CHAPTER 1

The Canary in the Coal Mine

How the First Signal of the Financial Crisis Wasn't Noticed

A year before the financial tsunami of October 2008 materialized and the words ''subprime mortgages'' became common language ingrained in our evening news, there was a subtle warning in the financial markets that the world's global economies were not in a state of balance. The warning materialized in the first week of August 2007, when global equity markets observed the worst stockmarket panic since Black Monday in October 1987. But nobody noticed.

On the morning of August 6, 2007, investment professionals were baffled with unprecedented stock patterns. Mining sector stocks were up 18 percent but manufacturing stocks were down 14 percent. It was an excessive 30 percent directional skew between sectors, yet the S&P index was unchanged on the day.

The next few days would continue with excessive stock volatility and dispersion patterns. MBI Insurance, a stock that had rarely attracted speculation would finish up 15 percent on August 6, followed by another 7 percent on August 7, and then finish down 22 percent over the subsequent two days. The rally in MBI was nothing more than an aberration as the gains reversed as quickly as they appeared.

Conventional wisdom suggests markets are efficient, random walks—stock prices rise and fall with the fundamentals of the company and preferences of investors. But on August 8, the housing sector would be the best performing in the market with a gain of 22 percent. Certainly, there was a deviation from ''fundamental'' values amid the emerging worries of a U.S. housing crisis.

Only weeks later would investors begin to have insights on the dispersion patterns. Prominent hedge funds that had never had a negative annual performance began disclosing excessive trading losses, with many notable managers reporting several hundred millions were lost—in a single day.

Hedge funds were haemorrhaging in excess of 30 percent of their assets while the S&P index was unchanged. They were losing on both sides of the ball—their long positions were declining and their short positions were rising. Sectors that were normally correlated were moving in opposite directions.

The market dispersion was the side effect of hedge funds synchronous portfolio ''de-leveraging,'' ignited by a deviation in equity markets from their historical trading patterns. It was the industry's first worldwide panic—by machines.

In the late 1990s, the Securities and Exchange Commission (SEC) introduced market reforms to improve the efficiency of the marketplace to allow for alternative trading systems—this marked the birth of electronic communications networks, as well as a new era of quantitative investment professionals. Over the past decade, computerized (or black-box) trading has become a mainstream investment strategy, employed by hundreds of hedge funds.

Black-box firms use mathematical formulas to buy and sell stocks. The industry attracts the likes of mathematicians, astrophysicists, and robotic scientists. They describe their investment strategy as a marriage of economics and science.

Their proliferation has come on the back of success. Black-box firms have been among the best performing funds over the past decade, the marquee firms have generated double-digit performance with few if any months of negative returns. Their risk-to-reward performance has been among the best in the industry.

Through their coming of age, these obscure mathematicians have joined the ranks of traditional buy-and-hold investors in their influence of market valuations. A rally into the market close is just as likely the byproduct of a technical signal as an earnings revision.

It has been speculated that black-box traders represent more than a third of all market volume in the U.S. markets and other major international markets, such as the London Stock Exchange (LSE), German Deutsch Boerse and Tokyo Stock Exchange (TSE), albeit their contributions to the daily markets movements go largely unnoticed. CNBC rarely comments on the sentiments of computerized traders.

Our conventional understanding of the stock market is a barometer for the economy. Stock prices reflect the prevailing sentiment on the health of the economy and the educated views of the most astute investment professionals. But what has become of the buy-and-hold investor when holding periods have slipped from years to months to days (or less)?

Although their success has largely been achieved behind the scenes, the postmortem of the August 2007 crisis brought black-box firms into the headlines. Skeptics suggested the demise of quantitative trading was a matter of time given that stock prices are a random walk.

But many black-box firms have weathered the market turbulence and continued to generate double-digit returns. They were the first hedge funds to experience the economic tsunami that would evolve into a widespread global crisis in 2008, when markets drifted from their historical patterns.

Adaptation, after all, has always been their lifeblood. Their investment strategy is a zero-sum game; they do not benefit from prosperous economic climates when the rising tide lifts all boats. Black-box traders compete with one another by *chasing the same signals*.

This is not a story about what signals they chase, but rather a story about how they chase them. It's a story about how an industry of automated investors, with unique risk preferences and investment strategies, have become the most influential liquidity providers from Wall Street to Shanghai.

THE SIGNAL OF IMBALANCE

On the morning of August 6, 2007, the canary on the trading floor of the world financial markets would stop singing. There was a foul smell in the air, resonating from the world economy, and it had materialized in the form of an early warning detection signal. World stock markets would begin to observe a unique form and unprecedented type of volatility. It was an early indication that the state of the global economy was at an inflection point of imbalance.

Just one hour into the morning session on August 6, traders in the S&P 500 would begin to observe some very unusual price patterns on their trading screens. The machinery sector was up 10 percent while the metals sector was down 9.5 percent. There was a net difference of 20 percent between the sectors, yet there was little news or earnings information to support such a direction skew between sectors.

Despite the excessive volatility across sectors, the S&P index was unchanged on the day at 0.2 percent from the previous day's close. Gains in one sector were being offset by losses in another.

Looking closer at the S&P 500 components was even further confusing—there were more than 50 stocks trading up 10 percent and 50 stocks down more than 10 percent. Yet the index as a whole was relatively unchanged.

Traders were confused. What was going on in the market? Who would be aggressively buying a portion of the index and aggressively selling the other side?

Traders would find no clues when speaking to their institutional clients. Mutual fund managers were equally as baffled by the confusing price charts. August was normally a quiet month, and there had been no release of major economic news and none was expected on the immediate horizon.

The unusual trading patterns of excessive dispersion would continue for the next several days. Many stocks were batted around for the entire week, taking huge gains one day and then snapping back to their previous level the next.

The unusual market volatility would spread from U.S. markets to Europe to Japan. These were unprecedented times in global equity markets, it was the greatest level of ''dispersion'' observed in history.

Dispersion, the difference between its best and worst performers, has historically been within a range of a few percentage points across S&P 500 stocks within a given day. The index's best performer might be up 5 percent and the worst down 4 percent. On August 6, 2007, the dispersion of S&P 500 constituents was all over the map (see figure 1.1). The best and worst stocks were 32 percent apart. This had never happened before.

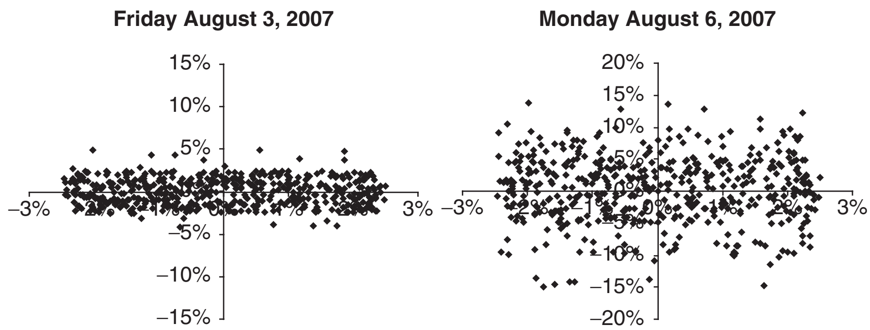

FIGURE 1.1 S&P index dispersion
Note: Scatter plot of that day's price movement against the previous day's price movement

Insights into the market volatility would begin to surface in the first weeks of September when several notable hedge funds began to communicate to their investors that they had taken excessive losses during the month of August. The first week of August, several funds reported declines in excess of 30 percent of their holdings. A couple of the most prominent hedge funds reported to have suffered losses of a few hundred million dollars in a single day.

These were not just a random collection of hedge funds that had an off month. These were a collection of the most prominent hedge funds, known as ''quant'' funds because they use complex mathematical models to invest in markets around the globe. Despite having produced some of the most consistent returns for the past decade, a similar story was being reported across the spectrum of managers. Articles appearing in a variety of sources highlighted a common tail of woes across several ''star'' hedge fund managers:

> Star managers racked up hefty mark-to-market losses within the first 10 days of August. **Renaissance Technologies'** institutional equities fund had lost −8.7 percent as of August 9; **Highbridge** statistical opportunities fund suffered −18 percent monthly decline; **Tykhe Capital's** statistical arbitrage and quantitative long/short masters funds ranged from −17 percent to −31 percent as of August 9; **Goldman Sachs Asset Management** global equities opportunities fund bled over −30 percent as of August 10; **D.E. Shaw's** composite fund was down −15 percent as of August 10; **Applied Quantitative Research's** flagship fund plummeted −13 percent between Aug 7 and Aug 9; **Morgan Stanley's Proprietary Trading** reported losses in their quantitative strategies of approximately $480 million, most of which occurred in a single day.[1]

These ''star'' managers had one thing in common: their investment strategy was faltering for no apparent reason. Historical patterns were breaking down. Similar stocks that in historical periods were highly correlated were now moving in opposite directions. The value sector, which normally outperformed the growth sector during periods of market dislocation, was now doing the opposite: growth outperformed value.

Hedge funds were suffering losses on both sides of their portfolio. Their long positions were declining and their short positions were rising. Portfolios that had been optimized to minimize variance were observing unpredictable volatility. Hedging long/short positions was intended to reduce the risk of a market correction, but they were experiencing a different kind of chaos event—dispersion. In a matter of days, they would take losses of upward of a third of their assets, when

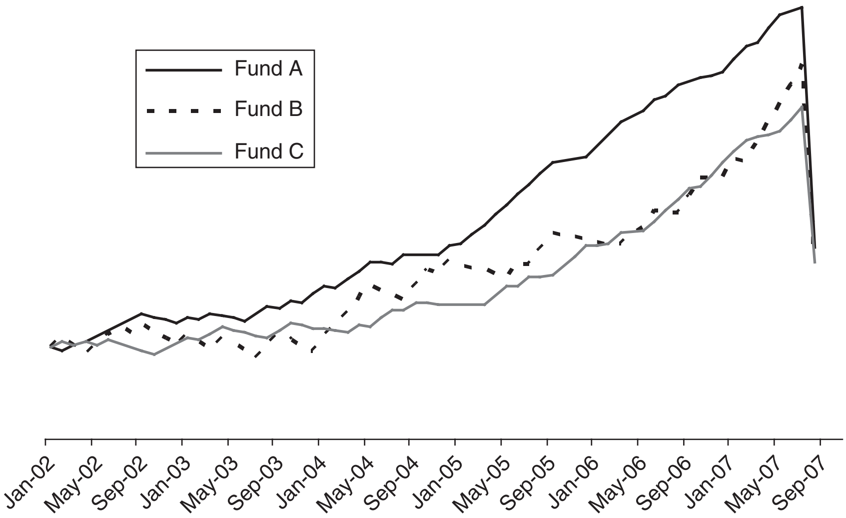

FIGURE 1.2 Quantitative fund losses
Note: Fund assets have been normalized from a base value of 1.0

their previous worst monthly declines had been a couple percentage points (see figure 1.2).

The canary had stopped singing because the global markets were at the beginning of a period of great imbalance between the equity markets and credit markets. Financial institutions were just starting to enter a prolonged process of ''de-leveraging'' in which they would reduce their equity positions to offset losses on subprime mortgage debt.

THE CROWDED TRADE EFFECT

A postmortem of the August 2007 quantitative funds meltdown would be inconclusive. There is no industry watchdog that could reverse engineer the set of computerized strategies. Understanding the nature of the problem would be further compounded by the secrecy of the ''black-box'' community, who are known for their privacy and seclusion, preferring the quiet suburbs of Connecticut or Chicago to the bright lights of Wall Street. The evidence from industry analysts and professionals was obvious: it was clear that most of these hedge funds were holding similar positions.

The most likely catalyst is that one or more large quantitative funds were forced into liquidation during the first week of August, possibly because of subprime losses in other areas of the fund, and to increase cash flow (or to raise balance-sheet assets), the fund flattened its quantitative strategies portfolio.[2] August 6, 2007 is likely the industry's first instance of what would become widespread in October 2008: de-leveraging.

A portfolio unwinding its positions wouldn't normally be a problem: unless there were several other funds holding the same positions. When the instigator begins to unwind, its trading would move the market; short positions would rise and long positions would decline. The other funds holding those same holdings would begin to suffer losses as their positions moved against them. As losses worsen, at some threshold, a fund might begin to reduce its own positions, perhaps decreasing its portfolio by 20 percent or more. Their unwinding, however, would both compound losses and start a chain reaction across the universe of funds holding the same portfolios.

This theory assumes that many quantitative funds were holding similar positions, which is known as the ''crowded trade'' phenomenon. When one firm began to liquidate, the other fund managers who were holding similar positions began to take losses as the positions reversed. This triggered a ''run for the exits'' phenomenon that moved markets to unprecedented patterns of dispersion.

The crowded trade theory is based on an assumption that black-box fund managers were employing a similar strategy. This may seem far-fetched—Renaissance, D.E. Shaw, Goldman Sachs, Highbridge—these were the marquee firms, presumably the ''rocket scientists'' of finance; was it a fair assumption to suggest their computer models were all chasing the same signals?

Although there is no hard evidence to decipher the strategies employed across the industry, there is evidence to support the contention that quantitative hedge funds were holding similar positions. One of the underpinnings of quantitative strategies was the empirical significance that value stocks would outperform growth stocks in times of market distress.

In practical terms, investors could profit from adopting a ''contrarian'' strategy, in which they sell all the winners and buy all the losers. This is the classic mean-reversion strategy, in which quantitative traders sell stocks that have outperformed the market and buy stocks that have underperformed, hedging the two sides based on historical correlations.

The postmortem of the events of August 2007 observed that historical relationships were breaking down across sectors. Technical studies highlighted that the one-month correlation between value and growth stocks had increased by 20-fold in the first week of August. Sectors that normally would have been good candidates for long/short hedging were moving in the opposite direction to their historical patterns. And any strategy trained on hedging based on historical correlations would have been susceptible to losses, regardless of the signals they had been chasing.

What had become painfully obvious in the wake of August 2007 turmoil was just how large and influential the footprint that quant models had attained in the global financial system. How did a handful of mathematicians and physicists grow to have so much influence on the valuations of global markets from Wall Street to Shanghai?

THE BLACK-BOX PHENOMENON

Quantitative trading had been around for decades, but in the late 1990s the industry underwent a massive transformation owing to newly available electronic trading technology, which lowered the costs of trading and provided access to global equity markets from a single location, whether New York or Des Moines. Correspondingly, quantitative trading blossomed into a new industry of ''black-box'' strategies.

A ''black box'' is a quantitative investment strategy in which the decisions are defined by mathematical formulas. Black-box firms design models to predict market movements based on analysis of historical trading patterns. Black-box firms rely on computerized implementation of their models to trigger the buying and selling of assets, so the prerequisite of a black-box model is to be an automated trading algorithm.

Firms that employ a black-box model are often referred to as ''quants'' because they employ mathematicians, physicists, and computer scientists, rather than the traditional MBAs and fundamental research analysts. They typically engineer their models to target small price movements, rather than search for long-term investment opportunities. Their holding periods might range from weeks to hours to minutes, rather than 12–18 months like a mutual fund.

These firms prosper on their ability to capitalize on ''price discrepancies,'' and most are agnostic to the long-term valuation of the stocks they hold. Their businesses thrive on liquidity and volatility, rather than the economic growth that traditional investors depend on for prosperity.

The language of ''black box'' originated out of the obscurity of the investment strategy. Investors began vaguely to refer to any strategy as a black box if the investment decisions were contained within formulas and equations. The analogy to the real aviation black box for the most part has been quite fitting—investors aren't really sure what happens on the inside.

The events of August 2007 not only turned the investment community's attention to black-box firms, but also raised awareness of how prominent quantitative trading had become over the past decade. It is not a single type of strategy, nor is it confined to hedge funds. Rather, a diverse variety of investment firms employ quantitative and algorithmic trading strategies.

A formal definition of a ''black-box strategy'' would be any trading system that relies on an empirical model to govern the timing and quantity of investment decisions. The prerequisite for the black-box description is automation through computerized trading algorithms.

The distinction between black-box strategies is much broader than simply the formulas and equations that govern the timing of their trading. A black-box strategy is distinct not only in the ''signals'' that trigger its trading decisions but also its investment objective and risk preferences. Even two computers that are monitoring the same market events may transact on the same signals in unique ways, differing by the entry and exit levels, holding period, and hedging methodologies.

Trend following (or momentum) is the best-understood form of black-box trading. Mathematical models are designed to forecast the stock price movement. The model is attempting to quantify the inflection points in the market and to profit by trading alongside the initiation of a trend and taking profits when a new price level has been reached.

Statistical arbitrage (or statarb) is a more complex form of quantitative trading than directional trend-following strategies. These models attempt to exploit price anomalies in correlated securities. They typically are nondirectional (therefore the term arbitrage) in that they buy one security and sell another, hoping to profit on the difference between the price margins of the directional positions.

The basic understanding of a statarb strategy is best expressed through a simple mean-reversion strategy between correlated securities, such as Coke and Pepsi or GM and Chrysler. The statarb strategy monitors the ''margin'' between these pairs of correlated securities and takes a position when the margin increases (or decreases) to a statistically significant distance from its historical mean.

Market-neutral strategies are a more comprehensive extension of combinations of correlated stocks. This investment strategy's objective is to manage portfolios of hundreds of stocks in equal dollar weight of long positions to short positions. These strategies can also enforce other types of neutral constraints, such as beta-neutral (balanced to the index movements), gamma-neutral (balanced to market volatility) or sector-neutral (dollar balanced per sector).

Market-neutral managers often trade in hundreds of securities to distribute risks across a broad spectrum of sectors and industries. They devise multifactor models using every imaginable type of financial information—balance sheets, risk factors, economic data, and analysts' forecasts—to rank the relative value of stocks.

Automated market making (AMM) has been the most recent evolution of black-box trading thanks to advancements in electronic commerce networks (ECNs) and liberalization of equity markets, such as decimalization and regulatory reforms. Automated market makers provide liquidity to investors, similar to the role of a traditional specialist or market maker, by being the intermediary on transactions between buyers and sellers, profiting on the difference between bid-to-offer prices for the risk of holding inventory momentarily.

AMM firms introduced technology to the process, designing algorithms to quote bids and offers to the investment community simultaneously across thousands of securities. These are the most high-frequency trading firms, transacting millions of orders a day and carrying few (or no) positions overnight.

Algorithmic trading (algos) strategies are the brokerage industry's contribution to black-box trading. These are automated strategies that manage an order's execution, usually optimized to minimize slippage to an industry benchmark, such as volume weight average price (vwap) or arrival price.

Traditional asset managers leverage these algos to improve the efficiency of their execution desks by automating the execution of small orders and unwinding block trades using financially engineered models. Electronic trading allowed them to streamline their businesses, reduce the tail of stocks transactions, and concentrate on their order flows that demanded liquidity. Within a few years of electronic trading commencing, traditional asset managers were executing as much as 20 percent of their order flows through algos.

The growth of black-box trading is better described as a ''phenomenon,'' the period in history when equity markets became largely dominated by computer-to-computer interactions as hedge funds, institutional investors, brokerage houses, and proprietary trading firms all moved in parallel to leverage electronic trading technology. In less than a decade after the arrival of electronic trading technology, computers would grow to become the most active investors.

THE EVOLUTION OF QUANTS

The origins of black-box trading are not constrained to one firm or period. The maturity of electronic trading technology was an iterative process, and there has been much resistance to inhibit its growth. Hedge funds, brokerages, and institutional investors each moved at a different pace in adopting technology by exploring areas in which electronic trading could complement their business strategy and revenue growth.

The most eager adopters of electronic trading were the multistrategy hedge funds and commodity trading advisors that had heavily leveraged quantitative research. Renaissance Technologies, D.E. Shaw, Trout Trading Management Co., and The Prediction Company were among the early quantitative hedge funds to pioneer high-frequency trading strategies. They would be among the few examples of hedge funds to market themselves as dedicated ''quant'' funds.

The largest multistrategy hedge funds have been the pioneers in this space; Citadel, Highbridge Capital, Two Sigma, SAC Capital, and Millennium Partners all are anecdotally thought to be several percentage points of U.S. market volume. Although it's only one facet of their businesses, black-box trading has become a large part of their footprint in the financial markets.

The major brokerage houses were some of the earliest and most aggressive sponsors of technical trading. They had the trading infrastructure to leverage their customer technology within proprietary trading groups. Goldman Sachs' Quantitative Alpha Strategies and Morgan Stanley's Process Driven Trading (PDT) were two of the most successful quantitative trading groups that would grow to rival the top-tier hedge funds in both performance and assets under management.[3]

Market-neutral investing blossomed in line with the maturity of electronic trading technology. Applied Quantitative Research (AQR) Capital, Black Mesa Capital, Numeric Investments, Marshall Wace, which were early entrants in market-neutral investment, grew into multibillion dollar funds. They would also employ the highest leverage in the industry, so they would trade hundreds of millions each day while rebalancing their long/short portfolios.

Electronic trading changed the economics of the quantitative investment strategies because it made markets more accessible to remote participants and it dramatically lowered the costs of trading. What the trading infrastructure did for a firm based in Santa Fe was to make it just as easy to execute on the LSE as on the Australian Stock Exchange. New opportunities were the result.

Correspondingly, the daily gyrations of the stockmarket are now largely influenced by the interactions among computerized investors, each pursuing their unique investment objectives, risk preferences, and trading logic.

WHAT SIGNALS ARE THEY CHASING?

In finance, the ''efficient market hypothesis'' has been one of the most widely accepted theories for the better part of three decades. The theory asserts that stock prices reflect all known information and they adjust instantaneously to new information. Since its initial publication by Eugene Fama in the 1960s, many academic studies have reiterated that stock prices do move along a ''random walk,'' and that investors cannot earn excess returns from speculating on news, earnings announcements, or technical indicators.

Despite all the evidence that markets are random, there is a sufficient body of academic research to contradict the theory—that markets observe periods of historical ''price anomalies.'' A price anomaly is an irregularity or deviation from historical norms that recurs in a data series. If investors can find these patterns, they can earn superior returns from exploiting the market inefficiency.

There are many anecdotal views on the existence of price anomalies due to the predictable behavior of investors, caused by overreacting to new information or by suffering from irrational risk aversion. Anomalies are manifested in seasonal effects, post-earnings drift, and events such as price reversals on news announcements. They can be rationalized with economic reasons, such as how investors react to surprise earnings announcements, or they can be rationalized by subtle and illogical causes, such as weather or seasonal effects.

There is a great body of academic research to quantify the existence of price anomalies. Researchers at New York University performed a 25-year study of the S&P 500 index from 1970 through 2005 to assess the ''day of the week'' effects, and they concluded that Mondays have the lowest expected returns of the week. An investor would have outperformed the market by buying on Wednesdays rather than Mondays.

Academics also suggest that market structure can create inefficiencies from differing tax regulation or the trading mechanisms. Future contract expiry days, for instance, may create imbalances in the market given the number of investors trying to roll their contracts from one month to the next. Many studies have confirmed that the last hour of trading on key monthly expiry dates observes accelerated market volatility.

Quantitative investors, by definition, are advocates of market inefficiency. They hold a belief in the existence of price anomalies and they dedicate elaborate efforts to devise models that quantify market behavior. The field of quantitative finance (also referred to as financial engineering) is a rich and diverse field, attracting all types of scientific disciplines from mathematics, economics, and the physical sciences.

Researchers use many resources to search for price anomalies. There is a seemingly infinite array of empirical metrics for analysts to search for inefficiencies. There are hundreds of empirical metrics on a stock's financial performance: price-to-earnings ratio, price-to-book ratio, debt-to-equity, year-to-date return, earnings growth, dividend yield, and so on. Similarly, macroeconomic information and surveys are released almost every week to update the investment community on unemployment levels, retail spending, inflation, and many other relevant metrics that influence the market's valuation.

Over the past decade, market data vendors such as Thomson Reuters, the Organization for Economic Co-operation and Development (OECD), and MSCI Barra have institutionalized vast arrays of financial metrics that are archived regularly across thousands of public securities. The standard sets of financial data fall into a few broad categories: balance-sheet, market data, risk factors, and macroeconomic data.

Balance-sheet metrics are the set of accounting metrics that describe a company's balance-sheet and cash-flow properties: debt-to-equity, earnings per share, expense ratio, and so on.

Market data indicators are the technical variables derived from trading data, such as the last trade price, open, high, low, close, and volume.

Macroeconomic data are statistics that affect the broad economy, such as unemployment or retail sales.

Risk factors are estimates of a stock's sensitivity to relevant industry factors: oil, interest rates, inflation, and so on.

Quantitative investors look at each and every available data series to search for market anomalies. Anything that can be measured will be measured. As the electronic trading infrastructure matured, the pursuit of market inefficiencies became a business of higher and higher frequency of trading. Firms have made this into a ''microstructure'' effort, searching for intraday movements that identify an imbalance in the supply and demand or an inflection point in the market.

Market data metrics change at every millisecond during the trading session with each and every market transaction. Correspondingly the industry of computerized trading has evolved towards the pursuit of real-time price anomalies. A quantitative investor will take a ''micro'' view, studying trade by trade in the order book to understand market inflections.

A breakout from a trading range is the most common ''signal'' that they are searching for. Quants want to understand the imbalances of supply and demand to infer how liquidity changes throughout the day. If they can identify an inflection point that represents the start of an upward trend, they can join the buying and cover the position when the momentum declines (see figure 1.3).

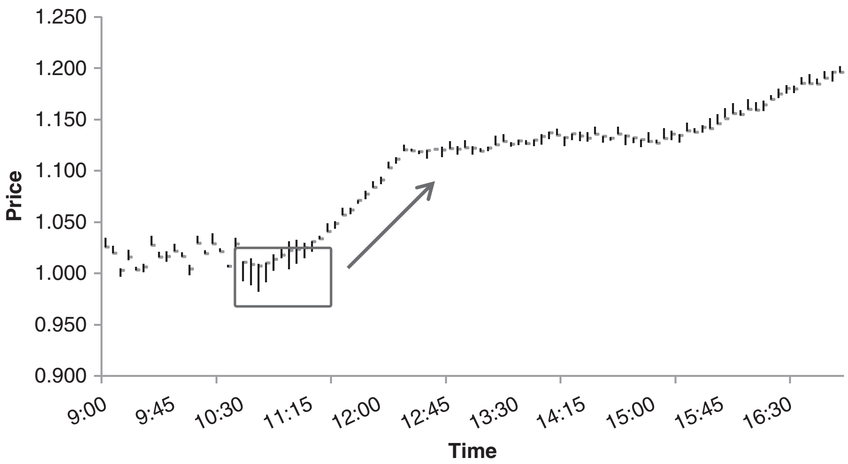

FIGURE 1.3 Momentum signals
Note: The price index has been normalized from a base value of 1.0

Correspondingly, for every market rally, there is often a market contraction. A ''contrarian'' signal attempts to identify the inflection points when a price movement has peaked (or bottomed) and that the market will likely revert to a previous level. If a trader can identify the upward (or lower) price barriers, they can profit off the reversion to the previous price level (see figure 1.4).

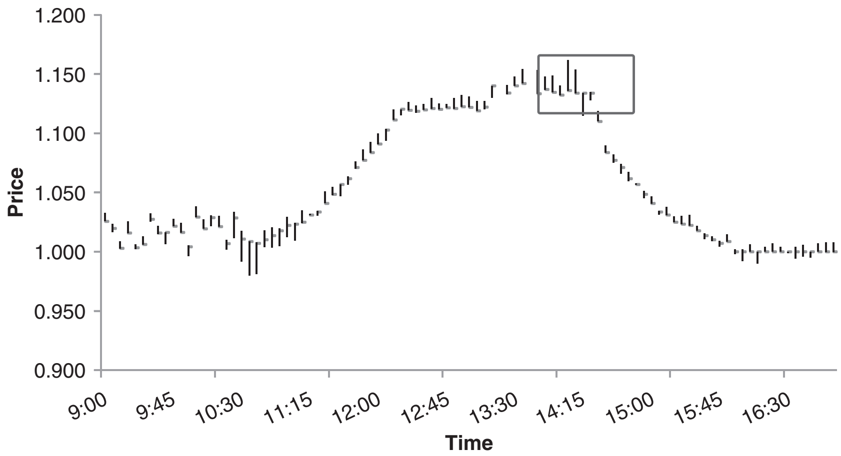

FIGURE 1.4 Contrarian signals
Note: The price index has been normalized from a base value of 1.0

Directional movements are not the only domains of price anomalies. The ''margin'' relationship between correlated securities represents an opportunity to play dispersion strategies. Dispersion represents a perceived price anomaly such as a historically large gap between two otherwise correlated stocks. On an intraday basis, dispersion can result from a price spike in one stock while a highly correlated stock lags the movement. Traders may buy the out-of-flavor stocks against the other, assuming that the gap between the two will revert to previous norms (see figure 1.5).

An ''anomaly'' only becomes an anomaly when it's irregular, such as a deviation from the norm. The quantitative analyst needs a reference frame to interpret what is within the normal range and what is a discrepancy. The common reference ''signals'' are volatility, bid–offer spread, and the volume distribution. These are the common denominators that allow the analyst to interpret the strength (or degree) of the deviation.

Volatility, the measure of the average change in stock prices, is one of the most important metrics. The differentiation of volatility across stocks is usually a representation of the risk of the asset: riskier

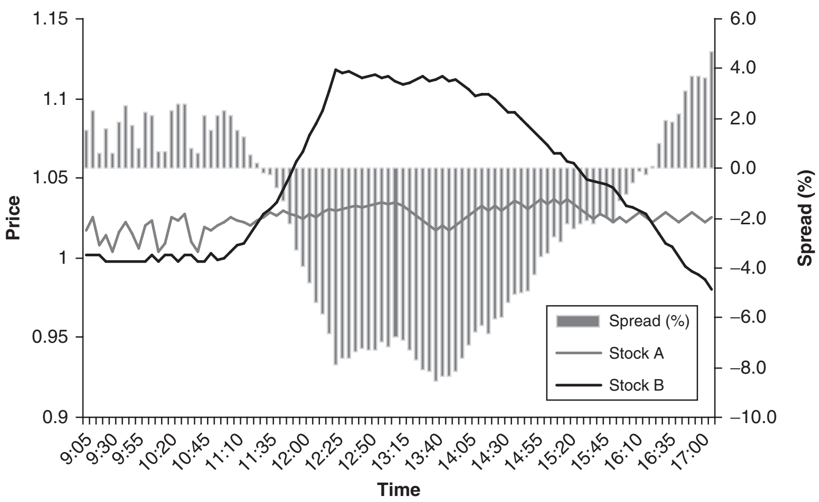

FIGURE 1.5 Arbitrage (or dispersion) signals
Note: The price index has been normalized from a base value of 1.0

stocks are assumed to have greater price volatility. Volatility also varies throughout the trading session, because of changes in the supply and demand from investors as well as periods of uncertainty in price movement.

Interval volatility, derived as the standard deviation of a stock's price return from the start of one interval (say 10 minutes) to the next, is a reference for understanding the expected price movement of stock throughout the trading session. A 5 percent price spike is obviously more pronounced in a low-volatile utility company that trades in a narrow price range over several months than a similar movement in a growth stock (see figure 1.6).

Spread is the difference between the market's best offer price and best bid price, referred to as bid–offer spread (see figure 1.7). Spread is associated with the costs of trading as it determines the round-trip frictional effects. Tighter spreads are common in liquid stocks where there are depths of investors willing to exchange at the prevailing market price. Larger spreads are more common in smaller capitalization stocks and less liquid securities. The fluctuations in the spread throughout the day are a reflection of imbalances in supply and demand and of periods of greater (or less) uncertainty in where the stock is headed.

Volume, the number of shares trading in a window of time, is a proxy for interpreting the relative activity level of a stock. The fluctuations in volume throughout the day can contain information on the sentiments

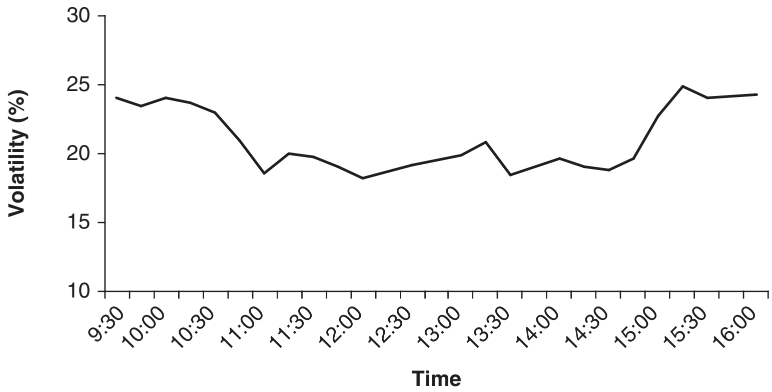

FIGURE 1.6 Interval volatility

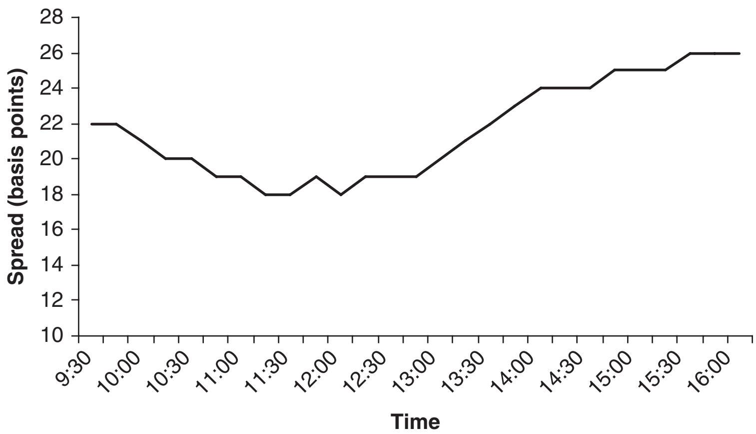

FIGURE 1.7 Bid–offer spread

of investors and they are also a proxy for relative aggressiveness of buyers and sellers. Volume distributions are the reference frame for interpreting price movements as in line with historical movements or irregular due to uncharacteristic volume expansion (see figure 1.8).

Although volatility, spread, and volume are only a few of many market data metrics to describe a stock's trading profile, they are arguably the three most common elements to all quantitative investment strategies because they provide a reference for apples-to-apples comparisons across stocks. Quantitative traders are searching

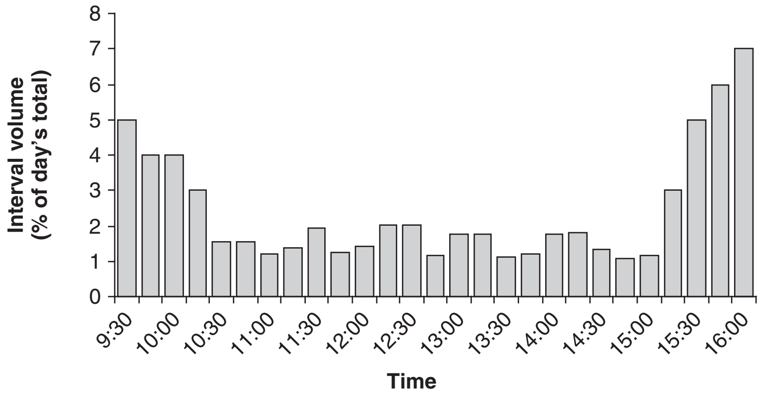

FIGURE 1.8 Volume distribution

for ''generalized'' models that describe the behavior across a broad group of stocks, rather than on an individual stock basis. How is a trader to understand whether a 3 percent price spike compares with a 2 percent price spike in a correlated security?

Quantitative traders ''normalize'' their signals into common units. They apply their distributions of volatility, spreads, and volume to rank signals into units of standard deviations. They want to quantify that a 3 percent price spike is actually within 1.0 standard deviation of an intraday movement in a small-capitalization stock, while a 2 percent spike is 2.5 standard deviations in a utility company. As a consequence, volume, volatility, and spread distributions have become ingrained as the common metrics that black-box strategies are referencing for their pursuit of price anomalies.

THE SAME SIGNALS

A casual spectator may wonder whether it's plausible to suggest that all these firms are chasing the ''same signals,'' given that there is a seemingly infinite array of data and unique combinations of trading strategies. The reference to ''same signals'' is not an implication that all indicators are alike, but rather it's an affirmation of the old expression ''there are only so many ways to skin a cat.''

It must be expected that there will be a high correlation among signals with the same intention. Momentum, for instance, is case in point of a variable with countless derivations and interpretations: top-and-bottoms, ascending triangles, candlesticks, relative strength indicators, stochastic oscillators, exponential moving averages—all have been profiled in countless technical trading books throughout the years and are available on Yahoo! Finance. They are only the tip of the iceberg in mathematical techniques that broach the vast corners of sciences: neutral networks, fuzzy logic, genetic algorithms, and more.

One firm may have a higher predictive model for momentum but it will have a common relationship with other trend followers—they will be looking at the same stocks, just entering at different times, in different ways, with unique holding periods. However, the byproduct of chasing the same signals is that these strategies will all influence one another.

Disturbances in volatility, volume, or spread are the basic references each firm is monitoring. And as they act on their signals, they influence the marketplace, triggering other computers to get involved. One machine's momentum signal is another machine's contrarian signal. Their longevity becomes a competition for signals, and not just knowing what signals to chase but knowing how to chase them.

Since the publication of the ''efficient market hypothesis,'' there has been endless academic debate on the randomness of stock price movements. The debate will continue; the stock market is always changing, but it is also always the same. The evidence, however, suggests that at least a few firms have been successful in discovering these inefficiencies. At the end of 2008, more than $90 billion dollars were invested with statistical arbitrage and market-neutral hedge funds. More than $40 billion dollars of the world's market transactions are instigated by automated investment strategies each day.

And as a consequence, when one machine is ''chasing a signal,'' it is just as influential to the stock price as the management team announcing a reorganization. The buy-and-hold investors are not forgotten, but they aren't what they used to be.