Volatility Overload – How Market Volatility Affects Self-Reported Life Satisfaction

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Abstract

We investigate how economic uncertainty, specifically stock market uncertainty, correlates to individuals' life satisfaction. Using expected price volatility (VIX) as our anticipatory indicator and life satisfaction as our measure of utility, our hypothesis is built on the Anticipatory Utility framework, which suggests that people also derive utility from their beliefs. After accounting for associations with the unemployment rate and stock ownership, we find a positive relationship between the VIX and low self-reported life satisfaction. This analysis captures the contemporaneous effects of future beliefs and indicate that economic sentiment about the future plays an important role in individuals' feelings about the present.

Keywords: economic uncertainty, stock market, life satisfaction, price volatility

Introduction

Coping with uncertainty is a fundamental necessity of life. Our ability to do so allows us to navigate the stochastic world we inhabit. Uncertainty is, of course, not a static concept, but instead varies with the confidence in our predictions about that which we anticipate. The more confidently we predict, the less uncertain we are about the consequences of our actions and others' actions, and the more stable we feel in the present. This paper hypothesizes that increases in future uncertainty negatively affect our current outlook, specifically our self-reported life satisfaction. While uncertain times may be a harbinger of opportunity for some, for most, unpredictability is met with contemporaneous stress and worry. Capturing the immediate impacts of anxiety about the economic future motivates this work.

Existing psychological evidence shows that stock market uncertainty correlates with individuals' decisions to engage in unhealthy behavior. In a similar fashion, we investigate how stock market uncertainty correlates to individuals' life satisfaction. To capture this effect, we build our hypothesis through the Anticipatory Utility framework, which suggests that people care about utility flow today and expected utility flows in the future. That is, the belief of a more optimistic future regarding employment status or wealth can bring contemporaneous enjoyment and correlate with higher utility. Conversely, a pessimistic future outlook can cause pain and disutility in the present. Specifically, we hypothesize that short-term volatility expectations relate to individuals' life satisfaction within the anticipatory framework in two major ways. First, increases in market uncertainty, which is directly related to stock market performance, negatively changes reported life satisfaction for stockholders through the income effect. Second, increases in market uncertainty may be negatively correlated with non-stockholders' reported life satisfaction through the fear of worsening economic conditions and other potential stressors.

Using observational survey data from the Behavioral Risk Factor Surveillance System (BRFSS), Current Population Survey (CPS) data, and Chicago Board Options Exchange (CBOE) Volatility Index (VIX) data from 2013 to 2017, this paper finds strong support for our hypothesis. Stock market uncertainty is measured using the S&P 500 options-implied volatility index (VIX), a 30 day-forward looking market index, which we use as our anticipatory indicator. Self-reported life satisfaction comes from BRFSS survey data, and stock ownership propensity is derived from the CPS data. Following prior research on this topic, we limit the income effect that would result from a change in macroeconomic conditions by controlling for unemployment, per capita personal income, and current market performance. Doing so allows us to capture the effects of market stress and uncertainty more effectively. This study reveals that the VIX negatively influences reported life satisfaction after adjusting for demographics, health conditions, and different fixed effects for time and states. Specifically, our results indicate that, at the mean, an additional percentage increase in the VIX decreases the probability of feeling "Very Satisfied" by 6.17% and increases the likelihood of feeling "Dissatisfied" by 1.32%. We also capture the presence of some income effects from stockholding activities. That is, the negative life satisfaction effect increases as the propensity to hold stocks increases, indicating that the stock market's impact is more prevalent for those with skin in the game, as expected.

During the recent stock market crashes, Americans showed large declines in self-reported life satisfaction (Deaton, 2011), showed increased symptoms of depression and poor mental well-being (McInerney, Mellor, & Nicholas, 2012), and experienced a spike in hospitalizations for psychological disorders (Engelberg & Parsons, 2013). Similar papers have used market price indicators, such as the Dow Jones Industrial Average (DJIA) as the independent variable of interest (Cotti, Dunn, and Tefft, 2013) to explore the market's impact on health measures. However, unlike previous research, we approach this question from a slightly different angle. Instead of assessing the correlation between life satisfaction and directional price changes in market indices, we measure the relationship between life satisfaction and changes in anticipated market uncertainty – options-implied market volatility. For example, the VIX index aggregates the S&P 500 call and put options in a way such that the index represents the implied volatility of the clearing prices of all S&P 500 options. Implied volatility in this sense is the amount of volatility required to set the options' expected value equal to zero, given the contracted prices. Therefore, the VIX can be thought of as an aggregate market sentiment regarding the anticipated price volatility of the S&P 500, expressed through the supply and demand dynamics of the options market. We believe this measure of future uncertainty is an improvement over past research for several reasons.

First, periods of market turmoil are characteristically marked by large price movements in both directions, a well-documented phenomenon termed volatility clustering (Mandelbrot (1963), Granger and Ding (1993), and Ding and Granger (1996)). Large market declines may be followed by a large transitory rebound, which is then followed by another large decline. In fact, these transitory price increases are themselves an indicator of uncertainty, not recovery. Therefore, we propose that these temporary price increases amidst a broader crisis do not provide psychological relief in equal proportion to the distress caused by a price decrease of equal magnitude. Thus, our empirical model should capture the market's uncertainty level (expected volatility) rather than noisy directional price changes if our goal is to capture the effect of economic stress on life satisfaction. Second, it is documented that the VIX is asymmetrical in its response to price changes in the underlying S&P 500 index, rising more following a price decrease relative to a price increase (Low 2004). This evidence supports the Volatility Clustering concept presented above, whereby price increases do not alleviate uncertainty in equal proportion to their negative counterparts. This non-linearity of response between gain and loss domains is consistent with Prospect Theory (Kahneman and Tversky, 1979). The VIX may, therefore, provide an independent variable closely linked to the expected emotional responses related to changes in economic outcomes and outlooks. Third, the VIX's presence in the news media and widespread recognition as the market's fear gauge provides an additional property of interest for this study. Research demonstrates a significant yet complicated role for the news media in shaping economic perceptions. Through increasingly accessible and rapid media coverage, market signals reach a significant percentage of the general population and help shape sentiment regarding the economic outlook and confidence about one's current and future socio-economic life satisfaction (Procopio, Terrell, & Wu, 2010). Within this context, signals of increased uncertainty have a diminishing effect on one's life satisfaction, both economically and emotionally. Thus, the VIX both creates and is created by a general sense of uncertainty and fear about future macroeconomic conditions, which, we propose, drives psychological and physical malaise.

Our results have a range of significant implications. First, our findings support prior work postulating an effect of anticipatory feelings (e.g., Lowenstein, 1987) on individual desires and behaviors. Caplin and Leahy (2001) demonstrate, for example, that adding sentiment to the utility function can help explain time inconsistency in preferences. We show that the effect of forward-looking volatility fits into the Anticipatory Utility framework. Second, our findings add to the literature regarding feedback models (e.g., Shiller, 2002). Specifically, as Engelberg and Parsons (2016) have pointed out, most behavioral finance work concentrates on how investor behavior affects markets and often neglects the inverse effect. As a result, our finding introduces a new connection to how markets influence investor behavior.

This study is not the first to investigate the relationship between market uncertainty and commodities within the utility function. In fact, our study is motivated by recent behavioral finance papers (Engelberg and Parsons, 2016; Sias, 2017). However, this study differs from previous studies in two significant ways. First, this study is the first to use market-implied volatility as the leading independent variable of interest and more effectively capture uncertainty. Second, we link the effect of market volatility on life satisfaction through the anticipatory theoretical framework and show that our model deviates from the traditional Neo-classical model. Specifically, we show that the VIX acts as a natural anticipatory index, which can be built into the life satisfaction utility function (Stevenson, Wolfers 2008).

Data

Descriptive Statistics

Our final data is presented in the most interpretable format. All variables and sub- categories are put into two different columns based on our primary variable of interest, life satisfaction. The first column is 3, which presents respondents who reported “Very Satisfied.” The second column is 2, which presents respondents who reported “Satisfied” while the last column represents "Dissatisfied. While one may argue on the reliability of these subjective questions, previous works (Apouey and Clark 2015) suggest that they capture an overall assessment of life satisfaction and a combination of mental and physical health. Further, Benjamins et al. 2004, Miilunpalo et al. 1997, Jylha 2009 have shown that these measures can predict various health outcomes, such as mortality and healthcare utilization. Thus, it is fair to conclude that self-reported life satisfaction measures from health surveys in our data plausibly correlate with objective health. These self-reported measures from reliable sources such as the BRFSS have been used in many economics studies. However, some previous studies suggest there may exist some reporting errors (Baker, Stabile, and Deri 2004), which can affect our estimates. As described above, we try our best to minimize these errors by omitting incomplete respondents, only including variables in the main panel, and getting rid of vaguely reported observations.

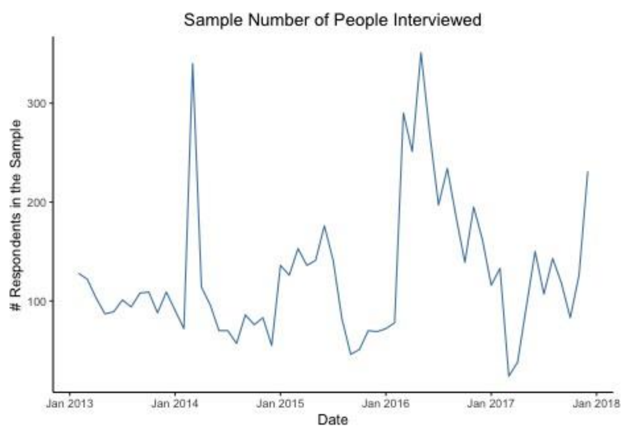

Figure 23: Number of People Interviewed in the Sample

In addition, our self-reported measures are particularly useful for a study of the short-run effects of market sentiments. It seems unlikely that more severe or objective measures of poor life satisfaction conditions (e.g., mortality, chronic conditions, hospitalizations) will respond in the short run to a change in market volatility (and the associated income and time cost changes). Thus, our analysis of self-reported life satisfaction, which captures how a person evaluates their life satisfaction at a point in time, is potentially more responsive, and therefore more suitable, for our study objectives than more severe or objective measures.

To provide a good view of the dataset, we show the following chart, representing the number of respondents who answered the survey throughout 2013-2017. Although there is a disproportion in the number of participants who respond to the survey across different months, our time control variables should capture seasonality in our model analysis. Note that we do not fully show the CPS data's descriptive statistics since they do not necessarily play a significant role in our analysis.

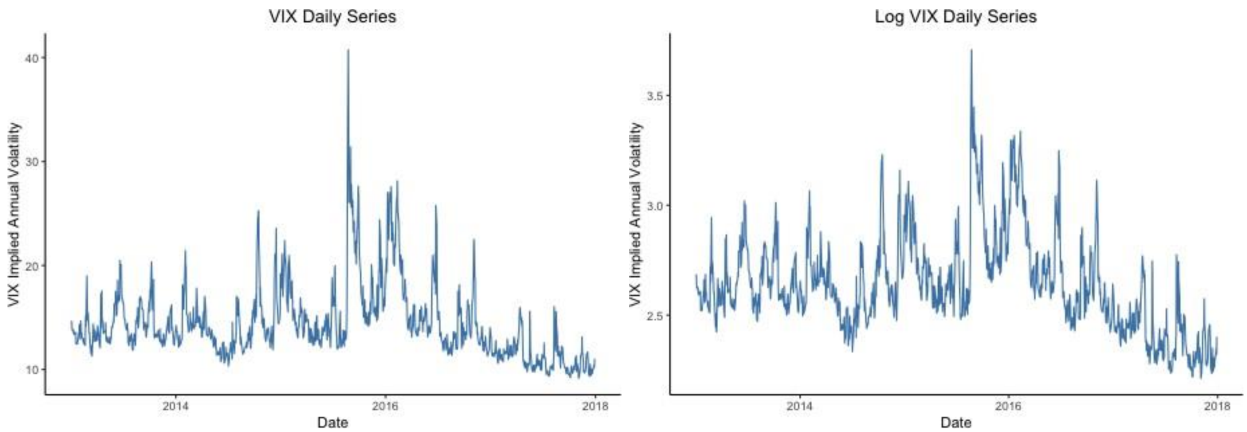

Figure 24: VIX Data

As discussed in the prior section, Market Volatility is the natural log of the VIX daily series. In performing this operation, we not only get an interpretable value, but we also get a stationary VIX times series. As shown in the graphs below, all Market Volatility series appear stationary. However, because market volatility tends to cluster into two distinct regimes, low volatility and high volatility, the S&P 500 returns exhibit non-constant variance over the full time-series. We do not observe the same variance characteristics for the VIX, which exhibits less heteroscedasticity, thus adhering more closely to our generalized linear estimation model's assumptions. This fact provides additional empirical justification for considering the VIX as our primary variable of interest. Nevertheless, we do indeed control for the S&P500 (Current Market), which controls for the current market movements and news. This variable takes the expression of SPY for all models. The S&P 500 return series, which are used as a control in this paper, pass standard stationarity tests at the 5% level.

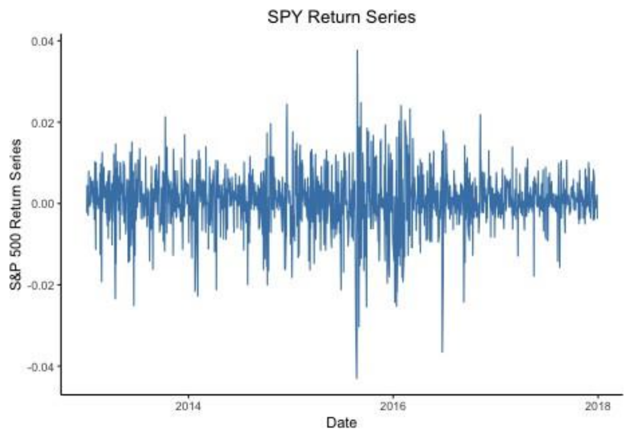

Figure 25: SPY Data

Descriptive Statistics - Demographics

By life satisfaction (1 = Dissatisfied, 2 = Satisfied, 3 = Very Satisfied)

Characteristic	**(1)**, N = 528	**(2)**, N = 3,784	**(3)**, N = 3,204
Age, n / N (%)			
18to24	3 / 528 (0.6%)	21 / 3,784 (0.6%)	15 / 3,204 (0.5%)
25to34	13 / 528 (2.5%)	106 / 3,784 (2.8%)	90 / 3,204 (2.8%)
35to44	38 / 528 (7.2%)	220 / 3,784 (5.8%)	174 / 3,204 (5.4%)
45to54	121 / 528 (23%)	582 / 3,784 (15%)	397 / 3,204 (12%)
55to64	199 / 528 (38%)	1,058 / 3,784 (28%)	781 / 3,204 (24%)
65older	154 / 528 (29%)	1,797 / 3,784 (47%)	1,747 / 3,204 (55%)
Gender, n / N (%)			
female	328 / 528 (62%)	2,146 / 3,784 (57%)	1,789 / 3,204 (56%)
male	200 / 528 (38%)	1,638 / 3,784 (43%)	1,415 / 3,204 (44%)
Income, n / N (%)			
50more	82 / 528 (16%)	1,144 / 3,784 (30%)	1,481 / 3,204 (46%)
15to25K	155 / 528 (29%)	899 / 3,784 (24%)	534 / 3,204 (17%)
25to35K	74 / 528 (14%)	511 / 3,784 (14%)	404 / 3,204 (13%)
35to50K	40 / 528 (7.6%)	585 / 3,784 (15%)	477 / 3,204 (15%)
le15K	177 / 528 (34%)	645 / 3,784 (17%)	308 / 3,204 (9.6%)
Education, n / N (%)			
COLgrad	115 / 528 (22%)	984 / 3,784 (26%)	1,122 / 3,204 (35%)
attendCOL	176 / 528 (33%)	1,187 / 3,784 (31%)	908 / 3,204 (28%)
HSgrad	160 / 528 (30%)	1,212 / 3,784 (32%)	934 / 3,204 (29%)
K	77 / 528 (15%)	401 / 3,784 (11%)	240 / 3,204 (7.5%)
Marital Status, n / N (%)			
married	144 / 528 (27%)	1,721 / 3,784 (45%)	1,989 / 3,204 (62%)
divorced	151 / 528 (29%)	705 / 3,784 (19%)	359 / 3,204 (11%)
membermarriedcoup	16 / 528 (3.0%)	53 / 3,784 (1.4%)	40 / 3,204 (1.2%)
nevermarried	100 / 528 (19%)	492 / 3,784 (13%)	242 / 3,204 (7.6%)
separated	38 / 528 (7.2%)	90 / 3,784 (2.4%)	43 / 3,204 (1.3%)
widowed	79 / 528 (15%)	723 / 3,784 (19%)	531 / 3,204 (17%)

Employment Status, n / N (%)			
wagesemployed	95 / 528 (18%)	1,097 / 3,784 (29%)	982 / 3,204 (31%)
homemaker	14 / 528 (2.7%)	132 / 3,784 (3.5%)	139 / 3,204 (4.3%)
noworkless1	14 / 528 (2.7%)	84 / 3,784 (2.2%)	35 / 3,204 (1.1%)
noworkmore1	33 / 528 (6.2%)	97 / 3,784 (2.6%)	33 / 3,204 (1.0%)
retired	126 / 528 (24%)	1,588 / 3,784 (42%)	1,561 / 3,204 (49%)
selfemployed	12 / 528 (2.3%)	191 / 3,784 (5.0%)	217 / 3,204 (6.8%)
student	2 / 528 (0.4%)	11 / 3,784 (0.3%)	20 / 3,204 (0.6%)
unable	232 / 528 (44%)	584 / 3,784 (15%)	217 / 3,204 (6.8%)
Race, n / N (%)			
white	429 / 528 (81%)	3,186 / 3,784 (84%)	2,749 / 3,204 (86%)
asian	1 / 528 (0.2%)	20 / 3,784 (0.5%)	23 / 3,204 (0.7%)
black	68 / 528 (13%)	441 / 3,784 (12%)	324 / 3,204 (10%)
native	23 / 528 (4.4%)	71 / 3,784 (1.9%)	68 / 3,204 (2.1%)
other	7 / 528 (1.3%)	60 / 3,784 (1.6%)	37 / 3,204 (1.2%)
pacific	0 / 528 (0%)	6 / 3,784 (0.2%)	3 / 3,204 (<0.1%)

Table 18 presents descriptive statistics based on general life satisfaction. As presented, there is a larger number of respondents who report “Satisfied” (N = 3,707) and “Very satisfied” (N = 3,149) compared to those who report “Dissatisfied” (N = 514). To put this in perspective, we show charts based on each group’s demographics.

Table 19: Descriptive Statistics - Chronic Conditions

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Health Insured	7,516	0.949	0.219	0	1	1	1
Heart Disease	7,516	0.142	0.349	0	0	0	1
Arthritis	7,516	0.493	0.500	0	0	1	1
Stroke	7,516	0.085	0.280	0	0	0	1
Asthma	7,516	0.155	0.362	0	0	0	1
Bronchitis	7,516	0.125	0.331	0	0	0	1
Cancer	7,516	0.143	0.350	0	0	0	1
Diabetes	7,516	0.915	0.279	0	1	1	1

Table 19 shows the descriptive statistics for all chronic condition covariates in the dataset. On average, 95% of respondents in the dataset have health insurance. About 14% of the respondents have heart disease, 50% have arthritis, more than 8% have had a stroke, more than 15% have asthma, 12% have bronchitis, 14% have cancer, and about 91% are diabetic.

Methodology

One challenging element of this analysis is the processing and merging of stockholding data extracted from the Current Population Survey. Unlike the BRFSS, where all of the variables are categorical, variables from the CPS are continuous. Thus, we recoded all demographic variables from the CPS to match those of the BRFSS dataset, allowing us to maintain variable consistency during the data integration process. The stock ownership variable within the CPS dataset is crucial to our analysis. Specifically, information regarding an individual's stockholdings helps us to define the effect of market uncertainty on the stockholding population and non-stock-holding population in our sample.

In order to properly extract and integrate stock ownership information with our BRFSS data, we developed a stock-ownership propensity score from the Current Population Survey (CPS). We do so by employing a logistic regression to derive the relationship between demographic variables and stock ownership. As suggested by previous literature (Kreinin et al. 1959), we use some of the most significant demographic predictors of stock ownership, including age, gender, income, education - status, and race, in our regression to achieve the propensity score at individual levels, which we were then able to merge onto the BRFSS dataset based on the demographics mentioned above.

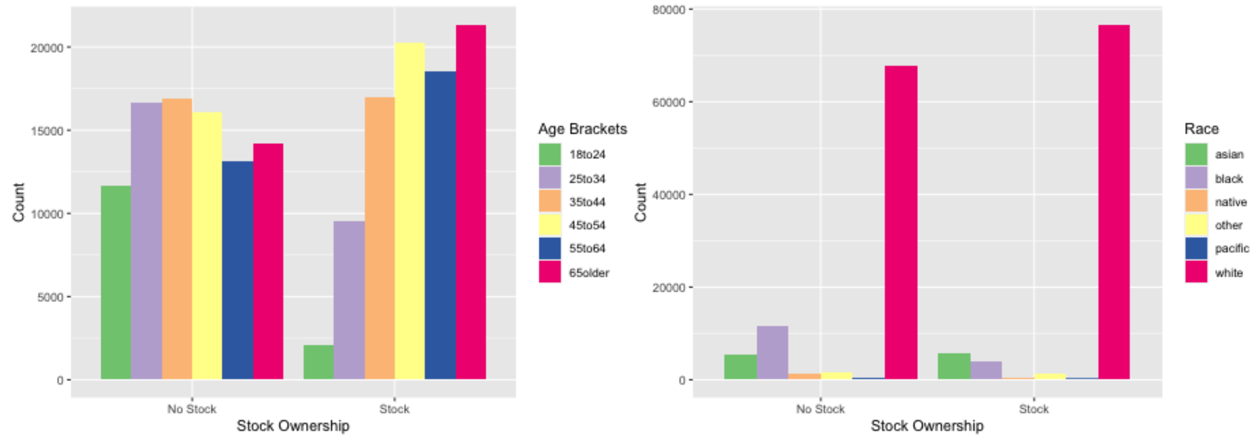

Figure 26: CPS Demographics - Age and Race

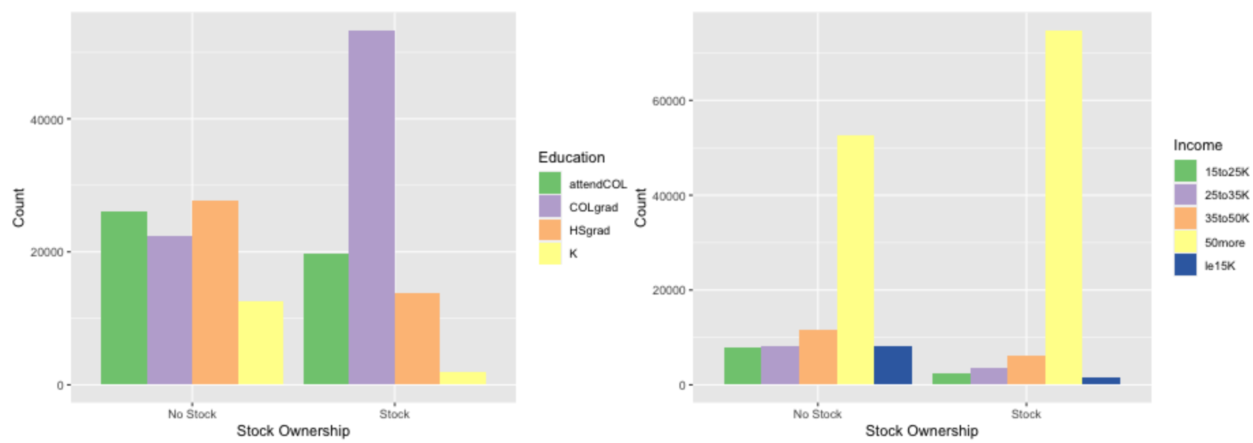

Figure 27: CPS Demographics - Education and Income

Our propensity results indicate that males are more likely to own stocks compared to females, as are respondents who have a college degree compared to those who do not. Further, income and age play a predictable role in an individual's propensity to participate in the stock market. Respondents who make at least 50 thousand dollars a year are the most likely to own stock, as are those 65 years of age and older. We also find that the Caucasian population is the most likely to own stocks, followed by mixed races and Asian. Following prior literature, we believe that propensity score methodology and subsequent results offer a decent representation of actual stock ownership characteristics.

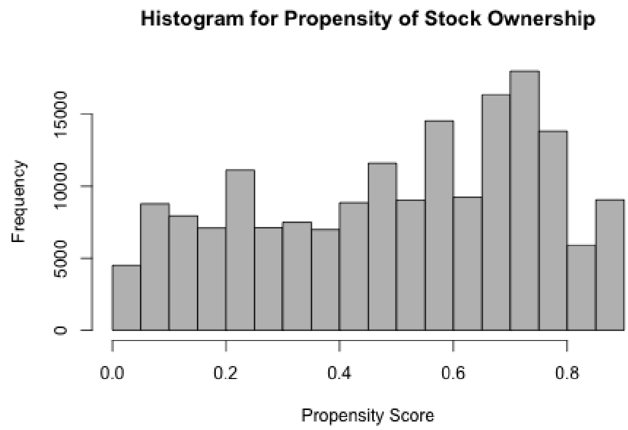

Figure 28: Propensity Score for Stock Ownership

Table 20: Regression Results for Stock Ownership

	Dependent Variable
	Stock Ownership
	(1)
	Logit
gendermale	0.242
	(0.011)
calculated_educationattendCOL	0.954
	(0.014)
calculated_educationHSgrad	1.411
	(0.014)
calculated_educationK	2.371
	(0.028)
calculated_income15to25K	1.244
	(0.027)
calculated_income25to35K	0.972
	(0.024)
calculated_income35to50K	0.724
	(0.019)
calculated_incomele15K	1.568
	(0.030)
calculated_age25to34	0.661
	(0.029)
calculated_age35to44	1.152
	(0.028)
calculated_age45to54	1.471
	(0.028)
calculated_age55to64	1.752
	(0.028)
calculated_age65older	2.183

	(0.028)
calculated_raceasian	0.287
	(0.022)
calculated_raceblack	0.933
	(0.021)
calculated_racenative	0.405
	(0.057)
calculated_raceother	0.153
	(0.043)
calculated_racepacific	0.717
	(0.088)
Constant	0.385
	(0.028)
Observations	177,296
Log Likelihood	98,710.070
Akaike Inf. Crit.	197,458.100

Note: Panel consists of the 2013-2017 survey sample waves of CPS. Model estimates with a Logistic Regression. Model controls for demographics, including age, gender, race, income, education status, marital status, employment status.

p<0.1; p<0.05; p<0.01

Full Logistic regression results of demographics on stock ownership are presented in Table 20. As shown in Figure 28, our propensity score distribution for stock ownership spreads perfectly from almost 0% chance of owning stock to nearly 100% chance of owning stocks. The results from CPS data indicate two significant signals. First, the logistic regression on stock ownership is appropriate. Each observation in the CPS dataset has its value for stock ownership. Second, the perfect propensity score will provide an advantage when merging in the BRFSS for analysis. It will ensure that each BRFSS observation will yield a unique propensity to own stocks, ranging from 0% to 100%.

The analysis proceeds with the ordinal logistics model. Our dependent variable is Life Satisfaction, which takes into three categories of “Very Satisfied,” “Satisfied,” and “Dissatisfied.” The main independent variable of interest is the natural log of the VIX, divided by 100. We also control for the current market performance (S&P500 return series), stock ownership (propensity to own stock), demographics, and a set of Fixed-Effects. As described above, controlling for a set of demographics variables is extremely useful in generating precise estimates, given different demographics in our survey. In addition, by controlling for State Fixed-Effects, Monthly Fixed-Effects, and Yearly Fixed-Effects, we aim to achieve the most precise estimates possible by accounting for the impact of seasonality that may exist in some behaviors, such as physical activity (Ruhm 2005), permanent differences across states that may affect health and health behaviors, such as lifestyles patterns, state infrastructures on health care, and confounding factors that may trend linearly. All the regressions are weighted using the BRFSS sampling weights.

Empirical Results

As previously mentioned, we have a robust set of controls, including gender, age (6 different categories), income (5 different categories), education status (4 categories), marital status (6 different categories), race (6 different categories), chronic health conditions, and employment status (8 different categories). Moreover, a set of fixed effects for months, years, and states ensures that we can capture the effect while minimizing modeling errors and biases. Although this study does not necessarily focus on the effect of demographics on life satisfaction, nor the effect of chronic conditions on life satisfaction, our results show that these effects across the board are expected.

The central panel, presented in Table 21, shows the effects of the VIX on life satisfaction outcomes. Across four different models, models (2) and (4) control for additional chronic health conditions, while models (1) and (3) do not. All models control for Stock Ownership, which is the propensity score value for stock ownership. Our results indicate that the effects of the VIX on life satisfaction are reasonably consistent overall. The magnitudes of the results do not fluctuate significantly across different specifications. Model (4) is our prime model, where it controls for chronic conditions, propensity score of stock ownership, the interaction of propensity score of stock ownership and the natural log of the VIX, and sample weights. The interaction term shows that as the market is under stress, increases in the likelihood of the respondents owning stock result in decreases in the probability of respondents moving toward the next category (feeling satisfied). We are likely capturing the income effect in the regression, as expected. In other words, the more likely it is that a respondent is a stockholder; the more likely they are to have poor life satisfaction during periods of market turmoil.

Table 21: Regression Results for life satisfaction and Daily VIX

	Dependent Variable			
	Life Satisfaction			
	(1)	(2)	(3)	(4)
	Ordinal Logit	Ordinal Logit	Ordinal Logit	Ordinal Logit
logvixadjusted100	-26.380	-26.347	-14.041	-14.812
	(1.019)	(1.025)	(1.627)	(1.631)
StockOwnership	0.308	0.272	1.092	1.006
	(0.035)	(0.035)	(0.088)	(0.088)
logvixadjusted100 StockOwnership			-30.208	-28.287
			(3.104)	(3.110)
spyrets1000	0.011	0.025	0.011	0.026
	(0.005)	(0.005)	(0.005)	(0.005)
health_insured	0.541	0.570	0.540	0.569
	(0.006)	(0.006)	(0.006)	(0.006)
Cancer		0.004		0.005
		(0.004)		(0.004)
heart_disease		-0.036		-0.036
		(0.004)		(0.004)
Arthritis		-0.345		-0.345
		(0.003)		(0.003)
Diabetes		-0.416		-0.416
		(0.006)		(0.006)
Stroke		-0.146		-0.146
		(0.005)		(0.005)
Asthma		-0.252		-0.252
		(0.004)		(0.004)
Bronchitis		-0.446		-0.446
		(0.005)		(0.005)
etc.				
Month FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Interaction	No	No	Yes	Yes
Chronic Health	No	Yes	No	Yes
Demographics	Yes	Yes	Yes	Yes
Survey Weights	Yes	Yes	Yes	Yes
Observations	7,516	7,516	7,516	7,516

Note: Panel consists of the 2013-2017 survey sample waves of BRFSS.BRFSS sample weights applied. Market volatility is defined as $\frac{log(VIX)}{100}$. All models estimated with Logistic Regression. All models control for demographics, including age, gender, race, education status, income, marital status, employment status.
p<0.1; p<0.05; p<0.01

To better understand the effects, we want to investigate the marginal effects of the VIX on life satisfaction. We achieve marginal effects at the mean and average marginal effects at Table 22. Our results indicate that at the mean, an additional percentage increase in the VIX decreases the probability of feeling “Very Satisfied” by 6.17%, holding all else constant, which is significant at the 1% level. Moreover, at the mean, an additional percentage increase in the VIX increases the probability of feeling “Dissatisfied” by 1.32%, holding all else constant, which is significant at the 1% level. On average, an additional percentage increase in the VIX decreases the probability of feeling “Very Satisfied” by 5.53%, holding all else constant, which is significant at the 1% level. Similarly, on average, an additional percentage increase in the VIX increases the probability of feeling “Dissatisfied” by 1.51%, holding all else constant, which is significant at the 1% level. Given the VIX’s standard errors, we are confident to reject the null hypothesis, concluding a negative association between the VIX and better-reported life satisfaction. Further, the 95% confidence interval lies within the negative zone of the effect, which also confirms that this effect is negatively correlated.

Table 22: Marginal Effect Table

	Dependent Variable			
	Life Satisfaction			
	(1)	(2)	(3)	(4)
	MEM	AME	MEM	AME
	Very Satisfied	Very Satisfied	Dissatisfied	Dissatisfied
logvixadjusted100	-6.166	-5.528	1.324	1.513
	(0.242)	(0.212)	(0.052)	(0.069)
StockOwnership	0.062	0.054	-0.013	-0.017
	(0.008)	(0.007)	(0.002)	(0.002)
SPY.rets1000	0.006	0.005	-0.001	-0.002
	(0.001)	(0.001)	(0.000)	(0.000)
etc.				
Month FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes
Chronic Health	Yes	Yes	Yes	Yes
Survey Weights	Yes	Yes	Yes	Yes
Observations	7,516	7,516	7,516	7,516

Note: Table includes Average Marginal Effects (AME) and Marginal Effects atMean (MEM). Market volatility is defined as $\frac{log(VIX)}{100}$. All models control for demographics, including age, gender, race, education status, income, maritalstatus, employment status.

p<0.1; p<0.05; p<0.01

Conclusion

This study explores the impact of financial and economic uncertainty on self-reported life satisfaction. Our results show clear patterns, similar to previous research, in which self-reported life satisfaction is worsened during periods of market turmoil and uncertainty. Using market volatility, or the VIX, we find evidence that self-reported life satisfaction is more likely to be reported in the category of "Very Satisfied" compared to the category of "Dissatisfied" when the implied volatility index declines, or when the market volatility indicates a relative decline in economic uncertainty. This study is novel in the sense that we employ expected volatility as our primary variable of interest instead of other mainstream stock market indicators, such as the S&P 500 or the Dow Jones Industrial Average. Thus, we assess the relationship between forward-looking volatility expectations and individual life satisfaction metrics.

Furthermore, since the future economic conditions are pertinent for both non-stockholders and stockholders, it is expected that human responses are widespread and not merely restricted to individuals actively participating in the market. In sum, with various tests and robustness checks, our results strongly support our hypothesis and confirm previous evidence on mainstream market indicators, such as the Dow Jones. Further, we fit our primary model into the Anticipatory Utility framework and show that the VIX daily series, acting as an anticipatory index, influences survey respondents' life satisfaction, which acts as our primary utility measure. This novel approach takes the financial market's association with life satisfaction and life satisfaction in a new direction. Prior research has extensively investigated the relationship of human behaviors on the stock market, but little work explores the inverse effects. We hope that this study can add to the behavioral economic and modern finance literature using that particular perspective.

Previous research has shown that the effect mechanism between financial markets and life satisfaction is derived from several possible factors. Earlier research (Brenner & Mooney, 1983;

Catalano & Dooley, 1983) suggests that the level of stress due to market conditions may lead to self-medication. Risky health behaviors can also be the result of market downturns. Behaviors such as smoking, overeating, and binge drinking are more likely to occur when market performance is poorer (Colman & Dave, 2011; Cotti & Tefft, 2011; 23 Ruhm & Black, 2002; Ruhm, 2005). In addition, Cotti, Dunn, Tefft (2013) found a diminished income effect when assessing the impact of the Dow Jones on health, suggesting that market and economic stress play a role in one's inclination to participate in risky health behaviors. Therefore, our

findings help explain why behavioral biases are more severe when expected market volatility is high (Kumar, 2009).

While the study's estimates are intensely investigated, there are several limitations to this study. Although we show a deep channel of how market volatility affects life satisfaction, we cannot conclude that this effect is causal. The income effect indeed plays a significant role in the negative relationship between market volatility and life satisfaction. Our partial effects show this to be the case. Nonetheless, we are not able to fully control for potential endogeneity issues. Individuals can be affected by market uncertainty in many ways, including market crashes, potential job loss, etc. Although we show that the VIX can act as an anticipatory index for the market uncertainty, we do not fully understand the link that connects market- implied financial indicators to human behaviors. For example, stock market participation has increased in recent years, capturing new demographics of individuals who can now more easily open trading accounts. Such increases in non-institutional trade activity may increase the presence of noise traders, which in turn may influence levels of volatility. We do not fully understand the impact of these changing market dynamics on our results.

Nonetheless, the paper underscores the exciting cross-section between the fields of behavioral economics, finance, and health. Although a handful of previous literature inspires the study, we are unaware of existing research that is similar or identical to our study. Finally, by better understanding the impact of stock market behavior on human behavior and life satisfaction, this paper sheds additional light on the contemporaneous consequences of an individual’s anticipated financial and economic uncertainty.

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