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AN EMPIRICAL ANALYSIS OF THE EFFICIENT MARKET HYPOTHESIS IN LIGHT OF THE 2008 FINANCIAL CRISIS

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Abstract

In this thesis, I investigate the validity of the efficient market hypothesis during the period surrounding the financial crisis of 2008 with a focus on efficiency in United States financial markets. The empirical analysis employs several different econometric methods investigating the random walk model and the martingale process. The thesis evaluates the implications of non-stationary time series on market efficiency employing the augmented Dickey-Fuller unit root test. I then conduct Lo and MacKinlay variance ratio tests on the same data to test whether returns exhibit a martingale process consistent with the efficient market theory. For the most part, my results are consistent with the efficient market hypothesis, but we do find cases where returns exhibit mean reversion or momentum, properties that violate the efficient market theory.

Table of Contents

List of Figures

List of Tables

Introduction

Market efficiency is a widely debated topic throughout the world of finance. In better understanding market movements, those working to create wealth through investing, such as traders or money managers, look to market efficiency in order to better understand the degree to which asset prices reflect all available and relevant information. Relevant information can include a wide range of news with some common examples being current and prospective earnings, current and prospective dividend payments, macroeconomic conditions, and any company specific information that may affect its immediate or future outlook. In better understanding efficiency, investors look to see what impacts an asset's price and how quickly that impact takes effect. The implication of an efficient market is that there are no arbitrage opportunities for investors who are said to be more informed than others since any new information that is released should be reflected immediately in the asset price.

Recently, there has been some reconsideration of market efficiency in response to the financial crisis of 2008. Interestingly, it seems that what many call the housing bubble had a foreseeable downturn for both the housing market specifically and the financial industry as a whole as detailed in Robert Shiller's book Irrational Exuberance (2005), which was published three years prior to the crisis. Psychological factors affecting investor behavior seems to have played a major factor in market movements before and during the financial crisis and may have major implications regarding price distortions in the markets on a daily basis.

In the first section of this paper, I review the literature on the efficient market theory discussing the various forms of market efficiency and examining historical instances of market bubbles. I then introduce the two models used to study the time series properties of financial data examined in the paper. In the second section, I provide empirical results utilizing the augmented Dickey-Fuller unit root test and the Lo and MacKinlay variance ratio test. Finally, I conclude by examining investment strategies associated with my results.

Review of the Literature

Over the course of the past fifty years, there has been an extensive amount of research regarding the efficient market hypothesis. In this section, I will discuss some of the findings as it relates to my analysis.

Economist Eugene Fama first formalized the efficient market hypothesis in his 1964 Ph.D. dissertation and his seminal 1970 paper "Efficient Capital Markets: A Review of Empirical Work". An efficient market, as defined by Fama, is a market in which the prices of an economy's capital stock "fully reflect" all information in the given information set (Fama, 1970). The implication of the hypothesis is that if the information set were to be revealed to all market participants, the price would remain unaffected. Furthermore, according to the efficient market hypothesis, any market inefficiencies are the result of temporary market disequilibria that are quickly eliminated by the actions of informed traders who arbitrage away those inefficiencies.

There is a significant amount of empirical evidence in favor of markets being efficient. Fortune (1991) justifies that market efficiency indicates that the current price of an actively traded asset is an optimal forecast of that asset's "fundamental value" and that the current price of an asset should have already incorporated all available information related to that asset:

$$P_t = E(P_t^*|\Omega_t) \tag{1}$$

According to equation (1), the current market price of an asset, P_t, is equal to its expected fundamental value, P_t^*, given the available information set, Ω_t. Stated simply, an asset's current price is the optimal estimate of its fundamental value.

From Fortune's definition of prices being an optimal forecast of the fundamental value of an asset, we see that the efficient market hypothesis implies a sequence of prices following a random walk with a drift (Fortune, 1991):

(2) $$P_{t+1} = (1+r)P_t + \varepsilon_{t+1} \quad \text{where } E(\varepsilon_{t+1}) = 0$$

According to equation (2), new and unexpected information that is announced will have an unpredictable effect on a company's stock price meaning that ε_{t+1} should have a mean of zero and should be without autocorrelation (Fortune, 1991). Equation (2) provides a basis for the random walk tests in determining whether or not the movements in stock prices are predictable utilizing the available information set, Ω_t. According to Fama (1970), stock price movements are independent of the information available at *t*. Therefore, new information available at *t+1* should be unpredictable and should move stock prices randomly as the information should be unexpected.

Market efficiency is dependent on the rate at which information can be disbursed. It is important to understand that not all markets can act as efficiently due to the speed at which information can be circulated which, in turn, affects the time it takes for investors to process the information and for asset prices to reflect that information. The speed at which new information is incorporated into a market is often dependent on the infrastructure of the country or region that the market operates in. Additionally, the availability of certain forms of information and cost at which that information can be obtained can also affect market efficiency.

When Fama outlined his hypothesis, he classified there to be varying levels of efficiency in markets consisting of the following:

weak-form efficiency The information set includes historical prices.

semistrong form efficiency The information set includes all publically available information (information known to all market participants).

strong-form efficiency The information set includes all information known to any market participant in addition to private information known only to an individual or group of market participants within the larger group.

Weak-form efficiency posits that low-cost information such as past prices, returns, and volume cannot be used to successfully forecast future price movements. Technical analysis is one field within the financial services industry that considers weak-form efficiency to be false. Technical analysts, or technicians, attempt to forecast price movements through the examination of past market data including prices, returns, and volume. Technicians do not consider the 'value' of a stock and, therefore, do not spend time observing information like earnings reports or dividend payments that value investors consider. They are simply concerned about price movements and patterns of price movements occurring in the market. Many technicians believe the market to be only 10 percent logical and 90 percent psychological often causing stock prices to be imprecise assessments of the underlying value of a firm (Malkiel, 2012, p. 112). As such, technical analysis considers the investment industry to be a game of anticipation of how other players will behave. Technical analysis follows trends and patterns seen in the market including factors like momentum, reversal, support, resistance, moving averages, and chart patterns. The rationale behind technical analysis is that mass psychology plays an important role in causing trends to perpetuate themselves.

There are several caveats with regards to technical analysis. Typically, technicians are 'forced' to buy into a trend once it has already been established limiting its profitability. Reversals also tend to occur suddenly making any profits limited or nonexistent if the technician has not closed the position in time. Additionally, traders tend to anticipate the buy signals, which can make the strategy less profitable if traders do not act simultaneously (Malkiel, 2012, p. 119).

Furthermore, the patterns identified by technical analysis do not occur on a consistent basis, which further complicates the implementation of any potentially profitable trading strategies.

Assuming semistrong-form efficiency, stock prices should theoretically reflect all publically available information including the weak-form information of past prices, earnings reports, data on the firm's product line, quality of management, accounting practices, balance sheet composition, and any other relevant information available to the public. Investors who believe semistrong-form efficiency to be false actively manage their portfolios in seeking out 'mispriced' securities. Market anomalies have been uncovered showing recurring events in the movements of prices that enable profitable investment strategies. An example of one such event is the small-firm effect. The small-firm effect was initially recorded by Rolf Banz in 1981 showing that the historical performance of portfolios composed of small-sized firms was consistently higher than those composed of large-sized firms after adjusting for risk using the capital asset pricing model. Subsequent investigations of the small-firm effect showed the abnormal returns occurring primarily in January where investors tend to dump their small stocks in December and purchase them back in January (Bodie, 2013).

In one study, Fama and French divided firms into deciles according to size and found that the returns of companies making up decile 1 with the smallest market capitalization outperformed the larger firms in decile 10 and that smaller firms with the same beta level as larger firms tended to outperform those larger firms (Fama and French, 1992). There may be certain aspects to the riskiness of investing in smaller firms that contribute to the outperformance of small firms relative to large firms. Furthermore, when using a model to adjust for risk like the capital asset pricing model, the risk-adjustment depends on how risk is measured. As a result, this can cause these risk-adjusted calculations to differ depending on how we measure risk.

There have been other examples of market inefficiencies with regards to the semistrong form of the efficient market hypothesis. These inefficiencies include the post-earnings-announcement price drift where the cumulative abnormal returns of positive and negative earnings announcements tend to see momentum in price movements after the initial movement higher or lower. The book-to-market effect was another anomaly uncovered by Fama and French in 1992 showing that high ratios of book value to market value produce abnormal returns. The neglected firm effect has also shown that firms that are not as well known tend to outperform on average (Bodie, 2013). Despite these findings, Fama continues to support his hypothesis showing that while these inconsistencies have existed, investors have not had access to the information regarding these inefficiencies and once that information was uncovered, the market has come to incorporate the inefficiencies into prices for the most part.

With regards to strong-form efficiency, there have been many occurrences where insider trading has proven profitable and the vast majority of investors do not expect markets to be strong-form efficient. Under the strict assumptions of the efficient market hypothesis, any and all relevant information should already be included in an asset price, including insider information. This means that successful insider trading schemes would be instances where we could disprove the strong form of the hypothesis. One relatively recent example of this is what is said to be the largest insider trading conspiracy to date. In July of 2008, Dr. Sidney Gilman, a professor of neurology at the University of Michigan, tipped off former portfolio manager of CR Intrinsic Investors Mathew Martoma regarding a clinical trial involving an Alzheimer's drug developed by Elan Corp. and Wyeth. On that tip alone, Martoma was able to produce over $200 million dollars in illegal profits (Goldstein, 2014). This is just one of many examples where insider trading has proven to be profitable. From these instances, we can conclude that the strong-form efficient market hypothesis is likely to be false in most circumstances.

Ultimately, the question over market efficiency boils down to exactly how efficient the markets are which is the source of much debate. Regarding weak-form efficiency and semistrong-form efficiency, both exhibit strong arguments against market efficiency when looking at specific instances of market inefficiency such as momentum or the small-firm (in January) effect. Fama argues that the seemingly unpredictable nature of the markets in reacting to these inefficiencies as well as the fact that the market tends to eliminate or greatly reduce inefficiencies that are uncovered is simply another aspect that characterizes efficient markets. He is essentially saying that inefficiencies that are not recognized cannot be incorporated into asset prices. Once they are recognized, they do tend to be incorporated into prices demonstrating one of the behaviors consistent with an efficient market.

Robert Shiller is one economist who does not agree with Fama's interpretation of the randomness of market movements. In particular, Shiller points out that there is excessive volatility in the financial markets that has gone unexplained by the efficient market hypothesis. Researching this effect, Shiller plotted the present value of dividend payments for the Standard & Poor's Composite Stock Price Index from 1871-2002 noting that the present value of dividend payments behave like a stable trend drifting upwards. The Standard & Poor's Composite Stock Price Index, however, exhibits large fluctuations around this trend (Shiller, 2003).

As a proponent of behavioral finance, Shiller explains this market volatility with two models based on stock market psychology. The feedback model considers what has now come to be known as irrational exuberance where an increase in speculative prices cause an enthusiasm in the markets and heightened expectations which produce further price increases. As a result, markets may become overpriced at times. In the same vein, periods where prices drop can produce expectations that have been lowered significantly where investors shy away from any potential investment opportunities. Again, this can produce sustained price decreases over a period that may not be in line with the present value calculation of dividend payments.

The second theoretical model introduced by Shiller (2003) discusses the assumption made by the efficient market hypothesis that the financial markets are composed entirely of rational investors. Shiller explains how nothing could be further from the truth. There is a common argument that if ordinary investors sell a certain security out of their irrational pessimism, ‘smart money’ would offset this price movement by purchasing that same number of securities. Shiller suggests that the smart money would not necessarily fully offset these price movement as the smart money investors should be rationally concerned about the effect irrational investors may have on price movements. This would lead to the smart money not wanting to fully take on the risk associated with returning the asset price to its fundamental value as the feedback may drive the speculative prices higher or lower. According to Goetzmann and Massa (2000), there is sufficient evidence indicating that there are two distinct classes of investors: feedback traders who are known to follow trends and smart money who routinely sell after prices rise. It can be difficult for smart money to fully compensate for the effects of irrational investors as they are always able to purchase a stock when feedback traders sell, but it can be much more difficult to short the stock especially when the smart money does not own the stock initially (Shiller, 2003).

With short selling being difficult in many cases and often an expensive strategy, markets tend to be more susceptible to becoming overpriced than underpriced. This especially came into play during the dot-com boom and bust and the 2008 financial crisis. Had the smart money been shorting the technology sector in early 2000 or the large mortgage lenders prior to the 2008 crisis, the markets may have been able to avoid such a large fall in market prices. One of the most critical deficiencies of the investment industry is the fact that there are limits to arbitrage. Investors that understand the true value of a security may not be able to take on the risk that comes with shorting a stock, especially in the case where irrational investors reinforce their own beliefs and bid the price up. Burton Malkiel (2003) notes, “The market can remain irrational longer than the arbitrageur can remain solvent. This is especially true when the arbitrageur is credit constrained” (p. 255). In this case, investors with a finite amount of wealth may not be able to finance their short positions because their arbitrage strategy may ‘lose’ before it can ultimately win out.

Some other behavioral factors to consider include overconfidence and loss aversion. Overconfidence manifests itself particularly in investors who tend to exaggerate their own abilities while underestimating the role of chance. Hindsight bias can produce a selective memory of success and excessive optimism in believing that events are more predictable than they may be which is known to cause individual investors to speculate more than they should based on the relevant market risks (Malkiel, p. 240-241). Loss aversion is another factor that can often cause investors to make costly mistakes. Prospect theory indicates that when investors are given the choice between probabilistic alternatives involving risk where there is the potential for gains or losses, losses are considered significantly more unfavorable than gains are considered favorable. These two factors may also play a role in the potential inefficiencies seen in the financial markets.

Implications of Market Efficiency

While market efficiency continues to be a broadly debated topic, investors are able to tailor their investment strategies to fit their individual understanding of price movements. There are certain products and funds that present investment opportunities for investors who recognize the markets to be efficient and there are separate practices and funds allowing investors to attempt to 'beat the market.' Although investors are able to access both types of investment strategies, they tend to choose one strategy or the other in line with their underlying belief regarding efficiency.

Investors who do adhere to the semistrong and weak-forms of efficiency tend to rely on passive investment strategies. Passive investors buy and hold a diversified portfolio of securities over the long-term horizon. Since the efficient market hypothesis is assumed to be true, these passive investors do not look to buy mispriced securities to make a profit from arbitrage opportunities. Instead, they invest in an index fund that looks to replicate the performance of a broad market index or in a passively managed mutual fund. Exchange traded funds (ETFs) are another form of investment that have recently come to be extremely popular with passive investors. Similar to index funds, ETFs track broad market indexes, industry-sector indexes, commodity-based funds, and many other variations of investment opportunities. The two key factors differentiating ETFs from mutual funds are that ETFs can trade throughout the day while mutual funds can only be bought or sold once a day and that ETFs can be sold short (Bodie, p. 98). As discussed before, the ability to sell an ETF short allows for markets to become relatively more efficient despite the potential difficulties investors may face from funding the short sale.

On the other hand, investors who do not believe in market efficiency are likely to seek out active investment strategies trying to identify mispriced securities or to forecast broad market trends. These investors look to invest their money in actively managed mutual funds or hedge funds that look for either market inefficiencies like the small-firm (in January) effect or patterns in stock price movements through the use of technical analysis in seeking to uncover predictable trends that can be profited from. For those instances where market inefficiencies have been uncovered such as the post-earnings-announcement drift or the small-firm (in January) effect, it is important to understand whether there are any profitable strategies that can be used to exploit the inefficiencies. Trading costs can come into play when attempting to short a stock by borrowing the security and selling it immediately with hopes to purchase the same security back at a lower price in the future and capitalize on the price differential, i.e. when investors believe prices are inflated.

The widely debated topic of market efficiency leads to questions about whether markets are efficient and how efficient they tend to be. From our understanding of the three forms of market efficiency, we now can look more closely at various tests to determine market efficiency. The semistrong-form inefficiencies that have already been uncovered seem to show specific circumstances under which inefficiency can be seen. These inefficiencies are said to be adjusted for any additional risk taken on by investors looking to purchase mispriced assets, but it can be difficult to understand whether the asset pricing models used to describe the relationship between risk and expected return incorporate all the relevant factors. This could mean that the semistrong-form inefficiencies that have been discovered may not properly adjust the returns for the associated risk being taken. Weak-form efficiency, however, can ultimately show an overall inefficiency in the market that would negate Fama’s efficient market hypothesis entirely. In proving there to be trend behaviors in price movements, market efficiency can be rejected at all levels of efficiency as it is incorporated in both the semistrong and strong forms of efficiency.

A History of Market Bubbles

For many years, over priced assets have played a factor in a wide range of the world's economies. Hyman Minsky's financial instability hypothesis illustrates how periods of prolonged prosperity and stability within an economy often can lead to increased risk taking by investors. When speculative investments become the dominant force in those economies, asset prices will increase further as expectations becoming more optimistic (Minsky, 1992). This self-fulfilling cycle has been said to have lead to the asset price bubbles during the stock market crash of 1987, the dot-com boom, and the period leading up to the 2008 financial crisis, as well as several historical examples including the Dutch tulipmania bubble in the 1600s and the South Sea bubble in the 1700s. In all cases, according to the theory, the excessive risk taking eventually led to the bubble bursting with significant ramifications not just for the industries where the bubbles had formed, but also for the economies as a whole.

The investor behavior involved in producing these cycles tends to be similar in nature. Research has been conducted regarding the role that social psychology plays in group behavior and how it may lead to incorrect decision making particularly for investors. Malkiel (2012) writes, "At times, there is a madness to crowd behavior, as we have seen from seventeenth-century tulip bulbs to twenty-first century Internet stocks" (p. 245). The existence of what is known as 'group think' has attracted the attention of behavioral finance. While individual's beliefs do not hold much weight when looking at the larger market, the beliefs of groups of individuals can, at times, reinforce one another into believing that a flawed point of view is, in fact, accurate. Looking at these social psychological aspects in action, it can be see that the "…wildly overoptimistic group forecasts regarding the earnings potential of the Internet and the incorrect pricing of New Economy stocks during early 2000 are examples of the pathology of herd behavior" (Minsky, 1992, p. 245). The positive feedback loop described by Robert Shiller results in a rise in price that "encourages people to buy, which in turn produces greater profits and induces a larger and larger group of participants" (Minsky, 1992, p. 248).

During the mid-1630s from 1634 to 1637, the Netherlands experienced the first documented financial bubble seen in the price of tulip bulbs. The Dutch found tulip bulbs to be extremely desirable after their introduction in the mid-1500s. In line with Minsky's financial instability hypothesis, the Dutch Golden Age during the mid-1600s brought about much speculation that is thought to have caused the price of tulip bulbs to rise twentyfold during the period from November 1636 to February 1637 (Fouque and Langsam, 2013). Futures contracts signed by traders promising to purchase tulip bulbs at a later date became an integral part of the flourishing tulip industry that lead speculators to reinvest their earnings into new tulip bulb contracts. This herd-type behavior lead to a peak in tulip bulb prices in 1637 when the tulip bulb bubble 'popped' leading to a drop in tulip bulb prices falling to a hundredth of their prior price in just a few days. Not only did the tulip bulb bubble end the Dutch Golden Age, but it also dragged the economy down into a depression.

The 1987 stock market crash presents a more recent example of the boom and bust cycle that characterizes the crowd behavior seen during tulipmania. In the early part of the 1980s, the stock market began a several year expansion that was fueled by low interest rates, hostile takeovers, leveraged buyouts, and company mergers. Tax benefits facilitating lower costs to financing mergers produced a greater number of companies as potential takeover targets bringing up their stock prices. In the months leading up to the stock market crash, global economic concerns began to develop with worries about the decline in the value of the dollar and the need for higher interest rates (Carlson, 2006). The combination of program trading strategies where computers traded specified amounts of a large number of stocks in accordance with the market specifications that had been designated and negative economic news produced an overwhelming effect during the week leading up to the crash. During that week, the Ways and Means Committee of the U.S. House of Representatives filed legislation intended to eliminate the tax benefits associated with financing mergers and the Commerce Department announced an unexpected increase in the trade deficit for the month of August (Carlson, 2006). The combination of these events appears to have delivered a shock to the stability of the financial system bringing about a significant drop in investor expectations.

In 2000, the stock market saw a market crash that displayed similar features to that of both tulipmania and the stock market crash of 1987. Known as the dot-com bubble, the 1990s were characterized by much speculation in the technology sector pushing stock prices higher and higher. As the boom continued into the late-1990s, investments in internet-based companies grew rapidly with the value of equity markets rising exponentially. Group psychology caused a substantial number of online businesses to go public in the late-1990s with employees often being paid in stock options, which caused further increases in price. The run-up in equity prices was a remarkable period of irrational exuberance that ended in 2000, when investors began to realize that the Internet boom had created inflated market prices. In early 2000, the speculative bubble "popped" with the NASDAQ Composite stock market index falling from 5,000 to 2,000 in a matter of months.

The recent financial crisis of 2008 has also displayed some strong indications that there may be inefficiencies in the markets in terms of asset pricing, particularly when irrational exuberance forms bubbles based on disproportionate expectations. Shiller defined irrational exuberance in his 2005 publication as "…the kind of social phenomenon that perceptive people saw with their own eyes happening in the 1990s, and that in fact, it appears, has happened again and again in history, when markets have been bid up to unusually high and unsustainable levels under the influence of market psychology" (p. 1). As Shiller had observed during the first half of the 2000s, the housing market bubble continued to grow by leaps and bounds, partially as a result of the securitization of subprime mortgages as well as the positive feedback loop increasing the confidence of investors and the price of homes. In Shiller's 2005 publication detailing his findings with regards to the housing boom and speculative market psychology, he notes:

> The housing market levels we have seen recently are not, as so many imagine, the outcome only of fundamental forces affecting the rational demand for and supply of housing. Of course home prices are set by the forces of supply and demand, as homebuyers so often say. The prices have to clear the market. But the factors influencing supply and demand include a lot of social and emotional factors, notably attention to the price increases themselves, a public impression that the experts know they will continue, and a predisposition to believe that they will continue to increase. These factors will change with our changing culture. (Shiller, 2005, p. 207)

Despite the apparent predictability of the housing bubble's demise, investors continued to bid up home prices into the latter half of the 2000s as investors expected prices to continue to rise indefinitely. When home prices unexpectedly began their decline, investors and financial institutions with large positions in the housing market found themselves selling assets at dislocated prices. In turn, the financial markets lost significant value and the United States economy went into the great recession.

Despite the history of boom and bust cycles, the debate over market efficiency continues. On the one hand, the efficient market hypothesis is based on investor's perceptions of market fundamentals, which in no way implies these perceptions to be correct (Haltom, 2009). On the other hand, the seemingly overpriced assets during periods of irrational exuberance appear to indicate that the markets may not be as rational and efficient as the efficient market hypothesis suggests. Renee Haltom of the Federal Reserve Bank of Richmond explains, "…the recent run-up in housing prices was, in retrospect, unjustified by economic fundamentals – the common definition of an asset price bubble. One possible explanation from the behavioral camp is herd behavior, in which some financial market participants mimicked the actions of others" (p. 17). This paper builds on the understanding of market psychology and investigates Fama's efficient market hypothesis empirically by examining the three most recent examples of market bubbles. While I do not directly research the psychological factors that may play a role in these boom and bust cycles, I look for market trends found in asset prices indicating predictability in the financial markets.

Data

The main thrust of this paper is to investigate the behavior of stock price movements as they relate to the weak-form of the efficient market hypothesis. As a result, the analyses conducted examine whether historical price data and price movements can be leveraged to forecast future movements in price. While weak-form efficiency assumes past prices to be inconclusive in forecasting future price level changes, investigations of trends in financial time series data have shown an unusual recurrence of similar patterns in price movements (Lo and MacKinlay, 1988).

The time series data used in my analysis is taken from the historical prices section of Yahoo! Finance. The data is provided to the general public free of charge on the Yahoo! Finance website (finance.yahoo.com). The analysis examines daily and weekly prices and price differences. In line with the definition of weak-form efficiency, the exploitation of past price information should be useless in developing successful trading strategies. Thus, the evaluation of weak-form efficiency only requires the consideration of time series data regarding past prices. Evidence involving higher cost information such as the price-earnings ratio, book value to market value ratio, dividend-to-price ratio, or any other comparable data that can potentially be used to predict future price levels would be considered information in the semistrong form of the efficient market hypothesis which this paper does not test.

The past price levels that are used in the analysis are comprised of broad market indexes. The purpose of looking at trends in index movements is to examine whether inefficiencies could potentially have resulted from a widespread market movement resulting from irrational investments throughout the stock market causing over priced securities to form a ‘bubble.’ The stock index data used to measure the efficiency of the broader market include the Standard &

Poor's 500 stock market index, the NASDAQ Composite stock market index, and the Russell 3000 index. These broad market indexes are tested for market efficiency during two five-year periods prior to and during the 1987 stock market crash. These periods are from January 2, 1980 through December 31, 1984 and January 2, 1985 through December 31, 1989. During the two periods, I test both the daily and weekly data for random walk and martingale behavior. These first two periods surrounds the stock market crash of 1987 attempting to identify any trend type behavior due to irrational investments that compound one another. The second data set looks at the S&P 500, the NASDAQ Composite, and the Russell 3000 for trends due to herding behavior around the time of the dot-com bubble with daily and weekly data during the periods of January 2, 1992 through December 31, 1996 and January 2, 1997 through December 31, 2001. Lastly, I investigate the same broad market indexes using historical data from January 2, 2001 through December 31, 2005 and from January 3, 2006 through December 31, 2010. These time periods look at the behavior of broad market indexes prior to and during the 2008 financial crisis when the housing bubble grew to be so large that its demise destabilized the United States economy.

In order to look more specifically at a smaller cohort of companies during the dot-com bubble and the 2008 financial crisis, I conduct tests for the identical time periods on the NASDAQ-100 index and the Russell 2000 index. The NASDAQ-100 index is comprised of the largest 100 non-financial securities listed on the NASDAQ Stock Market based on market capitalization. Conversely, the Russell 2000 index measures the performance of small market capitalization stocks being composed of the smallest companies within the Russell 3000 index. The Russell 2000 represents roughly 10% of the market capitalization of the Russell 3000.

It is important to note that all of the historical price data used are taken from indexes tracking the United States stock market performance. While the United States market is likely more efficient in comparison to the global markets because of liquidity factors, this paper investigates the implications of the boom and bust cycles surrounding downturns in the United States financial markets. To conduct this investigation, there are several econometric models used to investigate potential trend-like behaviors in the financial markets.

Methodologies

Random Walk Model

One of the models used in determining whether a market is efficient is the random walk model. The random walk hypothesis theorizes that stock market prices evolve with an identical distribution and are independent of each other meaning they cannot be predicted (Fama, 1970). A random walk occurs when the path of a numerical data set consists of a series of random steps. The random walk model is one of the main models used in determining market efficiency because, if markets are indeed efficient, the price of each asset should have already incorporated all available and relevant information. This means that movements in asset prices only occur due to news, and if news is random, so will be the asset's price. By testing time series for random walks, we are able to determine if the series is a stochastic process. If the time series is a stochastic process, this confirms that the evolution of the series is random over time. There are several tests I will be conducting in determining whether the data follows a random walk.

Ordinary Least Squares Regression

According to the definition of efficient markets, current asset prices should have already incorporated all relevant and available information and any new information released that is unexpected should be immediately reflected in an asset's price. In order for markets to be efficient in accordance with Fama's hypothesis, an ordinary least squares regression model conducted using tomorrow's stock price as the dependent variable and today's stock price as the independent variable should yield a coefficient equal to 1 (or very close to 1) and a high R-squared value suggesting that today's price is the optimal forecast of what tomorrow's price will be. In fact, if there is no news, then today's stock price will be a perfect predictor of tomorrow's stock price, i.e. $\beta = 1$. This proposition is tested by estimating the following equation:

(3) $$AAPL^{e}_{t+1} = \alpha + \beta\ AAPL_t + FE^{e}_{t+1}$$

Where:
$AAPL^{e}_{t+1}$ = Apple's Stock Price in the Following Period (*t+1*)
$AAPL_t$ = Apple's Current Stock Price
FE^{e}_{t+1} = Forecast Error between *t* and *t+1*

Stress that if $\beta = 1$, then changes in Apple's stock price are driven by the forecast error as shown below:

(4) $$\Delta AAPL = \alpha + (\beta\text{-}1)AAPL_t + FE^{e}_{t+1}$$

Therefore, in order to predict changes in AAPL, you must be able to predict FE^{e}_{t+1}, which is often referred to as news.

Table 1: OLS Regression of $AAPL_t$ on $AAPL^{e}_{t+1}$

Dependent Variable: AAPLCLOSE
Method: Least Squares
Date: 05/22/14 Time: 14:28
Sample (adjusted): 2 1103
Included observations: 1102 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.351415	0.831106	1.626044	0.1042
AAPLCLOSE(-1)	0.997678	0.001859	536.6308	0.0000

R-squared	0.996195	Mean dependent var	429.1206
Adjusted R-squared	0.996191	S.D. dependent var	126.5000
S.E. of regression	7.806936	Akaike info criterion	6.949715
Sum squared resid	67043.08	Schwarz criterion	6.958799
Log likelihood	-3827.293	Hannan-Quinn criter.	6.953151
F-statistic	287972.6	Durbin-Watson stat	1.956395
Prob(F-statistic)	0.000000		

The table above supports Fama's efficient market hypothesis in showing that today's price of Apple is a very good fit in reflecting what tomorrow's price will be with a high level of significance and a coefficient of 0.997678, which is very close to 1. From equation (3) above, we can make the assumption that the aggregate representation of a portion of the market (i.e. a stock index) should similarly reflect an efficient market when looking, for instance, at the Standard & Poor's 500 (S&P 500) index or the Dow Jones Industrial Average (DJIA). Running an OLS regression using non-stationary time series data, however, often produces a spurious regression where the results can produce invalid inferences. Therefore, we must conduct additional tests in determining whether the data set exhibits more specific qualities of random behavior, i.e. does $\beta = 1$, before concluding that the data follows a random walk (see the augmented Dickey-Fuller test results below).

Estimating a least squares regression with the future forecast error as the dependent variable and the current stock price as the independent variable should yield a poor fit with a low R-squared approaching zero and all coefficients equal to 0 (or very close to 0). To test for this poor fit, I estimate the following model:

$$FE^{e}_{t+1} = \alpha + \beta \, AAPL_{t} + \varepsilon_{t+1} \qquad (5)$$

Where:
FE^{e}_{t+1} = Forecast Error between *t* and *t+1*
$AAPL_{t}$ = Apple's Current Stock Price
ε_{t+1} = Error Term between *t* and *t+1*

The OLS regression results can be seen in table 2:

Table 2: OLS Regression of $AAPL_t$ on FE^e_{t+1}

Dependent Variable: CHANGEAAPL
Method: Least Squares
Date: 05/22/14 Time: 14:54
Sample (adjusted): 2 1103
Included observations: 1102 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.351415	0.831106	1.626044	0.1042
AAPLCLOSE(-1)	-0.002322	0.001859	-1.248748	0.2120

R-squared	0.001416	Mean dependent var	0.355989
Adjusted R-squared	0.000508	S.D. dependent var	7.808919
S.E. of regression	7.806936	Akaike info criterion	6.949715
Sum squared resid	67043.08	Schwarz criterion	6.958799
Log likelihood	-3827.293	Hannan-Quinn criter.	6.953151
F-statistic	1.559372	Durbin-Watson stat	1.956395
Prob(F-statistic)	0.212023		

Once again our results are consistent with the efficient market hypothesis as we can see a very low R-squared and a statistically insignificant independent variable in Apple's stock price.

Furthermore, all past forecast errors should not be useful in predicting future forecast errors. To test the proposition, I estimate the equation below:

(6) $$FE^e_{t+1} = \alpha + \beta_1 FE_t + \beta_2 FE_{t-1} + \beta_3 FE_{t-2} + \ldots + \varepsilon_{t+1}$$

Where:
FE^e_{t+1} = Forecast Error in the Following Period (*t+1*)
FE_t = Forecast Error in the Current Period
FE_{t-1} = Forecast Error in the Prior Period (*t-1*)
FE_{t-2} = Forecast Error Two Periods Prior to the Current Period (*t-2*)
ε_{t+1} = Error Term between *t* and *t+1*

Table 3: OLS Regression of FE_t, FE_{t-1}, FE_{t-2} on FE^e_{t+1}

Dependent Variable: CHANGEAAPL
Method: Least Squares
Date: 05/22/14 Time: 15:21
Sample (adjusted): 9 1103
Included observations: 1095 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.357974	0.237744	1.505716	0.1324
CHANGEAAPL(-1)	0.029735	0.030312	0.980982	0.3268
CHANGEAAPL(-2)	-0.016550	0.030283	-0.546528	0.5848
CHANGEAAPL(-3)	-0.030340	0.030258	-1.002688	0.3162
CHANGEAAPL(-4)	0.059637	0.030233	1.972557	0.0488
CHANGEAAPL(-5)	-0.049179	0.030280	-1.624141	0.1046
CHANGEAAPL(-6)	0.051949	0.030310	1.713909	0.0868
CHANGEAAPL(-7)	-0.035203	0.030338	-1.160366	0.2462

R-squared	0.011145	Mean dependent var	0.361333
Adjusted R-squared	0.004777	S.D. dependent var	7.831821
S.E. of regression	7.813092	Akaike info criterion	6.956758
Sum squared resid	66355.28	Schwarz criterion	6.993277
Log likelihood	-3800.825	Hannan-Quinn criter.	6.970576
F-statistic	1.750152	Durbin-Watson stat	2.006200
Prob(F-statistic)	0.093845		

As we can see, the data once again supports Fama's hypothesis. All seven lags produce very low coefficients close to zero with a low R-squared value indicating that the model is not a good fit. Put differently, there is no autocorrelation in returns, which is defined by changes in AAPL stock from one period to the next.

Augmented Dickey-Fuller Unit Root Test

When testing if time series data follows a random walk, we must determine whether the data set is stationary or nonstationary. A data set is said to be stationary if its properties are not affected by any change in the time origin meaning its probability distribution does not change over time. To test for stationarity, we must conduct an augmented Dickey-Fuller unit root test. Simply conducting an ordinary least squares regression is insufficient because it is incompatible with non-stationary time series data. A data set does not follow a random walk if it is stationary since a stationary set of data displays a trend through time as its parameters, such as its mean and variance, do not change over time. To determine whether the historical time series stock price is non-stationary, it is common to conduct an augmented Dickey-Fuller test. Stationarity can, at times, be identified visually. For example, figure 1 displays a stationary series while figure 2 displays a nonstationary series.

Figure 1: Stationary Time Series

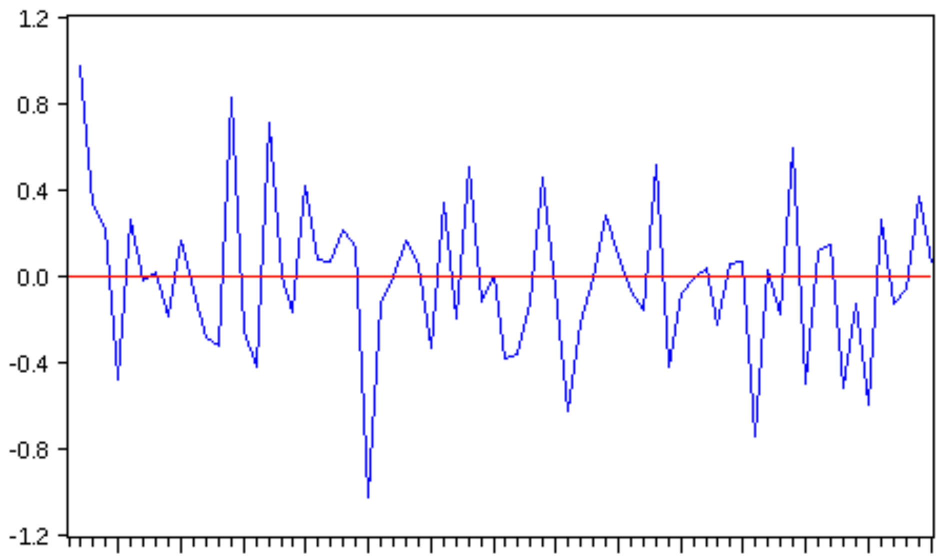
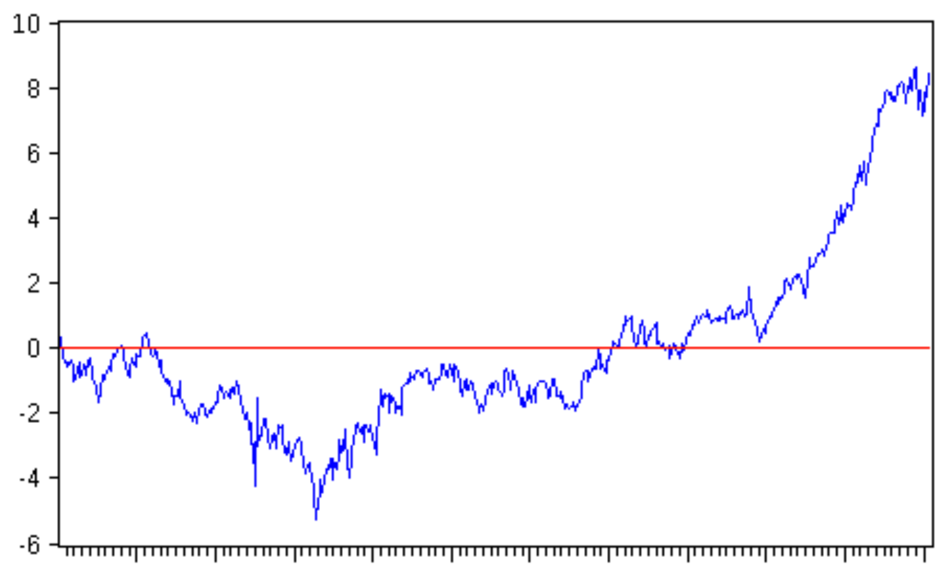


Figure 2: Nonstationary Time Series



By running an augmented Dickey-Fuller test, we are able to test for a unit root in the data, i.e. is $\beta = 1$ in equation (4). Testing for a unit root is the equivalent to testing for stationarity. The presence of a unit root means the data is a nonstationary or integrated process. As we are looking for the time series to be nonstationary, the augmented Dickey-Fuller test must fail to reject the null hypothesis of a unit root. The augmented Dickey-Fuller equation and results are below:

(7) $$\Delta AAPL = \alpha + (\beta\text{-}1)AAPL_t + \varepsilon_t$$

Table 4: Augmented Dickey-Fuller Test on Apple Stock Price

Null Hypothesis: AAPLCLOSE has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=21)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.248748	0.6550
Test critical values:	1% level	-3.436067	
	5% level	-2.863953	
	10% level	-2.568106	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(AAPLCLOSE)
Method: Least Squares
Date: 11/15/14 Time: 16:19
Sample (adjusted): 2 1103
Included observations: 1102 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AAPLCLOSE(-1)	-0.002322	0.001859	-1.248748	0.2120
C	1.351415	0.831106	1.626044	0.1042

R-squared	0.001416	Mean dependent var	0.355989
Adjusted R-squared	0.000508	S.D. dependent var	7.808919
S.E. of regression	7.806936	Akaike info criterion	6.949715
Sum squared resid	67043.08	Schwarz criterion	6.958799
Log likelihood	-3827.293	Hannan-Quinn criter.	6.953151
F-statistic	1.559372	Durbin-Watson stat	1.956395
Prob(F-statistic)	0.212023		

The augmented Dickey-Fuller test does fail to reject the null hypothesis that the historical price of Apple stock has a unit root, i.e. ($\beta - 1$) in equation (4) is insignificantly different from zero. Since we fail to reject the null hypothesis, we conclude that Apple's stock price does have a unit root. If time series data such as the Apple data set above follows a random walk, the data set by definition is nonstationary. From these results, it can be concluded that Apple's stock price is nonstationary as it has a unit root. Thus, the Apple stock price over the observed time period does meet this criterion for following a random walk, which is consistent with the efficient market hypothesis.

The presence of a random walk within stock prices, however, is not sufficient in concluding that the efficient market hypothesis holds true. Proving that the stock price of Apple follows a random walk simply shows that price changes are independent of one another.

Martingale Process

The martingale process presents an important condition in determining market efficiency. In probability theory, a martingale is a stochastic process for which, in the present time period, the expected value of the next value in the sequence is equivalent to the current value given the information regarding all past values. This paper conducts two tests for market efficiency in considering a martingale process. The first test is the autocorrelation test. Autocorrelation, also known as serial correlation, determines whether a time series has any relationship to itself through time (Sewell, 2012). The second test is the variance ratio test. While similar to the autocorrelation test, the Lo and MacKinlay variance ratio test is able to examine whether a time series exhibits properties of mean reversion or momentum across varying time intervals.

Autocorrelation Test

By testing for autocorrelation in the time series data set, we are able to measure the correlation between the current and lagged observations of returns. In accordance with the martingale hypothesis, time series data must display no autocorrelation. Martin Sewell conducted an analysis of the United States' Dow Jones Industrial Average (DJIA) stock index analyzing daily, weekly, monthly, and annual data. In his analysis, he tests for autocorrelation determining the serial correlation of the DJIA historical prices. By conducting the autocorrelation test, Sewell seeks to determine whether the current DJIA price is cross-correlated with historical DJIA prices given a time lag between 'signals'. Conducting his study using historical stock prices from the DJIA from October 1, 1928 through March 23, 2012, Sewell finds that the first-order autocorrelation of DJIA log returns is small but positive for all time periods, and that the serial correlation of the daily and weekly returns are closest to zero suggesting an efficient market within these time lags.

This paper examines market efficiency using the autocorrelation test by looking specifically at time periods characterized by boom and bust episodes. The intuition behind testing specifically during these periods is that, according to behavioral finance, periods of bubble growth are characteristic of momentum (positive autocorrelation) where investor irrationality boosts expectations lifting overpriced assets even higher. When the bubble finally 'bursts,' we expected to see a period of mean reversion (negative autocorrelation).

Lo and MacKinlay Variance Ratio Test

The Lo and MacKinlay variance ratio test examines the predictability of time series data by comparing variances of an asset's returns, $y_t - y_{t-k}$, calculated over various time intervals. If a time series follows a random walk, then the variance of the sum of returns during a specified interval should be equivalent to the sum of the variance of the individual returns during that same interval (Charles and Darné, 2009). For example, the variance of a four-day period should be equivalent to the sum of the variances of each of the one-day periods making up that four-day interval.

With returns that are independent, the covariance of X,Y should be equal to zero. The formal definition for the variance of the sum of two variables is given by equation (8) below:

(8) $$\mathrm{Var}(X+Y) = \mathrm{Var}(X) + \mathrm{Var}(Y) + 2(\sigma_X)(\sigma_Y)(\rho_{X,Y})$$

Under the condition that returns are uncorrelated, the last term in equation (8), $[2(\sigma_X)(\sigma_Y)(\rho_{X,Y})]$, which is equal to the Cov(X,Y), should be zero, [Cov(X,Y) = 0]. This being the case, we can conclude that the sum of the variance of individual period returns should equate to the variance of the sum of independent returns:

(9) $$\mathrm{Var}(X) + \mathrm{Var}(Y) = \mathrm{Var}(X+Y)$$

Furthermore, the ratio of Var(X+Y) divided by Var(X) + Var(Y) should converge to unity if a time series truly follows a random walk. Under the assumption that the returns are independent of one another, the variance of the q-period difference should be q times the variance of the one-period difference making the variance ratio equivalent to 1. Given a data set follows a random walk with a drift, the variance of its q^{th} differences will grow linearly with q. The variance ratio of the q-period return is defined as:

(10) $$V(q) = \frac{\mathrm{var}(x_t + x_{t-1} + \ldots + x_{t-q+1})/q}{\mathrm{var}(x_t)} = \frac{\mathrm{var}(y - y_{t-q})/q}{\mathrm{var}(y_t - y_{t-1})} = 1 + 2\sum_{i=1}^{q-1}\frac{(q-i)}{q}\rho_i$$

where ρ_i is the ith lag autocorrelation coefficient of x_t. Simplifying the model, we can see that the central idea of the variance ratio test is that if returns are uncorrelated over time, then $\mathrm{var}(x_t + x_{t-1} + \ldots + x_{t-q+1}) = q\,\mathrm{var}(x_t)$. Therefore, the null hypothesis can be thought of as H_0: $\rho_1 = \rho_2 = \ldots = \rho_q$

= 0, which is essentially indicating that returns are serially uncorrelated (Charles and Darné, 2009).

If returns are serially correlated, the variance ratio will not be equal to 1, indicating that the series is not a martingale process violating the efficient market theory. When returns exhibit momentum, the returns are more likely to continue moving in the same direction than to change direction. As a result, there will be a positive serial correlation with $\rho_i > 0$ resulting in the variance ratio to being greater than 1. If returns exhibit negative serial correlation, indicating that returns are more likely to change direction than move in the same direction, then $\rho_i < 0$, and the variance ratio will be less than 1. In this case, returns display mean reversion. Some trading strategies associated with results from the variance ratio tests are described in the conclusion.

Results and Discussion

A synopsis of the empirical results for each of the periods tested can be found in Appendix A. The more detailed numerical results specific to each test and time period are located in Appendix B.

1980-1989 Period

From 1980 to 1989, we find three of the eight test periods to be consistent with the efficient market hypothesis and five of the eight test periods to be inconsistent. The behavior of returns indicates that an optimistic economic environment may have influenced stock prices positively. The Lo and MacKinlay variance ratio tests indicate momentum for all significant periods with the variance ratios being statistically greater than 1. Notably, the Nasdaq Composite Index (Nasdaq) exhibits momentum for all variance ratio tests conducted during this time period. The factors that potentially contributed to this momentum during the 1980s include International Business Machines' (IBM) introduction of the first ever personal computer (PC) in 1981, which boosted stock prices in the technology sector. The comparatively higher momentum displayed by the Nasdaq relative to the Standard and Poor's 500 Index (S&P 500) illustrates this investor sentiment. Additionally, on August 13, 1981, President Ronald Reagan signed the Economic Recovery Tax Act into law slashing individual and corporate taxes and ushering in a new era of economic growth (Mandel, 2004). These factors played a large role in the momentum seen throughout the 1980s, particularly when looking at the Nasdaq, and contributed to the underlying strength of the economy that seems to have diminished any long-term effects of the 1987 stock market crash.

1992-2001 Period

From 1992 to 2001, we find nine of the twenty test periods to be consistent with the efficient market hypothesis and eleven of the twenty test periods to be inconsistent. The variance ratio test results indicate momentum for the daily time series of all indexes during the 1992-1996 period with variance ratios greater than 1. The daily data of the S&P 500 and Nasdaq-100 as well as the weekly data for the Russell 3000 demonstrate statistically significant mean reversion during the 1997-2001 period while the Russell 2000 continues to exhibit momentum.

The momentum observed in the 1992-1996 period perhaps can be attributed to a pick up in the overall economic outlook as the economy recovered from the early 1990s (Gulf War) recession. It is important to observe that the Russell 2000 daily time series presents the highest variance ratio and the highest autocorrelation relative to all other indexes tested with the Nasdaq exhibiting the second highest variance ratio and autocorrelation coefficient. Since the Russell 2000 is an index composed of the smallest stocks by market capitalization within the Russell 3000, this may indicate increased investment in small-cap firms, especially within the technology sector. The continued momentum of the Russell 2000 during the 1997-2001 period provides further indication that traders were following the trend by investing in small-cap firms with strong potential for future growth, consistent with Shiller's positive feedback model. After the dot-com bubble peaked in March 2000, the Russell 2000 continued to see momentum, albeit of a smaller magnitude and to the downward side.

2001-2010 Period

From 2001 to 2010, we find fifteen of the twenty test periods to be consistent with the efficient market hypothesis and five of the twenty test periods to be inconsistent. The empirical results from the period surrounding the financial crisis of 2008 indicate a tendency for markets to revert to the mean during a market-wide downturn. During the 2001-2005 period, the variance ratio test presents no rejections of a martingale indicating market efficiency during that period. The 2006-2010 period, however, exhibits a mean reverting variance ratio for all indexes when testing daily data. Perhaps the unexpected decline in housing prices during the mid-to-late 2000s led to the 2008 financial crisis reversing the upward trend in stock prices contributing to the mean reverting behavior. Unlike during the 1987 stock market crash, the systemic shock to the markets in 2008 had a momentous effect on the outlook for the financial industry as a whole. In defining systemic risk, Scott Harrington (2009) writes:

> "Systemic risk refers to the risk of widespread harm to financial institutions and associated spillovers on the real economy that may arise from interdependencies among those institutions and associated risk of contagion. Systemic risk is conceptually distinct from the risk of common shocks to the economy, such as widespread reductions in housing prices, which have the potential to harm large numbers of people and firms directly." (p. 2)

While the decrease in housing prices was not, in and of itself, the systemic shock, it was the catalyst that produced the subsequent financial instability. The implications of this financial instability are likely to have contributed to the mean reverting behavior we observe in stock price movements during the 2006-2010 period.

Conclusion

While there are some indications of market inefficiencies when looking at price movements characterized by broad market indexes, the efficient market hypothesis is accepted more often than not. From the forty-eight time periods / indexes tested, twenty-seven of those periods indicate market efficiency and twenty-one exhibit market inefficiency. The economic environment specific to the time period of each time series may give some indication as to why stocks exhibited inefficient behaviors.

The momentum during the 1980s is in line with the economic expansion occurring during that period and illustrates how a market downturn (1987) not caused by a systemic shock may not affect the financial markets as significantly as it might otherwise. The Russell 2000's momentum before and after the dot-com bubble's burst may be attributed to a build up of investments in small-cap stocks as well as their continued decline after the fact. The market-wide mean reversion around the time of the 2008 financial crisis suggests that systemic shocks affecting the stability of the financial industry as a whole can produce a significant shift in price behavior that moves the broader market towards its mean return.

In an inefficient market, there is the potential for outperformance by individual investors or fund managers. When looking to capitalize on market inefficiencies, the trading costs associated with the strategies implemented must be considered, as there are many cases when these costs will eliminate any profits gained. I have summarized some of the possible strategies that can be used to capitalize on price movements in both an efficient and inefficient environment.

Investment Strategies

Assuming that the stock market is efficient, the only profitable investment strategy would be a passive or neutral strategy. A passive strategy occurs when an investor looks to invest in an exchange-traded fund, an indexed fund, or a passively managed mutual fund. Exchange-traded funds tend to offer lower expenses meaning they would offer the best investment opportunity when looking to invest in a broad market index like the S&P 500 or the Nasdaq Composite. Similar to ETFs, indexed funds are mutual funds that look to provide broad market exposure by constructing a portfolio that tracks the components of an index. Passively managed mutual funds invest with a pre-determined strategy where the fund manager does not use any forecasting techniques, such as market timing or stock picking, to beat the market. Instead, the fund manager looks to replicate the returns from a specific sector or a specific instrument such as bonds or commodities (Bodie, 2013). These strategies are optimal under the assumption of market efficiency because an efficient market implies that investors are unable to outperform the market on average. Thus, replicating the market returns and diversifying away any firm-specific risk would be the most logical of investment strategies.

A neutral investment strategy is one where an investor seeks to profit from price movements, or lack of movements, regardless of whether those movements are in a bullish or bearish direction. If markets are efficient meaning today's price is equivalent to its fundamental value and there is no indication that there will be any news announcements revealing unexpectedly negative or positive news in the near future, an investor can employ a short-term market neutral strategy to capitalize on the lack of price movement. A short straddle is an investment strategy using stock options where an investor would simultaneously write (sell) one call option and one put option at the same strike price. By writing both of these options, the investor collects the associated premiums and profits in a low volatility environment by effectively collecting the associated term premiums. On the other hand, if there is an impending news announcement where there is uncertainty regarding what that announcement will indicate or what direction stock prices will move as a result of the announcement, there is likely to be a significant amount of price volatility once the news has been released. In this circumstance, an investor is able to capitalize on the likelihood of a significant market movement in either a bullish or bearish direction by going long on volatility. A neutral option strategy that could be used in this circumstance would be through purchasing a long straddle. Mirroring a short straddle, a long straddle involves the purchase of opposing stock option positions. In this case, the investor would purchase a call option and a put option at the same strike price meaning the investor will profit from a significant movement in price regardless of whether it is a bullish or bearish movement, as long as that movement is large enough to offset the costs associated with purchasing both options.

If an investor finds inefficiency in the market with a negative autocorrelation and a significant variance ratio less than 1 where prices revert to the mean, the optimal strategy this investor could implement would be the short straddle. When prices exhibit mean reverting behavior, price movements will exhibit low volatility for a period. Recall that the variance ratio test is the variance of the sum of returns over q-periods divided by the sum of the individual variances over that same period. The short straddle is best in this case because it presents a neutral strategy betting on low volatility. If instead that investor observes market inefficiency with a positive autocorrelation and a significant variance ratio greater than 1, this would indicate high volatility. With high volatility, the ideal neutral investment strategy would be to implement a long straddle in order to capitalize on large price movements.

Further Research

When looking to extend research on market efficiency during periods of market downturns, the logical next-step would be to look further into semistrong-form efficiency. With several market inefficiencies having already been uncovered such as the small-firm (in January) effect and the book-to-market effect, it may be the case that that these effects are magnified during the recovery from a market-wide decline. It could also be the case that these effects are eliminated as investors have increased risk aversion after incurring large losses causing them to hoard their investments in larger, more stable large-cap stocks and Treasuries. Conducting research on semistrong-form efficiency could potentially uncover inefficiencies that build upon some of the market trends shown in the empirical work from this paper. This could potentially shed additional light on why these trends occurred in times of financial market turmoil informing what the future may bring.

Appendix

Key

***	Significant at the .01 level
**	Significant at the .05 level
*	Significant at the .10 level

Appendix A

Table 5: 1980-1989 Augmented Dickey-Fuller Unit Root Test, Variance Ratio Test Results

Variables	Consistent with EMH*	Autocorrelation
Sample from 1980-1984:		
Daily S&P 500 Closing Price	No	0.087
Daily NASDAQ Closing Price	No	0.269
Weekly S&P 500 Closing Price	Yes	-
Weekly NASDAQ Closing Price	No	0.199
Sample from 1985-1989:		
Daily S&P 500 Closing Price	Yes	-
Daily NASDAQ Closing Price	No	0.298
Weekly S&P 500 Closing Price	Yes	-
Weekly NASDAQ Closing Price	No	0.273

* EMH stands for efficient market hypothesis

Table 6: 1992-2001 Augmented Dickey-Fuller Unit Root Test, Variance Ratio Test Results

Variables	Consistent with EMH	Autocorrelation
Sample from 1992-1996:		
Daily S&P 500 Closing Price	No	0.075
Daily NASDAQ Closing Price	No	0.175
Daily NASDAQ-100 Closing Price	No	0.009
Daily Russell 3000 Closing Price	No	0.123
Daily Russell 2000 Closing Price	No	0.267
Weekly S&P 500 Closing Price	Yes	-
Weekly NASDAQ Closing Price	Yes	-
Weekly NASDAQ-100 Closing Price	Yes	-
Weekly Russell 3000 Closing Price	Yes	-
Weekly Russell 2000 Closing Price	No	0.058
Sample from 1997-2001:		
Daily S&P 500 Closing Price	No	-0.002
Daily NASDAQ Closing Price	Yes	-
Daily NASDAQ-100 Closing Price	No	-0.063
Daily Russell 3000 Closing Price	Yes	-
Daily Russell 2000 Closing Price	No	0.104
Weekly S&P 500 Closing Price	No	-0.177
Weekly NASDAQ Closing Price	Yes	-
Weekly NASDAQ-100 Closing Price	Yes	-
Weekly Russell 3000 Closing Price	No	-0.159
Weekly Russell 2000 Closing Price	Yes	-

Table 7: 2001-2010 Augmented Dickey-Fuller Unit Root Test, Variance Ratio Test Results

Variables	Consistent with EMH	Autocorrelation
Sample from 2001-2005:		
Daily S&P 500 Closing Price	Yes	-
Daily NASDAQ Closing Price	Yes	-
Daily NASDAQ-100 Closing Price	Yes	-
Daily Russell 3000 Closing Price	Yes	-
Daily Russell 2000 Closing Price	Yes	-
Weekly S&P 500 Closing Price	Yes	-
Weekly NASDAQ Closing Price	Yes	-
Weekly NASDAQ-100 Closing Price	Yes	-
Weekly Russell 3000 Closing Price	Yes	-
Weekly Russell 2000 Closing Price	Yes	-
Sample from 2006-2010:		
Daily S&P 500 Closing Price	No	-0.130
Daily NASDAQ Closing Price	No	-0.085
Daily NASDAQ-100 Closing Price	No	-0.093
Daily Russell 3000 Closing Price	No	-0.116
Daily Russell 2000 Closing Price	No	-0.086
Weekly S&P 500 Closing Price	Yes	-
Weekly NASDAQ Closing Price	Yes	-
Weekly NASDAQ-100 Closing Price	Yes	-
Weekly Russell 3000 Closing Price	Yes	-
Weekly Russell 2000 Closing Price	Yes	-

Appendix B

Table 8: Augmented Dickey-Fuller Unit Root Test Results, 1987 Stock Market Crash

Variables	Coefficient	Probability
S&P 500 Daily Closing Price from 1/2/1980 to 12/31/1984	-0.002130	0.2110
S&P 500 Weekly Closing Price from 1/2/1980 to 12/31/1984	-0.010180	0.2403
S&P 500 Daily Closing Price from 1/2/1985 to 12/29/1989	-0.002138	0.2428
S&P 500 Weekly Closing Price from 1/2/1985 to 12/26/1989	-0.008205	0.2897
NASDAQ Daily Closing Price from 1/2/1980 to 12/31/1984	-0.001589	0.1323
NASDAQ Weekly Closing Price from 1/2/1980 to 12/31/1984	-0.008953	0.1584
NASDAQ Daily Closing Price from 1/2/1985 to 12/29/1989	-0.002994*	0.0523
NASDAQ Weekly Closing Price from 1/2/1985 to 12/26/1989	-0.018099**	0.0453

Table 9: OLS Regression of Today's Price on FE^{e}_{t+1} Results, 1987 Stock Market Crash

Variables	Coefficient	Probability	R-squared
S&P 500 Daily Closing Price from 1/2/1980 to 12/31/1984	0.001727	0.3112	0.000813
S&P 500 Weekly Closing Price from 1/2/1980 to 12/31/1984	0.009308	0.2833	0.004444
S&P 500 Daily Closing Price from 1/2/1985 to 12/29/1989	0.002083	0.2551	0.001028
S&P 500 Weekly Closing Price from 1/2/1985 to 12/26/1989	0.007301	0.3465	0.003436
NASDAQ Daily Closing Price from 1/2/1980 to 12/31/1984	-2.11E-05	0.9846	0.000000
NASDAQ Weekly Closing Price from 1/2/1980 to 12/31/1984	0.001487	0.8183	0.000204
NASDAQ Daily Closing Price from 1/2/1985 to 12/29/1989	0.000369	0.8194	0.000041
NASDAQ Weekly Closing Price from 1/2/1985 to 12/26/1989	0.004881	0.6022	0.001054

Table 10: OLS Regression of FE_t on FE^e_{t+1} Results, 1987 Stock Market Crash

Variables	Coefficient	Probability	R-squared
S&P 500 Daily Closing Price from 1/2/1980 to 12/31/1984	0.086866***	0.0020	0.007544
S&P 500 Weekly Closing Price from 1/2/1980 to 12/31/1984	-0.040201	0.5178	0.001623
S&P 500 Daily Closing Price from 1/2/1985 to 12/29/1989	0.036275	0.1981	0.001315
S&P 500 Weekly Closing Price from 1/2/1985 to 12/26/1989	0.014915	0.8113	0.000222
NASDAQ Daily Closing Price from 1/2/1980 to 12/31/1984	0.269293***	0.0000	0.072588
NASDAQ Weekly Closing Price from 1/2/1980 to 12/31/1984	0.199302***	0.0012	0.039914
NASDAQ Daily Closing Price from 1/2/1985 to 12/29/1989	0.298817***	0.0000	0.089145
NASDAQ Weekly Closing Price from 1/2/1985 to 12/26/1989	0.274220***	0.0000	0.074945

Table 11: Lo and MacKinlay Variance Ratio Test Results, 1987 Stock Market Crash

Variables	Periods: 2	Periods: 5	Periods: 10	Periods: 30
S&P 500 Daily Closing Price from 1/2/1980 to 12/31/1984	1.0883***	1.1477**	1.1211	1.0267
S&P 500 Weekly Closing Price from 1/2/1980 to 12/31/1984	0.9648	0.9464	0.9746	1.2221
S&P 500 Daily Closing Price from 1/2/1985 to 12/29/1989	1.0376	0.9313	0.9446	0.8727
S&P 500 Weekly Closing Price from 1/2/1985 to 12/26/1989	1.0207	1.0917	1.2591	1.1345
NASDAQ Daily Closing Price from 1/2/1980 to 12/31/1984	1.2704***	1.5901***	1.8340***	2.4185***
NASDAQ Weekly Closing Price from 1/2/1980 to 12/31/1984	1.2060***	1.5826***	1.9568***	3.0269***
NASDAQ Daily Closing Price from 1/2/1985 to 12/29/1989	1.2996**	1.6312**	2.0347***	2.3071**
NASDAQ Weekly Closing Price from 1/2/1985 to 12/26/1989	1.2795*	1.5405**	1.8384**	1.5059

Table 12: Augmented Dickey-Fuller Unit Root Test Results, 2000 Dot-com Bubble

Variables	Coefficient	Probability
S&P 500 Daily Closing Price from 1/2/1992 to 12/31/1996	0.001237	0.1971
S&P 500 Weekly Closing Price from 1/2/1992 to 12/30/1996	0.006774	0.1492
S&P 500 Daily Closing Price from 1/2/1997 to 12/31/2001	-0.004572**	0.0280
S&P 500 Weekly Closing Price from 1/2/1997 to 12/31/2001	-0.020541**	0.0384
NASDAQ Daily Closing Price from 1/2/1992 to 12/31/1996	0.000630	0.5211
NASDAQ Weekly Closing Price from 1/2/1992 to 12/30/1996	0.003803	0.4209
NASDAQ Daily Closing Price from 1/2/1997 to 12/31/2001	-0.002830	0.1425
NASDAQ Weekly Closing Price from 1/2/1997 to 12/31/2001	-0.0145	0.1373
NASDAQ-100 Daily Closing Price from 1/2/1992 to 12/31/1996	-0.004081	0.1502
NASDAQ-100 Weekly Closing Price from 1/2/1992 to 12/30/1996	-0.017329	0.1841
NASDAQ-100 Daily Closing Price from 1/2/1997 to 12/31/2001	-0.002826	0.1424
NASDAQ-100 Weekly Closing Price from 1/2/1997 to 12/31/2001	-0.012514	0.1604
Russell 3000 Daily Closing Price from 1/2/1992 to 12/31/1996	0.001017	0.2738
Russell 3000 Weekly Closing Price from 1/2/1992 to 12/30/1996	0.006190	0.1768
Russell 3000 Daily Closing Price from 1/2/1997 to 12/31/2001	-0.004686**	0.0295
Russell 3000 Weekly Closing Price from 1/2/1997 to 12/31/2001	-0.021320**	0.0416
Russell 2000 Daily Closing Price from 1/2/1992 to 12/31/1996	0.000128	0.8877
Russell 2000 Weekly Closing Price from 1/2/1992 to 12/30/1996	0.000995	0.8412
Russell 2000 Daily Closing Price from 1/2/1997 to 12/31/2001	-0.007665**	0.0197
Russell 2000 Weekly Closing Price from 1/2/1997 to 12/31/2001	-0.043535**	0.0125

Table 13: OLS Regression of Today's Price on FE^{e}_{t+1} Results, 2000 Dot-com Bubble

Variables	Coefficient	Probability	R-squared
S&P 500 Daily Closing Price from 1/2/1992 to 12/31/1996	0.001431	0.1350	0.001769
S&P 500 Weekly Closing Price from 1/2/1992 to 12/30/1996	0.006774	0.1492	0.008016
S&P 500 Daily Closing Price from 1/2/1997 to 12/31/2001	-0.004572**	0.0280	0.003844
S&P 500 Weekly Closing Price from 1/2/1997 to 12/31/2001	-0.021336**	0.0320	0.017702
NASDAQ Daily Closing Price from 1/2/1992 to 12/31/1996	0.000768	0.4403	0.000472
NASDAQ Weekly Closing Price from 1/2/1992 to 12/30/1996	0.003803	0.4209	0.002503
NASDAQ Daily Closing Price from 1/2/1997 to 12/31/2001	-0.002830	0.1425	0.001715
NASDAQ Weekly Closing Price from 1/2/1997 to 12/31/2001	-0.014454	0.1373	0.008536
NASDAQ-100 Daily Closing Price from 1/2/1992 to 12/31/1996	-0.004081	0.1502	0.001640
NASDAQ-100 Weekly Closing Price from 1/2/1992 to 12/30/1996	-0.017329	0.1841	0.006802
NASDAQ-100 Daily Closing Price from 1/2/1997 to 12/31/2001	-0.002826	0.1424	0.001715
NASDAQ-100 Weekly Closing Price from 1/2/1997 to 12/31/2001	-0.012514	0.1604	0.007621
Russell 3000 Daily Closing Price from 1/2/1992 to 12/31/1996	0.001277	0.1711	0.001484
Russell 3000 Weekly Closing Price from 1/2/1992 to 12/30/1996	0.006190	0.1768	0.007032
Russell 3000 Daily Closing Price from 1/2/1997 to 12/31/2001	-0.004686**	0.0295	0.003774
Russell 3000 Weekly Closing Price from 1/2/1997 to 12/31/2001	-0.022334**	0.0328	0.017539
Russell 2000 Daily Closing Price from 1/2/1992 to 12/31/1996	0.000264	0.7781	0.000063
Russell 2000 Weekly Closing Price from 1/2/1992 to 12/30/1996	0.000995	0.8421	0.000155
Russell 2000 Daily Closing Price from 1/2/1997 to 12/31/2001	-0.007711**	0.0194	0.004350
Russell 2000 Weekly Closing Price from 1/2/1997 to 12/31/2001	-0.043535**	0.0125	0.023942

Table 14: OLS Regression of FE_t on FE^e_{t+1} Results, 2000 Dot-com Bubble

Variables	Coefficient	Probability	R-squared
S&P 500 Daily Closing Price from 1/2/1992 to 12/31/1996	0.076192***	0.0071	0.005728
S&P 500 Weekly Closing Price from 1/2/1992 to 12/30/1996	-0.096663	0.1237	0.009159
S&P 500 Daily Closing Price from 1/2/1997 to 12/31/2001	-0.001908	0.9462	0.000004
S&P 500 Weekly Closing Price from 1/2/1997 to 12/31/2001	-0.177286***	0.0042	0.031418
NASDAQ Daily Closing Price from 1/2/1992 to 12/31/1996	0.175128***	0.0000	0.030681
NASDAQ Weekly Closing Price from 1/2/1992 to 12/30/1996	0.003958	0.9492	0.000016
NASDAQ Daily Closing Price from 1/2/1997 to 12/31/2001	0.019457	0.4911	0.000379
NASDAQ Weekly Closing Price from 1/2/1997 to 12/31/2001	-0.043064	0.4902	0.001854
NASDAQ-100 Daily Closing Price from 1/2/1992 to 12/31/1996	0.008790	0.7550	0.000077
NASDAQ-100 Weekly Closing Price from 1/2/1992 to 12/30/1996	-0.059005	0.3429	0.003488
NASDAQ-100 Daily Closing Price from 1/2/1997 to 12/31/2001	-0.062983**	0.0257	0.003966
NASDAQ-100 Weekly Closing Price from 1/2/1997 to 12/31/2001	-0.096619	0.1210	0.009332
Russell 3000 Daily Closing Price from 1/2/1992 to 12/31/1996	0.123785***	0.0000	0.015255
Russell 3000 Weekly Closing Price from 1/2/1992 to 12/30/1996	-0.083839	0.1801	0.006954
Russell 3000 Daily Closing Price from 1/2/1997 to 12/31/2001	0.019585	0.4882	0.000383
Russell 3000 Weekly Closing Price from 1/2/1997 to 12/31/2001	-0.159351**	0.0102	0.025384
Russell 2000 Daily Closing Price from 1/2/1992 to 12/31/1996	0.267019***	0.0000	0.071388
Russell 2000 Weekly Closing Price from 1/2/1992 to 12/30/1996	0.057775	0.3513	0.003369
Russell 2000 Daily Closing Price from 1/2/1997 to 12/31/2001	0.104278***	0.0002	0.010869
Russell 2000 Weekly Closing Price from 1/2/1997 to 12/31/2001	-0.051096	0.4129	0.002610

Table 15: Lo and MacKinlay Variance Ratio Test Results, 2000 Dot-com Bubble

Variables	Periods: 2	Periods: 5	Periods: 10	Periods: 30
S&P 500 Daily Closing Price from 1/2/1992 to 12/31/1996	1.0699**	1.0754	0.9579	0.7570
S&P 500 Weekly Closing Price from 1/2/1992 to 12/30/1996	0.9004	0.7432	0.7385	0.8682
S&P 500 Daily Closing Price from 1/2/1997 to 12/31/2001	0.9992	0.9210	0.8008*	0.7579
S&P 500 Weekly Closing Price from 1/2/1997 to 12/31/2001	0.8287**	0.7967	0.6955	0.7037
NASDAQ Daily Closing Price from 1/2/1992 to 12/31/1996	1.1767***	1.2000**	1.1701	1.2161
NASDAQ Weekly Closing Price from 1/2/1992 to 12/30/1996	1.0084	1.1399	1.2262	0.9819
NASDAQ Daily Closing Price from 1/2/1997 to 12/31/2001	1.0208	0.9811	0.9349	1.1178
NASDAQ Weekly Closing Price from 1/2/1997 to 12/31/2001	0.9642	1.0251	1.0913	1.3725
NASDAQ-100 Daily Closing Price from 1/2/1992 to 12/31/1996	1.0103	0.9501*	0.8893**	0.8608
NASDAQ-100 Weekly Closing Price from 1/2/1992 to 12/30/1996	0.9464	0.9608	0.9980	1.1571
NASDAQ-100 Daily Closing Price from 1/2/1997 to 12/31/2001	0.9383	0.8169*	0.7189*	0.8104
NASDAQ-100 Weekly Closing Price from 1/2/1997 to 12/31/2001	0.9102	0.8800	0.9631	1.4631
Russell 3000 Daily Closing Price from 1/2/1992 to 12/31/1996	1.1200***	1.1467*	1.0299	0.8388
Russell 3000 Weekly Closing Price from 1/2/1992 to 12/30/1996	0.9184	0.7972	0.7988	0.9088
Russell 3000 Daily Closing Price from 1/2/1997 to 12/31/2001	1.0207	0.9532	0.8338	0.7887
Russell 3000 Weekly Closing Price from 1/2/1997 to 12/31/2001	0.8467*	0.7968	0.7108	0.6891
Russell 2000 Daily Closing Price from 1/2/1992 to 12/31/1996	1.2660***	1.4341***	1.4804***	1.6692***
Russell 2000 Weekly Closing Price from 1/2/1992 to 12/30/1996	1.0593	1.2780*	1.3206	1.0138
Russell 2000 Daily Closing Price from 1/2/1997 to 12/31/2001	1.1056***	1.1309	1.1088	1.2066
Russell 2000 Weekly Closing Price from 1/2/1997 to 12/31/2001	0.9558	0.9714	0.9548	0.5844

Table 16: Augmented Dickey-Fuller Unit Root Test Results, 2008 Financial Crisis

Variables	Coefficient	Probability
S&P 500 Daily Closing Price from 1/2/2001 to 12/30/2005	-0.004729*	0.0753
S&P 500 Weekly Closing Price from 1/2/2001 to 12/27/2005	-0.020434*	0.0859
S&P 500 Daily Closing Price from 1/3/2006 to 12/31/2010	-0.002590	0.2518
S&P 500 Weekly Closing Price from 1/3/2006 to 12/27/2010	-0.012679	0.1983
NASDAQ Daily Closing Price from 1/2/2001 to 12/30/2005	-0.005876**	0.0491
NASDAQ Weekly Closing Price from 1/2/2001 to 12/27/2005	-0.026824**	0.0448
NASDAQ Daily Closing Price from 1/3/2006 to 12/31/2010	-0.003878	0.1684
NASDAQ Weekly Closing Price from 1/3/2006 to 12/27/2010	-0.017124	0.1706
NASDAQ-100 Daily Closing Price from 1/2/2001 to 12/30/2005	-0.008424***	0.0086
NASDAQ-100 Weekly Closing Price from 1/2/2001 to 12/27/2005	-0.038190***	0.0045
NASDAQ-100 Daily Closing Price from 1/3/2006 to 12/31/2010	-0.003285	0.2529
NASDAQ-100 Weekly Closing Price from 1/3/2006 to 12/27/2010	-0.014335	0.2596
Russell 3000 Daily Closing Price from 1/2/2001 to 12/30/2005	-0.003728	0.1417
Russell 3000 Weekly Closing Price from 1/2/2001 to 12/27/2005	-0.015709	0.1690
Russell 3000 Daily Closing Price from 1/3/2006 to 12/31/2010	-0.002709	0.2396
Russell 3000 Weekly Closing Price from 1/3/2006 to 12/27/2010	-0.013336	0.1900
Russell 2000 Daily Closing Price from 1/2/2001 to 12/30/2005	-0.001328	0.4942
Russell 2000 Weekly Closing Price from 1/2/2001 to 12/27/2005	-0.005854	0.5250
Russell 2000 Daily Closing Price from 1/3/2006 to 12/31/2010	-0.004400	0.1262
Russell 2000 Weekly Closing Price from 1/3/2006 to 12/27/2010	-0.019658	0.1254

Table 17: OLS Regression of Today's Price on FE^{e}_{t+1} Results, 2008 Financial Crisis

Variables	Coefficient	Probability	R-squared
S&P 500 Daily Closing Price from 1/2/2001 to 12/30/2005	0.004729*	0.0753	0.002522
S&P 500 Weekly Closing Price from 1/2/2001 to 12/27/2005	-0.020434*	0.0859	0.011432
S&P 500 Daily Closing Price from 1/3/2006 to 12/31/2010	-0.003285	0.1503	0.001647
S&P 500 Weekly Closing Price from 1/3/2006 to 12/27/2010	-0.012679	0.1983	0.006407
NASDAQ Daily Closing Price from 1/2/2001 to 12/30/2005	-0.005876**	0.0491	0.003086
NASDAQ Weekly Closing Price from 1/2/2001 to 12/27/2005	-0.026824**	0.0448	0.015574
NASDAQ Daily Closing Price from 1/3/2006 to 12/31/2010	-0.004347	0.1230	0.001893
NASDAQ Weekly Closing Price from 1/3/2006 to 12/27/2010	-0.017124	0.1706	0.007264
NASDAQ-100 Daily Closing Price from 1/2/2001 to 12/30/2005	-0.008424***	0.0086	0.005503
NASDAQ-100 Weekly Closing Price from 1/2/2001 to 12/27/2005	-0.038190***	0.0045	0.030905
NASDAQ-100 Daily Closing Price from 1/3/2006 to 12/31/2010	-0.003892	0.1761	0.001457
NASDAQ-100 Weekly Closing Price from 1/3/2006 to 12/27/2010	-0.014335	0.2596	0.004924
Russell 3000 Daily Closing Price from 1/2/2001 to 12/30/2005	-0.003728	0.1417	0.001722
Russell 3000 Weekly Closing Price from 1/2/2001 to 12/27/2005	-0.015709	0.1690	0.007348
Russell 3000 Daily Closing Price from 1/3/2006 to 12/31/2010	-0.003357	0.1480	0.001665
Russell 3000 Weekly Closing Price from 1/3/2006 to 12/27/2010	-0.013336	0.1900	0.006647
Russell 2000 Daily Closing Price from 1/2/2001 to 12/30/2005	-0.001328	0.4942	0.000373
Russell 2000 Weekly Closing Price from 1/2/2001 to 12/27/2005	-0.005854	0.5250	0.001574
Russell 2000 Daily Closing Price from 1/3/2006 to 12/31/2010	-0.004868*	0.0911	0.002271
Russell 2000 Weekly Closing Price from 1/3/2006 to 12/27/2010	-0.019658	0.1254	0.009080

Table 18: OLS Regression of FE_t on FE^e_{t+1} Results, 2008 Financial Crisis

Variables	Coefficient	Probability	R-squared
S&P 500 Daily Closing Price from 1/2/2001 to 12/30/2005	-0.021634	0.4386	0.000479
S&P 500 Weekly Closing Price from 1/2/2001 to 12/27/2005	0.057892	0.3544	0.003352
S&P 500 Daily Closing Price from 1/3/2006 to 12/31/2010	-0.130275***	0.0000	0.016973
S&P 500 Weekly Closing Price from 1/3/2006 to 12/27/2010	-0.057528	0.3565	0.003310
NASDAQ Daily Closing Price from 1/2/2001 to 12/30/2005	0.033290	0.2196	0.001203
NASDAQ Weekly Closing Price from 1/2/2001 to 12/27/2005	0.082702	0.1761	0.007136
NASDAQ Daily Closing Price from 1/3/2006 to 12/31/2010	-0.085201***	0.0025	0.007261
NASDAQ Weekly Closing Price from 1/3/2006 to 12/27/2010	-0.010687	0.8641	0.000114
NASDAQ-100 Daily Closing Price from 1/2/2001 to 12/30/2005	0.005005	0.8510	0.000028
NASDAQ-100 Weekly Closing Price from 1/2/2001 to 12/27/2005	0.081446	0.1801	0.007009
NASDAQ-100 Daily Closing Price from 1/3/2006 to 12/31/2010	-0.092924***	0.0010	0.008637
NASDAQ-100 Weekly Closing Price from 1/3/2006 to 12/27/2010	0.006982	0.9110	0.000049
Russell 3000 Daily Closing Price from 1/2/2001 to 12/30/2005	-0.009403	0.7363	0.000091
Russell 3000 Weekly Closing Price from 1/2/2001 to 12/27/2005	0.053995	0.3871	0.002924
Russell 3000 Daily Closing Price from 1/3/2006 to 12/31/2010	-0.116121***	0.0000	0.013485
Russell 3000 Weekly Closing Price from 1/3/2006 to 12/27/2010	-0.045236	0.4685	0.002046
Russell 2000 Daily Closing Price from 1/2/2001 to 12/30/2005	-0.009416	0.7379	0.000089
Russell 2000 Weekly Closing Price from 1/2/2001 to 12/27/2005	-0.010412	0.8674	0.000109
Russell 2000 Daily Closing Price from 1/3/2006 to 12/31/2010	-0.086293***	0.0022	0.007446
Russell 2000 Weekly Closing Price from 1/3/2006 to 12/27/2010	-0.039831	0.5233	0.001587

Table 19: Lo and MacKinlay Variance Ratio Test Results, 2008 Financial Crisis

Variables	Periods: 2	Periods: 5	Periods: 10	Periods: 30
S&P 500 Daily Closing Price from 1/2/2001 to 12/30/2005	0.9681	0.9214	0.9005	0.9348
S&P 500 Weekly Closing Price from 1/2/2001 to 12/27/2005	1.0632	1.0965	0.9500	1.0063
S&P 500 Daily Closing Price from 1/3/2006 to 12/31/2010	0.8711***	0.7427***	0.6845**	0.7619
S&P 500 Weekly Closing Price from 1/3/2006 to 12/27/2010	0.9498	0.9779	1.0959	1.5210
NASDAQ Daily Closing Price from 1/2/2001 to 12/30/2005	0.9953	0.9113	0.9275	1.0489
NASDAQ Weekly Closing Price from 1/2/2001 to 12/27/2005	1.0684	1.1444	1.0863	0.9288
NASDAQ Daily Closing Price from 1/3/2006 to 12/31/2010	0.9161**	0.8273*	0.7945	0.9120
NASDAQ Weekly Closing Price from 1/3/2006 to 12/27/2010	0.9968	1.0783	1.2605	1.4377
NASDAQ-100 Daily Closing Price from 1/2/2001 to 12/30/2005	0.9509	0.8121	0.8107	0.9205
NASDAQ-100 Weekly Closing Price from 1/2/2001 to 12/27/2005	1.0617	1.1214	1.0577	0.8657
NASDAQ-100 Daily Closing Price from 1/3/2006 to 12/31/2010	0.9083**	0.8263*	0.8147	0.9604
NASDAQ-100 Weekly Closing Price from 1/3/2006 to 12/27/2010	1.0146	1.1389	1.3596	1.4922
Russell 3000 Daily Closing Price from 1/2/2001 to 12/30/2005	0.9798	0.9363	0.9112	0.9686
Russell 3000 Weekly Closing Price from 1/2/2001 to 12/27/2005	1.0577	1.1165	0.9909	1.0540
Russell 3000 Daily Closing Price from 1/3/2006 to 12/31/2010	0.8852***	0.7696**	0.7174*	0.8007
Russell 3000 Weekly Closing Price from 1/3/2006 to 12/27/2010	0.9621	0.9961	1.1166	1.5027
Russell 2000 Daily Closing Price from 1/2/2001 to 12/30/2005	0.9872	0.9702	0.9332	1.0291
Russell 2000 Weekly Closing Price from 1/2/2001 to 12/27/2005	0.9902	1.0786	1.0564	1.0915
Russell 2000 Daily Closing Price from 1/3/2006 to 12/31/2010	0.9149**	0.8239**	0.7540*	0.7796
Russell 2000 Weekly Closing Price from 1/3/2006 to 12/27/2010	0.9672	0.9324	1.0062	1.0534

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