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Downside risk: what the consumer sentiment index reveals

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Abstract

This article examines the ability of consumer sentiment for different age groups to forecast short-term as well as long-term equity returns. Using a long-horizon asymmetric response regression format, we show that negative changes in sentiment have a greater influence on stock returns than positive changes in sentiment. Our findings are supportive of the prospect theory. However, we observe that younger individuals appear to be less risk-averse than older individuals. We provide evidence that reminds individual investors and financial planners that risk is an important consideration when investing, and that demographic characteristics matter when determining appropriate investing approaches and risk tolerance. © 2014 Academy of Financial Services. All rights reserved.

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1. Introduction

Consumer sentiment is based on factors such as unemployment rates, wages, expected inflation, interest rates, and other prevailing market circumstances. Research indicates that consumer sentiment concerning current and future economic conditions can affect the outcomes of financial assets.[1] Further clarification of the dynamics of this relationship will improve the understanding of how the sentiment affects equity returns. The importance of

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this relationship has the potential to aid investors, especially individual investors, and financial planners as they seek to understand and identify useful economic indicators that can potentially help forecast stock returns.

Consumer sentiment surveys generally ask individuals how they feel about their current economic situation and how they perceive their future economic situation. By incorporating such data into economic models, we ask the following questions: Assuming consumer sentiment affects equity returns, how long of a holding period can be predicted? Does negative sentiment have a larger effect on equity returns than positive sentiment? Do the sentiments of different age groups have the same or similar effects on equity returns? Do different sizes of firms react to the sentiment equally? By answering these questions, we can deepen our understanding of the relationships between consumer behavior and stock returns in the United States. Furthermore, because household consumption is such a significant portion of gross domestic product (GDP) in the United States, understanding the outlook of consumers can impact economic growth and corporate profitability.

To address these questions, we utilize the asymmetric response model with long-horizon regressions. To test asymmetric responses with respect to consumer sentiment, the consumer sentiment index compiled by the University of Michigan is divided into positive changes and negative changes, where negative consumer sentiment indicates pessimistic feelings about future economic prospects, or aggravation of losing wealth and positive sentiment indicates the opposite. According to the prospect theory developed by Kahneman and Tversky (1979), losses matter more to individuals than gains because of the risk averse nature of investors, and is closely related to the concept of downside risk. This specific type of risk is critical for individual investors and financial planners to monitor, given the findings of the prospect theory. Furthermore, downside risk has been studied in other scenarios (e.g., when is the ideal time for an individual to receive Social Security benefits (Friedman and Phillips, 2010). The current article seeks to add to the downside risk literature by looking at individuals through the lenses of consumer sentiment and how changes in sentiment may foretell forthcoming equity returns.

We look at 1, 3, 6, 12, and 24 month holding period horizons to investigate whether changes in consumer sentiment have the ability to forecast equity returns. If changes in consumer sentiment have this predictive ability, this can assist individual investors and financial planners, regardless of whether their investment horizon is short-term or long-term. The sentiments of three different age groups are investigated to address the idea of life cycle investment hypothesis.[2] Existing research has shown that an aging population results in higher average risk aversion and subsequently, higher risk premiums. For example, an individuals' age and their appetite (or tolerance) for risk has been studied by Hariharan et al. (2000), Gibson et al. (2013), Larkin et al. (2013), and Schooley and Worden (1996). The current article contributes to the literature by presenting comprehensive analysis of the effects of consumer sentiment on the U.S. stock returns that includes data from the recent financial crisis. By including the recent financial crisis in our sample period, we are able to provide results that include a time period that has been referred to as an once-in-a-lifetime event. Fisher and Statman (2003) successfully show that there is a relationship between consumer sentiment and stock returns. Specifically, they find evidence that changes in consumer sentiment and contemporaneous stock returns have a positive, statistically significant relationship. Additionally, they present that the relationship between changes in consumer sentiment and the returns of small-cap stocks is stronger than the relationship between sentiment and a broad market index such as the S&P 500.[3] Baker and Wurgler (2006) study the relationship between cross-sectional differences of stock returns and investor sentiment by constructing the investor sentiment index based on six market variables, and categorizing sentiment as either optimism or pessimism about stocks markets.[4] They show 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. Akhtar et al. (2011) and Qui and Welch (2006) and show that consumer sentiment is a good proxy for investor sentiment.

Lemmon and Portniaguina (2006) present a way of capturing pessimism and optimism by using a consumer sentiment index (CSI) as a function of a large number of macroeconomic variables such as inflation, the default spread, changes in personal consumption expenditures, Gross Domestic Product, and the unemployment rate. They argue that any consumer sentiment based on fundamental economic conditions is reasonable, justifiable, and rational. On the other hand, consumer sentiment based on factors other than economic conditions is interpreted as unjustifiable and irrational, where they define the residual from the regression as a proxy for unjustifiable sentiment. Their results support the noise trader hypothesis that sentiment will have a greater effect on asset returns held by individuals. Ho and Hung (2009) examine the performance of asset pricing models by using sentiment as conditioning information as it reflects investors' expectations about future forecasts of financial markets. By including various sentiment measures, they show that the capital asset pricing models perform better when sentiment is included, and conclude that sentiment helps explain market anomalies such as momentum, liquidity, size, and book-to-market effects.

Schmeling (2009) utilizes consumer confidence as a proxy for individual investor sentiment to investigate whether lagged sentiment explains stock returns for eighteen industrialized countries as examined through a long-run horizon regression model. The author shows that international investor sentiment predicts future aggregate market returns, and the impact of sentiment on returns is stronger for countries that have less developed markets since they are more prone to investor overreaction. The results indicate a statistically significant coefficient for the sentiment variable, and this significance holds for various forecast horizons. Schmeling finds that lagged sentiment has a stronger effect on stock returns in countries such as Germany, Japan, Italy, and the United States, but little or no evidence of such a relationship in countries such as the United Kingdom, Australia, and New Zealand. Further, Akhtar et al. (2011) study the reaction of the Australian stock market by using the asymmetric response model, and show that negative changes in the Australian CSI have statistically significant effects on market returns, whereas positive changes do not.

Other recent studies such as Chung et al. (2012), Stambaugh et al. (2012), and Yu and Yuan (2011) look at sentiment's impact on stock returns as well. Yu and Yuan (2011) show the influence of sentiment on the market's mean–variance tradeoff using the Baker and Wurgler (2006) sentiment index. Stambaugh et al. (2012) also use the Baker and Wurgler (2006) sentiment index and test sentiment's role when accounting for documented anomalies in investing strategies such as a long-short strategy. Both of these studies show evidence related to the stock return predictive ability of sentiment. Chung et al. (2012) incorporates business cycles (i.e., economic expansions and recessions) into their modeling to show that during recessions, the predictive power of sentiment is not nearly as strong and can possibly be insignificant.

Our benchmark model provides evidence that sentiment matters more in forecasting near-term market risk premiums versus farther out time horizons. By including various time horizons of equity holding-period returns into consideration, we find that sentiment has a greater ability to explain market risk premiums and forecast equity returns in the short-run than in the long-run. As a result, individual investors and financial planners that track consumer sentiment as an economic indicator used in investing should exercise caution when using sentiment as an indicator to forecast equity returns too far into the future.

We show that negative changes in sentiment matters more in explaining market risk premiums than positive changes in sentiment based on asymmetric response models that account for unequal responses to negative events and positive events. This finding supports the prospect theory developed by Kahneman and Tversky (1979) as to possible losses mattering more to individuals than possible gains. This can benefit individual investors and financial planners because if consumer sentiment begins to decrease (increase) because of macroeconomic conditions, more (less) credence can be placed on consumer sentiment as a potential forecaster of future equity returns. However, we observe that younger individuals appear to be less risk-averse than older individuals. Finally, the current article examines the noise trader hypothesis by using 10 size-sorted portfolio returns, and finds that smaller market cap stocks are more impacted by changes in consumer sentiment, a result consistent with the previous literature. Our final finding further reminds individual investors and financial planners that small-cap stocks have the potential to be riskier than large-cap stocks.

2. Methodology and data

2.1. Empirical models

To test if consumer sentiment has a near-term or long-term impact on the stock market, we utilize long-horizon regressions. By testing different future time periods (horizons), we investigate whether or not changes in CSI have such future explanatory power. Long-horizon financial models are popular and have been used in prior studies. For example, Rich and Reichenstein (1993) use a type of long-horizon model to see if individual investors can time the stock market.

Our benchmark long-horizon regression model is given as:[5]

$$r_{i,t+1} + \cdots + r_{i,t+K} = \alpha(K) + \beta(K)\Delta CSI_t + \varepsilon_{t+K},\ k = 1, 3, 6, 12, 24, \tag{1}$$

where $r_{i,t+K}$ is the excess return of equity index i over K month periods, and excess returns are defined as the equity returns minus the risk free rate. The risk free rate is the monthly yield on a 30 day Treasury bill. ΔCSI_t is the monthly percentage change in the CSI, that is, $\Delta CSI_t = (CSI_{t+1} - CSI_t)/CSI_t$ and ε_{t+K} is the residual term for horizon k.

A direct test of downside risk within the context of the prospect theory would be to observe how negative or positive changes in consumer sentiment alter the stock returns. Harlow and Rao (1989) provide a simple way of measuring asymmetric responses to account for individuals exhibiting downside risk. In the context of this article, the asymmetric response model is one way of blending the prospect theory and downside risk based on the documented fact that responses to losses and gains are not the same. By using an asymmetric response model, we isolate improvements and deteriorations in sentiment and allow for interpretations of how changes in CSI identify downside risk for different holding period returns. The following long-horizon asymmetric response regression model is estimated:

$$r_{i,t+1} + \cdots + r_{i,t+K} = \alpha(K) + \beta^{-}(K)\Delta CSI_t^{-} + \beta^{+}(K)\Delta CSI_t^{+} + \varepsilon_{t+K},$$
$$k = 1, 3, 6, 12, 24, \qquad (2)$$

where ΔCSI_t^{-} is the negative change in CSI ($\Delta CSI_t < 0$) or zero otherwise, and ΔCSI_t^{+} is the positive change in CSI ($\Delta CSI_t > 0$) or zero otherwise.[6] The coefficients β^{-} and β^{+} indicate the downsize β and upside β, respectively.

If stock returns respond similarly to positive changes in consumer sentiment as they do to negative changes in consumer sentiment, β^{-} would be equal to β^{+}. However, if investors are averse to downside risk, β^{-} will be positive, representing a positive risk premium (e.g., the higher the downside risk, the higher the stock returns). This effect is a type of risk that investors tend to be more sensitive towards when discussing the potential for loss in the value of an asset even though many investors may anticipate a particular asset's value to increase over a long time. The estimates of β^{+} will also be smaller in magnitude and positive if individuals prefer upside potential (e.g., the higher the upside potential, the lower the stock returns).

2.2. Data description

The primary sources of consumer sentiment data in the United States are the University of Michigan's Surveys of Consumers (CSI) and the Conference Board's Consumer Confidence Index. Fisher and Statman (2003) and Lemmon and Portniaguina (2006) confirm that the indices are highly correlated and provide similar empirical results, despite survey design differences. Ludvigson (2004) recognizes that many studies use CSI. Studies that utilize CSI in relation to stock returns include Fisher and Statman (2003), Ho and Hung (2009), Lemmon and Portniaguina (2006), and Schmeling (2009).

In this study, we use monthly CSI data from January 1978 to December 2010, encompassing more than 30 years of sentiment observations. We segment the data into the widely cited composite index as well as indices for three age groups, respectively: persons 18 to 34 years old; persons 35 to 54 years old; and persons 55 years old and older. This partition of age groups within the CSI allows for a demographic investigation that has previously been unexplored regarding how stock markets can be understood in relation to the sentiment of persons of different ages. The Center for Research in Security Prices (CRSP) equally weighted returns (CRSP EW) and CRSP value-weighted returns (CRSP VW) are used to capture the overall stock market performance. We use 30 day U.S Treasury bill yields to represent risk-free rates to estimate the risk free returns. These data sets are obtained from Wharton Research Data Services (WRDS).

Table 1 presents the summary statistics of the variables used in this study. Panel A shows all of the CSI data for the composite index as well as for the three age groups. The mean sentiment value for the youngest age group, 18 to 34 years old, is the highest among all age groups (95.169) and the mean value for the oldest age group, persons 55 years old and older, is the lowest among all age groups (78.297). To test whether the mean sentiment values across age groups are the same, we test the null hypothesis that $\mathrm{CSI}_{\text{Age Group } 18-34} = \mathrm{CSI}_{\text{Age Group } 35\text{–}54} = \mathrm{CSI}_{\text{Age Group 55 and older}}$. On the other hand, the alternative hypothesis is that at least one of the mean age group sentiment values is different from the others. When tested, we find an F-statistic of 160.257 ($p = 0.000$) and reject the null hypothesis. This finding implies that differences exist in the various age groups' mean sentiment values.

The results suggest that over the sample period, younger consumers tend to be more optimistic than older consumers and this is consistent with the life cycle investment hypothesis. 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 or future saving and consumption whereas older individuals have fewer years of their life to participate in the labor force. At the same time, families with children see their children enter adulthood and as a result, they may not foresee increased consumption.

With respect to volatility of the CSI index for the age groups, the 35 to 54 years old age group has the largest standard deviation (14.413) and the oldest age group has the lowest volatility (11.791). And although the percentage changes of CSI are similar across different groups and close to zero on average, there is a large range between the minimum and the maximum of percentage changes of CSI.[7] The corresponding standard deviations are relatively large and are somewhat similar to those for the stock returns. According to Ando and Modigliani (1963), the desire or propensity to consume and invest is higher in the lives of younger people, whereas middle to older-aged individuals tends to have higher incomes with lower propensities to consume. Those in the younger age group are more likely to be in the early professional years of their careers, attempting to acquire more permanent assets, possibly preparing to start a family.

Panel B presents the excess returns of the CRSP EW and CRSP VW indices over five horizons. For both indices, as the number of horizons increases, the mean returns increase as well as the *SD*s. Panel C presents the returns data for the CRSP market capitalization of 10 size-sorted portfolios. A brief look at Panel C provides data on the well-documented fact that small cap stocks have higher returns than large cap stocks but are also riskier, as evident by the standard deviations of the two portfolios. The mean returns for size-sorted portfolios deciles 3 through decile 8 appear the same because they represent the mid cap stock segment. As a result, these six portfolios have similar risk-return characteristics. We use all 10 size-sorted portfolios to see if the size of the firm matters in terms of the short-run or long-run effects of sentiment. Akhtar et al. (2011), Baker and Wurgler (2006), Lemmon and Portniaguina (2006), Schmeling (2009), and others find that sentiment does impact firms of various sizes differently.

Fig. 1 displays the time series movements of CSI for different groups over the sample period. The major declines in CSI over the sample period occur in the late 1970s, early

Table 1 Summary statistics

	Mean	*SD*	Minimum	Maximum
Panel A: CSI and percent changes				
CSI composite	86.120	13.096	51.700	112.000
CSI - age group 18–34	95.169	13.456	60.400	120.000
CSI - age group 35–54	86.409	14.413	43.600	113.300
CSI - age group 55 and older	78.297	11.791	43.400	105.300
$\Delta CSI_{Composite}$	0.001	0.050	−0.181	0.246
$\Delta CSI_{18–34\ age\ group}$	0.002	0.061	−0.174	0.287
$\Delta CSI_{35–54\ age\ group}$	0.002	0.066	−0.231	0.241
$\Delta CSI_{55\ and\ older\ age\ group}$	0.002	0.069	−0.196	0.339
$\Delta CSI_{Composite} < 0$	−0.018	0.029	−0.181	0.000
$\Delta CSI_{Composite} > 0$	0.019	0.031	0.000	0.246
$\Delta CSI_{18–34\ age\ group} < 0$	−0.022	0.033	−0.174	0.000
$\Delta CSI_{18–34\ age\ group} > 0$	0.023	0.040	0.000	0.287
$\Delta CSI_{35–54\ age\ group} < 0$	−0.024	0.037	−0.231	0.000
$\Delta CSI_{35–54\ age\ group} > 0$	0.026	0.042	0.000	0.294
$\Delta CSI_{55\ and\ older\ age\ group} < 0$	−0.025	0.039	−0.196	0.000
$\Delta CSI_{55\ and\ older\ age\ group} > 0$	0.027	0.043	0.000	0.339
Panel B: Stock index returns for different horizons				
CRSP EW index returns				
K = 1	0.011	0.056	−0.273	0.224
K = 3	0.033	0.111	−0.470	0.417
K = 6	0.065	0.158	−0.565	0.588
K = 12	0.128	0.212	−0.613	0.736
K = 24	0.245	0.242	−0.751	0.796
CRSP VW index returns				
K = 1	0.008	0.046	−0.227	0.127
K = 3	0.024	0.083	−0.374	0.258
K = 6	0.046	0.118	−0.539	0.364
K = 12	0.092	0.168	−0.565	0.485
K = 24	0.179	0.222	−0.599	0.542
Risk-free rate (30 day *t*-bill)	0.004	0.003	0.000	0.014
Panel C: Returns of equity size portfolios				
Capitalization decile 1	0.014	0.064	−0.277	0.329
Capitalization decile 2	0.011	0.065	−0.303	0.285
Capitalization decile 3	0.012	0.063	−0.289	0.261
Capitalization decile 4	0.012	0.061	−0.294	0.226
Capitalization decile 5	0.012	0.061	−0.281	0.255
Capitalization decile 6	0.012	0.056	−0.259	0.222
Capitalization decile 7	0.012	0.055	−0.259	0.224
Capitalization decile 8	0.012	0.054	−0.241	0.188
Capitalization decile 9	0.011	0.051	−0.225	0.225
Capitalization decile 10	0.010	0.048	−0.204	0.136

Note. All data is monthly and is from January 1978 until December 2010. Panel A consumer sentiment data was obtained from the University of Michigan Surveys of Consumers (http://www.sca.isr.umich.edu). Panel B and Panel C stock index returns and equity size-sorted portfolio returns data were obtained from Center for Research in Security Prices (CRSP). K stands for monthly cumulated K horizon returns.

1990s, early 2000s, and in 2007 and 2008 during the recent financial crisis. Of interestingly to the authors, these periods correspond closely with the dates of recessions in the United States as defined by the National Bureau of Economic Research (NBER). For example,

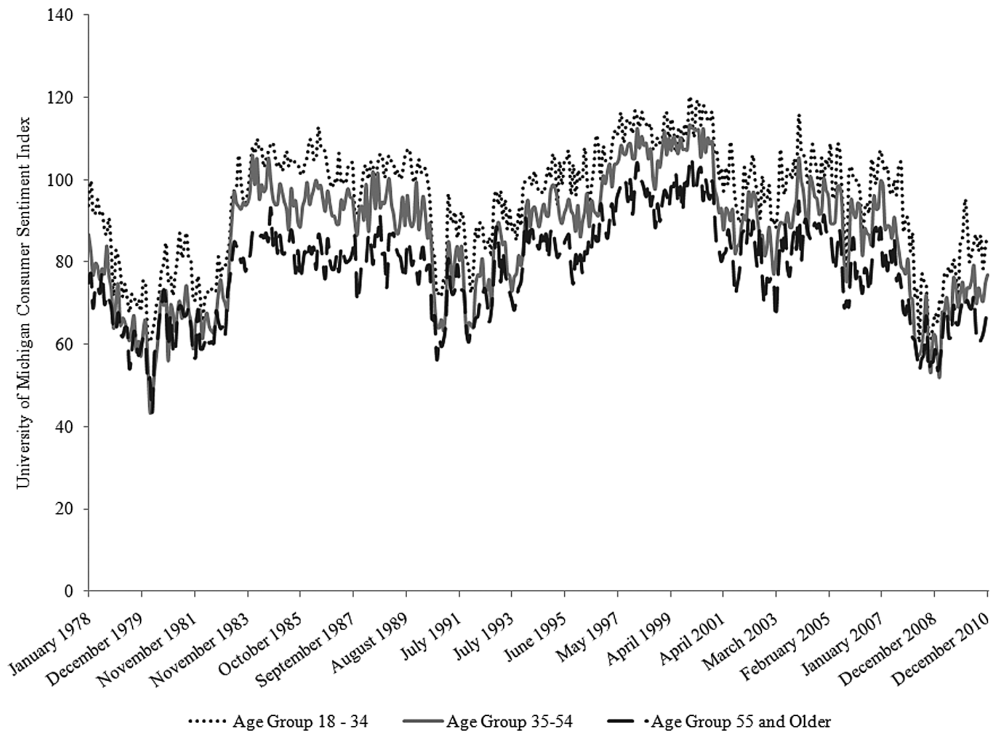

Fig. 1. Time-series plot of consumer sentiment based on age groups. This figure plots the consumer sentiment indexes of three age groups: between 18 to 34 years old; between 35 and 54 years old; and 55 years old and older.

recessionary periods in the United States occurred from July 1990 until March 1991, March 2001 until November 2001, and December 2007 until June 2009.[8] The most recent decline in CSI corresponds with the widely regarded "Great Recession," which was sparked by the abrupt contraction in home prices and spike in home foreclosures because of the subprime crisis and other banking problems. The financial crisis ultimately resulted in the sharp increase in the unemployment rate and a rise in the number of nonperforming loans on the balance sheets of financial institutions among other sudden negative economic conditions.

Consistent with Panel A of Table 1, Fig. 1 shows that the younger consumers (18 to 34 years old) tend to be more optimistic than the older consumers, and this gap is persistent for much of the sample period. The 55 years old and older age group tends to record the lowest sentiment reading throughout the sample period. Further, we observe substantial movements of these indices over time, resulting in large *SD*s. This figure also shows how the sentiment of individuals, regardless of age, tends to move in tandem.

3. Empirical results

3.1. Benchmark case

Table 2 reports the results of the benchmark regression model from Eq. (1). The coefficients for ΔCSI_t are positive as well as statistically significant at the 1% level for both stock

Table 2 Benchmark model

Dependent variable	Forecast horizon (K)									
	1		3		6		12		24	
	EW returns	VW returns	EW returns	VW returns	EW returns	VW returns	EW returns	VW returns	EW returns	VW returns
Intercept α	0.006	0.003	0.019	0.010	0.038	0.019	0.073	0.037	0.135	0.069
SE	(0.003)	(0.002)	(0.009)	(0.006)	(0.016)	(0.012)	(0.024)	(0.019)	(0.029)	(0.026)
p Value	[0.032]	[0.151]	[0.025]	[0.131]	[0.017]	[0.113]	[0.003]	[0.053]	[0.000]	[0.008]
Slope β	0.362	0.204	0.736	0.534	0.635	0.425	0.487	0.287	0.338	0.092
SE	(0.064)	(0.054)	(0.107)	(0.081)	(0.142)	(0.098)	(0.214)	(0.161)	(0.256)	(0.188)
p Value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.023]	[0.076]	[0.187]	[0.626]
R^2	0.104	0.049	0.109	0.103	0.040	0.033	0.013	0.008	0.005	0.000

Note. This table represents long-horizon ordinary least square regressions of one month excess returns ($r_{i,t}$) of various indices on changes in the Consumer Sentiment Index (CSI). The dependent variable is the excess return of either the CRSP equally weighted portfolio or the CRSP value weighted portfolio. K stands for monthly cumulated K horizon returns and when K is greater than one, the regressions use overlapping monthly data. All data is monthly and is from January 1978 until December 2010. Statistical significance is determined by the Newey-West *p* values.

market indices used for six month horizons or less. For the 12 month horizon, the coefficients for ΔCSI_t are significant at the 5% level for the CRSP EW index.[9] The results are also economically significant. For example, for the three month horizon for the CRSP EW (VW) index, a 10% change in overall consumer sentiment (consumers of all ages) results in a market risk premium change of 7.36% (5.34%). It can be interpreted from these findings that a positive change in CSI results in positive future excess stock returns for subsequent holding period returns. However, for the 24 month horizon, changes in consumer sentiment are no longer statistically significant in forecasting stock returns. The results indicate that sentiment is more important in the nearer term instead of the distant future that can help individual investors and financial planners as they consider using this sentiment indicator to make equity investment decisions.

The long-horizon regressions that Schmeling (2009) uses also show that the impact of sentiment on average future returns declines as the forecast horizon increases. Furthermore, given that CSI data are released monthly, recent data points provide better insights pertaining to consumers and their outlooks regarding the stock returns.

Another immediate observation present in Table 2 is that the values of the slope coefficients are much larger for the CRSP EW excess returns compared to the CRSP VW excess returns. We attribute the lower excess returns of the VW index β coefficients to the documented findings of Lemmon and Portniaguina (2006) and Schmeling (2009). They show that sentiment affects the stocks of firms of various sizes differently. In the VW index, large firm stock returns are inherently weighted more heavily than those returns of smaller firms. Thus, the effect of changes in sentiment becomes harder to disentangle because of this size effect. The EW index β coefficients shows that holding firm size constant, changes in CSI are still important.

We also observe that the values of R^2 are the largest for the one month and three month horizons, and they gradually decrease as the horizon increases. As we found in Table 2, nearer term economic data impacts sentiment more, this in turn, is then priced into the stock market shortly thereafter. Campbell et al. (1997) presents long-horizon regression results with increasing R^2's for longer horizons. However, Valkanov (2003) shows that the interpretation of the R^2's for long-horizon regressions is not straightforward and can be misleading for comparisons of regression results.

3.2. Asymmetric response model

Table 3 presents the findings of the asymmetric response models in Eq. (2) for the overall CSI composite. We observe that all of these coefficients of the downside βs (β^-) are positive and statistically significant, with most at the 1% level of significance, and two coefficients at the 5% level of significance (EW index, 12 and 24 month horizons). The results support that the ideas of a positive risk premium since investors are averse to downside risk and the higher the downside risk, the higher the stock returns. These results are consistent with studies such as Ang, Chen, and Xing (2006) and Akhtar et al. (2011), and capture the essence of the prospect theory of Kahneman and Tversky (1979). Referring to the estimates of downside βs, as the forecast horizon increases, so does the magnitude of β^-. For example, the values are 0.428 (EW returns) and 0.338 (VW returns) for the one month horizon but 1.319 (EW returns) and 1.463 (VW returns) for the 24 month horizon. This implies that risk premiums that can compensate for downside risk become increasingly important as the time horizon increases. Ang et al. (2006) show that cross-sectional stock returns indicate evidence of reflecting a premium for downside risk as measured by negative market returns because individuals place greater emphasis on downside risk and less emphasis on potential gains. Further, they find that past downside β has forecasting ability for future stock returns for most of their cross-sectional sample.

Turning our attention to upside βs (β^+), the coefficients are not equal in magnitude and are consistently smaller compared to the downside βs for all horizons studied. For the five different horizons estimated, many of the β^+ coefficients are statistically insignificant, and in fact, only three are significant at the 5% level. Akhtar et al. (2011) also report the statistical insignificance of the upside β. An interesting observation regarding the β^+ coefficients is their declining nature over the forecasting horizons. The one month forecast horizon magnitudes are 0.303 (EW returns) and 0.084 (VW returns) respectively, and when compared to the 24 month forecast horizon, the upside β coefficients are -0.493 (EW returns) and -1.070 (VW returns). Thus, the upside β magnitudes decrease and even turn negative as the time horizons increase. The results imply that as forecast horizons increase, upside potential becomes of less importance, and even more so when compared to downside risk. Individuals start to exhibit behavior that is consistent with focusing less on increasing wealth and more on not losing wealth.

When we test the null hypothesis of $\beta^- = \beta^+$ for all horizons, we do not reject the null hypothesis for the majority of these tests. The results are because of the statistical insignificance of the estimates of β^+ and the fact that the denominators of the *t*-statistics tend to be large relative to the numerator. However, this should not undermine the results of our long-horizon asymmetric regressions that show statistically significant downside βs for all cases, and provides support to the concepts of the prospect theory. Akhtar et al. (2011) state

Table 3 Asymmetric response model: CSI composite

Dependent variable	Forecast horizon (K)									
	1		3		6		12		24	
	EW returns	VW returns	EW returns	VW returns	EW returns	VW returns	EW returns	VW returns	EW returns	VW returns
Intercept α_i	0.009	0.008	0.025	0.021	0.048	0.035	0.099	0.073	0.168	0.115
SE	(0.004)	(0.003)	(0.009)	(0.007)	(0.015)	(0.012)	(0.024)	(0.019)	(0.027)	(0.028)
p Value	[0.041]	[0.018]	[0.006]	[0.001]	[0.002]	[0.004]	[0.000]	[0.000]	[0.000]	[0.000]
Slope β^{-1}	0.428	0.338	0.907	0.862	0.937	0.892	1.216	1.324	1.319	1.463
SE	(0.150)	(0.129)	(0.239)	(0.190)	(0.357)	(0.286)	(0.552)	(0.401)	(0.658)	(0.461)
p Value	[0.005]	[0.009]	[0.000]	[0.000]	[0.009]	[0.002]	[0.028]	[0.001]	[0.046]	[0.002]
Slope β^{+}	0.303	0.084	0.584	0.243	0.370	0.014	−0.152	−0.621	−0.493	−1.070
SE	(0.106)	(0.082)	(0.212)	(0.151)	(0.295)	(0.229)	(0.445)	(0.355)	(0.560)	(0.442)
p Value	[0.004]	[0.303]	[0.006]	[0.109]	[0.210]	[0.950]	[0.733]	[0.081]	[0.380]	[0.016]
R^2	0.105	0.058	0.111	0.118	0.043	0.048	0.025	0.046	0.021	0.040

Note. This table represents long-horizon ordinary least square regressions of asymmetric response model incorporating changes in consumer sentiment. K stands for monthly cumulated K horizon returns and when K is greater than one, the regressions use overlapping monthly data. The dependent variable is the excess return of either the CRSP equally weighted portfolio or the CRSP value weighted portfolio. The independent variables are defined in the following manner: β^{-} is the change in CSI if sentiment decreases (i.e., $\Delta CSI < 0$) and zero otherwise, and β^{+} is the change in CSI if sentiment increases (i.e., $\Delta CSI > 0$) and zero otherwise. All data is monthly and is from January 1978 until December 2010. Statistical significance is determined by the Newey-West p values.

that negative (positive) consumer sentiment news will induce a negative (zero) stock market reaction. As a result, they hypothesize that the coefficient for the negative change in sentiment would be negative, and their baseline regression results support this hypothesis. Because their estimated coefficient on the positive change in sentiment variable is not significant, they argue that the result provides more support for the negativity effect hypothesis.

However, if investors are averse to downside risk, the coefficient for downside β would be positive because of the idea that a higher downside risk would correspond to higher returns. Furthermore, we find that as the forecast horizon increases, the magnitudes of the downside βs increase while the magnitudes of the upside βs decrease. This divergence between the general trends of these coefficients shows an increasing importance of downside risk to investors, individual and institutional, over time.

We now turn our attention to shedding light on the life cycle investment hypothesis by incorporating the changes in sentiment of different age groups. Panel A of Table 4 presents the empirical results of Eq. (2) for the CSI index of individuals 18 to 34 years old. Focusing on the downside β for this youngest age group that we study, we observe that β^{-} has the expected positive sign and is statistically significant at the 1% or 5% level of significance in the majority of the one, three, and six month forecast horizons. However, we do not observe in Table 4 an increasing tendency of the downside β coefficients as we presented in Table 3 when the forecast horizon increases, implying that aversion to losses among younger individuals does not necessarily increase over longer periods with respect to excess market

Table 4 Asymmetric response model: CSI for Individuals 18–34 years old, 35–54 years old, and 55 years old and older

Dependent variable	Forecast horizon (K)									
	1		3		6		12		24	
	EW returns	VW returns	EW returns	VW returns	EW returns	VW returns	EW returns	VW returns	EW returns	VW returns
Panel A: CSI for individuals 18–34 years old										
Slope β^-	0.336	0.283	0.441	0.459	0.394	0.492	0.217	0.525	0.137	0.633
SE	(0.128)	(0.105)	(0.184)	(0.142)	(0.266)	(0.190)	(0.456)	(0.301)	(0.480)	(0.326)
p Value	[0.009]	[0.007]	[0.017]	[0.001]	[0.139]	[0.010]	[0.635]	[0.082]	[0.775]	[0.053]
Slope β^+	0.120	0.007	0.389	0.147	0.303	0.025	0.412	−0.047	0.187	−0.452
SE	(0.058)	(0.047)	(0.159)	(0.096)	(0.186)	(0.135)	(0.332)	(0.190)	(0.317)	(0.245)
p Value	[0.041]	[0.886]	[0.015]	[0.126]	[0.104]	[0.852]	[0.215]	[0.805]	[0.555]	[0.066]
R^2	0.060	0.043	0.050	0.048	0.017	0.020	0.009	0.010	0.002	0.011
Panel B: CSI for individuals 35–54 years old										
Slope β^-	0.273	0.195	0.740	0.667	0.738	0.695	0.982	0.980	1.151	1.104
SE	(0.110)	(0.093)	(0.220)	(0.177)	(0.341)	(0.272)	(0.481)	(0.369)	(0.614)	(0.424)
p Value	[0.014]	[0.038]	[0.001]	[0.000]	[0.031]	[0.011]	[0.042]	[0.008]	[0.061]	[0.010]
Slope β^+	0.191	0.066	0.248	0.070	0.206	−0.020	−0.248	−0.494	−0.557	−0.807
SE	(0.083)	(0.063)	(0.175)	(0.128)	(0.244)	(0.186)	(0.362)	(0.293)	(0.472)	(0.330)
p Value	[0.023]	[0.302]	[0.156]	[0.586]	[0.398]	[0.916]	[0.493]	[0.093]	[0.239]	[0.015]
R^2	0.072	0.035	0.086	0.097	0.040	0.046	0.025	0.042	0.026	0.038
Panel C: CSI for individuals 55 years old and older										
Slope β^-	0.238	0.178	0.547	0.495	0.443	0.370	0.560	0.602	0.733	0.806
SE	(0.102)	(0.083)	(0.164)	(0.134)	(0.236)	(0.188)	(0.348)	(0.255)	(0.396)	(0.317)
p Value	[0.020]	[0.033]	[0.001]	[0.000]	[0.061]	[0.050]	[0.109]	[0.019]	[0.065]	[0.011]
Slope β^+	0.169	0.049	0.264	0.119	0.195	0.047	−0.074	−0.295	−0.307	−0.611
SE	(0.075)	(0.061)	(0.137)	(0.101)	(0.182)	(0.135)	(0.285)	(0.210)	(0.338)	(0.258)
p Value	[0.025]	[0.426]	[0.055]	[0.239]	[0.284]	[0.728]	[0.795]	[0.160]	[0.364]	[0.018]
R^2	0.061	0.030	0.062	0.069	0.019	0.017	0.009	0.017	0.011	0.022

Note. This table represents long-horizon ordinary least square regressions of asymmetric response model incorporating changes in consumer sentiment. K stands for monthly cumulated K horizon returns and when K is greater than one, the regressions use overlapping monthly data. The dependent variable is the excess return of either the CRSP equally weighted portfolio or the CRSP value weighted portfolio. The independent variables are defined in the following manner: β^{-1} is the change in CSI if sentiment decreases (i.e., $\Delta CSI < 0$) and zero otherwise, and β^+ is the change in CSI if sentiment increases (i.e., $\Delta CSI > 0$) and zero otherwise. All data is monthly and is from January 1978 until December 2010. Statistical significance is determined by the Newey-West *p* values.

returns. The magnitudes of the estimated coefficients β^- are in general greater than those of β^+ for long-horizon models estimated except for two cases (both estimates are not statistically significant).

The upside β for this age group is statistically significant at the 5% level of significance in only 2 out of the 10 long-horizon models estimated, whereas the downside β is statistically significant in 5 out of the 10 long-horizon models estimated. We conjecture that the focus on avoiding losses is present among younger individuals, especially given that they are in the accumulation phase that Reilly and Brown (2008) describe and possibly cannot afford to lose what assets they do have at this particular point in their lives.

Panel B of Table 4 presents results that pertain to changes in consumer sentiment among individuals 35 to 54 years old and their relationship to excess market returns. We observe that all downside βs are greater than the upside βs in all long-horizon models estimated for this age group. Additionally, 9 out of the 10 β^{-} coefficients are positive and statistically significant at the 1% or 5% level of significance, and mostly increase in magnitude as the forecast horizons increase. For the forecast horizons of 3, 6, 12, and 24 months, the downside βs for individuals 35 to 54 years old are greater than the corresponding downside βs for individuals 18 to 34 years old. The results support Bakshi and Chen (1994) who show that risk aversion increases with age and conclude that demographic changes will cause price fluctuations in the capital markets as they affect macroeconomic variables. Furthermore, the consolidation phase described by Reilly and Brown (2008) involves the time when it is most likely that an individual's earnings exceed their expenses and as a result, they can invest this difference in additional assets such as stocks. Reilly and Brown state that "because individuals in this phase are concerned about capital preservation, they do not want to take very large risks that may put their current nest egg in jeopardy." As their careers and age advance, individuals typically begin investing their wealth more conservatively as they near retirement.

Our asymmetric response model results for individuals 55 years of age and older are presented in Panel C of Table 4. They indicate that 6 of the 10 downside βs estimated are statistically significant. Additionally, β^{-} for the oldest age group exhibits a mostly increasing trend that is consistent with the other asymmetric response models, as well as all downside βs being greater than the upside βs in all long-run horizons. The upside βs exhibit a mostly decreasing trend as the forecast horizon increases, but only 2 out of the 10 β^{+} coefficients are statistically significant at a 5% level of significance. It should be noted that the β^{-} coefficients for this age group are all smaller than the corresponding horizon β^{-} coefficients for the 35 to 54 age group. This implies that individuals 35 to 54 years old exhibit more aversion towards downside risks than individuals 55 and older. Given that stock market excess returns are used as the dependent variable in our asymmetric models, we conjecture that older individuals are less likely to have significant stock market exposure because of their nearer-term focus upon retirement and inclination to possibly hold a larger portion of fixed income securities.

In summary, we observe that the magnitudes of the downside β coefficients are greater than those of the upside βs because downside risk matters more. This finding holds true in the majority of our results for the composite CSI, as well as the CSI for each respective age group. Further, our results show that the sizes of the downside βs are generally greater for consumers 35 to 54 years old and 55 years and older, than those of the downside β coefficients for the youngest age group, consumers 18 to 34 years old. The results confirm that the older we get, the more risk averse we become. Our findings are also consistent with Riley and Chow (1992) and Halek and Eisenhauer (2001) who show how risk aversion can be explained by demographic attributes. Thus, financial planners should continue to thoroughly assess the risk tolerance levels of their clients as they recommend risky assets for their portfolios. Individual investors should also recognize this risk-return relationship and take the necessary steps to diversify their holdings, consider risk-reduction strategies as they approach retirement, and consider seeking professional investment assistance to ensure appropriate investing approaches.

3.3. Size effects

Baker and Wurgler (2006) and Lemmon and Portniaguina (2006) find that sentiment has more of an impact on small-firm stocks versus large-firm stocks. However, does this noise trader argument hold among changes in consumer sentiment for all ages? To empirically test this question, we estimate Eq. (1) but use a one month forecast horizon ($K = 1$) and use CRSP market capitalization portfolios. The dependent variable in the modified Eq. (1) is the stock return of the decile i portfolio minus the risk-free rate, and the independent variable is used and defined in the same manner as in Eq. (1). CRSP segments these sized-sorted decile portfolios into deciles based on a firm's market capitalization, whereby small firms will appear in lower decile portfolios and larger firms appear in higher decile portfolios.

Table 5 presents the results of the size effects. Our findings are consistent with Lemmon and Portniaguina (2006) and Baker and Wurgler (2006) for all age groups; smaller firms' market risk premiums are affected more by changes in sentiment than those of larger firms. For example, the coefficient for ΔCSI_t for the CSI composite (Panel A) is 0.430 for the decile 1 portfolio and 0.185 for the decile 10 portfolio. The implication of this is important, both statistically and economically; a 10% change in overall consumer sentiment (consumers of all ages) results in a market risk premium change of 4.30% in the following month for the smallest firms versus a market risk premium change of 1.85% for the largest firms. Lee, Shleifer, and Thaler (1991) suggest that small-cap stocks are more closely followed by individual investors. This size effect is, for the most part, linear in that the smallest firms are affected the most and this effect gradually decreases as firm size increases. This pattern is true for changes in consumer sentiment for all age groups. Our finding thus confirms to individual investors and financial planners that investing in small-cap stocks can be risky and proper risk-return tradeoff analyses must be performed to confirm suitability for one's portfolio and risk tolerance.

4. Concluding remarks

In this article, we examine the ability of consumer sentiment to forecast short-term as well as long-term equity returns and whether or not negative sentiment has a larger effect on the returns than positive sentiment for three different age groups. We observe that negative changes in sentiment have a greater influence on stock returns than positive changes in sentiment. Further, sentiment is more effective forecasting short-term holding period returns than long-term holding period returns, and these results are consistent across all ages. These empirical findings are consistent with the documented behavior that agents place greater weight on downside risk than they place on upside gains, and are agreeable with the notion of the prospect theory proposed by Kahneman and Tversky (1979).

Our results also document a difference in age groups' sentiment, and that younger individuals appear to be less risk-averse than older individuals. The finding supports the

Table 5 Size effects approach

	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
Panel A: All age groups: CSI composite										
Intercept α	0.009	0.007	0.008	0.007	0.008	0.008	0.008	0.007	0.007	0.006
SE	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
p Value	[0.008]	[0.032]	[0.009]	[0.011]	[0.007]	[0.004]	[0.004]	[0.008]	[0.007]	[0.015]
Slope β	0.430	0.417	0.383	0.346	0.323	0.283	0.270	0.245	0.225	0.185
SE	(0.064)	(0.073)	(0.077)	(0.075)	(0.076)	(0.068)	(0.070)	(0.066)	(0.066)	(0.055)
p Value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Panel B: Age group 18–34 years old										
Intercept α	0.009	0.007	0.008	0.007	0.008	0.008	0.008	0.007	0.007	0.006
SE	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
p Value	[0.012]	[0.041]	[0.013]	[0.014]	[0.010]	[0.006]	[0.005]	[0.011]	[0.009]	[0.017]
Slope β	0.252	0.247	0.219	0.202	0.186	0.165	0.153	0.145	0.139	0.121
SE	(0.060)	(0.061)	(0.060)	(0.058)	(0.057)	(0.053)	(0.053)	(0.051)	(0.047)	(0.042)
p Value	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.002]	[0.004]	[0.004]	[0.004]	[0.004]
Panel C: Age group 35–54 years old										
Intercept α	0.009	0.007	0.007	0.007	0.008	0.008	0.008	0.007	0.007	0.006
SE	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
p Value	[0.011]	[0.042]	[0.013]	[0.014]	[0.010]	[0.006]	[0.005]	[0.010]	[0.009]	[0.017]
Slope β	0.266	0.264	0.253	0.226	0.208	0.186	0.183	0.155	0.147	0.109
SE	(0.045)	(0.057)	(0.061)	(0.056)	(0.059)	(0.052)	(0.053)	(0.050)	(0.051)	(0.040)
p Value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.002]	[0.004]	[0.006]
Panel D: Age group 55 years old and older										
Intercept α	0.009	0.007	0.007	0.007	0.008	0.008	0.008	0.007	0.007	0.006
SE	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
p Value	[0.012]	[0.043]	[0.013]	[0.015]	[0.010]	[0.006]	[0.006]	[0.011]	[0.009]	[0.018]
Slope β	0.245	0.231	0.207	0.190	0.177	0.148	0.138	0.129	0.112	0.096
SE	(0.043)	(0.044)	(0.046)	(0.046)	(0.044)	(0.041)	(0.041)	(0.040)	(0.037)	(0.034)
p Value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.002]	[0.003]	[0.005]

Note. This table represents ordinary least square regressions of one month excess returns of various size-sorted decile portfolios on lagged one month changes in the Consumer Sentiment Index (CSI). The indices used are the 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. Decile 1 represents firms that have smaller market capitalizations versus the firms with higher market capitalizations (higher decile indices). Decile 10 represents firms that have some of the largest market capitalizations of listed firms. All data is monthly and is from January 1978 until December 2010. Statistical significance is determined by the Newey-West *p* values.

existing literature and the concept of the life cycle investment hypothesis. Finally, we present additional evidence for the notion that the risk premiums of smaller firms are more affected by sentiment than larger firms; a result that is in line with the noise trader hypothesis. We provide evidence that reminds individual investors and financial planners that risk is an important consideration when investing. Moreover, demographic characteristics such as age matter when determining appropriate investing approaches and risk tolerance. This article applies well-known concepts in behavioral economics and finance, and deepens our understanding of the relationship and importance of consumer sentiment in evaluating the equity returns.

Notes

1 For example, these studies include Akhtar et al. (2011), Baker and Wurgler (2006), Baker and Wurgler (2007), Chung et al. (2012), Fisher and Statman (2003), Lemmon and Portniaguina (2006), Schmeling (2009), Stambaugh et al. (2012), and Yu and Yuan (2011).
2 Reilly and Brown (2008) identify four life cycle phases: the accumulation phase, consolidation phase, spending phase, and gifting phase.
3 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.
4 The market variables used are the closed-end fund discount, NYSE share turnover, the number of initial public offerings (IPOs), the average first day return of IPOs, the dividend premium, and the equity share in new issues.
5 We follow the description of the long-horizon regression model presented by Campbell et al. (1997).
6 These are not dummy variables and provide the magnitude of sentiments' negative and positive effects.
7 We note that the CSI composite is not the average of three different age groups because of slightly different survey methods.
8 U.S. business cycle expansions and contractions according to the National Bureau of Economic Research (http://www.nber.org/cycles.html).
9 Newey-West methods are used to obtain robust parameter estimates by correcting the possible autocorrelation and heterocedasticity.

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