The Dow is Killing Me: Risky Health Behaviors and the Stock Market

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Abstract: We investigate how risky health behaviors and self-reported health vary with the Dow Jones Industrial Average (DJIA) and during stock market crashes. Because stock market indices are leading indicators of economic performance, this research contributes to our understanding of the macro-economic determinants of health. Existing studies in this literature typically rely on the unemployment rate to proxy for economic performance, but this measure captures only one of many channels through which the economic environment may influence individual health decisions. After accounting for associations with the unemployment rate, we find that large, negative monthly DJIA returns, decreases in the level of the DJIA, and the 1987 and 2008-2009 stock market crashes are associated with worsening self-reported mental health and riskier health behaviors including more cigarette smoking, binge drinking, and fatal car accidents involving alcohol. These results are consistent with models of consumption behavior such as rational addiction models, and they have important implications for research studying the association between consumption and stock prices.

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1. Introduction

The capital asset pricing model predicts that the stock prices capture all publicly available information about the discounted expected future cash flows of firms. Thus, a large decline in stock market indices may signal impending wide-spread economic distress. Research demonstrates that these signals reach a large share of the general population and influence attitudes both about the economy and the level of life-satisfaction.

In the United States, stock indices such as the Dow Jones Industrial Average (DJIA) are reported in the popular press on a nearly daily basis and are one of the principal sources of information that individuals use when forming their expectations of economic performance of the overall marketplace (Goidel, Procopio, Terrell, & Wu, 2010; Hester & Gibson, 2003). During the recent stock market crashes, Americans reported large declines in self-reported well-being (Deaton, 2011), exhibited increased symptoms of depression and poor mental health (McInerney, Mellor, & Nicholas, 2012), and experienced a spike in hospitalizations for psychological disorders (Engelberg & Parsons, 2013).[1] Becker (2007) has argued that exogenous events that impact individual attitudes about the future will impact behavioral choices. To the extent that fluctuations in stock indices influence attitudes about the future, rates of depression, and overall life valuation, we might anticipate important behavioral changes in health-related activities during stock market crashes or general fluctuations in the DJIA.

Therefore, this paper investigates how health-related behaviors and outcomes vary with the DJIA. Specifically, using information from the Behavioral Risk Factor Surveillance System

[1] Other studies have noted that that precipitous stock market declines and increased stock market volatility are associated with increased risk negative physical health outcomes, as well, such as myocardial infarction (Fiuzat, Shaw, Thomas, Felker, & O'Connor, 2010; Ma, Chen, Jiang, Song, & Kan, 2011).

(BRFSS) between 1984 and 2010, we estimate the relationship between stock returns and smoking, alcohol consumption, physical activity, and self-reported physical and mental health. We also investigate whether alcohol and cigarette purchasing effects are observable in the Nielsen Homescan Consumer Panel Dataset (NHCPD), which is a household-level panel of consumer purchase data, and if drunk driving outcomes are affected by looking in the Fatality Reporting System (FARS) data on automobile accidents. Further, we explore possible non-linearity in these relationships by considering whether behavioral changes depend upon large negative or positive monthly DJIA returns.

Because stock market indices are leading indicators of economic performance, this research serves as an important contribution to our understanding of the macro-economic determinants of health. Existing studies in this literature typically rely on the unemployment rate as the measure of economic performance, e.g. Ruhm (2000). Yet, as a lagging indicator of macroeconomic activity (Stock & Watson, 1989), the unemployment rate only captures one dimension of the many channels through which the economic environment could influence individual health decisions.

For instance, all-cause mortality in developed economies tends to decrease when the unemployment rate increases.[2] It is hypothesized that behaviors associated with increased mortality such as consumption of alcohol and cigarettes are sufficiently normal so that health improves when the economy worsens. This explanation is consistent with empirical studies showing that the decline in mortality during times of higher unemployment is concentrated in acute causes, e.g., motor vehicle accidents and injuries, rather than slowly developing causes,

[2] This pattern has been documented in the United States (Ruhm, 2000), the European Union (Krüger & Svensson, 2008; Neumayer, 2004; Tapia Granados, 2005), and Japan (Tapia Granados, 2005).

such as cancer or kidney disease (Evans & Moore, 2012).[3] In addition, numerous studies have shown that risky behaviors such as alcohol consumption (C. D. Cotti, Dunn, & Tefft, 2012; Ettner, 1997; Freeman, 1999; Ruhm & Black, 2002; Ruhm, 1995), cigarette consumption (Charles & DeCicca, 2008; Ruhm, 2000, 2005), and drunk driving (C. Cotti & Tefft, 2011) are negatively related to the unemployment rate in the United States.

But for most Americans, large fluctuations in the DJIA do not translate into immediate or significant income changes. For individuals with substantial equity holdings, losses are only realized if stocks are sold, typically during retirement. Thus, estimating the relationship between the DJIA and risky health behaviors while simultaneously controlling for unemployment and per capita personal income allows us to effectively shut-down the income effect that seems to explain the pro-cyclicality demonstrated in previous work. By doing so, we hope to learn whether other important mechanisms are at play, e.g., the psychological effects of stress or the role of expectations.

In a preview of our results, we find that cigarette consumption and the number of days that a respondent reports experiencing poor mental health increases during a large monthly decline in the DJIA, independent of other measures of macroeconomic conditions. When restricting attention to the stock market crashes of 1987 and 2008-2009, BRFSS respondents additionally reported more binge drinking. This broader increase in the riskiness of health behaviors during acute, protracted stock market declines is then confirmed in the FARS data by a sharp increase in drunk driving fatalities during the 2008-2009 market crash. The alcohol and

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[3] An important exception to the counter-cyclical relationship between macroeconomic performance and mortality is suicide, which is generally found to be positively related to both the unemployment rate (Ruhm, 2000), other measures of job loss and the duration of unemployment (Classen & Dunn, 2012).

cigarette consumption behavior patterns are also confirmed by considering household purchase data in the NHCPD. Collectively, these estimates are consistent with the idea that the general state of the stock market impacts individual's behavioral choices in meaningful ways.

As we will demonstrate, findings are robust to the inclusion of controls for demographics characteristics (e.g. gender, race), income and employment status, changes in policies that may impact behavior outcomes, area, time, and where appropriate household fixed effects, as well as a myriad of other factors that may influence outcomes in question and vary depending on the model. The results are consistent across several different behavior and outcome measures, for three distinct measures of the stock market, across both panel and repeated cross-section data aggregated at the individual, household, and state levels, and for several different estimation methods.

2. Individual-level analysis using the Behavioral Risk Factor Surveillance System

2.1. Data

In order to explore the response of several risky health behaviors to stock market changes and crashes, we first use data drawn from the Behavioral Risk Factor Surveillance System (BRFSS) between 1984 and 2010. BRFSS is maintained by the Centers for Disease Control and Prevention (CDC) to monitor health and related behavioral risks of the U.S. population. The survey is collected by U.S. states and territories throughout each year. For this analysis, the availability of each respondent's state of residence allows for the inclusion of controls for unobserved state-level determinants that are fixed over time, as well as state-specific time trends.

Summary statistics for the risky health behaviors and covariates of interest are reported in Table 1. We study behaviors known to have implications for current and future health including cigarette smoking, binge drinking, and exercise, and we also consider self-reported measures of mental, physical, and overall health. Some of the measures were first collected during the early- to mid-1990s, as reported in Table 1, and in those cases identification is based only on the 2008-2009 crash. For questions on alcohol consumption, current smoking status, and exercise participation responses are available for the entire sample period, however, so we are able to study these measures in the context of both the 1987 stock market crash and the 2008-2009 crash.

In addition to studying how health and risky health behaviors during the 1987 and 2008-2009 stock market crash periods (as defined below) we also study associations with changes in the U.S. stock market for the entire sample period between 1984 and 2010. We selected the Dow Jones Industrial Average index (DJIA), a market indicator constructed from the stock prices of 30 manufacturers of industrial and consumer goods, to summarize the market. The DJIA is highly correlated with other broad stock market indices, e.g., the NASDAQ and S&P500, and it is the most widely cited market index in newspapers, television, and the internet.[4] We consider two measures of the DJIA aggregated by month: the natural log of the monthly mean daily market closing index[5] and the monthly percent return between the first and last closes for each

[4] For a more complete summary of the DJIA see http://www.djaverages.com/index.cfm?go=industrial-overview (last accessed December 20, 2012)
[5] The natural log is used instead of the level for ease of interpretation. Deflation of the market index is not necessary because when logged the inflators are transformed to annual constant shifts in the log index, which are then absorbed by the year indicator variables included in each regression model.

month. The data series was downloaded from the St. Louis Fed's FRED Economic Data web site.[6] We summarize each measure when it is introduced in the analysis below.

We also merge in state-level measures of economic conditions that have been commonly considered in previous studies. State-by-month unemployment rates are extracted from the Local Area Unemployment Statistics of the Bureau of Labor Statistics, U.S. Department of Labor[7] and state-by-year personal per capita income data are from the U.S. Department of Commerce Bureau of Economic Analysis, Regional Economic Accounts.[8]

2.2. Methods

We estimate versions of the following model:

(1) $$H_{ist} = \beta_0 + \Psi_t\beta_\Psi + M_{st}\beta_M + X_{ist}\beta_X + \tau_t + \gamma_s + \gamma_s * t + \varepsilon_{ist}$$

H_{hst} is a measure of health or risky health behavior for individual *i* in geographic area *s* at time *t*, including indicators for whether or not an individual participates in a behavior, the natural log of the quantity of consumption (i.e. binge drinking events), or the level quantity of days in which mental or physical health was reported to be poor. The primary variables of interest are represented by Ψ_t which summarize the U.S. stock market. In models studying stock market crashes an indicator for the crash is set equal to one during October and November of 1987 as well as during the fourth quarter of 2008 and the first quarter of 2009. These time periods were defined by the months in which each crash was generally accepted as beginning (October 19, 1987 and the last week of September 2008, respectively) through the month in which a positive

[6] http://research.stlouisfed.org/fred2/series/DJIA/ (last accessed December 20, 2012)
[7] http://www.bls.gov/lau/home.htm (last accessed October 31, 2012)
[8] http://www.bea.gov/regional/index.htm (last accessed November 5, 2012)

DJIA return was observed.[9] In other models, we define Ψ_t as the natural log of the DJIA index or the monthly return in the DJIA.

Included in all models are several covariates. First, M_{st} includes indicators for macroeconomic conditions, in this case the state-level unemployment rate and per capita income, since the goal of this study is to isolate how changes in the stock market are specifically related to health and risky health behaviors. X_{ist} contains individual-level demographic characteristics as reported in Table 1. The vector τ_t consists of indicator variables for each year and month[10], γ_s is a vector of indicator variables for state of residence, and γ_s are state-specific trends. β_0 is a constant coefficient and ε_{ist} is the error term. All standard errors are clustered at the state level.

2.3. Results

Since our aim is to isolate stock market effects independent of business cycle factors previously identified as influencing health behaviors e.g., the state unemployment rate and per capita personal income, and in all models we control for these macroeconomic conditions. Many of these coefficients are not precisely estimated, but when significant they are consistent with previous work reporting that individuals generally participate in healthier behaviors as economic conditions, proxied by state-level unemployment, worsen (Ruhm, 2000).

Table 2 reports results for the full set of BRFSS outcomes and their association with the DJIA according to three different specifications. Panel A shows regressions in which an

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[9] This definition is qualitatively robust to modifications including delaying the definition of the crash by one month to account possible timing delays in BRFSS responses. It is also robust to the inclusion of the 2002 stock market decline, although the results are somewhat weaker (the 2002 decline is not generally considered to be nearly as severe so we did not include it when report results).

[10] It is not possible control for period indicators since these would absorb all variation in the stock market measures.

indicator for the 1987 and 2008-2009 stock market crashes is included as defined earlier. Overall, the results repeatedly suggest that individuals participate in riskier health behaviors and experience worse self-reported mental and general health during a stock market crash. This is in notable contrast to the findings from the literature studying health and the unemployment rate, but it is consistent with more recent work studying the well-being and mental health effects of the 2008-2009 market crash (Deaton, 2011; McInerney et al., 2012). During a crash, an individual is 0.17 percentage points more likely to binge drink (although the p-value for this coefficient estimate is a marginally insignificant 0.11), and the number of times that an individual participates in binge drinking increases by 1.5%. A respondent is 0.36 percentage points more likely to report being a current smoker and 0.43 percentage points more likely to report smoking every day. Respondents report nearly one more poor mental health day, on average, and there is a significant worsening of average reported general health on a five point scale (where 1 = excellent health and 5 = poor health). Exercise activity declines, although the coefficient is not precisely estimated, and there is no significant change in the number of poor physical health days (this measure might not be expected to respond as rapidly to a market crash as both risky behaviors and mental health).

Although the 1987 and 2008-2009 stock market crashes are generally accepted as notably severe stock market events, it is also important to study how risky health behaviors are related to underlying stock market indicators. Panel B of Table 2 therefore presents results when specifying the natural log of the monthly average daily close of the DJIA instead of the crash indicator variable. This set of regressions seeks to answer the question of whether a higher or lower DJIA is broadly related to self-reported health and risky health behaviors.

Indeed, the results parallel those found in Panel A, where a lower DJIA is associated with a greater number of poor mental health days, more binge drinking, and more frequent cigarette consumption. For example, the number of binge drinking events increases by 0.39% and the likelihood of smoking every day increases by 0.08 percentage points during a month in which the DJIA is 10% lower, *ceteris paribus*.

The third set of specifications is presented in Panel C of Table 2, where two thresholds of within-month stock returns are included simultaneously. Specifically, we constructed an indicator for whether a month's DJIA return was less than -10% and an indicator for whether the month's DJIA return was greater than 10% in order to capture months in which there are unusually large changes in the DJIA. Relative to small fluctuations in the DJIA (less than 10% in absolute value) there is for the most part an asymmetric relationship between negative or positive returns and outcomes. Respondents report a greater frequency of smoking, a greater number of poor mental health days, and worse general health in months in which there is a large market decline. A statistically significant and notable exception to this asymmetry is that self-reported general health status *improves* during months of high DJIA returns. Also, binge drinking is not significantly associated with return thresholds. That there is a generally weaker relationship between these outcomes and large negative DJIA returns than there is between market crashes and outcomes is perhaps counterintuitive when it is noted that some, but not all, of the monthly returns during the studied crashes were less than 10%.[11] This offers

[11] Only two of the months during the 2008-2009 crash had returns of less than -10%: -14.1% in October 2008 and -11.7% in February 2009.

suggestive evidence that market crashes magnify health and health behavior effects beyond what might otherwise occur during an isolated monthly market decline.

To conclude the BRFSS analysis, Table 3 reports results stratified by demographic and economic characteristics for models including an indicator for the 1987 and 2008-2009 market crashes. Results when estimating models using the other two specifications show broadly similar patterns and are available for comparison in appendix Tables A1 and A2. We report results for three outcomes which may be particularly relevant for adverse health outcomes: the (natural log) number of binge drinking events in the past 30 days, whether a respondent smokes every day, and the number of poor mental health days in the last 30 days. The first measure is identified for both the 1987 and 2008-2009 crashes while the second and third are identified for the latter crash only.

Compared with results for the full sample in Panel A of Table 2, men experienced larger increases in the number of binge drinking events. Interestingly, low income respondents, who one might expect to be impacted the least by a contemporaneous income effects exhibited somewhat larger increases in their likelihood of smoking every day and poor mental health. Moreover, respondents between the ages of 25 and 54, men, and married respondents also show signs of larger increases in the number of poor mental health days in the last 30 days. This pattern of responses during the stock market crash should be interpreted with caution since not all differences are statistically significant, but the overall pattern suggests that the crash effects were widespread across the population and not limited to likely stockholders. In section 5 we discuss several potential mechanisms that can explain the observed pattern of risky health behaviors, many of which are also applicable to non-stockholders.

3. Household-level analysis using the Nielsen Homescan Consumer Panel Dataset

3.1. Data

We use data from the Nielsen Homescan Consumer Panel Dataset (NHCPD) in order to test the robustness of the findings from the BRFSS analysis across datasets that have different strengths. First, the panel of between 40,000 and 60,000 households allows us to study in detail whether within-household purchases change in accordance with changes in stock market measures (since BRFSS is cross-sectional, comparisons were made across persons when analyzing those data). The Nielsen Corporation samples U.S. households by providing each participating household with a device that enables scanning of every UPC code of retail items purchased on all shopping trips. This feature of the NHCPD allows for a complete tally of purchases, in this case alcohol and cigarettes, rather than self-reports of consumption. An important limitation of the alcohol purchases (but not cigarettes), is that the NHCPD does not include information on purchases at bars, restaurants, or other on-premise establishments.

Table 4 shows summary statistics for the NHCPD, which includes a rich set of household characteristics. Since purchases are recorded for each household, demographics are organized by male or female household head or aggregated to the household level. The sample is not representative of the U.S. population along some dimensions, e.g. household heads under the age of 25 or without a high school degree are under-represented. Since we are primarily interested in within-household changes in purchases, however, this limitation would not be troublesome unless there is substantial heterogeneity in responses for unobserved subgroups conditional on the other demographic characteristics.

The purchase measures are constructed using the monthly count of cigarettes purchased by each household and the total ounces of alcohol by volume (ABV) estimated to be purchased by each household. To construct the ABV variable, we first sum the total purchased ounces of each alcohol subtype (beer, wine, and liquor) by each household in each month. We then assign beer a content of 4.5% ABV, wine a content of 15% ABV, and liquor a content of 45% ABV and sum total estimated ABV for each category. Results reported below are robust to reasonable adjustments of the ABV for alcohol subtypes.

In the analysis below, we merge the DJIA measures, state-by-month unemployment rates, and state-by-year personal per capita income as described in the BRFSS data section. We also include state-by-year beer and cigarette taxes drawn from the Tax Foundation web site[12,13] and quarter-by-county supply-side controls for the number of establishments selling alcohol and total employment in the establishment categories. These data are downloaded from the Quarterly Census of Employment and Wages of the Bureau of Labor Statistics, U.S. Department of Labor.[14]

3.2. Methods

[12] http://taxfoundation.org/ (last accessed October 31, 2012)

[13] Since tax data was only available beginning in 2000 we did not include beer and cigarette taxes in the main BRFSS estimation specifications. However, the main results are robust to restricting attention to the 2000-2010 BRFSS waves and including these tax rates when analyzing the BRFSS sample.

[14] http://www.bls.gov/cew/ (last accessed October 31, 2012)

We estimate versions of the following household fixed effects model:

(2) $$H_{hst} = \beta_0 + \Psi_t \beta_\Psi + M_{st}\beta_M + X_{hst}\beta_X + D_{st}\beta_D + \tau_t + \gamma_s + \delta_h + \varepsilon_{hst}$$

The variables are the same as those defined for equation (1), with three differences. First, the *i* subscripts in equation (1) are replaced with *h* subscripts to indicate that observations are recorded at the household, not individual, level. Second, the state-specific trends in equation (1) are replaced with household fixed effects δ_h. Third, the vector of area controls mentioned above (D_{st}) is now included.[15] H_{hst} also now refers to measures of alcohol or cigarette purchases rather than health status or risky health behaviors as in the BRFSS analysis. As shown in Table 4, purchases are expressed either as an indicator for whether or not the household made any purchase, or as the quantity purchased. In the latter case, we study the natural log of quantity purchased, which yields estimates conditional on positive purchases.

We cluster all standard errors at the household level since observations within each household may not be independent. Clustering at the state-level may be preferable, but some households relocate between states during the sample period and thus not all households are not nested within state clusters (which prohibits state-level clusters). We follow Cotti, Dunn, and Tefft (2012) in using household-level clustering since they demonstrate that the relationship between household-level alcohol purchases and the business cycle are nearly identical to results when dropping households that migrate and when using state-level clustering.

3.3. Results

[15] Vector D_{st} includes measures of area beer taxes, cigarette taxes, and supply-side factors (e.g. the number of supermarkets, bars, liquor stores, and convince stores, as well as the corresponding number of employees in each industrial group).

The full set of results for the NHCPD analysis is reported in Table 5. The first three columns display regression results when studying whether a household made any purchase in the given category, and the next three columns display results when studying the natural log of the quantity of purchases (conditional on positive purchases). Panels A and B show results for alcohol and cigarette purchases, respectively.

In almost every specification, the results line up with the results from the BRFSS analysis. The first and third columns reveal that, after adjusting for other macroeconomic indicators, households are both more likely to purchase any and purchase a greater quantity of ABV and cigarettes during an event like the 2008-2009 crash. Interpreted directly, a household is slightly more likely to make any purchases, by 0.1 and 0.2 percentage points for ABV and cigarettes. The quantity purchased, conditional on any purchases, responds more strongly, with a 1% increase in ABV purchases and a 5% increase in cigarettes during a stock market crash.

The remainder of the columns explores the relationship between alcohol and cigarette purchases and the DJIA and stock return thresholds, as in the BRFSS analysis. These results again show a consistent relationship between risky health behaviors and the stock market. As indicated in the second and fourth columns, a household is 0.1 percentage points more likely to purchase alcohol, and the quantity purchased, conditional on any purchases, increases by 0.3% for a month in which the DJIA declines 10% lower (the analogous differences for cigarettes are 0.03 percentage points and 0.7%). Studying within-month returns, the only significant finding is that a household purchases 1.8% more cigarettes during a month in which the DJIA return was less than 10% (the variable indicating monthly returns greater than 10% was dropped in this Nielsen analysis because no such month occurred between 2004 and 2009). Again, these patterns broadly match findings from the BRFSS analysis, suggesting that risky health behaviors worsen when the DJIA declines, and they are especially poor during a stock market crash.

4. Fatal automobile accident analysis using the Fatality Analysis Report System

4.1. Data

Increased alcohol consumption related to stock market activity may translate into an increase in negative health outcomes associated with excessive drinking. Specifically, drinking and driving has high social costs and large negative externalities. Levitt and Porter (2001) show that drunk drivers impose an externality per mile driven of at least 30 cents because of their greater likelihood of causing fatal accidents. As a result, we investigate the role of the DJIA average and indicators for the 2008-2009 stock market crash in fatal automobile accidents involving alcohol.

We link our stock market measures to data on fatal vehicle crashes obtained through the Fatality Analysis Reporting System (FARS) of the National Highway Traffic Safety Administration (NHTSA) for the years 2003 -2010. The variable of primary interest is a state's monthly number of fatal accidents in which a driver's blood alcohol content (BAC) is positive (alcohol-related fatal accidents or ARFAs, hereafter).[16] By utilizing the FARS data we aggregate

[16] Although Federal law requires that BAC levels be obtained from every fatal crash, it is frequently not and can lead to bias. The NHTSA provides imputed measures of BAC for all drivers not tested. Imputed values are obtained using a multitude of characteristics including time of day, day of week, contents of the police report, position of car in the road, etc. (NHTSA, 2002). This follows suggestions from Rubin et al. (1998) and improves on the former procedure based on discriminant analysis (Klein, 1986; NHTSA, 2002). Many drunk driving studies restrict attention

counts of ARFAs by state, and linking these measures to other data available by state (e.g., state population data, vehicle miles traveled, beer taxes, etc.) we investigate whether increased alcohol consumption associated with market fluctuations impacts drunk driving fatalities.

4.2. Methods

Our primary analysis employs a fixed-effects research design using the 50 US states (plus the District of Columbia):

(3) $$H_{st} = \beta_0 + \Psi_t\beta_\Psi + M_{st}\beta_M + X_{hst}\beta_X + \tau_t + \gamma_s + \varepsilon_{hst}$$

Standard errors are clustered by state to allow for non-independence of observations (Bertrand, Duflo, & Mullainathan, 2004). *H* is now defined as the natural logarithm of the count of ARFAs in a state-month-year. Although using a logarithmic transformation is a standard practice in the literature, equation (3) will not be defined when the number of ARFAs is equal to zero in a state-month. This is an exceedingly rare occurrence in our data, but we verify that these occasional exclusions cause no meaningful change in the results in a robustness analysis to follow. Also, given that the number of accidents may be more variable in smaller states and our data is aggregated to the state-month level, we weight all estimates by month-year population size obtained from the Census Bureau (Dee, 1999; Ruhm, 1996).[17] Estimation of

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to certain types of accidents (e.g., those that occurred on weekend evenings) in order to isolate accidents more likely to involve alcohol, but this is unnecessary given the multiple imputation procedure. This newer approach is increasingly used in the literature (Adams, Blackburn, & Cotti, 2012; Cotti & Walker, 2010; Cummings, Rivara, Olson, & Smith, 2006; Hingson, Heeren, Winter, & Wechsler, 2004; Villaveces, 2003). The estimated effects may yet be biased if the rate of imputation is systematically related to the variables of interest. It is unlikely, however, that stock market fluctuations affect how officers investigate a crash scene.

[17] In our case utilizing a WLS approach yields the most efficient estimates.

equation (3) will therefore be by weighted least squares, but we do show later that using different estimating specifications or empirical methods yields nearly identical results.[18]

Variable Ψ is a measure of the stock market, as defined in earlier sections. Thus, estimates of β can be interpreted as an estimate of the percent increase in ARFAs during the 2008-2009 stock market crash, the elasticity between changes in the DJIA close price, or percentage increase during months with large declines in monthly returns, respectively.

Analogous to the individual- and household-level analyses, state fixed effects (α) capture differences in states that might affect accidents and are constant over time, while year and month time fixed effects (τ_t) account for uniform year and season effects across the sample time frame that may influence estimates. The X vector also includes covariates that capture state-specific changes in a state's ARFAs over time including state population obtained from the US Census Bureau and monthly state vehicle miles traveled (VMT) data from the US Federal Highway Administration. Next, there is concern that the underlying propensity for *all* traffic accidents might change due to economic activity, highway construction, weather patterns, insurance rates, number of drivers, age composition of drivers, etc. We therefore include the number of accidents per county that were *not* alcohol related (NARFAs), also from the FARS. This control allows for isolation of the effect of stock market fluctuations apart from the many potentially omitted factors that make it more dangerous to drive in a particular location. Given that this variable and measures of state VMT capture underlying traffic trends in

[18] For example, we could have utilized a Poisson regression (which is appropriate for the count structure of the data but reports understated standard errors due to over-dispersion), negative binomial regression (which does not understate standard errors but may not provide true fixed effects estimates), logit regression, and linear regression using the accident rate. We settle on weighted least squares as the least problematic and most easily interpretable measure to use in presenting the basic results. However other methods are presented in Table 7.

the data, they should capture any differences in general accident risk that may arise between states during the sample period analyzed.

Several studies (C. Cotti & Tefft, 2011; Dee, 2001; Freeman, 1999; Ruhm, 1995) show that fluctuations in economic conditions also impact alcohol consumption and ARFAs in a meaningful way. Therefore, we also included measures of each state's monthly unemployment rate and real per capita personal income in vector *M*. Lastly, we recognize that stock market fluctuations may also be correlated with government policies that also impact drunk driving outcomes. To address this concern, all specifications include controls for real beer taxes, real gas taxes, and a dummy variable indicating whether a state has a 0.08 blood alcohol content limit in place in each state.

4.3. Results

In the first column of Table 6 we investigate the association between the 2008-2009 stock market crash and the natural log of ARFAs. The highly significant coefficient estimates indicate that the market crash led to an increase in alcohol-related accidents by 5.92%. Since the average number of monthly accidents involving a drunk driver is approximately 21, this increase is equivalent to 1.24 additional accidents per month in a typical state. This result is estimated while controlling for the state unemployment rate, which, consistent with past research on the issue (C. Cotti & Tefft, 2011; Ruhm, 1995), and shows a statistically significant negative relationship with ARFAs.

In the second column we replace the stock market crash indicator with the natural log of the average DJIA close, and the same pattern emerges. Estimates suggest that a 10% decline in the DJIA close is associated with an increase in ARFAs by nearly 1.3%, suggesting that the real level of the market plays an important role in determining drunk driving behavior. Lastly, in the third column we explore how large declines in DJIA returns impact ARFAs. We include an indicator variable which equals one if a month's return is less than negative 10 percent. Results are similar to the stock market crash estimates found in the first column. While it should be noted that not all months during the stock market crash exhibited a greater than 10% decline in returns, all of the months during the sample time frame investigated here that did exhibit a greater than 10% decline did occur during the stock market crash time period.

If the estimated increases in ARFAs shown in Table 6 are the direct result of increases in alcohol consumption identified earlier, then there should be no impact on NARFAs. We therefore replicated the estimates presented in Table 6 with the natural log of NARFAs as the LHS variable (and excluded from the RHS). Results show no meaningful effect of either the stock market crash (Coef. = -0.0137, SE = 0.0158), changes in the log of the DJIA close (Coef. = -0.0438, SE = 0.0401), or large declines in DJIA returns (Coef. = 0.0160, SE = 0.0237) on NARFAs, demonstrating that it is only the alcohol-related crashes that are impacted by fluctuations in the value of the stock market, *ceteris paribus*.

Overall, these results demonstrate evidence of a relationship between ARFAs and the stock market crash of 2008-2009, market value as captured by the DJIA, and monthly DJIA returns. Results presented in the first and second columns run parallel with the consumption and purchases results presented earlier, and, as such, suggest that increased ARFAs is a consequence of increased drinking related to stock market fluctuations. A notable difference is that the analogous investigations of the relationship between market returns and consumption and purchases presented earlier yield the same direction of impact but are not statistically significant. This difference could be explained by the fact that BRFSS and NHCPD are samples, thus impacting precision, while the FARS offers close to a full census of fatal automobile accidents. Also, large declines in market returns may impact some individuals' willingness to drive while intoxicated independently of how much they decide to drink, which seems to be meaningfully impacted only by large persistent losses in market value (crashes) or generally low market levels. In section 5 we discuss mechanisms which can account for consistent patterns of increased risk-taking, which in this example may combined to magnify the increase in drunk driving fatalities during a stock market crash.

Table 7 presents several alternative approaches to verify the robustness of this analysis. First, earlier drunk driving research (Dee, 1999) has demonstrated that the omission of state-level trends may bias the results. While the measures of VMT and NARFAs should capture any general trends in a state's traffic safety, in the first column of Table 7 we re-estimate equation (3) but also add state-specific trends and find that their inclusion does not alter the main results. Next, although the primary analysis employs a weighted least squares regression model, a logit or negative binominal approach, among others, is equally viable. As shown in the second and third columns of Table 7, results are not sensitive to the functional form selected.[19]

We also test the sensitivity of our findings to including state-months in which zero ARFAs occur. The negative binomial model results presented in the third column and results when replacing the log of ARFAs with the ARFA rate per 100,000 persons, presented in the fourth column, suggest that the loss of the zero ARFA months does not impact findings. Lastly, we test for the robustness of the estimates to the choice of dependent variable. In Table 6, the

[19] Not shown, results are also robust to the use of Poisson and probit specifications.

dependent variable was restricted to the log of the number of fatal accidents involving any alcohol. Alternatively, it may be defined as the log number of fatal accidents with a BAC of 0.08 or higher, which is now the legal limit in all states in the US. When defining the dependent variable as such, (shown in the last column of Table 7), the results are robust.

5. Discussion

The preceding analysis explored whether severe stock market crashes, and measures of the stock market more generally, are related to self-reported health status and behaviors that are widely known to affect health. Our results reveal clear patterns: self-reported mental health and well-being worsens and risky health behaviors increase during periods of poor market performance. Although we detect in the context of several measures of the stock market, it is most pronounced during the most severe market downturns such as the 2008-2009 stock market crash.

These findings offer a substantial departure from previous research on the state of the economy and health. That self-reported mental health and well-being worsen during market crashes is consistent with research specifically studying the crash of 2008-2009 (Deaton, 2011; McInerney et al., 2012) and is not unexpected given that when economic conditions weaken as indicated by measures such as the unemployment rate or personal per capita income, mental health also worsens (Ruhm, 2000, 2005; Tefft, 2011). Broadly speaking, however, risky health behaviors such as binge drinking, drunk driving, smoking, overeating, and sedentary activity have been repeatedly shown to *decrease* during economic downturns as measured by the unemployment rate and personal per capita income (Colman & Dave, 2011; Cotti & Tefft, 2011;

Ruhm & Black, 2002; Ruhm, 2005). Therefore, the pattern of results presented in this paper strongly suggests that the way in which individuals behave with respect to their health during economic downturns depends critically on how which aspects of the downturn are being considered.

There are several potential mechanisms that might explain why we observe poorer mental health in conjunction with riskier health behaviors during stock market downturns. An important difference between experiencing adverse economic conditions as measured by the stock market rather than the unemployment rate is that for most individuals the former may primarily convey information about *future* real economic conditions. In contrast, measures of the unemployment rate and per capita household income more specifically capture contemporaneous economic constraints faced by households.

Cotti, Dunn, and Tefft (2012) report that total monthly household expenditures in the NHCPD are lower for higher levels of the unemployment rate, consistent with a negative income effect. We investigated whether measures of the DJIA or stock market crashes are associated with total monthly expenditures and find no evidence that total expenditures decrease during a stock market downturn, conditional on the unemployment rate (the negative relationship with the unemployment rate also persisted). To the extent that total expenditures are a reasonable proxy for a household's budget constraint, then these findings are consistent with stock market downturns having a relatively small net contemporaneous income effect. As a result, the income effect that seems to explain many of the results connection economic downturns to less risky behavior may simply be less salient during stock market fluctuations.

Additionally, since future real economic conditions are relevant for stockholders and non-stockholders alike, we would expect any behavior responses to be widespread and not restricted to stockholders.

If behavior responses to stock market downturns are relatively prospective, then worse mental health and more risky behaviors may naturally co-occur. There is a relatively small contemporaneous income effect for most households, so if individuals are present-biased (e.g. living "month-to-month" by spending their entire paycheck) they may not cut back on expenses overall if their employment status and income remains unchanged. Instead, they may substitute toward consuming immediately pleasurable goods to alleviate worse well-being that arises in the face of a bleaker future. Additionally, individuals may be responding rationally to a reduced expected future utility stream. Models of rational addiction, for example, demonstrate that decreased future expected utility (e.g. through reduced life expectancy) can lead to greater present consumption of addictive goods (Becker & Murphy, 1988; Becker, 2007).

When the contemporaneous income effect is diminished, the role of stress in determining participation in risky health behaviors may also become more prominent. Earlier research on lifestyle changes in the face of worsening employment conditions hypothesized that greater stress among the unemployed and those fearing unemployment or reduced work hours may lead to self-medication (Brenner & Mooney, 1983; Catalano & Dooley, 1983). Although subsequent research found less evidence to support this hypothesis when proxying for economic conditions with the unemployment rate (Ruhm, 1995, 2005), the evidence presented here is consistent with the possibility that stress about economic conditions drive participation in risky health behaviors during stock market downturns.

The findings from our study also have broader implications for research that relates stock returns to consumption. The consumption capital asset pricing model (CCAPM) predicts that changes in consumption will be positively correlated with stock returns (Breeden, 1979; Lucas Jr., 1978). However, researchers have had difficulty finding supporting evidence for the CCAPM to the point where the "equity premium puzzle" (Mehra & Prescott, 1985), the consistent finding that the observed consumption-return correlation implies an implausibly high level of risk aversion, has become widely known. Our findings exhibit the opposite relationship predicted by the CCAPM: alcohol and cigarette consumption is overall *negatively* correlated with the DJIA during a market crash and more generally, and with monthly DJIA returns. This suggests future research that modifies the CCAPM to account for heterogeneous responses across consumption goods, for example by modeling the utility function to include features such as present bias or rational addiction.

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Table 1. Summary, BRFSS 1984-2010

	Waves	*N*	Mean	Std. Dev.	Min	Max
Any binge drinking events in last 30 days	1984-2010	3,795,152	0.128		0	1
# of binge drinking events in last 30 days	1984-2010	3,795,152	0.513	2.428	0	76
Current smoker	1984-2010	4,193,644	0.209		0	1
Smokes every day	1996-2010	3,483,660	0.155		0	1
Any exercise	1984-2010	3,847,263	0.737		0	1
Poor physical health days in last 30 days	1993-2010	3,601,796	3.856	8.325	0	30
Poor mental health days in last 30 days	1993-2010	3,608,242	3.368	7.575	0	30
Health status (1 = Excellent, 5 = Poor)	1993-2010	3,763,381	2.469	1.094	1	5
Age	1984-2010	4,206,151	49.964	17.114	18	99
Male	1984-2010	4,206,151	0.406		0	1
White	1984-2010	4,206,151	0.854		0	1
Black	1984-2010	4,206,151	0.084		0	1
Other race	1984-2010	4,206,151	0.063		0	1
Hispanic	1984-2010	4,206,151	0.057		0	1
High School Grad	1984-2010	4,206,151	0.309		0	1
Some College	1984-2010	4,206,151	0.272		0	1
College Grad	1984-2010	4,206,151	0.313		0	1
Married	1984-2010	4,206,151	0.558		0	1
Income $10k to $15k	1984-2010	4,206,151	0.070		0	1
Income $15k to $20k	1984-2010	4,206,151	0.087		0	1
Income $20k to $25k	1984-2010	4,206,151	0.105		0	1
Income $25k to $35k	1984-2010	4,206,151	0.147		0	1
Income $35k to $50k	1984-2010	4,206,151	0.171		0	1
Income > $50k	1984-2010	4,206,151	0.347		0	1
Employed for wages	1984-2010	4,206,151	0.511		0	1
Self-employed	1984-2010	4,206,151	0.089		0	1
Out of work for > 1 year	1984-2010	4,206,151	0.019		0	1
Out work for < 1 year	1984-2010	4,206,151	0.025		0	1
Homemaker	1984-2010	4,206,151	0.074		0	1
Student	1984-2010	4,206,151	0.023		0	1
Retired	1984-2010	4,206,151	0.212		0	1
Unable to work	1984-2010	4,206,151	0.048		0	1

Notes: Summary of observations without non-responses from the 1984-2010 waves of BRFSS.

Table 2. The 1987 and 2008-2009 stock market crashes, DJIA, and self-reported health and health behaviors

	Any binge drinking in 30 days	Ln # binge drinking events	Current smoker	Smokes every day	Any exercise activity	Poor physical health days	Poor mental health days	Health status (1 = Excellent, 5 = Poor)
Panel A. Stock market crash								
Stock market crash indicator	0.0017	0.0147*	0.0036***	0.0043***	-0.0015	-0.0208	0.0894***	0.0106***
	(0.0010)	(0.0086)	(0.0010)	(0.0009)	(0.0014)	(0.0322)	(0.0242)	(0.0035)
State unemployment rate	0.0003	-0.0041**	-0.0009*	-0.0007	-0.0008	-0.0036	0.0154	-0.0005
	(0.0005)	(0.0019)	(0.0004)	(0.0005)	(0.0010)	(0.0121)	(0.0133)	(0.0015)
State per capita income (1000s)	0.0000	-0.0031	0.0008	0.0001	-0.0035***	0.0109	0.0189	0.0034*
	(0.0008)	(0.0029)	(0.0005)	(0.0004)	(0.0009)	(0.0164)	(0.0208)	(0.0019)
Panel B. DJIA								
Ln average daily close, DJIA	-0.0105***	-0.0390*	-0.0061*	-0.0078***	-0.0001	-0.0680	-0.2502***	-0.0057
	(0.0024)	(0.0217)	(0.0032)	(0.0027)	(0.0048)	(0.0787)	(0.0661)	(0.0083)
State unemployment rate	0.0002	-0.0045**	-0.0009**	-0.0008*	-0.0008	-0.0049	0.0124	-0.0005
	(0.0005)	(0.0019)	(0.0004)	(0.0005)	(0.0010)	(0.0123)	(0.0137)	(0.0016)
State per capita income (1000s)	-0.0000	-0.0033	0.0008	0.0001	-0.0035***	0.0104	0.0179	0.0034*
	(0.0008)	(0.0028)	(0.0005)	(0.0004)	(0.0009)	(0.0164)	(0.0209)	(0.0019)
Panel C. DJIA monthly returns								
DJIA monthly return < -10%	0.0002	0.0066	0.0014	0.0027***	0.0027*	0.0210	0.0868***	0.0054*
	(0.0010)	(0.0080)	(0.0010)	(0.0009)	(0.0015)	(0.0271)	(0.0283)	(0.0027)
DJIA monthly return > 10%	0.0032	0.0072	0.0004	0.0010	0.0041	-0.0544	-0.0191	-0.0103*
	(0.0022)	(0.0139)	(0.0025)	(0.0024)	(0.0028)	(0.0594)	(0.0721)	(0.0061)
State unemployment rate	0.0004	-0.0040**	-0.0008*	-0.0007	-0.0008	-0.0037	0.0167	-0.0004
	(0.0005)	(0.0019)	(0.0004)	(0.0005)	(0.0010)	(0.0123)	(0.0133)	(0.0015)
State per capita income (1000s)	0.0000	-0.0030	0.0008	0.0001	-0.0035***	0.0109	0.0194	0.0034*
	(0.0008)	(0.0029)	(0.0005)	(0.0004)	(0.0009)	(0.0164)	(0.0208)	(0.0019)
N	3,795,152	484,381	4,193,644	3,483,660	3,847,263	3,601,796	3,608,242	3,763,381
R-squared	0.099	0.056	0.085	0.077	0.102	0.186	0.094	0.250

Notes: The sample consists of the 1984-2010 survey waves of BRFSS. Each panel and column represents a separate regression. All models include controls for a respondent's demographics, income, employment, and indicators for year, month, state of residence as well as state-specific trends. Robust standard errors clustered by state of residence are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3. The 1987 and 2008-2009 stock market crashes, self-reported health and health behaviors, subgroups

	Age < 25	25 ≤ Age < 55	Male	College grad	Married	Income ≤ $35k	Employed	Retired
Panel A. Ln # binge drinking events in last 30 days								
Stock market crash indicator	0.0201	0.0104	0.0262**	0.0057	0.0108	0.0067	0.0089	0.0443
	(0.0313)	(0.0103)	(0.0117)	(0.0100)	(0.0108)	(0.0153)	(0.0085)	(0.0267)
N	61,826	339,337	308,677	151,698	240,074	200,754	319,935	36,525
R-squared	0.062	0.057	0.041	0.042	0.046	0.056	0.053	0.048
Panel B. Smokes every day								
Stock market crash indicator	-0.0019	0.0064***	0.0040**	0.0025**	0.0021**	0.0061***	0.0041***	0.0041**
	(0.0056)	(0.0013)	(0.0018)	(0.0011)	(0.0010)	(0.0018)	(0.0013)	(0.0016)
N	175,241	1,868,867	1,402,539	1,149,433	1,951,207	1,535,925	1,760,336	751,987
R-squared	0.094	0.101	0.080	0.025	0.065	0.080	0.076	0.046
Panel C. Poor mental health days in last 30 days								
Stock market crash indicator	-0.0522	0.1175***	0.1125***	0.0763**	0.1096***	0.0888**	0.0613**	0.0817**
	(0.1327)	(0.0300)	(0.0318)	(0.0301)	(0.0253)	(0.0414)	(0.0304)	(0.0392)
N	191,312	1,956,751	1,459,843	1,179,373	2,027,940	1,626,205	1,838,886	768,471
R-squared	0.033	0.112	0.090	0.067	0.074	0.105	0.032	0.021

Notes: The sample consists of the 1984-2010 survey waves of BRFSS. All models include controls for a respondent's demographics, income, employment, and indicators for year, month, state of residence as well as state-specific trends. Robust standard errors clustered by state of residence are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 4. Summary statistics, NHCPD 2004-2009 (*N* = 3,038,521)

	Mean	Std. Dev.	Min	Max
ABV (oz) > 0	0.285		0	1
ABV (oz)	12.530	37.974	0	3267.337
Cigarettes > 0	0.096		0	1
Cigarettes	33.126	154.649	0	8900
Female head present	0.897		0	1
Male head present	0.735		0	1
Female Age < 25	0.003		0	1
Female 25 ≤ Age < 55	0.472		0	1
Female 55 ≤ Age < 65	0.224		0	1
Female Age > 65	0.199		0	1
Male Age < 25	0.001		0	1
Male 25 ≤ Age < 55	0.377		0	1
Male 55 ≤ Age < 65	0.185		0	1
Male Age > 65	0.171		0	1
Female < H.S. grad	0.028		0	1
Female < college grad	0.524		0	1
Female college grad	0.345		0	1
Male < H.S. grad	0.040		0	1
Male < college grad	0.398		0	1
Male college grad	0.296		0	1
Household race white	0.828		0	1
Household race black	0.097		0	1
Household race oriental	0.026		0	1
Household race other	0.049		0	1
Household Hispanic	0.942		0	1
Household married	0.595		0	1
Household widowed	0.090		0	1
Household divorced/separated	0.155		0	1
Household single	0.161		0	1
Household income < $30k	0.240		0	1
$30k ≤ Household income < $60k	0.370		0	1
Household income ≥ $60k	0.390		0	1
Female employ hrs < 30	0.108		0	1
30 ≤ Female employ hrs < 35	0.045		0	1
Female employ hrs ≥ 35	0.373		0	1
Female not employed	0.371		0	1
Male employ hrs < 30	0.035		0	1
30 ≤ Male employ hrs < 35	0.019		0	1
Male employ hrs ≥ 35	0.453		0	1
Male not employed	0.227		0	1

Table 5. The 2008-2009 stock market crash, DJIA, and monthly alcohol purchases

Panel A. Alcohol purchases	*Any*			*Ln oz (ABV)*		
Stock market crash indicator	0.0013*			0.0103***		
	(0.0008)			(0.0036)		
Ln average daily close, DJIA		-0.0067**			-0.0281**	
		(0.0026)			(0.0119)	
DJIA monthly return < -10%			0.0010			0.0004
			(0.0009)			(0.0044)
State unemployment rate	-0.0021***	-0.0022***	-0.0021***	-0.0104***	-0.0109***	-0.0101***
	(0.0004)	(0.0005)	(0.0004)	(0.0021)	(0.0021)	(0.0021)
State per capita income (1000s)	-0.0002	-0.0002	-0.0002	-0.0045*	-0.0047**	-0.0049**
	(0.0005)	(0.0005)	(0.0005)	(0.0023)	(0.0023)	(0.0023)
N	3,038,521	3,038,521	3,038,521	865,558	865,558	865,558
R-squared^	0.009	0.009	0.009	0.008	0.008	0.008
Panel B. Cigarette purchases	*Any*			*Ln quantity*		
Stock market crash indicator	0.0021***			0.0513***		
	(0.0005)			(0.0072)		
Ln average daily close, DJIA		-0.0027*			-0.0745***	
		(0.0016)			(0.0241)	
DJIA monthly return < -10%			0.0007			0.0180**
			(0.0005)			(0.0073)
State unemployment rate	0.0014***	0.0013***	0.0014***	0.0001	-0.0012	0.0009
	(0.0003)	(0.0003)	(0.0003)	(0.0044)	(0.0046)	(0.0044)
State per capita income (1000s)	0.0009**	0.0008**	0.0008**	0.0158***	0.0143***	0.0138***
	(0.0004)	(0.0004)	(0.0004)	(0.0052)	(0.0052)	(0.0051)
N	3,038,521	3,038,521	3,038,521	292,022	292,022	292,022
R-squared^	0.005	0.005	0.005	0.021	0.021	0.021

Notes: All models include controls for household demographics, income, employment, area-level characteristics as well as household fixed effects and indicators for year, month, and state of residence. Robust standard errors clustered by household are in parentheses.

^Estimates are generated using the XTREG command in Stata/MP 12.1, therefore reported R-squared values only reflect the amount of variation explained by the model after the inclusion of household fixed-effects.

*** p<0.01, ** p<0.05, * p<0.1

Table 6. The effects of the 2008-2009 stock market crash and changes in the Dow Jones Industrial Average (DJIA) on the natural log of monthly alcohol-related fatal accidents (ARFAs)

	(1)	(2)	(3)
2000-2009 Stock market crash indicator	0.0592***		
	(0.0174)		
Ln average monthly close, DJIA		-0.1299**	
		(0.0547)	
DJIA monthly return < -10%			0.0525***
			(0.0186)
State unemployment rate	-0.0296***	-0.0313***	-0.0287***
	(0.0102)	(0.0078)	(0.0078)
State per capita income (1000s)	-0.0004	-0.0004	-0.0004
	(0.0004)	(0.0004)	(0.0004)
N	4,712	4,712	4,712
R-squared	0.9300	0.9300	0.9300

Notes: All models include controls for gas taxes, beer taxes, blood alcohol content restrictions, vehicle miles traveled, state population, and non-alcohol-related fatal accident (NARFAs), as well as fixed effects for year, month, and state. Robust standard errors clustered by state are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 7. Robustness checks, FARS analysis

Panel A	State Time Trends	Logit	Negative Binomial	ARFA rate	BAC> 0.08
Stock market crash indicator	0.0582***	0.0649***	0.0573***	0.0246***	0.0629***
	(0.0174)	(0.0159)	(0.0156)	(0.0057)	(0.0179)
N	4,712	4,712	4,784	4,784	4,684
Panel B	State Time Trends	Logit	Negative Binomial	ARFA rate	BAC> 0.08
Ln average monthly close, DJIA	-0.1250**	-0.1355***	-0.1487***	-0.0463**	-0.1319**
	(0.0611)	(0.0498)	(0.0375)	(0.0180)	(0.0596)
N	4,712	4,712	4,784	4,784	4,684
Panel C	State Time Trends	Logit	Negative Binomial	ARFA rate	BAC> 0.08
DJIA monthly return < -10%	0.0529***	0.0525***	0.0352***	0.0173**	0.0746***
	(0.0188)	(0.0185)	(0.0132)	(0.0064)	(0.0190)
N	4,712	4,712	4,784	4,784	4,684

Notes: All models include controls for gas taxes, beer taxes, blood alcohol content restrictions, vehicle miles traveled, state population, and non-alcohol-related fatal accident (NARFAs), as well as fixed effects for year, month, and state. Robust standard errors clustered by state are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A1. The DJIA, self-reported health and health behaviors, subgroups

	Age < 25	25 ≤ Age < 55	Male	College grad	Married	Income ≤ $35k	Employed	Retired
Panel A. Ln # binge drinking events in last 30 days								
Ln average daily close, DJIA	-0.0677	-0.0307	-0.0350	-0.0235	-0.0298	-0.0078	-0.0266	-0.0277
	(0.0514)	(0.0279)	(0.0289)	(0.0274)	(0.0315)	(0.0350)	(0.0246)	(0.0687)
N	61,826	339,337	308,677	151,698	240,074	200,754	319,935	36,525
R-squared	0.062	0.057	0.041	0.042	0.046	0.056	0.053	0.048
Panel B. Smokes every day								
Ln average daily close, DJIA	0.0157	-0.0128***	-0.0080*	-0.0078**	-0.0041	-0.0088*	-0.0108***	-0.0051
	(0.0137)	(0.0038)	(0.0043)	(0.0037)	(0.0034)	(0.0046)	(0.0039)	(0.0046)
N	175,241	1,868,867	1,402,539	1,149,433	1,951,207	1,535,925	1,760,336	751,987
R-squared	0.094	0.101	0.080	0.025	0.065	0.080	0.076	0.046
Panel C. Poor mental health days in last 30 days								
Ln average daily close, DJIA	0.2449	-0.3169***	-0.2976***	-0.2013***	-0.2641***	-0.2698**	-0.1721**	-0.2457**
	(0.3262)	(0.0727)	(0.0833)	(0.0751)	(0.0707)	(0.1207)	(0.0820)	(0.1181)
N	191,312	1,956,751	1,459,843	1,179,373	2,027,940	1,626,205	1,838,886	768,471
R-squared	0.033	0.112	0.090	0.067	0.074	0.105	0.032	0.021

Notes: The sample consists of the 1984-2010 survey waves of BRFSS. All models include controls for a respondent's demographics, income, employment, and indicators for year, month, state of residence as well as state-specific trends. Robust standard errors clustered by state of residence are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A2. DJIA returns, self-reported health and health behaviors, subgroups

	Age < 25	25 ≤ Age < 55	Male	College grad	Married	Income ≤ $35k	Employed	Retired
Panel A. Ln # binge drinking events in last 30 days								
DJIA monthly return < -10%	-0.0026	0.0058	0.0163	-0.0103	0.0149	0.0088	0.0019	0.0601**
	(0.0287)	(0.0082)	(0.0099)	(0.0123)	(0.0103)	(0.0131)	(0.0089)	(0.0263)
DJIA monthly return > 10%	0.0367	0.0017	-0.0017	0.0210	0.0265	-0.0118	0.0165	-0.0400
	(0.0314)	(0.0183)	(0.0166)	(0.0248)	(0.0180)	(0.0198)	(0.0178)	(0.0713)
N	61,826	339,337	308,677	151,698	240,074	200,754	319,935	36,525
R-squared	0.062	0.057	0.041	0.042	0.046	0.056	0.053	0.048
Panel B. Smokes every day								
DJIA monthly return < -10%	-0.0031	0.0033**	0.0013	0.0011	0.0017	0.0030*	0.0014	0.0022
	(0.0041)	(0.0015)	(0.0016)	(0.0013)	(0.0011)	(0.0018)	(0.0015)	(0.0020)
DJIA monthly return > 10%	-0.0029	0.0045	0.0033	0.0031	0.0017	0.0039	0.0027	-0.0056
	(0.0088)	(0.0033)	(0.0035)	(0.0035)	(0.0030)	(0.0035)	(0.0033)	(0.0044)
N	175,241	1,868,867	1,402,539	1,149,433	1,951,207	1,535,925	1,760,336	751,987
R-squared	0.094	0.101	0.080	0.025	0.065	0.080	0.076	0.046
Panel C. Poor mental health days in last 30 days								
DJIA monthly return < -10%	-0.0716	0.1299***	0.1292***	0.0795**	0.1109***	0.0522	0.0826**	0.0867*
	(0.1231)	(0.0350)	(0.0306)	(0.0325)	(0.0302)	(0.0507)	(0.0309)	(0.0455)
DJIA monthly return > 10%	0.1185	-0.0014	-0.0234	0.0687	0.0410	0.0039	-0.0080	-0.0147
	(0.2623)	(0.0860)	(0.0973)	(0.0885)	(0.0759)	(0.1198)	(0.0767)	(0.1225)
N	191,312	1,956,751	1,459,843	1,179,373	2,027,940	1,626,205	1,838,886	768,471
R-squared	0.033	0.112	0.090	0.067	0.074	0.105	0.032	0.021

Notes: The sample consists of the 1984-2010 survey waves of BRFSS. All models include controls for a respondent's demographics, income, employment, and indicators for year, month, state of residence as well as state-specific trends. Robust standard errors clustered by state of residence are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1