The Volatility Edge in Options Trading

New Technical Strategies for Investing in Unstable Markets

Jeff Augen

Instructor, New York Institute of Finance

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Jeff Augen

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Publishing as FT Press
Upper Saddle River, New Jersey 07458

www.ftpress.com

Printed in the United States of America
Sixth Printing: December 2011
ISBN-10: 0-13-235469-1
ISBN-13: 978-0-13-235469-1

Pearson Education Ltd.
Pearson Education Australia PTY, Limited.
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Augen, Jeffrey.
The volatility edge in options trading : new technical strategies for investing in unstable markets / Jeff Augen.
p. cm.
Includes bibliographical references.
ISBN 0-13-235469-1 (hardback : alk. paper) 1. Options (Finance) 2. Investment analysis. 3. Securities—Prices. 4. Stock price forecasting. I. Title.
HG6024.A3A923 2008
332.63’2283—dc22
2007026094

To Lisa, whose kindheartedness and unending patience rescued me from oblivion.

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ACKNOWLEDGMENTS

I would like to thank the team who helped pull the book together. First and foremost is Jim Boyd, who provided sound advice that, among other things, resulted in a guide for readers and improved flow and readability throughout. That said, Anne Goebel, who carefully read every word and made final decisions about phraseology, and Gayle Johnson, who edited the original text, provided a critical eye that an author can never have for his own work. Likewise, Dr. Edward Olmstead was the driving force behind the expansion of several sections that improved overall clarity and made the book accessible to a larger audience. The options trading world is expanding at a remarkable rate, and investors are becoming more sophisticated with each financial event. Adding value to their efforts has been our principal goal.

ABOUT THE AUTHOR

Jeff Augen, currently a private investor and writer, has spent more than a decade building a unique intellectual property portfolio of algorithms and software for technical analysis of derivatives prices. His work includes more than one million lines of computer code reflecting powerful new strategies for trading equity, index, and futures options.

Augen has a 25-year history in information technology. As a co-founding executive of IBM's Life Sciences Computing business, he defined a growth strategy that resulted in $1.2 billion of new revenue, and he managed a large portfolio of venture capital investments. From 2002 to 2005, Augen was President and CEO of TurboWorx, Inc., a technical computing software company founded by the chairman of the Department of Computer Science at Yale University. He is author of *Bioinformatics in the Post-Genomic Era: Genome, Transcriptome, Proteome, and Information-Based Medicine* (Addison-Wesley, 2004). Much of his current work on options pricing is built on algorithms for predicting molecular structures that he developed as a graduate student.

PREFACE

This book is written for experienced equity and index option traders who are interested in exploring new technical strategies and analytical techniques. Many fine texts have been written on the subject, each targeted at a different level of technical proficiency. They range from overviews of basic options positions to graduate-level reviews of option pricing theory. Some focus on a single strategy, and others are broad-based. Not surprisingly, many fall into the "get rich quick" category. Generally speaking, books that focus on trading are light on pricing theory, and books that thoroughly cover pricing theory usually are not intended as a trading guide.

This book is designed to bridge the gap by marrying pricing theory to the realities of the market. Our discussion will include many topics not covered elsewhere:

- Strategies for trading the monthly options expiration cycle
- The effects of earnings announcements on options volatility and pricing
- The complex relationship between market drawdowns, volatility, and disruptions to put-call parity
- Weekend/end-of-month effects on bid-ask spreads and volatility

A cornerstone of our discussion will be a new set of analytical tools designed to classify equities according to their historic price-change behavior. I have successfully used these tools to trade accounts as small as $80,000 and as large as $20M.

Ten years ago, having studied the markets for some time, I believed I could be a part-time investor with a full-time professional career. At the time I was a computer-industry executive—a director at IBM—with a large compensation package and a promising future. My goal was to develop a successful trading strategy that could be implemented as an income supplement. It was a naïve idea. Successful investing is a demanding pursuit. The work described in this book took more than ten years. It involved writing hundreds of thousands of lines of computer code, constructing numerous financial-history databases, creating new data visualization tools, and, most important, executing more than 3,000 trades. During that time I also read dozens of books and thousands of technical articles on economic theory, technical analysis, and derivatives trading. The most important result was not the trading system itself, but the revelation that nothing short of full-time effort could possibly succeed. The financial industry is populated with bright, hard-working, well-educated professionals who devote every waking hour to making money. Moreover, there is virtually no limit to the funds that can be made available to hire outstanding talent. An amateur investor should not expect to compete with these professionals in his or her spare time. The market is a zero-sum game—every dollar won must also be lost. Option trading represents the winner-take-all version of the game. Consistently making money requires focus and dedication. That said, experienced private investors often have a distinct advantage over large institutions in the equity options world. The advantage relates to scale. A private investor trading electronically can instantly open or close typical positions consisting of tens or even hundreds of option contracts. Conversely, institutions often manage very large positions worth hundreds of millions of dollars. Efficient execution becomes a barrier at this level. Furthermore, many equity option issues do not have enough open interest to support trades of this size. The result is that institutional traders tend to focus on index options—which are much more liquid—and some of the more heavily traded equity options. Large positions take time to negotiate and price. They have an element of permanence because they can't be unwound with the press of a button. Liquidity and scaling are central to this work, and we will return to this discussion many times in the context of trading logistics.

Generally speaking, the work is not done—not even close. But I've come a long way. Today I can comfortably generate a return that would make any investment bank or hedge fund proud. Needless to say, I no longer work in the computer industry, and I have no interest in a salary. I'm free. My time belongs to me. I trade for a living.

A GUIDE FOR READERS

This book introduces a charting technique that is designed to help option traders visualize price change behavior. Although the form is new, the underlying mathematics are that of standard option-pricing theory. Many of the charts presented in this book contain a series of bars that measure individual price changes in standard deviations against a sliding window of predetermined length. The exact method for creating these charts is described in the "Profiling Price Change Behavior" section of Chapter 3. All the charts presented were created using standard Microsoft desktop tools and readily available data sources. If you subscribe to a data service and you want to create charts of the same form, you will find that Excel's statistical analysis and charting functions support these efforts very efficiently and that no programming is necessary.

Many readers who are familiar with the Microsoft Office environment will also want to construct a database containing historical price change information and volatility calculations for thousands of securities and indexes. For the present work, price and volume information was downloaded to a Microsoft Access database from a variety of readily available public and subscription-based data services. A large number of calculations were generated across the dataset and results for individual tickers were exported to Microsoft Excel, where the charts were created. The complete infrastructure is described in Chapter 9.

Just a few years ago desktop computers lacked the capacity and performance to support the work described in this book. Recent improvements in these machines' size and performance have significantly reduced the complexity of such work. The change has been dramatic. Today's multigigahertz multicore CPU desktop computers often come equipped with 3 gigabytes or more of memory and hundreds of gigabytes of disk storage. Microsoft desktop products such as Excel, Access, and Visual Basic provide all the necessary tools to build an infrastructure for managing millions of stock records on such a machine. These changes have been a welcome advance for those of us who previously programmed exclusively in C and C++ and struggled with the complexity and expense associated with a large computing infrastructure.

If you want to replicate the database system described in Chapter 9, you will discover that Microsoft Access can support relatively large designs. Most programmers will find the performance of the VBA programming language to be quite acceptable. The actual design includes a large number of Access VBA programs, macros, and SQL queries in addition to modeling tools written in Excel VBA.

Finally, the past few years have witnessed a leveling of the playing field in the sense that a serious private investor can, at reasonable cost, obtain all the tools necessary to build a sophisticated infrastructure. Information sources such as Bloomberg provide a robust set of programming interfaces for capturing and analyzing tick-by-tick data. They can become the content source for custom databases built with Microsoft SQL Server, Oracle, or IBM DB2, whose single-user versions are relatively inexpensive. Depending on the size, such systems can run on a single desktop computer or a cluster of machines linked with publicly available free Linux software. Five years ago this level of computing infrastructure was available only to financial institutions. Today, hundreds of thousands of private investors and small hedge funds are developing customized data mining and analysis tools as part of their effort to gain a technical edge in the market. This trend has become a dominant force in the investment world.

This book begins with an introduction to pricing theory and volatility before progressing through a series of increasingly complex types of structured trades.

The chapters are designed to be read in sequence. No particular technical background is required if you start at the beginning. However, you might find value in reading them in a different order. The following table will help you. It relates the level of technical background that is most appropriate for the subject matter presented. The two categories are option trading experience (Opt) and computer software skills (Comp):

Opt 1: No prior knowledge of pricing theory or structured positions.

Opt 2: Some familiarity with option pricing and basic trades.

Opt 3: Familiarity with option pricing concepts, including the effects of time decay and delta. Experience with structuring option positions.

Comp 1: Familiarity with basic software tools such as Microsoft Excel.

Comp 2: Experience using trading tools such as stock-charting software.

Comp 3: Experience building customized spreadsheets and moving data between software packages. The ability to download and use data from a subscription service. Familiarity with basic database concepts.

	Comp 1	**Comp 2**	**Comp 3**
Opt 1	Chapters 1, 2, and 3		
Opt 2		Chapters 4 and 5	
Opt 3		Chapters 6, 7, and 8	Chapter 9

If you plan to study the chapters out of sequence, you should become familiar with the method for creating price spike charts that is outlined in Chapter 3. Because these charts are used throughout the book, it will be helpful for you to understand how they are calculated. Chapter 3 also includes a related discussion of variable-length volatility windows that will be helpful to most option traders. It builds on the discussion of pricing theory presented in Chapter 2.

Chapter 4 contains practical trading information that is often lost to oversimplification. Many authors have written about complex trades without mentioning the effects of bid-ask spreads, volatility swings, put-call parity violations, term structure, and changes in liquidity. Chapter 4 also discusses price distortions generated by earnings and options expiration—topics that are covered in greater detail in Chapters 7 and 8. We close with a discussion of the level II trading queue, which is now available to all public customers. Chapter 4 is meant to stand alone and can be read out of sequence if you're an experienced trader who understands the basics of pricing.

Chapters 5 and 6 present a broad review of structured positions. Beginners will learn to create mathematically sound trades using a variety of pricing strategies. Advanced traders who are already familiar with the material will find the approach unique. Particularly important are the discussions of dynamic position management and the use of price spikes as trade triggers. Price-spike charts of the form presented in Chapter 3 are used throughout. Chapter 6 also includes an analysis of the VIX as a hedging vehicle—a topic that has recently come sharply into focus on Wall Street.

Chapters 7 and 8 present new information not found anywhere else. The strategies revealed in these discussions leverage price distortions that are normally associated with earnings and options expiration. They are tailored to investors seeking substantial returns with limited market exposure. The focus, as always, is practical trading. Chapter 8 also includes a review of the "stock pinning" phenomenon that has become the driving force behind the expiration day behavior of many securities. Some investors exposed to these methodologies have found that they can generate a substantial return on expiration day and remain out of the market the rest of the month.

Chapter 9 was written for the large and growing population of traders who want to optimize their use of online data services. The database infrastructure described in this chapter was built using the Microsoft desktop tools and databases mentioned previously. Detailed descriptions of the tables and data flows are included, and the layout is modular so that you may replicate the portions that best fit your needs. Investors who are primarily interested in bond, currency, future, or stock trading will also find value in the design elements presented in this chapter.

1

INTRODUCTION

On October 27, 1997, the Dow Jones Industrial Average (DJIA) fell a breathtaking 554 points, or 7.2%, to close at 7161. This massive collapse represented the largest absolute point decline in the history of the index and the tenth-largest percent loss since 1915. That evening, the financial news featured a parade of experts, each prepared to explain exactly what had happened and why. Despite the confusion, they all seemed to have two things in common: their failure to predict the drawdown before it happened, and their prediction that the next day would be worse. They were dead wrong. The next day the market resumed its decline before rallying sharply to close up 337 points (4.7%) on then-record volumes of over a billion shares. The experts were back that evening to explain why. Such is always the case with market analysts—they tend to be short on accurate predictions and long on after-the-fact analysis.

October 27 was also the first time that the cross-market trading halt circuit-breaker procedures had been used since their adoption in 1988. By 2:36 p.m., the DJIA had declined 350 points, triggering a 30-minute halt to the stock, options, and index futures markets. After trading resumed at 3:06 p.m., prices fell rapidly until they reached the 550-point circuit-breaker level, causing the trading session to end 30 minutes early. The Division of Market Regulation of the Securities and Exchange Commission launched an investigation to reconstruct the events of these two days and to review the effects of the circuit breakers on the velocity of price movements. The study concluded that the sell-off was prompted by concerns over the potential impact on U.S. corporate earnings of the growing market turmoil in Asia and repercussions from the potential economic slowdown and deflationary pressures. The Asian market turmoil evidently caused a number of institutional and professional traders to attempt to reduce their equity exposure or increase their hedges in the U.S. markets, either directly through stock sales or indirectly through trades in futures. When the sell-off reduced U.S. stock prices to attractive levels on the morning of October 28, a broad-based buying trend emerged to support a strong rebound in share prices.

As significant as it might have seemed at the time, this one-day 554-point decline is nearly invisible in the relentless march that took the Dow from 828 in March 1982 to 11,750 in January 2000. However, the October 1997 drawdown was important for many reasons. Most important among these was the lesson that all bubbles eventually burst. In this case the bubble was caused by a huge influx of foreign money into Asian markets that lasted for a decade and resulted in a credit crisis. Moreover, the ripple effect clearly demonstrated the importance of balanced trade between regions and the risks implied by deficits and surpluses. It also signaled the beginning of a hyper growth era that lasted for three years and nearly doubled the value of the U.S. equity markets.

My goal was to develop an investment strategy based on the fundamental mathematical properties that describe financial markets. Properly executed, such a strategy should provide excellent returns in a variety of market conditions. It should also be persistent in the sense that it transcends short-term trends. A perfect strategy would embody risk-management mechanisms that allow an investor to precisely calculate the expected return and worst-case loss for a given set of trades. Finally, and most important, a successful strategy should not depend in any way on personal opinion. As we shall see, the strategies that ultimately emerged from this work involve trading positions without regard to underlying financial assumptions about the performance of any particular company, index, or industry.

The work was enormously complex and time-consuming, because there was much less scientific analysis to build on than I had expected.

Unfortunately, the financial world has chosen to substitute careful scientific analysis with something far less precise—the opinions of financial analysts. These analysts are the same "experts" who have failed to forecast every major equity market drawdown in history. Most often their analyses are based on untested relationships, infrequent events, or both. It is easy to point to the last time interest rates rose by a certain percentage or oil prices fell more than a certain amount, but it is impossible to compare the effects of hundreds of such events. The modern era, characterized by electronic trading of equities, futures, options, fixed-income securities, and currencies is simply not old enough.

A significant example of the problem occurred at the very moment these words were being written. The Chairman of the U.S. Federal Reserve, the largest central bank on Earth, declared publicly that he could not explain why the yield on ten-year treasury notes had fallen 80 basis points during a time frame marked by eight consecutive quarter-point increases in the Federal Funds rate (the interest rate charged on overnight loans between banks). He used the word "conundrum" to describe the phenomenon that continued, to the surprise of many, for another year as rates continued rising.

Unfortunately, the lack of well-defined mathematical models that describe the world's economy is more than an academic problem. In June 2005, for example, GLG Partners, the largest hedge fund in Europe, admitted that flaws in the mathematical model it used to price complex credit derivative products caused a 14.5% drop in its Credit Fund over the span of a single month. Unfortunately, the model did not comprehend the tremendous market swings that followed ratings downgrades of General Motors and Ford. The problem arose because risk simulations based on historic data were blind to moves of this magnitude. The fund sent letters to all investors, assuring them that the model had been fixed. Such destruction of wealth is not nearly as rare as you might imagine because even the best financial models can be confounded by news. During the past several years, many billions of dollars have been lost in self-destructing hedge funds with faulty trading models. The risk is enormous. The U.S. gross domestic product (GDP) is approximately $13 trillion, the world's GDP is $48 trillion, and the world's derivatives markets are generally estimated to be worth more than $300 trillion. It's no longer possible to recover from a true crash.[1]

Such observations shaped my thinking, and over time my focus narrowed. Today it matters very little to me whether an individual stock rises or falls, because I am much more concerned with fundamental mathematical properties such as the shape of the curve that describes the distribution of daily price changes. Furthermore, it is often more important to have an accurate view of the potential change in a stock's implied volatility than to be able to predict short-term changes in its price. Volatility is also much easier to predict than price. This simple concept was almost lost during the great bull market of the '90s, when thousands of successful investors declared themselves geniuses as they rode a tidal wave of equity appreciation. However, those who missed (or misunderstood) the sharp rise in the implied volatilities of NASDAQ technology stocks during the second and third quarters of 2000 were putting themselves at extreme risk. Many continued to hold on to these stocks throughout the ensuing NASDAQ crash because they misinterpreted small bear market rallies as technical bottoms. These investors were repeating the mistakes of an earlier generation that was decimated during the prolonged crash that began in October 1929 and ended three years later in 1932. It has been suggested that the likelihood of a significant market crash increases with time as older investors who remember the previous crash drop out of the investment community. Very few victims of the 1929 crash were still around to invest in the NASDAQ bubble of the late 1990s.

The strategies I describe in this book are entirely focused on analyzing and trading fundamental mathematical properties of stocks and indexes. Options are the trading vehicle. Our focus is the underlying pricing models that are firmly rooted in the mathematical constructs of volatility and time. Furthermore, a reliable strategy for dynamically managing option positions has turned out to be as important as a strategy for selecting and structuring trades. Adaptive trading is a central theme of this book, and a great deal of space is devoted to discussing specific processes built on precise metrics and rules for making adjustments to complex positions. Unbiased use of these rules and a thorough understanding of the mathematical basis of option pricing are core components of this approach.

Unfortunately, few if any of today's books on option trading devote any space to this complex topic. Without these tools, an option trader simply places bets and either wins or loses with each trade. In this scenario, option trading, despite its solid mathematical foundation, is reduced to gambling. The rigorous approach that I will describe is much more difficult; fortunately, hard work and persistence usually pay off.

Not surprisingly, our discussion will focus on a precisely bounded and closely related set of option trading strategies with a great deal of rigor. Developing these strategies has revealed many inconsistencies in the models used to price options. At first it seemed counterintuitive that such inconsistencies could exist, because they amount to arbitrage opportunities, and such opportunities normally are rare in modern financial markets. Not surprisingly, brokerage houses that write option contracts are taking advantage of precisely the same opportunities on a much broader scale. Moreover, it is not surprising to find inconsistencies in a market that is barely 30 years old. The Chicago Board Options Exchange (CBOE) began trading listed call options on a scant 16 stocks on April 26, 1973. The CBOE's first home was actually a smoker's lounge at the Chicago Board of Trade. Put options were not traded until 1977. The Black-Scholes model, the underlying basis for modern option pricing, was not fully applied to the discipline until the early 1980s. Other sophisticated pricing models have also come into existence, and the CBOE recently retuned its mechanism for calculating the incredibly important volatility index (VIX). Option trading is an evolving discipline, and each new set of market conditions provides opportunities for further tuning of the system.

However, before we embark on a detailed option pricing discussion, I would like to examine the most basic assumptions about the behavior of equity markets.

Price Discovery and Market Stability

The crash of 1987 and the prolonged NASDAQ drawdown of 2000 clearly contain important but somewhat obscure information about the forces that regulate the behavior of equity markets. Three relatively simple questions come to mind:

- Why do markets crash?
- What are the stabilizing forces that end a crash?
- What, if anything, differentiates a "crash" from a typical drawdown?

The answers to these questions are rooted in the most basic assumptions about why an individual stock rises or falls. Simply stated, a stock rises when buyers are more aggressive than sellers, and it falls when sellers are more aggressive than buyers. Basic and simple as this concept might seem, many investors incorrectly believe that a stock rises if there are more buyers than sellers and falls if there are more sellers than buyers. The distinction is important. By definition there are always an equal number of buyers and sellers, because every transaction has two sides. The sole determinant of the next transaction price in any market is always the highest bid and lowest ask. When these two prices align, a transaction takes place regardless of the number of other offers to buy or sell. More precisely, the transaction takes place because an aggressive buyer raises the price that he or she is willing to pay or an aggressive seller lowers the price that he or she is willing to accept. In most markets such price adjustments take place over long periods of time; in the stock market they occur instantaneously.

Uninterrupted smooth execution of a continuous stream of transactions creates market liquidity. High levels of liquidity fuel the price discovery engine that keeps the market running. Without a price discovery mechanism, both individual stocks and the entire market would be prone to uncontrolled crashes or runaway rallies. The mechanism occasionally fails with catastrophic results. The U.S. equity market crashes of 1929, 1987, and 2000 are notable examples, as is the collapse of the Nikkei index from 38,915 in December 1989 to 14,194 in August 1992. The September 1929 crash was especially significant. The Dow Jones

Industrial Average fell from 386 in September 1929 to 40.6 in July 1932. The market did not fully recover until December 1954, when the Dow Jones Industrial Average finally rose above the September 1929 level. However, even during the prolonged crash of 1929–1932, price discovery allowed the market to plateau many times, and, in some cases, short-term rallies ensued. These rallies made the crash particularly devastating, because optimistic investors reentered the market believing that the collapse had ended. Contrary to popular belief, the largest losses were not experienced in a single one-day event. They happened over long periods of time by investors who were fooled by bear market rallies disguised as a stable rising market. Stabilization events and bear market rallies are triggered by the same price discovery mechanisms that set everyday trading prices in healthy markets. Without these mechanisms, the 1929–1932 crash would have happened in a single day.

Price Discovery Is a Chaotic Process

Surprisingly, price discovery cannot operate properly unless the market is chaotic. It must be characterized by large numbers of investors pursuing divergent strategies based on different goals and views of the market. On a microscopic scale, a particular situation might appear as follows: Investor #1, on hearing a piece of bad news, decides to sell a stock. The stock falls slightly and triggers another investor's (#2) stop-sell limit order. This new sell order causes the price to fall further. However, investor #3, who has a longer-term view of the company and believes that the stock is undervalued, has been waiting for a dip in the price. He aggressively buys a large number of shares, momentarily stabilizing the price. However, a large institutional investor with a computer program that tracks this particular stock, looking for such behavior, suddenly receives notice that a sell-short trigger has been activated. The large institutional sell order causes the stock to fall rapidly. It also triggers stop-sell limit orders from other investors who are protecting their profits. The sell-off accelerates as investors aggressively run from their positions in the stock. However, a small group of speculators who previously anticipated the bad news and sold short now begin buying the stock to cover their short sales and lock in a profit. They are using automated systems with triggers that generate a buying decision as soon as a certain profit level has been reached. The stock begins to climb again as aggressive buy-to-cover orders accumulate. As the stock climbs, short sellers begin to see their profits evaporate. They become increasingly aggressive about buying back the stock. The trend begins to slow as short sellers take themselves out of the market by unwinding positions. The price does not stabilize, however, because other investors witnessing the sudden rise and looking at particular chart patterns interpret the emerging rally as a buying opportunity and flock to purchase the stock before it runs up too much. The process continues indefinitely because price discovery is a dynamic and never-ending process.

Although it is meant as a simple illustration, this example embodies many important market drivers including program trading, short selling and buying to cover, technical charting with triggers, stop-buy and stop-sell limit orders, and a variety of complex buying and selling behaviors. If in the very first moments of the scenario every investor had made the same sell decision as investor #1, the stock would simply have plummeted. A new fair-market value would not have been discovered until a very low point had been reached. In this scenario the lack of market chaos would have caused a small drawdown to become a crash. Such events occur regularly. The size of the resulting decline is closely related to the lack of chaos exhibited just prior to the sell-off. Major crashes that begin as minor drawdowns are rare but certainly not unknown. The initial days of the '29, '87, and '00 crashes all had a distinctly nonchaotic character. So did the prolonged Nikkei crash and the general collapse of the Asian markets that occurred during the late 1990s (sometimes referred to as the Asian Miracle Bubble). Furthermore, the word "chaotic" in this context should be taken in the true mathematical sense—a system that appears random but behaves according to a well-defined set of rules. If liquidity is the fuel that powers the price discovery engine, chaos is certainly the principal ingredient in that fuel.

It is not surprising that many different types of events can affect the level of chaos exhibited by individual equities and entire markets. For example, if tomorrow morning, just before the opening bell, company X reported surprisingly strong earnings with an even more surprising outlook for the next quarter, the stock would surely rise as soon as the market opened. This effect might seem obvious, but the underlying dynamics are complex. During the first few moments of trading, new buyers would aggressively bid up the stock, but not nearly as fast as panicked short sellers trying to cover their positions. Not all short sellers, however, would be forced to cover. Some might consider the run-up to be an acceptable risk—especially if they maintain a contrary view of the company's future performance. Others might view the immediate run-up to be inflated, and at the first pullback they might sell short again. Finally, other investors who own the stock might decide to sell and realize a profit. The early-morning run-up could easily be halted by a mad rush to take profit or establish new positions on the short side at discounted prices. Such behavior almost always generates a high level of frustration for investors, who interpret the news in a straightforward way and try to make a rational buy or sell decision based on financial metrics. This is also why markets often appear confusing and unpredictable. We will return to a detailed analysis of the relationship between market chaos and equity prices, with a focus on predicting crashes and rallies (both minor and major).

Practical Limitations of Technical Charting

Equity markets are event-driven. In a highly liquid environment, investors are constantly reacting to events, news, and each other. Even the most seasoned technical analyst would concede that large unanticipated events trigger large unpredictable moves in stock prices. Like many investors, I have spent thousands of hours staring at chart patterns, trying to predict the next move of a stock or index. Sometimes it works, and sometimes it doesn't. Like any discipline, technical charting has its strengths and weaknesses. In the absence of major corrective events, stocks tend to trade within predictable ranges. Well-characterized support and resistance lines certainly have some predictive value, as do many of the more rigorous mathematical techniques. However, it would be unfair not to mention the numerous studies showing that stock picks by technical analysts tend to lag behind the leading benchmark indexes by a significant margin. In 2003, for example, the S&P 500 increased by 26% and the NASDAQ by 50%, while an imaginary portfolio built on the recommendations of an average Wall Street analyst increased by only 11%. In 79 of 81 market sectors, an investor would have outperformed the experts by simply purchasing the stocks in an index and holding them. This data suggests the importance of adopting a balanced view of technical analysis.

Operationally speaking, the stock market behaves like a school of fish. The lead fish behaves like a well-informed investor by reacting quickly to changes in the environment. The other fish react to both the environment and the direction and speed of the lead fish. In the absence of a major event, the school's behavior is somewhat predictable. However, if you drop a pebble in the water, the lead fish will suddenly change direction—and the rest of the school will almost certainly follow. Betting on the fish's direction and speed is somewhat like investing in a stock. The human eye is remarkably adept at finding patterns in charts and pictures. It is easy to be fooled by randomness. Figure 1.1 is a response to those who will undoubtedly disagree. It contains two charts. The first was created using a computer program that randomly generates the numbers 0 or 1. Each tick of the chart was created by summing 100 such numbers and dividing by a number less than 100. Changing the divisor can make the charts appear more or less volatile. The starting point was chosen at random. The second chart, the real one, is a New York Stock Exchange stock. So far I have not found a single technical analyst who can tell the difference. The reaction is always the same: "This one has a support line here and a resistance line there, this one is trending above its 50-day moving average, this one is real because it contains a well-formed breakout pattern followed by a move to a new trading level..." I have had many opportunities to show such charts to professional investors. None has ever found a reliable way to spot the fakes.

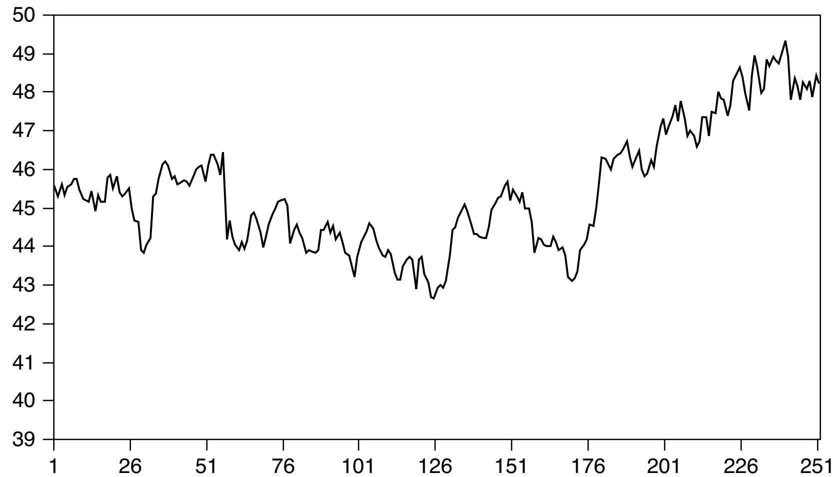

Figure 1.1 One random and one real stock chart. A random-number generator was used to generate the first chart. The second is real (250 days of Kellogg Co. stock). Nobody has ever found a reliable way to spot the fake.

I have also tried to learn from forecasters in other technical areas. Weather forecasting techniques are especially relevant. There are two basic strategies for predicting the weather. The first involves analyzing basic physical principles—cloud physics, thermals, temperature gradients, and so on. The second involves building a database containing historical information about atmospheric parameters and the weather conditions that followed. Predicting the weather involves searching the database for a set of parameters that correspond closely to those currently being observed. If the theory is correct, the weather will follow the previously observed pattern. Both techniques have some relevance to predicting the performance of stocks. Proponents of the first method often refer to financial metrics, price-earnings ratios, 50-day moving averages, relative strength, stochastics, and the like. The second approach typically involves unbounded pattern discovery techniques, neural network software, genetic algorithms, and a variety of data-mining strategies to identify repeating patterns in stock market data. This approach has a decidedly statistical flavor. Both are important. Each has been overused.

Background and Terms

This book is written for experienced option traders. However, serious beginners with an interest in understanding and exploiting the technical nuances of option pricing will realize many of the same benefits. Although somewhat technical, the discussion should be comprehensible to anyone with a firm grasp of basic statistics. We will focus on a relatively small number of trading strategies while spending a considerable amount of time discussing execution-related technical details such as bid-ask spreads, put-call parity, and price distortions related to weekends, holidays, expiration cycles, and earnings releases.

Before continuing, however, we need to define and discuss some terms:

Call options are contracts that entitle the buyer to purchase stock at a predetermined price, also known as the *strike price*. They are priced according to a model that takes into account the price and volatility of the underlying equity or index, time until the contract expires, and the risk-free interest rate that the money could otherwise earn.

Put options entitle the buyer to sell stock at a predetermined strike price. The value of a put option is related to its corresponding call through a relationship known as *put-call parity*. Put-call parity presents a striking opportunity. It is important to note that the original theory on which today's option pricing methodologies are built did not comprehend puts. We will discuss option pricing strategies and the implications of put-call parity in great detail throughout this book. For now, suffice it to say that the pricing strategy is designed to prevent a risk-free arbitrage. For example, if the put side were to be priced out of proportion to the call, a savvy investor would sell the put and buy the call while simultaneously selling the stock and buying a riskless zero-coupon bond maturing in the option's expiration time frame. The position would be unwound at the time of options expiration for a guaranteed profit. Although such trades are beyond the scope of this book, the important point is that a true disruption in put-call parity can automatically generate a profit. However, public customers who buy at the asking price and sell at the bidding price are unable to take advantage of these price distortions because they normally are accompanied by uncharacteristically wide bid-ask spreads. Parity distortions also present an opportunity to option traders who do not seek completely riskless arbitrage.

A trade consisting of puts and calls where both sides have the same strike price is commonly called a *straddle*. When the strike prices differ, the position is called a *strangle*. Positions that result from selling options are known as *short* positions. When the seller does not own a protective position, either stock or options, the position is referred to as being *uncovered* or *naked*. We will spend a considerable amount of time discussing strategies for trading and dynamically managing naked straddles and strangles. Very few options texts devote any space to such a strategy. There are two reasons. First, because the positions are uncovered, the seller has no protection against large unanticipated price movements. Such positions normally are considered very risky, because there is no limit to the amount that a stock can rise or fall. Practically speaking, though, there are limits. Effective risk management is a cornerstone of successful option trading, and we will spend extensive amounts of time discussing risk management strategies. That said, certain stocks are more prone to unanticipated price changes than others, and the magnitude of the risk varies over time. Moreover, option prices are often inflated with excess volatility to guard against unanticipated price changes. Therefore, accurate volatility assessment is central to a successful option trading strategy. Furthermore, a thorough analysis reveals that many investment strategies thought to be safe are actually riskier than most investors believe. For example, some stock portfolios lost more than 10% of their value during the September 11, 2001 terrorist attacks. Conversely, naked call sellers profited tremendously as all the options they sold expired worthless and they were able to keep the premium. Surprisingly, many put option sellers also profited, because the market remained closed for several days and the options lost much of their remaining time value. Many out-of-the-money options lost more time value than they gained from downward price movements. Short combinations were the most stable. In most cases the call side lost all its value, more than compensating for increases on the put side.

The events of September 11 joined many other market drawdowns by contradicting another important piece of conventional trading wisdom—the view that naked calls are riskier than naked puts. Nothing could be further from the truth; large negative price changes pose a greater risk to option sellers than large positive ones. The reason for the traditional view is that a stock can rise without limit but can only fall by an amount equal to its current price. For example, a $10 stock can suddenly fall to $0.00, making the $7.50 strike price put worth exactly $7.50 at expiration. The loss is limited. However, the same stock could theoretically rise to $50, taking the $12.50 strike price call $37.50 into-the-money—a catastrophic event by any measure. Practically speaking, both scenarios are highly unlikely. However, it is clear that a variety of events can cause investors to "panic" out of stocks, but very few news items have the capacity to drive an instantaneous catastrophic run-up. One in particular, the surprise announcement of a company acquisition at a price far above fair market value, can be very destructive to naked call sellers. One notable example was IBM's tender offer to purchase all outstanding shares of Lotus Development Corp. for $60 per share—nearly twice its trading price—in June 1995. Fortunately, there were clear indications that something was about to happen. The volume of $35 strike price calls more than tripled over three days from 672 to 2,028 contracts, the stock price climbed 10%, and volatility soared. Moreover, the $35 strike price call climbed from 1/8 to 1 15/16 during the three days preceding the announcement, and any investor short that call would certainly have closed the position. Finally, our trading strategy involves creating a statistical profile that compares the historical frequency of large price changes to the normal distribution. Lotus Development Corp. had a history of large price changes—often larger than 4 standard deviations from the mean. It would never have been a trading candidate for any uncovered positions. That Lotus might be a candidate for such an acquisition was one of the forces that caused its stock to behave poorly with regard to the standard model. Such stocks frequently respond to rumors with surprisingly large price movements. Conversely, we will see that it is entirely possible to identify stocks that are very unlikely to react in this way. Lotus notwithstanding, stocks rarely crash up, and indexes never do.

The second reason that few strategies have been built around uncovered combinations is psychological. Option traders focus on leverage and upside in their positions. If XYZ is trading at $98 and the $100 call option is selling for $1.50, a move to $102 will generate a call option price of $2.00 at expiration—a 30% profit. Moreover, because the call price depends heavily on volatility and time left before expiration, any rapid increase in the stock price will be accompanied by an increase in the option price. Option traders structure positions to capitalize on such moves. Conversely, the upside of a short position is limited to the value of the *premium*—the amount received for selling the option contracts. Short sellers maximize their profits when an option contract they have sold expires worthless. If XYZ trades below $100 at the time the call option contract expires, the seller keeps the $1.50 premium paid by the buyer. Likewise, he breaks even at expiration if XYZ trades at $101.50, because the calls will be worth precisely $1.50. Buyers have a quantifiable risk that is limited to the purchase price and an unlimited upside; sellers have an unlimited downside risk and their upside is limited to the selling price. However, an optimized volatility selling program based on a mechanism for selecting the best stocks and indexes to trade—those with a statistical history of behaving within the boundaries of the standard bell curve—can often provide an excellent return. Such systems must include a firm set of rules for timing trades and adjusting positions. Large institutional investors often favor such systems because they tend to deliver a steady, predictable return. As always, limiting risk necessarily involves limiting profit. For example, deep out-of-the-money options with little time left until expiration sell for very small amounts of money but present relatively little risk. Unfortunately, these trades do not always represent the most efficient use of collateral. (Option sellers are required to keep a certain amount of money on hand to cover the cost of closing in-the-money positions. It is important to understand the requirements and to optimize the use of collateral.)

We will also devote considerable time to complex multipart trades containing both short and long components. Part of our discussion will compare strategies that involve different expiration dates and strike prices. Many are direction-dependent in the sense that they rely on major economic trends. For example, the 28% dollar devaluation that occurred during 2002–2004 presented tremendous opportunities to option traders who understood the trend. The devaluation was an inescapable consequence of falling interest rates in the U.S. and a desire to lower the price of American goods to slow the growth of the trade deficit. It was part of a government stimulus package that was launched as a response to the recession that followed the NASDAQ crash and 9/11 terrorist attacks. Gold was destined to strengthen in this environment because it is priced in dollars. However, options on gold stocks and gold indexes were not necessarily a sound investment, because they were aggressively priced, with high volatility. Furthermore, occasional downward corrections proved dangerous to both call buyers and put sellers. The solution involved complex combinations of short and long positions with different expiration dates and strike prices. Managing such positions requires statistical insight into the dynamics of price change behavior and volatility—central themes of this book.

Finally, it is important to understand the effects of market movement on volatility. Falling markets, for example, normally are characterized by rising volatility, and short positions must be used with caution in such environments. We will review a set of strategies for trading in these markets that involve long positions on underpriced options where the amount of premium paid does not adequately compensate the seller for risk. As we shall see, the right statistical filters can be used to select "poorly behaved" stocks. Properly structured long option positions on these stocks tend to return very large profits.

Securing a Technical Edge

If options markets were perfectly efficient, it would be impossible to earn more than the risk-free rate of return. Fortunately, they are not.

Even the most refined option pricing models cannot anticipate earnings surprises, hostile takeovers, stock buybacks, fraud, wars, trade embargos, terrorist attacks, political upheavals, and the like. Conversely, the market sometimes overreacts to upcoming events by overinflating the volatility priced into option contracts. The strategies presented in this book are designed to quantify and exploit these price distortions.

Underlying this approach is a set of analytical tools that can be used to compare daily price changes. One straightforward approach involves recasting absolute price changes as standard deviations using a stock's volatility. For example, if a \$100 stock exhibits 30% volatility, a 1 standard deviation price change over the course of a year will be \$30. If the stock behaves in a way that is consistent with the normal distribution, there is a 68% chance that it will end the year between \$70 and \$130 (1 standard deviation in each direction). The chance of staying within the boundaries of a 2 standard deviation change is 95%, and the 3 standard deviation boundaries include more than 99% of all price changes. For reasons that we will discuss later, the conversion to a daily calculation involves dividing by the square root of the number of trading days in a year (252 trading days gives a divisor of 15.87). For the stock just mentioned, a one-day, 1 standard deviation change is \$1.89.

Volatility on a given day is often calculated using a window that contains the previous month's price changes. However, many different-size windows are possible, and each provides a slightly different view of a stock's volatility. Comparisons are straightforward. For example, if we use a one-month window to obtain a volatility of 10%, we must multiply that number by the square root of 12 to obtain annual volatility (a year has 12 one-month time frames). Such a stock would have a 34.6% annual volatility. Using daily volatility values and the change in a stock's closing price, we can determine the number of standard deviations for each day's price change. Charts of these price changes expressed in standard deviations are excellent comparative tools for an option trader, because they take into account both the price and volatility of the underlying stock. From a risk-adjusted perspective, often seemingly inexpensive options on a low-volatility stock turn out to be overpriced. Expensive options on high-volatility stocks are just as likely to be underpriced.

The most subtle and important cases involve stocks that exhibit similar volatilities and prices but differ with regard to their price change distribution. Very few stocks exhibit a close fit with the normal price change distribution curve that underlies today's option pricing models. The discrepancies represent statistical arbitrages that can be traded for a profit. Figure 1.2 illustrates this concept by comparing the price change history of two very different stocks whose option prices are based on roughly the same volatility.

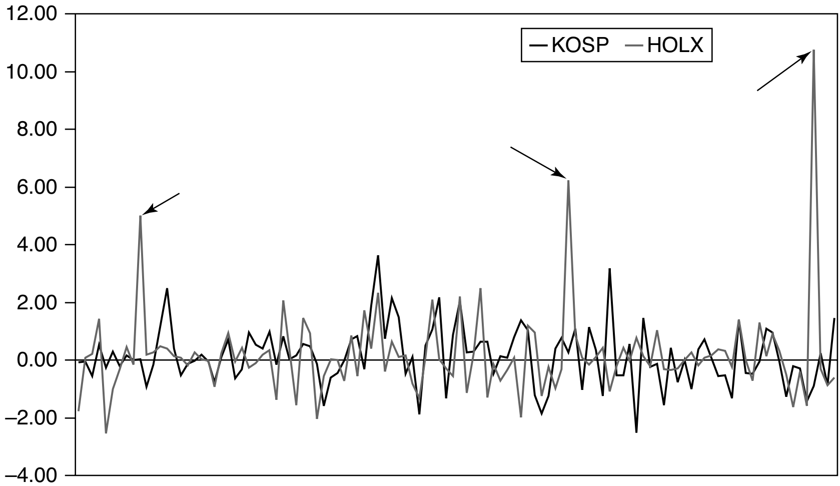

Figure 1.2 Two stocks exhibiting the same volatility but different price change behavior. The chart displays 110 daily changes measured in standard deviations. Standard option pricing models assume that each of the large spikes will occur with a frequency of less than once in 10,000 years. The largest spike should never occur.

Price changes in the chart are expressed in standard deviations calculated using a sliding 20-day volatility window. During the selected time frame, options on both stocks traded near 50% volatility. However, HOLX (Hologic, Inc.) regularly exhibited uncharacteristic spikes that are not comprehended by any option pricing model. These changes—each larger than four standard deviations—represent excellent trading opportunities. Conversely, KOSP (KOS Pharmaceuticals, Inc.) would be a reasonable candidate for short combinations consisting of out-of-the-money puts and calls.

Certain events such as earnings releases also represent excellent trading opportunities. Figures 1.3, 1.4, and 1.5 illustrate this concept using Amazon.com (AMZN). The stock predictably exhibits large price spikes with each earnings release. As a result, option prices typically soar as earnings approach and often reflect more than 3 times normal volatility. These high prices overly compensate sellers for risk. In such cases it is not uncommon for $15 out-of-the-money puts and calls to trade for more than 80 cents per contract on the day preceding an earnings release and to collapse to worthless immediately after.

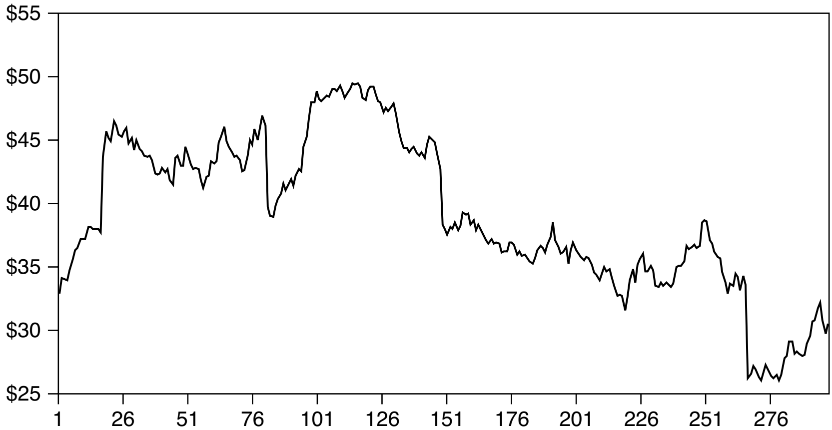

Figure 1.3 AMZN: 300 days of closing prices.

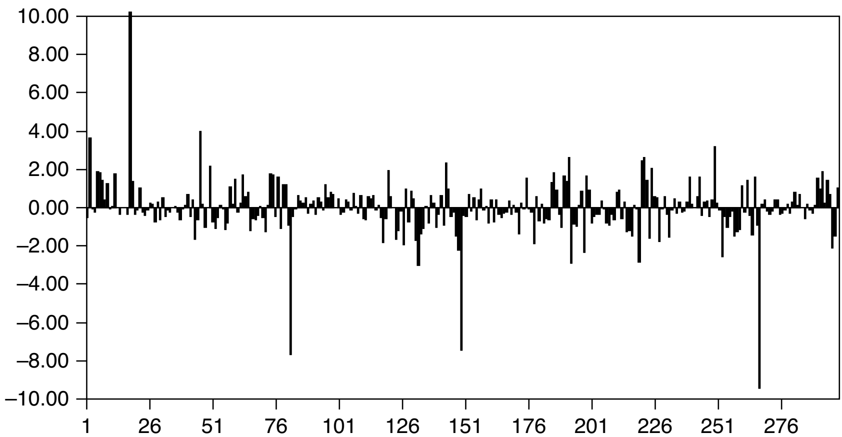

Figure 1.4 AMZN: 300 days of closing price changes expressed in standard deviations.

Figure 1.5 AMZN: 300 days of closing price changes translated from standard deviations into September 2006 dollars (1 StdDev = $1.31 on Sept 8, 2006).

Figure 1.3 displays daily closing prices for AMZN. Daily price changes are translated into standard deviations using a 20-day sliding volatility window. These changes are displayed in Figure 1.4. The final transformation expresses daily price changes in September 2006 dollars (a 1 standard deviation change was equal to $1.31 on September 8, 2006). The results displayed in Figure 1.5 facilitate direct comparisons between spikes. Unfortunately, many traders fall into the trap of comparing price changes in percentages rather than standard deviations. This process would have ignored the widely varying volatility that ranged from a low of 15% to a high of 95% during the time frame displayed. The data would have been skewed, causing price changes during periods of high volatility to appear much larger than those occurring during low volatility. However, when volatility is taken into account, the spikes are relatively similar in size. Armed with this information, an option trader can determine the fair price of puts and calls at each strike price.

Building on these themes, we will explore a large number of analytical techniques and trading strategies. Some will depend on specific events, and others will be more generic. In each case the goal is to link careful mathematical analysis with market reality. As always, the devil is in the details. Options don't have a price; they have a range of prices dictated by bid-ask spreads and trading queues. They don't trade at a single volatility either. The difference sometimes represents a significant put-call parity violation in which the two sides trade as if they represent different underlying stocks. Such distortions occur because the market has a view that risk is not equal on both sides. In such cases bid-ask spreads often widen, preventing public customers from taking advantage of the risk-free arbitrage that would normally accompany such an anomaly. We will discuss put-call parity and its implications at length. That discussion will form part of a more general focus on trading opportunities that arise from the underlying mathematics of the market.

Endnote

1 Lina Saigol and Gillian Tett, "Europe's Largest Hedge Fund Admits Flaws," *Financial Times*, June 13, 2005 22:12.

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