5-14-2010

Studying How Changes in Consumer Sentiment Impact the Stock Markets and the Housing Markets

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Studying How Changes in Consumer Sentiment Impact the Stock Markets and the Housing Markets

A Dissertation

Submitted to the Graduate Faculty of the
University of New Orleans
in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy
in
Financial Economics

by

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May, 2010

Dedication

This dissertation is dedicated to my parents. They encouraged me to embark on this journey and I will always be grateful for their love, support, guidance, sacrifices and prayers. To my brothers, Paul and Eric Jr., and to my sister, Wendy, I am also extremely grateful for your encouragement throughout all of my years in college. And to my grandparents, I am forever appreciative for your constant prayers.

Acknowledgements

I am extremely grateful to many individuals for helping me through my doctoral studies at the University of New Orleans. I am privileged to have studied under my dissertation chair, Professor Atsuyuki Naka, for the past few years. I will never forget that it was Professor Naka who served as the Graduate Coordinator of our Financial Economics graduate program and was instrumental in helping me gain admittance into the program. I thank him for his knowledge, advice, time and patience as I developed as a student under his supervision.

While at the University of New Orleans, I was able to take classes with many outstanding faculty members. In particular, the guidance of Professor Tarun Mukherjee, Professor Atsuyuki Naka, Professor Arja Turunen-Red, Professor Wei Wang and Professor Gerald Whitney has been extremely helpful. These faculty members have taught me as a student in their classes, assisted me with my dissertation development and have been very supportive of my research. I am extremely appreciative for their suggestions, comments and commitment to my learning. I also thank Professor Mukherjee and Professor Whitney for allowing me to work with them as the Editorial Assistant for the *Review of Financial Economics*.

I have benefited a great deal from the friendship of a graduate of our doctoral program, Naseem Al Rahahleh. Naseem, I thank you for your support as I entered the difficult stages of our program. Also, I thank all of the other faculty and staff in the College of Business Administration for their fellowship and encouragement. In particular, Liane Carboni, Professor Yvette Green, Professor M. Kabir Hassan, Russell Holliday, Mohammed Hossain, Professor Sudha Krishnaswami, Professor Walter Lane, Dean James Logan, Napoleon Ortiz, Ashley Merheb, Martha Said, Professor Peihwang Wei and Professor Kim Williams.

And to my family and friends, I cannot express enough appreciation for all that you have done for me.

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Abstract

Consumer sentiment has the ability to provide researchers with many avenues to test existing Finance and Economic theories. Chapter 1 introduces the issues that I seek to explore within the area of Behavioral Finance. Chapter 2 utilizes thirty years of consumer sentiment data to explore extant economic theories and hypotheses. In particular, I study the Prospect Theory and the Life Cycle Investment Hypothesis. In addition, I also study how changes in consumer sentiment can foretell future stock returns for firms in different industries and of different sizes.

By studying how individuals of different ages display optimism and pessimism through consumer sentiment surveys, I am able to contribute to the literature by shedding additional light on just how the important age is with respect to a person's economic outlook. One particular phenomenon that I discuss in this chapter is downside risk. I will provide further support to the existing literature which shows that gains and losses are not viewed equally by individuals. To account for this discrepancy, this paper models the time series relationship between consumer sentiment and stock returns using asymmetric response models.

Chapter 3 builds upon the previous chapter's findings by using consumer sentiment to explore if this index can forecast housing market variables such as changes in home sales and home prices. Given the recent financial market turmoil that stemmed from the U.S. housing market debacle, this chapter is timely. Using widely cited housing indices, I explore regional differences in the U.S. housing market and how the sentiment of local consumers can possibly affect their housing markets. I also include analyses in which the age of the consumer is accounted for to see if evidence of the Life Cycle Investment Hypothesis emerges. This theory postulates that younger individuals are more likely to demand housing as a financial asset and if this were true, I hypothesize that changes in younger individuals' sentiment would have more forecasting power with respect to future housing sales and price changes. Lastly, I conclude this dissertation with Chapter 4 which includes additional discussions of the issues studied.

Keywords: Behavioral Finance, Consumer Sentiment, Asymmetric Response Modeling, Downside Risk, Housing Market, Home Sales, Home Prices

Chapter 1

1. Introduction

The first essay of this dissertation is presented in Chapter 2. It examines changes in consumer sentiment how these changes in individuals' optimism and pessimism can aid in forecasting future stock returns. Consumer sentiment is regularly maintained and monitored. At the beginning of the month, this monthly figure is released as a way for traders and market participants to take the pulse of the U.S. consumer. And with behavioral studies being presented and published more and more, the acceptance and acknowledgement for this somewhat new discipline as a possible alternative explanation for market occurrences is becoming more common.

What makes this essay's contribution different from prior sentiment studies is the rich consumer sentiment data that is partitioned based on the survey-respondents' age. The existing literature that looks at this sentiment variable cannot and does not account for differences in age with respect to the outlook of that respondent (e.g., investor respondents or consumer respondents). My study provides a thorough investigation of just how important this sentiment variable can be when discussing how changes in consumer sentiment have the potential to be able to forecast stock returns of firms in different industries and of different sizes. Additionally, I seek to investigate how the sentiment of different age groups appears in the risk characteristics of individuals. Using changes in consumer sentiment, do different age groups display similar downside risk attributes? This question is one of the central themes of this study. I also include changes in consumer sentiment into the context of asset pricing to see if sentiment has the ability to forecast future stock returns when it is combined with other well known asset pricing variables such as the Fama-French factors.

The results of this essay are interesting and show the economical and statistical significance of consumer sentiment's ability to foretell stock market activity. First, I find that consumers show evidence of exhibiting positive risk premiums which implies that negative changes in consumer sentiment in the previous period translate into higher forecasted returns in the next period. This is consistent with the presence of downside risk and the higher the downside risk, the higher next period's stock returns are.

Downside risk also shows to be more important to consumers than upside gains when forecasting next period's stock returns. Second, when using macroeconomic variables to distinguish between sentiment based on economic conditions and sentiment not based on economic conditions, I employ a regression in which the residual of the model represents the component of consumer sentiment that is unwarranted by economic fundamentals. Similar to Lemmon and Portniaguina (2006), I find this residual to be statistically significant for my entire sample period, which is consistent with their findings and also provides additional support for consumer sentiment's predicting power with respect to stock returns. Third, I modify the Fama-French three factor model and the asset pricing model of Ho and Hung (2009) and show that when included as an asset pricing factor, sentiment exhibits statistical significance. Lastly, I study how changes in consumer sentiment can impact firms of different sizes and industries.

The second essay of this dissertation is presented in Chapter 3. It employs consumer sentiment but instead of studying relationships within the stock market, I transition to investigating the housing market. Along similar lines, I set forth to study changes in sentiment and how this impacts the housing market. One of the methodological contributions this study makes is that I match regional housing data (home sales and home prices) to regional sentiment. The consumer sentiment index that is utilized throughout my dissertation is available partitioned by ages and regions. My research question is: Accounting for the city-specific attributes that local housing markets inherently possess, do local surveys of sentiment identify and explain future changes in that particular region? In addition, I explore age differences amongst the survey participants and ultimately I am able to test the Life Cycle Investment Hypothesis which specifies that certain age groups will demand certain financial assets based on their stage in life. I utilize various econometric specifications such as panel data regressions and vector autoregressions in addition to simple linear regression. I conclude this dissertation with Chapter 4 which presents further discussions pertaining to the results offered.

Chapter 2

Changes in Consumer Sentiment and Stock Returns - Does Age Matter?

1. Introduction

Sentiment, as it relates to economic and financial decisions, has come to represent a representative agent's pessimism or optimism regarding current and/or future economic conditions. Behavioral aspects such as beliefs or outlooks by these same agents have been disregarded for years in favor of market efficiency and rational expectations arguments. As Baker and Wurgler (2006) state, "classical finance theory leaves no role for investor sentiment." Despite market efficiency theories and rational agent arguments, Baker and Wurgler (2006) and others have found that sentiment, investor sentiment and consumer sentiment, have explanatory power with respect to asset returns and macroeconomic variables.

It is important though to discern the differences between investor sentiment and consumer sentiment. Both groups, investors and consumers, have expectations. Investors' expectations come into existence via the stock market. Optimism in the stock market can lead to an increasing stock market (i.e., a bull market) whereas investor pessimism can lead to a declining stock market (i.e., a bear market). These market movements come about through the buying and selling of stocks to reflect the corresponding sentiment at the time. On the other hand, consumers' expectations typically come into existence in the form consumption and saving; optimistic consumers can result in higher aggregate consumption and lower savings for consumers, whereas more pessimistic consumers can result in the opposite (lower aggregate consumption and higher savings). Much sentiment research has focused on how to measure investor sentiment and its interaction with the stock market (e.g., Fisher and Statman (2000), Qiu and Welch (2005) and Baker and Wurgler (2006)). Furthermore, investor sentiment has been approximated using many gauges but some of the more popular methods of capturing this variable are via proxies such as the put-call ratio, the net cash flow into mutual funds, Barron's Confidence Index and the VIX-Investor Fear index.

Consumer sentiment data, unlike investor sentiment data, is tracked and made available to include the age of the survey respondent. This is an important aspect about sentiment research that has yet to have been fully investigated is how the age of the person impacts their outlook. One advantage of the consumer sentiment data used in this underlying study is that the sentiment of the economic agents in question is divided into age groups. This is an important advancement in my study in that prior investor sentiment literature has not yet incorporated the age of the survey respondent into econometric models. Also, prior literature has primarily focused on investor sentiment. Baker and Wurgler (2006) study cross-sectional differences of stock returns and how investor sentiment can influence returns. They find that investor sentiment has a larger effect on hard-to-price securities such as small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks growth stocks and distressed stocks. Baker and Wurgler (2006) also create their own investor sentiment index based on the following six variables – the closed-end fund discount (the discount between net asset value of closed-end stock fund shares and their market prices), NYSE share turnover (ratio of reported share volume to average shares listed), the number of initial public offerings (IPOs), the average first day return of IPOs, the dividend premium (log difference of the average market-to-book ratios of payers and nonpayers) and the equity share in new issues (comparison of proportion of equity and debt in new issues). Baker and Wurgler (2007) ponder the idea of viewing sentiment "as simply optimism or pessimism about stocks in general."

More recently, consumer sentiment has been studied in relation to asset pricing and stock returns as investor sentiment. Many previous studies have identified that consumer sentiment has explanatory power for predicting changes in macroeconomic contexts such as current household spending, GDP and consumption growth.[1] Some studies have examined consumer sentiment in conjunction with asset pricing and stock returns. Fisher and Statman (2003) find that consumer sentiment moves in tandem with stock returns. When looking at the types of stocks individual investors are more likely to invest in, Lemmon and Portniaguina (2006) find that consumer sentiment has forecasting power in relation to the returns on

[1] See Carroll, Fuhrer, and Wilcox (1994), Acemoglu and Scott (1994), Matsusaka and Sbordone (1995) and Souleles (2004).

small stocks (stocks more likely to be held by individuals). And when studied in the context of asset pricing models, Ho and Hung (2009) find that sentiment plays an important role in conditional asset-pricing for capturing anomalies such as the value, liquidity and momentum effects.[2]

Consumer sentiment has the ability to provide researchers with many avenues to test behavioral economic theories. This is possible because consumer sentiment surveys ask individuals how they feel about their current economic situation and how they perceive their future economic situation to be. By having data from individuals regarding their feelings and perceptions, this type of behavioral data can be incorporated into econometric modeling to test for statistical and economic significance in relation to variables such as stock returns, inflation, consumer spending and many others. Using consumer sentiment data that is partitioned by age groups, I seek to explore the relationship between consumer sentiment and stock returns to test the prospect theory (Kahneman and Tversky (1979)) and the life cycle investment hypothesis (Modigliani and Brumberg (1954), Modigliani (1986)). Each of these economic theories has the ability to be explored with the help of behavioral economics; thus providing interesting insights regarding how sentiment varies amongst individuals of different ages. To date, the prospect theory and the life cycle investment hypothesis have not been investigated using consumer sentiment data, making for an interesting econometric examination.

This research shows how consumer sentiment across different age groups impacts capital markets. This different generational investigation allows this paper's results to contribute to the literature in many ways. Research has shown that an aging population results in higher average risk aversion and subsequently, higher risk premiums. An implication of this is that older individuals are more risk averse than younger individuals. This paper is able to investigate results such as these while at the same time testing for homogenous sentiment (or beliefs). If different age groups have different forecasting abilities for stock returns and market risk premiums, this would enable the three testable hypotheses presented in this paper to be discussed at length with the aid of behavioral economics. One other issue presented is the

[2] Ho and Hung (2009) allow factor loadings to vary with sentiment and test a plethora of asset-pricing models such as the Capital Asset Pricing Model (CAPM), the Fama-French three factor model, the Fama-French model including the winners-minus-losers portfolio and others.

issue of downside risk. This one type of risk is simply the chance that an asset could potential lose value. Some assets of course have greater chances of significant losses as compared to other assets. But in the context of this paper, if the sentiment of consumers is such that negative changes in sentiment have greater stock return forecasting ability than positive changes, this could shed light on the concept of downside risk. This is directly related to the prospect theory (Kahneman and Tversky (1979)) which shows that losses matter more to individuals than gains.

Using micro-level data containing consumer survey respondents' ages from the University of Michigan's Surveys of Consumers (hereafter referred to as CSI), the two theories presented, the prospect theory and the life cycle investment hypothesis, are explored. Along the way to testing these theories, different age groups may exhibit biases towards certain investments (small versus big stocks and industry preferences such as technology versus retail). I also study changes in consumer sentiment based on the ages of consumers and compare it to stock returns of stocks in different industries and firms of different sizes. As demographic changes take hold in the U.S., it is important to continue to explore the relatively new area of behavioral economics in conjunction with finance and population composition. The results of this paper allows for further insight into how behavioral economics can be applied to the before mentioned extant economic theories as well as provide interesting insights regarding how changes in sentiment forecast future stock returns.

2. Literature Review

2.1 Consumer Sentiment, Stock Returns and Asset Pricing

The basic testing of the relationship between stock returns and consumer confidence has been undertaken by other researchers. Fisher and Statman (2003) ask the following questions: i) Does consumer sentiment predict stock returns? ii) Do stock returns affect consumer confidence? and iii) What is the relationship between consumer confidence and investor sentiment? These interesting and valid questions are even more so important being that consumer confidence is a component of economic activity measures such as the Conference Board's Index of Leading Economic Indicators.[3] Using monthly changes in overall consumer confidence as the dependent variable and changes in monthly individual investor sentiment as the independent variable, they find a positive and statistical significant relationship among the two does exist. There explanation of this result is due to the possibility that "(individual) investors fail to understand the forward-looking and discounting nature of the stock market." On the other hand, they find no statistical significant relationship between changes in institutional investor sentiment and changes in consumer confidence (institutional investor sentiment is approximated by the Merrill Lynch Index of Wall Street Strategists' sentiment). These are two very opposite results using similar time periods (1987 until 2002 for the individual investors data as compared to 1985 until 2002 for the institutional investors).

Fisher and Statman (2003) also find that S&P 500 returns predict monthly changes in overall consumer confidence (contemporaneous relationship). They find similar results for small-cap stocks and NASDAQ; positive, statically significant coefficients.[4] As they mention, low stock returns result in the deterioration of consumer confidence while high stock returns have the ability to raise consumer confidence. As for forecasting, they use stock returns as the dependent variable and the level of consumer confidence as the independent variable and find a negative relationship between the two. Their motivation for such is to see the ability of consumer confidence to predict future stock returns (one-month, six-month and twelve-month ahead forecasts) and again, they find a negative relationship between consumer confidence and future stock returns.

Lemmon and Portniaguina (2006) study consumer confidence in a similar regard but find a unique way of capturing pessimism and optimism. They state that the goal of their research is to determine the extent to which sentiment affects different stocks. They make consumer sentiment a

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[3] The Conference Board's Leading Economic Index (LEI) includes the following indicators which are to represent predictors of economic activity: supplier deliveries, interest rate spread, stock prices, real money supply, index of consumer expectations (consumer sentiment), building permits, manufacturers' new orders for nondefense capital goods, average weekly manufacturing hours, average weekly initial claims for unemployment insurance and manufacturers' new orders for consumer goods and materials. Source: Conference Board's website.

[4] Fisher and Statman (2003) define small-cap stocks as the average of the returns on the bottom three deciles of CRSP decile 1 to decile 10 portfolios formed based on market capitalization.

function of a set of a large number of macroeconomic variables (e.g., inflation, the default spread, changes in personal consumption expenditures, Gross Domestic Product and unemployment) to determine consumer sentiment based on economic conditions. The argument for measuring sentiment in this manner is that by doing so, any consumer sentiment based on fundamental economic conditions is reasonable, justifiable and rational. On the other hand, consumer sentiment based on influences or factors other than economic conditions is unreasonable, unjustifiable and irrational. They use the residual from this ordinary least squares equation as an approximation for unjustifiable sentiment because of the fact that in order for sentiment to rational, it must be based solely on measurable, observable economic conditions – otherwise it is unwarranted by fundamentals as they argue.

Lemmon and Portniaguina (2006) first test the relationship between consumer confidence and the size premium. They define the size premium as the difference between the returns on the smallest decile portfolio in CRSP portfolios formed based on market capitalization and the returns of the largest decile. To carry out their size premium test, they regressed the returns of their size premium portfolio on lagged consumer confidence and some control variables and show that current levels of sentiment predict the size premium as well as show that stocks with low institutional ownership (small stocks) show evidence of mispricing from changes in sentiment. They state that these results provide support for the noise trader hypothesis which states that stock returns for assets held by individuals (noise traders) should be affected more so by sentiment. More specifically, Lemmon and Portniaguina (2006) reference Baker and Wurgler (2006) who find investor sentiment, which is similar to consumer sentiment, has more of an impact on small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks and distressed stocks. Also, Lemmon and Portniaguina (2006) show that consumer sentiment is not strongly related to Baker and Wurgler's (2005) sentiment index nor does it forecast variations in returns to value and momentum strategies.

The issue of consumer sentiment and its impact on asset returns has already been studied in an international context. With a sample including eighteen industrialized countries, Schmeling (2009) uses consumer confidence as an approximation for individual investor sentiment to investigate whether lagged sentiment explains stock returns. The eighteen countries included in the study are: Australia, Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, the United Kingdom and the United States. Schmeling (2009) hypothesizes that international investor sentiment predicts future aggregate market returns, that the effect of sentiment on returns is stronger for stocks that are hard to value and/or hard to arbitrage[5] and that the impact of sentiment on returns is stronger for countries that have less well developed markets and are more prone to investor overreaction.

Among the other methodological tests conducted, Schmeling (2009) performs a Granger causality test using the bivariate relationship of consumer sentiment and stock returns. His results of this test confirm a two-way causality – sentiment depends on previous returns and returns depend on previous sentiment. These results hold for the aggregate market, value stocks and growth stocks. He argues that this provides evidence that is consistent with his hypotheses of sentiment predicting future aggregate market returns and sentiment affects being stronger for growth stocks, value stocks and small stocks. Schmeling (2009) estimates a fixed-effects panel regression to capture country differences whereby stock returns are the dependent variable and lagged consumer sentiment and macroeconomic variables such as lagged annual inflation, change in industrial production and the term spread (difference between long-term interest rates and short-term interest rates) are included as independent variables.

His results show a statistically significant negative coefficient on the sentiment variable, indicating that sentiment has a negative impact on future stock returns and does so for multiple periods (i.e., forecast horizons 1 month, 6 months, 12 months and 24 months). In terms of specific countries, the relationship between sentiment and returns is not significant for all countries. Schmeling (2009) shows that lagged sentiment has a stronger affect on stock returns in countries such as Germany, Japan and Italy while there is no evidence or little evidence of such a relationship in countries such as the United Kingdom, Australia and New Zealand. Interestingly, he shows that this relationship holds in the United States, but between sentiment and the aggregate stock market as well as between sentiment and value

[5] Schmeling (2009) identifies these as growth stocks, small stocks and value stocks.

stocks, but not between sentiment and growth stocks. As a result, he argues that the stock returns in the United States, for the most part, are not as affected by sentiment, as some other industrialized countries.

In addition to studying consumer sentiment affect on asset returns and international stock markets, consumer sentiment has also been recently incorporated into asset pricing. In testing asset pricing models, Ho and Hung (2009)[6] include the consumer sentiment proxies CSI, the Consumer Conference Board's Consumer Confidence Index, and the Investors' Intelligence Survey Index (as well as construct their own index) to see which asset pricing model performs best when this behavioral component is included.[7] They are motivated by one question – does incorporating investor sentiment in asset pricing models improve the model's performance? Their motivation stems from Avramov and Chordia (2006) who test conditional asset pricing models in a way such that factor loadings (e.g., beta) are able to vary not only with time but also with the firm-specific market capitalization, firm specific book-to-market ratio and business cycle variables. Avramov and Chordia (2006) ultimately find that time-varying beta versions of multifactor models can capture the size and book-to-market effects as well as turnover and past returns are important determinants of the cross-section of stock returns.

Ho and Hung (2009) replicate the methodology of Avramov and Chordia (2006) except that Ho and Hung (2009) include one additional factor to test conditional asset pricing models – consumer sentiment. They found by adding sentiment to asset pricing models, the conditional model specifications (conditioned on sentiment) do better than the unconditional models with respect to indentified market anomalies such as the value, liquidity and momentum effects (see Fama and French (1993)). These asset pricing models conditioned with sentiment are better able to explain the value, liquidity and momentum effects. Also, they observe that including sentiment as a conditioning item in the models results in value, momentum and liquidity effects still be detected. Fama and French (1996) argue that market anomalies such as these disappear within their three factor model but Ho and Hung (2009) reach a different

[6] It can be misleading in that Ho and Hung (2009) use consumer sentiment proxies in this paper and in the literature yet, they call them investor sentiment measures.
[7] Asset pricing models tested: the Capital Asset Pricing Model (CAPM), the Fama-French three factor model, the Fama-French model with a liquidity factor, the Fama-French model with the winners-minus-losers portfolio and Fama-French model which incorporates liquidity and momentum factors.

conclusion, arguing that even with asset pricing models such as the three factor model, when behavioral proxies such as sentiment are included, the anomalies are still present but the models do a better job explaining them. The implications of Ho and Hung (2009) are that in order to better price assets, consumer sentiment possibly needs to be given more credit being that it has the ability to explain the before mentioned documented market anomalies.

2.2 Behavioral Economics

Before proceeding, it is important to briefly shed light on exactly what behavioral economics is and how consumer sentiment is a related to this line of literature. Mullainathan and Thaler (2000) define behavioral economics as a blend of psychology and economics that studies the impact of human behavior on markets. One argument that they make for the creation of this area of economics was "empirical and experimental evidence mounted against the stark predictions of unbounded rationality." By unbounded rationality, Mullainathan and Thaler (2000) imply that what traditional economic models predict as outcomes and the actual outcomes themselves are very different. These differences though are not problematic because the economic models themselves could then be calibrated to be more precise in the future. Actually, these differences are such that new economic modeling is not the issue, but in actuality, it is the human elements in which econometrics and mathematics struggle to account for. These human elements can include decision-making skills, biases, errors, incomplete information, herd-like behavior and preferences to name a few. These before mentioned elements when observed, have the possibility to suggest that individuals are not utility maximizing, rational economic agents.

According to Camerer (2006), behavioral economics includes human irrationality in its models. Consistent with the motivation of my paper, he makes a point to argue the importance of exploring to see if differences amongst individuals exist. This, he argues, is important in the literature of behavioral economics to see if differences in rationality and/or learning exist. He goes as far as to say that the entire literature of behavioral economics is a direct consequence of relaxing the assumption of rationality. By making such a statement, he implies that when rationality in modeling and theory is brushed aside, some economic models do not stand up well. But rather than discard traditional, mathematical proven relationships, deficiencies in the traditional models are acknowledged, providing fertile ground for a related, but distinct line of literature that is willing to take into account this "irrationality" that Camerer (2006) alludes to.

Ritter (2003) states that behavioral economics is rooted in how people think. Ritter (2003) points out that in the psychology literature, it is established that people make systematic errors in the way that they think, are overconfident and rely heavily on recent experience. With these before mentioned psychologically identified human tendencies that Ritter (2003) acknowledges, this helps in motivating why it is important to focus in on one particular aspect of human behavior, confidence, and using behavioral explanations to explain empirical results. One more important distinction with respect to behavioral economics to make is whether or not the field is separate or included in the body of economics such as labor economics, econometrics, industrial economics and other areas. Camerer (2006) argues that behavioral economics is not a separate branch of economics but rather a style of modeling that has many applications in both the areas of economics and finance. This is the exact approach that our paper takes with regards to our hypotheses and models. With the inclusion of a behavioral variable, changes in consumer confidence, we seek to incorporate existing models from the literature with the intention of exploring and explaining how and why our results fit in with current behavioral arguments. But since our paper takes place in a financial setting with the inclusion of stock returns, a discussion a behavioral finance is presented as well.

With respect to the inclusion of behavioral applications in the field of finance, a related but distinct literature to behavioral economics is behavioral finance. Just as behavioral modeling has become applicable to economics, it has also become applicable to finance. Ritter (2003) states that behavioral finance models allow for flexibility and some deviation from classic expected utility arguments of economics. This of course is similar to what Kahneman and Tversky (1979) found decades earlier with their seminal paper introducing the prospect theory. To further argue how similar both behavioral economics and behavioral finance are, Ritter (2003) states that "behavioral finance uses models in which some agents are not fully rational, either because of preferences or because of mistaken beliefs." This statement is similar to Mullainathan and Thaler's (2000) definition of behavioral economics. The main arguable difference between the two related disciplines lies in the setting of their application. For example, a more traditional behavioral economics paper would pertain to forecasting inflation, accounting for human elements, where as a more traditional behavioral finance paper would pertain to forecasting stock returns and also making adjustments for human behavior.

Subrahmanyam (2007) provides a good review of the recent literature pertaining to behavioral finance. Along the lines of our paper, he includes studies exploring the issue of the cross-section of average stock returns. He points out that the fundamental capital asset pricing model states that a security's risk is all that is needed to determine its expected return. Asset pricing studies have found that stock returns can be explained by more than a stock's beta (two of the more notable papers would be Fama and French (1992), Fama and French (1993)). Fama and French are able to introduce two additional factors besides beta to explain stock returns – market capitalization and book-to-price ratios. Shortly thereafter behavioral issues such as momentum (Jagadeesh and Titman (1993)) and stock price reversals (DeBondt and Thaler (1985, 1987)) began to catch on more so in the literature and since then, has showed few signs of slowing down in turns of identifying possible behavioral trends or behavioral anomalies that can affect stock returns. There are numerous studies on these issues regarding stock returns but the primary objective of bringing the before mentioned issues up is to convey the point that the behavioral finance has a place in studying stock returns and continues to be an area that could be studied with the assistance of new ideas, new data and/or new methodologies.

Consumers' sentiment or their beliefs/feelings towards current and future economic conditions are the result of many factors such as the current and future state of inflation, labor wages, unemployment, home values and other general economic conditions to name a few. Clearly, macroeconomic variables have the ability to shape a consumer's sentiment. But when consumer sentiment has the ability to forecast stock returns (e.g., Fisher and Statman (2003), Baker and Wurgler (2006), Lemmon and Portniaguina (2006), Baker and Wurgler (2007) and Schmeling (2009)), this is when the three worlds are more clearly seen as affecting one another. This paper will explore how sentiment fits within behavioral economics and behavioral finance with the aid of economic theories and financial market returns. Both of these behavioral literatures typically aim at the study of heterogeneous beliefs and irrational behavior. What typically makes the literatures distinct is the setting in which they are applied with behavioral finance typically studied in the context of financial markets and asset prices and behavioral economics in the context of macroeconomic models. For example, a behavioral economics paper may involve forecasting a macroeconomic variable such as inflation whereas a behavioral finance paper may test if irrational behavior affects stock returns. Using consumer sentiment in conjunction with finance data such as stock returns, I will test economic theories such as the theory of rational expectations, the prospect theory and the life cycle investment hypothesis.

3. Basic Theory

3.1 Prospect Theory and Downside Risk

Risk and uncertainty in economics benefited greatly from the prospect theory of Kahneman and Tversky (1979) which forever changed the way academicians study risk and its important role in deciding between alternatives. This theory has become a cornerstone for behavioral economics and how sometimes, economic models cannot account for human behavior. Laibson and Zeckhauser (1998) go as far as to state that it was in fact this theory that justified the need for the area of Behavioral Economics because it identified behavior that was not rational and showed how these unexpected deviations from the traditional expected utility theory consistently appear in human behavior. Kahneman and Tversky (1979) suggest their prospect theory as another way to view how decisions in the presence of uncertainty are made.

Kahneman and Tversky (1979) report observable findings from experiments conducted on faculty and students at the University of Stockholm and the University of Michigan. These findings are summarized into what Kahneman and Tversky (1979) call ‘effects’ and include the certainty effect, reflection effect and isolation effect. The certainty effect is described by the authors as the propensity for people to place more weight on events that are more likely to occur and less weight on events that are less likely to occur. They make sure to note how this is inconsistent with the expected utility theory in that the expected utility theory states that utilities are weighted by probabilities whereas according to the certainty effect, outcomes with more certainty tend to correspond with higher utilities.

When negative outcomes (or prospects) are introduced, Kahneman and Tversky (1979) observe what they call the reflection effect. They observe from the sampled individuals opposite preferences for positive outcomes as compared to negative outcomes. An example using positive prospects would be the following: they find that their subjects prefer 3,000 with 100 percent certainty versus 4,000 with 80 percent certainty. Conversely, the authors note the following under conditions of negative prospects: subjects prefer -4,000 with 80 percent certainty versus -3,000 with 100 percent certainty. This was observed consistently for various payoff combinations, thus leading them to conclude that positive prospects correspond with risk aversion and negative prospects correspond with risk seeking. Again, this is inconsistent with expected utility theory. Next, they discuss how people compare alternatives by decomposing the choices into similarities and differences amongst the alternatives. They state that people disregard common characteristics shared by the choices and focus exclusively on the different characteristics amongst the choices. The problem, they argue, is that different decompositions can lead to different selections, resulting in inconsistent decisions.

These discussions of Kahneman and Tversky (1979) from their observations motivate their justification for the proposal of an alternative to the expected utility theory when risk and uncertainty is present. The result is the prospect theory. Their prospect theory is systematic in its approach to explaining how people make decisions in that decision making is broken down into two steps – editing followed by evaluation. In the first step, the decision maker begins the process of determining their preference and organizing the prospects to make the following step, evaluation, easier. Once the first step is complete, they state that the decision maker proceeds onto the evaluation stage. This is when the person chooses amongst the edited prospects by assigning weights to uncertain outcomes and deciding on the prospect with the highest value.

Kahneman and Tversky (1979) state that value has two components: the starting place or reference point and the magnitude of change from that starting place. Importantly, the authors do note that when discussing wealth and changes in wealth, losses matter more than gains. They state that "the aggravation that one experiences in losing a sum of money appears to be greater than the pleasure associated with gaining the same amount." Mullainathan and Thaler (2000) note that the prospect theory's loss function is steeper than the gain function, thus illustrating how much individuals dislike avoiding losses as compared to obtaining gains (i.e., loss aversion). It is this link between the prospect theory, loss aversion and downside risk that enable the three related issues to be integrated into similar discussions. To further illustrate this idea of how widely loss aversion has been studied, the notion of downside risk is described.

Downside risk is simply the potential loss in value of an asset should a loss occur. This idea has been around for more many years, primarily beginning with Roy (1952), who finds that small changes in expectations about prices may produce very big changes in an individual's demand for some assets. These changes can be the result of what Roy (1952) calls a "dread event" or significant loss. Harlow and Rao (1989) provide a nice way of measuring asymmetric response to account for individuals exhibiting downside risk. In the context of this paper, it is important to note that asymmetric response modeling is one particular way of attempting to approach the prospect theory and downside risk because of the documented fact that responses to losses and gains are not the same.

Ang, Chen and Xing (2006) extend the literature on downside risk by showing that since individuals place greater emphasis on downside risk and less emphasis on potential gains, cross-sectional stock returns show evidence of reflecting a premium for downside risk. Their results hold after controlling for factors such as coskewness, size, book-to-market, liquidity risk and past returns. More specifically, the downside premium that they find is roughly 6 percent per year. In addition, Ang, Chen and Xing (2006) find evidence that for most of their cross-sectional sample, past downside beta has forecasting ability for future stock returns. They observe that high past downside beta predicts high subsequent returns but this relationship seems not to hold for stocks with significant volatility. But regarding the factors that Ang, Chen and Xing (2006) control for, they note that downside risk is different from coskewness risk because coskewness statistics do not focus on the asymmetries of down versus up markets.

In terms of theoretically modeling downside risk, Ang, Bekaert and Liu (2005) and Ang, Chen and Xing (2006) utilize a disappointment aversion utility function (Gul (1991)) as their basic downside model. The following equation is a model of downside risk from their exposition:

$$U(\mu_W) = \frac{1}{K}\left(\int_{-\infty}^{\mu_W} U(W)dF(W) + A\int_{\mu_W}^{\infty} U(W)dF(W)\right) \qquad (1)$$

where $U(W)$ is the felicity (well-being/happiness) function representing the end of period wealth W of consumers, which is of the power utility form $U(W) = W^{(1-\gamma)}/(1-\gamma)$. It is important to note that $A \leq 1$ is the coefficient of disappointment aversion, $F(\cdot)$ is the cumulative distribution function for consumer wealth and μ_W is the certainty equivalent or the certain wealth level that generates the same utility as a portfolio of risky assets. The scalar *K* is described as:

$$K = Pr(W \leq \mu_W) + A\,Pr(W > \mu_W) \qquad (2)$$

and since $A \leq 1$, outcomes above the certainty equivalent ($W > \mu_W$) are weighted less heavily than the outcomes below the certainty equivalent($W \leq \mu_W$). The natural connection between this framework and changes in consumer sentiment is that reductions in wealth result in negative changes in consumer sentiment (i.e., pessimism) and increases in wealth result in positive changes in consumer sentiment (i.e., optimism).

Equations (1) and (2) present a model of downside risk (Gul (1991), Ang, Bekaert and Liu (2005) and Ang, Chen and Xing (2006)). In terms of actually measuring downside risk, Ang, Chen and Xing (2006) reference Bawa and Lindenberg (1977), who provide an actual measure of downside risk and label this variable as downside beta (β^-). More specifically, downside beta can be represented as:

$$\beta^- = \frac{cov(r_i, r_m | r_m < \mu_m)}{var(r_m | r_m < \mu_m)} \qquad (3)$$

where r_i is the excess return of security i and r_m is the excess return of the market and μ_m is the average excess return of the market. Equation (3) is what downside risk can be thought as – the beta of a given security with the intention of capturing its risk only when the security performs worse than the market as a whole. With respect to consumer sentiment, a direct test of downside risk within the context of the prospect theory would be to observe how changes in consumer sentiment explain stock returns. How does the downside beta fair when empirically tested? Along these lines, what about the upside beta (β^+) and do changes in consumer sentiments explain stock returns?

3.2 Life Cycle Investment Hypothesis

The life cycle investment hypothesis has been studied for some time now. Modigliani and Brumberg (1954), Ando and Modigliani (1963), Modigliani (1966), Ben-Porath (1967) to name a few, made significant contributions to this theory by showing theoretically that the desire to consume and invest is higher in the lives of younger people whereas middle to older-aged individuals tend to have higher incomes with lower propensities to consume. Reilly and Brown (2008) state “investment needs change over a person’s life cycle” which makes sense in that different people of different ages demand different assets. Reilly and Brown (2008) identify four life cycle phases: accumulation phase, consolidation phase, spending phase and gifting phase. In the early professional years of a person’s career, they are most likely attempting to save and demand more permanent assets (such as housing) as they are attempting to accumulate assets and possible even prepare for a family. As their careers advance and they age, individuals typically begin investing their wealth more conservatively as they near retirement. Once retired and work force labor is significantly reduced, individuals spend their accumulated wealth to supplement any retirement income and possibly even donate portions of their wealth to relatives or charitable organizations for either philanthropic purposes or the avoidance of taxes (Reilly and Brown (2008)).

The notion that the stage of a person’s life may determine their demand for certain asset classes or their ability to obtain certain types of financial assets is explained as the life cycle hypothesis. Now, this theory is more commonly referred to as the life cycle investment hypothesis. According to Bakshi and Chen (1994), the life cycle investment hypothesis states that the age of individuals is a large determinant of the financial asset demanded. They investigate the life cycle investment hypothesis and the life-cycle risk aversion hypothesis and are able to successfully test both and conclude that risk premiums can be affected by a rise in the average age of people. They state that “if demographic changes affect such macroeconomic variables (aggregate consumption, saving, labor supply and social programs), they can also, directly and indirectly, cause price fluctuations in the capital markets." They are able to argue that the demand for financial investments rises and the demand for housing declines as the population ages and the opposite effect can be observed as the population becomes younger (in accordance with the life cycle investment hypothesis).

This paper makes significant use of the consumer sentiment figures of different age groups. Figure 1 shows that throughout the sample period, the younger consumers (age 18 -34) tend to be more optimistic than the older consumers (age 55 and older). This observation alone is interesting and possibly can be explained by the future outlook of the survey respondent. Could it be that since younger individuals expect to live longer and are more hopeful for future personal and economic conditions to improve? This question, although interesting, is not the focus of this paper. This paper seeks to use the life cycle investment hypothesis as a tool in aiding the interpretation of the results. If younger, middle-age and older individuals display differences amongst the coefficient for changes in CSI, this could be explained partly on the grounds of the demographic characteristic of the individual's age.

4. Data

Consumer sentiment is typically captured by either CSI or the Conference Board's Consumer Confidence Index. It is important to note that investor sentiment, on the other hand, has been studied with many proxies such as the closed-end fund discount, NYSE share turnover and dividend premium (proxy for investor demand for dividend paying stocks).[8] For the purposes of studying consumer sentiment and seeing how pessimism or optimism amongst consumers materializes into financial markets, consumer sentiment variables are most appropriate. Ludvigson (2004) points out that much of the academic research focuses on CSI. Fisher and Statman (2003) and Lemmon and Portniaguina (2006) acknowledge that despite survey design differences between CSI and the Conference Board's Consumer Confidence Index, the indices are highly correlated. Due to this correlation as well as Ludvigson (2004) recognizing that many studies employ CSI, this study uses CSI as the proxy for consumer sentiment. Another reason why

[8] Baker and Wurgler (2006) survey these investor sentiment proxies and introduce a new measure for investor sentiment which incorporates these.

CSI is the appropriate proxy for this study is because the literature acknowledges that it asks questions about the economic conditions in the country as a whole while the Conference Board survey focuses on the respondent's specific area of residence.

Monthly CSI data for individuals surveyed by the University of Michigan is available beginning in January 1978. Because of this, the sample period thus begins at the beginning of 1978 and ends in December 2008, resulting in 30 years of monthly time-series data. This data is segmented into three age groups by the University of Michigan; 18 to 34 year olds, 35 to 54 year olds and persons 55 years old and older. This convenient partition of CSI allows a demographic investigation which has previously been unexplored regarding how the sentiment of persons of different ages can be understood in relation to stock markets.

A casual look at the descriptive statistics of CSI across age groups from Table 1 shows that the mean sentiment value over the sample period for the youngest age group, 18 – 34 year olds, is the highest amongst all age groups (96.150) and the mean sentiment value over the sample period for the oldest age group, persons 55 years old and older, is the lowest amongst all age groups (79.166). This is important to note in that it suggests over the sample period, younger consumers tend to be more optimistic than older consumers. One behavioral explanation for this would be that younger individuals have more years of their life to participate in the labor force and earn money resulting in hopeful current/future consumption whereas older individuals have fewer years of their life to participate in the labor force and as a result, do not foresee increased consumption.

The other data incorporated are stock returns. The following questions will be able to be explored as a result: i) Which industries are impacted more by the optimism of pessimism of consumers? ii) Does firm size have any role in relation to changes in consumer sentiment (i.e., are smaller firms affected more that larger firms)? Being able to explore the before mentioned questions such of firm size and firm industry with the assistance of micro-level data of the age of the consumers surveyed allows for an interesting econometric exercise.

All industry returns are obtained from Kenneth French's website. The construction of these portfolios is such that all NYSE, AMEX and NASDAQ stocks are assigned to one of forty-nine industry portfolios based on the particular firm's four-digit Standard Industrial Classification (SIC) code in June of each year. Size sorted portfolios are available from the Center for Research in Security Prices (CRSP). CRSP annually divides NYSE, AMEX and NASDAQ firms into one of ten portfolios based on the market capitalization of the firm. Firms belonging in lower deciles represent smaller firms and firms placed into higher deciles represent larger firms. In other words, the largest firms are placed in portfolio decile ten and the smallest firms are placed in portfolio decile one. For both the industry and size sorted portfolios, the monthly stock returns are available for the entire thirty year sample period.

Table 1
Summary Statistics

	Mean	Standard Deviation	Minimum	Maximum	*N*
CSI Composite	87.221	12.682	51.700	112.000	372
CSI - Age Group 18 – 34	96.150	13.176	60.400	120.000	372
CSI - Age Group 35 – 54	87.447	14.173	43.600	113.300	372
CSI - Age Group 55 and older	79.166	11.578	43.400	105.300	372
$\Delta CSI_{Composite}$	0.000	0.050	-0.181	0.246	371
$\Delta CSI_{18-34\text{ Age Group}}$	0.001	0.061	-0.174	0.287	371
$\Delta CSI_{35-54\text{ Age Group}}$	0.001	0.065	-0.231	0.241	371
$\Delta CSI_{55\text{ and older Age Group}}$	0.002	0.069	-0.196	0.339	371
CRSP EW Index Return	0.010	0.055	-0.273	0.224	372
CRSP VW Index Return	0.007	0.045	-0.227	0.127	372
Risk-free Rate (U.S. Treasury Bill)	0.005	0.003	2.90E-05	0.015	372
HML (High minus Low)	0.004	0.030	-0.124	0.139	372
SMB (Small minus Big)	0.002	0.032	-0.169	0.220	372
MOM (Momentum)	0.009	0.043	-0.250	0.184	372
Macroeconomic Variables					
Default Spread	0.011	0.005	0.006	0.034	372
Inflation	0.003	0.004	-0.019	0.015	372
Industrial Production (Log Difference)	0.001	0.003	-0.018	0.009	372
Unemployment Rate	0.061	0.014	0.038	0.108	372
CRSP Size Decile Portfolio Returns					
Capitalization Decile 1	0.016	0.073	-0.285	0.543	372
Capitalization Decile 2	0.012	0.064	-0.284	0.353	372
Capitalization Decile 3	0.011	0.060	-0.298	0.285	372
Capitalization Decile 4	0.010	0.059	-0.293	0.260	372
Capitalization Decile 5	0.011	0.058	-0.302	0.210	372
Capitalization Decile 6	0.010	0.057	-0.288	0.199	372
Capitalization Decile 7	0.010	0.057	-0.297	0.163	372
Capitalization Decile 8	0.011	0.055	-0.286	0.153	372
Capitalization Decile 9	0.011	0.052	-0.279	0.140	372
Capitalization Decile 10	0.009	0.045	-0.212	0.131	372
Fama-French Equally Weighted Industry Portfolio Returns					
Agriculture	0.010	0.073	-0.294	0.520	372
Aircraft	0.016	0.069	-0.300	0.329	372
Apparel	0.009	0.061	-0.304	0.191	372
Automobiles and Trucks	0.007	0.065	-0.355	0.254	372
Banking	0.013	0.046	-0.205	0.222	372
Beer and Liquor	0.014	0.052	-0.194	0.278	372
Business Services	0.013	0.066	-0.306	0.305	372
Business Supplies	0.009	0.053	-0.283	0.178	372
Candy and Soda	0.013	0.064	-0.230	0.335	372
Chemicals	0.011	0.054	-0.307	0.172	372

Table 1 continued

Coal	0.009	0.101	-0.400	0.324	372
Communication	0.012	0.079	-0.274	0.529	372
Computers	0.013	0.097	-0.333	0.492	372
Computer Software	0.015	0.098	-0.294	0.577	372
Construction	0.010	0.074	-0.302	0.511	372
Construction Materials	0.011	0.057	-0.289	0.203	372
Consumer Goods	0.009	0.056	-0.297	0.184	372
Defense	0.018	0.074	-0.309	0.278	372
Electrical Equipment	0.011	0.066	-0.304	0.196	372
Electronic Equipment	0.016	0.091	-0.329	0.455	372
Entertainment	0.009	0.070	-0.327	0.255	372
Fabricated Products (Metal Work)	0.007	0.067	-0.269	0.216	372
Food Products	0.011	0.043	-0.255	0.112	372
Healthcare	0.015	0.072	-0.353	0.254	372
Insurance	0.013	0.045	-0.228	0.144	372
Machinery	0.012	0.062	-0.316	0.201	372
Measuring and Control Equipment	0.015	0.076	-0.303	0.376	372
Medical Equipment	0.013	0.072	-0.302	0.304	372
Non-Metallic and Industrial Metal Mining	0.012	0.082	-0.328	0.385	372
Other	0.011	0.064	-0.328	0.245	372
Personal Services	0.010	0.060	-0.307	0.169	372
Petroleum and Natural Gas	0.011	0.079	-0.323	0.267	372
Pharmaceutical Products	0.017	0.089	-0.329	0.641	372
Precious Metals	0.012	0.123	-0.398	0.617	372
Printing and Publishing	0.008	0.057	-0.332	0.179	372
Real Estate	0.007	0.063	-0.331	0.239	372
Recreation	0.006	0.068	-0.298	0.323	372
Restaurants, Hotels and Motels	0.007	0.060	-0.287	0.193	372
Retail	0.011	0.063	-0.315	0.309	372
Rubber and Plastic Products	0.012	0.060	-0.306	0.204	372
Shipbuilding and Railroad Equipment	0.008	0.075	-0.431	0.339	372
Shipping Containers	0.013	0.063	-0.274	0.242	372
Steel Works	0.011	0.071	-0.309	0.268	372
Textiles	0.006	0.067	-0.315	0.311	372
Tobacco Products	0.019	0.082	-0.248	0.535	372
Trading (Financial)	0.013	0.049	-0.219	0.222	372
Transportation	0.010	0.058	-0.298	0.215	372
Utilities	0.011	0.034	-0.117	0.129	372
Wholesale	0.010	0.059	-0.292	0.253	372

5. Methodology and Empirical Results

5.1 Basic Model

It is important to see first, whether different demographic groups (hereafter referred to as age groups) exhibit statistical relationships consistent with the literature. Similar to Schmeling (2009)[9], the following relationship is estimated:

$$r_{i,t} = \alpha + \beta \Delta CSI_{t-1} + \varepsilon_t \qquad (4)$$

where $r_{i,t}$ is the excess return of index i regressed on the monthly change in CSI (ΔCSI). Excess returns ($r_{i,t}$) on index i in time period t are computed as $Index_{i,t} - TBILL_t$, where $Index_{i,t}$ is the monthly stock returns of a given stock index or portfolio (size sorted portfolio or decile sorted portfolio) and $TBILL_t$ is the monthly yield on a 30 day representative Treasury bill appearing in CRSP. The change in CSI (ΔCSI) is computed as $\Delta CSI = \frac{(CSI_t - CSI_{t-1})}{CSI_{t-1}}$. Equation (4) examines if previous changes in CSI have forecasting ability in regards to next period's excess stock returns. This equation is estimated for the CSI composite (what is most commonly reported monthly by the media) as well as for the changes in consumer sentiment among each age group.

Equation (4) is tested on the returns of market indices (CRSP Value Weighted Market Index and CRSP Equally Weighted Index) and these results are reported in Table 2. The coefficient for ΔCSI is statistically and economically significant for all market indices employed. Also, these coefficients are all positive for changes in the composite CSI and changes for CSI amongst each age group respectively. These results can be interpreted as a positive change in CSI results in positive future excess stock returns. Looking at Panel A, the β coefficient for one-period lagged changes in the CSI composite regressed on excess CRSP EW index returns is 0.0.348. This means that a 10 percent increase in overall consumer sentiment (consumers of all ages) predicts next period's EW excess return to increase by 3.48 percent. This coefficient shows that when the size of companies is held constant, an increase in the optimism of

[9] Schmeling (2009) estimates the following relationship $r_{t+1} = \alpha + \beta\ sentiment_t + \eta_t$. Equation (10) is different from Schmeling (2009) in that Equation (10) has changes in consumer sentiment as the independent variable and excess stock returns as the dependent variable.

consumers results in an even higher increase in subsequent excess returns of nearly all stocks regardless of size. Also presented in Panel A of Table 2 is the β coefficient for one-period lagged changes in the CSI composite regressed on excess CRSP VW index returns.

Panels B through D of Table 2 report the results from equation (4) incorporating changes in consumer sentiment amongst different age groups. For all age groups, changes in the prior period's CSI forecasts the next period's excess return of each market index. It can be observed that the age group 55 and older has the lowest β coefficients for ΔCSI amongst all age groups. For example, when the excess returns of the EW index are the dependent variable for the age group 55 and older (Panel D of Table 2), the β coefficient for the ΔCSI variable is 0.186. Again, this can be interpreted as a 10 percent increase in the consumer sentiment of consumers 55 and older results in a EW excess return increase of 1.86 percent in the following month after CSI has been publicly reported. The magnitude of this coefficient is half the size of that of the CSI composite β coefficient (Panel A of Table 2).

On the other hand, the youngest consumer age group (18 – 34 years old) and the middle age consumer group (35-54 years old) exhibit very similar β coefficients in terms of magnitude. Also, both of the before mentioned consumer age groups have β coefficients for changes in CSI that are larger in magnitude than those coefficients of the consumer age group 55 and older. This is can be explained along the lines of what Reilly and Brown (2008) argue; individuals in their early to middle career years are more likely saving and investing as the accumulation phase explains. As they are saving, investing and consuming more than older individuals, when younger to middle-aged consumers become increasingly optimistic (pessimistic) about current and future economic conditions, the stock market reacts favorably (negatively). Optimistic consumers feel better about their current/future personal situations as well as the state of the economy in general and are more likely to consume more, resulting in higher firm profitability. Conversely, pessimistic consumers are more likely to consume less due to a lack of confidence, resulting in lower firm profitability. And with the stock market serving as a leading economic indicator, the positive coefficients for lagged ΔCSI is consistent with this argument.

Table 2

This table represents ordinary least square regressions of one month excess returns ($r_{i,t}$) of various indices on lagged one month changes in the University of Michigan's Consumer Sentiment Index (CSI). All data is monthly and is from January 1978 until December 2008. The indices used are the CRSP value-weighted portfolio (excluding dividends) and the CRSP equally-weighted portfolio (excluding dividends). Excess returns ($r_{i,t}$) on index i in time period t are computed by the formula, $Index_{i,t} - TBILL_t$, where TBILL is the monthly yield on a 30 day representative Treasury bill appearing in CRSP. The change in CSI (ΔCSI) is computed as $\Delta CSI = \frac{(CSI_t - CSI_{t-1})}{CSI_{t-1}}$. To avoid the possibility of autocorrelation and heterocedasticity, which could possibly make the coefficients inefficient, Newey-West variance-covariance estimators are employed. All statistical significance is determined by the Newey-West p-values and *, **, *** indicates significance at the 10, 5, and 1 percent levels.

$$r_{i,t} = \alpha + \beta \Delta CSI_{t-1} + \varepsilon_t$$

	CRSP EW Index	CRSP VW Index
Panel a) *All Age Groups - CSI Composite*		
Intercept α	0.005*	0.002
Standard error (Newey-West)	(0.003)	(0.002)
p-value (Newey-West)	[0.096]	[0.271]
Slope β	0.348***	0.205***
Standard error (Newey-West)	(0.059)	(0.052)
p-value (Newey-West)	[0.000]	[0.000]
Panel b) *Age Group 18 – 34*		
Intercept α	0.005	0.002
Standard error (Newey-West)	(0.003)	(0.002)
p-value (Newey-West)	[0.112]	[0.289]
Slope β	0.209***	0.124***
Standard error (Newey-West)	(0.057)	(0.047)
p-value (Newey-West)	[0.000]	[0.009]
Panel c) *Age Group 35 – 54*		
Intercept α	0.005	0.002
Standard error (Newey-West)	(0.003)	(0.002)
p-value (Newey-West)	[0.118]	[0.300]
Slope β	0.218***	0.127***
Standard error (Newey-West)	(0.044)	(0.038)
p-value (Newey-West)	[0.000]	[0.001]

Table 2 continued

Panel d)
Age Group 55 and Older

	CRSP EW Index	CRSP VW Index
Intercept α	0.005	0.002
Standard error (Newey-West)	(0.003)	(0.002)
p-value (Newey-West)	[0.122]	[0.305]
Slope β	0.186^{***}	0.104^{***}
Standard error (Newey-West)	(0.037)	(0.030)
p-value (Newey-West)	[0.000]	[0.001]

5.2 Asymmetric Response Model of Downside Risk

Ang, Chen and Xing (2006) show that since individuals place greater emphasis on downside risk and less emphasis on potential gains, cross-sectional stock returns show evidence of reflecting a premium for downside risk. To further explore the issue of risk aversion, changes in CSI are employed to see whether changes in CSI in an asymmetric response framework exhibit empirical evidence of explaining stock returns. By using asymmetric response modeling, it is possible to isolate improvements and deteriorations in sentiment and allow for easier interpretations of changes in CSI.

This paper modifies the asymmetric response estimation model of Harlow and Rao (1989), Cheng (2005) and Ang, Chen and Xing (2006). The equation is as follows:

$$R_t = \alpha \quad + \beta^{-} \Delta CSI_{t-1}^{-} + \beta^{+} \Delta CSI_{t-1}^{+} + \gamma \quad D^{+} + \varepsilon_t \qquad (5)$$

where R_t is the return of the market, $\Delta\mathrm{CSI}^{-}$ is the change in CSI if sentiment decreases (i.e., ΔCSI < 0) and zero otherwise, $\Delta\mathrm{CSI}^{+}$ is the change in CSI if sentiment increases (i.e., ΔCSI > 0) and zero otherwise and D^{+} representing a dummy variable equal to one if the change in CSI is positive and zero otherwise. Equation (5 is modified from a comparable asymmetric response model from these papers except I separate the changes in sentiment into two parts - positive changes in consumer sentiment and negative changes in consumer sentiment. If stock returns respond similarly to positive changes in consumer sentiment as they do to negative changes in consumer sentiment, β^{-} would be equal β^{+}.[10] Since changes in CSI and stock returns are a focal point of this paper, it is important to include independent variables which can separately account for asymmetric responses.

In addition, the dummy variable D^{+} is included to attempt to capture any effects of the noise trader hypothesis.[11] This hypothesis states that sentiment should affect stocks most likely to be held by individuals – small firm stocks. Lemmon and Portniaguina (2006), who also study consumer confidence, find support for the noise trader hypothesis by finding that “that sentiment unrelated to macroeconomic fundamentals can affect the prices of assets that are predominantly held by noise traders (i.e., small stocks

[10] Simpson, Ramchander and Webb (2007) also use an asymmetric model and postulate a similar condition.
[11] Lee, Shleifer and Thaler (1991) propose this theory.

and stocks with low levels of institutional ownership)." As such, a natural alternative way of testing such is via the dummy variable in equation (5).

In terms of predicted results from this equation, according to Cheng (2005), β^- measures downside risk whereas β^+ measures upside potential. He continues by saying that if investors are averse to downside risk, β^- will be positive, representing a positive risk premium (higher downside risk, higher returns). Conversely, he states that β^+ will be smaller in magnitude (and possibly even negative) if individuals prefer upside potential (higher upside potential, lower returns). Ang, Chen and Xing (2006) argue that the cross-section of stock returns reflects a premium for downside risk. They find that agents place greater weight on downside risk than they place on upside gains and that individuals with aversion to downside risk require a premium to hold assets that have high sensitivities to market downturns. This paper hypothesizes that this asymmetric model of capturing downside risk will provide an indirect way of viewing the prospect theory's findings of risk aversion to losses using changes in consumer sentiment and stock returns. discuss

Table 3 presents the results from equation (5).[12] Looking first at the results for the changes in the CSI composite, it can be observed that β^- is positive and statistically significant at a level of significance of 1 percent. Consumers in general thus show evidence of exhibiting positive risk premiums – negative changes in consumer sentiment in the previous period translate into higher forecasted returns in the next period. This is consistent with the presence of downside risk in that the higher the downside risk, the higher next period's stock returns are.

Also observed for the CSI composite, β^+ is positive and significant at the 5 percent level of significance when the dependent variable is CRSP EW index returns. With this coefficient being positive when Cheng (2005) predicts that β^+ should be lower than β^- if individuals prefer upside potential and do not demand higher returns to correspond with these gains (as opposed to losses). The results of equation (12) are consistent with this hypothesis. The magnitude of the coefficient of β^+ is less than the magnitude

[12] Table 3a and Table 3b are similar except that Table 3a has the dependent variable as simple market returns and Table 3b has the dependent variable as excess market returns. All of the discussions in this paper refer to Table 3a.

of the coefficient of β^- for the CSI composite as well as for all age groups, supporting the notion that when comparing upside gains to downside risk, downside risk is of more importance as indicated by the larger coefficient. This is in agreement with Mullainathan and Thaler (2000) who note that the prospect theory's loss function is steeper than the gain function.

Looking further at the age group results presented in Table 3, it is interesting to note that the coefficients for negative changes in CSI (β^-) are the largest for the 18-34 year old age group. Also, for all age groups, β^- has the predicted positive sign. But with the youngest age group, they show signs of exhibiting the highest aversion to downside risk because of the magnitude of the β^- coefficient (0.450 for CRSP EW returns and 0.423 for CRSP VW returns). The oldest age group, 55 years old and older, show signs of exhibiting the lowest aversion to downside risk because of the magnitude of the β^- coefficient (0.279 for CRSP EW returns and 0.247 for CRSP VW returns). This contradicts Bakshi and Chen (1994) who argue that risk aversion increases with age but overall results for changes in the composite CSI and CSI for age groups display evidence that is consistent with the prospect theory of Kahneman and Tversky (1979) as losses appear to be of greater concern than gains. One possible explanation is that of Reilly and Brown (2008) with individuals in the accumulation life cycle phase. Even though younger and middle aged individuals are both in this life cycle phase, the youngest age group should naturally have a desire to accumulate more being that they probably have their least amount of assets amongst all age groups since they are relatively young. As such, when their consumer sentiment deteriorates, the potential for lower stock returns could be larger being that this is most likely candidate for having seeking the most amount of consumption and investment.

One final observation regarding Table 3 is that the only age group for which the dummy variable D^+ is statistically significant is for the 18-34 year old age group. The dummy variable D^+ is included to attempt to capture any effects of the noise trader hypothesis and is equal to one if the change in CSI is positive and zero otherwise. It is observed that this coefficient is negative and implies a negative relationship between whether or not changes in CSI were positive and stock returns which are inconsistent with the other results presented indicating a positive relationship between changes in CSI and stock returns. Lemmon and Portniaguina (2006) find support for the noise trader hypothesis by finding that sentiment unrelated to fundamentals can affect the prices of assets that are predominantly smaller investors who are primarily individual investors.

Table 3a

The following table presents an asymmetric response model incorporating changes in consumer sentiment. The dependent variable, R_i, is the return of either the CRSP equally weighted portfolio or the CRSP value weighted portfolio. The independent variables are defined in the following manner: β_i^- is the change in CSI if sentiment decreases (i.e., $\Delta CSI < 0$) and zero otherwise, β_i^+ is the change in CSI if sentiment increases (i.e., $\Delta CSI > 0$) and zero otherwise and D^+ represents a dummy variable equal to one if the change in CSI is positive and zero otherwise. All statistical significance is determined by the Newey-West p-values and *, **, *** indicates significance at the 10, 5, and 1 percent levels.

$$R_{i,t} = \alpha_i + \beta^- \Delta CSI_{t-1}^- + \beta^+ \Delta CSI_{t-1}^+ + \gamma D^+ + \varepsilon_{i,t}$$

	CSI Composite		Age Group 18 -34		Age Group 35-54		Age Group 55 and older	
Dependent Variable	CRSP EW Portfolio Returns	CRSP VW Portfolio Returns	CRSP EW Portfolio Returns	CRSP VW Portfolio Returns	CRSP EW Portfolio Returns	CRSP VW Portfolio Returns	CRSP EW Portfolio Returns	CRSP VW Portfolio Returns
Intercept α_i	0.014**	0.013***	0.022***	0.023***	0.019***	0.014***	0.016**	0.016***
Standard error (Newey-West)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.007)	(0.006)
p-value (Newey-West)	[0.019]	[0.006]	[0.000]	[0.000]	[0.003]	[0.003]	[0.018]	[0.005]
Slope β^-	0.466***	0.370***	0.450***	0.423***	0.363***	0.254**	0.279**	0.247**
Standard error (Newey-West)	(0.162)	(0.137)	(0.138)	(0.116)	(0.130)	(0.106)	(0.122)	(0.101)
p-value (Newey-West)	[0.004]	[0.007]	[0.001]	[0.000]	[0.005]	[0.017]	[0.022]	[0.015]
Slope β^+	0.265**	0.048	0.151**	0.056	0.208**	0.066	0.169**	0.075
Standard error (Newey-West)	(0.103)	(0.087)	(0.075)	(0.058)	(0.081)	(0.072)	(0.076)	(0.058)
p-value (Newey-West)	[0.010]	[0.583]	[0.047]	[0.338]	[0.011]	[0.362]	[0.027]	[0.202]
γ	-0.002	1.29E-04	-0.012*	-0.016**	-0.011	-0.005	-0.006	-0.010
Standard error (Newey-West)	(0.008)	(0.007)	(0.007)	(0.006)	(0.008)	(0.007)	(0.009)	(0.008)
p-value (Newey-West)	[0.792]	[0.985]	[0.094]	[0.011]	[0.182]	[0.463]	[0.458]	[0.213]

Table 3b

The following table presents an asymmetric response model incorporating changes in consumer sentiment. The dependent variable, $R_{m,t}$ - $R_{f,t}$, is the excess market return using either the CRSP equally weighted portfolio or the CRSP value weighted portfolio as the market return and the 30 day U.S. treasury bill yield as the risk-free rate. The independent variables are defined in the following manner: β_i^- is the change in CSI if sentiment decreases (i.e., $\Delta CSI < 0$) and zero otherwise, β_i^+ is the change in CSI if sentiment increases (i.e., $\Delta CSI > 0$) and zero otherwise and D^+ represents a dummy variable equal to one if the change in CSI is positive and zero otherwise. All statistical significance is determined by the Newey-West p-values and *, **, *** indicates significance at the 10, 5, and 1 percent levels.

$$R_{m,t} - R_{f,t} = \alpha_i + \beta^- \Delta CSI_{t-1}^- + \beta^+ \Delta CSI_{t-1}^+ + \gamma D^+ + \varepsilon_{i,t}$$

	CSI Composite		Age Group 18 -34		Age Group 35-54		Age Group 55 and older	
Dependent Variable	CRSP EW Portfolio Returns	CRSP VW Portfolio Returns	CRSP EW Portfolio Returns	CRSP VW Portfolio Returns	CRSP EW Portfolio Returns	CRSP VW Portfolio Returns	CRSP EW Portfolio Returns	CRSP VW Portfolio Returns
Intercept α_i	0.010	0.009*	0.018***	0.018***	0.015**	0.010**	0.011	0.011**
Standard error (Newey-West)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.007)	(0.006)
p-value (Newey-West)	[0.101]	[0.062]	[0.003]	[0.000]	[0.017]	[0.031]	[0.107]	[0.049]
Slope β^-	0.478***	0.382***	0.451***	0.424***	0.380***	0.271**	0.278**	0.246**
Standard error (Newey-West)	(0.160)	(0.135)	(0.140)	(0.118)	(0.127)	(0.103)	(0.121)	(0.100)
p-value (Newey-West)	[0.003]	[0.005]	[0.001]	[0.000]	[0.003]	[0.009]	[0.023]	[0.015]
Slope β^+	0.266**	0.050	0.159**	0.064	0.203**	0.062	0.171**	0.077
Standard error (Newey-West)	(0.102)	(0.087)	(0.075)	(0.058)	(0.081)	(0.073)	(0.078)	(0.060)
p-value (Newey-West)	[0.010]	[0.583]	[0.035]	[0.270]	[0.013]	[0.399]	[0.028]	[0.199]
γ	-0.002	1.74E-04	-0.013*	-0.016**	-0.012	-0.006	-0.006	-0.009
Standard error (Newey-West)	(0.008)	(0.007)	(0.007)	(0.006)	(0.008)	(0.007)	(0.009)	(0.008)
p-value (Newey-West)	[0.763]	[0.979]	[0.084]	[0.010]	[0.164]	[0.422]	[0.474]	[0.223]

5.2.1 Alternative Model of Downside Risk

Another econometric specification I introduce to measure downside risk is the following model:

$$R_t = \alpha \quad + \beta_1 \ \Delta CSI_{t-1} + \beta_2 \ \left(\Delta CSI_{t-1} * D^-\right) + \gamma D^- + \varepsilon \qquad (6)$$

where R_t is the return of the market, ΔCSI^- is the change in CSI if sentiment decreases (i.e., $\Delta CSI < 0$) and zero otherwise, and D^+ representing a dummy variable equal to one if the change in CSI is positive and zero otherwise. Similar to equation (5), equation (6) accounts for asymmetric responses for gains in consumer sentiment versus losses in consumer sentiment. The coefficients of this model that are of particular interest are β_1 and β_2. β_1 can be interpreted as indicating the impact of positive changes in the previous month's consumer sentiment on future stock returns. And if both β_1 and β_2 are added together, they represent the coefficient for negative changes in forecasting next month's market return.

The results of equation (6) are presented in Table 4. The first observation for the results is that the β_1 coefficient is statistically significant and positive when the dependent variable used is CRSP equally-weighted returns. Additionally, when looking at β_2, this coefficient is significant for the CSI composite and for the 18 – 34 age group. Since β_1 and β_2 added together represent the coefficient for negative changes, the youngest age group having a positive and statistically significant coefficient with respect to negative changes in consumer sentiment as opposed to positive changes in sentiment is consistent with an asymmetric response. Alternatively, when separating positive changes in sentiment from positive changes in sentiment, the negative changes in consumer sentiment have a greater forecasting ability and especially for the youngest age group.

The results of equations (5) and (6) are consistent with prior studies which investigate age and its relation to downside risk in the context of risk aversion. Studies such as Riley and Chow (1992) and Halek and Eisenhauer (2001) discuss risk aversion and how demographic attributes affect this phenomenon. In particular, Riley and Chow (1992) examine asset allocation decisions and find risk aversion to decline with age until the age of 65. They argue that it is beginning at this age in which risk aversion begins to increase. The results presented in my study are consistent with the before mentioned statements. I find risk aversion to be the highest amongst younger individuals and decreasing with age using asymmetric response modeling to capture optimism and pessimism reflected in consumer sentiment.

Table 4

The following table presents an asymmetric response model incorporating changes in consumer sentiment. The dependent variable, R_i, is the return of either the CRSP equally weighted portfolio or the CRSP value weighted portfolio. The independent variables are defined in the following manner: β_i^- is the change in CSI if sentiment decreases (i.e., $\Delta CSI < 0$) and zero otherwise and D^- represents a dummy variable equal to one if the change in CSI is negative and zero otherwise. All statistical significance is determined by the Newey-West p-values and *, **, *** indicates significance at the 10, 5, and 1 percent levels.

$$R_t = \alpha \quad + \beta_1 \, \Delta CSI_{t-1} + \beta_2 \, \left(\Delta CSI_{t-1} * D^-\right) + \gamma D^- + \varepsilon_t$$

	CSI Composite		Age Group 18-34		Age Group 35-54		Age Group 55 and older	
Dependent Variable	CRSP EW Portfolio Returns	CRSP VW Portfolio Returns	CRSP EW Portfolio Returns	CRSP VW Portfolio Returns	CRSP EW Portfolio Returns	CRSP VW Portfolio Returns	CRSP EW Portfolio Returns	CRSP VW Portfolio Returns
Intercept α	0.013**	0.015***	0.010**	0.007*	0.009	0.009*	0.009	0.007
Standard error (Newey-West)	(0.005)	(0.005)	(0.005)	(0.004)	(0.006)	(0.005)	(0.006)	(0.004)
p-value (Newey-West)	[0.019]	[0.003]	[0.044]	[0.074]	[0.170]	[0.092]	[0.101]	[0.102]
Slope β_1	0.257**	0.028	0.148*	0.055	0.194**	0.062	0.168**	0.071
Standard error (Newey-West)	(0.100)	(0.086)	(0.075)	(0.058)	(0.081)	(0.072)	(0.074)	(0.058)
p-value (Newey-West)	[0.011]	[0.745]	[0.050]	[0.346]	[0.017]	[0.389]	[0.024]	[0.216]
Slope β_2	0.203	0.324*	0.300*	0.369***	0.158	0.189	0.116	0.180
Standard error (Newey-West)	(0.220)	(0.186)	(0.158)	(0.131)	(0.166)	(0.138)	(0.162)	(0.133)
p-value (Newey-West)	[0.356]	[0.083]	[0.058]	[0.005]	[0.341]	[0.173]	[0.477]	[0.176]
γ	0.001	-0.003	0.012	0.016**	0.009	0.005	0.007	0.010
Standard error (Newey-West)	(0.008)	(0.007)	(0.007)	(0.006)	(0.008)	(0.007)	(0.009)	(0.008)
p-value (Newey-West)	[0.883]	[0.700]	[0.106]	[0.012]	[0.264]	[0.509]	[0.457]	[0.226]

5.3 Macroeconomic Residual Model

If consumers base their outlook on fundamental current and past economic conditions, then consumer sentiment should be able to be explained by macroeconomic variables. And the residual from such an estimated model should capture the sentiment of consumers that is not based on fundamental economic conditions. Baker and Wurgler (2006) and Lemmon and Portniaguina (2006) estimate regression models and the residual from their models is the primary focus of their analyses. Both argue this and I introduce a modified Lemmon and Portniaguina (2006) macroeconomic model whereby I am seeking to explain as much variation as possible in the consumer sentiment index. The model that I propose includes monthly data for the Treasury bill rate (TBILL), the default spread (DEF), inflation measured using the consumer price index (CPI), the log difference of industrial production (IP) and the civilian unemployment rate (URATE). This model is the following:

$$\begin{aligned} CSI_t = \alpha \quad &+ \beta_1\ TBILL_t\ + \beta_2\ DEF_t + \beta_3\ CPI_t + \beta_4\ IP_t\ + \beta_5\ URATE_t \\ &+ \beta_6\ TBILL_{t-1} + \beta_7\ DEF_{t-1} + \beta_8\ CPI_{t-1} + \beta_9\ IP_{t-1} + \beta_{10} URATE_{t-1} + \epsilon_t \end{aligned} \qquad (7)$$

The results of this model are presented in Table 6. Most of the explanatory variables are significant which provides support for a well-rounded model that accounts for many critical macroeconomic variables. The only variable that is statistically insignificant is $TBILL_t$ and $TBILL_{t-1}$. The adjusted R^2 of this macroeconomic model is 53.83 percent which indicates that the variables chosen explain more than half of the variability in consumer sentiment.

The next step that I perform is to store the residuals from equation (7). With this as my proxy for unwarranted sentiment, I then employ Lemmon and Portniaguina's (2006) size premium residual model as follows:

$$R_{Decile\ 10,t} - R_{Decile\ 1,t} = \alpha \quad + \beta_1\ RES_{t-1} + \beta_2\ R_{m,t} + \beta_3\ CSI_{t-1} * R_{m,t} + \epsilon_t \qquad (8)$$

In this equation, the dependent variable represents a size premium which is the difference between the returns of the smallest CRSP decile portfolio and the returns of the largest CRSP decile portfolio. The residual from the macroeconomic model is denoted RES_{t-1}, $R_{m,t}$ is the excess return on the CRSP VW index and CSI_{t-1} is the prior month's consumer sentiment level for the composite index. The results of this equation are presented in Table 6.

I present the results of this model for three time periods: January 1978 to December 2008 (entire sample period), January 1978 to December 2002 and January 2003 to December 2008. The intuition for estimating these three time periods is to explore the results over the entire sample period, to compare my results to Lemmon and Portniaguina's (2006) who investigate January 1978 to December 2002 and to attempt to explore any possible relationships that may have existed leading up to the current financial crisis. My results show that the residual (RES_{t-1}) from my macroeconomic model when estimated in equation (8) is statistically significant for all time periods except the financial crisis time period.

Lemmon and Portniaguina (2006) predict that the coefficient for this variable will be negative if the size premium is to be affected by noise trader sentiment. My results are not consistent with their hypothesis because the sign of this variable in my results is positive. One possible explanation for this discrepancy is the fact that I used different macroeconomic variables and my macroeconomic model's adjusted R^2 was not high enough to capture only noise trader effects. Because roughly half of the variation in consumer sentiment was not explained, possibly other factors were captured by my residual. Moreover, the other coefficients in my equation (8) were not significant. This was most likely due to the same model limitation. It should be mentioned that because the residual was statistically significant, there is support for the fact that consumer sentiment can forecast the size premium but I do not find similar support for the noise trader hypothesis of Lee, Shleifer and Thaler (1991).

Table 5

The following table presents a macroeconomic model in which contemporaneous and lagged variables are employed in order to best predict consumer sentiment. The variables included are the Treasury bill rate (TBILL), the default spread (DEF), inflation measured using the consumer price index (CPI), the log difference of industrial production (IP), the civilian unemployment rate (URATE) and the level of the CSI composite. Monthly data from January 1978 until December 2008 is used and all statistical significance is determined by the Newey-West p-values and *, **, *** indicates significance at the 10, 5, and 1 percent levels.

$$\begin{aligned} CSI_t = \alpha \; &+ \beta_1\ TBILL_t\ + \beta_2\ DEF_t + \beta_3\ CPI_t + \beta_4\ IP_t\ + \beta_5\ URATE_t \\ &+ \beta_6\ TBILL_{t-1} + \beta_7\ DEF_{t-1} + \beta_8\ CPI_{t-1} + \beta_9\ IP_{t-1} + \beta_{10} URATE_{t-1} + \epsilon_t \end{aligned}$$

Dependent Variable	Consumer Sentiment
Intercept α	112.81***
Standard error (Newey-West)	(4.20)
p-value (Newey-West)	[0.000]
Slope β_1	169.34
Standard error (Newey-West)	(622.20)
p-value (Newey-West)	[0.786]
Slope β_2	-2199.28***
Standard error (Newey-West)	(464.66)
p-value (Newey-West)	[0.000]
Slope β_3	-635.82***
Standard error (Newey-West)	(218.94)
p-value (Newey-West)	[0.004]
Slope β_4	719.33***
Standard error (Newey-West)	(169.48)
p-value (Newey-West)	[0.000]
Slope β_5	-923.20***
Standard error (Newey-West)	(298.47)
p-value (Newey-West)	[0.002]
Slope β_6	721.31
Standard error (Newey-West)	(561.98)
p-value (Newey-West)	[0.200]

Table 5 continued

Slope β_7	1534.88***
Standard error (Newey-West)	(457.08)
p-value (Newey-West)	[0.001]
Slope β_8	-969.87***
Standard error (Newey-West)	(171.03)
p-value (Newey-West)	[0.000]
Slope β_9	731.24***
Standard error (Newey-West)	(192.04)
p-value (Newey-West)	[0.000]
Slope β_{10}	622.27**
Standard error (Newey-West)	(276.50)
p-value (Newey-West)	[0.025]

Table 6

The following table presents the Lemmon and Portniaguina's (2006) size premium residual model in which I estimate the residual from equation (14). The dependent variable represents a size premium which is the difference between the returns of the smallest CRSP decile portfolio and the returns of the largest CRSP decile portfolio, the residual from the macroeconomic model (RES_{t-1}), $R_{m,t}$ is the excess return on the CRSP VW index and CSI_{t-1} is the prior month's consumer sentiment level for the composite index. The sample period of estimation is January 1978 until December 2008 and all statistical significance is determined by the Newey-West p-values and *, **, *** indicates significance at the 10, 5, and 1 percent levels.

$$R_{Decile\ 10,t} - R_{Decile\ 1,t} = \alpha \quad + \beta_1\ RES_{t-1} + \beta_2\ R_{m,t} + \beta_3\ CSI_{t-1} * R_{m,t} + \epsilon_t$$

Time Period	1/1978 – 12/2008	1/1978 – 12/2002	1/2003 – 12/2008
Dependent Variable	$R_{Decile\ 10} - R_{Decile\ 1}$	$R_{Decile\ 10} - R_{Decile\ 1}$	$R_{Decile\ 10} - R_{Decile\ 1}$
Intercept α	-0.007*	-0.008*	-0.008
Standard error (Newey-West)	(0.003)	(0.004)	(0.006)
p-value (Newey-West)	[0.053]	[0.051]	[0.203]
Slope β_1	0.001***	0.002***	-0.001
Standard error (Newey-West)	(3.59E-04)	(4.08E-04)	(0.001)
p-value (Newey-West)	[0.004]	[0.004]	[0.204]
Slope β_2	-0.131	0.038	1.001
Standard error (Newey-West)	(0.455)	(0.617)	(0.923)
p-value (Newey-West)	[0.774]	[0.951]	[0.282]
Slope β_3	0.002	0.001	-0.015
Standard error (Newey-West)	(0.005)	(0.007)	(0.013)
p-value (Newey-West)	[0.674]	[0.916]	[0.227]

5.4 Modified Asset Pricing Model

The study of asset pricing is constantly being investigated. This is the case because the popular Capital Asset Pricing Model beta does not fully explain the cross section of stock returns. With this in mind, many academicians set on a quest to find better models that included more factors. Fama and French (1992) and Fama and French (1993), as well as others, were successful in their quest to better explain stock returns. More recently, studies have included consumer sentiment as a possible factor to explain stock returns and improve existing asset pricing models. Ho and Hung (2009) do exactly this and find improved asset pricing models when sentiment is included as a factor.

To investigate the age group differences that exist in consumer sentiment data, I estimate a modified asset pricing model. The equation is the following:

$$R_i = \alpha + \beta_1 \Delta CSI + \beta_2 HML + \beta_3 MOM + \beta_4 SMB + \varepsilon \qquad (9)$$

where R_i represents the return of a given market index (CRSP VW or EW) and SMB and HML are small minus big portfolio returns and high minus low portfolio returns. Also included is a control for momentum, MOM, which is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. The results of this equation are presented in Table 7.

The results of this model provide many insights. First, for all age groups and the CSI composite index, changes in consumer sentiment have a strong positive relationship when forecasting future stock returns. The youngest age group, 18 – 34 year olds, has the largest coefficient for changes in CSI when compared to the other age groups. This is consistent with the Life Cycle Investment Hypothesis because younger individuals are more likely to acquire stocks as they begin saving. As for the other variables in this model, HML is negative and statistically significant in all models. This negative relation between HML and the market returns shows that, after accounting for changes in consumer sentiment, this value premium does not appear to drive market returns for the sample period. A similar statement can be made for the MOM factor as it also has a negative and statistically significant coefficient. The SMB factor which accounts for firm size, is positive and statistically significant and argues that firm size played a role in driving market returns. This is consistent with other studies which show smaller firm stocks tend to outperform large firm stocks over time. After estimating this modified asset pricing model, I find that consumer sentiment as a factor in explaining stock returns is significant and that age differences exist when comparing the results of sentiment from different age groups.

Table 7

This table represents a modified asset pricing model which includes changes in consumer sentiment and some of the Fama and French (1993) factors. R_i represents the return of a given market index and SMB and HML are small minus big portfolio returns and high minus low portfolio returns. Also included is a control for momentum, MOM. All data is monthly and is from January 1978 until December 2008. Statistical significance is determined by the Newey-West p-values and *, **, *** indicates significance at the 10, 5, and 1 percent levels.

$$R_i = \alpha + \beta_1 \Delta CSI + \beta_2 HML + \beta_3 MOM + \beta_4 SMB + \varepsilon$$

	CSI Composite		Age Group 18-34		Age Group 35-54		Age Group 55 and older	
Dependent Variable	CRSP EW Portfolio	CRSP VW Portfolio	CRSP EW Portfolio	CRSP VW Portfolio	CRSP EW Portfolio	CRSP VW Portfolio	CRSP EW Portfolio	CRSP VW Portfolio
Intercept α	0.012***	0.010***	0.012***	0.010***	0.012***	0.010***	0.012***	0.010***
Standard error (Newey-West)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
p-value (Newey-West)	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Slope β_1	0.221***	0.194***	0.153***	0.131***	0.135***	0.119***	0.094***	0.085***
Standard error (Newey-West)	(0.049)	(0.050)	(0.044)	(0.043)	(0.034)	(0.035)	(0.027)	(0.027)
p-value (Newey-West)	[0.000]	[0.000]	[0.001]	[0.002]	[0.000]	[0.001]	[0.001]	[0.002]
Slope β_2	-0.484***	-0.678***	-0.485***	-0.678***	-0.475***	-0.671***	-0.461***	-0.659***
Standard error (Newey-West)	(0.088)	(0.072)	(0.089)	(0.074)	(0.090)	(0.073)	(0.097)	(0.078)
p-value (Newey-West)	[0.005]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Slope β_3	-0.245***	-0.096	-0.261***	-0.110	-0.256***	-0.105	-0.256***	-0.105
Standard error (Newey-West)	(0.073)	(0.067)	(0.074)	(0.071)	(0.075)	(0.070)	(0.078)	(0.070)
p-value (Newey-West)	[0.001]	[0.152]	[0.000]	[0.124]	[0.001]	[0.133]	[0.001]	[0.134]
Slope β_4	0.823***	0.057	0.859***	0.089	0.852***	0.082	0.866***	0.094
Standard error (Newey-West)	(0.150)	(0.118)	(0.151)	(0.120)	(0.150)	(0.120)	(0.157)	(0.128)
p-value (Newey-West)	[0.000]	[0.629]	[0.000]	[0.459]	[0.000]	[0.496]	[0.000]	[0.463]

5.5 Size Effect Model

Do changes in sentiment appear to impact small firms the same as larger firms? Lemmon and Portniaguina (2006) and Baker and Wurgler (2006) both say yes, finding that sentiment has more of an impact on small stocks. But does this noise trader argument hold amongst changes in consumer sentiment for all ages? In order to empirically test this question, equation (4) is modified and estimated using CRSP market capitalization portfolios. CRSP segments these portfolios into deciles based on a firm's market capitalization whereby deciles 1 to 2 represent large cap stocks, deciles 3 to 5 represent mid-cap stocks, deciles 6 to 8 represent small cap stocks and portfolios 9 to 10 represent micro-cap stocks.[13] The results of this equation are presented in Table 8.

From this table, it can be inferred that changes in sentiment affect larger firms' market risk premiums more than smaller firms. This is consisted with my previous results that were not in agreement with the noise trader hypothesis. For example, the coefficient for ΔCSI for the CSI composite (Panel A) is 0.405 for the decile 1 portfolio and 0.185 for the decile 10 portfolio. The implication of this is significant, statistically and economically; a 10 percent change in overall consumer sentiment (consumers of all ages) forecasts a market risk premium change of 4.05 percent in the following month for the largest firms versus a market risk premium change of 1.85 percent for the smallest firms. This size effect is, for the most part, linear in that the largest firms are affected the most and this effect gradually decreases as firm size decreases. This pattern is true for changes in consumer sentiment for all age groups.

5.6 Industry Effect Model

Baker and Wurgler (2006) argue that sentiment has more of an impact on non-dividend-paying stocks and extreme growth stocks. Firms that meet these two characteristics are typically technology firms and it is hypothesized that changes in sentiment amongst all age groups should affect technology firms as well as other similar industries. Modifying equation (4) again, the following model is estimated:

$$R_{Industry\ i,t} = \alpha + \beta \Delta CSI_{t-1} + \varepsilon_t \qquad (10)$$

[13] CRSP Documentation Manual

where excess returns on the forty-nine Fama-French industry portfolios ($R_{\text{Industry } i,t}$) are regressed on lagged one month changes of CSI (ΔCSI_{t-1}). The industries used are the Fama-French forty-nine equally weighted industries. Equally weighted industry portfolios are employed because a size effect is identified (Table 8) and in order to only capture industry-specific effects (and not size effects), equally weighted portfolios are chosen. All industry returns are excess returns (i.e., $R_{\text{Industry } i,t} - TBILL_t$) where $TBILL_t$ is the monthly yield on a 30 day representative Treasury bill appearing in CRSP. The results of this equation are presented in Table 9.

Many observations from this table can be made. First, out of the forty-nine Fama-French industries, changes in CSI for the composite index and individual age groups have explanatory power in forty-six out of the forty-nine industry excess returns. The only three industries where the coefficient for ΔCSI is not significant are the Coal industry, the Tobacco Products industry and the Utilities industry.[14]

The second result from equation (10) is that the top nine industries which changes in CSI impact the most (in numerical order with the greater impacted industries first):

Changes in the CSI composite (Table 9 – Panel A): Construction, Computers, Electronic Equipment, Computer Software, Precious Metals, Automobiles and Trucks, Apparel, Retail and Recreation

18 – 34 year old changes in sentiment (Table 9 – Panel B): Shipping Containers, Precious Metals, Aircraft, Defense, Automobiles and Trucks, Electronic Equipment, Retail, Recreation and Restaurants, Hotels and Motels

35 – 54 year old changes in sentiment (Table 9 – Panel C): Construction, Precious Metals, Textiles, Apparel, Computer Software, Automobiles and Trucks, Computers, Electronic Equipment and Real Estate

[14] The coefficient for changes in CSI is not significant for the Utilities industry only for the 35 – 54 age group and the 55 and older age group.

55 and older changes in sentiment (Table 9 – Panel D): Computers, Computer Software, Pharmaceutical Products, Electronic Equipment, Measuring and Control Equipment, Retail, Medical Equipment, Recreation and Electrical Equipment

The results, albeit somewhat mixed, show industries that consistently appear in most, if not all age groups, as being affected the most by prior changes in consumer sentiment. Changes in sentiment across age groups tend to affect technology industries (e.g., Computer industry, Computer Software and Electronic Equipment industries), the Automobile and Trucks industry, the Precious Metal industry and the Retail industry. These before mentioned industries appear to be consistently affected by prior changes in consumer sentiment regardless of the age of the survey respondent. The technology industries being affected significantly makes sense in that they are typically the non-dividend paying firms and growth firms. This result is consistent with Baker and Wurgler (2006).

As for the Automobile and Trucks industry and Retail industry appearing amongst various age groups as being affected by changes in consumer sentiment, this is also explainable. Vehicle purchases are sizeable purchases for most consumers and possible only second to the purchase of a home in terms of the magnitude of the purchase price. Therefore, if consumers are optimistic about the future and feel comfortable with their personal financial situation and the economy, they are more likely to purchase a vehicle. On the other hand, if consumers are pessimistic about the future, surely they will delay this purchase. The Retail industry is heavily reliant on consumer spending and the sentiment of their primary customer, consumers, will greatly affect their profitability, and in turn their stock's returns. Lastly, the Precious Metal industry can be explained in that metals such as gold, platinum and silver are also considered 'safe' investments. As a result, they can see flows of investment during both economic expansions and (most likely) economic contractions in order to aid in asset allocation amongst different asset classes.

6. Conclusions

Very little research has been undertaken to investigate how consumer sentiment across different age groups impacts capital markets. Using micro-level data from the University of Michigan's Consumer

Sentiment Index, the relationship between consumer sentiment and stock returns is tested in the context of the prospect theory and the life cycle investment hypothesis. This paper seeks to test whether discernable differences amongst consumers of different ages are reflected in their sentiment and how these changes in sentiment in turn, appear in the stock returns of different size firms and firms in various industries. Differences in age groups' sentiment appears in the magnitude of the coefficients reported and evidence is presented showing that larger firms are affected more so by changes in sentiment than smaller firms.

In addition, younger consumers appear to show signs of exhibiting the highest aversion to downside risk while older consumers (55 years old and older) show signs of exhibiting the lowest aversion to downside risk. This contradicts Bakshi and Chen (1994) who argue that risk aversion increases with age but overall results for changes in CSI display evidence that is consistent with the prospect theory of Kahneman and Tversky (1979) as losses appear to be of greater concern than gains. These results are also consistent with Riley and Chow (1992) and Halek and Eisenhauer (2001). They show how risk aversion can be explained by demographic attributes and moreover, their results support my findings of younger individuals exhibiting higher risk aversion than older individuals. Further research on consumer sentiment is needed to continue to investigate the importance of behavioral variables in the areas of Investments, Corporate Finance and Financial Markets.

7. References

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Table 8

This table represents ordinary least square regressions of one month excess returns ($r_{i,t}$) of various indices on lagged one month (t-1) changes in the University of Michigan's Consumer Sentiment Index (CSI). All data is monthly and is from January 1978 until December 2008. The indices used are the Center for Research in Security Prices (CRSP) annual rebalanced indices based on individual stock market capitalization values. The market capitalization portfolios are formed from stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and the National Association of Securities Dealers Automated Quotations (NASDAQ) and are rebalanced each year and separated based on deciles. Excess returns on index i in time period t are computed by the formula, $Index_{i,t} - TBILL_t$, where TBILL is the monthly yield on a 30 day representative Treasury bill appearing in CRSP. All statistical significance is determined by the Newey-West p-values and *, **, *** indicates significance at the 10, 5, and 1 percent levels.

$$r_{Decile\ i,t} = \alpha + \beta \Delta CSI_{t-1} + \varepsilon_t$$

Panel a) *All Age Groups - CSI Composite*

	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
Intercept α	0.011***	0.007*	0.006*	0.006*	0.006*	0.006**	0.006**	0.006**	0.006**	0.005**
p value	0.002	0.026	0.041	0.056	0.049	0.050	0.047	0.027	0.026	0.035
p value (Newey-West)	0.007	0.063	0.073	0.088	0.066	0.054	0.038	0.025	0.023	0.032
Slope β	0.405***	0.379***	0.365***	0.367***	0.379***	0.342***	0.334***	0.296***	0.259***	0.185***
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p value (Newey-West)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel b) *Age Group 18 – 34*										
Intercept α	0.011***	0.007**	0.006*	0.006	0.006*	0.006*	0.006**	0.006**	0.006**	0.005**
p value	0.003	0.031	0.048	0.065	0.057	0.057	0.054	0.031	0.029	0.038
p value (Newey-West)	0.009	0.073	0.085	0.100	0.079	0.065	0.047	0.031	0.029	0.037
Slope β	0.254***	0.228***	0.214***	0.232***	0.234***	0.203***	0.197***	0.174***	0.150***	0.113**
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.003
p value (Newey-West)	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.003	0.008	0.015

Table 8 continued
Panel c)
Age Group 35 -54

	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
Intercept α	0.011**	0.007*	0.006*	0.005	0.006*	0.005*	0.006*	0.006**	0.006**	0.005**
p value	0.003	0.032	0.050	0.068	0.060	0.059	0.056	0.032	0.030	0.039
p value (Newey-West)	0.010	0.076	0.089	0.107	0.084	0.069	0.051	0.033	0.031	0.039
Slope β	0.271***	0.241***	0.239***	0.230***	0.241***	0.221***	0.210***	0.192***	0.166***	0.113***
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002
p value (Newey-West)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003
Panel d) *Age Group 55 and Older*										
Intercept α	0.011***	0.007*	0.006*	0.005	0.006*	0.005*	0.006*	0.006**	0.006**	0.005**
p value	0.002	0.034	0.053	0.071	0.064	0.062	0.059	0.034	0.032	0.040
p value (Newey-West)	0.010	0.079	0.092	0.110	0.087	0.072	0.053	0.035	0.032	0.041
Slope β	0.195***	0.202***	0.195***	0.194***	0.198***	0.181***	0.181***	0.156***	0.134***	0.090***
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.006
p value (Newey-West)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003

Table 9

These regressions are performed using monthly data from January 1973 until December 2008. This table represents ordinary least square regressions of excess returns on the forty-nine Fama-French industry portfolios ($R_{\text{Industry i,t}}$) regressed on lagged one month (t-1) changes of the University of Michigan's Consumer Sentiment Index (CSI). The industries used are the Fama-French forty-nine equally weighted industries. All industry returns are excess returns (i.e., $R_{\text{Industry i,t}} - TBILL_t$) where TBILL is the monthly yield on a 30 day representative Treasury bill appearing in CRSP. All statistical significance is determined by the Newey-West p-values and *, **, *** indicates significance at the 10, 5, and 1 percent levels.

$$R_{Industry\ i,t} = \alpha + \beta \Delta CSI_{t-1} + \varepsilon_t$$

Panel a) CSI Composite

	Agriculture	Aircraft	Apparel	Automobiles and Trucks	Banking	Beer and Liquor	Business Services	Business Supplies
Intercept α	0.005	0.011***	0.004	0.002	0.008***	0.008***	0.008**	0.004
p value	0.201	0.001	0.161	0.475	0.001	0.001	0.012	0.131
p value (Newey West)	0.230	0.002	0.220	0.545	0.008	0.002	0.021	0.169
Slope β	0.334***	0.387***	0.441***	0.444***	0.271***	0.292***	0.406***	0.344***
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p value (Newey West)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	Candy and Soda	Chemicals	Coal	Communication	Computers	Computer Software	Construction	Construction Materials
Intercept α	0.008***	0.006**	0.004	0.007	0.008	0.010*	0.005	0.007**
p value	0.011	0.022	0.413	0.070	0.107	0.046	0.182	0.020
p value (Newey West)	0.008	0.041	0.485	0.111	0.127	0.070	0.245	0.038
Slope β	0.205***	0.292***	0.106	0.355***	0.483***	0.465***	0.487***	0.374***
p value	0.002	0.000	0.316	0.000	0.000	0.000	0.000	0.000
p value (Newey West)	0.002	0.000	0.452	0.000	0.000	0.000	0.000	0.000

Table 9 continued

	Consumer Goods	Defense	Electrical Equipment	Electronic Equipment	Entertainment	Fabricated Products (Metal	Food Products	Healthcare
Intercept α	0.004	0.013***	0.006	0.011**	0.005	0.002	0.006***	0.010**
p value	0.136	0.001	0.071	0.019	0.189	0.482	0.003	0.004
p value (Newey West)	0.187	0.002	0.107	0.032	0.267	0.518	0.004	0.017
Slope β	0.396***	0.371***	0.407***	0.473***	0.405***	0.285***	0.235***	0.384***
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p value (Newey West)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	Insurance	Machinery	Measuring and Control	Medical Equipment	Non-Metallic and Industrial	Other	Personal Services	Petroleum and Natural Gas
Intercept α	0.008***	0.007*	0.010**	0.008**	0.008	0.006*	0.006*	0.007
p value	0.000	0.031	0.011	0.019	0.071	0.077	0.065	0.103
p value (Newey West)	0.001	0.052	0.029	0.043	0.117	0.089	0.089	0.187
Slope β	0.274***	0.357***	0.435***	0.399***	0.375***	0.364***	0.386***	0.191*
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.022
p value (Newey West)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.063

	Pharmaceutical Products	Precious Metals	Printing and Publishing	Real Estate	Recreation	Restaurants, Hotels and	Retail	Rubber and Plastic
Intercept α	0.012**	0.007	0.004	0.002	0.001	0.002	0.006*	0.007**
p value	0.010	0.278	0.198	0.582	0.794	0.400	0.065	0.016
p value (Newey West)	0.024	0.317	0.271	0.660	0.803	0.474	0.094	0.027
Slope β	0.425***	0.464***	0.335***	0.407***	0.437***	0.419***	0.441***	0.439***
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p value (Newey West)	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000

Table 9 continued

	Shipbuilding and Railroad	Shipping Containers	Steel Works	Textiles	Tobacco Products	Trading (Financial)	Transportation	Utilities
Intercept α	0.003	0.009***	0.006	0.001	0.015***	0.009***	0.006*	0.007***
p value	0.380	0.007	0.080	0.663	0.001	0.000	0.053	0.000
p value (Newey West)	0.415	0.008	0.107	0.699	0.000	0.003	0.068	0.000
Slope β	0.390***	0.350***	0.378***	0.420***	0.136	0.319***	0.378***	0.077**
p value	0.000	0.000	0.000	0.000	0.112	0.000	0.000	0.028
p value (Newey West)	0.000	0.000	0.000	0.000	0.102	0.000	0.000	0.035

	Wholesale
Intercept α	0.005*
p value	0.058
p value (Newey West)	0.088
Slope β	0.410***
p value	0.000
p value (Newey West)	0.000

Table 9 continued

Panel b) Age Group 18 - 34

	Agriculture	Aircraft	Apparel	Automobiles and Trucks	Banking	Beer and Liquor	Business Services	Business Supplies
Intercept α	0.005	0.011***	0.004	0.002	0.008**	0.008***	0.008**	0.004
p value	0.210	0.001	0.182	0.501	0.001	0.001	0.014	0.145
p value (Newey West)	0.239	0.003	0.246	0.571	0.010	0.003	0.027	0.190
Slope β	0.179**	0.293***	0.261***	0.291***	0.181***	0.211***	0.236***	0.240***
p value	0.004	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p value (Newey West)	0.013	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	Candy and Soda	Chemicals	Coal	Communication	Computers	Computer Software	Construction	Construction Materials
Intercept α	0.008***	0.006**	0.004	0.007	0.008	0.010*	0.005	0.007**
p value	0.011	0.026	0.411	0.075	0.116	0.050	0.201	0.024
p value (Newey West)	0.009	0.047	0.482	0.120	0.141	0.050	0.267	0.047
Slope β	0.159***	0.182***	0.020	0.187***	0.263***	0.238***	0.278***	0.257***
p value	0.004	0.000	0.821	0.006	0.001	0.005	0.000	0.000
p value (Newey West)	0.003	0.003	0.873	0.004	0.003	0.005	0.001	0.000

	Consumer Goods	Defense	Electrical Equipment	Electronic Equipment	Entertainment	Fabricated Products (Metal	Food Products	Healthcare
Intercept α	0.004	0.013***	0.006	0.011**	0.005	0.002	0.006***	0.010**
p value	0.154	0.001	0.081	0.022	0.204	0.496	0.003	0.005
p value (Newey West)	0.214	0.002	0.120	0.039	0.286	0.533	0.005	0.020
Slope β	0.242***	0.291***	0.244***	0.276***	0.254***	0.195***	0.162***	0.238***
p value	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000
p value (Newey West)	0.000	0.000	0.000	0.001	0.000	0.007	0.001	0.001

Table 9 continued

	Insurance	Machinery	Measuring and Control	Medical Equipment	Non-Metallic and Industrial	Other	Personal Services	Petroleum and Natural Gas
Intercept α	0.008***	0.007*	0.010**	0.008**	0.007	0.006	0.005	0.007
p value	0.000	0.036	0.013	0.023	0.077	0.086	0.075	0.105
p value (Newey West)	0.001	0.059	0.035	0.048	0.123	0.102	0.103	0.189
Slope β	0.165***	0.210***	0.249***	0.224***	0.257***	0.176***	0.249***	0.100
p value	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.145
p value (Newey West)	0.002	0.002	0.001	0.002	0.004	0.007	0.000	0.298

	Pharmaceutical Products	Precious Metals	Printing and Publishing	Real Estate	Recreation	Restaurants, Hotels and	Retail	Rubber and Plastic
Intercept α	0.012**	0.007	0.004	0.002	0.001	0.002	0.006	0.007**
p value	0.011	0.287	0.213	0.604	0.814	0.427	0.077	0.020
p value (Newey West)	0.027	0.326	0.292	0.677	0.825	0.502	0.114	0.036
Slope β	0.227***	0.301***	0.184***	0.241***	0.272***	0.272***	0.274***	0.313***
p value	0.003	0.004	0.000	0.000	0.000	0.000	0.000	0.000
p value (Newey West)	0.004	0.005	0.005	0.001	0.000	0.000	0.000	0.000

	Shipbuilding and Railroad	Shipping Containers	Steel Works	Textiles	Tobacco Products	Trading (Financial)	Transportation	Utilities
Intercept α	0.009**	0.009***	0.006	0.001	0.015***	0.009***	0.005*	0.007***
p value	0.008	0.007	0.088	0.684	0.001	0.001	0.061	0.000
p value (Newey West)	0.010	0.008	0.118	0.718	0.000	0.004	0.081	0.000
Slope β	0.214***	0.350***	0.232***	0.257***	0.100	0.201***	0.255***	0.059*
p value	0.000	0.000	0.000	0.000	0.155	0.000	0.000	0.040
p value (Newey West)	0.002	0.000	0.002	0.000	0.231	0.000	0.000	0.054

Table 9 continued

	Wholesale
Intercept α	0.005
p value	0.069
p value (Newey West)	0.103
Slope β	0.254***
p value	0.000
p value (Newey West)	0.000

Panel c) Age Group 35 - 54

	Agriculture	Aircraft	Apparel	Automobiles and Trucks	Banking	Beer and Liquor	Business Services	Business Supplies
Intercept α	0.005	0.011***	0.004	0.002	0.008**	0.008***	0.008**	0.004
p value	0.220	0.002	0.190	0.520	0.001	0.002	0.015	0.153
p value (Newey West)	0.255	0.003	0.261	0.590	0.011	0.003	0.029	0.201
Slope β	0.259***	0.236***	0.288***	0.278***	0.161***	0.180***	0.251***	0.222***
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p value (Newey West)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	Candy and Soda	Chemicals	Coal	Communication	Computers	Computer Software	Construction	Construction Materials
Intercept α	0.008**	0.006*	0.004	0.007	0.008	0.010*	0.005	0.006*
p value	0.012	0.027	0.424	0.078	0.120	0.052	0.210	0.025
p value (Newey West)	0.010	0.051	0.498	0.125	0.145	0.080	0.280	0.050
Slope β	0.145**	0.199***	0.116	0.232***	0.278***	0.281***	0.328***	0.247***
p value	0.005	0.000	0.156	0.000	0.000	0.000	0.000	0.000
p value (Newey West)	0.010	0.000	0.220	0.000	0.000	0.000	0.000	0.000

Table 9 continued

	Consumer Goods	Defense	Electrical Equipment	Electronic Equipment	Entertainment	Fabricated Products (Metal	Food Products	Healthcare
Intercept α	0.004	0.013^{***}	0.006	0.011^{**}	0.004	0.002	0.006^{***}	0.010^{**}
p value	0.162	0.001	0.085	0.023	0.212	0.510	0.004	0.006
p value (Newey West)	0.225	0.002	0.128	0.040	0.297	0.550	0.005	0.021
Slope β	0.244^{***}	0.225^{***}	0.257^{***}	0.278^{***}	0.254^{***}	0.199^{***}	0.163^{***}	0.249^{***}
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p value (Newey West)	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000

	Insurance	Machinery	Measuring and Control	Medical Equipment	Non-Metallic and Industrial	Other	Personal Services	Petroleum and Natural Gas
Intercept α	0.008^{***}	0.007^{*}	0.010^{**}	0.008^{*}	0.007	0.005	0.005	0.007
p value	0.001	0.037	0.014	0.024	0.080	0.089	0.079	0.108
p value (Newey West)	0.001	0.064	0.037	0.051	0.131	0.107	0.109	0.195
Slope β	0.181^{***}	0.234^{***}	0.262^{***}	0.242^{***}	0.265^{***}	0.241^{***}	0.240^{***}	0.129^{*}
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.045
p value (Newey West)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.058

	Pharmaceutical Products	Precious Metals	Printing and Publishing	Real Estate	Recreation	Restaurants, Hotels and	Retail	Rubber and Plastic
Intercept α	0.012^{**}	0.007	0.003	0.002	0.001	0.002	0.006	0.007^{**}
p value	0.012	0.296	0.223	0.629	0.836	0.444	0.081	0.023
p value (Newey West)	0.029	0.337	0.307	0.703	0.846	0.521	0.121	0.040
Slope β	0.242^{***}	0.320^{***}	0.234^{***}	0.278^{***}	0.266^{***}	0.261^{***}	0.276^{***}	0.266^{***}
p value	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000
p value (Newey West)	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000

Table 9 continued

	Shipbuilding and Railroad	Shipping Containers	Steel Works	Textiles	Tobacco Products	Trading (Financial)	Transportation	Utilities
Intercept α	0.003	0.008**	0.006	0.001	0.015***	0.009***	0.005*	0.007***
p value	0.405	0.008	0.092	0.713	0.001	0.001	0.065	0.000
p value (Newey West)	0.444	0.011	0.125	0.748	0.000	0.004	0.087	0.000
Slope β	0.201***	0.263***	0.257***	0.300***	0.034	0.192***	0.253***	0.042
p value	0.001	0.000	0.000	0.000	0.603	0.000	0.000	0.123
p value (Newey West)	0.004	0.000	0.000	0.000	0.581	0.000	0.000	0.131

	Wholesale
Intercept α	0.005
p value	0.072
p value (Newey West)	0.111
Slope β	0.261***
p value	0.000
p value (Newey West)	0.000

Panel d) Age Group 55 and Older

	Agriculture	Aircraft	Apparel	Automobiles and Trucks	Banking	Beer and Liquor	Business Services	Business Supplies
Intercept α	0.005	0.011***	0.004	0.002	0.008**	0.008***	0.008**	0.004
p value	0.219	0.002	0.198	0.528	0.001	0.002	0.016	0.158
p value (Newey West)	0.248	0.003	0.267	0.597	0.012	0.003	0.030	0.206
Slope β	0.139***	0.171***	0.221***	0.223***	0.146***	0.141***	0.220***	0.157***
p value	0.011	0.001	0.000	0.000	0.000	0.000	0.000	0.000
p value (Newey West)	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 9 continued

	Candy and Soda	Chemicals	Coal	Communication	Computers	Computer Software	Construction	Construction Materials
Intercept α	0.008**	0.006*	0.004	0.007	0.008	0.010*	0.005	0.006*
p value	0.012	0.028	0.415	0.081	0.125	0.054	0.216	0.028
p value (Newey West)	0.010	0.051	0.486	0.127	0.148	0.082	0.285	0.053
Slope β	0.076*	0.134***	0.033	0.197***	0.296***	0.279***	0.245***	0.170***
p value	0.115	0.001	0.668	0.001	0.000	0.000	0.000	0.000
p value (Newey West)	0.065	0.000	0.677	0.001	0.000	0.000	0.000	0.000

	Consumer Goods	Defense	Electrical Equipment	Electronic Equipment	Entertainment	Fabricated Products (Metal	Food Products	Healthcare
Intercept α	0.004	0.013***	0.006	0.011**	0.004	0.002	0.006***	0.010**
p value	0.169	0.001	0.089	0.024	0.218	0.507	0.004	0.006
p value (Newey West)	0.232	0.002	0.131	0.041	0.302	0.543	0.006	0.022
Slope β	0.220***	0.144***	0.224***	0.270***	0.214***	0.125***	0.100***	0.201***
p value	0.000	0.010	0.000	0.000	0.000	0.012	0.002	0.000
p value (Newey West)	0.000	0.005	0.000	0.000	0.000	0.006	0.000	0.000

	Insurance	Machinery	Measuring and Control	Medical Equipment	Non-Metallic and Industrial	Other	Personal Services	Petroleum and Natural Gas
Intercept α	0.008***	0.007*	0.010**	0.008*	0.007	0.005	0.005	0.007
p value	0.001	0.039	0.014	0.025	0.081	0.093	0.083	0.109
p value (Newey West)	0.002	0.065	0.038	0.052	0.129	0.110	0.113	0.195
Slope β	0.141***	0.182***	0.249***	0.228***	0.133**	0.207***	0.191***	0.103*
p value	0.000	0.000	0.000	0.000	0.031	0.000	0.000	0.085
p value (Newey West)	0.000	0.000	0.000	0.000	0.020	0.000	0.000	0.060

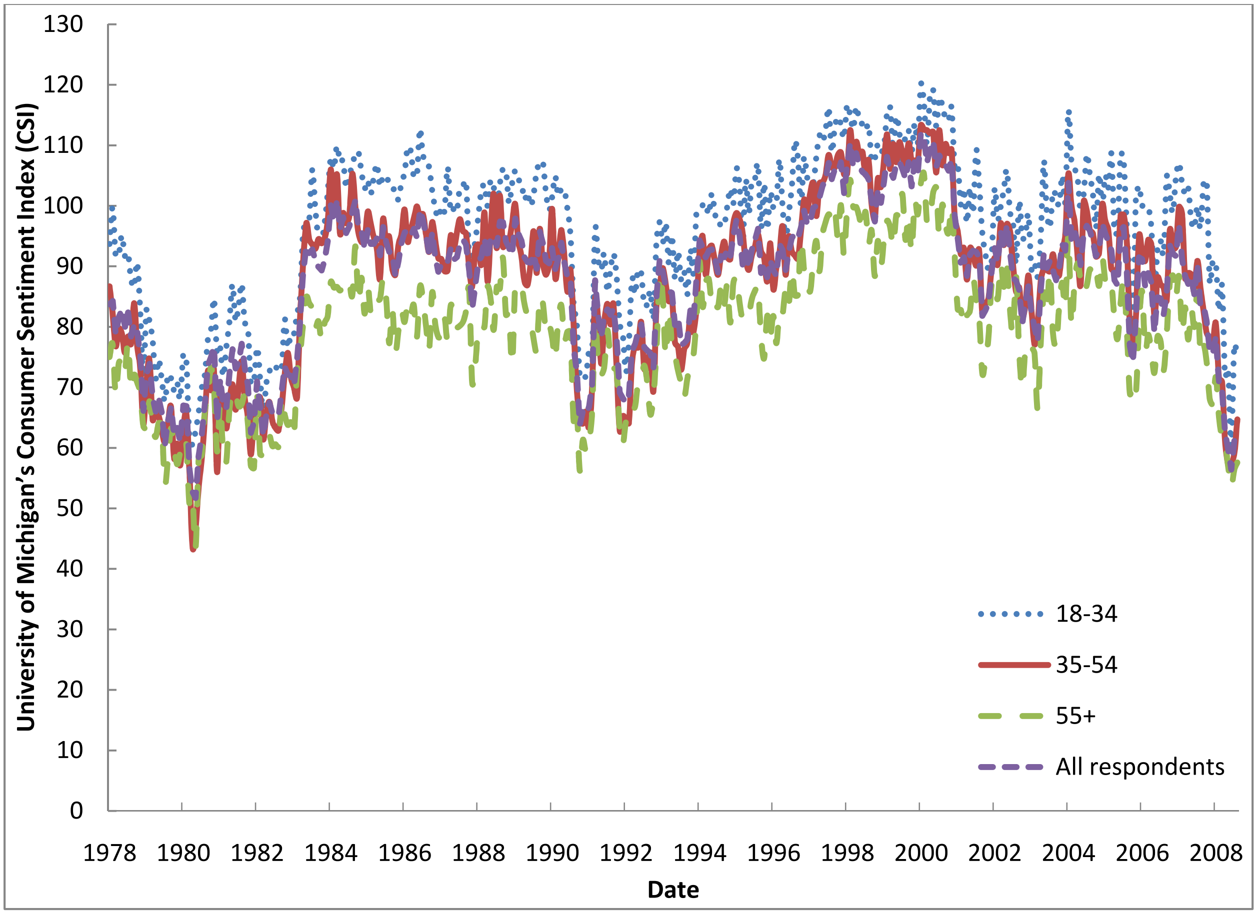
Table 9 continued

	Pharmaceutical Products	Precious Metals	Printing and Publishing	Real Estate	Recreation	Restaurants, Hotels and	Retail	Rubber and Plastic
Intercept α	0.011**	0.007	0.004	0.002	0.001	0.002	0.005	0.007**
p value	0.012	0.296	0.227	0.628	0.846	0.454	0.086	0.025
p value (Newey West)	0.029	0.336	0.309	0.698	0.855	0.527	0.125	0.042
Slope β	0.273***	0.217**	0.163***	0.185***	0.225***	0.214***	0.229***	0.216***
p value	0.000	0.019	0.000	0.000	0.000	0.000	0.000	0.000
p value (Newey West)	0.000	0.028	0.000	0.000	0.000	0.000	0.000	0.000

	Shipbuilding and Railroad	Shipping Containers	Steel Works	Textiles	Tobacco Products	Trading (Financial)	Transportation	Utilities
Intercept α	0.003	0.008**	0.006	0.001	0.014***	0.008***	0.005*	0.007***
p value	0.417	0.009	0.095	0.705	0.001	0.001	0.069	0.000
p value (Newey West)	0.454	0.011	0.127	0.738	0.000	0.005	0.090	0.000
Slope β	0.215***	0.145***	0.183***	0.183***	0.136**	0.178***	0.165***	0.034
p value	0.000	0.002	0.001	0.000	0.027	0.000	0.000	0.170
p value (Newey West)	0.000	0.004	0.000	0.000	0.036	0.000	0.000	0.175

	Wholesale
Intercept α	0.005
p value	0.077
p value (Newey West)	0.115
Slope β	0.216***
p value	0.000
p value (Newey West)	0.000

Figure 1



Time-Series Plot of Consumer Sentiment Based on Age Groups

If optimism is represented by high consumer sentiment levels, over time, survey respondents from the 18 – 34 age group appear to be more optimistic, followed by the 35 – 54 age group, and lastly, individuals 55 and older appearing to be the least optimistic (more pessimistic) out of all age groups.

Chapter 3

Consumer Sentiment's Impact on Home Prices and Home Sales

1. Introduction

"The same forces of human psychology that have driven the stock market over the years have the potential to affect other markets."
Robert J. Shiller (2005), *Irrational Exuberance*
Introduction to Chapter Two: The Real Estate Market in Historical Perspective

The importance of the real estate market and its place amongst other financial markets (e.g., stock markets, credit markets and commodities markets) cannot be emphasized enough, especially with respect to the global economic crisis that began to take shape in late 2007 as the unimaginable at the time occurred – real estate values began to decline. Subsequently, financial institutions began to lose substantial amounts of money as a global economic slowdown took hold and business conditions deteriorated while real estate foreclosures increased. In January 2009, RealtyTrac reported that in the year 2008, there was an 81 percent increase in foreclosure filings for U.S. real estate properties when compared to 2007 and a 225 percent increase from foreclosure filings in 2006. Moreover, in 2008 one out of fifty-four residential properties received at least one foreclosure filing during the year. To continue, the before mentioned economic debacle has been argued to be rooted in many causes such as a low interest rates from 2001 to 2004, oil prices that began to rise sharply beginning in 2007 and what some argue as a housing bubble that, sooner or later, had to deflate.

To further emphasize the scope and magnitude of the U.S. real estate market, it is important to offer a comparison. In 2008, home mortgage debt accounted for nearly three-fourths (73 percent) of U.S. gross domestic product.[15] To better illustrate this statistic, at the end of the fourth quarter of 2008, the Federal Reserve reported that the mortgage debt outstanding for one- to four-family residences was $11,033,793,000,000 (roughly $11 trillion dollars).[16] Soros (2008) argues that the housing bubble of the

[15] Barr, Colin. "The $4 trillion housing headache." *CNN Money* 27 May 2009.
[16] Federal Reserve website

mid-to-late 2000s was characterized by the excessive use of leverage and with such large real estate related debt obligations outstanding, such an argument can seem plausible.

With the importance of the housing market, it is important to see if empirically, some of the human psychological factors that Shiller (2005) alludes to can be quantified and captured with respect to their effects on the housing market. One such elusive factor would be consumer sentiment. Sentiment is defined as an attitude towards something or opinion. Consumer sentiment is typically interpreted as the attitude of consumers whereby higher levels of consumer sentiment are interpreted as consumer optimism and lower levels of consumer sentiment are interpreted as consumer pessimism. Optimistic consumers are perceived as more likely to make purchases related to consumption and simply consume. On the other hand, pessimistic consumers are perceived as less likely to make purchases related to consumption and save more while consuming less.

One such tangible good that consumers consume (i.e., buy) are homes. It may be true that people do in fact have to reside in some dwelling, somewhere but whether to rent their housing accommodation versus purchase it is another issue. The homeownership rate in the U.S. as of the second quarter of 2009 was 67.4 percent.[17] But with more than two-thirds of Americans owning a home, one basic question immediately presents itself: Can consumer sentiment foretell home prices and home sales? Additionally, do good times as indicated by optimistic consumer sentiment numbers translate into more home sales, which in turn result in higher residential home prices? Questions such as these will be empirically explored.

This paper makes significant use of the widely reported University of Michigan Survey of Consumers (CSI) as its measure of consumer sentiment. This survey reports its findings monthly and is based on approximately 500 telephone interviews of households in the U.S.[18] Furthermore, CSI provides its results as a composite figure (a nationwide number widely reported in the media) and also regionally. Regional CSI is simply the consumer sentiment of the residents of the respective geographic region in

[17] U.S. Census Bureau Housing Vacancy Survey
[18] "Surveys of Consumers" by Richard T. Curtin. Available from University of Michigan Surveys of Consumers website.

which these individuals live. The University of Michigan provides the consumer sentiment of four geographically identified areas of the U.S.: the Northeast, Midwest, South and West. For example, the Northeast CSI number is the sentiment of the survey respondents living in the following states: Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island and Vermont. Table 2b presents this information regarding the composition of each region and their corresponding states.

In addition to the question of possible regional differences amongst consumers and housing markets, a related issue regarding sentiment and the housing market is whether or not the age of the consumer responding to the survey displays differences among the results. This is issue of age and the housing market is brought up in Bakshi and Chen (1994). They study the life-cycle investment hypothesis and investigate the link between age and the type of assets demanded. Bakshi and Chen (1994) make the following statement: “as the population ages, the aggregate demand for housing decreases, which, ceteris paribus, depresses housing prices.” They make this statement based on the fact that younger individuals are less likely to have a home and as a result, more likely to demand homes. Conversely, older individuals are more likely to have purchased a home in which to possible raise a family and therefore, less likely to demand homes, especially at the same rate of younger individuals. Using consumer sentiment partitioned by age, this theory can be tested to find results that either support or reject the life-cycle investment hypothesis.

Case and Shiller (2003) argue that factors that can influence demand within the housing market are variables such as demographics, interest rate changes and location characteristics. This paper seeks to explore whether consumer confidence appears to forecast and explain home prices and home sales. Not only will the composite CSI be used, but given that different real estate markets behave differently (with respect to home prices and home sales), regional differences will be explored. This will be accomplished using Standard and Poor’s S&P/Case-Shiller Home Price Indices and S&P/Case-Shiller home sales data. This housing data is available in a composite index as well as city-by-city for twenty metropolitan areas in the U.S. measured over time. This cross-sectional time series of fertile housing data allows for a panel data analysis to be undertaken to explore the link between CSI and the housing market while incorporating the dynamic aspect of each city's housing market. Furthermore, given that the University of Michigan separates their CSI survey respondents into age groups, the life-cycle investment hypothesis will be explored empirically. This is undertaken to see if CSI can provide evidence consistent with Bakshi and Chen (1994) and answer the following question: Does the sentiment of older individuals, as measured using CSI, have less forecasting ability regarding the housing market and home prices?

These issues will be explored. But first, given the relatively recent events of the U.S. housing market and what has been coined by some as the bursting of the "housing bubble" and consequently, an erosion of consumer sentiment, a brief discussion of bubbles is presented in Section I alongside the related literature and literature review. The remainder of the paper is the following: Section II presents a discussion of the data employed, Section III describes the econometric specifications and results and Section IV provides concluding remarks.

2. Literature Review

2.1 What Constitutes A Housing Bubble? A Discussion of Bubbles

According to LeRoy (2004), bubbles imply irrationality. He goes on to say that loosely speaking, a bubble in any asset implies that the asset's price has realized a significant rise and will most likely realize an equally significant reduction in price. Case and Shiller (2003) begin by stating the following: "The term "bubble" is widely used but rarely clearly defined. We believe that in its widespread use the term refers to a situation in which excessive public expectations of future price increases cause prices to be temporarily elevated. During a housing price bubble, homebuyers think that a home that they would normally consider too expensive for them is now an acceptable purchase because they will be compensated by significant further price increases."

Case and Shiller (2003) argue that the market participants of the housing market (buyers and sellers), are inexperienced and refer to both parties as amateurs. If true, this immediately poses a problem being the housing market may be a market dominated by individuals who do not or cannot make buy and sell decisions based on market fundamentals, current/future economic conditions and/or full, relevant information. But whether or not this is true, another fundamental question is important: What causes bubbles? More specifically, what causes housing bubbles? They believe that housing bubbles (or as they refer to them, speculative bubbles) are the result of impulsive elements the affect the beliefs of individuals. Since impulses can influence buyers and sellers, this further illustrates their point of inexperience on the behalf of housing market participants.

An earlier exposition regarding bubbles can be found in Blanchard and Watson (1983), who present the discussing of bubbles in a more general context – financial markets as a whole. They provide a discussion of the conditions in which an asset's price may deviate from its fundamental value. They too argue that bubbles are also the result of irrationality. They state that the only reason to hold any asset whose current price is above its fundamental value is to sell this asset at a later date and realize the resulting price appreciation (i.e., capital gain or profit). The problem is that if every person who held assets with these characteristics did likewise at some finite future date, no one would own the assets in the future. This would be a result of everyone selling and future potential buyers, recognizing these higher prices, not willing to pay irrational or non-fundamental driven prices. This is why Blanchard and Watson (1983) argue that bubbles for any asset are a result of irrationality. They continue by saying that any asset is susceptible to bubbles with respect to their current market price but bubbles are more likely in asset markets where the fundamental valuation of the asset may be hard to determine.

They also use real estate as an example. They state that with the real estate market, the prices of homes are equal to the present value of the service in which homes provide (i.e., rent). They continue, saying that a housing bubble would be a situation in which individuals are willing to pay more than the market fundamental price of homes. In this event, higher home prices would give suppliers of homes (e.g., home builders) higher returns to housing construction and an incentive to supply more homes to the market. And without a change in the demand for homes, a result would be lower future rents. Later on in the future as the bubble continues to grow, the housing market would go on to experience higher home prices, a greater supply of homes and lower rents. The lower rents would be a result of the overproduction of homes, indicating a lower fundamental value for housing. The bursting of a housing bubble would result in price levels for homes which would be lower than the pre-bubble prices because of a greater supply of homes.

Interestingly, they note that a bubble market for any asset will usually affect the prices of other assets, regardless of whether or not the other assets are subject to bubbles. The primary reason for such is that a significant price increase in the price of the bubble asset will result in an increase in total wealth. Assuming that many individuals own bubble assets (e.g., homes), a large number of individuals will experience wealth increases, resulting in additional consumption, investment in other real assets or financial assets and/or saving. These other market ripple effects of a bubble in another asset class are termed 'real effects' by Blanchard and Watson (1983). Thinking of the recent housing bubble, simultaneously within the same relative period of time in which home prices had reached record highs in the U.S., the Dow Jones Industrial Average reached 14,093.08 in October 2007 and the price of one barrel of crude oil in the commodities market reached $147.30 in July 2008. These real effects that occurred in the U.S. economy provide support for Blanchard and Watson (1983) and their argument that the irrational price of one asset (homes) has the ability to affect the prices of other assets (stocks and oil).

On the other hand, there are studies that dispute the claim that the recent housing bubble even existed. McCarthy and Peach (2004) ask the following question: Are home prices the next "bubble?" They do not find that the recent rise in home prices was the result of irrationality or a bubble in the housing market. They state that despite home prices rising significantly in the 1990s and early 2000s, there would not be collapse in the housing market caused by large losses in home values. They find that the increases in home prices during the recent housing boom were due to increases in family income and low interest rates – not unwarranted exuberance. They even go as far as to state that if the economy were to contract, there would be a low probability that home prices would drop drastically because such an event has not happened in U.S. history.

Smith and Smith (2006), like McCarthy and Peach (2004), do not find support for the notion that the recent significant rise in home prices were not symptomatic of a bubble in home prices. One of their main arguments is that the papers that argue in favor of a housing bubble use incorrect measures of home price appreciation because they are not capturing the homes' fundamental value. They estimate the fundamental home values for ten U.S. metropolitan areas and do not find evidence consistent with unwarranted rises in the fundamental values of homes. Using hindsight after these articles were published, it can easily be argued that in fact the macroeconomic events that transpired in 2008 and early 2009 in the U.S. and the world debunk the results of both McCarthy and Peach (2004) and Smith and Smith (2006).

Rotemberg (2008) states that the current housing market debacle and bubble burst were the result of lenders who began to lend money to subprime borrowers. The distinction lies in the fact that the prime borrowers are borrowers who meet traditional definitions of credit worthiness whereas subprime borrowers are typically less creditworthy and are charged higher interest rates to compensate lenders for the increased risk. In 2007 and 2008, the economy began to deteriorate due to homes losing their values, homebuyers facing foreclosure, rising gas prices at the time and unemployment. Ultimately, a bad situation for the housing market became worse and many acknowledged that the housing bubble did in fact burst. The events that followed the severe U.S. economic contraction is consistent with Blanchard and Watson (1983) and their real effect concept. The collapse of the U.S. housing market would go on to cause devastating consequences that ultimately resulted in real adverse effects for not only the U.S., but the world.

2.2 Other Related Literature

The link between the real estate market and the stock market is an area previously studied. For example, Quan and Titman (1999) empirically examine the relationship between stock prices and real estate prices. Moreover, they use an exhaustive data set which includes international data alongside more than ten years of data in an attempt to study this puzzle. They hypothesize that real estate values and stock returns move in the same direction because of expectations of future economic conditions. They mention the issue of the rationality of these expectations. They do not delve deep into the issue of rationality but do seek to investigate whether current economic conditions versus expectations of future economic growth help explain the positive relationship between stock returns and changes in real estate values. They find a positive relationship between stock returns and changes in commercial real estate values.

They note that a contemporaneous relationship between annual real estate price changes and stock returns is statistically not significant but the relationship does in fact begin to emerge when lagged variables are utilized. The one variable that they found to affect real estate prices the most is the growth rate of GDP.

One of the more directly related papers related to consumer sentiment and its relationship with the housing market can be found within Dua (2008) who investigate consumers' perceptions regarding buying conditions for homes. More specifically, she studies which variables tend to have the greatest impact on consumers' attitudes as to when they feel is a good time to buy a home. Variables that she includes are house prices, mortgage rates, wealth, employment and income levels. She is able to study how such variables have an impact on consumers' home buying perceptions by construction a buying index[19] using the following question from the University of Michigan Survey of Consumers: "Generally speaking, do you think now is a good time or a bad time to buy a house?" Survey respondents are able to respond by saying that it is a good time to buy, it is a bad time to buy or that they are uncertain as to whether or not it is an appropriate time to buy a home. She argues that her home buying index measures the percentage of respondents saying that now is a good time to buy relative to the percentage of respondents saying that now is a bad time to buy.

She uses a vector autoregression methodology alongside Johansen and Juselius' cointegration test to study the impact of house prices, mortgage rates, wealth, employment and income levels on her home buying index. She finds that consumers' home buying opinions, as measured by her home buying index, are cointegrated with current and expected interest rates, wealth, expected real disposable income, financial status and current prices of homes. In addition, all before mentioned variables Granger cause home buying opinions or perceptions.

Clayton, Ling and Naranjo (2009) also incorporate behavioral analyses within the context of real estate. They are motivated by the lack of research undertaken investigating how investor sentiment plays a role in commercial real estate pricing and capital flows. The authors note that one explanation for the

[19] Dua's (2008) Home Buying Index = Good + Uncertain*[Good/(Good + Bad)]. This index can have a value between 0 and 100 where an increase in the index indicates consumers feeling buying conditions for homes are becoming more attractive.

limited related research undertaken is data limitations. They cite the fact that the commercial real estate market is extremely heterogeneous as a possible hurdle severely limiting such research to be undertaken.[20] A good example that they provide is the example of real estate as an asset compared to stocks. Because of the heterogeneity inherent in real estate (e.g., location, size, purpose, etc.), the authors note the lack of close substitutes. Stocks on the other hand, have close substitutes (e.g., similar firm size, similar risk characteristics, etc.). Another important market characteristic that makes the real estate market and the stock market is the fact that short selling and arbitrage are not an innate aspect of the real estate market as they are in the stock market. As a result, the real estate market is more vulnerable to misevaluations and mispricing.

Clayton, Ling and Naranjo (2009) examine how real estate fundamentals and investor sentiment can explain the time-series variation in property-specific national capitalization rates. The capitalization rate used is simply a measure of the ratio between the net operating income produced by the commercial real estate property and its acquisition cost. Using such data and an error correction specification, they are able to show that relevant real estate and overall economic fundamentals (equity risk premiums, Treasury bond yields and changes in expected rental growth) as well as investor sentiment are important determinants in shaping capitalization rates.

But in the context of a more general framework regarding studies on the importance of the effects of changes in the real estate market, Case, Quigley and Shiller (2005) compare the wealth effects that can be measured as a result of both the stock market and the housing market. They acknowledge that changes in stock prices are associated with changes in consumption (changes in consumption correspond with changes in stock market wealth with the relationship being positive). They test the novel idea that changes in housing wealth can have effects on household behavior in a manner similar to the wealth effects caused by the stock market. By housing wealth effects, they are using changes in home prices and using two panel data sets, one international and one state-by-state using the U.S., they find strong evidence that

[20] All real estate (commercial, residential and agriculture) is heterogeneous in the sense that any two properties will not possess the same characteristics that another property may possess.

variations in housing market wealth have important effects upon consumption. Employing an error-correction model, for the U.S. sample they find that the immediate effect of a ten percent increase in housing wealth is an increase in consumption of 0.4 percent while a ten percent increase in financial wealth has no effect. They conclude their article by making a strong argument that changes in housing prices appear to have more of an impact on consumer consumption as compared to changes in stock market prices.

Campbell and Cocco (2007), along the lines of Case, Quigley and Shiller (2005), study how house prices affect consumption using data from the United Kingdom. They discuss some possible reasons as to why house prices could impact consumption. They state that it would be naïve to merely argue that an increase in house prices increases housing wealth which translates into increased consumption. They mention that it is important to note that housing is an asset that can be used as collateral to obtain a loan. As a result, an increase in house price could therefore increase a household's borrowing ability which, in turn, could allow for increased consumption. They study the response of household consumption to house prices using United Kingdom data. They too utilize a micro data set incorporating characteristics of households such as age, homeownership status and region of inhabitance.

They find large disparities in consumption amongst differing households when house prices change and they label their findings as "considerable heterogeneity," especially with respect to the age variable used. Defining age as the year of birth of the head of household, they find a large positive effect of changes in house prices on consumption for older household homeowners versus an effect that is close to zero for the group of younger households who are renters. They state that such a difference is important because it implies that as the individuals become older, aggregate consumption may become more responsive to changes in house prices.

Continuing with the importance of real estate in an international setting, Maroney and Naka (2006) study the Japanese real estate market and how real estate can contribute to diversification gains. With the use of spanning tests, they find that over a 47 year sample period from 1957 to 2004, it was not until 1990 that diversification gains into real estate appear more economically significant, helping establish that allocating investment monies into real estate has been important for some time but more so more recently. Others, even without the use of international data, also note the importance of real estate in the context of an individual's portfolio. One such article, Cocco (2004), mentions that "owner-occupied housing is the single most important asset in many investors' portfolios." He seeks to investigate how the investment in housing affects the overall composition of an investor's portfolio and he finds that individuals' investment in housing affects both asset accumulation and portfolio choice among stocks and Treasury bills. Younger individuals, who also have lower financial net-worths, keep fewer liquid assets low and participate less in the stock market. Thus, he argues that housing investment has the ability to "crowd out" the proportion of stockholdings. He concludes that an investment in housing plays an important role in explaining the patterns of cross-sectional variation in the composition of wealth and the level of stockholdings observed in portfolio composition data.

3. Data

The variable consumer sentiment used in this paper is available from the University of Michigan Surveys of Consumers (CSI). The frequency of this data is monthly. For this paper, due to the housing data availability, the sample is available beginning in January 1987 and ends in December 2008, resulting in 21 years of data. Mothly consumer sentiment data is available beginning in 1978 but the S&P/Case-Shiller Composite index time series begins in January 1987. CSI is segmented into three age groups: 18 to 34 year olds, 35 to 54 year olds and persons 55 years old and older. Additionally, CSI is also segmented based on regions of the U.S.; the Northeast, Midwest, South and West. Table 1 provides a description of which U.S. states are included in which region. A benefit of sentiment data which is separated based on both age and region is that it provides more thorough insight into specific statistical relationships between the housing market and consumer sentiment. In particular, I am able to incorporate both age and geographic location into my analyses, allowing for a richer investigation.

Table 1

Data Descriptions

Panel a) S&P/Case-Shiller data

Metropolitan area	Dates of Data Availability
AZ-Phoenix	1/1989 – 12/2008
CA-Los Angeles	1/1987 – 12/2008
CA-San Diego	1/1987 – 12/2008
CA-San Francisco	1/1987 – 12/2008
CO-Denver	1/1987 – 12/2008
DC-Washington	1/1987 – 12/2008
FL-Miami	1/1987 – 12/2008
FL-Tampa	1/1987 – 12/2008
GA-Atlanta	1/1991 – 12/2008
IL-Chicago	1/1987 – 12/2008
MA-Boston	1/1987 – 12/2008
MI-Detroit	1/1991 – 12/2008
MN-Minneapolis	1/1989 – 12/2008
NC-Charlotte	1/1987 – 12/2008
NV-Las Vegas	1/1987 – 12/2008
NY-New York	1/1987 – 12/2008
OH-Cleveland	1/1987 – 12/2008
OR-Portland	1/1987 – 12/2008
TX-Dallas	1/2000 – 12/2008
WA-Seattle	1/1990 – 12/2008
Composite-10	1/1987 – 12/2008
Composite-20	1/2000 – 12/2008

Panel b) University of Michigan Survey of Consumers Region Specifications

Northeast	*Midwest*
Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island and Vermont	Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota and Wisconsin
South	*West*
Alabama, Arkansas, Delaware, District of Columbia, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia and West Virginia	Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington and Wyoming

As for the home price data, this is available via Standard and Poor's S&P/Case-Shiller Home Price Indices. There are two respective indices: 1) S&P/Case-Shiller Composite-10 index and 2) S&P/Case-Shiller Composite-20 index. The S&P/Case-Shiller Composite-10 is a home price index that is the value-weighted average of ten individual metropolitan areas/cities and is available beginning in January 1987. Similarly, the S&P/Case-Shiller Composite-20 is a home price index that is the value-weighted average of twenty individual metropolitan areas/cities and is available beginning in January 2000. S&P/Case-Shiller Home Price Indices are typically used to gauge the price appreciation/depreciation of residential real estate. The purpose of each respective index is to track the price of typical single-family homes located in the respective metropolitan area. Along with the S&P/Case-Shiller Home Price Indices, S&P/Case-Shiller provide home sales data for each metropolitan area as well as for the Composite-10 and Composite-20 indices. These values are the number of single-family homes that were sold in a given month in that particular city.[21] One benefit of having more than two decades of monthly demographic-separated consumer sentiment data, home prices and home sales data is that it allows the ability to undertake a cross-sectional investigation to capture rich differences that may exist across geographical regions and amongst age groups.[22]

[21] Standard and Poor's website

[22] The S&P/Case-Shiller Composite-10 data is available from January 1987 until December 2008 and the S&P/Case-Shiller Composite-20 is available from January 2000 until December 2008.

Table 2
Summary Statistics

	Mean	Standard Deviation	Minimum	Maximum	*N*
ΔHome Prices	94.94	20.31	67.44	135.88	254
ΔHome Sales	116.98	51.42	65.89	234.78	254
ΔCSI Composite	116.83	49.53	72.29	215.83	254

Home Prices

	Mean	Standard Deviation	Minimum	Maximum	*N*
AZ-Phoenix	109.78	48.60	64.35	227.42	240
CA-Los Angeles	126.98	64.15	69.36	273.94	254
CA-San Diego	121.35	61.89	60.12	250.34	254
CA-San Francisco	109.99	52.69	52.64	218.37	254
CO-Denver	90.22	34.00	47.21	140.28	254
DC-Washington	126.44	55.30	74.88	251.07	254
FL-Miami	125.16	63.35	71.68	280.87	254
FL-Tampa	117.88	48.42	79.21	238.09	254
GA-Atlanta	100.35	22.13	69.05	136.47	216
IL-Chicago	103.77	33.70	62.78	168.60	254
MA-Boston	106.55	42.89	62.94	182.45	254
MI-Detroit	93.34	22.86	57.63	127.05	216
MN-Minneapolis	105.70	38.23	62.43	171.12	240
NC-Charlotte	94.94	20.31	67.44	135.88	254
NV-Las Vegas	116.98	51.42	65.89	234.78	254
NY-New York	116.83	49.53	72.29	215.83	254
OH-Cleveland	92.16	20.39	56.45	123.49	254
OR-Portland	98.92	41.68	41.48	186.51	254
TX-Dallas	116.16	6.43	100.00	126.47	108
WA-Seattle	106.50	40.19	58.23	192.30	228
Composite-10	116.75	51.62	70.77	226.29	254
Composite-20	157.44	34.53	100	206.52	108

Home Sales

	Mean	Standard Deviation	Minimum	Maximum	*N*
AZ-Phoenix	7349.66	3289.82	2622	18859	240
CA-Los Angeles	13030.66	4128.85	4176	24510	258
CA-San Diego	3619.36	1108.45	1419	5855	258

Table 2 continued

CA-San Francisco	5418.10	1574.67	1929	9450	258
CO-Denver	4782.68	1435.6	2165	8312	258
DC-Washington	5925.75	2626.85	2433	15514	258
FL-Miami	7481.61	2208.10	2670	12916	258
FL-Tampa	3974.81	955.17	1687	6833	258
GA-Atlanta	5458.19	2400.89	1832	13315	216
IL-Chicago	4402.18	2735.22	663	12467	258
MA-Boston	3454.85	958.33	1602	6614	258
MI-Detroit	3366.88	1132.93	247	6000	216
MN-Minneapolis	3716.85	1800.19	780	9124	240
NC-Charlotte	2023.99	713.23	910	4721	258
NV-Las Vegas	2132.24	1742.20	202	7448	258
NY-New York	9970.30	3702.77	4409	21890	258
OH-Cleveland	1848.40	565.49	554	3320	258
OR-Portland	2727.51	1093.43	1008	5991	258
TX-Dallas	3734.19	2308.51	119	8132	108
WA-Seattle	4209.63	1268.55	2130	8162	228
Composite-10	60217.72	16073.95	31384	111099	258
Composite-20	115342.93	29368.13	58807	185773	108

4. Econometric Specification/Methodology

4.1 Basic Model

To first see if CSI has explanatory power in terms of forecasting changes in home prices, the following equation is estimated:

$$\Delta Home\ Prices_t = \alpha + \beta \Delta CSI_{t-i} + \varepsilon_t \qquad i = 1, \ldots, 6 \qquad (1)$$

where the dependent variable, ΔHome Prices_t, is the percent change in the S&P/Case-Shiller Composite-10 home price index and ΔCSI_{t-i}, is the change in CSI. I begin with the basic relationship between the CSI Again, the CSI composite index is a widely reported national gauge of the sentiment of consumers across the U.S. The purpose of using lags from one month (*t*-1) through six months (*t*-6) is that consumers in the market to purchase a home usually decide to make such a large purchase far in advance. Furthermore, the process of buying a home can be a lengthy process between finding a realtor to aid in the search process, securing financing for the purchase, selecting the right property to purchase and actually completing the deal. For 2006 to 2008, the National Realtors Association reported that typical homebuyers search for eight to ten weeks before finding the home that they ultimately purchased. With this in mind, I estimate equation (1) over different time horizons.

Table 3 reports the results of equation (1). It can be seen from this table that for the CSI composite, the statistically significant coefficients for ΔCSI_{t-i} is at the four (*t*-4), five (*t*-5) and six (*t*-6) month lags. Also, the coefficients for the variable are positive, indicating that there is a positive relationship between changes in consumer sentiment and changes in home prices. In other words, increases in consumer sentiment (i.e., optimism) tend to be followed by price increases in homes. In terms of economic significance, the coefficient for ΔCSI_{t-5} is 0.035 and is significant at the 1 percent level and means that an increase in the consumer sentiment composite index by 10 points results in the S&P/Case-Shiller Composite home price index rising by 0.35 points. Similar interpretations can be made for the other statistically significant coefficients.

Also included in Table 3 are the results from changes in the different age groups' sentiment and their relationship to changes in home prices. A few results emerge from looking at these results. First, the only lag that is significant for the 18-34 year old age group is *t*-4. As for the next age group (35-54 age group), the lags in sentiment that are significant are *t*-5 and *t*-6. Lastly, the 55 years old and older age group exhibits significant lags at *t*-4, *t*-5 and *t*-6. These results are consistent with what the CSI composite index conveys but it is interesting that for the 18-34 year old age group, only one statistically significant relationship exists because younger individuals and families typically are seeking their first home.

Table 3

This table represents ordinary least square regressions of monthly changes in home prices on lagged changes in the consumer sentiment. The home prices are from the S&P/Case-Shiller Composite-10 which is available from January 1987 until December 2008. All statistical significance is denoted by *, **, *** which indicates significance at the 10, 5, and 1 percent levels.

$$\Delta Home\ Prices_t = \alpha + \beta \Delta CSI_{t-i} + \varepsilon_t \quad i = 1, \ldots, 6$$

CSI Composite

	ΔCSI_{t-1}	ΔCSI_{t-2}	ΔCSI_{t-3}	ΔCSI_{t-4}	ΔCSI_{t-5}	ΔCSI_{t-6}
Intercept α	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
Standard error	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Slope β	0.009	0.014	0.017	0.028**	0.035***	0.029**
Standard error	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)
p-value	[0.420]	[0.212]	[0.129]	[0.015]	[0.003]	[0.012]

Age Group 18-34

	ΔCSI_{t-1}	ΔCSI_{t-2}	ΔCSI_{t-3}	ΔCSI_{t-4}	ΔCSI_{t-5}	ΔCSI_{t-6}
Intercept α	0.004***	0.004***	0.004***	0.004***	0.004***	0.003***
Standard error	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Slope β	0.008	0.009	0.012	0.012	0.012	0.016*
Standard error	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
p-value	[0.357]	[0.286]	[0.146]	[0.158]	[0.147]	[0.078]

Age Group 35-54

	ΔCSI_{t-1}	ΔCSI_{t-2}	ΔCSI_{t-3}	ΔCSI_{t-4}	ΔCSI_{t-5}	ΔCSI_{t-6}
Intercept α	0.004***	0.004***	0.004***	0.004***	0.004***	0.003***
Standard error	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Slope β	0.007	0.009	0.010	0.017	0.026***	0.018**
Standard error	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
p-value	[0.435]	[0.331]	[0.285]	[0.062]	[0.006]	[0.046]

Age Group 55 and older

	ΔCSI_{t-1}	ΔCSI_{t-2}	ΔCSI_{t-3}	ΔCSI_{t-4}	ΔCSI_{t-5}	ΔCSI_{t-6}
Intercept α	0.004***	0.004***	0.004***	0.004***	0.004***	0.003***
Standard error	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Slope β	0.002	0.007	0.009	0.015*	0.018**	0.014*
Standard error	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
p-value	[0.786]	[0.371]	[0.288]	[0.062]	[0.029]	[0.081]

4.1.1 Bivariate Causality

To further investigate how CSI affects the housing market, it is also important to explore bivariate Granger causality relationships, especially over different time periods to see if one economic variable can help forecast another economic variable. Table 4 reports these results. From this table, a lag of one month shows no causality relationships among changes in CSI, changes in home prices and changes in the number of homes sold. It can be observed that at a lag of six months, causality begins to appear. At a 1 percent level of significance, two-way causality appears between changes in home sales and change in home prices. This logically makes sense – lower prices result in more sales while higher prices result in fewer sales. Similar to the results of Table 3, there is a delay in which changes in CSI Granger cause changes in home prices. The causality relationships in existence at a lag of six months persist, continuing further to a lag of twelve months and twenty-four months. It should be pointed out that at a lag of twenty-four months changes in CSI do Granger cause changes in Home Sales. These results are interesting in that changes in consumer sentiment are long lasting in the housing market. With results such as these, other time-series econometric specifications are pursued.

Table 4

Granger Causality using changes in the composite CSI and changes in the e S&P/Case-Shiller Composite-10 home price index and sales count data.

Number of Lags = 1		
Null hypothesis	F-statistic	p-value
ΔCSI does not Granger Cause ΔHome Prices	2.620	0.107
ΔCSI does not Granger Cause ΔHome Sales	1.612	0.205
ΔHome Prices does not Granger Cause ΔCSI	0.400	0.527
ΔHome Prices does not Granger Cause ΔHome Sales	0.701	0.403
ΔHome Sales does not Granger Cause ΔCSI	0.121	0.728
ΔHome Sales does not Granger Cause ΔHome Prices	0.080	0.778
Number of Lags = 6		
ΔCSI does not Granger Cause ΔHome Prices	3.184	0.005
ΔCSI does not Granger Cause ΔHome Sales	0.390	0.885
ΔHome Prices does not Granger Cause ΔCSI	0.674	0.671
ΔHome Prices does not Granger Cause ΔHome Sales	4.828	0.000
ΔHome Sales does not Granger Cause ΔCSI	0.485	0.819
ΔHome Sales does not Granger Cause ΔHome Prices	6.980	0.000
Number of Lags = 12		
ΔCSI does not Granger Cause ΔHome Prices	1.731	0.062
ΔCSI does not Granger Cause ΔHome Sales	0.660	0.789
ΔHome Prices does not Granger Cause ΔCSI	0.642	0.805
ΔHome Prices does not Granger Cause ΔHome Sales	3.167	0.000
ΔHome Sales does not Granger Cause ΔCSI	0.783	0.668
ΔHome Sales does not Granger Cause ΔHome Prices	4.310	0.000
Number of Lags = 24		
ΔCSI does not Granger Cause ΔHome Prices	1.686	0.029
ΔCSI does not Granger Cause ΔHome Sales	1.573	0.051
ΔHome Prices does not Granger Cause ΔCSI	0.640	0.902
ΔHome Prices does not Granger Cause ΔHome Sales	2.111	0.003
ΔHome Sales does not Granger Cause ΔCSI	0.985	0.488
ΔHome Sales does not Granger Cause ΔHome Prices	2.455	0.000

4.2 Panel Data Analyses

To fully utilize the time series data available with consumer sentiment data available across various regions and the S&P/Case-Shiller home price indices and home sales across metropolitan areas, panel data regressions are employed. By using this approach, differences across individual housing markets in their respective cities can be studied. Since the S&P/Case-Shiller housing market data across cities have different time periods for which the data is available, the panel of data is unbalanced. To see how CSI affects the housing market in certain areas, I match the metropolitan area for which S&P/Case-Shiller data is available to the regional consumer sentiment level. For example, for the housing sales and housing price data for Seattle, Washington, I matched its housing market data with the CSI 'West' consumer reading. By doing this for all U.S. metropolitan areas, I am able to capture how consumer sentiment in a particular area more specifically affects the housing market in that particular area.

Upon selecting a panel data model, two of the more popular methodologies are the random effects and fixed effects models. According to Greene (2007), the random effects model assumes that the individual specific effects are uncorrelated with the independent variables. On the other hand, the fixed effects model assumes that the individual specific effect is correlated with the independent variables. I assume that the unobservable factors that may simultaneously affect the dependent and independent variables are time invariant and thus utilize a fixed effects model.

4.2.1 Fixed Effects Regressions

The first model estimated using fixed effects panel data regressions is the following:

$$\Delta Home\ Prices_{i,t} = \beta \Delta CSI_{i,t-j} + u_i + \varepsilon_{i,t} \quad j = 1, \ldots, 6 \qquad (2)$$

where the dependent variable, ΔHome $Prices_{i,t}$, is the change in the S&P/Case-Shiller home price index across 20 different metropolitan areas in the U.S. and $\Delta CSI_{i,t-j}$, is the change in the CSI index region-by-region for the four regions as specified in Table 1. Also, u_i is the individual-level effect and $\varepsilon_{i,t}$ is the idiosyncratic disturbance term that changes across t as well as across i. The results of equation (2) are presented in Table 5.

From this table, a few observations immediately appear. First, when incorporating regional aspects of the housing market and regional consumer sentiment, changes in CSI do forecast changes in home prices. This holds for the following lags: $\Delta CSI_{t-1,}$ ΔCSI_{t-2}, $\Delta CSI_{t-3,}$ $\Delta CSI_{t-4,}$ ΔCSI_{t-5} and $\Delta CSI_{t-6.}$ In addition to forecasting changes in home prices at various lags, interestingly, the coefficient for the statistically significant changes in CSI is the largest at the *t*-5 and *t*-6 lags. This result is consistent with the basic model results presented in Table 3 whereby the larger magnitude coefficients were larger at later lags. What these panel regression results from equation (2) show is that there appears to be a stronger effect on longer prior period changes in sentiment versus more near-term changes in sentiment. This is consistent with the argument that since home buying can be a lengthy process, immediate changes in consumer sentiment are more likely to affect people not presently in the housing market but who were merely possibly considering entering the market. It would be these individuals that may not have completed any concrete steps in the home buying process.

Table 5

The following table is the results of a fixed effects panel regression examining changes in consumer sentiment and if it can forecast future changes in home prices. The S&P/Case-Shiller housing market data is from cities across the U.S. and this data is available for cities for different time periods. As a result, the panel of data is unbalanced. To see how CSI affects the housing market in certain areas, I match the metropolitan area for which S&P/Case-Shiller data is available to the University of Michigan Surveys of Consumers regional consumer sentiment level. All statistical significance is denoted by *, **, *** which indicates significance at the 10, 5, and 1 percent levels.

$$\Delta Home\ Prices_{i,t} = \beta \Delta CSI_{i,t-j} + u_i + \varepsilon_{i,t}$$

	ΔCSI_{t-1}	ΔCSI_{t-2}	ΔCSI_{t-3}	ΔCSI_{t-4}	ΔCSI_{t-5}	ΔCSI_{t-6}
Slope β	0.004*	0.006***	0.004**	0.011***	0.013***	0.013**
Standard error	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
p-value	[0.079]	[0.001]	[0.034]	[0.000]	[0.000]	[0.000]

Table 6

The following table is the results of a fixed effects panel regression to see if changes in consumer sentient forecast changes in the number of homes sold. The S&P/Case-Shiller housing market data is from cities across the U.S. and this data is available for cities for different time periods. As a result, the panel of data is unbalanced. To see how CSI affects the housing market in certain areas, I match the metropolitan area for which S&P/Case-Shiller data is available to the University of Michigan Surveys of Consumers regional consumer sentiment level. All statistical significance is denoted by *, **, *** which indicates significance at the 10, 5, and 1 percent levels.

$$\Delta Home\ Sales_{i,t} = \beta \Delta CSI_{i,t-j} + u_i + \varepsilon_{i,t}$$

	ΔCSI_{t-1}	ΔCSI_{t-2}	ΔCSI_{t-3}	ΔCSI_{t-4}	ΔCSI_{t-5}	ΔCSI_{t-6}
Slope β	0.037	0.049*	0.130***	0.123***	0.032***	-0.007
Standard error	(0.028)	(0.028)	(0.028)	(0.028)	(0.029)	(0.029)
p-value	[0.190]	[0.084]	[0.000]	[0.000]	[0.264]	[0.812]

In addition to investigating changes in home prices, I also study changes in home sales. The second panel data model that I estimate using a fixed effect regression is the following:

$$\Delta Home\ Sales_{i,t} = \beta \Delta CSI_{i,t-j} + u_i + \varepsilon_{i,t} \qquad (3)$$

where the dependent variable, ΔHome $Sales_{i,t}$, is the change in the S&P/Case-Shiller home sales index across 20 different metropolitan areas in the U.S. and $\Delta CSI_{i,t-j}$, is the change in the region-specific CSI index. Similar to equation (2), u_i is the individual-level effect and $\varepsilon_{i,t}$ is the disturbance term. The results of equation (3) are presented in Table 6.

First, it can be observed from the table that the following coefficients for changes in consumer sentiment are statistically significant in terms of forecasting changes in the number of homes sold: ΔCSI_{t-2}, ΔCSI_{t-3}, ΔCSI_{t-4} and ΔCSI_{t-5} Also noticeable is that these statistically significant coefficients are positive, indicating that increased consumer optimism corresponds with future increases in home sales. This makes sense that people are more willing to make a major purchase such as this when they are upbeat about future economic conditions and personal circumstances. The panel regression results from equations (2) and (3) indicate that changes in consumer sentiment do appear in the housing market. It could be argued that these results are of statistical significance and not of economic significance. This paper argues that these findings indicate that consumer sentiment has forecasting abilities similar to other leading macroeconomic indicators in that it predicts future economic conditions.

4.3 Vector Autoregression (VAR) Analysis

It is important to note that since changes in consumer sentiment foretell future housing market activity at different lags, another way to go about investigating this relationship would be to incorporate all of these variables into dynamic modeling whereby the simultaneous interaction of these variables could be investigated. To make sure that a very important consideration with respect to when individuals consider purchasing a home is not omitted, I also introduce another variable that is important with respect to housing market activity – the 30 year conventional mortgage rate.[23] Dua (2008) finds that current and

[23] St. Louis Federal Reserve Economic Data (FRED)

expected interest rates explain a significant proportion of when consumers consider entering the housing market.

To see the time series relationship between changes in CSI, changes in home prices, changes in home sales and changes in the 30 year mortgage rate, a VAR model is employed. One advantage of estimating such a model is that it would provide a system of equations that would make full use of the lags needed to capture the long-nature effects that changes in CSI appear to have in the housing market. A reduced-form VAR is thus utilized because it is assumed that each variable is a liner function of its own past values, the past values of all other variables being considered and a serially uncorrelated error term (Stock and Watson (2001)). The VAR model used is the following:

$$\begin{aligned}\Delta Home\ Prices_t &= \alpha_1 + \sum_{i=1}^{10} \beta_{1i}\Delta CSI_{t-i} + \sum_{j=1}^{10} \beta_{1j}\Delta Home\ Sales_{t-j} + \sum_{k=1}^{10} \beta_{1k}\Delta Home\ Prices_{t-k} \\ &+ \sum_{l=1}^{10} \beta_{1l}\Delta Mortgage\ Rates_{t-l} + \varepsilon_2 \qquad (4a)\end{aligned}$$

$$\begin{aligned}\Delta Home\ Sales_t &= \alpha_2 + \sum_{i=1}^{10} \beta_{2i}\Delta CSI_{t-i} + \sum_{j=1}^{10} \beta_{2j}\Delta Home\ Sales_{t-j} + \sum_{k=1}^{10} \beta_{2k}\Delta Home\ Prices_{t-k} \\ &+ \sum_{l=1}^{10} \beta_{1l}\Delta Mortgage\ Rates_{t-l} + \varepsilon_2 \qquad (4b)\end{aligned}$$

$$\begin{aligned}\Delta CSI_t &= a_3 + \sum_{i=1}^{10} \beta_{3i}\Delta CSI_{t-i} \\ &+ \sum_{j=1}^{10} \beta_{3j}\Delta Home\ Sales_{t-j} \\ &+ \sum_{k=1}^{10} \beta_{3k}\Delta Home\ Prices_{t-k} + \sum_{l=1}^{10} \beta_{3l}\Delta Mortgage\ Rates_{t-l} + \varepsilon_3 \qquad (4c)\end{aligned}$$

$$\Delta Mortgage\ Rates_t$$

$$= a_4 + \sum_{i=1}^{10} \beta_{4i} \Delta CSI_{t-i}$$

$$+ \sum_{j=1}^{10} \beta_{4j} \Delta Home\ Sales_{t-j}$$

$$+ \sum_{k=1}^{10} \beta_{4k} \Delta Home\ Prices_{t-k} + \sum_{l=1}^{10} \beta_{4l} \Delta Mortgage\ Rates_{t-l} + \varepsilon_4 \qquad (4d)$$

where ΔHome Prices_t is the monthly change in the S&P/Case-Shiller Composite-10 home price index, ΔHome Sales_t is the monthly change in the S&P/Case-Shiller number of homes sold, ΔCSI_t represents the monthly change in consumer sentiment as captured by CSI and ΔMortgage Rates_t is the change in the 30 year conventional mortgage rate.

As the VAR model indicates, 10 lags were determined to be the optimal lag length according to the Akaike Information Criterion (AIC) test. This method of determining the number of lags best suited to estimate this model is argued to be better than other lag length determining methods such as the likelihood ratio test. One noted advantage of AIC versus the likelihood ratio test is that AIC requires no normality assumption concerning the distribution of the errors.

4.3.1 VAR Granger Causality and Block Exogeneity Tests

To test these lags and their relation to the dependent variable in question, VAR Granger Causality and Block Exogeneity Wald Tests are undertaken and presented in Table 7. From these tests, it can be determined which variables have a significant effect on the dependent variables in the system. Moreover, these tests are useful because they allow the restriction of the lags of a particular variable to zero.

Supportive of the notion that lagged changes in consumer explain changes in the housing market, Table 7 shows encouraging results in agreement with this. Beginning with the CSI composite, it can be observed that there is bi-directional causality between ΔHome Sales and ΔHome Prices. This is expected given that home sales are likely to be a result of attractive prices and the selling of homes will, in turn, drive up prices. There is unidirectional causality between ΔHome Sales and ΔCSI and ΔHome Prices and ΔCSI confirming the prior tests that changes in consumer sentiment do impact the housing market.

For all age groups, there is the bi-directional causality between ΔHome Sales and ΔHome Prices that appears for CSI composite. Also, there is unidirectional causality between ΔHome Prices and ΔCSI for all age groups but there is unidirectional causality between ΔHome Sales and ΔCSI only for the oldest age group, 55 years old and older. This result contradicts the Life Cycle Hypothesis because it is argued by the literature that older individuals and families are less likely to demand real estate assets. As a result, their sentiment would not be expected to appear to impact home sales, especially more than the two other age groups.

Table 7

The values in each box represents chi-square (wald) statistics for the joint significance of each other lagged endogenous variables in that equation. The statistics in the last column are the chi-square statistics for joint significance of all other lagged endogenous variables in the equation. Statistical significance is denoted by *, **, *** which indicates significance at the 10, 5, and 1 percent levels.

CSI Composite

	Excluded Variables				Block Exogeneity
Dependent Variable	ΔHome Sales	ΔHome Prices	ΔMortgage Rates	ΔCSI	All Variables Together
ΔHome Sales		42.68*** (0.000)	22.90** (0.011)	18.46** (0.048)	88.97*** (0.000)
ΔHome Prices	42.46*** (0.000)		13.45 (0.200)	32.37*** (0.000)	101.44*** (0.000)
ΔMortgage Rates	8.32 (0.598)	14.72 (0.143)		7.64 (0.664)	33.73 (0.292)
ΔCSI	10.17 (0.426)	12.95 (0.227)	7.40 (0.687)		29.80 (0.476)

Age Group 18-34

	Excluded Variables				Block Exogeneity
Dependent Variable	ΔHome Sales	ΔHome Prices	ΔMortgage Rates	ΔCSI	All Variables Together
ΔHome Sales		41.82*** (0.000)	21.96** (0.015)	9.45 (0.490)	77.21*** (0.000)
ΔHome Prices	43.18*** (0.000)		11.96 (0.288)	19.63** (0.033)	85.10*** (0.000)
ΔMortgage Rates	7.39 (0.688)	16.55* (0.085)		8.96 (0.535)	35.22 (0.235)
ΔCSI	6.39 (0.781)	6.35 (0.785)	4.81 (0.903)		17.65 (0.964)

Age Group 35-54

	Excluded Variables				Block Exogeneity
Dependent Variable	ΔHome Sales	ΔHome Prices	ΔMortgage Rates	ΔCSI	All Variables Together
ΔHome Sales		40.66*** (0.000)	21.38** (0.019)	6.43 (0.778)	73.25*** (0.000)
ΔHome Prices	48.00*** (0.000)		13.80 (0.182)	33.80*** (0.000)	103.27*** (0.000)
ΔMortgage Rates	7.21 (0.705)	17.32* (0.068)		11.18 (0.344)	37.70 (0.158)
ΔCSI	9.34 (0.501)	16.78* (0.079)	13.25 (0.210)		39.39 (0.117)

Table 7 continued
Age Group 55 and older

	Excluded Variables				Block Exogeneity
Dependent Variable	ΔHome Sales	ΔHome Prices	ΔMortgage Rates	ΔCSI	All Variables Together
ΔHome Sales		41.41*** (0.000)	21.78** (0.016)	22.78* (0.012)	94.60*** (0.000)
ΔHome Prices	44.51*** (0.000)		11.07 (0.352)	24.18*** (0.007)	90.34*** (0.000)
ΔMortgage Rates	8.27 (0.603)	13.58* (0.193)		10.29 (0.416)	36.70 (0.186)
ΔCSI	10.94 (0.363)	5.66 (0.843)	5.53 (0.853)		23.64 (0.788)

4.3.2 Variance Decompositions

From the VAR estimation, forecast error decompositions are also of relevance with respect to assessing the model's equations. It is these decompositions that provides the fraction of movements in a time series due to a variable's own shocks as compared to the shocks of other variables (Enders (2004)). Table 8 provides these results. For the first variable, ΔCSI, the majority of its variance over 36 months can be attributed to its own shocks. Additionally, it can be observed that variations in ΔHome Prices explain more variation in changes in consumer sentiment than ΔHome Sales, albeit the discrepancies between both are minor in nature. As for decomposing the variation in ΔHome Prices, within 12 months, ΔCSI captures roughly 6 percent of the variation in home prices and but after 36 months, ΔCSI captures 26.9 percent of the variance of changes in home prices. This provides evidence that with the passage of time, changes in consumer confidence have sizeable explanatory power with respect to the changes of home prices.

A similar story can be told with the decomposition of ΔHome Sales, except that with the passage of time, changes in home prices explain more of its variance than changes in CSI. This makes sense from an economics point of view in that supply and demand forces interact in such a way that the price of a good is the clearing mechanism in which buyers and sellers respond. Home sales are simply the sale of a good, housing, and a decrease in home prices should bring potential buyers to the market place just as an increase in home prices would bring potential sellers to the market.

But what may be of more interest is the variance decomposition for in ΔHome Prices. Price changes can occur for a number of reasons, one of which may be excess supply or excess demand. Looking at the variance decompositions for changes in ΔHome Prices, changes in home sales had a relatively constant explanatory role in the variance decomposition of changes in home prices. But what is interesting is ΔCSI went from capturing 6 percent of the variance decomposition of ΔHome Prices in a 6 month horizon to capturing nearly 27 percent of the variance decomposition of ΔHome Prices in a 36 month horizon. Over time, changes in consumer sentiment appear more so in changes in home prices as opposed to changes in home sales. One would think it would be the other way around; consumers become more pessimistic and home sales decrease and changes in CSI should be more apparent in the data analysis. But arguably what Table 8 is showing is that consumer pessimism and optimism appear primarily in home prices. As consumers grow weary or hopeful, home prices appear to reflect that sentiment better than looking at buying and selling patterns (i.e., home sales).

Table 8

Variance Decompositions

Variance Decomposition of ΔCSI

Forecast Horizon	Forecast Standard Error	Percentage of forecast error variance explained by		
		ΔCSI	ΔHome Sales	ΔHome Prices
6	0.071	0.959	0.018	0.022
12	0.073	0.915	0.055	0.030
24	0.077	0.886	0.056	0.057
36	0.078	0.875	0.060	0.065

Variance Decomposition of ΔHome Sales

Forecast Horizon	Forecast Standard Error	Percentage of forecast error variance explained by		
		ΔCSI	ΔHome Sales	ΔHome Prices
6	0.042	0.069	0.796	0.135
12	0.045	0.105	0.725	0.170
24	0.053	0.118	0.648	0.234
36	0.063	0.130	0.643	0.227

Variance Decomposition of ΔHome Prices

Forecast Horizon	Forecast Standard Error	Percentage of forecast error variance explained by		
		ΔCSI	ΔHome Sales	ΔHome Prices
6	0.005	0.060	0.227	0.714
12	0.005	0.058	0.249	0.693
24	0.008	0.145	0.243	0.612
36	0.010	0.269	0.203	0.528

5. Concluding Remarks

This paper aims at showing how optimism and pessimism appear in the housing market. Given the importance of the housing market, an interesting econometric exercise is to test how behavioral economics can provide forecasting evidence in the housing market. This paper makes significant use of the widely reported University of Michigan Survey of Consumers (CSI) as its measure of consumer sentiment. I find that there is a positive relationship between changes in consumer sentiment and changes in home prices. Increases in consumer sentiment (i.e., optimism) tend to be followed by price increases in homes. I also find that there is a delay in which changes in CSI Granger cause changes in home prices. The causality relationships in existence at a lag of six months persist, continuing further to a lag of twelve months and twenty-four months. It should be pointed out that at a lag of twenty-four months changes in CSI do Granger cause changes in Home Sales. These results are powerful in that changes in consumer sentiment are long lasting in the housing market, having ramifications for years. In addition, using a vector autoregressive model, I find that the lags of changes in CSI predict future values for both housing market variables. Fixed effect panel regressions confirm these results.

More research in the area of behavioral economics is needed, given its appearance in other markets around the world. The housing market, being so large of a market and important of a market, provides a great testing ground for which to conduct these tests. Moreover, with consumer sentiment providing a gauge of the attitude of U.S. consumer, more use of this data set should be employed in not only the housing market but the stock market as well.

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Table 9

Stationarity Tests

This table tests the levels of CSI, the S&P/Case-Shiller Composite-10 Home Price Index and the S&P/Case-Shiller Composite-10 Home Sales Index for stationarity using the Augmented Dickey-Fuller test (ADF), Phillips-Perron test (PP) and the Kwiatkowski, Phillips, Schmidt and Shin test (KPSS). For all three tests, a drift term is included. Only 1 percent levels of significance were used to determine whether variables were stationary

<u>ADF/PP Tests</u>

H_O: $y_t \sim$ I(1)

H_1: $y_t \sim$ I(0)

<u>KPSS Test</u>

H_O: $y_t \sim$ I(0)

H_1: $y_t \sim$ I(1)

Variable	ADF Test	PP Test	KPSS Test	Result
CSI Composite	I(1)	I(1)	I(0)	Nonstationary
S&P/Case-Shiller Composite-10 Home Price Index	I(1)	I(1)	I(1)	Nonstationary
S&P/Case-Shiller Composite-10 Home Sales Index	I(1)	I(0)	I(1)	Nonstationary

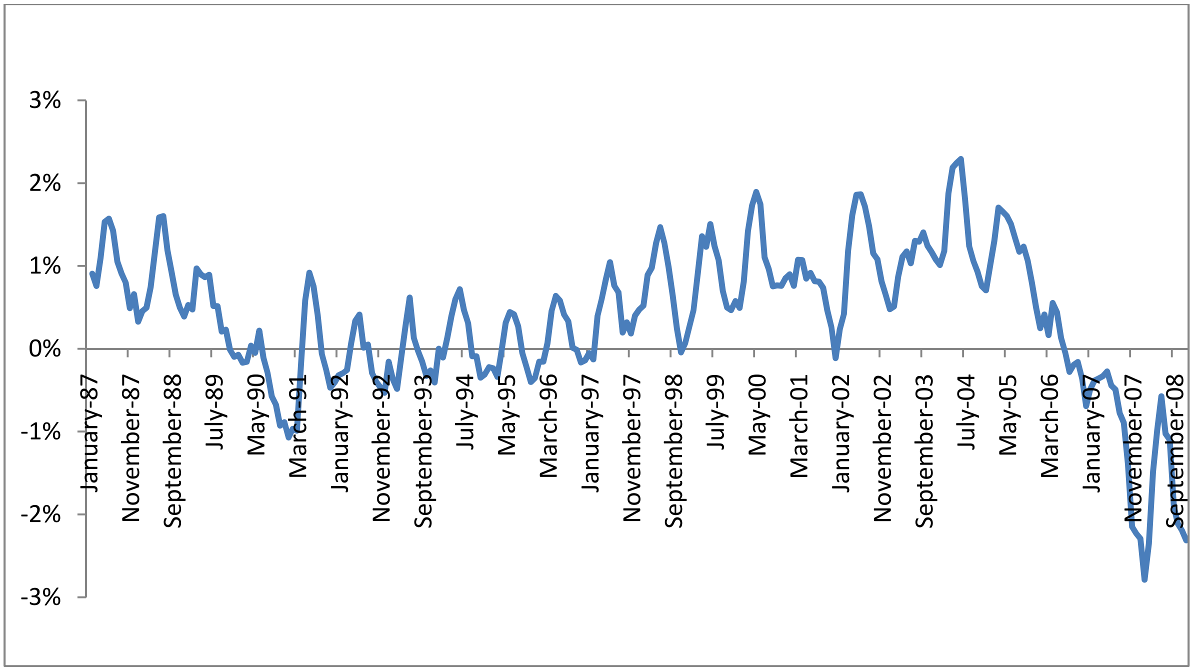

Figure 2a) Percent change in the 10 city S&P/Case-Shiller Home Price Composite Index (January 1987 to December 2008)

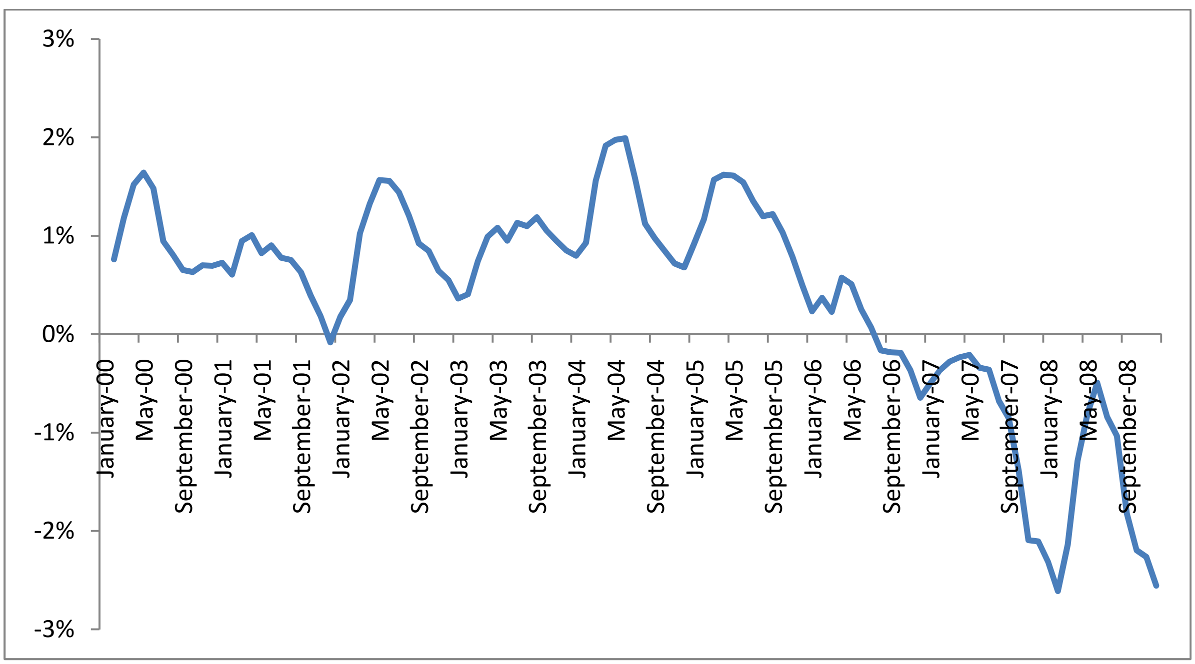

Figure 2b) Percent change in 20 city S&P/Case-Shiller Home Price Composite Index (January 2000 to December 2008). Metropolitan areas included: Atlanta, GA, Charlotte, NC, Cleveland, OH, Dallas, TX, Detroit, MI, Minneapolis, MN, Phoenix, AZ, Seattle, WA, Tampa, FL, Boston, MA, Chicago, IL, Denver, CO, Las Vegas, NV, Portland, OR, Los Angeles, CA, Miami, FL, New York, NY, San Diego, CA, San Francisco, CA and Washington D.C.

Chapter 4

This body of work represents an investigation into a relatively new and emerging discipline in the social sciences - Behavioral Finance. This new and exciting area is cautiously embraced by the masses because it has the ability to bring into question cornerstone financial theories that have existed for decades. The results presented in this dissertation argue that by measuring people's economic outlooks, it is possible to forecast stock market and housing market activity. As intuitive as this may sound, efficient market gurus may cringe at the mere sound of the previous statement because asset markets so gyrate around supply and demand and new information that needs to be priced into an asset's price.

In Chapters 2 and 3, looking at years of monthly frequency data provided an excellent avenue to study just how consumer sentiment moves. In this multi-decade year tenure, recessions have begun and ended, financial calamities have taken root and subsided and more global countries have advanced their standard of living and production. With this being said, the consumer sentiment index used in this studied has seen extremely good times and extremely cautionary times. The same of course can be said for the stock market with experienced the dot com bubble as well as the subprime meltdown of recent years.

But all things being considered, consumers still form outlooks. Some of course may be more optimistic than others (and some more pessimistic than others), but it is inherent for an individual to look forward and perceive better times or worse times. It is not uncharacteristic for a person to plan and prepare for an uncertain road ahead. But what this study sought out to investigate is if when individuals change their outlooks, exactly what happens to the stock markets and the housing market. Given the results presented, I would strongly argue that yes, when consumer sentiment improves or deteriorates, shortly thereafter, markets begin to move too.

In the competitive race to test hypotheses and explore new data sets, I believe that by writing this body of work, I have familiarized myself with a field bustling with future econometric exercises to be explored. In addition, with the recent financial hardships of the U.S. economy, both practitioners and academicians are looking for better ways to study existing issues such as asset pricing and forecasting stock returns to name a few. The work contained within this dissertation represents the use of existing econometric techniques in conjunction the use of new ideas and insights.

Appendix

University of Michigan's Consumer Sentiment Index Calculation[24]

To calculate the CSI, x_i represents the percent of respondents giving favorable responses minus the percent of respondents giving unfavorable replies. After this, 100 is added to x_i. These are called 'relative scores' and are rounded to the nearest whole number.

$$Index\ of\ Consumer\ Sentiment = \frac{\sum_{i=1}^{5} x_i}{Base\ Period\ Total} + 2.0$$

where Base Period Total = 7.7558

Each x_i represents the relative score for a particular question regarding current and future economic conditions. More specifically,

x_1 = We are interested in how people are getting along financially these days. Would you say that you (and your family) are better off or worse off financially than you were a year ago?

x_2 = Now looking ahead - do you think that a year from now you (and your family) will be better off financially, or worse off, or just about the same as now?

x_3 = Now turning to business conditions in the country as a whole - do you think that during the next twelve months we'll have good times financially, or bad times, or what?

x_4 = Looking ahead, which would you say is more likely - that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?

x_5 = About the big things people buy for their homes - such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or a bad time for people to buy major household items?

[24] University of Michigan Surveys of Consumers website.

Vita

Mark Anthony Johnson was born in New Orleans, Louisiana, and lived the early years of his life in Miami, Florida. He then moved to Tallahassee, Florida, with his family and went on to graduate from Florida Agricultural and Mechanical Developmental Research School and then Florida State University where he received his undergraduate degree in Finance. After completing his undergraduate studies, he enrolled in the Master's of Science in Finance program at Florida International University.

Later he returned to Tallahassee, Florida, where he prepared for his doctoral studies by taking advanced mathematics and economics courses at Florida State University. In 2006, he moved back to New Orleans, Louisiana, and began the Financial Economics doctoral program at the University of New Orleans and earned a Master's of Science degree in Financial Economics in 2007.

While at the University of New Orleans, he was given the opportunity to instruct undergraduate students, tutor Executive MBA students, work with the editors of the *Review of Financial Economics* and take numerous courses in his areas of concentration - Investments, Financial Markets and Institutions and Corporate Finance. During the doctoral program, Mark received the Toussaint Hocevar Memorial Award for Outstanding Ph.D. Candidate in Financial Economics and went on to complete his dissertation under the supervision of his dissertation chair, Professor Atsuyuki Naka, in the Spring 2010 semester.