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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 macroeconomic determinants of health. Existing studies 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. We find that large, negative monthly DJIA returns, decreases in the level of the DJIA, and stock market crashes are widely associated with worsening self-reported mental health and more cigarette smoking, binge drinking, and fatal car accidents involving alcohol. These results are consistent with predictions from rational addiction models and have implications for research on the association between consumption and stock prices. Copyright © 2014 John Wiley & Sons, Ltd.

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1. INTRODUCTION

This article considers how health-related behaviors vary with the Dow Jones Industrial Average (DJIA). Although recent work has documented widespread negative psychological effects[1] of the 2008 stock market crash, including large declines in life evaluation (Deaton, 2011a), increased symptoms of depression and poor mental health (McInerney *et al*., 2012), and a spike in hospitalizations for psychological disorders (Engelberg and Parsons, 2013), there is no research on how risk-taking behavior that influences health outcomes responds to fluctuations in stock market indices.

For households that possess significant stock holdings—either through direct ownership or indirectly through retirement, mutual fund, and pension accounts—a large decline in stock prices could have a substantial effect on total wealth. For example, between 2007 and 2011, 54–65% of the US population owned stock (Gallup Inc., 2011). Thus, a large fraction of the population likely experienced a negative wealth shock during the 2008 stock market crash. Previous research has identified that population health generally improves when

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[1]Other studies have noted that precipitous stock market declines and increased stock market volatility are associated with increased risk negative physical health outcomes, as well, such as MI (Fiuzat *et al*., 2010; Ma *et al*., 2011).

the unemployment rate increases: all-cause mortality in developing countries tends to decrease[2], and this decline is concentrated in acute causes, for example, motor vehicle accidents and injuries, rather than slowly developing causes, such as cancer or kidney disease (Evans and Moore, 2012).[3] Moreover, numerous studies have shown that risky behaviors such as alcohol consumption (Ruhm, 1995; Ettner, 1997; Freeman, 1999; Ruhm and Black, 2002; Cotti *et al*., 2012), cigarette consumption (Ruhm, 2000, 2005; Charles and DeCicca, 2008), and drunk driving (Cotti and Tefft, 2011) are negatively related to the unemployment rate in the USA. These results suggest that health behavior may also improve in response to a negative wealth shock, for example, a decline in stock prices.

But, there are good reasons to believe that how individuals respond to changes in stock values will differ from their response to changes in the unemployment rate. First, if changes in the unemployment rate also capture changes in the real wage, the income shock resulting from a change in the wage rate also alters the marginal value of time. As demonstrated by Becker (1965), this type of labor market shock induces both income and substitution effects.[4] Hence, the negative relationship between the unemployment rate and deleterious health choices may result either because unhealthy behaviors are normal (income effect) or because they are relatively goods-intensive to produce (substitution effect).

Second, stock market indices are leading indicators of economic performance, whereas the unemployment rate is a lagging indicator (Stock and Watson, 1989). The capital asset pricing model predicts that 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 widespread economic distress. Research demonstrates that these signals reach a large share of the general population and are one of the principal sources of information that individuals use when forming their expectations of economic performance of the overall marketplace (Hester and Gibson, 2003; Goidel *et al*., 2010). Further, 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 economic expectations, we might anticipate important, widespread behavioral changes in health-related activities during stock market crashes or general fluctuations in the DJIA. Hence, stock indices may influence the behavior of non-stockholders, as well as stockholders.

Given the lack of research considering the effect of stock market outcomes on individual health behaviors, our primary empirical aim is to fill this gap in the existing literature. We focus our attention on two frequently studied risky health behaviors, alcohol consumption and smoking. Although other risky behaviors may be of interest for policy purposes, for example, seat-belt usage, illicit drug use, and unhealthy eating, information on alcohol and cigarette usage are available in many datasets, allowing us to validate results to ensure they are robust to self-reporting bias and measurement error. Using information from the Behavioral Risk Factor Surveillance System (BRFSS) between 1984 and 2010, we estimate the relationship between stock returns, that is, the DJIA, and smoking, alcohol consumption, and self-reported mental health—a potential channel through which returns influence behavior. We also investigate whether alcohol and cigarette purchasing effects are observable in the Nielsen Homescan Consumer Panel Dataset (NHCPD), a household-level panel of consumer purchase data. Further, we examine whether drunk-driving fatalities respond to stock returns using the Fatality Analysis Reporting System (FARS) data on automobile accidents. We also explore possible non-linearity in these relationships by considering whether behavioral changes depend upon large negative or positive monthly DJIA returns.

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

[3]An important exception to the countercyclical 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 and Dunn, 2012).

[4]Specifically, Becker (1965) demonstrates that an increase in the wage will cause substitution toward goods-intensive commodities, thereby overstating the true income effect for goods used in the production of goods-intensive household production activities and understating the true income effect for goods used in time-intensive production activities.

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The findings presented here therefore contribute to the literature in several ways. We present the first evidence, to our knowledge, identifying the responses of alcohol consumption, drunk-driving fatalities, and smoking to business cycle and stock market fluctuations separately. We confirm the observed relationships with the DJIA in several data sources and across multiple stock market crashes. In the process of studying these relationships, we also ground our approach by reproducing the association between (self-reported) mental health and stock returns identified in earlier studies. We extend their findings by showing that the relationship with mental health generalizes across multiple stock market crashes, therefore also contributing to the literature on the determinants of mental health.

In a preview of our results, we find that the relationship between health behaviors and stock returns is notably different from the relationship between health behaviors and other measures of macroeconomic performance employed by existing studies, for example, the unemployment rate. Specifically, 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. The negative association between stock returns and consumption of alcohol or cigarettes is confirmed by the household purchase data in the NHCPD. 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. As we will demonstrate, our findings are robust to the inclusion of controls for demographic characteristics (e.g., gender and 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. Collectively, these estimates are consistent with the idea that the general state of the stock market impacts individual's behavioral choices in meaningful ways, but in a way that is distinct from the relationship between the unemployment rate and health behaviors.

As an extension, we also explore possible explanations for why the relationship between stock market indices and health differs from the relationship between the unemployment rate and health. First, we consider whether our results linking stock market crashes to health-related behavior are driven by contemporaneous shocks to housing market values. We find no evidence that individuals who resided in states most affected by the housing market bubble that precipitated the 2008 financial crisis responded more strongly to the subsequent decline in stock prices than residents of other states. Second, we utilize the Survey of Consumer Finances (SCF) to impute the probability of stock ownership, as well as the predicted value of stock holdings, for our sample of BRFSS participants. We find limited evidence to suggest that the behavioral responses we document are correlated with stock ownership, but rather the observed behavioral changes are widespread across households types.

2. DATA

2.1. Macroeconomic performance indicators

To summarize stock market performance, we utilize the DJIA index, a market indicator constructed from the stock prices of 30 manufacturers of industrial and consumer goods. The DJIA is highly correlated with other broad stock market indices, for example, the NASDAQ and S&P500, and it is the most widely cited market index in newspapers, television, and the internet.[5] We consider two measures of the DJIA aggregated by month: the natural log of the monthly mean daily market closing index[6] and the monthly percent return between

[5]For a more complete summary of the Dow Jones Industrial Average (DJIA), see http://www.djaverages.com/index.cfm?go=industrial-overview (last accessed December 20, 2012).

[6]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.

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the first and last closes for each month. The data series was downloaded from the St. Louis Fed's FRED Economic Data web site.[7]

In addition to studying how health behaviors respond to changes in the US stock market for the entire sample period between 1984 and 2010, we also examine whether particularly sharp declines in the DJIA during the 1987 and 2008–2009 stock market crash periods (as defined in the succeeding text) influence consumption decisions.

To address other, potentially confounding measures of macroeconomic performance, we also include 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, US Department of Labor[8] and state-by-year personal per capita income data are from the US Department of Commerce Bureau of Economic Analysis, Regional Economic Accounts.[9]

2.2. Individual consumption behavior

In order to explore the response of individual consumption behavior to stock market changes and crashes, we first use data drawn from the BRFSS between 1984 and 2010. BRFSS is maintained by the Centers for Disease Control and Prevention to monitor health and related behavioral risks of the US population. The survey is collected by US 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. We study behaviors known to have implications for current and future health including cigarette smoking and binge drinking, and we also consider a self-reported measure of mental health.[10] Summary statistics for the risky health behaviors and covariates of interest are reported in Table I.

2.3. Household purchasing behavior

We use data from the NHCPD in order to test the robustness of the findings from the BRFSS analysis across datasets that have different strengths. First, the longitudinal 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 (because BRFSS is cross-sectional, comparisons were made across persons when analyzing those data). The Nielsen Corporation samples US 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 household purchases overtime, in this case alcohol and cigarettes, rather than self-reports of consumption across repeated cross-sections observed in the BRFSS. 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 II shows summary statistics for the NHCPD, which includes a rich set of household characteristics. Because 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 US population along some dimensions, for example, household heads under the age of 25 years or without a high school degree are under-represented. Because 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 estimated to be purchased by each household. To construct the ABV

[7]http://research.stlouisfed.org/fred2/series/DJIA/ (last accessed December 20, 2012).
[8]http://www.bls.gov/lau/home.htm (last accessed October 31, 2012).
[9]http://www.bea.gov/regional/index.htm (last accessed November 5, 2012).
[10]Not reported in the tables, we also considered measures of self-reported physical and overall health (well-being) as outcomes. The former yielded insignificant relationships with the DJIA, whereas the latter closely mirrored the results when estimating mental health associations.

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Table I. Summary, Behavioral Risk Factor Surveillance System 1984–2010

	Waves	*N*	Mean	Standard deviation	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
Poor mental health days in last 30 days	1993–2010	3,608,242	3.368	7.575	0	30
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 graduate	1984–2010	4,206,151	0.309		0	1
Some college	1984–2010	4,206,151	0.272		0	1
College Graduate	1984–2010	4,206,151	0.313		0	1
Married	1984–2010	4,206,151	0.558		0	1
Income \$10 k–\$15 k	1984–2010	4,206,151	0.070		0	1
Income \$15 k–\$20 k	1984–2010	4,206,151	0.087		0	1
Income \$20 k to \$25 k	1984–2010	4,206,151	0.105		0	1
Income \$25 k–\$35 k	1984–2010	4,206,151	0.147		0	1
Income \$35 k–\$50 k	1984–2010	4,206,151	0.171		0	1
Income >\$50 k	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 of 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

Summary of observations without non-responses from the 1984–2010 waves of Behavioral Risk Factor Surveillance System.

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 12.9% ABV, and liquor a content of 41.1% ABV (LaVallee and Yi, 2012) and sum total estimated ABV for each category. Results reported in the succeeding text are robust to reasonable adjustments of the ABV for alcohol subtypes.

In the analysis in the succeeding text, 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[11, 12] 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, US Department of Labor.[13]

2.4. Fatal motor vehicle accidents

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.

[11]http://taxfoundation.org/ (last accessed October 31, 2012).
[12]Because tax data were only available beginning in 2000, we did not include beer and cigarette taxes in the main Behavioral Risk Factor Surveillance System (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.
[13]http://www.bls.gov/cew/ (last accessed October 31, 2012).

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Table II. Summary statistics, Nielsen Homescan Consumer Panel Dataset 2004–2009 ($N = 3{,}038{,}521$)

	Mean	Standard Deviation	Min	Max
ABV (oz) > 0	0.285		0	1
ABV (oz)	11.530	34.853	0	3262.722
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 < high school graduate	0.028		0	1
Female < college graduate	0.524		0	1
Female college graduate	0.345		0	1
Male < high school graduate	0.040		0	1
Male < college graduate	0.398		0	1
Male college graduate	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 < \$30 k	0.240		0	1
\$30 k ≤ Household income < \$60 k	0.370		0	1
Household income ≥ \$60 k	0.390		0	1
Female employ hours < 30	0.108		0	1
30 ≤ Female employ hours < 35	0.045		0	1
Female employ hours ≥ 35	0.373		0	1
Female not employed	0.371		0	1
Male employ hours < 30	0.035		0	1
30 ≤ Male employ hours < 35	0.019		0	1
Male employ hours ≥ 35	0.453		0	1
Male not employed	0.227		0	1

ABV, alcohol by volume.

We link our stock market measures to data on fatal vehicle crashes obtained through the FARS of the National Highway Traffic Safety Administration 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 (ARFAs), hereafter].[14] By utilizing the FARS data, we aggregate counts of

[14]Although Federal law requires that blood alcohol content levels be obtained from every fatal crash, it is frequently not and can lead to bias. The National Highway Traffic Safety Administration (NHTSA) provides imputed measures of blood alcohol content 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, and so on. (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 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 (Villaveces, 2003), Hingson *et al.*, 2004; Cummings *et al.*, 2006; Cotti and Walker, 2010; Adams *et al.*, 2012). 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.

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

3. EMPIRICAL APPROACH

To investigate the role of stock market fluctuations on individual consumption of alcohol and cigarettes, mental health status, household consumption of alcohol and cigarettes, and fatal motor vehicle accidents, we estimate three primary models. First, our individual-level analysis is detailed as the following:

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

H_{ist} 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 health was reported to be poor. The primary variables of interest are represented by Ψ_t, which summarize the US 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 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 DJIA return was observed.[15] In other models, we define Ψ_t as the natural log of the DJIA index or the monthly return in theDJIA.

All specifications also include the following sets of covariates: M_{st} includes measures of contemporaneous macroeconomic conditions, for example, the state-level unemployment rate and per capita income:[16] X_{ist} contains individual-level demographic characteristics as reported in Table I; the vector τ_t consists of indicator variables for each year and month[17]; γ_s is a vector of indicator variables for state of residence; γ_s are state-specific linear time trends; β_0 is a constant coefficient; and ε_{ist} is the error term. All standard errors are clustered at the state level.

To investigate household purchasing behavior, we estimate versions of the following household fixed effects model:

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

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

[14]Although Federal law requires that blood alcohol content levels be obtained from every fatal crash, it is frequently not and can lead to bias. The National Highway Traffic Safety Administration (NHTSA) provides imputed measures of blood alcohol content 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, and so on. (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 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 (Villaveces, 2003), Hingson *et al.*, 2004; Cummings *et al.*, 2006; Cotti and Walker, 2010; Adams *et al.*, 2012). 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.

[15]This definition is qualitatively robust to modifications including delaying the definition of the crash by 1 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).

[16]We will demonstrate that results are robust to the exclusion of business cycle factors.

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

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δ_h. Third, the vector of area controls mentioned earlier (D_{st}) is now included.[18] 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 II, 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 because 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 *et al.* (2012) in using household-level clustering because 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.

Lastly, when investigating the role of market fluctuations on fatal motor vehicle accidents, our primary analysis employs a fixed-effects research design using the 50 US states (plus the District of Columbia):

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

Standard errors are clustered by state to allow for non-independence of observations (Bertrand *et al.*, 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. 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 (Ruhm, 1996; Dee, 1999).[19] Estimation of equation (3) will therefore be by weighted least squares, but we show later that using different estimating specifications or empirical methods yields nearly identical results.[20]

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-level and household-level analyses, state fixed effects (γ_s) capture differences in states that might affect accidents and are constant over time, whereas 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 because of economic activity, highway construction, weather patterns, insurance rates, number of drivers, age composition of drivers, and so on. We therefore include the number of accidents per county that were *not* ARFAs (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 the data, they should capture any differences in general accident risk that may arise between states during the sample period analyzed.

[18]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 convenience stores, as well as the corresponding number of employees in each industrial group).
[19]In our case utilizing a WLS approach yields the most efficient estimates.
[20]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 A6 in the online appendix .

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Several studies (Ruhm, 1995; Freeman, 1999; Dee, 2001; Cotti and Tefft, 2011; Cotti *et al*., 2014) 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 BAC limit in place in each state.

4. RESULTS

4.1. Individual consumption behavior

Because our aim is to isolate stock market effects independent of business cycle factors previously identified as influencing health behaviors, for example, the state unemployment rate and per capita personal income, 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 III 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 indicator for the 1987 and 2008–2009 stock market crashes is included as defined earlier. Overall, the results strongly suggest that individuals participate in riskier health behaviors and experience worse self-reported mental 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, 2011b; 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.

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 a more general measure of stock market performance. Panel B of Table III 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 III, 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 and a greater number of poor mental health days in months in which there is a large market decline. 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

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Table III. The 1987 and 2008–2009 stock market crashes, Dow Jones Industrial Average, and self-reported mental health and risky health behaviors

	Any binge drinking in 30 days	Ln # binge drinking events	Current smoker	Smokes every day	Poor mental health days
Panel A. Stock market crash					
Stock market crash indicator	0.0017	0.0147*	0.0036***	0.0043***	0.0894***
	(0.0010)	(0.0086)	(0.0010)	(0.0009)	(0.0242)
State unemployment rate	0.0003	−0.0041**	−0.0009*	−0.0007	0.0154
	(0.0005)	(0.0019)	(0.0004)	(0.0005)	(0.0133)
State per capita income (1000s)	0.0000	−0.0031	0.0008	0.0001	0.0189
	(0.0008)	(0.0029)	(0.0005)	(0.0004)	(0.0208)
Panel B. DJIA					
Ln average daily close, DJIA	−0.0105***	−0.0390*	−0.0061*	−0.0078***	−0.2502***
	(0.0024)	(0.0217)	(0.0032)	(0.0027)	(0.0661)
State unemployment rate	0.0002	−0.0045**	−0.0009**	−0.0008*	0.0124
	(0.0005)	(0.0019)	(0.0004)	(0.0005)	(0.0137)
State per capita income (1000s)	−0.0000	−0.0033	0.0008	0.0001	0.0179
	(0.0008)	(0.0028)	(0.0005)	(0.0004)	(0.0209)
Panel C. DJIA monthly returns					
DJIA monthly return $< -10\%$	0.0002	0.0066	0.0014	0.0027***	0.0868***
	(0.0010)	(0.0080)	(0.0010)	(0.0009)	(0.0283)
DJIA monthly return $> 10\%$	0.0032	0.0072	0.0004	0.0010	−0.0191
	(0.0022)	(0.0139)	(0.0025)	(0.0024)	(0.0721)
State unemployment rate	0.0004	−0.0040**	−0.0008*	−0.0007	0.0167
	(0.0005)	(0.0019)	(0.0004)	(0.0005)	(0.0133)
State per capita income (1000s)	0.0000	−0.0030	0.0008	0.0001	0.0194
	(0.0008)	(0.0029)	(0.0005)	(0.0004)	(0.0208)
N	3,795,152	484,381	4,193,644	3,483,660	3,608,242
R-squared	0.099	0.056	0.085	0.077	0.094

The sample consists of the 1984–2010 survey waves of Behavioral Risk Factor Surveillance System. 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 the state of residence are in parentheses.
DJIA, Dow Jones Industrial Average; Ln, Natural log.
$^{***}p < 0.01$. $^{**}p < 0.05$. $^{*}p < 0.1$.

less than 10%.[21] This offers 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 primary BRFSS analysis, we explore the robustness of the aforementioned results to reasonable changes in sample definition and empirical specification. First, although our primary analysis incorporates two different stock market crashes (1987 and 2008–2009), we might expect that the impacts differ given the nature of each crash. In particular, in the 1987 crash, the DJIA declined by more than 20% in 1 day and remained depressed for several weeks, whereas the 2008–2009 crash was larger (more than 40% in total) and the decline extended over a longer period (5 months) before stability in stock prices returned. Hence, we might expect a larger impact of the 2008–2009 recession. To investigate, we isolate the two crashes, and, although the crash estimates are not statistically different from each other, the impact of the 2008–2009 crash is more identifiable, as results are estimated with greater precision (see Tables A1 and A2 in the online appendix for more details).

Next, although controlling for business cycle effects in our model is imperative to separately identify the behavioral response of the stock market fluctuations from business cycle fluctuations, we do test the sensitivity of our results to the exclusion of the business cycle controls (state unemployment and per capita personal income)

[21]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.

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from the model. The results are very similar, demonstrating that the conditional stock market effects are relatively independent of the business cycle (see Table A3 in the online appendix for more details).[22]

Finally, we investigate the sensitivity of some of our empirical choices. We have been using a linear specification for our baseline estimates, so we re-estimate our primary results using probit and ordered probit methods (depending on which is appropriate). The results are robust to specification. Also, given that stock market fluctuations occur at the national level, it may not be appropriate to assume that errors are independent across states. There is no meaningful change in statistical significance or interpretation when standard errors are clustered at the year level. See Tables A4 and A5 in the online appendix for more details.

4.2. Household purchasing behavior

The full set of results for the NHCPD analysis is reported in Table IV. 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 such as 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.

4.3. Fatal motor vehicle accidents

In the first column of Table V, 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%. Because 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 (Ruhm, 1995; Cotti and Tefft, 2011), 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

[22]This is not surprising given that in the BRFSS estimation sample, the state-by-month unemployment rate is somewhat weakly contemporaneously correlated with the natural log daily average DJIA close, the stock market crash indicator, and the indicator for DJIA monthly return less than −10% (correlation coefficients of −0.25, 0.14, and 0.01, respectively).

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Table IV. The 2008–2009 stock market crash, Dow Jones Industrial Average, and monthly alcohol and cigarette purchases

Panel A. alcohol purchases		Any			Ln oz (alcohol by volume)	
Stock market crash indicator	0.0013*			0.0104***		
	(0.0008)			(0.0036)		
Ln average daily close, DJIA		−0.0067**			−0.0285**	
		(0.0026)			(0.0118)	
DJIA monthly return < −10%			0.0010			0.0006
			(0.0009)			(0.0044)
State unemployment rate	−0.0021***	−0.0022***	−0.0021***	−0.0104***	−0.0110***	−0.0102***
	(0.0004)	(0.0005)	(0.0004)	(0.0020)	(0.0021)	(0.0020)
State per capita income (1000 s)	−0.0002	−0.0002	−0.0002	−0.0046**	−0.0048**	−0.0050**
	(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

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.
DJIA, Dow Jones Industrial Average.
^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 V. The effects of the 2008–2009 stock market crash and changes in the Dow Jones Industrial Average on the natural log of monthly alcohol-related fatal accidents

	(1)	(2)	(3)
2008–2009 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	4712	4712	4712
R-squared	0.93	0.93	0.93

All models include controls for gas taxes, beer taxes, blood alcohol content restrictions, vehicle miles traveled, state population, and non-alcohol-related fatal accidents, as well as fixed effects for year, month, and state. Robust standard errors clustered by state are in parentheses.
DJIA, Dow Jones Industrial Average.
*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

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 −10%. Results are similar to the stock market crash estimates found in the first column. Although 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 period.

If the estimated increases in ARFAs shown in Table V 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 V with the natural log of NARFAs as the left-hand side (LHS) variable (and excluded from the right-hand side (RHS)). Results show no meaningful effect of either the stock market crash (coefficient = −0.0137, SE = 0.0158), changes in the log of the DJIA close (coefficient = −0.0438, SE = 0.0401), or large declines in DJIA returns (coefficient. = 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 independent of how much they decide to drink, which might explain why changes in consumption or purchase behavior are only meaningfully impacted by large persistent losses in market value (crashes) or generally low market levels. In Section 5, we discuss mechanisms that 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.

We test several alternative approaches to verify the robustness of this analysis (see Table A6 in the online appendix for more details). First, earlier drunk-driving research (Dee, 1999) has demonstrated that the omission of state-level trends may bias the results. Although the measures of VMT and NARFAs should capture any general trends in a state's traffic safety, we re-estimate equation (3) but also add state-specific trends. Their inclusion does not alter the main results. Next, although the primary analysis employs a weighted least squares

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regression model, a logit or negative binominal approach, among others, is equally viable. Results are not sensitive to the functional form selected.[23]

We also test the sensitivity of our findings to including state-months in which zero ARFAs occur. The negative binomial model results, and the results when replacing the log of ARFAs with the ARFA rate per 100,000 persons, suggest that the loss of the zero ARFA months does not impact our findings. Lastly, we test for the robustness of the estimates to the choice of dependent variable. First, we restrict to the log of the number of fatal accidents involving any alcohol. Next, we define it 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 USA. The results are robust to these definitions.

5. MECHANISM INVESTIGATION

The findings reported thus far reveal that the relationship between stock market returns and risky health behaviors is nearly the opposite of that documented for the unemployment rate. Although the latter generally points to a countercyclical relationship, lower stock prices tend to be associated with worse mental health and an increase in risky health behaviors. In this section, we explore two possible explanations for these findings. First, we consider whether the stock market is simply capturing changes in the housing market. Second, we examine whether the relationship between stock market performance and health behaviors is concentrated among individuals most likely to own stock.

5.1. Housing market versus stock market

The 2008 stock market crash was closely linked to the preceding collapse of the real estate market. To address potential concerns that the results reported previously are driven by changes in home-ownership and housing values rather than stock market performance, we evaluate whether individuals living in states most affected by the housing market crisis responded differently to the subsequent stock market crash. Following Currie and Tekin (2011), we identify the following states as housing market bubble states in the recent foreclosure crisis: Arizona, California, Florida, Nevada, and New Jersey. Table VI presents the main stock market crash results with the addition of an indicator for these bubble states and its interaction with the stock market crash variable. The primary results remain mostly unaffected with the exception of mixed changes in the binge drinking effects. In particular, the introduction of the interaction weakens the intensive margin effect but strengthens the extensive margin effect.

5.2. Stockholders versus non-stockholders

In order to explore whether these relationships are present only for stockholders or for a broader segment of the population, we calculated predicted probabilities of holding stock and expected portfolio values conditional on holding stock for BRFSS respondents using the 2007 cross-section SCF (Board of Governors of the Federal Reserve System, 2013). Specifically, we regressed a dichotomous measure of any stock holdings (probit model), reported as stocks or stock mutual funds, and the natural log of the total dollar value of stock holdings (linear model), on SCF variables that could be mapped to the BRFSS analysis control variables. These include measures of sex, age, education, race/ethnicity, marital status, employment status, and income. For each BRFSS respondent between 2007 and 2009, we predicted whether the respondent owned stock and the natural log of the portfolio value conditional on positive predicted stock holdings using the estimated model. The 2007 SCF model was assumed to be representative of stock holdings among the population prior to the 2008–2009 stock market crash.

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

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Table VI. The 1987 and 2008–2009 stock market crashes, Dow Jones Industrial Average, and self-reported health and health behaviors, housing market bubble states

	Any binge drinking in 30 days	Ln # binge drinking events	Current smoker	Smokes every day	Poor mental health days
Panel A. Stock market crash					
Stock market crash indicator	0.0019*	0.0111	0.0029**	0.0040***	0.0764***
	(0.0010)	(0.0091)	(0.0011)	(0.0009)	(0.0239)
Housing market bubble state	−1.4062***	1.6521	4.9074***	0.5373***	71.9162***
	(0.4134)	(1.5681)	(0.2209)	(0.1887)	(8.8007)
Interaction effect	−0.0022	0.0313*	0.0057	0.0021	0.1076
	(0.0030)	(0.0171)	(0.0036)	(0.0031)	(0.0725)
State unemployment rate	0.0003	−0.0041**	−0.0009*	−0.0007	0.0152
	(0.0005)	(0.0019)	(0.0004)	(0.0005)	(0.0133)
State per capita income (1000s)	0.0000	−0.0031	0.0008	0.0001	0.0193
	(0.0008)	(0.0029)	(0.0005)	(0.0004)	(0.0209)
N	3,857,425	490,690	4,264,011	3,554,027	3,671,777
R-squared	0.099	0.056	0.085	0.077	0.094

The sample consists of the 1984–2010 survey waves of Behavioral Risk Factor Surveillance System. 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. Arizona, California, Florida, Nevada, and New Jersey are coded as housing market bubble states. Robust standard errors clustered by the state of residence are in parentheses.
***$p<0.01$. **$p<0.05$. *$p<0.1$.

Results from an analysis of whether stockholders were more likely to report the observed changes in health status and risky health behaviors during the 2008–2009 market crash are reported in Table VII. The stock market crash indicator effects remain largely unchanged. In addition, holding stocks and a higher stock portfolio value are associated with less binge drinking, more smoking, and worse mental health. The interaction effects show mixed evidence that stockholders responded differently to stock market crashes than the respondents who did not own stock. On the extensive margin, owning stock reinforced the crash effects, but this was only statistically significant for the quantity of binge drinking events. In contrast, on the intensive margin holding a larger stock portfolio tended to mitigate the stock market crash effect, significantly for binge drinking.

Imputation issues aside, these results do not demonstrate that responses to the stock market crash were restricted to stockholders, which supports the notion discussed earlier that as a leading indicator of economic activity, a stock market crash can have effects that are widely shared among the population. If there was any additional effect among stockholders, the signs of the coefficients suggest that holding stocks reinforced the stock market crash responses except among respondents with large portfolio values. One potential explanation for this exception is that holding large initial wealth may not materially affect alcohol or cigarette purchasing behavior and is protective against adverse mental health changes. Alternatively, individuals with large stock holdings may possess a greater level of financial literacy, and therefore view short-term variability in stock values, even extreme declines, as 'paper losses' that are an inevitable eventuality.

6. 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. Further, we find that these relationships vary little with attributes associated with stock ownership and are consistent across three different data sets.

These findings stand in stark contrast from previous research on macroeconomic conditions and health. Moreover, the finding that self-reported mental health and well-being worsen during market crashes is consistent with research specifically studying the crash of 2008–2009 (Deaton, 2011b; McInerney *et al*., 2012) and is

Table VII. Behavioral Risk Factor Surveillance System stock market crash effects interacted with imputed stock holdings from the 2007 Survey of Consumer Finances

	Any binge drinking in 30 days	Ln # binge drinking events	Current smoker	Smokes every day	Poor mental health days
Panel A. Imputed probability of holding any stock					
Stock market crash indicator	0.0015	0.0039	0.0036***	0.0037***	0.0977***
	(0.0010)	(0.0106)	(0.0012)	(0.0010)	(0.0329)
Probability of stock holdings	−0.0055***	−0.0842***	0.0150***	0.0125***	0.1501***
	(0.0016)	(0.0109)	(0.0034)	(0.0031)	(0.0348)
Interaction effect	0.0037	0.0249*	0.0003	0.0007	0.0098
	(0.0022)	(0.0147)	(0.0018)	(0.0016)	(0.0376)
N	1,042,735	124,846	1,061,772	1,061,772	1,052,873
R-squared	0.079	0.054	0.091	0.075	0.107
Panel B. Imputed ln value of stock holdings, conditional on holding stock					
Stock market crash indicator	0.0590**	0.0657	0.0237	0.0154	−0.1169
	(0.0229)	(0.1409)	(0.0153)	(0.0132)	(0.2874)
Ln stock portfolio value	−0.1880***	−0.1294	0.1352***	0.1363***	0.6302***
	(0.0166)	(0.1054)	(0.0093)	(0.0088)	(0.1614)
Interaction effect	−0.0044**	−0.0022	−0.0016	−0.0010	0.0172
	(0.0018)	(0.0122)	(0.0012)	(0.0010)	(0.0227)
N	203,301	25,627	206,038	206,038	205,555
R-squared	0.077	0.028	0.020	0.015	0.026

The sample consists of the 2007–2009 survey waves of Behavioral Risk Factor Surveillance System with imputed stock holdings using the 2007 Survey of Consumer Finances. Each panel and column represents a separate regression. All models include controls for state unemployment rate and per capita income, 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 the state of residence are in parentheses.
$^{***}p < 0.01$. $^{**}p < 0.05$. $^{*}p < 0.1$.

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 (Ruhm and Black, 2002; Ruhm, 2005; Colman and Dave, 2011; Cotti and Tefft, 2011). 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 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 *et al*. (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, these findings are consistent with stock market downturns having a relatively small net income effect. As a result, the usual explanation given for

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the observance of a negative relationship between health and the unemployment rate may simply be less salient during stock market fluctuations. Additionally, because 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 and 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 and Mooney, 1983; Catalano and Dooley, 1983). Although subsequent research found less evidence to support this hypothesis when proxying for economic conditions with state-level unemployment rates (Ruhm, 1995, 2005), the evidence presented here is consistent with the possibility that stress about economic conditions drives 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 (Lucas, 1978; Breeden, 1979). However, researchers have encountered difficulties generating supporting evidence for the CCAPM to the point where the 'equity premium puzzle' (Mehra and 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.

CONFLICT OF INTEREST

The authors have no conflict of interest.

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REFERENCES

Adams S, Blackburn ML, Cotti C. 2012. Minimum wages and alcohol-related traffic fatalities among teens. *The Review of Economics and Statistics* **94**: 828–840. Available from: http://ideas.repec.org/a/tpr/restat/v94y2012i3p828-840.html. [accessed April 29, 2014].

Becker GS. 2007. Health as human capital: synthesis and extensions. *Oxford Economic Papers* **59**: 379–410. Available from: http://oep.oxfordjournals.org/content/59/3/379.short.

Becker GS, Murphy KM. 1988. A theory of rational addiction. *Journal of Political Economy* **96**: 675–700. Available from: http://www.jstor.org/stable/1830469.

Becker GS. 1965. A theory of the allocation of time. *The Economic Journal* **75**: 493–517.

Bertrand M, Duflo E, Mullainathan S. 2004. How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics* **119**: 249–275. Available from: http://qje.oxfordjournals.org/content/119/1/249.abstract.

Board of Governors of the Federal Reserve System. 2013. Survey of consumer finances. Available from: http://www.federalreserve.gov/econresdata/scf/scf_2007.htm.

Breeden DT. 1979. An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics* **7**: 265–296.

Brenner MH, Mooney A. 1983. Unemployment and health in the context of economic change. *Social Science & Medicine* **17**: 1125–1138.

Catalano R, Dooley D. 1983. Health effects of economic instability: a test of economic stress hypothesis. *Journal of Health and Social Behavior* **24**: 46–60.

Charles KK, DeCicca P. 2008. Local labor market fluctuations and health: is there a connection and for whom? *Journal of Health Economics* **27**: 1532–1550. Available from: http://www.sciencedirect.com/science/article/pii/S0167629608000817.

Classen TJ, Dunn RA. 2012. The effect of job loss and unemployment duration on suicide risk in the United States: a new look using mass-layoffs and unemployment duration. *Health Economics* **21**: 338–350. DOI: 10.1002/hec.1719.

Colman GJ, Dave DM. 2011. Exercise, physical activity, and exertion over the business cycle. National Bureau of Economic Research Working Paper Series No. 17406. Available from: http://www.nber.org/papers/w17406.

Cotti C, Walker DM. 2010. The impact of casinos on fatal alcohol-related traffic accidents in the United States. *Journal of Health Economics* **29**: 788–796. Available from: http://www.sciencedirect.com/science/article/pii/S0167629610001013.

Cotti C, Tefft N. 2011. Decomposing the relationship between macroeconomic conditions and fatal car crashes during the great recession: alcohol- and non-alcohol-related accidents. *The B.E. Journal of Economic Analysis & Policy* **11**. Available from: http://www.degruyter.com/view/j/bejeap.2011.11.issue-1/bejeap.2011.11.1.2860/bejeap.2011.11.1.2860.xml.

Cotti C, Dunn RA, Tefft N. 2012. Alcohol purchases and the business cycle: evidence from the Nielsen homescan panel data. DOI: 10.2139/ssrn.2184415.

Cotti C, Dunn RA, Tefft N. 2014. Alcohol-impaired motor vehicle crash risk and the location of alcohol purchase. *Social Science & Medicine* DOI: 10.1016/j.socscimed.2014.03.003.

Cummings P, Rivara FP, Olson CM, Smith KM. 2006. Changes in traffic crash mortality rates attributed to use of alcohol, or lack of a seat belt, air bag, motorcycle helmet, or bicycle helmet, United States, 1982–2001. *Injury Prevention* **12**: 148–154. Available from: http://injuryprevention.bmj.com/content/12/3/148.abstract.

Currie J, Tekin E. 2011. Is there a link between foreclosure and health? National Bureau of Economic Research Working Paper Series No. 17310. Available from: http://www.nber.org/papers/w17310.

Deaton AS. 2011a. The financial crisis and the well-being of Americans. National Bureau of Economic Research Working Paper Series No. 17128. Available from: http://www.nber.org/papers/w17128.

Deaton AS. 2011b. The financial crisis and the well-being of Americans: 2011 OEP Hicks Lecture. Oxford Economic Papers. Available from: http://oep.oxfordjournals.org/content/early/2011/11/02/oep.gpr051.abstract.

Dee TS. 1999. State alcohol policies, teen drinking and traffic fatalities. *Journal of Public Economics* **72**: 289–315. Available from: http://www.sciencedirect.com/science/article/pii/S0047272798000930.

Dee TS. 2001. Alcohol abuse and economic conditions: evidence from repeated cross-sections of individual-level data. *Health Economics* **10**: 257–270. DOI: 10.1002/hec.588.

Engelberg J, Parsons C. 2013. Can the stock market make you sick? San Diego, CA.

Ettner SL. 1997. Measuring the human cost of a weak economy: does unemployment lead to alcohol abuse? *Social Science & Medicine* **44**: 251–260. Available from: http://www.sciencedirect.com/science/article/pii/S0277953696001608.

Evans WN, Moore TJ. 2012. Liquidity, Economic Activity, and Mortality. *Review of Economics and Statistics* **94**: 400–418. DOI: 10.1162/REST_a_00184.

Fiuzat M, Shaw LK, Thomas L, Felker GM, O'Connor CM. 2010. United States stock market performance and acute myocardial infarction rates in 2008–2009 (from the Duke Databank for Cardiovascular Disease). *The American Journal of Cardiology* **106**: 1545–1549. Available from: http://www.sciencedirect.com/science/article/pii/S0002914910014979.

Freeman DG. 1999. A note on `Economic conditions and alcohol problems'. *Journal of Health Economics* **18**: 661–670. Available from: http://www.sciencedirect.com/science/article/pii/S0167629699000053.

Gallup Inc. 2011. In U.S., 54% have stock market investments, lowest since 1999. Available from: http://www.gallup.com/poll/147206/stock-market-investments-lowest-1999.aspx.
Goidel K, Procopio S, Terrell D, Wu HD. 2010. Sources of Economic News and Economic Expectations. *American Politics Research* **38**: 759–777. Available from: http://apr.sagepub.com/content/38/4/759.abstract.
Hester JB, Gibson R. 2003. The economy and second-level agenda setting: a time-series analysis of economic news and public opinion about the economy. *Journalism & Mass Communication Quarterly* **80**: 73–90. Available from: http://jmq.sagepub.com/content/80/1/73.abstract.
Hingson R, Heeren T, Winter M, Wechsler H. 2004. Magnitude of alcohol-related mortality and morbidity among U.S. college students ages 18–24: changes from 1998 to 2001. *Annual Review of Public Health* **26**: 259–279. DOI: 10.1146/annurev.publhealth.26.021304.144652.
Klein T. 1986. A Method for Estimating Posterior Bac Distributions for Persons Involved in Fatal Traffic Accidents. Available from: Available from: http://trid.trb.org/view.aspx?id=310222.
Krüger NA, Svensson M. 2008. Good times are drinking times: empirical evidence on business cycles and alcohol sales in Sweden 1861–2000. *Applied Economics Letters* **17**: 543–546. DOI: 10.1080/13504850802167215.
LaVallee RA, Yi H. 2012. Surveillance Report #95: Apparent Per Capita Alcohol Consumption: National, State, and Regional Trends, 1977–2010, Bethesda, MD.
Levitt S, Porter J. 2001. How dangerous are drinking drivers? *Journal of Political Economy* **109**: 1198–1237. Available from: http://www.jstor.org/stable/10.1086/323281.
Lucas RE, Jr. 1978. Asset prices in an exchange economy. *Econometrica* **46**: 1429–1445. Available from: http://www.jstor.org/stable/1913837.
Ma W, Chen H, Jiang L, Song G, Kan H. 2011. Stock volatility as a risk factor for coronary heart disease death. *European Heart Journal* **32**: 1006–1011. Available from: http://eurheartj.oxfordjournals.org/content/32/8/1006.abstract.
McInerney M, Mellor J, Nicholas LH. 2012. Recession depression: physical and mental health effects of the 2008 stock market crash. College of William and Mary Working Paper.
Mehra R, Prescott EC. 1985. The equity premium: a puzzle. *Journal of Monetary Economics* **15**: 145–161.
Neumayer E. 2004. Recessions lower (some) mortality rates: evidence from Germany. *Social Science & Medicine* **58**: 1037–1047. Available from: http://www.sciencedirect.com/science/article/pii/S0277953603002764.
NHTSA. 2002. Transitioning to multiple imputation –a new method to impute missing blood alcohol concentration (BAC) values in FARS.
Rubin D, Shafer J, Subramanian R. 1998. Multiple imputation of missing blood alcohol concentration (BAC) values in FARS.
Ruhm CJ. 1995. Economic conditions and alcohol problems. *Journal of Health Economics* **14**: 583–603. Available from: http://www.sciencedirect.com/science/article/pii/0167629695000240.
Ruhm CJ. 1996. Alcohol policies and highway vehicle fatalities. *Journal of Health Economics* **15**: 435–454. Available from: http://www.sciencedirect.com/science/article/pii/S0167629696004900.
Ruhm CJ. 2000. Are recessions good for your health? *The Quarterly Journal of Economics* **115**: 617–650. Available from: http://qje.oxfordjournals.org/content/115/2/617.abstract.
Ruhm CJ. 2005. Healthy living in hard times. *Journal of Health Economics* **24**: 341–363. Available from: http://www.sciencedirect.com/science/article/pii/S0167629604001250.
Ruhm CJ, Black WE. 2002. Does drinking really decrease in bad times? *Journal of Health Economics* **21**: 659–678. Available from: http://www.sciencedirect.com/science/article/pii/S0167629602000334.
Stock JH, Watson MW. 1989. New indexes of coincident and leading economic indicators. In NBER Macroeconomics Annual, vol. **4**. MIT Press: Cambridge, MA; 351–409.
Tapia Granados J. 2005. Recessions and mortality in Spain, 1980–1997. *European Journal of Population/ Revue Européenne de Démographie* **21**: 393–422 LA – English. DOI: 10.1007/s10680-005-4767-9.
Tefft N. 2011. Insights on unemployment, unemployment insurance, and mental health. *Journal of Health Economics* **30**: 258–264. Available from: http://www.sciencedirect.com/science/article/pii/S0167629611000129.
Villaveces A. 2003. Association of alcohol-related laws with deaths due to motor vehicle and motorcycle crashes in the United States, 1980–1997. *American Journal of Epidemiology* **157**: 131–140. Available from: http://aje.oxfordjournals.org/cgi/content/abstract/157/2/131.

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