Stock Market Uncertainty and Unhealthy Choices

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Abstract

Based on more than 6.1 million interviews over 22 years, we demonstrate a positive relation between expected stock market volatility, measured by VIX, and individuals' propensity to make poor lifestyle choices including a greater fraction of the population drinking alcohol, a larger number of drinks consumed, higher levels of binge drinking, higher obesity, and higher smoking rates. Our results are consistent with the hypothesis that stress due to high economic uncertainty increases temporal discounting leading to decreased impulse control and an associated increase in unhealthy decisions. The decline in impulse control provides a channel that links market uncertainty and investors' behavior.

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1. Introduction

We investigate how stock market uncertainty relates to individuals' decisions to engage in unhealthy behaviors. Our hypothesis is motivated by the evidence in health, economics, and psychology research that suggests *delayed reward discounting* can help explain what appear to be poor choices (e.g., binge drinking) made by individuals. Beginning with studies of Rae (1834), Senior (1836), and Samuelson (1937), one can frame an individual's decision to engage in a given behavior as a tradeoff between immediate gratification and the "present value" of not engaging in the behavior. Equivalently, the delayed reward discounting framework can be viewed as a model of how decisions relate to self-control/impulsiveness (see, e.g., da Matta, Goncalves, and Bizarro, 2012; Reed and Luiselli, 2011). A given individual's choice to binge drink, for instance, may be viewed as the immediate utility of binge drinking versus the present value (discounted at the person's delayed reward discount rate) of the costs associated with such behavior (e.g., future health costs, future employment costs).

We hypothesize that the expected market volatility relates to poor health choices within the delayed reward discounting framework for two non-mutually exclusive reasons. First, if an increase in market volatility is associated with an increase in stress, the instant gratification (utility) of poor health choices (e.g., drinking, overeating, and smoking) may rise. For instance, an individual may have a greater urge for "another drink" in periods of high expected market volatility if high levels of economic uncertainty induces stress.[1] Second, higher expected market volatility may be associated with higher delayed reward discount rates resulting in a decline in the present value of not engaging in the poor health choice. That is, when economic uncertainty is high, an individual may care "less" about the

[1] The American Psychological Association reports that about 43 percent of all adults suffer from stress-related health issues. In their 2006 survey, "money" and "work" were the two leading sources of stress (see http://www.apa.org/news/press/releases/2006/01/stress-management.aspx).

future consequences of their poor decisions today. A number of previous studies suggest increases in stress are associated with higher levels of temporal discounting.[2]

Although the limitation of Samuelson's (1937) delayed reward discounting model are well-recognized (e.g., see reviews by Frederick, Loewenstein and O'Donoghue, 2002; Reynolds, 2006), a wide range of studies suggest that delayed reward discounting can help explain variation in obesity, gambling, alcohol use, tobacco use, and illegal drug use (see reviews by Barlow, Reeves, McKee, Galea, and Stuckler, 2016, 2017; MacKillop, Amlung, Few, Ray, Sweet, and Munafo, 2011). Moreover, our hypothesis linking market stress to impulse control only requires that the utility of immediate gratification associated with a poor health choice increases with expected stock market volatility and/or individuals' discount rate associated with the utility of the future benefits associated with a good health choice increases with stock market volatility.

Using Chicago Board Options Exchange (CBOE) Volatility Index (VIX) as the measure of expected stock market uncertainty and 22 years of Behavioral Risk Factor Surveillance System (BRFSS) data of more than 6.1 million interviews with individuals, we find strong support for our hypothesis. Specifically, controlling for market returns, state fixed effects, state time-trends, state unemployment rates, state income, and individuals' demographics (such as gender, education, employment, and age), we find a strong positive relation between expected stock market volatility and poor health choices—including the likelihood of engaging in drinking, the number of drinks consumed, the likelihood of engaging in binge drinking, higher body mass index (BMI), and the likelihood of smoking. The positive relation between the stock market uncertainty and people's unhealthy choices is also economically significant—a one standard deviation larger VIX is associated

[2] For example, Giordano, Bickel, Loewenstein, Jacobs, Marsch, and Badger (2002) find that opioid addicts exhibit substantially greater temporal discount rates for both heroin and money when opiate-deprived. See also Cornelisse, Ast, Haushofer, Seinstra, and Joëls (2014); Delaney, Fink, and Harmon (2014); Haushofer, Jang, and Lynham (2017); and Koppel, Andersson, Morrison, Posadzy, Västfjäll, and Tinghög (2017).

with increases in binge drinking, overweight individuals, and smoking that account for 7%, 4%, and 3%, respectively, of the time-series variation in these metrics.

Our results have a number of important implications. First, the relation between market uncertainty and impulse control may help explain individuals' financial decisions. For instance, a decline in impulse control can help explain why behavioral biases are more severe when expected market volatility is high (Kumar, 2009) and why higher expected market volatility is associated with money flowing from equity mutual funds to bond mutual funds (Ben-Rephael, Kandel, and Wohl, 2012). In a broader sense, as Engelberg and Parsons (2016) point out, if behavioral factors impact prices, then anything that influences widespread changes in individuals' behavior has asset pricing implications. That is, understanding what drives investors' decisions is key to understanding behavioral finance. Our results suggest that the relation between the expected market uncertainty and impulse control may be one of the channels that links economic conditions to investors' behavior.

Second, our results provide support for models that suggest anticipatory feelings (e.g., Lowenstein, 1987) lead to time inconsistency of individual preferences (and, therefore, behaviors). Caplin and Leahy (2001) demonstrate, for example, that adding anxiety (in addition to consumption) to the utility function can help explain time inconsistency in preferences and both the equity premium puzzle and the risk-free rate puzzle. Specifically, in the Caplin and Leahy model, holding risk aversion constant, safe assets provide an additional benefit (beyond the utility generated from smoothing consumptions over states) of reducing anxiety. Similarly, risky assets require additional expected return to account for the disutility of the extra anxiety they provide. The authors argue that risk aversion and anxiety are different concepts—risk aversion is related to the curvature of the utility function within a period (and therefore static) whereas anxiety is an emotion associated with uncertainty (and therefore time-varying). Thus, as uncertainty increases, so does anxiety. Our results, for example, are consistent with the Caplin and Leahy's mechanism contributing to the Guiso, Sapienza, and Zingales' (2017) finding that qualitative and quantitative measures of risk aversion increased dramatically (in Italy) following the 2008 financial crisis. Our results also support Guiso, Sapienza, and Zingales' conclusion that, "emotion based changes in the utility function" drive the change in the risk aversion measures.[3]

Third, our results provide a potential link for feedback models (e.g., Shiller, 2002). Specifically, as further pointed out by Engelberg and Parsons (2016), most behavioral finance work focuses on how investor behavior impacts markets and ignores the other half of the feedback loop—how markets impact investor behavior. Thus, our results provide a new link—higher market volatility is associated with a decline in impulse control.

Fourth, our study adds to the growing literature linking investors' emotions and their preferences and choices. For example, evidence suggests that investor decisions and/or stock return are impacted by seasonal affective disorder (SAD) (e.g., Kramer and Weber, 2012; Kamstra, Kramer, and Levi, 2003, 2015), cortisol levels (Kandasamy et al., 2014), testosterone (Nadler, Jiao, Alexander, Johnson, and Zak, 2017), weather (e.g., Saunders, 1993; Hirshleifer and Shumway, 2003; Bassi, Colacito, and Fulghieri, 2013), the results of sporting events (Edmans, Garcia, and Norli, 2007), and general mood (e.g., Bollen, Mao, and Zeng, 2011).

Last, our study contributes to the growing literature that links health decisions to economic factors. Society faces enormous economic and emotional costs associated with poor health decision. Sacks et al. (2015), for example, estimates that the cost of excessive alcohol use in the United States was $249 billion in 2010. Therefore, as much of the health literature points out (e.g., Barlow, Reeves, McKee, Galea, and Stuckler, 2016), understanding the factors that contribute to poor health decisions is critical to developing policies and programs that encourage better health choices.

[3] Although the semantics differ, Guiso, Sapienza, and Zingales' (2017) study (in which the authors interpret as potentially, an "emotion-based changes of the utility function") appears complementary to Caplin and Leahy's (2001) model that formally adds an emotion to the utility function (both suggesting that time varying emotions drive time-series variation in preferences).

As far as we are aware, our study is the first that investigates the relation between the expected market volatility and individuals' unhealthy choices. Several recent studies examine the impact of realized stock returns on health outcomes. Evidence suggests that large negative market returns are associated with increases in smoking and binge drinking, declines in self-reported mental health, and increases in fatal car accidents involving alcohol (Cotti, Dunn, and Tefft, 2015). Similarly, McInerney, Mellor and Nichols (2013) find the 2008 stock market crash was associated with increased feelings of depression and use of antidepressant drugs. Fiuzat, Shaw, Thomas, Felker, and O'Connor (2010) report that acute myocardial infractions (i.e., heart attacks) are negatively related to stock returns.[4]

In the finance literature, our paper is most closely related to Engelberg and Parsons (2016) who find that admissions to California hospitals (especially admissions related to psychological conditions such as anxiety and panic disorders) are inversely related to the returns of California stocks. We differ from Engelberg and Parsons in two important ways. First, unlike previous studies, we focus on stock market uncertainty rather than stock returns. Specifically, we examine if higher levels of uncertainty are associated with poor choices after controlling for stock market returns, local economic conditions, individual demographics, and other factors. Second, we focus on a *decision* made by individuals, rather than an involuntary reaction by individuals—individuals choose to have a drink, a cigarette, or an Applebee's 1,660 calorie Chocolate Chip Cookie Sundae; yet, they do not decide to have an anxiety attack. Thus, our results suggest that higher expected market volatility is associated with individuals' choices associated with impulse control.

2. Methodology and Data

[4] A related literature focuses on health issues and state unemployment rates or employment status (see, for example, Ruhm and Black, 2002, and Dee, 2001). As Cotti, Dunn, and Tefft (2015) point out, it is hard to compare the literature using unemployment rates with the literature using stock returns because (1) unemployment is a lagging indicator whereas stock market valuations are a leading indicator and (2) unemployment shocks may have both income and substitution effects.

Our baseline regression specification to examine the relation between stock market uncertainty and individuals' unhealthy choices is:

$$Unhealthy\ \ choice_{i,s,t} = \beta_1 VIX_t + \beta_2 Mkt_t + \beta_X X_{i,s,t} + \beta_s X_{s,t} + \tau_t + \gamma_s + \gamma_s * t + \varepsilon_{i,s,t} \tag{1}$$

The dependent variable, $Unhealthy\ choice_{i,s,t}$, is a measure of an unhealthy choice (e.g., binge drinking) made by an individual i in state s in month t. VIX_t is the natural logarithm of the daily average of the Chicago Board Options Exchange (CBOE) Volatility Index during month t (henceforth denoted VIX for ease of exposition).[5] Equation (1) also control for factors that previous work suggests may influence unhealthy choices (see, e.g., Engelberg and Parsons, 2016; Cotti, Dunn, and Tefft, 2015; Davalos, Fang, and French, 2011; Fiuzat, Shaw, Thomas, Felker and O'Connor, 2010; Ruhm, 2005; Ruhm and Black, 2002). Specifically, Mkt_t is the contemporaneous monthly value-weighted market return; $X_{i,s,t}$ is a matrix of individual-level demographic data (e.g., gender, marital status, age groups, employment, race, and education), $X_{s,t}$ is a matrix of state-level per-capita income (in 1990 dollars) and unemployment in month t, τ_t are indicator variables for calendar months, γ_s are state fixed effects, and $\gamma_s * t$ are state-specific time-trends. Appendix A contains details regarding definitions, data sources, and construction of all variables used in this study.

VIX captures the expected (annualized) volatility of the S&P 500 over the next 30 days.[6] Previous work demonstrates that economic uncertainty plays a large role in driving market uncertainty. For instance, time-series variation in VIX is strongly related to measures of uncertainty based on cross-sectional dispersion of firm-level profit growth and stock returns, cross-sectional dispersion in manufacturing productivity measures, and cross-sectional dispersion in GDP forecasts (e.g., Bloom, 2009). As a result, VIX is widely used as an indication of investors' expectations of economic

[5] Because VIX is highly skewed, we follow previous work (e.g., Connolly, Stivers, and Sun, 2005) and use the natural logarithm of VIX in our empirical tests.

[6] See http://cfe.cboe.com/cfe-education/cboe-volatility-index-vx-futures/vix-primer/cboe-futures-exchange-nbsp-nbsp-education for details of VIX construction.

uncertainty and referred to as an investor "fear" gauge (Whaley, 2000; Baker and Wurgler, 2007; Da, Engelberg, and Gao, 2014). Related, our analysis does not require that individuals know or understand VIX. Rather, VIX serves as a measure of individuals' expected economic and market uncertainty. Consistent with this view, previous work demonstrates that individuals are largely aware of economic uncertainty levels (e.g., Da, Engelberg, and Gao, 2014; Smales, 2014; Dzielinski, 2012; Goidel, Procopio, Terrell, and Wu, 2010; Hester and Gibson, 2003).

Because the number of individuals surveyed has increased over time (as detailed below), more recent time periods are weighted more heavily in our panel regressions. Moreover, states with large populations have a disproportionate impact on our results due to larger sample sizes.[7] Therefore, we further examine the relation between unhealthy choices and uncertainty by aggregating individual-level data to state-month level data:

$$\overline{\textit{Unhealthy choice}}_{s,t} = \beta_1 VIX_t + \beta_2 Mkt_t + \beta_X \overline{X}_{s,t} + \beta_s X_{s,t} + \tau_t + \gamma_s + \gamma_s * t + \varepsilon_{i,s,t} \tag{2}$$

where $\overline{\textit{Unhealthy choice}}_{s,t}$ is the fraction of individual in state *s* in month *t* who reported a specific unhealthy behavior (e.g. binge drinking), and $\overline{X}_{s,t}$ is a matrix of average characteristics (e.g., fraction of respondents who are female) for state *s* in month *t*.

2.1 Sample and Measures of Unhealthy Choices

Our measures of unhealthy choice come from the Behavioral Risk Factor Surveillance System (BRFSS), maintained by the Center for Disease Control and Prevention (CDC) to monitor health and behavioral risk in the U.S. The phone survey has been administered each year since 1984. Because VIX data are not available until 1990, our sample period is 1990-2015. In the early years, not all states

[7] Because we are interested in widespread effects, the disproportionate observations from larger states is appropriate. Nonetheless, the state-level analysis provides a robustness test that still allows for variation across geographies.

participated, and for those that did, some modules (such as questions related to alcohol) were optional (at the state level).[8] Table 1 reports the number of states participating in each year and the number of individuals surveyed with adequate data related to alcohol consumption. Because only a small number of states collected information on alcohol consumption in 1994, 1996, 1998, and 2000, we exclude these four years from our sample.[9] The final sample we use in our baseline alcohol regression analyses consists of 263 months (22 years minus one month)[10] and 6,137,122 individual surveys. In addition to collecting behavioral risk factors, the surveys are also the source of demographic variables used as controls in our regression analyses.

[Insert Table 1 about here]

Using the BRFSS data, we construct three measures of each individual's alcohol use over the past 30 days: (1) an indicator variable (*Drinker*) for whether the person had at least one alcoholic drink; (2) the natural logarithm of one plus the total number of alcoholic beverages consumed (*ln*(*1+no. drinks*));[11] and (3) and indicator for whether the person had five or more drinks on one occasion (*Binge*).[12] We acknowledge that responsible alcohol use is not necessarily a poor health decision, i.e., that an increase in the fraction of the population that drinks alcohol does not necessarily imply poor health choices. Nonetheless, we expect the decision to have any alcohol is related to impulse control/temporal discounting for many individuals and examination of this variable allows comparison to previous work (e.g., Dee, 2001; Ruhm and Black, 2002).

8 See https://www.cdc.gov/brfss/about/about_brfss.htm for additional details.
9 Our results remain intact when including these four years.
10 The drinking related questions that we use to construct measures of unhealthy behavior are about people's drinking activities in the previous month. So we match survey month to the one month lag of VIX. Since VIX data are available from January 1990, we lose one month of observations due to the one month lag of VIX at the beginning of our sample period. Our results also hold when we match survey month to the same month of VIX.
11 Following Ruhm and Black (2002), we winsorize the number of drinks per month at 450 (15 drinks per day).
12 There is some variation over time in the exact questions asked and in the recorded metrics. Details are provided in Appendix A. For instance, in the early years of the sample binge drinking is defined as five or more drinks on one occasion for all respondents; in the later part of the sample period binge drinking is defined as five or more drinks for men or four or more drinks for women.

The first three rows of Panels in Table 2 report summary statistics for the dependent variables used in the individual-level regressions. The results indicate that approximately half the individuals surveyed drank some alcohol (the mean for the *Drinker* indicator is 0.49). Because our interest is in whether expected market uncertainty is associated with time-series variation in unhealthy decisions, the last three rows in Panel A report the time-series descriptive statistics of the cross-sectional means. The results reveal there is variation over time in the level of drinking, e.g., although the mean is 0.49, the fraction of the survey respondents reporting having a drink in a given month ranges from 0.45 to 0.55 and has a time-series standard deviation of 2%.

Panel B in Table 2 reports analogous statistics for the sample limited to drinkers. Those who do drink average 10 drinks per month (from Panel B, $e^{2.38}-1 = 9.80$) and 24% of drinkers report binge drinking. Once again, however, the results reveal variation over time, e.g., the bottom row reports that the faction of respondents reporting binge drinking ranges from 20% to 29% across the 264 months in our sample.

Panels C and D report the summary statistics of the drinking behavioral variables aggregated to the state-month level for the sample of both drinkers and nondrinkers and the sample of only drinkers, respectively.[13] The results show pooled averages of state-month averages are similar to the averages based on the individual surveys, i.e., averages in Panels A and B are nearly identical those in Panels C and D.

[Insert Table 2 about here]

[13] If the number of respondents in a month in a state is less than 100, we exclude that state-month observation from the state-month level regressions. Specifically, (i) in the drinking sample we have 12,317 state-months observations after we exclude 238 state-months observations (Table 5); (ii) in the BMI sample we have 14,760 state-month observations after we exclude 283 state-month observations (Table 7); and (ii) in the smoking sample we have 14,285 state-month observations after we exclude 696 state-month observations (Table 8). Note that not all fifty states participate in the survey in each year during our sample period (Table 1).

Although we initially focus on measures of alcohol, we also construct two other measures of unhealthy choices used in previous work (e.g., Ruhm, 2005). First, BRFSS surveys ask respondents for weight and height data which allows BRFSS to compute body mass index (i.e., BMI=weight in kilograms/(height in centimeters squared)). The World Health Organization defines BMI greater than or equal to 25 as overweight and above 30 as obese. Based on this data we generate three BMI-related measures: *BMI*; an *Overweight* dummy variable equal to one if the individual's BMI ≥ 25, and an *Obese* dummy variable equal to one if the individual's BMI ≥ 30. The mean for *BMI*, *Overweight*, and *Obese* for the individual-level analysis are 27.21, 0.61, and 0.25, respectively. Second, BRFSS surveys also ask respondents about their smoking habits. We create a dummy variable (*Smoker*) (mean=0.21 for the individual-level analysis) to identify those who are identified as smokers. Because the survey questions we use to construct *BMI* and *Smoker* populates throughout our sample period, the sample sizes are slightly greater than for the tests based on alcohol.[14]

2.2 Control Variables

The first three rows in Table 2 Panel E report summary statistics for variables with monthly data—the daily average VIX each month, the natural logarithm of the daily average (VIX), and the value-weighted market return from the Center for Research in Security Prices (CRSP). The second to last row in Panel E reports descriptive statistics for per capital income which is observed at the state-year level. The last row in Panel E report descriptive statistics for state unemployment rate which is observed at the state-month level. As noted above, Appendix A provides details on the source and construction of all variables.

[14] Specifically, the BMI and smoking samples consist of 6,612,765 and 6,810,614 observations, respectively.

Finally, Panel F reports demographic descriptive statistics at the individual level. Appendix B reports analogous statistics for the sample limited to drinkers only and for the state-month level data for both samples (all versus drinkers only). Demographic variables describe survey participants' gender, employment status, marital status, education background, and race.

3. Empirical Results

3.1 Alcohol – Individual-Level Analysis

We begin by estimating the pooled cross-sectional time-series regression given in Equation (1) at the individual level (i.e., observations are the level of individual *i* in state *s* at time *t*) for the three dependent variables related to alcohol: the drinker indicator (*Drinker)*, the number of drinks (*ln(1+no. drinks)*), and the binge drinking indicator (*Binge).* All models include market return, state-level per capita income and unemployment rate, individual-level demographic characteristics, state fixed effects, state-specific time-trends, and calendar month fixed effects as control variables.[15] Standard errors are heteroscedasticity-consistent.

The first three columns report the results for the sample including both drinkers and non-drinkers. Consistent with our hypothesis that increased market uncertainty is associated with decreased impulse control, the coefficient associated with VIX is positive and statistically significant at the 1% level for all three alcohol-related measures. That is, the results are consistent with the hypothesis that individuals exhibit a greater propensity to make unhealthy lifestyle choices (drink alcohol, consume more drinks, and binge drink) when market uncertainty is higher. The coefficients associated with the control variables are largely consistent with previous work (e.g., men tend to drink more than

[15] We exclude indicator variables for refusing to answer marital status (*Refused_ans_married_dum*), the final age group (*Age_group_ge_65*), unreported race group (*Race_notreported_dum*), and unreported education group (*Educa_notreported_dum*), January, and Alaska to avoid a dummy variable trap.

women).[16] The results are also economically meaningful. Specifically, given VIX is a time-series variable, we evaluate the magnitude of the relation between time-series variation in VIX and time-series variation in poor decision making. Recall from Table 2 that the time-series standard deviations of ln(VIX) and the fraction of survey respondents drinking any alcohol are 0.0034 and 0.0215, respectively. Therefore a one standard deviation higher VIX is associated with a 4.6% standard deviation higher level of drinking, i.e., (0.286*0.0034)/0.0215=0.0416. Analogous calculations show that a one standard deviation higher VIX is associated with 10.2% standard deviation higher level of number of drinks consumed and 7.2% standard deviation high level of binge drinking.

[Insert Table 3 about here]

The last two columns of Table 3 repeat the tests examining the relations between VIX and both the number of drinks and binge drinking for the sample limited to drinkers. Once again, the coefficient associated with VIX is positive and statistically significant at the 1% level indicating that drinkers are more likely to drink more and binge drink when market volatility is higher. Moreover, the magnitudes remain substantial—a one standard deviation larger VIX is associated with a 12.9% standard deviation higher number of drinks and a 6.0% higher standard deviation of binge drinking.[17]

Because the two of the dependent variables (*Drinker* and *Binge*) are binary, we repeat our tests with a logistic regression model (with the same set of control variables). The results reported in the first two columns of Table 4 are based on the entire sample. The last column in Table 4 estimates a logistic regression for binge drinking test for the sample limited to drinkers. The analysis continues to

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[16] Although not the focus of our study, the positive relation between unemployment and drinking behaviors is consistent with Dee (2001) but inconsistent with Ruhm and Black (2002). In untabulated analysis we repeat our tests limiting the sample to Ruhm and Black's sample period (ending in 1999) and find evidence consistent with Ruhm and Black for this subsample.

[17] From Table 2, σ_{ts}(ln(VIX))=0.0034, σ_{ts}(ln(no. drinks))=0.0593, and σ_{ts}(binge)=0.0171 (where *ts* indicates time-series). Thus, given the coefficients of 2.228 and 0.300, the impact of time-series variation in VIX on time-series variation in the number of drinks and the likelihood of binge drinking are estimated as (2.228*0.0034)/0.0593 and (0.300*0.0034)/0.017, respectively.

reveal a strong positive relation between expected market volatility (VIX) and the likelihood of any drinking (*Drinker*) and binge drinking (*Binge*).

[Insert Table 4 about here]

3.2 Alcohol – State-Month Level Analysis

As noted above, sample sizes vary by time and state. To ensure the results are not driven by variations in the sample size through time or large states, we aggregate the individual-level data to state-month-level averages and estimate regression model Equation (2). Specifically, we compute: (1) the fraction of drinkers (*%Drinkers*) as the fraction of survey participants who report dinking, (2) the average number of drinks (*Ave. No. Drinks*) across survey participants in each state-month, and (3) the fraction of survey participants binge drinking (*%Binge Drinkers*) in each state-month. We analogously compute state-month fractional demographic data, e.g., the fraction of female participants in each state-month observation. We also compute values for the average number of drinks and fraction binge drinking for the sample limited to drinkers in each state-month.

The first three columns of Table 5 report state-month-level OLS regression results for the sample including both drinkers and non-drinkers. As before, all models include macroeconomic controls (e.g., state unemployment rate), demographic data (percentage female), state specific time trend, month fixed effects, and state fixed effects. Standard errors are heteroscedasticity-consistent and clustered by state. The results continue to support our hypothesis. Specifically, the coefficient associated with VIX is positive and statistically significant in all three cases indicating a positive relation between expected market uncertainty and individuals' propensity to make unhealthy alcohol decisions. The last two columns in Table 5 repeat the analysis of average number of drinks and percentage of the state-month population binge drinking for the sample limited to drinkers. We continued to find a strong positive relation between poor health choices and expected market volatility.

[Insert Table 5 about here]

Our results also remain economically significant. For example, a one standard deviation larger VIX is associated with a 12% standard deviation larger fraction of the population binge drinking, i.e., coefficient from the third column (0.359) times the standard deviation of VIX (0.0034) divided by the time-series standard deviation in binge drinking from Table 2 (0.0102).

Because two of the dependent variables in the state-month level analyses, *%Drinker* and *%Binge*, are proportions (bound between zero and one), the OLS regression can generated invalid predicted values above one or below zero. In addition, proportion data often exhibits an S-shaped (rather than linear) relation with independent variables. Thus, as a robustness test, we repeat the analysis with a beta-logistic maximum likelihood estimation model that overcomes these limitations.[18] The results, reported in Table 6, continue to support the hypothesis that high market volatility is associated with decreased impulse control as the coefficients associated with VIX are all statistically significant at the 1% level.

[Insert Table 6 about here]

3.3 VIX and Body Weight

We next examine the relation between BMI and expected market volatility. Previous work suggests that variation in time-discounting can help explain unhealthy dietary and exercise choice (e.g., see the review by Barlow, Reeves, McKee, Galea, and Stuckler, 2016). We use body weight based measures as proxies for people's unhealthy choice and re-estimate the OLS individual-level (Equation (1)) and state-month level regressions (Equation (2)). Table 7 reports the results. All models include market return, state-level per capita income and unemployment rate, demographic characteristics,

[18] Specifically, we use the SAS Proc Glimmix procedure with beta distribution and logit link options. See, for example, http://support.sas.com/kb/57/480.html.

calendar month fixed effects, state fixed effects, and state-specific time-trends as control variables. Standard errors are heteroscedasticity-consistent for all models and are also clustered by state in the state-month regression specifications.

[Insert Table 7 about here]

The first three columns of Table 7 report the results of OLS regressions (from Equation (1)) for the three measures related to obesity: *BMI*, *Overweight* indicator (BMI≥25), and *Obese* indicator (BMI≥30).[19] The results in the first three columns of Table 7 continue to support our hypothesis that expected market volatility is inversely related to impulse control. Specifically, the coefficient associated with VIX is statistically significant at the 1% level for all three measures—a higher VIX is associated with higher BMIs, a larger fraction of the population being overweight, and a larger faction of the population being obese.

The time-series standard deviation of the mean levels of BMI, overweight, and obese (analogous to the standard deviation figures reported in the bottom three rows of Panel A in Table 2) are 0.997, 0.070, and 0.060, respectively (untabulated). Thus, a one standard deviation higher VIX is associated with a 2.4% standard deviation higher BMI, 4.4% standard deviation higher fraction of the population overweight, and a 2.4% standard deviation higher fraction of the population obese.[20]

[Insert Table 7 about here]

The last three columns of Table 7 report the analysis for the body weight variables estimated at the state-month level (i.e., Equation (2)). The dependent variables are therefore redefined as the average BMI for each state-month observation, the fraction of individuals identified as overweight in

[19] As noted in the discussion of the data, because height and weight are collected for all participating states at each point in time (versus the alcohol questions which are in optional modules in the early sample period for some years), the sample size for the weight related measures is larger than those reported for alcohol related measures.
[20] From Table 2, σ_{ts}(ln(VIX))=0.0034; as noted above, σ_{ts}(BMI)=0.997, σ_{ts}(overweight)=0.070, and σ_{ts}(obese)=0.060 (where *ts* indicates time-series). Thus, given the coefficients of 7.083, 0.898, and 0.417, the impact of time-series variation in VIX on time-series variation in BMI, the fraction of the population overweight, and the fraction of the population obese are estimated as (7.083*0.0034)/0.997, (0.898*0.0034)/0.070, and (0.417*0.0034)/0.060, respectively.

each state-month, and the fraction of individuals identified as obese in each state-month. Once again, our results continue to support the hypothesis that higher expected market volatility is associated with an increased likelihood of poor health choices.[21]

3.4 VIX and Smoking

The first column of Table 8 reports the analysis of the relation between VIX and smoking rates estimated at the individual level (i.e., Equation (1)). The second column 8 reports the smoking analysis at the state-month level (i.e., Equation (2)). As in prior tables, standard errors are heteroscedasticity-consistent in all models, include market return, state-level per capita income and unemployment rate, individual-level demographic characteristics, state fixed effects, state-specific time-trends, and calendar month fixed effects as control variables. Standard errors are clustered by state in all state-month regression specifications.

[Insert Table 8 about here]

Once again, we find evidence that higher expected market volatility is associated with lower impulse control as VIX is positively associated with smoking rates.[22] The results again suggest that time-series variation VIX is associated with a substantial portion of the time-series variation in smoking rates (the time-series standard deviation of the average smoking rate is 3.75%, untabulated). Thus, for instance, the results in the first column suggest a one standard deviation increase in VIX is associated with a 2.9% standard deviation higher smoking level.[23]

[21] We also repeat the tests in Table 7 using a logit for models (2) and (3) to account for the fact the dependent variables are indicators and using the beta-logistic maximum likelihood estimate for models (5) and (6) to account for the fact the dependent variables are proportions. Our conclusions remain unchanged.

[22] In untabulated tests we repeat the analysis in the first column of Table 8 with a logistic regression. Analogously, we repeat the analysis in the second column with the beta-logistic maximum likelihood estimation model that accounts for the fact that the dependent variable is a fraction bound between zero and one. Both tests confirm the positive relation between VIX and smoking rates (statistically significant at the 1% level in both cases).

[23] From Table 2, σ_{ts}(ln(VIX))=0.0034; as noted above, σ_{ts}(smoking)=0.038 (where *ts* indicates time-series). Thus, given the coefficients of 0.314, the impact of time-series variation in VIX on time-series variation in smoking rates is estimated as (0.314*0.0034)/0.038.

4. Conclusion

We examine the relation between market uncertainty and individuals' propensity to make unhealthy decisions. We propose that variation in expected market uncertainty influences individuals' impulse control. Specifically, we hypothesize that an increase in market uncertainty results in a decline in individual's impulse control because market uncertainty is likely to (a) increase stress and the immediate utility of a poor health decisions (e.g., having an extra helping of dessert or another drink) and (b) decrease the utility of the future gain from making the healthy choice. In sum, we posit that greater market uncertainty is associated with greater temporal discounting, deterioration in self-regulation and impulse control, and a decline in reward-delaying behavior.

The empirical tests support our hypothesis that higher levels of expected market volatility are associated with a higher propensity to make unhealthy decisions with respect to drinking, eating/exercise, and smoking behaviors. Moreover, our analysis controls for other variables that may help explain variation in individual's health decisions including individuals' characteristics, state economic conditions, state time-trends, state fixed effects, calendar month fixed effects, and market returns.

Our results provide evidence of a behavioral link between market volatility and individuals' choices. For instance, our results can help explain why behavioral biases are more severe when expected market volatility is high (Kumar, 2009). Further, the results provide support for the explanation that variation in market conditions contribute to variation in anticipatory feelings which could help explain, for example, why individual investors' exhibit different risk preferences pre- and post- the financial crisis (Guiso, Sapienza, and Zingales, 2017). Related, the results provide empirical support for Caplin and Leahy's (2001) model that demonstrates adding anxiety to the utility function can help explain a number of market phenomena including the equity premium puzzle and the risk-free rate puzzle. Our analysis also provide evidence of a link for feedback models as market uncertainty is associated with individuals' choices and individuals choices may impact market volatility, e.g., money flows from equity to debt mutual fund when expected market volatility is high (Ben-Rephael, Kandel, and Wohl, 2012). Last our results provide evidence of an important new link between economic conditions and individuals' health decisions. In short, the link between market volatility and individuals' poor health choices has a number of important implications.

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Appendix A. Variables and Data Sources

Variable Name	Source	Definition (subscription is dropped for brevity)
VIX_t	Chicago Board Options Exchange (CBOE) website: http://www.cboe.com	Market's expectation of 30-day volatility. In each month, we calculate *VIX*=log [mean (daily VIX)]/100.
Mkt_t	Center for Research in Security Prices (CRSP)	The value-weighted market return in month *t*.
Income per capita$_{s,y}$	The Federal Reserve Bank of St. Louis: https://www.stlouisfed.org/	The per capita income adjusted by 1990 dollars for state *s* in year *y*. We apply state-annual *Income per capita* in year *y* to all months in that year for state *s*. We use *Income per capita* divided by 10,000 in all regression models.
Unemploy_rate$_{s,t}$	The Federal Reserve Bank of St. Louis: https://www.stlouisfed.org/	The unemployment rate (in decimals) for state *s* in month *t*.
Drinker$_{i,s,t}$	BRFSS. The survey question of whether the participant has had at least one drink of alcohol in the past 30 days. A drink of alcohol is one can or bottle of beer, one glass of wine, one can or bottle of wine cooler, one cocktail, or one shot of liquor.	An indicator variable for whether an individual *i* in state *s* in month *t* had at least one alcoholic drink over the past 30 days. We only keep observations where a direct answer of either "yes" or "no" is provided by a survey participant.
%Drinker$_{s,t}$	BRFSS	*%Drinker* is the fraction of drinkers in state *s* in month *t*. That is, in each state *s* and month *t*, we divide the number of surveys with *Drinker*=1 by the total number of drinkers and nondrinkers to obtain *%Drinker*.

Appendix A. Variables and Data Sources (Continued)

ln(1+no. drinks) $_{i,s,t}$	BRFSS. The survey calculates and reports the total number of drinks per month for 1990-2014 and per week in 2015 based on the computed number of drinks of alcohol beverages per day. The survey calculates the number of drinks of alcohol beverages per day using two survey questions. One question asks the survey participant how many days per week or per month she had at least one drink of any alcoholic beverage during the past 30 days. The other question asks how many drinks the participant had on average during the past 30 days when she drank.	The natural logarithm of one plus the total number of alcoholic beverages consumed over the past 30 days by individual *i* in state *s* in month *t*. *ln(1+no. drinks)* is a measure of unhealthy choice and is the dependent variable in the individual-level regression analyses. We cap the number of drinks per month at 450 following Ruhm and Black (2002).
Avg. No. Drinks $_{s,t}$	BRFSS	In each state *s* and month *t*, we calculate the average of *ln (1+no. drinks)* to obtain *Ave. No. Drinks*.
Binge $_{i,s,t}$	BRFSS. 1990-2000: The survey question of whether a participant had five or more alcoholic beverages in past month on one or more occasions. 2006-2016: The survey question of how many times in the past month a male participant had five or more drinks (a female participant had four or more drinks) on an occasion.	An indicator for binge drinking conducted by a survey participant *i* in state *s* in month *t*. For men, this is defined as five or more drinks on one occasion. For women, this is defined as five or more drinks on one occasion between 1990 and 2005 and four or more drinks on one occasion between 2006 and 2015

Appendix A. Variables and Data Sources (Continued)

%Binge Drinkers $_{s,t}$	BRFSS	*%Binge Drinker* is the fraction of binge drinkers in state *s* in month *t*. That is, in each state *s* and month *t*, we divide the number of surveys with *Binge Drinker*=1 by the total number of drinkers and nondrinkers to obtain *%Binge Drinker* (for the sample including both drinkers and non-drinkers). Analogously, we divided the number of surveys with *Binge Drinker*=1 by the total number of drinkers to obtain *%Binge Drinker* (for the sample including drinkers only).
BMI $_{i,s,t}$	BRFSS surveys collect individual's weight and height information, and use this information to compute the body mass index (BMI).	BMI=weight in kilograms/height in centimeters squared. The body mass index (BMI) of participant *i* in state *s* in month *t*.
Avg. BMI $_{s,t}$	BRFSS	The average *BMI* in each state *s* and month *t*.
Overweight $_{i,s,t}$	BRFSS	The World Health Organization defines BMI greater than or equal to 25 as overweight. *Overweight* is an indicator variable (=1 if BMI≥25) for participant *i* in state *s* in month *t*.
%Overweight $_{s,t}$	BRFSS	In each state *s* and month *t*, we compute the fraction of the population with BMI≥25, i.e., fraction with *Overweight*=1.
Obese $_{i,s,t}$	BRFSS	The World Health Organization defines BMI greater than or equal to 30 as obese. *Obese* is an indicator variable (=1 if BMI≥30) for participant *i* in state *s* in month *t*.
%Obese $_{s,t}$	BRFSS	In each state *s* and month *t*, we compute the fraction of the population with BMI≥30, i.e., fraction with *Obese*=1.

Appendix A. Variables and Data Sources (Continued)

Smoker$_{i,s,t}$	BRFSS. The survey asks whether a participant has smoked at 100 cigarettes in her entire life. The participants who answer "yes" to this survey question will be asked whether they currently smoke cigarettes in 1990-1995 or whether they smoke cigarettes every day, some days or not at all in 1996-2015.	An indicator variable for whether an individual *i* in state *s* in month *t* is currently a smoker.
%*Smoker*$_{s,t}$	BRFSS	In each state *s* and month *t*, we compute the fraction of the population (with adequate data) that are smokers, i.e., fraction with *Smoker*=1.
Female_dum $_{i,s,t}$	BRFSS	A d dummy variable that takes a value of one if an individual *i* in state *s* in month *t* is female and zero for male.
Employed_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if an individual *i* in state *s* in month *t* is employed and zero otherwise.
Age_group_18_24_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if the age of an individual *i* in state *s* in month *t* is between18 and 24.
Age_group_25_34_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if the age of an individual *i* in state *s* in month *t* is between 25 and 34.
Age_group_35_44_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if the age of an individual *i* in state *s* in month *t* is between 35 and 44.
Age_group_45_54_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if the age of an individual *i* in state *s* in month *t* is between 45 and 54.
Age_group_55_64_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if the age of an individual *i* in state *s* in month *t* is between 55 and 65.
Age_group_ge_65_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if the age of an individual *i* in state *s* in month *t* is 65 and above.

Appendix A. Variables and Data Sources (Continued)

Married_cohab_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if an individual *i* in state *s* in month *t* is either married or a member of an unmarried couple.
Divorced_sep_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if an individual *i* in state *s* in month *t* is either divorced or separated.
Widowed_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if an individual *i* in state *s* in month *t* is widowed.
Never_married_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if an individual *i* in state *s* in month *t* has never married.
Refused_ans_married_dum $_{i,s,t}$	BRFSS	A dummy variable that takes a value of one if an individual *i* in state *s* in month *t* refuses to answer the marital status questions.
Race_white_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if an individual *i* in state *s* in month *t* is white.
Race_black_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if an individual *i* in state *s* in month *t* is black.
Race_hispanic_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if an individual *i* in state *s* in month *t* is Hispanic.
Race_other_nonwhite_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if an individual *i* in state *s* in month *t* is neither white, or black, or Hispanic.
Race_notreported_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if an individual *i* in state *s* in month *t* refuses to answer the race demographics question.
Educa_dropout_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if an individual *i* in state *s* in month *t* does not finish high school.

Appendix A. Variables and Data Sources (Continued)

Educa_hs_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if an individual *i* in state *s* in month *t* is a high school graduate.
Educa_some_college_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if an individual *i* in state *s* in month *t* has some college or technical school education but not graduate.
Educa_college_grad_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if an individual *i* in state *s* in month *t* graduated from a college.
Educa_notreported_dum $_{i,s,t}$	BRFSS	A dummy variable that equals one if an individual *i* in state *s* in month *t* refuses to answer the education background survey question.

Appendix B: Summary Statistics of Demographic Variables

Appendix B reports the summary statistics of demographic variables of the regression models. Panel A reports the summary statistics of the demographic variables for individual-level regressions that use the sample of only drinkers. Panels B and C report the summary statistics for the state-month demographic variables for state-level regressions that use the sample of all participants and the sample of only drinkers, respectively. See Appendix A for detailed variable definition, data source, and construction.

Panel A: Demographic Variable for Individual Level Regressions – Drinkers Only

Variable	N	Mean	Median	Std Dev	Min	Max
Female_dum	3,015,962	0.53	1	0.50	0	1
Employed_dum	3,015,962	0.64	1	0.48	0	1
Age_group_18_24_dum	3,015,962	0.06	0	0.23	0	1
Age_group_25_34_dum	3,015,962	0.14	0	0.35	0	1
Age_group_35_44_dum	3,015,962	0.18	0	0.39	0	1
Age_group_45_54_dum	3,015,962	0.21	0	0.41	0	1
Age_group_55_64_dum	3,015,962	0.19	0	0.40	0	1
Age_group_ge_65_dum	3,015,962	0.21	0	0.41	0	1
Married_cohab_dum	3,015,962	0.61	1	0.49	0	1
Divorced_sep_dum	3,015,962	0.16	0	0.36	0	1
Widowed_dum	3,015,962	0.08	0	0.27	0	1
Never_married_dum	3,015,962	0.15	0	0.36	0	1
Refused_ans_married_dum	3,015,962	0.00	0	0.05	0	1
Race_white_dum	3,015,962	0.84	1	0.36	0	1
Race_black_dum	3,015,962	0.05	0	0.22	0	1
Race_hispanic_dum	3,015,962	0.05	0	0.21	0	1
Race_other_nonwhite_dum	3,015,962	0.05	0	0.22	0	1
Race_notreported_dum	3,015,962	0.01	0	0.09	0	1
Educa_dropout_dum	3,015,962	0.05	0	0.22	0	1
Educa_hs_dum	3,015,962	0.25	0	0.43	0	1
Educa_some_college_dum	3,015,962	0.28	0	0.45	0	1
Educa_college_grad_dum	3,015,962	0.42	0	0.49	0	1
Educa_notreported_dum	3,015,962	0.00	0	0.03	0	1

Appendix B: Summary Statistics of Demographic Variables (continued)

Panel B: Demographic Variable for State-Month Level Regressions – Drinkers and Nondrinkers

Variable	N	Mean	Median	Std Dev	Min	Max
Female_frac	12,317	0.60	0.60	0.04	0.41	0.76
Employed_frac	12,317	0.56	0.57	0.08	0.31	0.81
Age_group_18_24_frac	12,317	0.06	0.06	0.03	0.00	0.26
Age_group_25_34_frac	12,317	0.14	0.13	0.06	0.03	0.36
Age_group_35_44_frac	12,317	0.18	0.17	0.05	0.05	0.39
Age_group_45_54_frac	12,317	0.18	0.19	0.04	0.05	0.35
Age_group_55_64_frac	12,317	0.18	0.18	0.05	0.03	0.32
Age_group_ge_65_frac	12,317	0.26	0.25	0.08	0.02	0.58
Married_cohab_frac	12,317	0.57	0.57	0.05	0.38	0.78
Divorced_sep_frac	12,317	0.16	0.16	0.03	0.04	0.30
Widowed_frac	12,317	0.12	0.12	0.03	0.02	0.27
Never_married_frac	12,317	0.14	0.14	0.04	0.03	0.34
Refused_ans_married_frac	12,317	0.00	0.00	0.00	0.00	0.07
Race_white_frac	12,317	0.81	0.83	0.12	0.26	1.00
Race_black_frac	12,317	0.07	0.05	0.08	0.00	0.44
Race_other_nonwhite_frac	12,317	0.05	0.04	0.08	0.00	0.68
Race_hispanic_frac	12,317	0.05	0.03	0.07	0.00	0.47
Race_notreported_frac	12,317	0.01	0.01	0.01	0.00	0.28
Educa_dropout_frac	12,317	0.11	0.10	0.05	0.02	0.40
Educa_hs_frac	12,317	0.31	0.31	0.05	0.14	0.61
Educa_some_college_frac	12,317	0.27	0.27	0.04	0.07	0.48
Educa_college_grad_frac	12,317	0.31	0.30	0.07	0.09	0.55
Educa_notreported_frac	12,317	0.00	0.00	0.00	0.00	0.03

Appendix B: Summary Statistics of Demographic Variables (continued)

Panel C: Demographic Variable for State-Month Level Regressions – Drinkers Only

Variable	N	Mean	Median	Std Dev	Min	Max
Female_frac	12,317	0.52	0.53	0.05	0.20	0.76
Employed_frac	12,317	0.66	0.67	0.08	0.34	0.95
Age_group_18_24_frac	12,317	0.07	0.06	0.04	0.00	0.33
Age_group_25_34_frac	12,317	0.17	0.16	0.07	0.03	0.48
Age_group_35_44_frac	12,317	0.20	0.20	0.06	0.05	0.45
Age_group_45_54_frac	12,317	0.20	0.20	0.05	0.01	0.40
Age_group_55_64_frac	12,317	0.17	0.17	0.07	0.00	0.36
Age_group_ge_65_frac	12,317	0.18	0.18	0.08	0.00	0.55
Married_cohab_frac	12,317	0.60	0.60	0.06	0.30	0.80
Divorced_sep_frac	12,317	0.16	0.16	0.04	0.01	0.40
Widowed_frac	12,317	0.07	0.07	0.03	0.00	0.22
Never_married_frac	12,317	0.16	0.15	0.05	0.00	0.45
Refused_ans_married_frac	12,317	0.00	0.00	0.00	0.00	0.04
Race_white_frac	12,317	0.84	0.86	0.11	0.31	1.00
Race_black_frac	12,317	0.06	0.04	0.07	0.00	0.50
Race_other_nonwhite_frac	12,317	0.05	0.03	0.07	0.00	0.62
Race_hispanic_frac	12,317	0.05	0.03	0.06	0.00	0.51
Race_notreported_frac	12,317	0.01	0.01	0.01	0.00	0.31
Educa_dropout_frac	12,317	0.06	0.06	0.03	0.00	0.33
Educa_hs_frac	12,317	0.27	0.27	0.06	0.09	0.62
Educa_some_college_frac	12,317	0.28	0.28	0.05	0.06	0.59
Educa_college_grad_frac	12,317	0.38	0.38	0.08	0.07	0.63
Educa_notreported_frac	12,317	0.00	0.00	0.00	0.00	0.04

Table 1: Sample Distribution

Table 1 reports the number of states participating and number of individual participants of the Behavioral Risk Factor Surveillance System (BRFSS) survey in each year with adequate data related to alcohol consumption.

(1)	(2)	(3)
year	Number of States	Number of Participants
1990	44	71,414
1991	47	84,143
1992	48	92,392
1993	49	98,234
1994	11	20,239
1995	50	109,700
1996	15	36,615
1997	49	122,771
1998	11	30,363
1999	49	145,334
2000	12	37,217
2001	50	196,233
2002	50	232,431
2003	50	249,980
2004	49	288,901
2005	50	335,519
2006	50	329,215
2007	50	402,122
2008	50	385,970
2009	50	401,381
2010	50	427,233
2011	50	453,366
2012	50	440,753
2013	50	451,070
2014	50	418,831
2015	50	400,129

Table 2: Summary Statistics

The first three rows of Panel A report summary statistics of dependent variables for individual-level regressions using the sample of both drinkers and nondrinkers. The bottom three rows report time-series descriptive statistics for the cross-sectional means. Panel B reports analogous figures for the sample limited to drinkers. Panels C and D report the summary statistics of dependent variables for state-month-level regressions that use the sample of both drinkers and nondrinkers and the sample of only drinkers, respectively. Panel E and F report the summary statistics for economic and demographic independent variables, respectively See Appendix A for detailed variable definition, data source, and construction.

Variable	N	Mean	Median	Std Dev	Min	Max
Panel A: Dependent Variables for Individual-Level Regressions - Sample of Both Drinkers and Nondrinkers						
Drinker	6,137,122	0.49	0.00	0.50	0.00	1.00
ln(1+no. drinks)	6,137,122	1.17	0.00	1.44	0.00	6.11
Binge	6,137,122	0.12	0.00	0.32	0.00	1.00
Drinker	263	0.49	0.49	0.02	0.45	0.55
ln(1 + no. drinks)	263	1.16	1.16	0.06	1.06	1.31
Binge	263	0.12	0.12	0.01	0.10	0.15
Panel B: Dependent Variables for Individual-Level Regressions – Drinkers Only						
ln(1+no. drinks)	3,015,962	2.38	2.30	1.16	0.69	6.11
Binge	3,015,962	0.24	0.00	0.43	0.00	1.00
ln(1 + no. drinks)	263	2.37	2.38	0.06	2.19	2.51
Binge	263	0.24	0.25	0.02	0.20	0.29
Panel C: Dependent Variables for State-Month-Level Regressions – Drinkers and Nondrinkers						
%Drinker	12,317	0.50	0.52	0.11	0.14	0.79
Avg. No. Drinks	12,317	1.16	1.19	0.28	0.32	2.00
%Binge Drinkers	12,317	0.12	0.12	0.04	0.02	0.34
%Drinker	259	0.50	0.49	0.02	0.45	0.55
Avg. No. Drinks	259	1.16	1.15	0.06	1.05	1.31
%Binge Drinkers	259	0.12	0.12	0.01	0.09	0.15
Panel D: Dependent Variables for State-Month-Level Regressions – Drinkers Only						
Avg. No. Drinks	12,317	2.32	2.32	0.16	1.60	3.28
%Binge Drinkers	12,317	0.24	0.24	0.05	0.05	0.50
Avg. No. Drinks	259	2.32	2.32	0.08	2.13	2.50
%Binge Drinkers	259	0.24	0.24	0.02	0.21	0.28
Panel E: Independent Variables (2000-2015, exclude 1994, 1996, 1998, 2000)						
Monthly VIX= *Daily VIX*	263	19.84	17.69	7.91	10.82	62.64
VIX=ln(Monthly VIX)/100	263	0.029	0.029	0.003	0.024	0.041
Mkt	264	0.01	0.01	0.04	-0.18	0.11
Income per capita ($)	1,100	22,419	21,959	4,142	13,288	37,886
Unemploy_rate (%)	13,200	5.85	5.50	1.96	1.60	15.40

Table 2: Summary Statistics (continued)

Variable	N	Mean	Median	Std Dev	Min	Max
Panel F: Demographic Variable for Individual Level Regressions – Drinkers and Nondrinkers						
Female_dum	6,137,122	0.61	1	0.49	0	1
Employed_dum	6,137,122	0.54	1	0.50	0	1
Age_group_18_24_dum	6,137,122	0.05	0	0.23	0	1
Age_group_25_34_dum	6,137,122	0.12	0	0.33	0	1
Age_group_35_44_dum	6,137,122	0.16	0	0.36	0	1
Age_group_45_54_dum	6,137,122	0.19	0	0.39	0	1
Age_group_55_64_dum	6,137,122	0.20	0	0.40	0	1
Age_group_ge_65_dum	6,137,122	0.28	0	0.45	0	1
Married_cohab_dum	6,137,122	0.57	1	0.49	0	1
Divorced_sep_dum	6,137,122	0.16	0	0.37	0	1
Widowed_dum	6,137,122	0.13	0	0.33	0	1
Never_married_dum	6,137,122	0.14	0	0.34	0	1
Refused_ans_married_dum	6,137,122	0.00	0	0.06	0	1
Race_white_dum	6,137,122	0.80	1	0.40	0	1
Race_black_dum	6,137,122	0.07	0	0.26	0	1
Race_hispanic_dum	6,137,122	0.05	0	0.23	0	1
Race_other_nonwhite_dum	6,137,122	0.06	0	0.24	0	1
Race_notreported_dum	6,137,122	0.01	0	0.10	0	1
Educa_dropout_dum	6,137,122	0.10	0	0.30	0	1
Educa_hs_dum	6,137,122	0.30	0	0.46	0	1
Educa_some_college_dum	6,137,122	0.27	0	0.44	0	1
Educa_college_grad_dum	6,137,122	0.33	0	0.47	0	1
Educa_notreported_dum	6,137,122	0.00	0	0.04	0	1

Table 3: Individual-Level OLS Regressions – Alcohol Measures

This table reports results of individual-level regressions examining the relation between expected market uncertainty (as captured by VIX) and individual's decisions regarding alcohol. Specifically, the three dependent variables are an indicator for whether an individual had a drink in the past month (*Drinker*), the number of drinks in the past month (*ln(1+no. drinks)*), and an indicator for binge drinking the last month (*Binge*). Independent variables also include contemporaneous market return (*Mkt*), unemployment rate, per capita state income, and individual level demographic characteristics. We exclude indicator variables for refusing to answer marital status (*Refused_ans_married_dum*), the final age group (*Age_group_ge_65*), unreported race group (*Race_notreported_dum*), unreported education group (*Educa_notreported_dum*), January, and Alaska to avoid a dummy variable trap. See Appendix A for detailed variable definition, source, and construction. Columns (1)-(3) use the sample of both drinkers and nondrinkers. Columns (4)-(5) are limited to drinkers only. All models include state-specific time trend, calendar month fixed effects, and state fixed effects. Standard errors are heteroscedasticity-consistent and reported in parentheses. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

	(1)	(2)	(3)	(4)	(5)
	Drinkers + Nondrinkers			Drinkers Only	
	Drinker	ln(1+no. drinks)	Binge	ln(1+no. drinks)	Binge
VIX	0.286***	1.764***	0.214***	2.228***	0.300***
	(0.061)	(0.174)	(0.040)	(0.206)	(0.075)
Mkt	0.009*	0.002	0.004	-0.034**	0.001
	(0.005)	(0.014)	(0.003)	(0.016)	(0.006)
Unemploy_rate (decimals)	0.014	0.747***	0.164***	1.506***	0.319***
	(0.015)	(0.044)	(0.010)	(0.053)	(0.019)
Income per capita/10,000	-0.007**	0.040***	0.016***	0.111***	0.034***
	(0.003)	(0.009)	(0.002)	(0.010)	(0.004)
Female_dum	-0.116***	-0.581***	-0.101***	-0.594***	-0.142***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Married_cohab_dum	0.088***	0.212***	0.014***	0.036***	0.003
	(0.003)	(0.009)	(0.002)	(0.013)	(0.004)
Divorced_sep_dum	0.091***	0.289***	0.051***	0.179***	0.070***
	(0.003)	(0.009)	(0.002)	(0.013)	(0.004)
Widowed_dum	0.044***	0.149***	0.036***	0.056***	0.030***
	(0.003)	(0.009)	(0.002)	(0.013)	(0.004)
Never_married_dum	0.068***	0.241***	0.057***	0.193***	0.088***
	(0.003)	(0.009)	(0.002)	(0.013)	(0.004)

Table 3: Individual-Level OLS Regressions – Alcohol Measures (continued)

	(1)	(2)	(3)	(4)	(5)
	Drinkers + Nondrinkers			Drinkers Only	
	Drinker	ln(1+no. drinks)	Binge	ln(1+no. drinks)	Binge
Age_group_18_24	0.139***	0.400***	0.199***	0.161***	0.357***
	(0.001)	(0.003)	(0.001)	(0.004)	(0.001)
Age_group_25_34	0.124***	0.315***	0.172***	0.047***	0.288***
	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Age_group_35_44	0.093***	0.213***	0.120***	0.005**	0.218***
	(0.001)	(0.002)	(0.000)	(0.002)	(0.001)
Age_group_45_54	0.064***	0.153***	0.079***	0.023***	0.160***
	(0.001)	(0.002)	(0.000)	(0.002)	(0.001)
Age_group_55_64	0.032***	0.074***	0.037***	0.006***	0.089***
	(0.001)	(0.002)	(0.000)	(0.002)	(0.001)
Employed_dum	0.105***	0.249***	0.034***	0.011***	0.009***
	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)
Race_white_dum	0.090***	0.262***	0.033***	0.119***	0.036***
	(0.002)	(0.005)	(0.001)	(0.008)	(0.002)
Race_black_dum	-0.017***	-0.093***	-0.018***	-0.167***	-0.035***
	(0.002)	(0.006)	(0.001)	(0.008)	(0.003)
Race_hispanic_dum	-0.009***	-0.058***	0.004***	-0.105***	0.030***
	(0.002)	(0.006)	(0.001)	(0.008)	(0.003)
Race_other_nonwhite_dum	-0.050***	-0.143***	-0.001	-0.053***	0.029***
	(0.002)	(0.006)	(0.001)	(0.008)	(0.003)
Educa_dropout_dum	-0.008**	0.028**	0.030***	0.157***	0.114***
	(0.004)	(0.011)	(0.002)	(0.022)	(0.007)
Educa_hs_dum	0.087***	0.228***	0.036***	0.108***	0.069***
	(0.004)	(0.011)	(0.002)	(0.022)	(0.007)
Educa_some_college_dum	0.165***	0.397***	0.036***	0.094***	0.032***
	(0.004)	(0.011)	(0.002)	(0.022)	(0.007)
Educa_college_grad_dum	0.255***	0.622***	0.021***	0.118***	-0.019***
	(0.004)	(0.011)	(0.002)	(0.022)	(0.007)
State fixed effects	Yes	Yes	Yes	Yes	Yes
State-specific time trends	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	6,137,122	6,137,122	6,137,122	3,015,962	3,015,962
R-squared	0.138	0.134	0.087	0.081	0.118

Table 4: Individual-Level Logistic Regressions – Alcohol Measures

This reports results of individual-level logistic regressions examining the relation between expected market uncertainty (as captured by VIX) and individual's decisions regarding alcohol. Specifically, the dependent variables are indicators for whether the individual had a drink in the past month (*Drinker*) or engaged in binge drinking in the past month (*Binge*). Additional independent variables include contemporaneous market return (*Mkt*), unemployment rate, income per capita, and individual level demographic characteristics. See Appendix A for detailed variable definition, source, and construction. Columns (1) and (2) use the sample of both drinkers and nondrinkers. Column (3) is limited to drinkers only. All models include state-specific time trend, month fixed effects, and state fixed effects. ***, **, and * indicate $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

	(1)	(2)	(3)
	Drinkers + Nondrinkers		Drinkers Only
	Drinker	Binge	Binge
VIX	1.337***	2.761***	2.048***
	(0.283)	(0.429)	(0.469)
Mkt	0.042	0.045	0.005
	(0.022)	(0.033)	(0.036)
Macroeconomic variables	Yes	Yes	Yes
Demographic variables	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
State-specific time trends	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Observations	6,137,122	6,137,122	3,015,962
R-squared	0.138	0.086	0.115

Table 5: State-Month-Level OLS Regressions – Alcohol Measures

This table reports results of state-month-level regressions examining the relation between expected market uncertainty (as captured by VIX) and individuals' decisions regarding alcohol. Specifically, the three dependent variables are the proportion of individuals that have had a drink in the past month (*%Drinker*), the average number of drinks in the past month (*Avg. No. Drinks*), and fraction of individuals who engaged in binge drinking in the past month (*%Binge Drinkers*). Other independent variables include contemporaneous market return (*Mkt*), unemployment rate, income per capita, and state-month level demographic characteristics. See Appendix A for detailed variable definition, source, and construction. Columns (1)-(3) use the sample of both drinkers and nondrinkers. Columns (4)-(5) are limited to drinkers only. All models include state-specific time trend, month fixed effects, and state fixed effects. Standard errors are heteroscedasticity-consistent, clustered by state, and reported in parentheses. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

	(1)	(2)	(3)	(4)	(5)
	Drinkers + Nondrinkers			Drinkers Only	
	%Drinker	Avg. No. Drinks	%Binge Drinkers	Avg. No. Drinks	%Binge Drinkers
VIX	0.531***	3.314***	0.359***	4.027***	0.423**
	(0.193)	(0.482)	(0.095)	(0.507)	(0.165)
Mkt	0.006	0.006	0.010*	-0.021	0.019*
	(0.011)	(0.028)	(0.006)	(0.029)	(0.010)
Macroeconomic variables	Yes	Yes	Yes	Yes	Yes
Demographic variables	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes
State-specific time trends	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	12,317	12,317	12,317	12,317	12,317
R-squared	0.874	0.845	0.647	0.401	0.394

Table 6: State-Month-Level Logistic Regressions – Alcohol Measures

This table reports results of state-month-level beta-logistic maximum likelihood estimation model examining the relation between expected market uncertainty (as captured by VIX) and individual's decisions regarding alcohol. Specifically, the two dependent variables are the proportion of survey respondents in a state-month that having any alcohol (*%Drinker*) and the proportion of survey respondents in a state-month that report binge drinking (*%Binge Drinkers*) in the last month. Other independent variables include contemporaneous market return (*Mkt*), unemployment rate, income per capita, and state-month level demographic characteristics. See Appendix A for detailed variable definition, source, and construction. Columns (1) and (2) use the sample of both drinkers and nondrinkers. Column (3) is limited to drinkers only. All models include state-specific time trend, month fixed effects, and state fixed effects. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

	(1)	(2)	(3)
	Drinkers + Nondrinkers		Drinkers Only
	%Drinker	%Binge Drinkers	%Binge Drinkers
VIX	2.192***	3.609***	2.678***
	(0.484)	(0.632)	(0.649)
Mkt	0.023	0.089*	0.105**
	(0.038)	(0.049)	(0.051)
Macroeconomic variables	Yes	Yes	Yes
Demographic variables	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
State-specific time trends	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Observations	12,317	12,317	12,317
R-squared	0.874	0.647	0.394

Table 7: Individual-Level and State-Month-Level OLS Regressions – Body Weight Measures

This table reports results of individual-level and state-month-level regressions examining the relation between expected market uncertainty (as captured by VIX) and body weight measures. Specifically, the dependent variables are the individual's BMI (*BMI*), an indicator for *Overweight* (BMI≥25), and an indicator for *Obese* (BMI≥30) for individual-level regressions. The dependent variables for the state-month level regressions are the average BMI, the proportion of respondents overweight (*%Overweight*), and the proportion of respondents obese (*%Obese*) for state *s* in month *t*. Other independent variables include contemporaneous market return (*Mkt*), unemployment rate, income per capita, and individual level (or state-month level) demographic characteristics. See Appendix A for detailed variable definition, source, and construction. Columns (1)-(3) report results for individual-level regressions and Columns (4)-(6) report results the state-month level regressions. All models include state-specific time trend, month fixed effects, and state fixed effects. Standard errors are heteroscedasticity-consistent and reported in parentheses. Standard errors are also clustered by state in Columns (4)-(6). ***, **, and * indicate $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Individual-Level Regression			State-Month-Level Regression		
	BMI	Overweight	Obese	Avg. BMI	%Overweight	%Obese
VIX	7.083***	0.898***	0.417***	2.586**	0.410***	0.177**
	(0.696)	(0.059)	(0.053)	(1.159)	(0.112)	(0.080)
Mkt	0.100*	0.012***	0.001	-0.053	0.000	-0.007
	(0.053)	(0.004)	(0.004)	(0.075)	(0.007)	(0.006)
Macroeconomic variables	Yes	Yes	Yes	Yes	Yes	Yes
Demographic variables	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,612,765	6,612,765	6,612,765	14,760	14,760	14,760
R-squared	0.068	0.070	0.041	0.876	0.844	0.868

Table 8: Individual-Level and State-Month-Level OLS Regressions – Smoking Measure

This table reports results of individual-level and state-month-level regressions examining the relation between expected market uncertainty (as captured by VIX) and smoking. Specifically, the dependent variable is an indicator for whether the individual is currently a smoker (for the individual-level regression) and the fraction of individuals who are smokes in state *s* in month *t* (for the state-month-level regression). Other independent variables include contemporaneous market return (*Mkt*), unemployment rate, income per capita, and individual level (or state-month level) demographic characteristics. See Appendix A for detailed variable definition, source, and construction. All models include state-specific time trend, month fixed effects, and state fixed effects. Standard errors are heteroscedasticity-consistent and reported in parentheses. Standard errors are also clustered by state in Column (2). ***, **, and * indicate $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

	(1)	(2)
	Individual-Level Regression	State-Month-Level Regression
	Smoker	%Smoker
VIX	0.314***	0.580***
	(0.047)	(0.079)
Mkt	0.013***	0.013***
	(0.004)	(0.005)
Macroeconomic variables	Yes	Yes
Demographic variables	Yes	Yes
State fixed effects	Yes	Yes
State-specific time trends	Yes	Yes
Month fixed effects	Yes	Yes
Observations	6,810,614	14,277
R-squared	0.086	0.756