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When the market drives you crazy: Stock market returns and fatal car accidents[*]

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Abstract

This paper provides evidence that daily fluctuations in the stock market have important– and hitherto neglected–spillover effects on fatal car accidents. Using the universe of fatal car accidents in the United States from 1990 to 2015, we find that a one standard deviation reduction in daily stock market returns is associated with a 0.6% increase in fatal car accidents that happen after the stock market opening. A battery of falsification tests support a causal interpretation of this finding. Our results are consistent with immediate emotions stirred by a negative stock market performance influencing the number of fatal accidents, in particular among inexperienced investors.

JEL Codes: D91, R41, G41, I12

Keywords: stock market, car accidents, emotions

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1 Introduction

One in two households in the US invest in the stock market directly or indirectly through ownership of mutual and pension funds (Christelis et al., 2013; Guiso and Sodini, 2013). It is well known that stock market performance influences some of the most fundamental economic decisions of investors, such as consumption, saving, and labor supply, through the financial wealth channel (Poterba, 2000). This paper provides evidence that daily fluctuations in the stock market have important–and hitherto neglected–spillover effects in another, unrelated domain of human behavior. Using the universe of fatal road car accidents in the United States from 1990 to 2015, we show that stock market returns influence the number of daily fatal accidents that took place over this period. In particular, we find that a one standard deviation reduction in daily stock market returns increases the number of fatal accidents that happen after the opening of the stock market by 0.6%. This result is robust to a number of falsification tests and is consistent with immediate emotions stirred by stock market fluctuations being the mechanism behind it. Our result thus highlights the broader economic and social consequences of stock market fluctuations.

Research in psychology and behavioral economics has shown that emotional and personality factors influence economic behavior and decision-making in general (Loewenstein, 2000; Lerner et al., 2004, 2015), including decision-making under risk (Loewenstein et al., 2001; Lerner and Keltner, 2001; Bassi et al., 2013; Cohn et al., 2015; Conte et al., 2016). Building on this evidence, we posit that the psychological distress (e.g., anxiety, anger, frustration) caused by negative stock market returns can make investors more prone to driving errors and lapses. Indeed, research in driving behavior and accident involvement has highlighted the important role of the human factor and the emotional state of the driver, with a particular emphasis on the causal influence of emotions such as anger, anxiety and sadness on driving performance (Elander et al., 1993; Garrity and Demick, 2001; Pêcher et al., 2009; Dula et al., 2010). Beyond emotions, previous literature has also examined the role of various road traffic safety programs and regulations–such as, taxes on alcohol and minimum legal drinking ages, smoking bans, minimum wage laws, mandatory seat belt laws and laws prohibiting text messaging–on driving behavior and traffic fatalities (Ruhm, 1996; Dee, 1999; Baughman et al., 2001; Levitt and Porter, 2001; Cohen and Einav, 2003; Adams and

Cotti, 2008; Adams et al., 2012; Abouk and Adams, 2013).[1]

Why do we focus on driving accidents? Driving is an activity that the vast majority of the adult population engages in daily for a considerable amount of time.[2] Therefore, it presents a context that allows for identification of the effect of high-frequency (daily) movements of the stock market on an activity that concerns a broad segment of the population. Furthermore, road accidents are a major public health issue. Indeed, they are a leading cause of mortality: the World Health Organization reports that road accidents claim more than 1.2 million lives each year rendering them the ninth leading cause of death across all age groups globally (World Health Organization, 2015). In the US, motor vehicle accidents were ranked 13^{th} overall as a cause of death in 2014, and were the leading cause of death for those aged 16 to 25 (Webb, 2016). In terms of economic impact, in 2010 the total economic costs of crashes in the US is estimated to have reached \$242 billion (Blincoe et al., 2015). Therefore, car accidents provide an ideal setting to examine the effect of stock market fluctuations on behavior in a different domain that has high-stakes consequences.

In our empirical analysis, we merge data from the Fatality Analysis Reporting System (FARS)– a nationwide census of fatal traffic crashes in the US–with financial data (S&P 500 and other indexes) for the 1990-2015 period. We find a negative association between daily stock returns and the number of accidents, which is robust to controlling for year, month and day-of-the-week and various other controls (such as weather and an index of economic uncertainty). When we examine whether the effect is non-linear across the terciles of the stock returns distribution, we find that the impact on accidents is asymmetric, in that–when compared to the reference (middle) tercile, which is roughly centered around zero–it is only present for the bottom tercile (negative returns) but not for the top tercile (positive returns). This result suggests that the connection between stock market and driving behavior is consistent with a framework of reference-dependent preferences (Kőszegi and Rabin, 2006) operating across domains, in which investors' proclivity to engage in

[1] Also, macroeconomic conditions, including unemployment and income per capita have been shown to affect road accident fatalities (Ruhm, 2000; Cotti and Tefft, 2011). Beyond these, weather conditions are an often-cited factor contributing to traffic accidents (Qiu and Nixon, 2008).

[2] According to the Federal Highway Administration, in 2009, 87% of the driving-age population (age 16 and over) had a license (see `https://www.fhwa.dot.gov/policyinformation/pubs/hf/pl11028/chapter4.cfm`, accessed 3 July 2019), while according to the AAA Foundation's 2016 American Driving Survey drivers reported spending 50.6 minutes on the road per day (see `http://aaafoundation.org/american-driving-survey-2015-2016/`, accessed 3 July 2019).

risky behavior while driving (e.g., speeding, drunk, aggressive or distracted driving) is affected by the gain/loss realized in a different domain–the financial market–so that losses in the stock market imply risk-seeking behavior at the wheel.[3] We also find that the effect is not driven by extreme low or high stock market returns and is robust to various checks involving alternative measures of returns (Dow Jones Industrial Average index, Value Weighted index) and outcomes (e.g., number of fatalities, number of vehicles involved). Finally, we document that the effect is strongest toward the end of the 1990s, a period associated with exuberance in the US financial market (Phillips et al., 2011) and an increase in stock market participation.

The main threat to identifying a causal link between stock market returns and driving accidents in our analysis is the possibility of omitted variable bias. The relationship that we uncover could be driven by an unobserved factor influencing both stock market and car accidents, rather than stock market performance having an impact on driving behavior and thus the number of accidents. Examples that come to mind include the weather and major political or sports events. It has indeed been shown that exogenous factors that influence investors' mood (e.g., weather, outcome of sporting events) can have an effect on stock market prices (Saunders, 1993; Kamstra et al., 2003; Hirshleifer and Shumway, 2003; Edmans et al., 2007) and these same events could well influence–through the channel of drivers' mood–the occurrence of fatal accidents. To address this issue, we first directly control for some potential confounding factors. The fact that the relationship between stock market and accidents is unaffected when we include in the regression controls for environmental conditions like rain or wind or daily indices of stock market and economic policy uncertainty is reassuring, although it is far from resolving the issue.

More importantly, we pursue several falsification tests. In the first set of tests, we exploit the timing of accidents. If the relationship that we find is due to uncontrolled-for events affecting both stock market valuation and driving behavior, we would also expect the relationship to be present for accidents happening before the opening of the stock market. However, we find no relationship in this part of the day, thus providing support for a causal interpretation of the link between stock market returns and accidents. With a similar logic, we show that there is no relationship between

[3] A growing body of literature provides field evidence on reference dependence in various domains (Mas, 2006; Crawford and Meng, 2011; Card and Dahl, 2011; Allen et al., 2016; DellaVigna et al., 2017).

car accidents and lead stock market returns.

In the second set of falsification tests, we pursue multiple approaches to compare the effect of the stock market on groups of drivers with different likelihoods of owning stocks. If the relationship that we uncover is due to uncontrolled-for events affecting the mood of both drivers and investors, then we would expect the relationship to be present for all categories of drivers, even those who do not invest in the stock market. Instead, if the relationship is causal, then we would expect the effect to be absent (or weaker) for drivers who do not hold stocks.[4] One approach to isolate drivers who are unlikely to hold stocks is to zoom in on accidents involving only people aged 25 or under. For this group, we do not find a statistically significant relationship between accidents and stock market performance, while we see the effect on accidents involving at least one driver older than 25. In another approach, we exploit differences in the geographical distribution of income, with the idea that people with a higher income are more likely to invest in the stock market. We consider average income in both the county of the accident and the drivers' zip code. In both cases, we find no relationship between stock market and accidents for the lower tercile of income, while there is a strong significant relationship for the upper tercile. Furthermore, we use data from the Panel Study of Income Dynamics (PSID) to construct a measure of stock market exposure (the ratio between the value of the stocks and the net worth) that is subsequently matched to car makes. We then compute the average stock market exposure of the cars involved in each accident. We only find an effect for accidents that are in the top two terciles in terms of stock market exposure, while there is no significant effect for those in the lower tercile. We also split accidents into terciles according to stock market participation in the state where the accident occurred, finding no substantial difference across terciles. Finally, when we divide accidents based on the popularity of google searches for the words "stock market" (measured at the Designated Market Areas level), we find the effect to be present only in the upper tercile. All in all, these tests support a causal interpretation of our results.

To better understand the potential behavioral channels explaining the estimated reduced-form

[4] Beyond the direct financial wealth effect on investors, the stock market might of course also have an indirect effect on non-investors to the extent that it might influence their expectations about own economic outlook. In section 4.1, we present empirical tests suggesting that the direct effect is the main channel.

relationship between stock market returns and car crashes, we classify accidents using data on the factors that have contributed to them. First, we find that there is no effect of the stock market on crashes attributed to non-human causes, which reinforces the causal interpretation of our results. Moreover, we can exclude the notion that factors such as speed and distraction are behind our results, while the effect seems to be driven by reckless driving and drunk driving.

Our paper is related to several strands of literature. One strand has identified a relationship between stock returns and physical and mental health, as well as subjective and emotional well-being (e.g., worry, stress, anger). McInerney et al. (2013) show that the 2008 stock market crash had an impact on mental health of older adults in the US, driven by persons with sizeable equity wealth holdings. Cotti et al. (2015) find a negative association between monthly performance of the Dow Jones Industrial Average and the log of monthly drunk-driving fatalities in the period 2003-2010, while they find no association with non-alcohol related fatal accidents.[5] Engelberg and Parsons (2016) find a negative inverse link between daily stock returns and hospitalizations in California, particularly for mental health issues.[6] Schwandt (2018) finds that stock market shocks affect health outcomes of the elderly in the US. Deaton (2012) shows that the Great Depression has influenced the self-reported well-being of Americans, while Frijters et al. (2015) report that stock market increases positively affects the wellbeing of Australians. Finally, using panel data from the UK, Ratcliffe and Taylor (2015) find that stock price changes are positively associated with mental well-being. Our study also connects to a recent and small but growing stream of literature examining the cross-domain effects of emotional shocks. For example, previous studies have shown that emotional cues triggered by a failure to obtain an expected outcome in the sports domain (unexpected loss) or by extreme traffic congestion, can influence domestic violence (Card and Dahl, 2011; Beland and Brent, 2018) and judicial decisions (Eren and Mocan, 2018). We add to this literature by showing that emotions stirred in the financial domain can have dire external

[5] In our analysis, we focus on the immediate (daily) impact of the stock market on fatal car accidents, finding an effect going through reckless and drunk driving, and exploiting the timing of accidents and various other falsification checks to support a causal interpretation of the finding. Another related study is Vandoros et al. (2014) that finds an increase in non-fatal road traffic accidents in Greece in days that immediately follow the announcement of austerity measures, which they attribute to the anxiety and stress brought about by the announcement.

[6] Our main econometric specification is closely related to Engelberg and Parsons (2016). Our work complements this previous study in that we examine the effect of stock market on a different outcome, being able to leverage data from the whole of the United States and making use of various identification strategies to advance on causality.

effects on behavior in unrelated activities.

The remainder of the paper is organized as follows. In section 2, we describe the data and the econometric methods. We report our main results and some robustness and specification checks in section 3. Section 4 addresses the causality of the effect and some potential behavioral channels. Finally, we offer some concluding remarks in section 5.

2 Econometric Model and Data

2.1 Econometric Model

The key hypothesis that we want to test is whether daily fluctuations in stock prices have an immediate effect (within the same day) on the number of accidents. For this purpose, we estimate the following regression model:

$$Accidents_t = \alpha + \beta \, Return_t + \mathbf{X_t'}\gamma + \upsilon_t + \mu_t + \omega_t + \varepsilon_t,$$

where $Accidents_t$ is the main outcome of interest, namely the daily number of fatal accidents that involve at least one car and occur after the stock market opening. $Return_t$ is the daily stock market return (S&P 500 index in our baseline analysis), which we standardize by dividing it by the rolling one-year standard deviation, to account for the fact that stock market volatility might be changing over time.[7]

The matrix $\mathbf{X_t}$ contains a series of control variables. One concern with identification of the causal effect of stock market returns on accidents is omitted variable bias: the stock market may be correlated with major events that also have an impact on the number of accidents. To partly address this concern, we include in $\mathbf{X_t}$ the daily Economic Policy Uncertainty index, a proxy for movements in policy-related economic uncertainty based on newspaper coverage frequency (Baker et al., 2016). The controls also include the CBOE Volatility Index (VIX) to account for the expected stock market volatility. We also add measures of weather conditions that are known to be important

[7] In further analysis we also consider alternative outcome variables, such as the number of vehicles and the number of fatalities, and alternative stock market indices, such as the Dow Jones Industrial Average and the Value Weighted Index.

determinants of road accidents, such as rain and wind, as well as a proxy for traffic conditions, as represented by the CO emissions. To account for the time series properties of car accidents (e.g., seasonality and persistence), we include a quadratic time trend, an indicator variable for the day surrounding public holidays (i.e., one day before and one day after) and dummy variables for each year (υ_t), month (μ_t) and day of the week (ω_t).[8]

2.2 Data

For the empirical analysis, we use data covering the 1990-2015 period. Our analysis is based on two key variables: daily road accidents and stock market returns. For the former, we use the FARS data, which is the census of fatal motor vehicle crashes in the US collected by the National Highway Traffic Safety Administration.[9] Financial data (S&P 500 and other indices) for the same period were downloaded from Datastream. Our sample period comprises 6,550 trading days from 01/01/1990 to 31/12/2015, omitting weekends and public holidays.

For each accident, the police reports contain detailed information about the time and location of its occurrence, the characteristics of the vehicles implicated, the drivers and other people involved, as well as the conditions that may have contributed to the accident. Note that in accidents involving multiple vehicles, we are not able to identify who is the driver responsible for causing the crash, if the accident is attributable to human action.

We construct a measure of daily rainfall (in mm) by averaging the daily rain reported across all US weather stations. We also accessed information on wind–namely the daily vectorial average of all wind directions and speeds across the US–and the average daily emissions of carbon monoxide in the US.[10] Finally, we included the Economic Policy Uncertainty (EPU) index (as obtained from http://www.policyuncertainty.com/us daily.html) and the measure of perceived stock market volatility (VIX) (from http://www.cboe.com).

Table 1 contains summary statistics of the main variables of interest, for the full sample, as well

[8] We also report a specification with month-by-year fixed effects.

[9] To capture the broader consequences of the stock market on driving behavior, it would be useful to examine also non-fatal accidents. However, a similar dataset of non-fatal accidents for the whole US does not exist.

[10] Rain data are obtained from the National Climatic Data Center. Wind and carbon monoxide emissions are obtained from the Environmental Protection Agency.

as for three subsamples defined on the basis of the terciles of the stock returns distribution. A full list of all variables used in the analysis is presented in Table A1 in the Appendix. The average daily number of accidents occurring after the stock market opening during the period was 37, involving on average 66 vehicles and 42 fatalities. The distribution of the daily number of accidents is reported in Figure A1 in the Appendix. The average stock market daily return (standardized by the rolling one-year standard deviation) is 0.04 %.[11]

Table 1: Summary statistics

	Full sample		Bottom tercile		Middle tercile		Top tercile	
	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
# of accidents	37.42	10.77	38	10.66	36.83	10.8	37.41	10.81
# of vehicles	66.23	19.8	67.5	19.69	65.17	19.89	66.02	19.77
# of fatalities	41.98	12.79	42.66	12.6	41.35	12.91	41.92	12.84
S&P 500 Daily returns	.04	1.04	-1.03	.73	.06	.19	1.08	.64
N	6550		2185		2182		2183	

Source: Road accidents fatalities are derived from the Fatality Analysis Reporting System (FARS) and refer to number of fatal crashes involving at least one car between the time of stock market opening (9:30 AM Eastern Time Zone) and 11:59 PM Eastern Time Zone. Daily returns (S&P 500) refers to the % change in the Standard and Poor's 500 Composite index between the day the index is observed and the previous day, divided by the one-year rolling standard deviation. S&P 500 data are obtained from Datastream services. The period covers all trading days from 01/01/1990 to 31/12/2015. Bottom, Middle and Top tercile refer to subsamples defined on the basis of the terciles of the stock returns distribution.

3 Results

3.1 Baseline Analysis

Table 2 contains our baseline regression results.[12] We begin by presenting the most basic specification that only includes returns and a quadratic time trend in column 1, and incrementally add controls in subsequent columns. Columns 2 and 3 add year and month fixed effects and day-of-the-week fixed effects, respectively. In column 4, we add controls for environmental conditions and CO emissions and in column 5 we add the VIX and the EPU index. We observe that the coefficient on returns is negative and statistically significant across the first five columns of the table. The coefficient estimate becomes smaller (in absolute value) when controlling for the year, month and day-of-the-week effects, with most of the reduction attributable to controlling for the day of the

[11]The average non-standardized daily return is 0.029%.

[12]Table A2 diplays the estimates of all control variables used in the regression.

week. However, when adding further controls in columns 4-5, the estimates have essentially the same size.[13] Quantitatively, taking the coefficient in column 5, we find that a one standard deviation reduction in daily stock market returns increases the number of fatal accidents by 0.6% (that is, by 0.23 accidents over an average of 37.4 daily accidents occurring after the stock market opens). This estimated effect is slightly larger than the effect of the stock market on hospitalizations in California reported by Engelberg and Parsons (2016). In column 6, we estimate the same specification as in column 5 restricting attention to accidents that happen after the stock market closes at 4:00pm ETZ. This is to address the concern that accidents that occur when the stock market is open might be affected by the within-day performance of the stock market that we are not accounting for. We note that the estimated coefficient on returns is still negative and statistically significant, implying a slightly larger effect (0.7%, that is, 0.16 more accidents over a daily average of 22.7 accidents occurring after the stock market closes) than what we find in column 5. Finally, in column 7, we estimate a more demanding specification that includes year by month fixed effects still yielding a robust negative and statistically significant effect.[14]

In Table 3, we explore the sensitivity of our key result to alternative specifications. In the first column, we estimate the model in column 5 of Table 2 using a Poisson regression and find that the implied marginal effect calculated at the mean (-0.23) is very similar to the OLS. In the second column, we test for non-linear effects by introducing a square term for daily returns. The square term is positive but statistically insignificant, while the estimate for the linear term is remarkably similar to the baseline, suggesting that the effect is not quadratic. In the third column, we allow for days with negative returns to have a differential level effect on accidents. The results indicate that days with negative returns are associated with significantly more accidents than positive days.

Finally, we explore non-linear effects by splitting the distribution of daily returns into three

[13] A cursory comparison of the coefficients between columns 3, 4 and 5 would suggest that the effect is very similar. To understand whether the coefficient of interest is confounded by these additional control variables, we followed the method of Pei et al. (2019) and conducted a balancing test whereby we regress our key independent variable (stock market returns) on all remaining controls, including the period fixed effects. We then test the joint significance of the parameter estimates for rain, wind, CO emissions, VIX and EPU index, finding that they are jointly relevant (F stat=18, p-val<0.000). This result suggests that the additional control variables should be included in the regression, since they have a small – but statistically significant – effect on the key parameter estimate.

[14] To explore whether the effect is heterogeneous across weekdays, we have also estimated a specification whereby we interact the stock market returns variable with the days of the week. We found that the effect is stronger–statistically and economically– on Monday, Tuesday and Friday.

Table 2: Baseline regression

	1	2	3	4	5	6	7
Daily returns	–0.263***	–0.242***	–0.248***	–0.240***	–0.227***	–0.161***	–0.165**
	(0.099)	(0.079)	(0.079)	(0.078)	(0.079)	(0.060)	(0.082)
Time trend	Y	Y	Y	Y	Y	Y	Y
Year, month & day of the week F.E.	N	Y	Y	Y	Y	Y	Y
Holidays F.E.	N	N	Y	Y	Y	Y	Y
Daily rain / wind / CO emissions	N	N	N	Y	Y	Y	Y
VIX / EPU index	N	N	N	N	Y	Y	Y
Year × month F.E.	N	N	N	N	N	N	Y
R^2	0.367	0.612	0.614	0.616	0.616	0.552	0.639
N	6550	6550	6550	6550	6550	6550	6550
$\bar{Y}$	37.42	37.42	37.42	37.42	37.42	22.69	37.42

Robust standard errors in parentheses. **/*** indicates significance at the 0.05/0.01 level.
The dependent variable is the daily number of fatal crashes involving at least one car between the time of stock market opening (9:30 AM Eastern Time Zone) and 11:59 PM Eastern Time Zone. The dependent variable in column 6 is the daily number of fatal crashes between the time of stock market closure (4:00 PM Eastern Time Zone) and 11:59 PM Eastern Time Zone.
The key independent variable is the % change in the Standard and Poor's 500 Composite index between the day the index is observed and the previous day, divided by the one-year rolling standard deviation.
Time trend refers to quadratic time trends. Holiday F.E. refers to an indicator that takes the value of 1 if the day is preceding or following a public holiday when the stock market is closed and 0 otherwise. Daily rain refers to the mean level of rain in millimeters calculated by averaging the amount of daily rain measured at available weather stations in each state where the accidents occur. Daily wind refers to the vectorial average of all wind directions and speeds across the U.S.. Daily CO emissions refer to the average daily emissions of carbon monoxide in the U.S.. VIX refers to expected volatility of the S&P 500. The EPU index measures economic policy uncertainty.
Source: Road accidents fatalities derived from the Fatality Analysis Reporting System (FARS). Standard and Poor's 500 Composite index obtained from Datastream services; precipitation data obtained from the National Climatic Data Center; wind and carbon monoxide emissions obtained from the Environmental Protection Agency. VIX obtained from http://www.cboe.com EPU index obtained from http://www.policyuncertainty.com/us_daily.html. The period covers all days from 01/01/1990 to 31/12/2015 for which car accidents and financial data are observed.

groups defined by terciles (see Table 1 for summary statistics of the main variables of interest by tercile) and allowing for the bottom and top group to have a differential level effect on the number of accidents than the omitted middle group. This specification yields a statistically significant coefficient of 0.456 (s.e. 0.210) for the bottom tercile. Since the average daily number of accidents is 37, this implies that days on which the stock market closes down are associated with roughly a 1.2% increase in the number of accidents, relative to days with returns that are around zero (the omitted category). The estimate for the top tercile is negative but small and statistically insignificant. This analysis thus shows that the effect is asymmetric with bad days on the stock market being associated with more car accidents relative to average days, while good days have no differential association. Additional insight about the size of welfare losses implied by our estimate is provided in figure A2. In the figure, we plot "back of the envelope" estimates of the annual number of fatal car accidents associated with bad days in the stock market (days with returns in the bottom tercile of the distribution of daily stock market returns) by multiplying the 0.456 coefficient by the annual number of days with stock market returns in the bottom tercile. Considering that the average annual number of days with bottom tercile returns in our sample is 84, this estimate would imply an average of 38 fatal accidents due to bad days in the stock market, compared to a counterfactual with no bad days in the stock market. What the figure illustrates is how this number varies over time, with years with an exceptionally large number of bad days (e.g., 2008), experiencing a 31% above average number of fatal accidents due to bad days in the stock market.

Table 3: Alternative specifications

Poisson		Quadratic		Dummy		Terciles	
Daily returns	–0.006***	Daily returns	–0.227***	Negative returns	0.460***	Bottom tercile	0.456**
	(0.002)		(0.080)		(0.168)		(0.210)
		Daily returns squared	0.008			Top tercile	–0.072
			(0.036)				(0.206)
Pseudo R^2	0.227	R^2	0.616	R^2	0.616	R^2	0.616
N	6550	N	6550	N	6550	N	6550

Robust standard errors in parentheses. **/*** indicates significance at the 0.05/0.01 level. All regressions include the variables in Table 2 column 5. Negative returns: they key independent variable is an indicator that takes the value of 1 if the daily returns are negative and 0 otherwise. Top and bottom tercile: the key independent variable are the first and third tercile of daily returns (the second tercile is the reference group). The range of (standardized) returns for the three terciles are: -6.611 to -0.282 for the bottom tercile; -0.282 to 0.401 for the second tercile; 0.401 to 6.158 for the top tercile.

We carried out further tests to check the sensitivity of the estimates to alternative stock market indices and different outcomes. In Table 4, we show that using–instead of the S&P 500–the Dow Jones Industrial Average index or the Value Weighted returns on all NYSE, AMEX, and NASDAQ stocks excluding dividends, produces results that are similar to our baseline. Same is true when using non-standardized daily returns or when eliminating observations for which returns are in the top or bottom 1%. Finally, in Table 5 we look at the log of accidents, as well as at other outcomes aside from number of accidents, such as the number of fatalities, vehicles or persons involved in the accidents. The pattern of the estimates is in line with the baseline results.

3.2 Robustness and Specification Checks

In Table 6, we report robustness checks to address the concern that the time series persistence of both accidents and the rolling standard deviation of returns might be giving rise to a spurious regression problem in our baseline specification (Granger and Newbold, 1974). In the first four

Table 4: Alternative stock market returns measure

	Dow Jones	Value weighted	Returns not std.	No extreme returns
Daily returns	–0.181**	–0.215***	–0.211***	–0.197**
	(0.079)	(0.080)	(0.076)	(0.091)
R^2	0.616	0.616	0.616	0.617
N	6549	6550	6550	6419

Robust standard errors in parentheses. **/*** indicates significance at the 0.05/0.01 level. All regressions include the variables in Table 2 column 5.

Dow Jones: the key independent variable is the % change in the Dow Jones Industrial Average index between the day the index is observed and the previous day, divided by the one-year rolling standard deviation. Value weighted: the key independent variable is the Value-Weighted returns on all NYSE, AMEX, and NASDAQ stocks divided by the one-year rolling standard deviation. Returns not standardized: the key independent variable is the % change in the Standard and Poor's 500 Composite index between the day the index is observed and the previous day. No extreme returns: observations that are in the top or bottom 1% of the daily returns distribution are excluded.

Table 5: Alternative outcomes

	Log accidents	# fatalities	# vehicles	# persons
Daily returns	–0.006***	–0.250***	–0.516***	–0.738***
	(0.002)	(0.095)	(0.156)	(0.281)
R^2	0.620	0.610	0.553	0.599
N	6550	6550	6550	6550
$\bar{Y}$	3.69	41.98	66.23	110.27

Robust standard errors in parentheses. *** indicates significance at the 0.01 level. All regressions include the variables in Table 2 column 5.

Log accidents: the dependent variable is the daily log number of fatal crashes involving at least one car between the time of stock market opening (9:30 AM Eastern Time Zone) and 11:59 PM Eastern Time Zone. Number of fatalities: the dependent variable is the daily number of fatalities in crashes involving at least one car between the time of stock market opening (9:30 AM Eastern Time Zone) and 11:59 PM Eastern Time Zone. Number of vehicles: the dependent variable is the daily number of vehicles in crashes involving at least one car between the time of stock market opening (9:30 AM Eastern Time Zone) and 11:59 PM Eastern Time Zone. Number of persons: the dependent variable is the daily number of persons in crashes involving at least one car between the time of stock market opening (9:30 AM Eastern Time Zone) and 11:59 PM Eastern Time Zone.

columns, we use as the dependent variable the difference between the observed number of daily accidents and the average of the previous 5, 20, 125 and 250 trading days, respectively, thereby considering the effect of stock market returns on changes in the number of car accidents over time horizons ranging from one week to one year. This ensures us that our results are not driven by other factors that might be impacting fatal accidents over longer time periods (e.g., cold spells lasting over a week). In all cases, the main coefficient of interest remains statistically significant and of a size similar to the baseline. In column 5, we estimate a model that includes the 1-day lag of accidents. The positive and statistically significant coefficient of the lag dependent variable suggests that accidents are indeed persistent. This may be due, for instance, to weather conditions. However, including the lag does not affect the estimate of returns in an appreciable way.

In the last two columns, we introduce the one-day lag return to assess whether a delayed effect is discernible in the data. In column 6, we use both contemporaneous and lagged returns, while in column 7 we only use lagged returns. In both cases, the coefficient for the one-day lag returns is very small and statistically insignificant. Importantly, its presence does not affect the estimate of the contemporaneous daily returns. Taken together, these results indicate that the stock market has an immediate effect on car accidents.

Table 6: Time series persistence of accidents and returns

	Daily accidents minus average of the previous:				Daily accidents		
	5 days	20 days	125 days	250 days			
Daily returns	–0.223***	–0.216***	–0.226***	–0.222***	–0.226***	–0.226***	
	(0.086)	(0.081)	(0.080)	(0.080)	(0.079)	(0.080)	
Lag accidents					0.051***		
					(0.013)		
Lag returns						0.018	0.030
						(0.078)	(0.078)
R^2	0.358	0.283	0.331	0.361	0.617	0.616	0.616
N	6550	6550	6550	6550	6549	6549	6549

Robust standard errors in parentheses. *** indicates significance at the 0.01 level. All regressions include the variables in Table 2 column 5.
5/20/125/250 days refers to specifications where the dependent variable is the difference between the number of daily accidents and the average of the previous 5/20/125/250 stock market days. Lag accidents refers to the one-day lag number of accidents. Lag returns refers to the one-day lag daily returns.

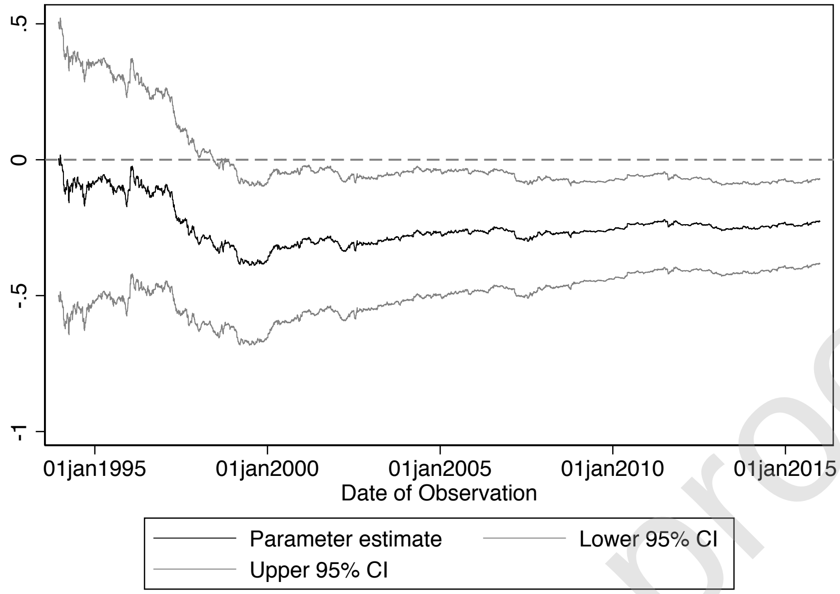
3.3 Is the Effect Constant over Time?

One might wonder whether the estimated effect is constant over the 26-year period analyzed. In Figure 1, we plot the estimated coefficients of a forward recursive regression (Panel A) and a rolling regression (Panel B) to identify the period of time when the impact of the stock market is stronger, following the logic in Phillips et al. (2011). In the forward recursive regression, we estimate the first regression using the specification in Table 2 column 5 on a window of 1,000 trading days (approximately 4 years of data, or 15% of the sample size) and add one observation (i.e., one trading day) at the time until the last regression is estimated using the full sample of 6,550 observations. The first estimated coefficient is for 14^{th} December 1993, and is estimated using the data from 1^{st} January 1990 until then. The graph shows that the estimated coefficient is mildly negative but statistically insignificant for the initial period, after which it becomes larger (in absolute terms) and statistically significant at the 5% level (after mid-1997). Subsequently, for a period of about four years, the coefficient reaches its largest magnitude (up to -0.39), before it starts converging to the value estimated in the full sample (-0.227).

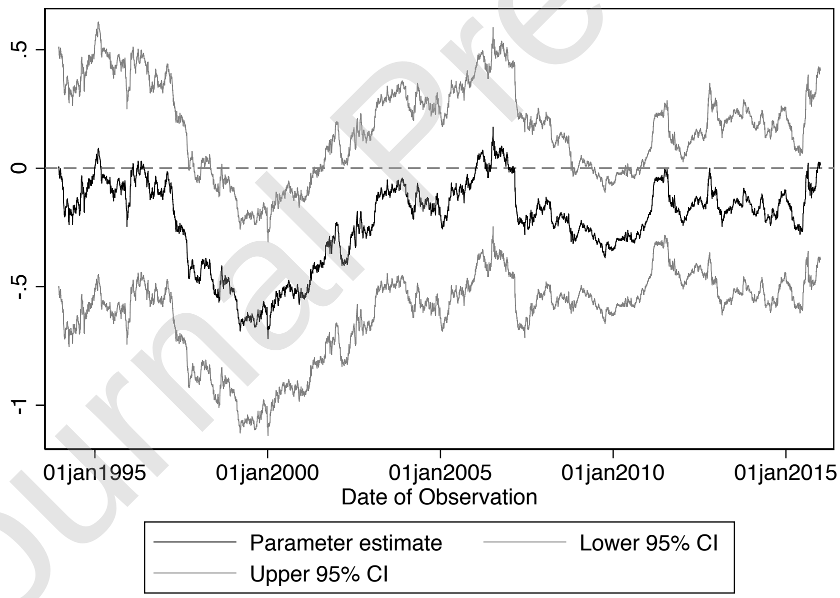
In Panel B, we implement a rolling regression using an identical window (1,000 trading days). The first estimated coefficient is hence identical to the one obtained in the previous graph, after which the four-year window moves one day forward. The last estimate (at the end of 2015) is hence obtained using data for the years 2012 to 2015 included. Similarly to what is seen in Panel A, the effect of stock market on accidents is particular strong between mid-1997 and early-2001, a period when stock market participation was increasing and stock prices were high (Guiso and Sodini, 2013; Phillips et al., 2011). The estimated coefficient is negative for most of the remaining period. However, it is not statistically significant with the exception of a short period around 2010. In the conclusions, as a possible explanation for this pattern, we discuss the notion that emotional reactions to negative stock market performance can be more dramatic in a period when there is a surge in stock market participation–with an increased presence of inexperienced investors–thereby increasing the likelihood of accidents.

Figure 1

Panel A: Forward recursive regression



Panel B: Rolling regression



The graph plots the estimates and 5% confidence intervals of the specification in Table 2 column 5. Panel A has an initial sample size of 1,000 days, recursively augmented by one day. Panel B has a rolling window of 1,000 days. The starting date in both plots is 14^{th} December 1993.

4 Causality and Channels

4.1 Falsification Tests

Our next objective is to establish that the results presented thus far reveal a causal relationship between the stock market and driving accidents. To this end, we pursue several falsification checks.

There are two main ideas behind these tests, the first of which exploits the timing of events. The main threat for the causal interpretation of the relationship between stock market performance and car accidents that we find above is that the association may be driven by events that are unaccounted for in our empirical specification, such as natural disasters or sport events that influence the mood of both drivers and investors. These events can happen throughout the 24 hours of a day and not only during the stock market trading hours. For example, suppose that an important event occurred late in the evening or during the night. This event could affect drivers during their morning commute before the opening of the stock market, while the stock market would react to the very same event after its opening, thus giving rise to a correlation between accidents happening before the stock market opening and stock market performance later that day. Similarly, an event happening after stock market closure may still affect drivers in their evening commute, but stock market only the day after, thus giving rise to a correlation between accidents and lead stock market returns. Instead, if the relationship is causal, with stock market performance affecting driving behavior, then we should not expect to find such correlations. This is the logic behind our first set of falsification tests.

The second type of falsification tests that we perform is based on the observation that not all drivers participate in the stock market. If the relationship that we uncover is causal, then we would not expect the effect to be present among drivers who do not own stocks. However, if some unobserved events like sport results or political scandals influence the mood of both drivers and investors, then we might also expect a correlation between accidents and the stock market to exist for drivers who are not invested in the stock market. We do not have direct information about the stock market participation of the drivers in our data; however, we can exploit driver characteristics that are correlated to stock market participation, such as age, average income in the zip code and car make to predict the stock market participation of the drivers involved in accidents. We also use two other measures of stock market penetration: one that uses information about stock market participation at the state-level and another one that relies on trends on google searches for the words "stock market" at the Designated Market Area (DMA) level. Note that it is conceivable that even people not directly investing in the stock market use its performance as an indicator of the general economic situation, thus drawing some informational value regarding their own economic prospects.[15] If this is indeed the case, a causal link could still exist between the stock market and driving behavior for drivers who are unlikely to invest in the stock market. Thus, this second type of tests can be useful also to assess whether the relationship between the stock market and accidents is only a direct one–in the sense of being mediated through a financial wealth effect of stock market holders–or whether an indirect effect on non-participants also exists. In what follows, we describe in detail each test and discuss the results.

First, in column 1 of Table 7 we re-estimate our baseline specification for accidents that happen before the opening of the stock market (9:30 AM).[16] The results clearly indicate that there is no association between the stock market and accidents that happen before the market opens. Second, in columns 2 and 3 we include the lead daily returns as a control in the regression, alone and in addition to contemporaneous returns. The results indicate that current accidents are unrelated with the stock market returns measured in the following day. These results point to the fact that the statistical link between stock market and accidents that we estimated in our baseline specification has a causal underpinning.

As a test that the relationship between accidents and stock market is driven by human behavior, in the last column we perform a test that involves subsetting accidents that occur for non-human causes. The FARS data contain information on the factors related to the crash, which can be attributed to the driver, the vehicle or the environment. Driver-related factors include unsafe driving actions; for instance, human error, drinking or reckless behavior. We will analyse these in subsection 4.2. In this test, we instead focus on accidents that can be uniquely attributed to non-

[15] This would be more meaningful for longer-term performance rather than for the daily fluctuations we focus on.

[16] The times of accidents were all converted into Eastern Time Zone, i.e., the time zone of the New York Stock Exchange. Hence, an accident happening at 8 AM in Los Angeles will be recorded as occurring at 11 AM ET, after the opening of the stock market.

human factors, namely to environmental conditions or vehicle defects. Environmental conditions include, for example, severe crosswind and slippery surfaces, while vehicle defects include, for example, tyre blow-out. To be classified as caused by non-human factors, an accident would have at least one driver/vehicle affected by external causes. Accidents involving at least one human-related cause are excluded. This leaves a small percentage of accidents that can be classified as being due to non-human factors (about 3% of the total accidents). Since our hypothesis is that drivers are directly affected by the stock market, one would not expect to see an effect when accidents do not involve a human factor. The results of this falsification test confirm this conjecture.

Table 7: Causality and falsification I

	Before mkt opening	Lead daily returns		Non-human cause
Daily returns	–0.044		–0.192**	–0.002
	(0.047)		(0.083)	(0.012)
Lead returns		0.047	0.088	
		(0.075)	(0.084)	
R^2	0.313	0.533	0.546	0.096
N	6550	6550	5243	6550
$\bar{Y}$	12.91	37.43	37.42	1.03

Robust standard errors in parentheses. ** indicates significance at the 0.05 level. All regressions include the variables in Table 2 column 5.

Before market opening refers to the time window between 00:00 and 9:29AM Eastern Time Zone. Lead returns refers to the one-day lead daily returns. Non-human cause refers to accidents only involving environmental or vehicle-related factors.

In Table 8 we move to the second type of falsification tests, based on the likelihood or extent of stock market participation, and first zoom in on young drivers. Motivated by the fact that young drivers are unlikely to be investors, we subset accidents where all drivers are 25 years old or younger and use this as the dependent variable (Panel A, column 1). We find that for these accidents there is no effect of the stock market, whereas there is a negative and statistically significant effect with daily returns for the remaining accidents (Panel A, column 2).

In the second method, we proxy the likelihood of owning stocks by using a measure for the income of the driver's residence. For this purpose, we first match income data from the 2010 Census with the driver's zip code. For each accident, we then calculate the average income of all involved drivers at the zip level. As before, we split accidents in terciles: those with high, intermediate and low income (Panel A, columns 3-5). For the third method, we adopted a very similar procedure, but instead of the driver's zip we use the income of the county where the accident took place. Again, we classified accidents in terciles depending on the county's income, using again data from the 2010 Census (Panel A, columns 6-8).

In the fourth method, we use a measure for the stock market exposure associated with the cars involved in the accident. To obtain this, we accessed household-level data on car ownership and car make, value of stocks and net worth from the PSID. We first construct a variable of household exposure defined as the ratio between the value of stocks for each household and the net worth. Then, we calculate the average exposure for each make of the cars available in the PSID and match them with the car makes in the FARS data. For each accident we then calculate the average stock market exposure of all cars involved. We finally split accidents into terciles: those with high, intermediate and low stock market exposure (Panel B, columns 1-3).[17]

In the fifth method, we use data from the PSID to compute stock market participation rates at state level. We then classify our accidents in three groups, on the basis of the distribution of state level stock market participation rates. We then analyse separately accidents that happened in states with high, intermediate and low participation rates (Panel B, columns 4-6). Finally, in the sixth method, we use data from google trends on the search for the words "stock market" which we can measure at the Designated Market Area (DMA) level (Panel B, columns 7-9). The idea is that areas where people search on the internet news about the stock market are also areas where there will be more people interested or active in the stock market.

Notice that these methods rely on measurement at different levels of aggregation: from car make, to county or state. Across all methods, we generally find a pattern whereby stock market returns have a strong and statistically significant effect in the top tercile, a similar or more moderate

[17] We could attribute a stock market exposure value for 646,599 out of 656,176 cars that are in our data. Since we select only accidents with at least one car, this means that we can characterize the great majority of our accidents in terms of stock market exposure of the involved drivers.

Table 8: Causality and falsification II

Panel A

	Age		Income of the driver's zip			Income in the county of accident		
	All $\leq$ 25	Others	High	Medium	Low	High	Medium	Low
Daily returns	0.002	–0.229***	–0.091**	–0.091**	–0.037	–0.123***	–0.065	–0.033
	(0.030)	(0.071)	(0.045)	(0.044)	(0.044)	(0.043)	(0.044)	(0.046)
R^2	0.345	0.560	0.286	0.354	0.443	0.350	0.369	0.395
N	6550	6550	6550	6550	6550	6550	6550	6550
$\bar{Y}$	5.93	31.49	12.07	12.05	12.83	11.98	12.19	13.09

Panel B

	Cars' stock market exposure			States' stock market participation			Google trends for <<stock market>>		
	High	Medium	Low	High	Medium	Low	High	Medium	Low
Daily returns	–0.093**	–0.100**	–0.038	–0.077*	–0.076*	–0.075	–0.098**	–0.065	–0.067
	(0.042)	(0.044)	(0.044)	(0.041)	(0.044)	(0.046)	(0.040)	(0.048)	(0.044)
R^2	0.209	0.514	0.427	0.373	0.419	0.353	0.405	0.381	0.351
N	6550	6550	6550	6550	6550	6550	6550	6550	6550
$\bar{Y}$	11.89	11.96	13.15	11.50	12.87	13.05	10.81	13.85	12.59

Robust standard errors in parentheses. */**/*** indicates significance at the 0.10/0.05/0.01 level. All regressions include the variables in Table 2 column 5.

All $\leq$25 refer to accidents involing only drivers below the age of 25. Others refers to the remaining accidents.

High, medium and low refer to the first, second and third tercile of the distribution of accidents according to the variable indicated in each panel's header.

Income of the driver's zip refers to the of the median household income in the zip of the driver (average for each accident). Income in the county of accident refers to the median household income in the county of accident. Income data are from the 2010 Census.

The cars' stock market exposure refers to the average ratio between the stocks values and net worth attributable to cars' make. It is calculated using data on values of stocks, net worth and vehicle make from the PSID. We use only car makes with at least 50 observations in the PSID data. The five car makes with top exposure are: Mercedes-Benz, Volvo, Mazda, Lexus, Audi. The five car makes with lowest exposure are: Plymouth, Lincoln, Cadillac, Mercury, Scion.

The states' stock market participation refers to the stock market participation in each state (share of persons who report owning stocks) and uses data from the PSID.

Google trends data refer to the period 2004-2015, with 2004 being the first year when data are available.

impact in the middle tercile and a very small and always insignificant effect on the bottom tercile. This pattern is not present in the results relying on stock market participation at state level in which the effect seems to be similar across the three terciles.

Overall, this pattern of a stronger relationship between stock market and accidents involving drivers who are the most likely to be stock holders or more likely to have high stock market exposure lends further support to the causal interpretation of the link between stock market returns and accidents. Furthermore, it suggests that the channel linking stock market performance and driving accidents is a direct financial wealth effect for investors, as the results indicate that drivers who are unlikely to be investors are not affected by stock market returns.

Finally, as a robustness test for our inference, we perform a simulation exercise whereby we estimate 10,000 regressions, each time replacing the observed stock market returns with random values obtained by reshuffling the actual returns. Each simulated estimate provides a placebo effect of (fictitious) returns on the number of accidents.[18] The t-statistic of the "true" estimate is located in the lower tail of the empirical distribution, implying a significance of 1% of our test.

4.2 Potential Channels

As a final step of analysis, we use the driver-level circumstances that contributed to the crash as reported in the FARS data to understand the potential behavioral channels behind the estimated reduced-form relationship between stock market and accidents. For each driver, we can identify up to four (out of about one hundred) possible "unsafe driving actions". We first group all the actions into four broad categories: distraction, recklessness, speed, and drunk driving. Then, we characterize accidents according to these categories. Specifically, an accident is classified as "distraction" if at least one of the drivers involved in the crash was reported as being distracted, and so on for the other three categories. This means that the same accident could be classified under multiple unsafe driving actions.

We estimate our baseline specification for each of the four broad causes and report the results

[18] In practice, in each regression, we replace the actual daily stock market return with a return from another day (randomly picked from the distribution of all returns and allowing replacement). We save the estimates of the key regressor (daily returns), along with standard errors and t-statistics. In Figure A3 in the Appendix, we plot the empirical distribution of the t-statistics of the estimates obtained from this simulation exercise.

in Table 9. We find a statistically significant effect for the "reckless" and the "drunk driving "categories, while for the remaining three categories the coefficient is small and statistically insignificant. While this exercise does not allow us to pinpoint exactly what type of behavior mediates the effect of the stock market on accidents, it is useful in that it allows us to exclude that some channels–such as speeding–are behind our results.

Table 9: Channels: Unsafe driving actions

	Distraction	Reckless	Speed	Drunk dr.
Daily returns	0.001	–0.219***	–0.042	–0.073**
	(0.029)	(0.070)	(0.040)	(0.035)
R^2	0.283	0.678	0.319	0.462
N	6550	6550	6550	6550
$\bar{Y}$	5.33	28.66	9.55	7.64

Robust standard errors in parentheses. **/*** indicates significance at the 0.05/0.01 level. All regressions include the variables in Table 2 column 5.

Distraction refers to accidents involving at least one driver for whom distraction is identified as one of the driver-related factors. Reckless refers to accidents involving at least one driver for whom improper, illegal or reckless driving (excluding speeding) is identified as one of the driver-related factors. Speed refers to accidents involving at least one driver for whom speeding is identified as one of the driver-related factors. Drunk driver refers to accidents involving at least one driver who was classified as drinking.

5 Conclusions

In this paper, we document a connection between stock market returns and road traffic accidents. We find that bad days in the stock market are associated with higher risk of a fatal accident relative to normal days. Exploiting the timing of accidents and differences in the propensity to own stocks along the age, geographic or the vehicle make ownership dimensions, we present evidence supporting a causal link between stock market performance and accidents. These estimates might just be the tip of the iceberg in terms of the total road accident costs associated with the stock market, since fatal accidents are a small percentage of the total reported crashes and, presumably, the link we uncover triggers also non-fatal accidents.[19]

While booms have generally been linked to higher motor vehicle fatality rates given that drinking and driving rises in good times (Ruhm, 2000), our finding highlights an effect going in the opposite direction, as positive stock market performances are more likely during booms. Our result is consistent with previous studies showing a relationship between negative stock market returns and health outcomes that is mediated through psychological factors (McInerney et al., 2013; Engelberg and Parsons, 2016; Schwandt, 2018). Our evidence also suggests the possibility of carry-over effects of emotions from the financial decision-making domain to another context, consistent with a framework of reference-dependent preferences operating across domains (Card and Dahl, 2011; Eren and Mocan, 2018).

We also find that the impact of stock market on accidents is particularly strong when stock market participation sharply increased in the second half of the 1990s. Indeed, data from the Survey of Consumer Finances show that, after a period of stability, households' direct stock market participation increased from 28.8% in 1995 to its highest ever historical level of 34.1% in 2001. During this period, naturally, many stock market participants were relatively inexperienced investors, who might have overreacted to a negative performance of their portfolio.[20] This is a potential explanation for the finding that the effect is more pronounced and detectable during that particular period of time.

Policy-makers should be aware of the mental and emotional consequences that the stock market has on investors to better respond to them. Specific to driving, if awareness can mitigate the negative effects of emotions, then there may be room to consider information campaigns about the impact of mental and emotional shocks triggered by stock market performance or other events on driving behavior. Such campaigns could be useful as several evaluations have found that road safety campaigns are indeed effective in reducing accidents, in particular when they are of short duration and targeted, that is, addressed to a specific group (Phillips et al., 2011). This study can contribute to the identification of periods (stock market downturns) when running campaigns may

[19] According to `https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812451`, accessed 14^{th} January 2019, only 0.5% of police-reported crashes in 2015 were fatal.

[20] There is indeed evidence that trading experience mitigates behavioral biases among investors, see, for instance, Feng and Seasholes (2005).

be particularly effective and groups (likely investors) to whom such campaigns could be addressed. Moreover, even if stock market participants have on average higher financial literacy than the rest of the population (Lusardi and Mitchell, 2014), financial literacy programs could be instrumental in mitigating overreactions to stock market downturns, in particular for new and inexperienced investors.

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6 Appendix

Figure A1: Histogram of daily number of accidents after the stock market opening

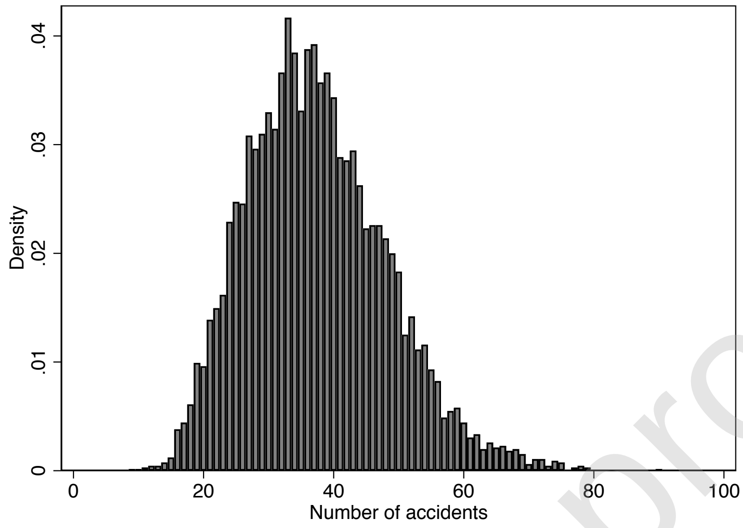
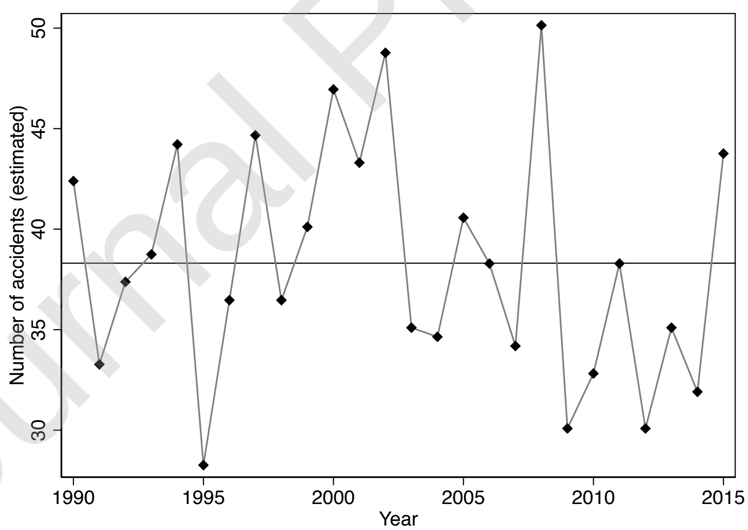
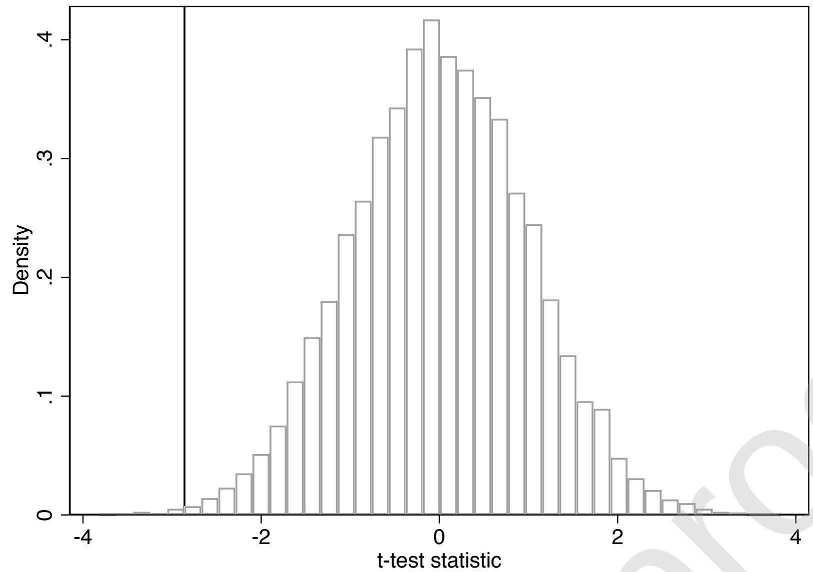


Figure A2: Estimated number of fatal accidents by year



The graph plots the estimated number of fatal accidents, obtained by multiplying the coefficient of the bottom tercile from the specification in Table 3 column 3 by the number of days with returns in the bottom tercile in each year. The horizontal line represents that average number of fatal accidents due to bad days (bottom tercile) in the stock market, compared to no bad days in the stock market.

Figure A3: Simulation: Randomized Stock Market Returns



The graph plots the t-statistics of the coefficient of returns from the specification in Table 2 column 5 obtained by simulating the value of stock market returns 10,000 times. The vertical line represents the t-statistic of the coefficient of returns from the specification in Table 2 column 5.

Table A1: Summary statistics - all variables

	Mean	St. Dev	Min	Max
# of accidents	37.42	10.77	9	90
# of vehicles	66.23	19.8	17	186
# of fatalities	41.98	12.79	11	105
S& P 500 Daily returns	.04	1.04	-6.61	6.16
Dow Jones Daily returns	.04	1.03	-6.6	6.35
Value weighted Daily returns	.04	1.04	-7.19	6.27
VIX	19.82	7.92	9.31	80.86
EPU index	.98	.68	.03	7.19
Holiday interval (D)	.04	.2	0	1
Rain	2.57	1.57	.1	12.31
Wind	96.92	7.09	67.68	122.19
CO emissions	.66	.34	.21	2.1

Source: Road accidents fatalities derived from the Fatality Analysis Reporting System (FARS). Daily returns (S& P 500, Dow Jones Industrial Average and Value Weighted) refer to the respective returns divided by the rolling yearly standard deviation. Indices are obtained from Datastream services. VIX refers to the CBOE Volatility Index and is obtained from http://www.cboe.com. Rain refers to the mean level of daily rain in millimeters calculated by averaging the amount of daily rain measured at available weather stations in the United States. Rain data are obtained from the National Climatic Data Center. Wind refers to the daily vectorial average of all wind directions and speeds across the U.S.. CO emissions refers to the average daily emissions of carbon monoxide in the U.S.. Wind and carbon monoxide emissions are obtained from the Environmental Protection Agency. The EPU index measures economic policy uncertainty and is obtained from http://www.policyuncertainty.com/us_daily.html. Period covers all trading days from 01/01/1990 to 31/12/2015.

Table A2: Baseline regression - details of controls

	1	2	3	4	5	6	7
Daily returns	–0.263***	–0.242***	–0.248***	–0.240***	–0.227***	–0.161***	–0.165**
	(0.099)	(0.079)	(0.079)	(0.078)	(0.079)	(0.060)	(0.082)
Holiday interval (D)			2.738***	2.729***	2.698***	1.297***	2.722***
			(0.511)	(0.510)	(0.509)	(0.390)	(0.513)
Rain				0.233***	0.232***	0.091**	0.302***
				(0.055)	(0.055)	(0.044)	(0.057)
Wind				–0.006	–0.005	–0.003	–0.010
				(0.012)	(0.012)	(0.009)	(0.013)
CO emissions				0.027	–0.045	0.765	3.178**
				(0.895)	(0.897)	(0.692)	(1.234)
VIX					0.010	0.012	0.082**
					(0.015)	(0.012)	(0.036)
EPU index					–0.460***	–0.263**	–0.449***
					(0.147)	(0.111)	(0.162)
Time trend	Y	Y	Y	Y	Y	Y	Y
Year, month & day of the week F.E.	N	Y	Y	Y	Y	Y	Y
Holidays F.E.	N	N	Y	Y	Y	Y	Y
Daily rain / wind / CO emissions	N	N	N	Y	Y	Y	Y
VIX / EPU index	N	N	N	N	Y	Y	Y
Year × month F.E.	N	N	N	N	N	N	Y
R^2	0.367	0.612	0.614	0.616	0.616	0.552	0.639
N	6550	6550	6550	6550	6550	6550	6550
$\bar{Y}$	37.42	37.42	37.42	37.42	37.42	22.69	37.42

Robust standard errors in parentheses. *** indicates significance at the 0.01 level.

The dependent variable is the daily number of fatal crashes involving at least one car between the time of stock market opening (9:30 AM Eastern Time Zone) and 11:59 PM Eastern Time Zone. The dependent variable in column 6 is the daily number of fatal crashes between the time of stock market closure (4:00 PM Eastern Time Zone) and 11:59 PM Eastern Time Zone.

The key independent variable is the % change in the Standard and Poor's 500 Composite index between the day the index is observed and the previous day, divided by the one-year rolling standard deviation.

Time trend refers to quadratic time trends. Holiday F.E. refers to an indicator that takes the value of 1 if the day is preceding or following a public holiday when the stock market is closed and 0 otherwise. Daily rain refers to the mean level of rain in millimeters calculated by averaging the amount of daily rain measured at available weather stations in each state where the accidents occur. Daily wind refers to the vectorial average of all wind directions and speeds across the U.S.. Daily CO emissions refer to the average daily emissions of carbon monoxide in the U.S.. VIX refers to expected volatility of the S&P 500. The EPU index measures economic policy uncertainty.

Source: Road accidents fatalities derived from the Fatality Analysis Reporting System (FARS). Standard and Poor's 500 Composite index obtained from Datastream services; precipitation data obtained from the National Climatic Data Center; wind and carbon monoxide emissions obtained from the Environmental Protection Agency. VIX obtained from http://www.cboe.com EPU index obtained from http://www.policyuncertainty.com/us_daily.html. The period covers all days from 01/01/1990 to 31/12/2015 for which car accidents and financial data are observed.