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NOISE: SENTIMENT AND VOLATILITY BY ASSET SIZE CLASS

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ABSTRACT

Noise trading is a pattern of buying and selling – typically of actively-traded assets like stocks or commodities or foreign currencies – that is not directly supported by the observed cash flows underlying those assets; uninformed momentum-trading of newly issued stocks or gold come to mind in the “noise-trading” context. Investor sentiment is the not-directly-observable willingness of investment decision-makers to assume risk; for example, the number of days a home sits on the market or the spread between the asking and selling price of the home are proxies for the “sentiment” of the real estate market. This study tests an extension of the noise trader theory on specific asset classes sorted by market capitalization – small, medium and large company stocks.

Investor sentiment can represent the susceptibility to noise traders’ overreactions and is found to be correlated with volatility. Thus, sentiment-driven trading’s effect is to introduce systematic risk. This systematic risk acts as a price pressure and drives down returns where sentiment trading is heavy. We use various proxies for, and one direct survey measure of, sentiment to find that weekly percent-changes in sentiment describe some weekly percent-change differently in each asset size class. We use the Russell 1000, the Russell Mid-cap, and the Russell 2000 to represent the differences in market capitalization. The Russell Mid-cap has had greater returns over the long term than its counterparts. While this disparity in returns can be attributed to several reasons, the under-allocation by noise traders or sentiment traders due in part to lesser amounts of media coverage is statistically significant. The direct survey measure is particularly interesting, as it serves to represent individual sentiment; previous research suggests that much of the noise trading comes from individual traders who are more apt to carry biases not justified by the facts.
DEDICATION

I would like to dedicate this work to my parents Marty and Peggy Hawks. Their love and support know no bounds and for that my potential is equally boundless. Their faithfulness to each other and to their work has inspired integrity and faithfulness in me. They trained me to honor authority, to live responsibly, to love mercy, and to walk humbly with the Lord. They taught me to learn from my mistakes. They taught me forgiveness and compassion, diligence and perseverance, enthusiasm and courage, repentance and integrity, and most of all how to love others. Their encouragement got me through the toughest of days. This thesis and the academic career before it I owe completely to my parents.

My Mom, a wonderful teacher and nurturer, has given me her enthusiasm, curiosity, and desire to learn. She has exemplified spiritual strength. She has always encouraged me and supported me in all the little ways moms rarely get credit for. So, in case you are reading, I like that you were interested in how my day was at school, I want you to approve of my future wife, I remember all the lunches you packed and even the stamped messages on the sandwiches, I remember all the games you never missed, and one of the most important lessons I learned in college is that laundry doesn’t do itself. No one comforts me and cares for me like you Mom. Thank you.

My Dad, a man of courage and honor for whom no task seems unachievable, has shown me that anything is possible if you put your mind to it. In case you are reading, I remember you doing all the repairs to our house and cars and even building my tree fort, which taught me I too could learn anything. I remember you always answering my millions of questions, you teaching me every sport and life lessons through them, and you always being there. You have reminded me that tough times don’t last, but tough people do. By your willingness to endure anything for
the sake of your family, you instilled in me a servant’s heart. I know you worked hard on things you didn’t necessarily love to do because you wanted to provide opportunities to increase my joy in life before worrying about your own. You demonstrated that effort, even in tasks you don’t love, is honorable and glorifying to God. I especially remember my utter amazement, when on the same day you were laid off you told me how excited you were that you could come to all my games. You have selflessly and constantly been concerned with my development as a man. Your perspective and wisdom is priceless and your knowledge seemingly endless. I still want to be like my dad when I grow up and in today’s culture that is a big deal. Thank you.

My family is without a doubt my inspiration and that starts with my parents, but extends also to my sisters and extended family. My sisters Avery and Ashley have been a constant wealth of encouragement and wonderful role models. Last, but certainly not least I must thank God Almighty who has sustained me throughout the tumultuous but beautiful journey through college, both undergraduate and graduate. In Christ, I can do all things, so I thank the many people who prayed for me along the way.
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I also want to acknowledge the helpful correspondence of Dr. Gregory Brown at UNC Chapel Hill who encouraged me that sorting asset classes for size may shed some light on the way sentiment affects the equity market.


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I. INTRODUCTION

The debate over valuation rages on between esteemed economists and financial analysts in an effort to discover mispriced assets and create a profitable trading scenario. The human aspect of the equity market will fuel the debate for many years to come; there is simply no way to eliminate it. Finance is a social science. Fundamental analysis must rely on humans making the decisions, creating the innovations, and providing the services that control the growth of a company. Technical analysis must rely on humans creating the investing trend in the future of these companies.

In a world where a computer armed with an algorithm can identify and make a trade on just about any key financial data within a company, the human aspect is increasingly important to monitor. In fact, a day is pressing where finding undervalued stocks will be dependent completely on the understanding of things a computer cannot calculate; for if it could be calculated from financial statements, computers will have already made the trade and the numeric information will have been reflected in the price. So what other information could be reflected in the price or missing from it? We must now seek to quantify under- and overreactions that make a price stray from simple fundamental models.

Conventional finance describes humans as rational and predictable, all with the same chance of profit, and under that assumption holds that logical theories, such as the capital asset pricing model and the efficient market hypothesis govern the valuation of an asset. Fama (1970) holds that under the Efficient Market Hypothesis (EMH) all information is reflected in the share price of a stock and there is nothing more to predict because the only way to obtain higher returns is to take on riskier investments. Under the EMH, returns follow a random walk.
Behavioral finance, conventional finance’s foe, seeks answers to the anomalies and divergences in behaviors that the EMH cannot explain, particularly under and overvalued stocks. Since the real world is made up of imperfect and biased humans who can behave unrationally and even move coherently in the opposite direction of fundamental values, behavioral finance has garnered a great deal of support. Behavioral finance uses psychology to figure out how the human aspect of finance plays into the valuation of an asset. Fama (1998) counters this move toward broad acceptance of behavioral finance arguing that many of the findings in behavioral finance appear to contradict each other, and that all in all, behavioral finance itself appears to be a collection of anomalies that can be explained by market efficiency. Skepticism of behavioral finance is understandable in the eye of an academic leery of ex-post studies that might just be “parlor tricks” – the luring of investors into belief of a predictable trend all the while knowing that past performance does not guarantee future returns.

After the most recent financial debacle in 2008 the EMH is at serious odds with behavioral finance. The excess volatility in the stock market and the infamous bubbles suggest that the conventional models are, if not broken, at least incomplete. Price swings in the post financial crisis era indicate that behavioral finance is more important than ever and that the efficient market is not holding true. Volatility, in the form of weekly price changes of over 18%, has a significant effect on the psyche and especially the risk appetite for investors realizing that either the stocks they had that were increasing in price were either doing so because of a trend mispricing beforehand or that their shares can violently overcorrect to mispriced after a crisis because of the fearful and over-reactive demand shift away from all assets of its kind. Perhaps it is a combination of the two. Stocks can be overvalued in times of bullish sentiment and violently over correct to undervalued states in times of heightened fear and bearish sentiment. At any rate,
this volatility must be priced into the assets now. It stands to reason that in seeking long term profits one would be wise to seek types of stocks that were less affected by these irrational sentiments.

For many years economists have been debating the effect that uninformed investors or “noise traders” have on the prices of financial assets. Black (1986) champions this phrase, noise trading, and suggests it will persist especially in the market for riskier assets like stocks because it helps to provide liquidity. Noise trading is the buying or selling of assets by uninformed investors acting coherently on a non-fundamental signal. Trading only happens when two parties have different information or sentiments on that information. People will sometimes trade on noise as if it were information, thus stock prices reflect information and noise. The trade does not imply market efficiency but rather equilibrium between traders that observe different information and/or have different sentiments. Delong, Shleifer, Summers, Waldmann (1990) (DSSW) hold that investors are subject to sentiment which in this study we consider to summarize our noisy signals. Brown (1999) documents a very important implication that irrational investors acting coherently on a noisy signal can cause systematic risk. Brown (1999) goes on to say that if noise traders affect prices, the noisy signal is sentiment and the risk is volatility, then sentiment should be correlated with volatility. Price pressure related to under- and overreactions (excess volatility) has been proven to lower long-term expected returns.

From Lee, Jiang, and Indro 2002:

In a market environment where noise traders are present, the ‘hold-more effect’ implies that noise traders’ increased holdings of risky assets when their sentiment becomes more bullish raises market risk and thereby increases expected returns; and conversely, when they are bearish. However, noise traders overreact to good and bad news. Consequently, asset prices are either too high or too low depending on whether noise traders are on average optimistic or pessimistic. The overreaction induces ‘price pressure’ and lowers expected returns. Market returns will correlate with changes in investor sentiment and the direction of the
correlation depends on which effect dominates.

In a time when users are connected to instant news at every waking moment, social media dominates the way we do business, and the ability to intake financial information and act upon it is literally at a trader’s fingertips with the increased popularity of the smart phone, I assert that the markets are subject to more information than ever before. Noise trading as it was introduced described mostly uninformed investors but it may now be more accurate to say it describes misinformed investors. Even describing them as misinformed investors might be misleading. Perhaps, it would be better to call them non-fundamental news reactionary traders or sentiment traders. As complexity of a decision increases the reliance on bias or belief also increases. Baker and Wurgler (2007) adeptly defined sentiment as a belief about future cash flows and investment risks that is not justified by the facts at hand.

The equities market, characterized by higher returns and higher risks than many other financial assets, are for various reasons a quintessential area to study volatility as it relates to non-fundamental information or news and sentiment. The equity premium puzzle has long been a point of contention between conventional and behavioral financial thinkers. The risk/return tradeoff is particularly appetizing to investors, both informed and uninformed. The equity market is the most followed by the public whether it is on television, online, print, or other media sources. Investors are likely not only to hear more about these assets, but also to actually do business or commerce with the companies that make up the equity market. It would not be unusual for an investor to carry a bias towards a company because the products of the company affect them. This is a decision making bias in which the decision maker mistakes a good company for a good investment. Various other decision making biases such as price anchoring and herding add to the complexity of behavioral driven volatility in the stock market. The
overwhelmingly human aspect of equities growth and price change is what makes it ideal for analysis in the field of behavioral finance.

Black (1986) alluded to divisions between the individual investor and the institutional investor, the latter being the informed investor and the prior being more susceptible to biases and decisions made on non-fundamental information. Since the equity market is incredibly popular and accessible to individual investors, there will be more noise trading as opposed to commodities, bonds, or foreign exchange. The behavioral concepts that contribute to the number of individual traders in the equity market as oppose to other markets and the behavior of the uninformed individual once in the market will be discussed later.

More so than other markets, the equity market is subject to momentum and speculation. Information traders must now consider technical analysis or risk straying farther from the real value of an asset or risk losing out on profits for themselves or their constituents. Information traders must make a decision taking into consideration the change in price caused by the cohesive movement of traders acting on non-fundamental information, noise. Technical information is often at odds with the fundamental information.

With millions of messages entering a trader’s conscience every day we should not expect a trader to discern all that is fundamental and all that is non-fundamental news. All these messages are like particles of water rushing towards the shore creating waves; everything in the universe, it seems, is ultimately a sine wave! If it is changing, a trigonometric algorithm will describe it. If enough of the aforementioned “messages” move cohesively with positive energy, the asset price will rise before the inevitable gravity induced return to earth. Gravity is a fundamental truth of the earth and thus parallels well with fundamental truths of a financial asset.
Waves are not inherently evil. In fact, much can be gained by an adept surfer or financial speculator.

There is nothing wrong with surfing (speculating). In fact you probably stand to make more money surfing than you do acting on latent fundamental information. However, when surfers (speculators) mess with nature by producing more news and jumping more heavily into positions solely based on momentum expecting an asset to stray even further from its expected return or mean, the waves become unsafe and the return to earth will be violent and put fear into the market. Shiller (2000) might call this momentum away from fundamental value “irrational exuberance.” The speculators become part of the momentum. They fuel sentiment, which fuels volatility.

Volatility we know to be a measure of dispersion of returns of a security based on standard deviation from the mean. Volatility implies risk, which should be priced into the asset. The more risk involved in taking a position in something that has already deviated far from its mean, the fewer people that will be willing and able to take on a position in this momentum driven asset, or in terms of surf, fewer surfers will be willing and able to take on a wave so high. Because of the risk of arbitrage, changes in investor sentiment are not fully countered by arbitrageurs and so affect security returns in meaningful ways for significant amounts of time. This is when we notice that models built on fully rational decision-makers suggesting arbitraging back to efficiency or the CAPM model lack greatly in explanatory power. If security returns are affected by sentiment then it may be wise to research which kinds or sizes of securities are most affected by sentiment and where a trader might want to go to either take advantage of the positive influences of sentiment or hide during times of negative sentiment.
In this study, we look at the variability in the sensitivity of small, medium and large companies’ stock returns to various measures of investor sentiment over the periods before, during and after the financial crisis. We use the appropriate Russell indices for each category. Investing $100,000 in 1997, the Russell Mid-cap Index grows to $287,441 by mid-year 2011, the small cap to $223,568 and the large cap increases to only $180,601. (See Figure 2 in section 2.5) We explore the reasons behind these differences and seek to discover whether noise trading or sentiment-related volatility are significant differentiators between the asset size classes.
II. BACKGROUND AND LITERATURE REVIEW

2.1 Efficient Market Hypothesis vs. Behavioral Finance

Fama’s (1970) efficient market hypothesis (EMH) suggests that at any point in time prices fully reflect all the available information on an asset and the market. According to this formula, no investor would have an advantage in trying to beat the market and efforts to find trends in mispricing would be useless since the returns would follow a random walk. Simply, since all market participants have the same information and all market participants want to maximize wealth, no one will have the opportunity to consistently out-profit others or the market.

Unfortunately for the EMH, there are a number of market anomalies that suggest serious inefficiency. There are some major problems with assuming market efficiency. Market efficiency, even if one could eliminate information asymmetry, wrongly assumes that traders will perceive all the information in a similar way. Just by looking at the multitude of valuation models we know there is a huge possibility for differing valuations using the same news. Additionally, the perception of the information may be changed by the amount of time a market participant has to understand and react to the information and his or her knowledge of the financial markets. A market participant who has university training in finance and is paid to spend time understanding and navigating the market will differ in perceived value of an asset compared to an individual investor trying to make trades in his or her spare time. This is part of the difference between institutional and individual investors that has been discussed at length by Verma and Verma (2008 and 2009). The perception of information is much different than the simple exposure to information. Market efficiency assumes that no single investor is able to consistently earn higher returns than the market or the other market participants. This assumption
eliminates the need for any active managers in the market. Mutual funds would share tightly bracketed profit numbers, which we know is not reality. On the same token, if the efficient market hypothesis is true how could one investor make a career and a fortune from investing? Take for example, Warren Buffet, who has risen to the upper echelon of the wealthiest people in America on a lifetime of sound investing. Yes, other traders had the same information and other institutions too, but they did not perceive and react to it in the same way. The biggest problem with the EMH is that it assumes that perception of information is consistent with exposure to information.

Anomalies are the other important argument against the EMH. The January Effect presented by Ritter (1988) would be an example of a pattern of higher returns expected in the first month of the year when no different information is made available. Some would argue that this can be fully explained by the cyclical dumping of losing assets before the new year for advantageous declarations on the capital gains tax, but the evidence suggests that the new-year trend is present even in countries that have no such tax. The stock market bubbles present another major opposition to efficiency in the market. The sudden volatility would suggest that the pricing was not efficient for an extended period of time. The dotcom bubble would be an example of human bias ignoring the facts as investors jumped into positions thinking that technical trends would continue to outweigh the fundamentals.

Could the efficient market hypothesis make resurgence with the introduction of better technology? This is not likely as technology is a double edged sword. The computer will allow for more automation based on financial statement information for those that can afford it, but it will also allow more access to traders that will act on biases not justified by facts. There will also be more messages and information for the traders to understand with the instantaneous news
cycles, which will cause information uncertainty and in turn longer periods of overreaction. Zhang (2006) explains that greater information uncertainty should produce relatively higher expected returns following good news and relatively lower expected returns following bad news. Adding to this tendency for investors under and overreaction is the myopic loss aversion introduced in Thaler, Tversky, Kahneman and Schwartz (1997). The aforementioned explained that investors displaying myopic loss aversion who received the most frequent feedback and the most information took the least risk and earned the least money in their study. For greater efficiency to be achieved, all of these automated trades would have to operate on the same analysis system and yet they would still need someone to provide liquidity. The possibility of eliminating human bias in investment decision making is really not feasible.

2.2 Support for Behavioral Finance

Since the efficient market hypothesis (EMH) clearly cannot explain the mispricing that leads to major anomalies, a growing number of financial economists have turned to behavioral finance in an attempt to predict human influence on the market. The EMH relies on a certain “homo economicus” (economic man) being a rational wealth maximizer but as Thaler (2000 *From Homo Economicus to Homo Sapiens*) rightly predicts the financial markets are teaching us that homo economicus is really just a homo sapien and often irrational. Using cognitive psychology we can observe what causes the market to move, aside from the earnings of a company.

There are many concepts of behavioral finance that explain the tendency of investors to make irrational decisions. Studies show the following are predictable and empirically evidenced: Kahneman and Tversky (1992 – prospect theory first introduced 1979) explains investors are “loss averse” or distinctly more sensitive to losses than to gains. Essentially, losses have more
emotional impact than equivalent amount of gains. Kahneman and Tversky (1974) shows that investors are subject to anchoring into irrelevant figures and statistics. Thaler (1985) explains that investors are subject to mental accounting. Hirshleifer (2001), and Kahneman and Tversky (1973) claim investors are subject to confirmation and hindsight bias. Hirshleifer (2001) also claims investors are subject to the gambler’s fallacy and investors are overconfident in their ability. Shiller (2000) claims investors are subject to herd behavior and multiple papers including French and Roll (1986) explain that the market is more volatile when the market is open. De Bondt and Thaler (1985) claim investors are subject to overreaction to unexpected and dramatic news.

Olsen (1998) gives an excellent overview of the many facets of behavioral finance. Decision attributes, as Olsen defines, contribute to the following:

- Formally chaotic stock prices (prices imperfectly predictable)
- Excessive stock-price volatility and bubbles in prices
- Follow-the-leader or herding behavior among investors
- Misestimating of the risk of loss
- Selling winning investments too early and selling losing investments to late
- Differing preferences among investors for cash dividends
- Belief in the value of time diversification (that risk diminishes with time)
- Popular investments earning poorer-than-desired returns
- Investors mistaking “good” companies for “good” investments
- Asset prices appearing to over or underreact to new market information
- Individual investors holding poorly diversified portfolios, and
- Superior short-run and inferior long-run performance of initial public offerings.
Note: See also Olsen (1998) Exhibit 1. Decision Behaviors Narrowly Defined for more specificity in decision attributes, which contains a list of 40.

Olsen (1998) digresses, pointing out that behavioral finance offers an explanation for the empirical evidence suggesting that the poor descriptive power of some current financial models stems from the fact that financial asset prices arise from a statistically complex and nonlinear process. Examples are presented that show the “nature” of the decision process and the many opportunities for positive feedback. When purchases are overly complex, decision makers anchor on the price and changes in the price indicate a value proposition for the decider. Decision makers also put more weight on the most recent information, tend to forecast continuance of regressive trends without understanding, overweight consensus beliefs, wish to be included in the herd, and seek confirmation of previous evidence. Stock drops are more severe than upward movements, consistent with the principle of loss aversion.

Barber (2009) analyzed thousands of trades made by individuals at discount and retail brokers and found that they maintained biases, which resulted in systematic buying of stocks of prior high performance and to be net buyers of stocks with very high volume. This systematic movement helps explain some of the relevance of behavioral finance. The risk introduced by the human aspect of the markets is not able to be completely diversified away or eliminated over longer time spans.

The evidence in favor of the irrational investor playing an important role in explaining volatility and value deviation is staggering. Allowing room for behavioral finance will provide creative and complex explanations to the complex mispricing and anomalies. In turn, behavioral finance’s additions to conventional finance will make better investors of those that are aware of
the market’s tendencies to be swayed by the nature of the decisions from its participants, and can make objective decisions for the long-term.

2.3 Noise Trading

Noise trading happens when investors trade on a lack of new information as if it were information. Black (1986) notes that noise trading is the participation in buying or selling of assets by uninformed, misinformed, or somehow biased investors; these traders are acting on a “noisy signal” or a non-fundamental signal. Black set up the basic fundamentals of noise trading and explained how it normally should affect the market. Further studies show that at times noise trading becomes so powerful, that it surpasses even Black’s once considered outlandish framework, and turns out scenarios where trading along with noise traders is most profitable.

Noise, which contrasts with real information, helps to make financial markets liquid (noise and liquidity have a positive relationship) and thus possible, but also imperfect or inefficient. Institutional investors, sometimes referred to as “smart money,” desire individual investors’ presence because the prior demands immediacy for trades which the individuals provide in the form of liquidity. For a trade to take place, a person must have different information than the person on the opposite end of the trade or at least a different interpretation of the same information. There is equilibrium but not efficiency in the markets for trades to exist. Black asserts that differences in beliefs must derive from differences in information. People who trade on noise are willing to trade even though from an objective point of view they would be better off not trading. Black speculates that they think the noise they are trading on is information. Or perhaps they just like to trade.

Black (1986) also noted that with a lot of noise traders in the market, it now pays for those with information to trade because most of the time, noise traders as a group will lose
money by trading while information traders as a group will make money, so as the amount of noise trading increases it will become more profitable for people to trade on information. Black also explains that information traders can never be sure they are not trading on noise because if they are trading on information that is already reflected in the prices, they are now trading on irrelevant information, noise.

Importantly, Black (1986) notes that the cumulative effect of noise traders causes prices to stray farther from their value. The farther the prices get from values, the more aggressive information traders will be and thus it will return to value more quickly. Black tells us that all estimates of value are noisy and thus we can never know exactly how far away a price is from its value. Additionally, it is possible for events that have no fundamental information content to affect price. For example, Shleifer (1986) explains that when a stock is added to the S&P 500 some investors will buy it simply because it is within that index, which will force the price up for a time. Information trading will eventually force it back, but often times this is gradual.

As Black (1986) explains, the short-term volatility of price will be greater than the short term volatility of value because noise is independent of information in this context. When the variance of the percentage move in price caused by noise is equal to the variance of the percentage move in price caused by information, the variance of percentage price moves from day to day will be roughly twice the variance of percentage value moves from day to day. Over longer intervals, the variances will converge because price tends to return to value. Anything that changes the amount or character of noise trading will change the volatility of price. This is fitting with the idea of over-reactive traders most sensitive to the newest news and susceptible to herding.
Because information traders trade with noise traders more than with other information traders, cutting back on noise trading also cuts back on information trading. Thus, prices will not move as much when the market is closed as when the market is open. The relevant period here is the period on which most of the noise traders trade. In fact, French and Roll (1986) suggest that the market is less volatile on closed Wednesdays than on open ones (even when no news releases took place). Brown (1999), in more recent research, concurs that the market is more volatile in open hours than in closed hours.

DeLong, Shleifer, Summers, and Waldmann (DSSW, 1990) and Shleifer and Summers (1990) remark that investors are subject to sentiment. Investors are not fully rational and their demand for risky assets is affected by their beliefs or sentiments that are not fully justified by fundamental news. Baker and Wurgler (2007) hold that “sentiment” is a predisposition concerning future cash flows and investment risks that is not justified by the facts. Brown (1999) shows that as noise traders affect prices, the noisy signal is sentiment and the risk is volatility; sentiment should be correlated with volatility.

Price deviations from fundamental value created by changes in investor sentiments, introduce a systematic risk, which is priced in the market. DSSW (1990) holds that systematic risk reduces the attractiveness of true information traders to carry out arbitrage. Shleifer and Summers (1990) explains that due to this risk, whether it is fundamental or the risk that the momentum carries prices farther from their real value, changes in investor sentiment is not fully countered by arbitrageurs and therefore may affect stock returns.

There are plenty of scenarios where non-fundamental factors can affect prices in a way that rational arbitrageurs can’t fully counter. Ritter (1988) claims the “January Effect” of small stocks traditionally having positive momentum at the beginning of the year, stems from either
risk or borrowing restraints that keep arbitrageurs from eliminating the price consequence of year-end trading. Somewhat contrary to original assumptions that all information traders stand to profit off of noise traders losses, DSSW (1991) finds it can actually pay to be investing along with noise traders as some models have shown that noise traders as a group can earn expected returns higher than rational investors and can survive in wealth gain in the long run, due to the unpredictability in their sentiments. Wang (2001) even says that in an imperfectly competitive market with risk adverse investors, noise traders may earn higher return than rational investors by arguing that bullish sentiments can survive while bearish sentiments cannot survive in the long run. DSSW (1990) asserts that the unpredictability of noise traders deters arbitrageurs so that the majority of traders holding the asset are noise traders bearing a disproportionate risk and subsequently finding a way to earn a higher expected return than rational investors. DSSW claims that this method will shed light on the financial anomalies like the excess volatility of asset prices, the mean reversion of stock returns, the underpricing of closed-end mutual funds, and the equity premium puzzle.

The plethora of financial messages has not created more certain investors, but overwhelmed investors acting on noisy signals. We should observe greater price drift when there is greater information uncertainty. Zhang (2006) supports the argument that with greater information uncertainty, there should be higher expected returns following good news and lower expected returns following bad news. The magnitude is greater on the downside than on the upside following Thaler’s myopic loss aversion.

Noise trading models help to quantify what is not typically considered directly observable. Introducing a measure of irrationality does not mean a model becomes worse; in fact it should offer clarity and allow us to explain the void in things like the equity premium puzzle.
The quantifying of noise trading allows explanation of arbitrage opportunities that were once mystery. Momentum does not have to be considered some “animal spirit” but actually a product of coherent movement by a groups typically influenced by different sentiments and news.

2.4 Sentiment Measures and Equities

2.4.1 Equities relationship with sentiment

DSSW (1990) establishes that investors are subject to sentiment, a belief about future cash flows that is not justified by the facts. Shleifer and Vishny (1997) establish that betting against sentiment traders is costly and risky. Thus, rational arbitrageurs abstain and prices are not aggressively forced down to the true value as an efficient market would suggest.

From Baker and Wurgler (2007):
“Now the question is no longer, as it was a few decades ago, whether investor sentiment affects stock prices, but rather how to measure investor sentiment and quantify its effects.”

The speculation in the dotcom bubble and the more recent real estate and financial crisis has helped to illustrate a belief in growth not justified by any real facts. Most studies find that positive sentiment contemporaneously elevates prices but over a slightly longer horizon, positive sentiment is a contrarian indicator for future returns. Liao, Huang, and Wu (2011) explain that fund managers actually herd to avoid overly optimistic sentiment. Clearly if the fund managers are herding the effects on the equity market are undeniable.

Brown and Cliff (2004) investigate sentiment and its relation to near-term stock market returns. They find that sentiment has little predictive power for near-term future stock returns and also that the evidence does not support conventional wisdom that sentiment primarily affects individual investors and small stocks.
Brown and Cliff (2005) concentrated empirical tests relating sentiment levels directly to stock price deviations from fundamental value and on the long-run effects of sentiment on stock returns. Notably, they chose a direct survey measure of investor sentiment instead of relying on other proxies such as closed-end fund discounts. The relation between long-run market returns and sentiment was appealing to them because sentiment is viewed as a persistent variable. People become more optimistic as their views are reinforced by others joining on the bandwagon. Thus, the importance of sentiment may build over time. Secondly, arbitrage forces are likely to eliminate short-run mispricing but may break down at longer horizons.

Brown and Cliff (2005) also explains that sentiment is positively related to changes in market valuations. High levels of sentiment result in significantly lower returns over the next two or three years. They note that while the effect is present for the aggregate stock market, it is concentrated in large-capitalization growth stocks. Schmeling (2009) shows us that sentiment’s effect on the equity market is not isolated to the United States. Using consumer confidence, the study finds that in 18 industrialized countries high positive sentiment leads to low future returns and vice versa.

The relationship of sentiment with equities is unique because of the amount of individual traders participating in the equity market. Sentiment should affect individuals more as much training is required to overcome the tendencies picked up on in cognitive psychology studies that pertain to finance, and subsequently make objective decisions on purely fundamental information. Additionally, the persistent nature of the variable we call sentiment often creates scenarios where the fundamental and technical analysis are at odds. Even institutional investors have to make decisions to herd towards or away from sentiment knowing full and well that sentiment in the short term can be positively related to price but in the long-term act as a
contrarian indicator. The inevitable reversion creates a scenario in which not all are willing to chase such a risky arbitrage opportunity as it nears a point of reversion. Studies will vary in identifying the time horizon at which these reversions take place, so this study looks to quantify only the price pressure created for the long-term by sentiment related excess volatility.

2.4.2 Types of Measures

There are a myriad of different sentiment measures in existence today. While some researchers have opted for proxies to measure sentiment, such as the put call ratio, others have opted for more direct measures, survey measures. Another distinction between measures is a bottom up approach or a top down approach. Top down refers to macroeconomic proxies, while bottom up refers to beliefs and opinions of decision makers. Measuring sentiment is not always obvious and straightforward. Baker and Wurgler (2007) hold that combining several imperfect proxies would be the most logical way of creating a telling sentiment index. Baker and Wurgler considered a combination of sentiment measures including surveys, mood proxies, retail trading volume, mutual fund flows, premia on dividend-paying stocks, closed end fund discounts, option implied volatility, first day returns on IPOs, volume of IPOs, new equity issues and insider trading, before selecting the ones with the most available data.

Fisher and Statman (2000) suggest that Wall Street strategists’ sentiment is unrelated to individual sentiment or newsletter writers. The latter two are correlated. The research also suggests sentiment is negatively related to future stock returns and statistically significant for the Wall Street strategists and the individuals.

Looking at the behavior of discounts in closed-end-funds governed by the sentiment of noise traders, Brown (1999) uses a direct measure of sentiment called the American Association of Individual Investors (AAII) Sentiment Survey. The AAII direct measure is particularly
interesting to this research because it is relevant to the noise trader theory (they did not ask only financial professionals) and asks survey takers for their expectations of the next six months, a horizon that cannot be accurately predicted on fundamental information alone. It forces the survey taker to give an indication of a belief not backed by solely the facts at hand. The survey measures a randomly selected group of its members about stock market expectations - bear, bull, and neutral – on a weekly basis. For Brown’s 1999 work, he constructed a sentiment index off of these percentages, but noted that using the simpler bull-bear spread (percentage bullish minus percentage bearish) did not change the qualitative results. He also notes that the series was moved back two weeks because of a reporting delay by AAII. Also of note, is that Brown tried various methods of interpolation to make up for the ill-matching frequencies of daily return data with weekly sentiment reports, but found that none significantly affected the results. He simply reports results by setting daily values equal to weekly values.

Brown and Cliff (2005) hold that commonly cited measures of sentiment are related to direct measures (surveys) of investor sentiment. However, past market returns are also an important determinant of sentiment. Brown and Cliff (2005) finds direct measures of investor sentiment prove to be useful for predicting market returns over the next 1-3 years.

Verma and Verma (2007) notes that institutional investor sentiments are more rational than individual investor sentiments. In the same study, there were significant positive effects of, market return and dividend yield and negative effect of inflation on both types of sentiments. These risk factors were more impactful in the institutional sector than in individuals. Verma and Verma also found that the link between sentiment and stock returns comes from a combination of rational information and noise, which are often hard to separate.

From Schmeling, 2006:
Furthermore, institutional investor sentiment and individual sentiment can proxy for smart money and noise trader risk, respectively. Trading strategies based on investor sentiment show tendencies for being profitable after controlling for systematic risk. Institutional investors will do this by taking into account individual investors’ expectation as a noise proxy for risk. Thus, sentiment does matter for stock returns, and there is a significant enough difference between institutional and individual investors that it may be used in trading strategy by institutional investors to quantify levels of noise trader risk…

Still more creative measures are being developed to quantify sentiment. Da Engleberg, Gao (2010) find that between the years 2004-2008 the volume of searches related to household financial concerns prove to be a contrarian indicator for sentiment. The “FEARS” (financial and economic attitudes revealed by search) indicate low returns initially with a reversal to high return in the future. The reversal affect was strongest in stocks that were attractive to noise traders and hard to arbitrage. “FEARS” also predicted excess volatility and high “FEARS” resulted in investors pulling money away from equity mutual funds.

Joseph, Wintoki, Zhang (2011) analyzing our online world, find that online ticker searches (e.g. KO for Coca-Cola Inc.) were a valid and creative proxy for investor sentiment. They find that over a weekly time-frame, search intensity predicts abnormal stock returns and trading volumes. Sensitivity of returns to search intensity is positively related to the difficulty of a stock being arbitraged.

To summarize, there are many types of sentiment measures, but not all can yield robust data, especially given the relative infancy of sentiment related research. Characterizing noise traders is best done by a sentiment measure that reflects opinions and biases of mostly individual traders. This study favors the AAII sentiment survey as most reflective of individual investors’ biases as we are searching for the presence of noise trading that creates volatility related price
pressure on long-term returns. However, we also include more basic proxies of investor sentiment for comparison.

2.5 Asset Classes Differences

Market capitalization is calculated by multiplying share price times the number of shares outstanding. It is useful because looking at share price alone cannot give an accurate measure of a company’s overall value. Classifying companies into different market capitalization categories allows an investor to gauge growth versus risk potential.

Market capitalization also plays an important role in the amount of analyst coverage and interest from large investment banks. Wall Street seems to be focused on a small number of large-cap stocks. Investment banking drives profitability and the biggest profits lie with the biggest deals, thus the biggest companies. Additionally, low volumes of shares on small caps tend to force firms to trade only the most liquid (large-cap) stocks. Mergers and acquisitions have eliminated small regional firms that once supported growth from small-cap to mid-cap. The profitability and liquidity appetites of the biggest investment banks have caused a serious information inequality between the large-caps and other segments of the equity market.

Comparing returns over the long-term, mid-caps have out earned their counterparts substantially for the 5, 10 and longer periods of time. Small-caps have out earned large caps but by less than the difference between mid-caps and large-caps. (See Table 1 and Figure 1)

<table>
<thead>
<tr>
<th>Index Name</th>
<th>01/17/1997 through 07/08/2011</th>
<th>1 Year</th>
<th>3 Years</th>
<th>5 Years</th>
<th>10 Years</th>
<th>Index Style</th>
</tr>
</thead>
<tbody>
<tr>
<td>Russell 1000® Index</td>
<td>6.1</td>
<td>29.54</td>
<td>4.65</td>
<td>3.78</td>
<td>3.7</td>
<td>Large-Cap Indexes</td>
</tr>
<tr>
<td>Russell Midcap® Index</td>
<td>9.38</td>
<td>36.45</td>
<td>7.96</td>
<td>5.98</td>
<td>8.17</td>
<td>Mid-Cap Indexes</td>
</tr>
<tr>
<td>Russell 2000®</td>
<td>7.37</td>
<td>39.11</td>
<td>9.22</td>
<td>5.16</td>
<td>7.24</td>
<td>Small-Cap Indexes</td>
</tr>
</tbody>
</table>

Table 1: Russell Indices Returns over Long-Term

Figure 1: Russell Indices Returns over Long-Term – Bar Chart
Our research has shown that a $100,000 investment beginning in the year 1997 for the Russell Mid-cap Index would have produced $287,441 compared to the Russell 2000 Index resulting in $223,568 and the Russell 1000 Index resulting in $180,601. (See Figure 2) For the long term investor, clearly the mid-cap index has advantageous returns.

Figure 2: Growth of $100,000 Investment over study time series
2.5.1 Large-cap equities

Large-cap equities, blue-chips, are considered to be relatively stable and secure. Large-cap equities are typically proven companies many of which are paying dividends. These companies are typically very well known, such as Exxon, Wal-Mart, IBM, and General Electric. They are the most covered by the media and most searched for on the internet. We use the Russell 1000 Index to represent the large-cap asset class. Typically large-cap equities have a market cap over $10 billion. Some analysts also separate mega-caps from this category. Mega-caps (ex. Exxon) are considered to be over $200 billion in market capitalization. The Russell 1000 Index does not separate large and mega-caps.

The Russell 1000 index measures the performance of the large-cap segment of the U.S. equity universe. It is a subset of the Russell 3000 Index and includes approximately 1000 of the
largest securities based on a combination of their market cap and current index membership. The Russell 1000 represents approximately 92% of the U.S. market. The Russell 1000 Index is constructed to provide a comprehensive and unbiased barometer for the large-cap segment and is completely reconstituted annually to ensure new and growing equities are reflected. (Russell Investments 2011)

The Russell 1000 index plus the Russell 2000 index equals the Russell 3000 Index. The Russell 1000 index has an average market capitalization of $77.622 billion but a median market cap of $4.519 billion. Exxon Mobil Corp, the largest company by market capitalization, is over $357 billion. As is expected, dividend growth is greatest in this index compared to the Russell midcap and Russell 2000. The earnings per share (EPS), portion of profit allocated to each common share, is highest in large caps at 7.26. (See Table 2)

Table 2: Russell 1000 Capitalization Statistics and Fundamental Characteristics

<table>
<thead>
<tr>
<th>Capitalization Statistics</th>
<th>Russell 1000 Index</th>
<th>Fundamental Characteristics</th>
<th>Russell 1000 Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weighted Average Market Cap ($)</td>
<td>77.622</td>
<td>Price/Book</td>
<td>1.89</td>
</tr>
<tr>
<td>Median Market Cap ($)</td>
<td>4.519</td>
<td>Dividend Yield</td>
<td>2.29</td>
</tr>
<tr>
<td>Largest Company by Market Cap ($)</td>
<td>357.782</td>
<td>EPS Growth 5 years</td>
<td>7.26</td>
</tr>
</tbody>
</table>

*Source: Copyright Russell Investments 2011*
2.5.2 Mid-cap equities

Mid-cap stocks typically range from $2 billion to $10 billion in market capitalization. The Mid-cap segment is made up of mostly companies considered to be in their growth phase. They are generally accepted to be more volatile than large-caps. Typically these companies have made it past funding worries and cash concerns and proven themselves to some extent. Since mid-caps are often small-caps that have succeeded they have an easier time obtaining additional financing. This asset class has begun to be accepted as a “sweet spot” between slower growth large-caps and faster growing small-caps. They have the benefit of money raising capabilities similar to the large-caps while maintaining the growth potential of the small-caps. The mid-caps receive much less analyst coverage and media attention. This may benefit them in that institutional investors are the only ones to show favor to mid-caps for a period of time before they become popular. The institutional support is important to their rising stock price. These companies are almost always profitable and have healthy financial attributes. Mid-caps have earned higher returns over the last 30 years than large and small-caps.

For the purposes of this study we use The Russell Midcap Index to represent the mid-cap segment. The Russell Midcap Index measures the performance of the mid-cap segment of the U.S. equity universe. The Russell Midcap Index is a subset of the Russell 1000 Index. It includes approximately 800 of the smallest securities based on a combination of their market cap and current index membership. The Russell Midcap Index represents approximately 31% of the total market capitalization of the Russell 1000 companies. The Russell Midcap Index is constructed to provide a comprehensive and unbiased barometer for the mid-cap segment. The Index is completely reconstituted annually to ensure larger stocks do not distort the performance and characteristics of the true mid-cap opportunity set. (Russell Investments 2011)
The Russell Midcap Index’s average market cap is $7.082 billion and the median market capitalization is $3.566 billion as of September 30, 2011. The largest company by market cap is over $16 billion. Dividend growth in this index of more proven companies is greater than small caps but less than large caps as expected. The EPS in mid-caps is lower than in the Russell 1000 which is intuitive for growth companies looking to take net income and heavily reinvest capital. The EPS is better in comparison to small-caps which indicate as companies become larger and more stable they are able to create additional income without seeking additional equity investments. (See Table 3)

Table 3: Russell Midcap Capitalization Statistics and Fundamental Characteristics

<table>
<thead>
<tr>
<th>Capitalization Statistics</th>
<th>Russell Midcap Index</th>
<th>Fundamental Characteristics</th>
<th>Russell Midcap Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weighted Average Market Cap ($B)</td>
<td>7.082</td>
<td>Price/Book</td>
<td>1.76</td>
</tr>
<tr>
<td>Median Market Cap ($B)</td>
<td>3.566</td>
<td>Dividend Yield</td>
<td>1.88</td>
</tr>
<tr>
<td>Largest Company by Market Cap ($B)</td>
<td>16.683</td>
<td>EPS Growth 5 years</td>
<td>5.81</td>
</tr>
</tbody>
</table>

Source: Copyright Russell Investments 2011

2.5.3 Small-cap equities

Small-caps typically range from $300 million to $2 billion in market capitalization. These companies are usually young companies with high growth potential. This potential for greater capital appreciation is matched by greater risk. Small-caps may still have difficulties obtaining funding, especially in bear markets. While these companies do not always have enough volume to be talked about regularly there are stories to be told of entrepreneurial potential. In times of very high sentiment investors may switch from a large-cap index to a small-cap and skip over the mid-cap class.
For the purposes of this study we use The Russell 2000 Index to represent the small-cap segment. The Russell 2000 Index measures the performance of the small-cap segment of the U.S. equity universe. The Russell 2000 Index is a subset of the Russell 3000 Index representing approximately 10% of the total market capitalization of that index. It includes approximately 2000 of the smallest securities based on a combination of their market cap and current index membership. The Russell 2000 is constructed to provide a comprehensive and unbiased small-cap barometer and is completely reconstituted annually to ensure larger stocks do not distort the performance and characteristics of the true small-cap opportunity set. (Russell Investments 2011)

The Russell 2000 Index’ average market cap is $1.055 billion. The median market cap is only $0.408 billion. The largest company by market cap is $3.286 billion as of September 30, 2011. The dividend growth here is smaller than both the Russell Midcap and the Russell 1000 as expected. The EPS is lowest in small-caps compared to the Russell Midcap and Russell 1000 indicating net income is heavily dependent on the amount of equity investments. This again is intuitive as these companies may still be seeking expansion through additional equity offerings. (See Table 4)

Table 4: Russell 2000 Capitalization Statistics and Fundamental Characteristics

<table>
<thead>
<tr>
<th>Capitalization Statistics</th>
<th>Russell 2000 Index</th>
<th>Fundamental Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weighted Average Market Cap ($B)</td>
<td>1.055</td>
<td>Price/Book</td>
</tr>
<tr>
<td>Median Market Cap ($B)</td>
<td>0.408</td>
<td>Dividend Yield</td>
</tr>
<tr>
<td>Largest Company by Market Cap ($B)</td>
<td>3.286</td>
<td>EPS Growth 5 years</td>
</tr>
</tbody>
</table>

*Source: Copyright Russell Investments 2011*
III. RESEARCH QUESTIONS AND HYPOTHESES

3.1 Questions

Prior research finds that mid-caps are less volatile and return more upside than their small and large cap counterparts. Could this be attributable to noise trader theory or sentiment related volatility? The noise trader theory has been suggested to hold true in other studies of specific asset classes, but further research is warranted on the differing effects on differing size of asset classes. It may be that noise trader theory has become more important than in past studies. Is there any empirical evidence supporting this? Specifically, the research seeks to find the variability in the sensitivity of small, medium and large companies’ stock returns to various measures of investor sentiment over the periods before during and after the financial crisis. Additionally what are the best measures of sentiment? Should a direct survey measure or a proxy be used? If direct measure, who is asked? If a proxy, which measure is the most telling proxy? We examine what the relationship is between volatility of these asset classes and the presence of noise traders acting on sentiment and discuss the possibility of using the results in a trading strategy.

3.2 Hypotheses

The noise trader theory has been suggested to hold true in many studies of specific asset classes. This research tests an extension of those studies.

Hypothesis 1: The noise trader is not a significant contributor to returns differences across asset classes; perceived arbitrage opportunities are no different for small, mid-size, and large assets.
Hypothesis 2: Direct surveyed sentiment measures (the bull-bear spread in the AAII sentiment survey) are not more statistically powerful descriptors of returns of small, mid-size and large assets than are indirect measures like the put call ratio and the VIX.
IV. DATA AND METHODOLOGY

4.1 Definition of Key Terms

The following definitions are from Bloomberg, while the AAII Bull-Bear Spread is from the AAII website.

RIY – Russell 1000 Index

The Russell 1000 Index consists of the largest 1000 companies in the Russell 3000 Index. This index represents the universe of large capitalization stocks from which most active money managers typically select. The index was developed with a base value of 130.00 as of December 31, 1986.

RMC – Russell Midcap Index

The Russell Midcap Index measures the performance of the 800 smallest companies in the Russell 1000 Index, which represent approximately 25% of the total market capitalization of the Russell 1000 Index.

RTY – Russell 2000 Index

The Russell 2000 Index is comprised of the smallest 2000 companies in the Russell 3000 Index, representing approximately 8% of the Russell 3000 total market capitalization. The index was developed with a base value of 134.00 as of December 31, 1986.

PCUSEQTR – Chicago Board Options Exchange Equity Options Put/Call Ratio

Chicago Board Options Exchange Equity Options Put/Call Ratio comprises only equity options. The CBOE equity options put/call ratio is the ratio between the total volume of equity put options over call options, as reported at the end of the day.

GOLDS Comdty – Gold Spot $/OZ

The gold spot price is quoted as US dollars per Troy Ounce.
VIX – Chicago Board Options Exchange SPX Volatility Index

The Chicago Board Options Exchange Volatility Index reflects a market estimate of future volatility, based on the weighted average of the implied volatilities for a wide range of strikes. 1st and 2nd month expirations are used until 8 days from expiration, then the 2nd and 3rd are used.

SPX – S&P 500 Index

Standard and Poor’s 500 Index is a capitalization-weighted index of 500 stocks. The index is designed to measure performance of the broad domestic economy through changes in the aggregate market value of 500 stocks representing all major industries. The index was developed with a base level of 10 for the 1941-43 base period.

AAII Bull-Bear Spread – American Association of Individual Investors

The AAII Investor Sentiment Survey (source: http://www.aaii.com/sentimentsurvey) measures the percentage of individual investors who are bullish, bearish, and neutral on the stock market for the next six months; individuals are polled from the ranks of the AAII membership on a weekly basis. Only one vote per member is accepted in each weekly voting period.

4.2 Methodology

The weekly percent change for each of the various indices and variables were gathered from the Bloomberg database from the years 1997 to 2011. Three multiple regression models were calculated using excel, one for each of the Russell indices. Each model contained the same four variables; the American Association of Individual Investors Sentiment Survey bull bear spread, Chicago Board Options Exchange Equity Options Put/Call Ratio, Gold Spot $/OZ, and the Chicago Board Options Exchange SPX Volatility Index (VIX).

The regression analysis allows for multiple variables to be evaluated in the same context, while not contaminating each other. Regression analysis examines what change in the dependent
variable (each of the Russell Indices) is determined or described by each of the independent variables (our sentiment measures). The three models follow.

With the first model:

\[
\text{Weekly } \% \triangle \text{ Russell } 1000_i = \beta_0 + \beta_1 (\text{Weekly } \% \triangle \text{ Put/Call}_i) + \beta_2 (\text{Weekly } \% \triangle \text{ AAII BB Spread}_i) + \beta_3 (\text{Weekly } \% \triangle \text{ Gold}_i) + \beta_4 (\text{Weekly } \% \triangle \text{ VIX}_i) + e_i
\]

This means that the weekly percent change in the Russell 1000 model is a function of the weekly change in the put/call ratio, the weekly change in the AAII BB spread, the weekly change in gold prices and the weekly change in the VIX. The first and last terms in the model are of course simply the intercept and the error term.

With this first model, we find that: Weekly \( \% \Delta \text{ Russell } 1000 = 0.25132 -0.03921 \) (Weekly \( \% \Delta \text{ Put/Call} \) + 0.02624 (Weekly \( \% \Delta \text{ AAII BB Spread} \) – 0.00164 (Weekly \( \% \Delta \text{ Gold} \) + 0.00666 (Weekly \( \% \Delta \text{ VIX} \) In other words, the gold and VIX factors are not significant with this first model. The put/call ratio and the AAII BB spread factors are highly significant in all three models.

Model two shows that, the dependent variable is the weekly \( \% \Delta \) in the Russell Midcap. With this second model, we find that: Weekly \( \% \Delta \text{ Russell Midcap} = 0.25694 + 0.00963 \) (Weekly \( \% \Delta \text{ Put/Call} \) + 0.02096 (Weekly \( \% \Delta \text{ AAII BB Spread} \) + 0.01818 (Weekly \( \% \Delta \text{ Gold} \) – 0.14596 (Weekly \( \% \Delta \text{ VIX} \) Model two shows that only the gold factor is insignificant. The Put-Call ratio, Bull Bear Spread, and VIX are statistically significant.

With the third model, the dependent variable is the weekly \( \% \Delta \) in the Russell 2000. With this third model, we find that: Weekly \( \% \Delta \text{ Russell } 2000 = 0.2252 -0.0109 \) (Weekly \( \% \Delta \text{ Put/Call} \) + 0.0283 (Weekly \( \% \Delta \text{ AAII BB Spread} \) – 0.0568 (Weekly \( \% \Delta \text{ Gold} \) – 0.1555
(Weekly % Δ VIX) As with the second model, only the gold factor is insignificant in the third model. The Put-Call ratio, Bull Bear Spread, and VIX are statistically significant.

4.3 Characterizing Sample Data

The descriptive statistics for the variables of intent are given in Table 5.

<table>
<thead>
<tr>
<th></th>
<th>LARGE</th>
<th>MID</th>
<th>SMALL</th>
<th>PUT CALL</th>
<th>AAII BB Spread</th>
<th>GOLD</th>
<th>VIX</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.11427</td>
<td>0.18283</td>
<td>0.15985</td>
<td>3.60720</td>
<td>-0.00892</td>
<td>0.22398</td>
<td>0.75382</td>
</tr>
<tr>
<td>Standard Error</td>
<td>0.09723</td>
<td>0.10617</td>
<td>0.11828</td>
<td>1.02290</td>
<td>0.576926</td>
<td>0.08877</td>
<td>0.45864</td>
</tr>
<tr>
<td>Median</td>
<td>0.17</td>
<td>0.35</td>
<td>0.37</td>
<td>1.64</td>
<td>0.015</td>
<td>0.28</td>
<td>-0.42</td>
</tr>
<tr>
<td>Mode</td>
<td>-0.97</td>
<td>0.89</td>
<td>0.38</td>
<td>0</td>
<td>11</td>
<td>-0.9</td>
<td>-9.43</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>2.67352</td>
<td>2.91920</td>
<td>3.25217</td>
<td>28.1251</td>
<td>15.86286</td>
<td>2.44087</td>
<td>12.6106</td>
</tr>
<tr>
<td>Sample Variance</td>
<td>7.14773</td>
<td>8.52178</td>
<td>10.5766</td>
<td>791.025</td>
<td>251.6303</td>
<td>5.95786</td>
<td>159.029</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>4.91087</td>
<td>5.82465</td>
<td>3.56855</td>
<td>5.86272</td>
<td>0.537743</td>
<td>3.71669</td>
<td>5.17587</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.47467</td>
<td>-0.53252</td>
<td>-0.41569</td>
<td>1.39377</td>
<td>0.024814</td>
<td>0.30724</td>
<td>1.29321</td>
</tr>
<tr>
<td>Range</td>
<td>30.74</td>
<td>34.71</td>
<td>32.82</td>
<td>283.48</td>
<td>110.55</td>
<td>23.3</td>
<td>116.62</td>
</tr>
<tr>
<td>Minimum</td>
<td>-18.22</td>
<td>-18.64</td>
<td>-16.44</td>
<td>-72.02</td>
<td>-56.97</td>
<td>-8.32</td>
<td>-30.91</td>
</tr>
<tr>
<td>Maximum</td>
<td>12.52</td>
<td>16.07</td>
<td>16.38</td>
<td>211.46</td>
<td>53.58</td>
<td>14.98</td>
<td>85.71</td>
</tr>
<tr>
<td>Sum</td>
<td>86.39</td>
<td>138.22</td>
<td>120.85</td>
<td>2727.05</td>
<td>-6.75</td>
<td>169.33</td>
<td>569.89</td>
</tr>
<tr>
<td>Count</td>
<td>756</td>
<td>756</td>
<td>756</td>
<td>756</td>
<td>756</td>
<td>756</td>
<td>756</td>
</tr>
</tbody>
</table>

The regression analysis employed 756 observations per variable. Weekly data was collected in order to match the sentiment survey posting dates, which occur only weekly. The data was collected back into 1997 because of the availability of data from the CBOE, which calculates the VIX and the Put/Call Ratio.

The standard deviation of the three indices increases as market capitalization decreases. However, the mean weekly percent change is highest in mid-caps, second highest in small-caps
and lowest in large-caps. Additionally, the mean change in all indices was positive while the mean change for the put-call was overall positive (increasingly bearish) and the mean change for the AAII Bull-Bear Spread was negative (increasingly bearish) which fits with cognitive psychology research showing that traders are more sensitive to losses and negative news than they are to the same amount of positive gain or news. The minimum and maximum of the put-call and the AAII Bull-Bear Spread also fit within this assumed nature of trader sensitivity. To sum up, negative changes are worse in our statistically significant variables.

The correlation matrix is provided in table 6.

### Table 6: Correlation Matrix

<table>
<thead>
<tr>
<th></th>
<th>LARGE</th>
<th>MID</th>
<th>SMALL</th>
<th>PUT CALL RATIO</th>
<th>AAII BB Spread</th>
<th>GOLD</th>
<th>VIX</th>
</tr>
</thead>
<tbody>
<tr>
<td>LARGE</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MID</td>
<td>0.96027</td>
<td>1</td>
<td></td>
<td>-0.41055</td>
<td>-0.19287315</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>SMALL</td>
<td>0.88293</td>
<td>0.94804</td>
<td>1</td>
<td>-0.38140</td>
<td>-0.37335</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>PUT CALL RATIO</td>
<td>-0.41055</td>
<td>-0.38140</td>
<td>-0.37335</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AAII BB Spread</td>
<td>0.26671</td>
<td>0.25904</td>
<td>0.27475</td>
<td>-0.19287315</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GOLD</td>
<td>0.00233</td>
<td>0.03436</td>
<td>0.06165</td>
<td>0.002296897</td>
<td>0.02367607</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>VIX</td>
<td>-0.71496</td>
<td>-0.68672</td>
<td>-0.64960</td>
<td>0.371436569</td>
<td>-0.21732134</td>
<td>-0.01897</td>
<td>1</td>
</tr>
</tbody>
</table>

The table shows that the mid and small caps weekly change are correlated with the large caps and each other to a large extent. This is intuitive, as the entire equity universe would share some market moves as demand for risky assets shifts into and out of the market. Simply, when investors are extremely risk adverse and bear market condition are forecast, investors will under allocate equity holdings in favor of less risky assets such as bonds. It is important to note that mid-caps correlate with large-caps 8 percentage points more than small-caps. Small-caps also correlate highly with mid-caps.

Gold does not seem to correlate with any of the indices or the other exogenous variables. The VIX proved to be the most heavily correlated variable with the indices, holding a strong
negative relationship with all three. VIX and put call have a positive relationship with each other in that they both have inverse relationships with the indices. The VIX was correlated with the large, mid and small cap indices at the -0.7149, the -0.6867 and the 0.6496 levels respectively; these numbers descend in correlation from large to small. The put call ratio correlated with the large, mid and small cap indices at the -0.41055, the -0.3814 and the 0.37335 levels respectively; these numbers also descend in correlation from large to small.

Interestingly enough, the AAII sentiment survey’s bull bear spread was correlated highest with small-caps at 0.27475 and second highest with large-caps at .26671. The mid-caps were the least correlated with individual investor sentiment confirming initial thoughts that there was less influence of sentiment traders or noise traders in the mid-cap market.

4.4 Large Caps

In the large cap model (see Table 7), we find that the weekly percent change in put call ratio is negatively correlated with weekly percent change in the Russell 1000 and this finding is significant at a 99% level. We also find that weekly percent change in the AAII Sentiment Index is positively correlated with weekly percent change in the Russell 1000 at 99% significance. The percent change in gold was not statistically meaningful in explaining weekly percent change in the Russell 1000. The VIX measure for the market’s expectation of volatility in the next 30 days was not statistically meaningful in explaining weekly percent change in the Russell 1000.

The signs for both the put-call and the VIX are different from the other two models. The put-call, being the only statistically significant variable is worth contemplating. The negative sign means that as put-call ratio decreases, the index increases. This confirms the idea that in short term increasing the volume of puts compared to calls is a bearish move and should decrease returns.
4.5 Mid-Caps

In the mid-cap model (see Table 8), we find that the weekly percent change in put call ratio is positively correlated with weekly percent change in the Russell Mid-cap Index at 99% significance. A high volume of puts compared to calls is a bearish indicator. This means that as volume of puts increases compared to calls, the mid-cap, surprisingly, does not negatively react in the near term. This is important in that a statistically significant proxy measure for sentiment becoming more bearish does not negatively affect returns of the Russell Midcap. The opposite is true of the Russell 1000 Index discussed beforehand.

We also find that weekly percent change in the AAII Sentiment Index positively impacts the weekly percent change in the Russell Mid-cap Index at a 99% significance level. This positive correlation was more highly correlated than the put call ratio as the coefficient multiplier was found to be 0.0209 compared to the put call at 0.0096. The coefficients for the AAII bull-bear spread decreased from 0.0262 in the large-cap regression to 0.02096 in the mid-cap regression. The coefficient increases again in the small-caps. General expectations that sentiment related volatility increases as market capitalization decreases do not hold. My original suspicion that mid-caps are less affected by individual investor sentiment or noise trading is confirmed by
this regression. Percent change in gold was again not statistically significant and even became less significant than in the large cap data regression.

The weekly percent change in the VIX measure for the market’s expectation of volatility in the next 30 days was negatively correlated with weekly percent change in the Russell Mid-cap Index and was found to be statistically significant at the 99% level. The coefficient multiplier was highest in this variable at -0.1495. This negative relationship indicates that as volatility decreases returns in mid-caps increase which is what is expected. With less volatility the equity market is usually better off and this holds true in the Russell Midcap Index.

| Table 8: Russell Midcap Regression Analysis Results |
|---------------|----------------|----------------|
| Intercept - Russell Mid-Cap               | 0.256945611 | 3.338437448 | 0.000884045 |
| PUT CALL                                           | 0.009629571 | 3.516618585 | 0.000463333 |
| AAII BB Spread (lagged one extra week)          | 0.020957886 | 4.277090024 | 2.13799E-05  |
| GOLD                                               | 0.018183436 | 0.584381925 | 0.559138883  |
| VIX                                                | -0.14957425 | -23.9544720 | 1.19731E-94   |

4.6 Small Caps

In the small-cap model (see Table 9), we find that the weekly percent change in put call ratio is positively related to weekly percent change in the Russell 2000 at a 99% significance level. This means that as volume of puts increases compared to calls, the small caps, do not negatively react in the near term. This is important because, like the Russell Midcap Index, a statistically significant proxy measure for sentiment becoming more bearish does not negatively affect returns of the Russell 2000 Index. The opposite is true of the Russell 1000 Index discussed beforehand.

Weekly percent change in the AAII Sentiment Index was again statistically significant at a 99% level and positively correlated with weekly percent change in the Russell 1000. We did
see the coefficient multiplier increase from .0209 in mid-cap to 0.0283 in the small-cap data. Gold’s weekly percent change was not statistically significant in describing weekly percent change in the Russell 1000.

The weekly percent change in the VIX measure was as expected, negatively correlated with the weekly percent change in the Russell 1000 at the 99% significance level. The coefficient multiplier was the largest in any of the data sets at -.1555.

Table 9: Russell 2000 Regression Analysis Results

<table>
<thead>
<tr>
<th></th>
<th>Coefficients</th>
<th>t Stat</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept - Russell 2000 (Small)</td>
<td>0.22525514</td>
<td>2.525822389</td>
<td>0.011747345</td>
</tr>
<tr>
<td>PUT CALL</td>
<td>0.010899701</td>
<td>3.435254974</td>
<td>0.000624519</td>
</tr>
<tr>
<td>AAII BB Spread (lagged one extra week)</td>
<td>0.028346474</td>
<td>4.99259132</td>
<td>7.41183E-07</td>
</tr>
<tr>
<td>GOLD</td>
<td>0.05685217</td>
<td>1.576862838</td>
<td>0.115248204</td>
</tr>
<tr>
<td>VIX</td>
<td>-0.15549682</td>
<td>-21.4920259</td>
<td>3.14938E-80</td>
</tr>
</tbody>
</table>
V. CONCLUSION

To begin this section, a reminder of our testable hypotheses is in order. These hypotheses are: Hypothesis 1: The noise trader is not a significant contributor to returns differences across asset classes; perceived arbitrage opportunities are no different for small, mid-size, and large assets. Hypothesis 2: Direct surveyed sentiment measures (the bull-bear spread in the AAII sentiment survey) are not more statistically powerful descriptors of returns of small, mid-size and large assets than are indirect measures like the put call ratio and the VIX.

We reject the (null) Hypothesis 1 and find that sentiment measures are statistically significant in predicting a portion of change in each asset class. While the VIX and Gold did not hold in all three regression models, the Put-Call Ratio and the AAII Bull-bear Spread did hold in all three models and yielded interesting results that confirmed that the difference in arbitrage opportunities in recent years is in part due to differences in sensitivity to investor sentiment. The mid-caps provided the best returns and were less affected by changes in sentiment than the other two asset classes. This implies that the absence of sentiment or noise traders alleviated some of the price pressure or implied risk that is associated with sensitivity to sentiment.

We do not reject Hypothesis 2. The direct survey measure was the only sentiment measure that held in all three models and did not change signs in its coefficient (the put-call ratio although statistically significant changed signs in the large-cap model compared to the other two models). While the coefficient was small it was statistically significant at high levels of accuracy. The measure was most useful in describing mid-cap stocks. Conventional wisdom would expect sentiment related volatility to increase as market capitalization decreased. The unconventional
theory that individual investors’ sentiment affects mid-caps the least was most accurately described by the direct survey measure of individual investors.

The VIX was the most powerful descriptor of weekly change in mid and small cap stocks but lost significance in the large cap model. Aside from the VIX strength in those two regressions, we would have to say that the AAII bull bear spread was the most statistically powerful descriptor of returns of small, mid-size and large assets.

While sentiment is not necessarily a perfect model for predicting near term returns, its effects on the volatility of a stock describe the price pressure or implied systematic risk that must be accounted for in long term returns. Finding that an asset class with less attention from the media and Wall Street analysts provides less sensitivity to sentiment is particularly useful for long-term investors. Mid-caps are the asset class least affected by individual investor sentiment and thus can sustain higher long-term earnings.
VI. FURTHER RESEARCH

This study could benefit from increased number of sentiment measures that might be able to form a combined index that best represents noise in an asset class. This study could also benefit from additional models looking at additional asset classes.

A more in-depth look is warranted at the media’s impact over time on the amount that noise traders impact the market and the importance of sentiment in describing that impact. Has sentiment become more important with the advent of cable television shows about finance, or the internet, or online trading platforms, or even the smartphone? In researching I found that returns for all classes followed a similar track until 2002 when the Russell Midcap index separated greatly from the Russell 1000 and Russell 2000.

It may be useful for managers of smaller firms to measure and improve their company-specific sentiment. It would be interesting to discover the role played by sentiment for small firms in general, and for specific industries or firms in particular.
REFERENCES


ADDITIONAL SOURCES

**Bloomberg Terminal**

http://www.bloomberg.com/professional/hardware/

**AAII Investor Sentiment Survey**

http://www.aaii.com/sentimentsurvey

**Russell Investments**


**Investopedia.com**

http://www.investopedia.com/