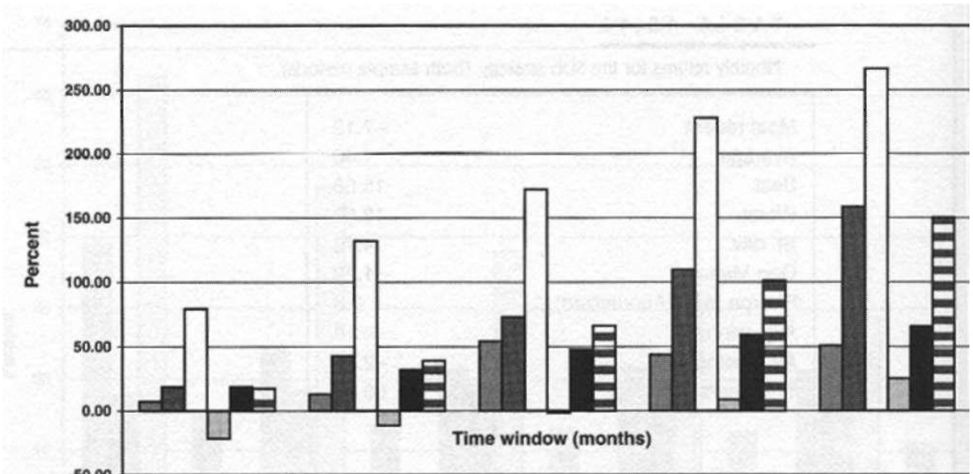
Most recent	-7.12
Average	1.40
Best	15.58
Worst	-13.63
St. dev.	4.70
Geo Mean	1.29
Sharpe ratio (Annualized)	0.3
Avg. winning	4.18
Avg. losing	-2.86
% winners	60.52

The Directional Slope Strategy

When we built the Directional Slope System, we used weekly data to filter out some of the daily noise. Unfortunately, to be able to track the system in real time, we now need to transfer it back to a daily strategy by multiplying all the input variables by five. My initial research shows that this inevitably lowers the results somewhat, but so far I have found no proof for ditching this system-building concept altogether, provided that original system logic has been sound and simple and that every effort has been made to keep the system as robust as possible. I must point out however, that my research in this area is still at its initial stages and that only time will prove me right or wrong. Nevertheless, the point here is not to give you the very best systems around, but simply to outline a few tips and tricks on how to go about building one yourself, or—perhaps even more important—to describe the underlying reasoning that you must consider before you sit down in front of the computer.

Table 15.11, and Figures 15.26 and 15.27 show the result of trading the directional slope system on all 16 markets used during the system-building process. As before, we started out with $1,000,000 in initial equity, deducting $75 for slippage and commission per contract traded. As you can see, these results aren't too tantalizing, mainly because of a largest drawdown closing in on 60% and a longest flat period of more than 28 months.

However, one major reason for this is that, during the optimization process, I deliberately used markets that I knew from experience would not sit well with a trend-following strategy, such as the S&P 500 index and the CRB index. I did this to pollute the final parameter setting with as many market conditions as possible to increase the likelihood for the model to hold up in the future. Inevitably there will come a day when such trend-following workhorses such as the Japanese yen will stop working and start behaving like the CRB index (which is a notoriously difficult market with any strategy). When that day comes I want to have made sure that I have taken every possible action to keep myself from going broke.



	12	24	36	48	60
Most recent	7.32	13.01	54.07	43.72	50.81
Average	18.96	42.60	72.79	109.65	158.72
Best	79.15	132.02	172.18	228.11	266.43
Worst	-21.34	-11.42	-1.67	8.71	25.23
St. dev.	18.79	31.91	47.55	59.03	65.57
Geo Mean	17.47	38.98	66.12	101.17	150.27

FIGURE 15.24

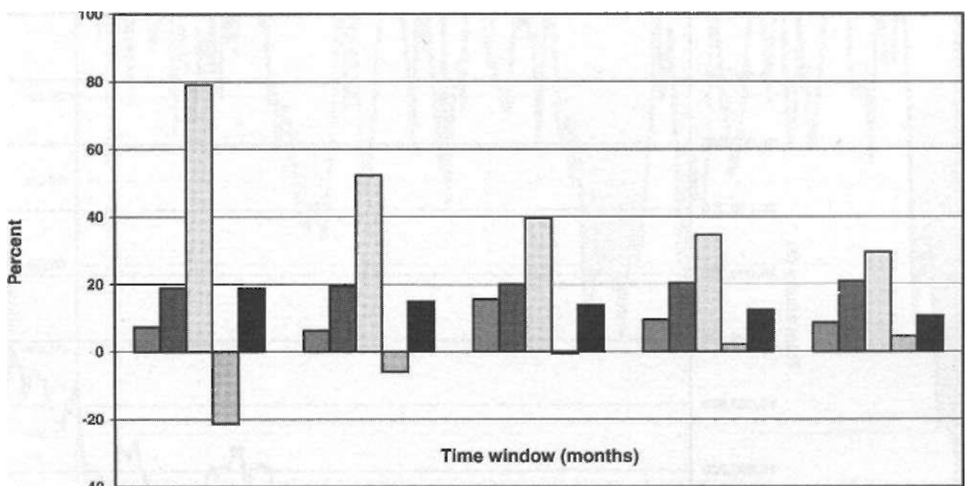
The cumulative monthly returns for the SDB strategy (both sample periods).

To get a feel for how much each market is contributing to the end result you can put together a table like Table 15.12, where I simply divided the total closed-out profit for each market by the total profit for the portfolio as a whole. In this case, we can see that the S&P 500 lowers the result by close to 25%, while the crude

TABLE 15.11

1.5% fixed fractional trading with the directional slope strategy.

Strategy summaries			
Profitability		**Trade statistics**	
End Eq ($)	17,011,080	No Trades	2,885
Total (%)	1,601	AvgTr($)	4,420
Year(%)	15.73	Tr/Mark/Year	9.3
P factor	1.06	Tr / Month	12.4
Risk measurers		**Time statistics**	
Max DD (%)	-57.56	Lng Flat (m)	28.24
Lrg Loss ($)	-2,374,435	TIM (%)	98.06
Winners (%)	29.71	Avg Days	7.00



	12	24	36	48	60
Most recent	7.32	6.31	15.5	9.49	8.56
Average	18.96	19.42	20	20.33	20.94
Best	79.15	52.32	39.62	34.59	29.66
Worst	-21.34	-5.88	-0.56	2.11	4.6
St. dev.	18.79	14.85	13.84	12.3	10.61

FIGURE 15.25

The annualized monthly returns for the SDB strategy (both sample periods).

oil alone is making up for more than 90% of the final profit. When interpreting these numbers, however, one must be very careful not to make any hasty conclusions. For one thing, just because one market happens to have a low or negative contribution factor doesn't mean it is inferior to other markets; it could be that particular market (no matter how profitable it seems to be by itself) simply happens to have all its profitable trades when the portfolio as a whole is in a drawdown, which will result in a lesser number of contracts traded when compared to a market that always happens to work at its best when the portfolio has reached a new equity high. Similarly, it could very well be that a market with a negative expectancy contributes positively to the portfolio as long as its winning trades tend to happen at the most opportune moment. Furthermore, even if it is reasonable to assume that a market will have a negative contribution to the portfolio result, it still might add positively to the very same bottom line by being uncorrelated enough to markets to keep the equity level up when the other markets are in a slump. Also, note that both the winning and losing percentages are surpassing 100%. This is because these numbers are picked from the aggregate portfolio, in which ending equity is not a straight line function of the equity of the individual markets.

Anyway, just for the heck of it, let us take a look at Table 15.13 and Figure 15.28 to see how the directional slope system would have performed, had we only traded only the nine markets that added the most to the bottom line. The nine mar-

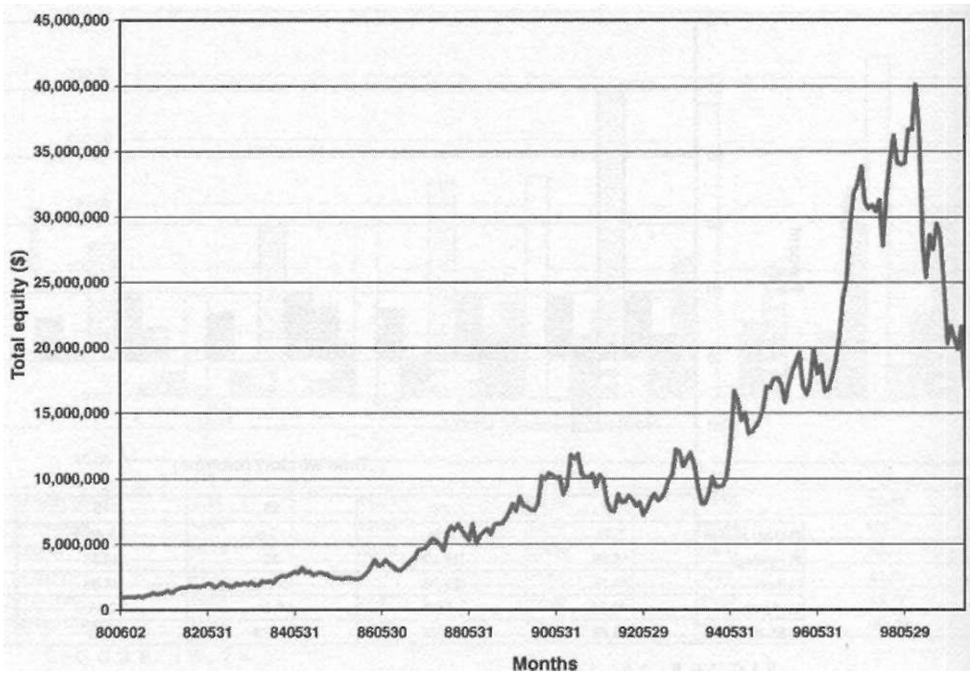


FIGURE 15.26

The equity curve for the directional slope strategy.

TABLE 15.12

Individual contribution factors for the directional slope strategy.

Market	Contributing
Corn	-24.98
S&P 500	-24.82
Juice	-59.71
Live cattle	-23.61
Lumber	4.77
Coffee	49.77
Japanese yen	51.33
Copper	12.25
Gold	-3.30
Eurodollar	0.16
Dollar index	-4.49
Cotton	7.40
CRB	-5.52
Crude oil	91.46
Canada dollar	7.34
T-bonds	21.96
Total	100.01

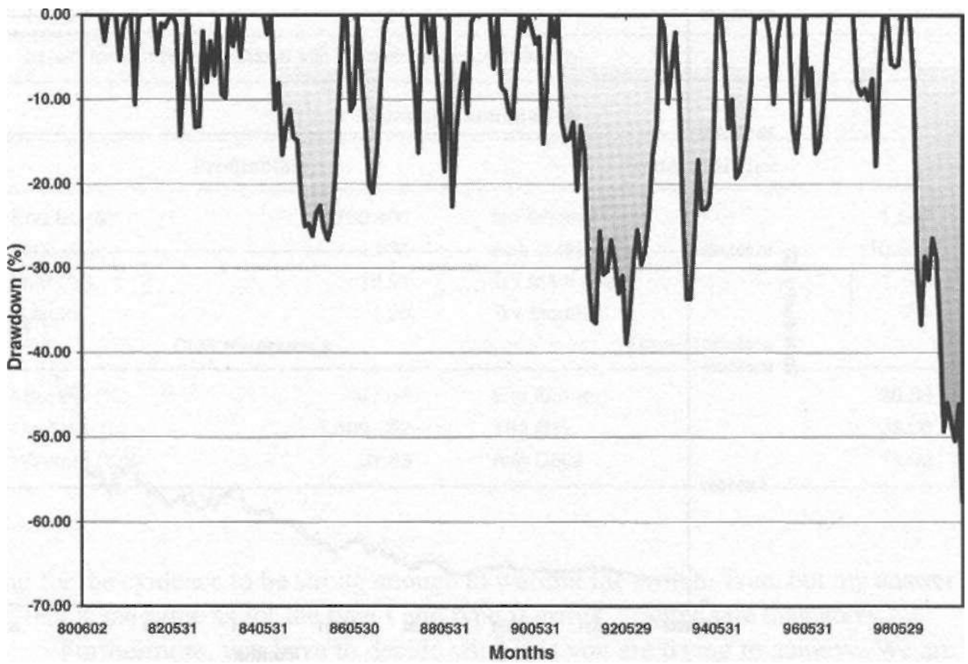


FIGURE 15.Z7

The drawdown curve for the directional slope strategy.

kets were lumber, coffee, Japanese yen, copper, dollar index, cotton, crude oil, Canada dollar, and T-bonds. As you can see, this time the maximum drawdown has decreased to 27.5%, which is considerably better than it was from trading all markets. Unfortunately, this is counterbalanced by a maximum flat period that is much too long. Another interesting observation that can be made from comparing Figures 15.26 and 15.28 is that Figure 15.26 at one point had a maximum total equity of close to $40,000,000, before the result started to turn south in the middle of 1998.

Honestly now, pretend it is early 1998 and that you just finished building this very same system using these very same markets. Would you then decide to trade it with all the available markets or only the nine markets that, in hindsight, turned out to produce the best result, considering the deep drawdown that started later that same year?

I bet most of you would have gone with the original portfolio, one reason being that common knowledge dictates that, "with a long-term strategy you should trade as many markets as possible, because you never know which one will take off next, producing that huge winner that will make it possible to build a house on the moon." This is very backward reasoning, however, because, for one thing, the more markets you trade the more likely it is that you will be caught on the wrong side when panic strikes any one of them. Additionally, because all our funds are

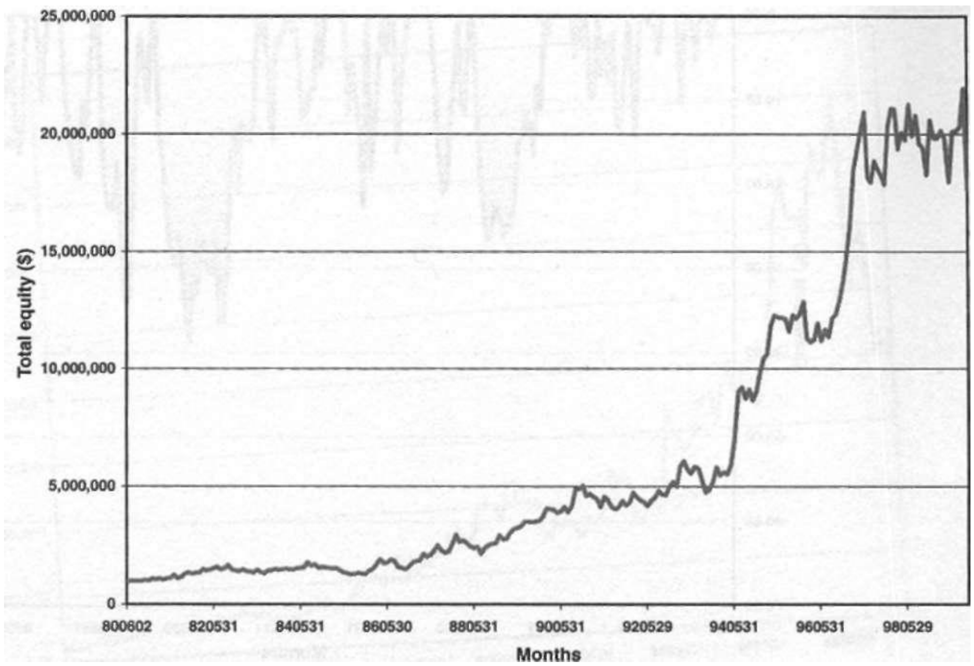


FIGURE 15.28

The equity curve for the directional slope strategy traded on the nine best markets.

limited, margin constraints might keep us from trading as many markets as we wish. Therefore, it makes sense only to trade those that can provide us with the highest likelihood of success. Just because we used markets like the S&P 500 and CRB index to build the system does not mean we have to trade them if there are more viable alternatives.

I am aware that this last statement to some extent contradicts my previous statements that there is no difference between any two time series and that we should place as many trades as possible. But that is in the long run, and is why we use markets like the S&P 500 and CRB index when we build the system, to make sure that when the Japanese yen starts to perform just as "badly" at least I have built in some sort of catastrophe protection. And that is why we are not trading at each market/system combination's historical optimal *f*

In the short run, however, I know that there are some differences (indicated by the different optimal *fs).* It would be foolish to try to squeeze in markets like those mentioned, or markets that are too correlated with each other, as long as I can't justify it for any other reasons, such as the likelihood of minimizing the drawdown or flat time by increasing the number of trades.

In ten years' time, however, the picture might look very different and perhaps then I will be better off substituting all markets completely. The argument against this last sentence is that, I would be leaving a lot of money on the table while wait-

TABLE 15.13

Results for a preferred portfolio with the directional slope strategy.

Strategy summaries			
Profitability		**Trade statistics**	
End Eq ($)	20,709,401	No Trades	1,646
Total (%)	1,971	AvgTr($)	10,867
Year(%)	16.91	Tr/Mark/Year	5.3
P factor	1.23	Tr / Month	7.1
Risk measurers		**Time statistics**	
Max DD (%)	-27.54	Lng Flat (m)	26.33
Lrg Loss ($)	-1,509,982	TIM (%)	98.06
Winners (%)	31.83	Avg Days	11.00

ing for the evidence to be strong enough to warrant the switch. True, but my answer to that is the same as for the type I and type II errors: "Better safe than sorry."

Furthermore, you have to decide what it is you are trying to achieve. We are discussing trend-following strategies, consisting of a money management regimen, a portfolio of markets, and a trend-following system, and the same reasoning holds true for the complete strategy as it does for the single system. That is, we are not trying to pick tops and bottoms, but rather to jump on a market in motion once the trend has proved itself and then ride that move until our stops and exit techniques tell us that it is no longer there.

Another practical reason why we shouldn't trade every market is that the more markets we trade the more inefficient the strategy will be, lowering the optimal f for the portfolio as a whole. And because we like to have plenty of room between the f we are using and the true optimal f we had better not bog down the portfolio too much. My research shows that a portfolio of 12 to 18 different, low-correlated markets, possibly traded with as many as three different systems, seems to work best. But this conclusion is based on my personal preferences, and I urge you to do your own research to come up with a portfolio that makes the most sense to you.

The DBS Strategy

For the DBS system the results are pretty much the same as those for the directional slope strategy, with the same markets producing similar results. This is indicated by Table 15.14, which shows that both the flat time and the drawdown are a little too steep. Rather than once again going through why this is the case, only repeating the discussion regarding the directional slop strategy, let's just move on.

TABLE 15.14

1.5% fixed fractional trading with th DBS strategy.

Strategy summaries			
Profitability		**Trade statistics**	
End Eq ($)	21,787,934	No Trades	1,581
Total (%)	2,079	AvgTr($)	11,425
Year (%)	17.21	Tr/Mark/Year	5.1
P factor	1.11	Tr / Month	6.8
Risk measurers		**Time statistics**	
Max DD (%)	-42.37	Lng Flat (m)	30.67
Lrg Loss ($)	-1,123,734	TIM (%)	99.98
Winners (%)	33.9	Avg Days	11.00

CHAPTER 16

Portfolio Composition

In many ways, we have already covered a large part of the complexity of portfolio composition. We discussed finding markets that are not too correlated with each other, but also that a market with a negative mathematical expectancy still might fill an important roll for the portfolio as a whole. Another important factor to consider is to use the same markets in several different market/system combinations to cover a wider range of scenarios and outcomes. Consider, too, not picking too many markets out of the same group of markets, such as the currencies, and to diversify over different time frames just as we should over different markets and systems. In this chapter we look at three different ways of putting together a portfolio, do some testing on historical data, and discuss a few pros and cons associated with each method.

TOTAL EQUITY CONTRIBUTION I

One of the most obvious (but maybe also one of the most naive) ways of picking the markets to trade in the future is simply to look at how they have performed in the past and select a group of top performers. For instance, if we decide to pick the 12 top markets from our long-term portfolios (four from each portfolio, without picking the same market twice), we end up with the following 12: rough rice, natural gas, D mark (Euro), dollar index, Japanese yen, coffee, cotton, T-bonds, orange juice, crude oil, copper, and Canada dollar.

Tables 16.1 and 16.2, and Figures 16.1 and 16.2 show the result from trading a portfolio consisting of all the above 12 markets, each one in combination with the three different long-term systems, plus four short-term systems applied to the S&P 500 (the two entry techniques in the original Black Jack system were divided into

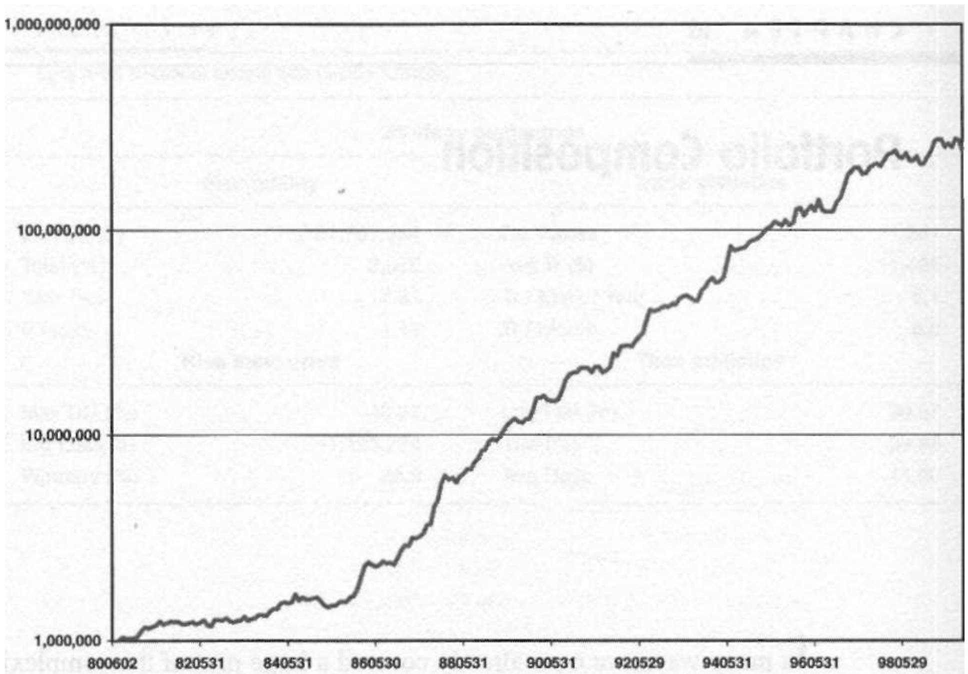


FIGURE 16.1

The equity curve for Charity I.

two separate systems), for a total of 40 different market/system combinations. The time period covered is January 1980 to October 1999 and the fixed fractional trading level is set to 0.5%. As usual, $75 per contract traded was deducted for slippage and commission. I call this portfolio Charity I.

As you can see Charity I made close to 33% per year, for a total ending equity of close to $250,000,000. From Table 16.1 we can see that the maximum intramonth drawdown peaked at close to 24 %, while Figure 16.2 shows that the lowest end-of-month drawdown did not grow past 15%. These are very good numbers,

FIGURE 16.1

0.5% fixed fractional trading with Charity I.

Strategy summary	
End Eq ($)	244,040,528
Total (%)	24,304
Year (%)	32.76
Max DD (%)	-23.81
Lng Flat (m)	17

TABLE 16.2

Percentage period returns, n months rolling window for Charity I.

Cumulative	1	3	6	12	24	36	48	60
Most recent	-11.06	-3.95	-11.76	16.03	15.67	97.60	131.19	196.04
Average	2.53	8.07	16.88	37.20	93.34	180.59	309.77	500.63
Best	21.98	59.01	92.24	131.99	257.59	425.66	744.94	1120.37
Worst	-11.06	-12.41	-11.76	-8.22	0.84	18.15	19.35	48.66
St. dev.	5.52	11.31	17.07	28.14	60.48	109.41	175.53	253.37
EGM	2.38	7.48	15.63	34.28	83.64	158.38	270.27	444.57
Sharpe	0.46	0.71	0.99	1.32	1.54	1.65	1.76	1.98
Avg. winning	4.98	11.80	20.30	39.30	93.34	180.59	309.77	500.63
Avg. losing	-3.04	-3.31	-4.03	-2.97	N/A	N/A	N/A	N/A
Annualized	**1**	**3**	**6**	**12**	**24**	**36**	**48**	**60**
Most recent	-75.5	-14.89	-22.14	16.03	7.55	25.49	23.31	24.24
Average	34.96	36.4	36.61	37.2	39.05	41.04	42.28	43.13
Best	985.08	539.29	269.56	131.99	89.1	73.87	70.49	64.93
Worst	-75.5	-41.14	-22.14	-8.22	0.42	5.72	4.52	8.25
St. dev.	90.55	53.51	37.05	28.14	26.68	27.94	28.84	28.72
Sharpe	0.39	0.68	0.99	1.32	1.46	1.47	1.47	1.5
% winners	69.53	75.32	85.96	95.05	100.00	100.00	100.00	100.00

indeed, once again showing the importance of trading as frequently as possible. The only not-so-good number is the flat period that might be considered a little too long, especially since that we are working with such a favorable portfolio of markets.

The reason behind the relatively long flat time probably can be found in this portfolio's greatest drawback: the high correlation and similarity between several of the markets. For one thing, there are as many as four currencies and two energies. It is doubtful this would be a preferable solution for a real-life portfolio. But, on the other hand, there are several traders who use only one system, trading nothing but a few currencies, or nothing but the S&P 500. So, in that regard, at least Charity I is far more diversified than many other real life examples.

One good thing is that we are not risking any more than 0.5% per trade, which must be considered very low. This means that at any particular time we never risk more than 1.5% of the total equity going into the trade, per market (2% for the S&P 500), which is no more than in any of the single system portfolios discussed earlier. Despite the very low risk and the fact that we are only trading 2.5 times as many system/market combinations as compared to the original long-term portfolios, we are still raising the total equity tenfold or more.

Unfortunately, however, one other thing that increases exponentially is the computational time. I did all this work on a computer with two Pentium III, 500 MHz

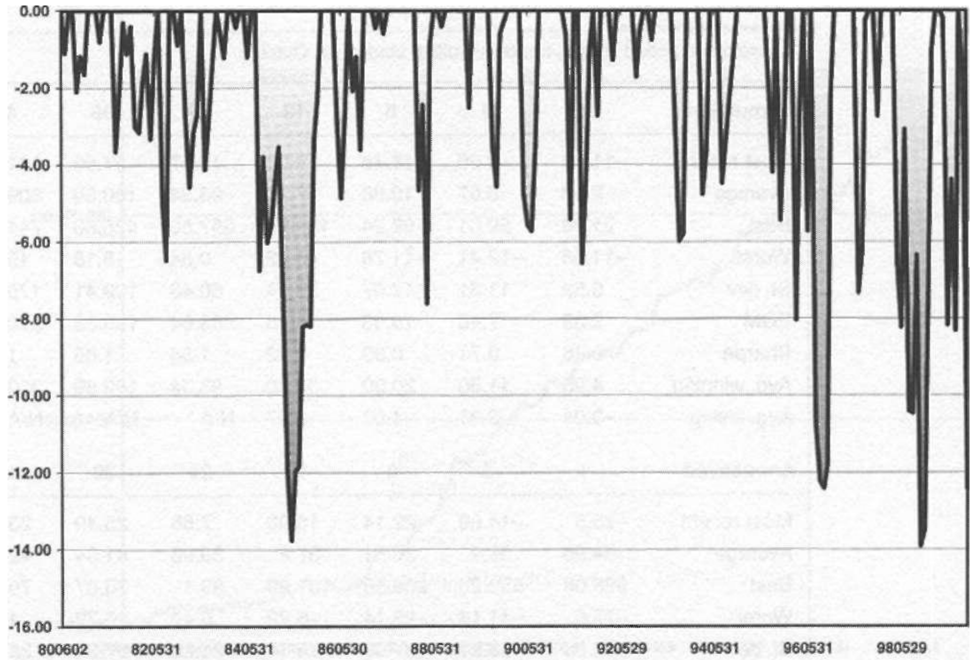


FIGURE 16.2

The drawdown for Charity I.

processors and 256 MB memory, but it still can take as long as half an hour or more for the computer to do all the necessary calculations. This is not something I recommend you to do unless you have plenty of computational power.

CORRELATIONS AND COVARIANCES

A more sophisticated method than just picking out the most profitable markets could be to look at their correlations and covariances with each other. The trick then is to put together a portfolio consisting of markets with as low correlation to or covariance from all the others as possible, while at the same time making sure that the markets suggested by the correlation analysis also are likely to keep their positive mathematical expectations and profit potentials when traded on previously unseen data. To analyze for correlations and covariances you could put together a spreadsheet like that in Figure 16.3. In this case, I chose to look at weekly data.

The correlation between crude oil and British pound in cell G10:

=CORREL(Data!$L3:$L1036,Data!F3:F1036)

The covariance between crude oil and British Pound in cell J7:

	D	E	F	G	H	I	J	K	L
4		S	BO	BP	CC	CD	CL	CR	C
5	S	8.73	7.24	0.14	0.92	0.07	-0.22	1.35	5.77
6	BO	0.75	10.58	0.12	0.62	0.13	-0.55	1.15	4.95
7	BP	0.03	0.02	2.42	1.02	0.16	0.45	0.13	0.13
8	CC	0.08	0.05	0.18	13.96	0.12	0.27	0.78	0.66
9	CD	0.04	0.06	0.16	0.05	0.42	0.29	0.05	0.05
10	CL	-0.02	-0.04	0.07	0.02	0.11	16.38	1.08	-0.05
11	CR	0.46	0.35	0.08	0.21	0.07	0.27	0.99	1.27
12	C	0.72	0.56	0.03	0.06	0.03	0.00	0.47	7.42
13	GC	0.15	0.13	0.27	0.13	0.14	0.13	0.24	0.08

FIGURE 16.3

Using Excel to calculate correlations.

=CORREL(Data!$F3:$F1036,Data!L3:L1036)*
STDEV(Data!$F3:$F1036)*STDEV(Data!L3:L1036)

With the help of the spreadsheet depicted in Figure 16.3,1 put together a second portfolio that I traded the very same way as Charity I. The long-term markets I selected were corn, Canada dollar, Eurodollar, heating oil, coffee, Nikkei index, orange juice, platinum, Swiss franc, T-notes, and wheat. The criteria for selecting the markets was—in order of importance—to pick only two markets from the same group of markets, to try to find previously unused markets, and to keep the correlations and covariances between different markets as low as possible. I called this portfolio Charity II. You can see the hypothetical results from trading Charity II in Table 16.2, and Figures 16.4 and 16.5.

I wanted to come up with a more or less new set of markets to see what the results would have looked like when traded on previously unseen and, in hindsight, not necessarily the most profitable markets. If you wish, you can look at this portfolio as a worst-case scenario of what we might have been able to produce had we failed to pick the most profitable markets but still used some common sense in the portfolio construction process.

As you can see from Table 16.3, we still would have made more than 20% per year, even with these secondary markets. Again, however, the flat time is a little too long and this time the maximum drawdown also has moved closer to what could be considered tolerable. Still, however, there are plenty of professional traders and analysts—myself included—who would be very happy for numbers like these, if produced in real-time trading. Taking $1,000,000 to close to $38,000,000 in less than 20 years is not bad at all and plenty more than what the stock market has produced over the same time period.

TOTAL EQUITY CONTRIBUTION II

Instead of just looking at the profit contribution, it also is possible to look at how many of the movements in a time series can be explained by the movements in

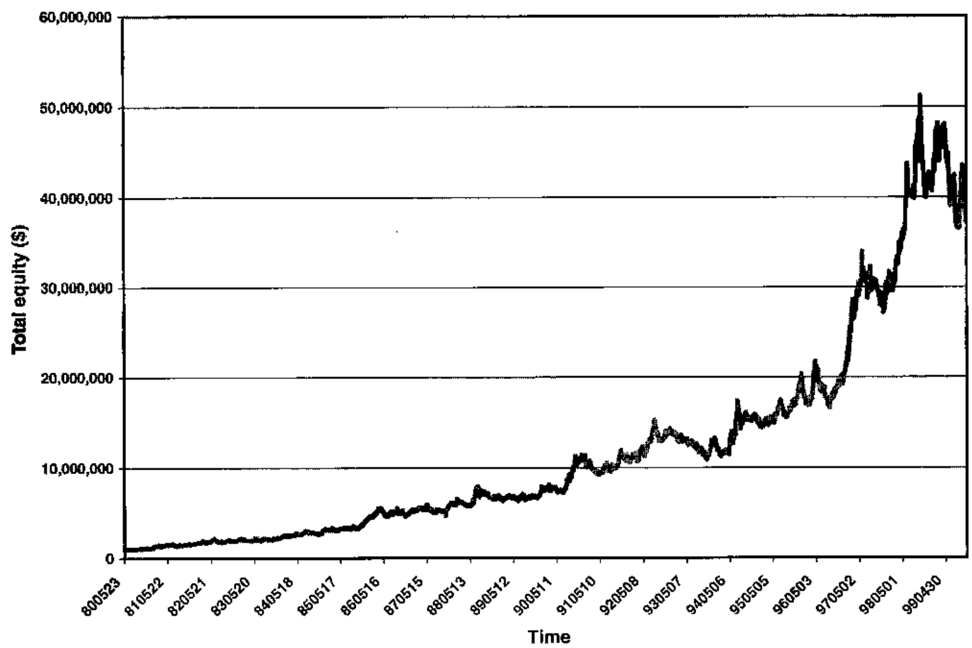


FIGURE 16.4

The equity curve for Charity II.

another time series. To do this we use the *Pearson correlation coefficient* which returns a value between 1 and —1, very much like the correlation coefficient. The difference between the Pearson correlation coefficient and the normal correlation coefficient is that the Pearson correlation coefficient requires that one of the variables be dependent on the other variable.

This means that if two markets have a Pearson correlation coefficient close to 1, almost the entire move of the dependent market can be explained by what is

TABLE 16.3

0.5% fixed fractional trading with Charity II.

Strategy summary	
End Eq ($)	37,797,489
Total (%)	3,680
Year(%)	20.59
Max DD (%)	-28.89
Lrg Loss ($)	-1,690,564
Lng Flat (m)	23.29

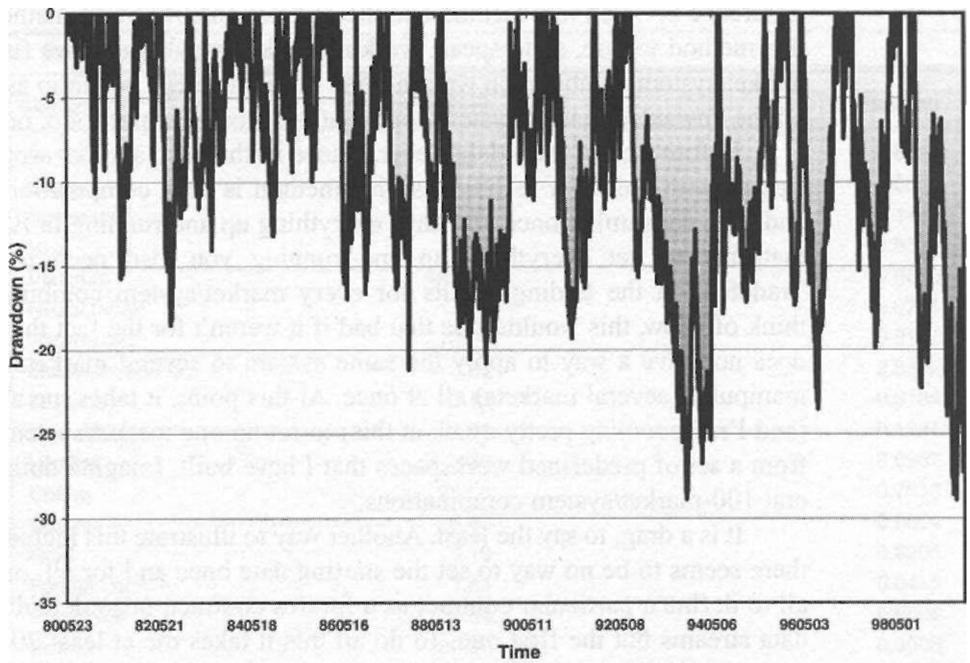


FIGURE 16.5

The drawdown for Charity II.

going on in the independent market. With a Pearson coefficient close to 0, the two markets move independently of each other. Tests like these are very common in the stock market, where many analysts look at how many of the movements in a particular stock can be explained by the movements of the market as a whole.

Note that this is a way of trying to explain how much of a particular stock's move can be explained by the move in the market, which is not the same as a stock's *beta,* which indicates how much a stock is likely to move, provided a certain move in the market. For instance, a stock with a beta higher than 1, say 2, is likely to move twice as much in the same direction as the rest of the market, but not all of that move must be explained by the move of the market—which is what we measure with the Pearson coefficient.

In this case, we do it the other way around and look at how much of the total equity can be explained by the total equity from a certain market/system combination. This is an especially good method to use when we have the possibility to trade the same market with several different systems and would like to narrow down the portfolio a little bit. What we look for is, first of all, markets that influence the total equity positively. We are also careful to choose markets that seem to be too good to be true, because this might make the portfolio too dependent on the performance of a few markets, when traded on previously unseen data in real-time trading. A major difference between this method and the correlation/covariance method is that with this method we are, so to speak, working backwards, because we first trade every market/system combination we can think of in one mega portfolio and then deduct all the unwanted market/system combinations from that portfolio, one at the time.

Before we get started, however, I need to throw in another word of warning. Just as with the other techniques, this method is very computationally intensive and time consuming once you have everything up and running in Excel. Not only that, but to get everything up and running you also need to export from TradeStation the trading results for every market/system combination you can think of. Now, this wouldn't be that bad if it weren't for the fact that TradeStation does not have a way to apply the same system to several markets (or otherwise manipulate several markets) all at once. At this point, it takes me about a minute (and I'm becoming pretty quick at this) to set up one market/system combination from a set of predefined workspaces that I have built. Imagine doing this on several 100-market/system combinations.

It is a drag, to say the least. Another way to illustrate this include the fact that there seems to be no way to set the starting date once and for all, or once and for all to define a particular contract as a futures contract, or to default as hidden all data streams but the first one. To do all this it takes me at least 20 mouse clicks (conservatively counting) for each market to set up the chart with the necessary system. I will tell you, I am not writing a book like this just because I think it is fun to tinker around with TradeStation.

Nonetheless, Table 16.4 shows the Pearson correlation coefficients together with the equity contribution factors for 23 different markets traded with the SDB system over the time period January 1980 to October 1999. Again, the initial markets were picked in such a way as not to use those obvious ones already used in many of the previous examples. Table 16.5 shows the summarized results for this portfolio. The initial equity was set to $1,000,000 and the percentage risked per trade was set to 1.5%. As usual, $75 was deducted for slippage and commission. With these settings, the strategy produced an ending equity of close to $29,000,000, corresponding to a percentage return of close to 19% per year. So far so good, but a maximum drawdown of close to 40% and a longest flat time of more than 47 months would have made this a very difficult portfolio to trade in real life.

From these 23 markets, I deducted the six markets with the lowest (Au dollar, soybeans, platinum, live cattle, cocoa, and British pound) and the three markets with the highest (rough rice, Eurodollar, and cotton) Pearson correlation coefficients, ending up with a portfolio consisting of sugar, Nikkei index, natural gas, municipal bonds, lean hogs, lumber, coffee, copper, gold, feeder cattle, crude oil, Canada dollar, corn, and wheat. These I then traded with a fixed fractional setting of 2%. (With fewer markets, we can increase the risk per trade somewhat, because the strategy now should be a little more efficient, while at the same time our overall margin requirements have decreased.)

TABLE 16.4

Initial markets for Charity III.

Market	Contributing	Pearson
Au dollar	-5.46	-0.6592
Sugar	0.66	0.0561
Soybeans	-2.52	-0.4445
Rice	15.85	0.9508
Platinum	-22.93	-0.8640
Nikkei index	7.55	0.8741
Natural gas	12.86	0.9137
Municipal bonds	3.80	0.8302
Lean hogs	-0.13	-0.3184
Live cattle	-2.09	0.1241
Lumber	8.83	0.6967
Coffee	28.58	0.7810
Copper	5.40	0.9064
Gold	5.19	0.6305
Feeder cattle	1.84	0.8413
Eurodollar	0.64	0.9099
Cotton	20.97	0.9098
Crude oil	32.29	0.8362
Canada dollar	-1.82	0.2626
Cocoa	-9.60	-0.6489
Corn	6.79	0.7143
British Pound	-4.17	-0.5608
Wheat	-2.54	0.4263

Table 16.6 shows the result from trading this portfolio. The ending equity is close to $40,000,000, corresponding to a percentage return of more than 20.50% per year. The drawdown has decreased to a tolerable 29%. The longest flat time also has decreased considerably but is still, at close to 31 months, a little too long.

TABLE 16.5

Initial strategy summary for Charity III.

Strategy summary	
End Eq ($)	29,016,313
Total (%)	2,802
Year(%)	18.96
Max DD (%)	-39.29
Lrg Loss ($)	-823,050
Lng Flat (m)	47.57

TABLE 16.6

Modified portfolio, strategy summary for Charity III.

Strategy summary	
End Eq ($)	38,565,334
Total (%)	3,757
Year (%)	20.72
Max DD (%)	-29.07
Lrg Loss ($)	-1,579,683
Lng Flat (m)	30.81

All in all, however, this is not too bad for a one-system strategy, traded on a bunch of markets that were basically chosen because they had not been used before or because they were plain average.

CHAPTER 17

Increasing Your Confidence

Let us briefly look at a few techniques for how you can increase your confidence in your paper tigers. The most obvious method is to save some of your data for out-of-sample testing. If the system still holds up when tested on this part of your data, chances are very good that you have managed to come up with a model that does not just manage to catch a phenomenon only associated with the data you used for your testing and optimization. The second method, and the one I prefer, is to alter the different input variables one at a time by approximately ±50%. If the result differs too much from the original result, chances are that particular variable might be too sensitive to be trusted with real-time data, and you must go back to the drawing board. To be sure, I also run a best- and a worst-case scenario and will say more about this shortly.

OUT-OF-SAMPLE TESTING

For the first method, we specifically put some data aside when we built the Standard Deviation Breakout (SDB) system. Table 17.1 shows how the original SDB system (without exits and filters) fared when tested on the out-of-sample data, covering the period October 1992 to October 1999, trading one contract only. This table is directly comparable to Table 10.18. If you compare the two, you find that 12 markets had both a higher profit factor and a lower standard deviation when tested on the out-of-sample data, and that nine markets also had lower drawdowns, but that only four markets managed to increase the value for the average trade. For the in-sample period, all 16 markets were tradable according to our rule-of-thumb, but for the out-of-sample period, only nine markets were tradable. Overall, this indicates that the system is still

TABLE 17.1

The SDB system tested on out-of-sample data.

Original system without exits and filters				
Market	**P. factor**	**Avg. trade**	**2 St. dev.**	**Drawdown**
Crude oil	4.29	1,479.39	7,057.42	-2,978.23
T-bonds	1.84	959.06	8,535.63	-14,922.51
T-bills	0.78	-53.19	1,082.75	-2,918.79
Rough rice	2.35	469.66	4,414.97	-2,471.24
Nikkei index	1.16	278.92	10,217.26	-13,980.23
Natural gas	1.27	370.80	8,909.49	-9,231.34
Live cattle	0.45	-302.45	1,924.89	-6,976.45
Lumber	0.75	-290.64	4,713.38	-14,987.61
Coffee	2.28	2,677.13	26,860.39	-15,845.70
Japanese yen	5.16	3,240.19	14,366.39	-6,369.00
Copper	1.18	93.38	3,015.47	-5,342.02
Gold	1.13	47.16	2,083.29	-4,622.61
Dollar index	2.47	1,060.05	7,014.18	-9,012.39
D mark (Euro)	1.90	536.96	4,705.28	-3,672.00
Cotton	1.26	203.75	6,475.78	-8,008.77
Wheat	1.40	124.61	2,077.13	-2,711.16

doing a good job keeping down the risk and the cost of doing business, but that it also is not as market insensitive as we would have liked.

Tables 17.2 and 17.3 show how the SDB system performed on the out-of-sample data, with the stops and exits added. Table 17.2 also is comparable to Table 10.19. Once again we managed to improve the profit factor for 12 markets, but unfortunately, the value of the average trade continued to decrease for 11 markets, resulting in only 6 tradable markets according to our rule of thumb, leaving only a few macroeconomic oriented markets with high point values as tradable alternatives. This is, of course, no good and might indicate that we have set the stops and exits too tightly. In the best of worlds, we should go back to the drawing board to examine what happens if we exclude or modify one or several of the exit techniques.

On the minus side is also the fact that we only managed to decrease the drawdown for four markets, which confirms the fact that the stops are not doing their jobs as intended. Then it does not matter that the standard deviation decreased for a total of nine markets, indicating a lower risk. If the profits are not there, something must be done. Hopefully, a filter adds to the performance again.

Tables 17.4 and 17.5 show the out-of-sample results for the final system, with both the exits and the filter added. With the filters added, we once again man-

TABLE 17.2

The SDB system tested on out-of-sample data.

Modified system with exits				
Market	**P. factor**	**Avg. trade**	**2 St. dev.**	**Drawdown**
Crude oil	3.05	1,044.50	6,317.99	-2,287.13
T-bonds	2.09	1,245.85	10,007.90	-14,927.71
T-bills	0.73	-69.61	1,190.71	-3,477.18
Rough rice	0.95	-18.33	1,616.97	-2,578.88
Nikkei index	1.34	596.12	11,407.45	-11,504.12
Natural gas	0.74	-333.44	6,770.50	-16,311.91
Live cattle	0.51	-271.59	2,053.99	-6,430.07
Lumber	0.94	-49.30	4,132.89	-12,826.20
Coffee	0.46	-724.16	4,815.83	-16,986.35
Japanese yen	2.79	2,131.80	12,359.79	-8,681.72
Copper	0.85	-88.57	2,617.81	-7,656.22
Gold	0.97	-11.36	2,035.93	-5,796.95
Dollar index	2.80	1,250.31	7,839.86	-9,211.56
D mark (Euro)	1.55	411.75	5,445.90	-4,172.52
Cotton	1.29	209.09	5,914.57	-9,608.86
Wheat	1.03	13.43	2,149.37	-3,231.83

aged to improve the profit factor for 12 markets, but the value of the average trade also continued to decrease for 10 markets. This time, however, the decrease came in markets that already were quite profitable, which in the end resulted in a total of 9 tradable markets.

If we compare the final system, traded on out-of-sample data (Table 17.4) to the very original system, tested on in-sample data (Table 10.18), we can see that all measures are both lower in value and more uniform (i.e. lower standard deviations) for the final out-of-sample system, than for its original in-sample counterpart. This also seems to hold true if we compare the final in-sample system (Table 13.7) with the final out-of-sample system (Table 17.4).

Of course there are plenty more research and comparative analyses that could—and should—go into this before you finally decide to start trading your model, but in conclusion we can say that the fact that the system seems to move toward a more uniform behavior when comparing the different markets is a good thing, as are the facts that the drawdown and standard deviation of the value of the average trade seem to stay at relatively low levels. An ever-increasing profit factor for most markets also is a positive. The bad news is that several markets did not manage to produce a tradable average profit per trade and that some even turned negative. But such are the traits of a non-market-specific model. It will work well,

TABLE 17.3

Differences between the original system and system with exits.

	Differences				
Market	P. factor	Avg. trade	2 St. dev.	Drawdown	Better
Crude oil	-28.77%	-29.40%	-10.48%	-23.21%	2
T-bonds	13.64%	29.90%	17.25%	0.03%	2
T-bills	-5.59%	30.87%	9.97%	19.13%	1
Rough rice	-59.79%	-103.90%	-63.38%	4.36%	1
Nikkei index	15.42%	113.72%	11.65%	-17.71%	3
Natural gas	-41.72%	-189.92%	-24.01%	76.70%	3
Live cattle	12.33%	-10.20%	6.71%	-7.83%	2
Lumber	26.14%	-83.04%	-12.32%	-14.42%	3
Coffee	-79.78%	-127.05%	-82.07%	7.20%	1
Japanese yen	-45.87%	-34.21%	-13.97%	36.31%	1
Copper	-28.18%	-194.85%	-13.19%	43.32%	1
Gold	-14.47%	-124.09%	-2.27%	25.40%	1
Dollar index	13.00%	17.95%	11.77%	2.21%	2
D mark (Euro)	-18.44%	-23.32%	15.74%	13.63%	0
Cotton	2.40%	2.62%	-8.67%	19.98%	3
Wheat	-25.99%	-89.22%	3.48%	19.20%	0
Better	12	5	9	4	—

on average, on all markets over a longer period of time, but there invariably will be times when some markets start to move against you.

ALTERING THE INPUTS

Altering the inputs is another good way to check the robustness of your system. As is the case with the out-of-sample testing, this can be done both before and after you have attached the money management. In this case, we will look at how the Gold Digger system would have performed on the S&P 500, on a one-contract basis, over the period January 1995 to October 1999. The parameters we will change are the breakout filter (60 days ± 30 days), the profit target (2.8% ± 1.4 percentage points), the trailing stop (0.6% ± 0.3 percentage points), and the stop loss (1.1% ± 0.5 percentage points).

We will change one parameter at the time keeping all the others constant on their original values. With four parameters to examine, this means that we must run the system test eight times. With these performance summaries as a base, we then look at which individual parameter settings produced the best and the worst results, and alter all the parameters at once to come up with the worst and the best

TABLE 17.4

The SDB system tested on out-of-sample data.

Modified (final) system with exits and filter

Market	P. factor	Avg. trade	2 St. dev.	Drawdown
Crude oil	3.11	1,160.48	6,926.93	-2,485.61
T-bonds	2.57	1,588.33	10,332.34	-8,757.69
T-bills	0.82	-37.29	1,048.49	-1,278.81
Rough rice	1.57	240.89	3,548.54	-3,438.43
Nikkei index	1.42	774.75	12,214.28	-13,084.91
Natural gas	0.92	-95.87	6,898.78	-8,022.83
Live cattle	0.52	-265.61	2,130.85	-5,406.43
Lumber	0.93	-58.91	3,895.54	-10,228.79
Coffee	1.71	905.00	14,273.04	-11,468.87
Japanese yen	1.82	1,260.72	12,526.50	-14,863.14
Copper	0.91	-52.43	2,726.10	-5,556.51
Gold ,	1.68	235.91	2,528.68	-4,544.11
Dollar index	2.75	1,348.52	8,472.42	-4,956.25
D mark (Euro)	0.90	-120.21	5,763.42	-9,866.05
Cotton	1.88	587.89	6,767.50	-6,758.33
Wheat	1.02	6.48	2,158.88	-3,341.48

parameter settings, respectively, possible. In this case, all parameter settings are judged by the average profit only. Of course, you can—and should—use other evaluation measures as well. And of course, you would come up with results that are more reliable if you do the comparisons over a whole portfolio instead of one single market.

Tables 17.6 and 17.7 show the results from the worst and the best parameter settings respectively. The worst possible setting turned out to be one with a 30-day filter, a profit target of 1.4%, a trailing stop of 0.6% and a stop loss of 1.6%. The best setting included a 90-day filter, a 2.8% profit target, a 0.3% trailing stop, and a 0.6% stop loss. The results are directly comparable to Table 12.8.

As you can see, even with the worst possible setting, the system is marginally profitable, which is a very good thing, indicating that even in the worst of times, we should not lose our shirts. The question is, however, if we deem it profitable enough or if we would have liked the results to be slightly more similar to those of the original parameter settings. In real life, only you can make that decision and only time and plenty of bad system-building attempts help you gain the experience necessary. In this case, I would say that I would have liked to see the worst-case scenario a little better than it is. With only one market tested over a very limited

TABLE 17.5

Differences between SDB system with exits only and final system.

Differences					
Market	P. factor	Avg. trade	2 St. dev.	Drawdown	Better
Crude oil	1.94%	11.10%	9.64%	8.68%	2
T-bonds	22.91%	27.49%	3.24%	-41.33%	3
T-bills	11.63%	-46.43%	-11.94%	-63.22%	3
Rough rice	65.73%	-1414.49%	119.46%	33.33%	1
Nikkei index	6.32%	29.96%	7.07%	13.74%	2
Natural gas	24.05%	-71.25%	1.89%	-50.82%	3
Live cattle	2.26%	-2.20%	3.74%	-15.92%	2
Lumber	-1.43%	19.49%	-5.74%	-20.25%	3
Coffee	270.30%	-224.97%	196.38%	-32.48%	2
Japanese yen	-34.70%	-40.86%	1.35%	71.20%	0
Copper	6.79%	^0.80%	4.14%	-27.42%	2
Gold	73.64%	-2176.69%	24.20%	-21.61%	2
Dollar index	-1.68%	7.85%	8.07%	-46.20%	2
D mark (Euro)	^t2.31%	-129.20%	5.83%	136.45%	0
Cotton	46.55%	181.17%	14.42%	-29.67%	3
Wheat	-1.66%	-51.73%	0.44%	3.39%	0
Better	12	6	2	10	—

time span and using one measurer only, however, we do not have enough data to come to a definite conclusion.

As for the combined best-case scenario, we can see that it too produces an average profit lower than that produced by the original parameter settings. This is actually good news, because it means that the original settings are doing a good job supporting each other in their respective roles and producing a final system where the whole is larger than its parts, although there might be times when the true best-parameter settings differ slightly.

TABLE 17.6

Gold Digger, worst-case scenario, January 1995-October 1999.

Total trades		194	Winners	118	60.82%	Losers	76	39.18%
Profit factor		1.05	Lrg winner	5.14%	17,348	Lrg loser	-8.30%	-28,013
Avg profit	0.04%	127	Avg winner	1.26%	4,250	Avg loser	-1.86%	-6,275
St Dev	1.72%	5,792	Cum profit	4.52%	15,255	Drawdown	-19.52%	-65,880

TABLE 17.7

Gold Digger, best-case scenario, January 1995-October 1999.

Total trades		206	Winners	10	50.00%	Losers	10	50.00%
Profit factor		1.31	Lrg winner	5.14%	17,348	Lrg loser	-8.30%	-28,013
Avg profit	0.17%	572	Avg winner	1.44%	4,874	Avg loser	-1.11%	-3,730
St Dev	1.73%	5,832	Cum profit	37.46%	126,428	Drawdown	-14.76%	-49,815

PART FIVE

A Few Final Thoughts About Part 5

The observant reader probably has noticed that up until Part 5 I have consistently talked about "systems" rather than "strategies," but that in Part 5 I have used the word "strategy" more frequently. This is because to me, a "system" is nothing but the basic entry and exit rules. A "strategy," on the other hand, is a complete trading plan, including a system, a money management regimen, and a well-thought-through reason for trading a particular set of markets. To me, a system without a proper money management regimen attached to it can never be a strategy.

I have noticed that Omega research recently went from using the word "system" to using the word "strategy." That is nothing but another ridiculous way for a software vendor to try to cash in on a new buzz word or distance itself from another word that might have lost a little bit of its sex appeal. There is no way you can use TradeStation as a standalone tool to build a complete strategy. You can't even do proper system testing on a single market, not to mention all the hassle you have to go through if you want to test a portfolio!

In Part 5 we took a closer look at how to put together a fixed fractional money management regimen, and we did so using percentage-based calculations throughout. It is important to understand that we would not have been able to do this had we not done our homework properly and gone through all the excruciating work in the previous chapters. It should now be clear that everything affects everything else; to build a trading strategy that is larger than its parts—the system, the money management, and the portfolio composition—we must know exactly what it is we want to achieve, and there is no way of cheating.

I am a big fan of Mr. Vince's work, but even so there have been a couple of occasions throughout this section were I have implicitly argued against him and what seems to have become "common wisdom," or otherwise argued for a different way of approaching a specific problem or topic. Before I end this book, I would like to take the opportunity to address these in more detail.

Concerning percentage-based versus point-based data, if I understand Mr. Vince correctly, it should not matter what data we use. Mr. Vince acknowledges the problem of using point- or dollar-based data in heavily trending markets, but also says that if you have to use so much data that the trend starts to become a problem, then you are probably using too much data anyway *(The Mathematics of Money Management,* p. 83 ff. John Wiley & Sons, 1992).

Nothing can be more wrong. You should use as many data as you possibly can to make your results as robust as possible. There is no way around this, because for a system to work in the future it needs to exploit a type of market anomaly that is not dependent on what level we are trading, what the most recent trend looked like, or who happened to be president at the time. It must be a phenomenon not dependent on any particular circumstances, only referable to that particular point in time. Furthermore, using percentage-based calculations is the only way to make your results comparable among different markets. Mr. Vince says that for a system to be robust, it should work on several markets, but he does not address the problem of how to get there. (Granted that is not the purpose of any of Mr. Vince's books, but still....)

Another key point throughout this section has been that you do not have to use your largest historical loser to calculate optimal *f*. The optimal *f* is the *f* that gives you the highest TWR value in accordance with the constraints you have applied to your model. Unfortunately, most analysts and system designers consistently refer to the optimal *f* as the *f* corresponding to the largest historical loser. This has stuck in people's minds and many have therefore dismissed the entire theory surrounding fixed fractional investing as something very dangerous. But this is only one way of many to relate optimal *f* to a specific constraint. That is, we do not want to experience a loser larger than our largest historical loser, the largest historical loser being the constraint. But we could equally as well have said that we do not want to experience a loser larger than our largest historical loser, times two, because this would result in an even higher optimal *f* than the optimal *f* most commonly referred to.

In this particular case I do not think it was Mr. Vince's intention to have everybody stare themselves blind on his way of doing it, but that is the way people work. They read something and take it for face value without putting their own thinking caps on. True, trading with an/based on your largest loser is very dangerous, but as we have seen, it is more or less impossible to use an *f* that high anyway if you like to trade a well-diversified portfolio, because of several practical reasons such as margin constraints, extremely high drawdowns, and an impossible number of contracts traded.

Instead of using your largest historical loser to calculate *f* I suggest that you simply use the stop loss level for each individual trade and that you keep that stop loss level the same, no matter what mode the market is in. Once you have calculated the optimal *f* in accordance with the constraints of your choice, make sure that you actually use an *f* far lower than that, because there is no guarantee that the future, unknown, *f* won't be far lower as well, especially for a market-specific system built with point-based data.

Many portfolio managers, especially in the stock market, probably also have tried to combine a fixed fractional money management regimen with the Capital Asset Pricing Model (CAPM) and the Efficient Market Hypothesis (EMH). However, as far as I understand, the two cannot be combined, because for a system to work equally as well on several different markets, we have to assume that there is no difference in the statistical traits of all these markets. This might or might not be so in real life, but for our purposes, this is what we must assume. And because we assume this, we cannot deviate from it when it is time to apply money management, to the system we are building, because it would result in a suboptimal solution. If we do not believe that the statistical traits for all markets are the same, then there is no way we can build systems that should work equally as well in all markets; all systems would, out of necessity, have to be market specific, curve fitted, not robust at all, and very, very dangerous to trade using any money management regimen.

A few also have argued that one should use different *f*s depending on whether the overall portfolio is in a drawdown, whether the market is in an uptrending or downtrending mode, or whether we are about to go long or short. However, in doing so we must assume that we had done a bad job constructing the underlying system and that we think we can increase the return from the individual trades by tinkering with the money management. But this is not so, because with a correctly built system there is no way of knowing, or even anticipating, the outcome of each individual trade. A well-working system makes no difference between trying to pick tops or bottoms, entering on breakouts to the up side or down side, whether the trend is up or down, or even in which markets all this occurs. This also argues against the possibility, within the confines of a specific strategy, to risk more going long (short) in an uptrend (downtrend) either by altering the stop loss level or by altering the bet size. That said, this does not mean that several market-specific or even trend-specific characteristics or anomalies do not exist (in fact, we have stumbled upon and acknowledged several such [short-term] anomalies within this book). If these are the types of market anomalies you would like to exploit, then you must build a system that exploits exactly that, one market anomaly at a time. Those systems would, however, no longer be universally applicable and therefore probably much less reliable and robust than any of the systems we have worked with in this book.

Finally, a few, more theoretically inclined, system builders and analysts have advocated that rather than just looking at the historical trades, it is better first to calculate the distribution of the outcomes of the trades, and from there calculate *f* parametrically. At first glance this makes a lot of sense, because using the mathematical expression for the expected distribution of our future trades would make our models even more forward looking than using the actual, historical trades. We looked into the distribution of our trades when we put together the stops and exits for our short-term systems. In this particular case, the distributions we came up with hardly lend themselves to any parametric calculations of *f* In fact, if they did, I would say that we had a bunch of bad systems on our hands. Because as soon as the distribution of our trades starts to resemble something that we can put a name to, especially if it turns out to be normally distributed, we are probably doing a very bad job in managing our trades, essentially leaving each trade to its own destiny as soon as we have entered into it, using no stop or exit techniques to streamline the outcome.

Instead, we should make sure that each trade only has a set of very few, very specific and clearly distinguished outcomes, one being the stop loss that we also used for our optimal *f* calculation. Remember, it is thanks to our stop and exit techniques we are able to exploit non-market-specific anomalies. If it were not for these techniques, we would not be able trust our systems to a fixed fractional money management regimen in the first place. That said, there still might be plenty of systems with normally distributed trades that work much better than those in this book. The systems and strategies we explored so far are simply "paper tigers."

BACK TO THE FUTURE

The financial markets are not random and there are ways to take advantage of this nonrandomness with the help of mechanical trading strategies. The good news is that you do not have to be a rocket scientist to do so. You only need a tad more knowledge than you hold about the topic already. Unfortunately, knowing too little about a specific topic sometimes can be more devastating than knowing nothing at all. The big fish in this industry realize that, so they have no incentive to educate you, because what is devastating for your economy is a gold mine to theirs.

Considering the above, it is no coincidence that our discussion on stop placements has the most exhaustive one, because when it comes to basic trading and investing, getting out of a position is what nobody really talks about. Go through all the recommendations from several analyst and brokerage companies and you will find a multitude of opinions such as "strong buy," "buy," "cheap," "outperform," "stronger than average," "long-term buy," "positive outlook," but seldom will you find the words "sell," "sell if it drops to," or "sell if it reaches." The strongest phrases in this regard seem to be "medium perform" or "hold." Why is this? It is because in this industry, selling something means bad news and your broker does not want you to think about bad news or what might go wrong. Transmitting bad vibes, whether professionally right or not, is not good for business.

But because neither you nor I can blow hundred dollar bills out of our noses, to buy something (or go long or short on a futures contract) usually means we need to get out of something else, either with a profit or a loss, but always, always at a point where we believe our money can come to better use elsewhere, in accordance with our research. This means that getting into a position is a one-time decision and once it is made it is over and done with. But the decision to get out of the same position is an ongoing process, where you constantly ask yourself "will my money come to better use elsewhere?" No matter if this "elsewhere" happens to be in the bank account, in another trading or investment opportunity, or under your mattress. That is why no trading or investment technique is complete without a set of thoroughly researched stops and exits. The stops and exits not only form the core in the trading process but also set the stage for a profitable money management regimen.

Unfortunately, to research how and where to place your stops and exits you must know a whole lot more about your system than its maximum historical drawdown in dollar terms. Because this figure tells you nothing about what to expect in the future, just as it gives you no clue whatsoever—absolutely none—about how to go about doing something about it. For this, you must know how to divide the drawdown into several different subcategories, such as the start trade drawdown (STD), the end trade drawdown (ETD), the closed trade drawdown (CTD), and the total equity drawdown (TED). And as if this were not enough, you also must know how to calculate each trade's maximum adverse excursion (MAE) and maximum favorable excursion (MFE).

In Part 3 I showed you how to do all that and more. For each of our example systems we put together a set of stop and exit techniques that enhanced the performance for every single one of them. Not only that, but for our short-term systems these techniques were generic and non-market-specific best compromises, principally developed with the help of random entries and later applied to a market other than those used during the testing procedure. This means that there was virtually no curve fitting involved and that we are exploiting are non-market-specific discrepancies that are likely to occur again and again in all markets.

This brings us to two other interesting conclusions:

- You get a long-term edge in almost every market if you only trade with the direction of the underlying trend.
- If you do not know or cannot form an opinion regarding the direction of the long-term trend, you are better off trading short term (i.e. approximately three to nine days) using as little historical data as possible for your decision making.

The statistical traits for the markets are pretty much the same whether the trend is up, down, or sideways. For instance, by just looking at the last five days of market action, you likely are not able to tell the direction of the underlying long-term trend. Therefore, for practical reasons, the short-term traits can be said to be static in nature, although the small, nonmeasurable changes that might occur over time lead up to and form the longer-term trend. At that level, the statistical traits become dynamic with measurable differences, distinguishing up, down, and sideways trends from each other. Another major advantage of trading short term, but only in the direction of the long-term trend, is that you dare to work with limit orders, trying to pick tops and bottoms, influenced by the increased security you feel about knowing the long-term trend.

To figure out where the market is heading, both in the short and the long run, and the theory why all this is happening in the first place, was what Part 4 was all about. When attaching the filters we also might have to go back and adjust the original idea a little, or perhaps even scrap it all together if it turns out that we cannot come up with a way to fit the filter to the rest of the machinery as efficiently as we would like to. Not until all the pieces from Parts 1 and 4 fit snugly together can we attach the money management that not only transforms the system to a strategy, but also will make the whole picture larger than any of its parts. To this set of rules and frameworks we also need to add the understanding of the trading process and the creation of a rule-based trading strategy as a flow of events and intervening decisions, rather than individual decisions separated from each other in time and space. Because if we do not understand and acknowledge this, we cannot see the benefits of the type of trading and that it is not a matter of optimizing your system's individual signals to the underlying data, but "optisizing" your trading positions in relation to your overall strategy and other personal constraints and preferences.

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Note: Boldface numbers indicate illustrations. Italic t indicates a table.

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