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

Corrado Giulietti, Mirco Tonin, Michael Vlassopoulos

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Corrado Giulietti† Mirco Tonin‡ Michael Vlassopoulos§

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Abstract

The stock market influences some of the most fundamental economic decisions of investors, such as consumption, saving, and labor supply, through the financial wealth channel. This paper provides evidence that daily fluctuations in the stock market have important–and hitherto neglected–spillover effects in another, unrelated domain, namely driving. Using the universe of fatal road 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 0.5% increase in the number of fatal accidents. 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, thus highlighting the broader economic and social consequences of stock market fluctuations.

JEL Codes: D91, R41, G41

Keywords: stock market, car accidents, emotions

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†University of Southampton; Centre for Population Change; Global Labor Organization. E-mail: C.Giulietti@soton.ac.uk

‡Free University of Bozen-Bolzano; CESifo; Dondena Centre for Research on Social Dynamics and Public Policy, Bocconi University; IZA. E-mail: Mirco.Tonin@unibz.it

§University of Southampton; IZA. E-mail: M.Vlassopoulos@soton.ac.uk

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 by 0.5%. 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 (anxiety, anger, frustration, etc.) 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).[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 clean 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

[1]Beyond emotions, previous literature has examined the role of various road traffic safety programs and regulations, such as alcohol-control policies, mandatory seat belt laws and laws prohibiting text messaging on driving behavior and traffic fatalities (Ruhm, 1996; Levitt and Porter, 2001; Cohen and Einav, 2003; Abouk and Adams, 2013).

[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 5 Dec 2017), 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 13 July 2018).

Organization, 2015). In the US, motor vehicle accidents were ranked 13th 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, this is 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 fixed effects 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 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, 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 markets (Phillips et al., 2011).

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 a third variable 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 etc.) 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 far from resolves the issue.

[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).

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. We exploit the information on the timing of the accidents available in the data to split the day into two parts: an early part involving the hours before the opening of the stock market and a later part involving the hours after the opening. We find the relationship to only be present in the second part and not the first, 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 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. Finally, 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 attributed to each vehicle make involved in the crash. We only find a relationship with stock market returns for accidents involving car makes in the upper tercile of the stock market exposure, while there is no significant relationship for the lower tercile. All of these tests support a causal interpretation of our results.

To better understand the potential behavioral channels explaining the estimated reduced-form 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 drunk driving, speed and distraction are behind our results, while the effect seems to be driven by reckless driving.

[4]Beyond the direct financial wealth effect on stock market 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 their own economic outlook. In section 4.1, we present empirical tests suggesting that the direct effect is the main channel.

Our paper is related to several strands of literature. One strand has identified a relationship between stock returns and physical and mental health (McInerney et al., 2013; Cotti et al., 2015; Engelberg and Parsons, 2016; Cotti and Simon, 2018; Schwandt, 2018), as well as subjective and emotional (worry, stress, anger) well-being (Deaton, 2012; Frijters et al., 2015; Ratcliffe and Taylor, 2015). We contribute to this literature by providing evidence that stock market fluctuations can have an impact on investors' health status through its effect on the likelihood of being involved in a driving accident.[5] 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 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:

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

where $Accidents_t$ is the main outcome of interest, namely the daily number of fatal accidents that involve at least one car. $Return_t$ 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.[6]

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

[5] In a related study, Vandoros et al. (2014) find 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] 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 and Value Weighted Index.

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 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).

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 are collected by the National Highway Traffic Safety Administration. FARS is a census of fatal motor vehicle crashes that occurred in 1975-2015 in the US.[7] 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.[8] 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. A full list of all variables used in the analysis is presented in Table A1. The average daily number of accidents during the period was 53, involving on average 90 vehicles and 59 fatalities. The distribution of the number of accidents is reported in Figure 3 in the Appendix. The average stock market daily return (standardized by the rolling one-year standard deviation) is 0.04 %.[9]

[7] 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.

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

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

Table 1: Summary statistics

	Mean	St. Dev	Min	Max
# of accidents	52.57	14.2	14	115
# of vehicles	89.86	24.84	25	237
# of fatalities	58.87	16.81	16	136
S&P 500 Daily returns	.04	1.04	-6.61	6.16

N=6550. Source: Road accidents fatalities derived from the Fatality Analysis Reporting System (FARS). Daily returns (S& P 500) refers to the Standard and Poor's 500 Composite Index divided by the rolling yearly 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.

3 Results

3.1 Baseline Analysis

Table 2 contains our baseline regression results.[10] 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 finally, in column 5 we add the VIX and the EPU index. We observe that the coefficient on returns is negative and statistically significant across all the columns. In particular, the coefficient estimate becomes smaller (in absolute value) when controlling for the year, month and day-of-the-week effects. However, when adding further controls, the estimates have essentially the same size. 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 0.5%. This estimated effect is slightly larger than the effect of the stock market on hospitalizations in California reported by Engelberg and Parsons (2016).

In Table 3, we explore the sensitivity of our key result to alternative functional form specifications. In the first 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 non-quadratic. In the second 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 on positive days.

Finally, we explore non-linear effects by splitting the distribution of daily returns into three groups defined by terciles 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 0.507 (s.e. 0.257) for the bottom tercile. Since the average

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

Table 2: Baseline regression

	1	2	3	4	5
Daily returns	–0.329**	–0.267***	–0.274***	–0.263***	–0.257***
	(0.129)	(0.096)	(0.095)	(0.095)	(0.096)
Time trend	Y	Y	Y	Y	Y
Year, month & day of the week F.E.	N	Y	Y	Y	Y
Holidays F.E.	N	N	Y	Y	Y
Daily rain / wind / CO emissions	N	N	N	Y	Y
VIX / EPU index	N	N	N	N	Y
R^2	0.380	0.668	0.670	0.671	0.671
N	6550	6550	6550	6550	6550

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.
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 linear and 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 the United States. 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.

daily number of accidents is 53, this implies that days on which the stock market closes down are associated with roughly a 1% 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 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.

In the Appendix, we report results from additional tests to check the sensitivity of the estimates to alternative stock market indices and different outcomes. In Table A3 in the Appendix, we show that using the Dow Jones and the Value Weighted indices instead of the S&P 500 produces results that are very similar to our baseline. Similarly, when using non-standardized daily returns or when eliminating observations for which returns are in the top or bottom 1%, the estimates are remarkably similar to the baseline in Table 2. Finally, in Table A4 we look at other outcomes aside from accidents, such as the number of fatalities, vehicles or persons involved in the accidents. The pattern of the estimates is remarkably in line with the baseline results.

Table 3: Alternative functional forms

Quadratic		Dummy		Terciles	
Daily returns	–0.257***	Negative returns	0.597***	Bottom tercile	0.507**
	(0.096)		(0.204)		(0.257)
Daily returns squared	0.002			Top tercile	–0.151
	(0.045)				(0.251)
R^2	0.671	R^2	0.671	R^2	0.671
N	6550	N	6550	N	6550

Robust standard errors in parentheses. **/*** indicates significance at the 0.05/0.01 level. All regressions include the control 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.

3.2 Robustness and Specification Checks

In Table 4, 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 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. 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 5 we use both contemporaneous and lagged returns, while in column 6 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.

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 2, we plot the estimated coefficients of a forward recursive regression (Panel A) and a

Table 4: 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	–0.205*	–0.233**	–0.258***	–0.259***	–0.253***	–0.255***	
	(0.107)	(0.098)	(0.098)	(0.098)	(0.096)	(0.096)	
Lag accidents					0.049***		
					(0.013)		
Lag returns						0.012	0.025
						(0.095)	(0.095)
R^2	0.503	0.376	0.416	0.449	0.672	0.671	0.671
N	6550	6550	6550	6550	6549	6549	6549

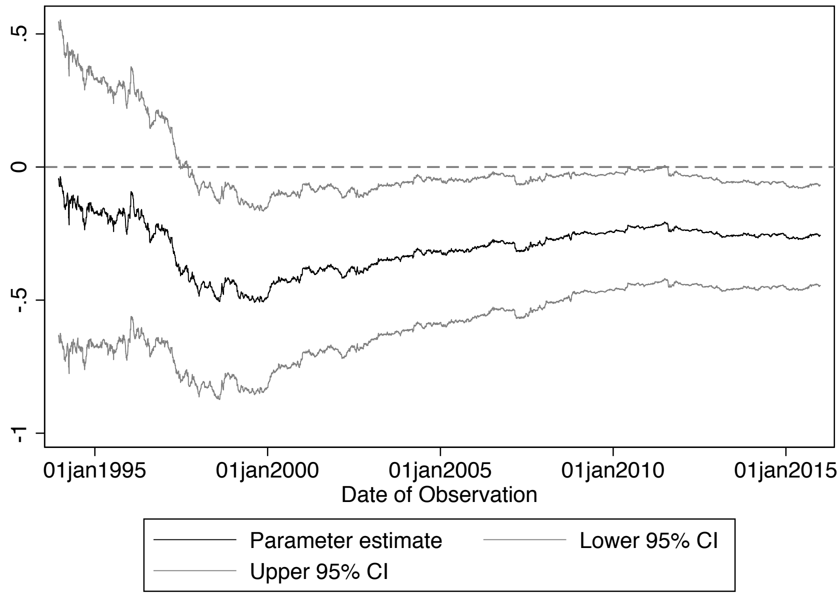
Robust standard errors in parentheses. */**/*** indicates significance at the 0.1/0.05/0.01 level. All regressions include the variables in Table 2 column 5.
5/20/125/250 days refers to specifications where the dependent variable is the difference between the daily accidents and the average of the previous 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.

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 1st January 1990 until then. The graph shows that the estimated coefficient is mildly negative but of constant size 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 -0.51), before it starts converging to the value estimated in the full sample (-0.26).

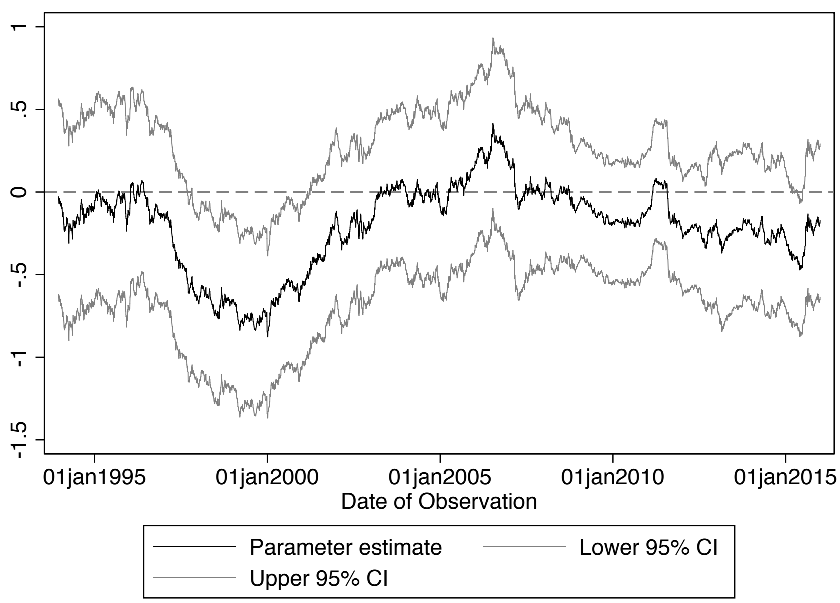
In Panel B, we implement a rolling regression using an identical window (1,000 trading days). The first estimated coefficient is hence identical to the one obtained in the previous graph, after which the four-year window moves one day forward. The last estimate (at the end of 2015) is hence obtained 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, albeit not statistically significant. 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 of exuberance–particularly for 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. Note that it is conceivable that even people not directly invested 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.[11] 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.

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

In what follows, we describe in detail each test and discuss the results.

First, in the first two columns of Table 5, we exploit the fact that we have information about the exact time of the day when each accident occurred. We use this information to split days into two time windows: before and after the opening of the stock market (9:30 AM).[12] We then re-estimate our baseline specification separately for accidents that happen in these two time windows of the day. The results clearly indicate that there is no association between the stock market and accidents that happen before the market opens, whereas there is a negative and statistically significant effect of the daily returns on accidents that happen after the stock market opens. Second, in columns 3 and 4 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-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.

In Table 6 we move to the second type of falsification tests, based on the likelihood of owning stocks, 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 (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 (column 2).

In the second 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

[12]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.

Table 5: Causality and falsification I

	Market opening		Lead daily returns		Non-human cause
	Before	After			
Daily returns	–0.044	–0.227***	–0.255***		–0.018
	(0.047)	(0.079)	(0.096)		(0.015)
Lead returns			0.112	0.117	
			(0.098)	(0.098)	
R^2	0.313	0.616	0.671	0.671	0.114
N	6550	6550	6549	6549	6550
$\bar{Y}$	12.91	37.42	52.57	52.57	1.41

Robust standard errors in parentheses. *** indicates significance at the 0.01 level. All regressions include the variables in Table 2 column 5. Before market opening refers to the time window between 00:00 and 9:29 Eastern Time Zone. After market opening refers to the time window between 9:30 and 23:59 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.

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.[13] We finally split accidents into terciles: those with high, intermediate and low stock market exposure.[14]

In the third 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 drivers involved at the zip level. As before, we split accidents in terciles: those with high, intermediate and low income. For the fourth 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.

The results of the three alternative methods based on wealth or income data are presented in columns 3-11 of Table 6. Across all three methods, we find a consistent pattern whereby stock market returns have a strong and statistically significant effect in the top tercile, a moderate impact in the middle tercile and a very small and always insignificant effect on the bottom tercile.

[13] Using the maximum stock market exposure among the cars involved in the accident instead of the average yields similar results.

[14] We could attribute a stock market exposure value for 655,848 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 6: Causality and falsification II

	Age		Cars' stock market exposure			Income of the driver's zip			Income in the county of accident		
	All $\leq$ 25	Others	High	Medium	Low	High	Medium	Low	High	Medium	Low
Daily returns	0.054	–0.312***	–0.129***	–0.092	–0.036	–0.137***	–0.096*	–0.010	–0.143***	–0.074	–0.040
	(0.040)	(0.083)	(0.048)	(0.058)	(0.054)	(0.051)	(0.051)	(0.054)	(0.053)	(0.052)	(0.054)
R^2	0.463	0.603	0.370	0.484	0.471	0.366	0.420	0.501	0.431	0.421	0.455
N	6550	6550	6550	6550	6550	6550	6550	6550	6550	6550	6550
$\bar{Y}$	9.97	42.60	14.28	19.81	18.44	16.98	16.73	18.10	17.23	17.16	17.95

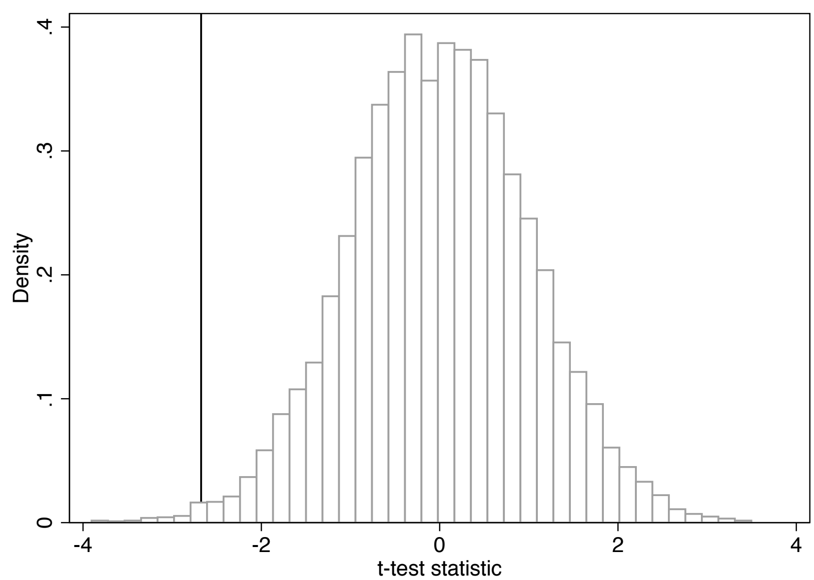
Robust standard errors in parentheses. */*** indicates significance at the 0.10/0.01 level. All regressions include the variables in Table 2 column 5. All $\leq$25 refer to accidents involing only drivers below the age of 25. Others refers to the remaining accidents.

High, medium and low refer to the first, second and third tercile of the distribution of the variable indicated in each panel's header. The cars' stock market exposure refers to the average ratio between the stocks values and net worth attributable to cars' make. It is calculated by aggregating data on values of stocks, net worth and vehicle make from the PSID. 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.

Overall, this pattern of a stronger relationship between stock market and accidents involving drivers who are the most likely to be stock holders found across the different methods 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, in our last test, we perform a simulation exercise whereby we estimate 10,000 regressions using our baseline specification in Table 2 column 5, 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. In Figure 2, we plot the empirical distribution of the t-statistics of the estimates obtained from the simulation exercise. The vertical line indicates the t-statistic of the "real" estimate in Table 2 column 5. This is located in the lower tail of the empirical distribution, implying a significance of 1% of our test.

Figure 2: 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.

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 in Table 7. We find a statistically significant effect only for the "reckless" category, 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 and drinking–are behind our results.

Table 7: Channels: Unsafe driving actions

	Distraction	Reckless	Speed	Drunk dr.
Daily returns	0.001	–0.258***	–0.032	–0.025
	(0.034)	(0.084)	(0.050)	(0.048)
R^2	0.382	0.742	0.424	0.573
N	6550	6550	6550	6550
$\bar{Y}$	7.30	40.03	14.82	13.34

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

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' 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.[15] 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.

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

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6 Appendix

Table A1: Summary statistics - all variables

	Mean	St. Dev	Min	Max
# of accidents	52.57	14.2	14	115
# of vehicles	89.86	24.84	25	237
# of fatalities	58.87	16.81	16	136
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

N=6550. Source: Road accidents fatalities derived from the Fatality Analysis Reporting System (FARS). Daily returns (S& P 500, Dow Jones and Value Weighted) refer to the respective indices 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.

Figure 3: Histogram of daily number of accidents

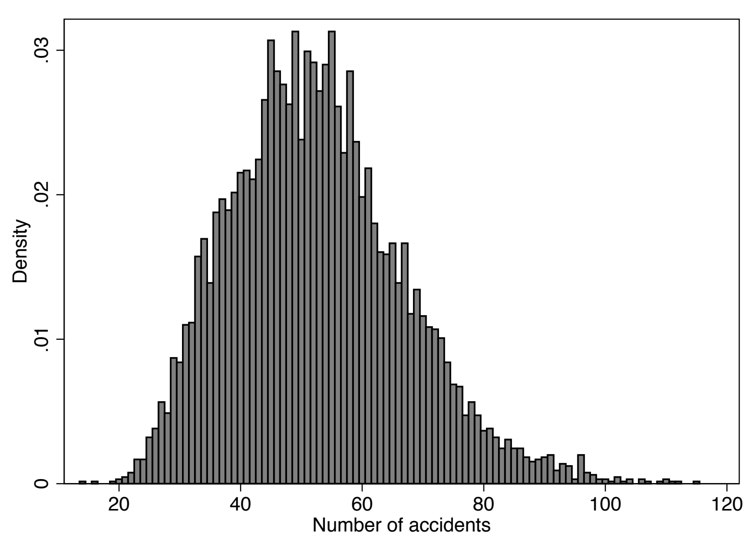

Table A2: Baseline regression - details of controls

	1	2	3	4	5
Daily returns	–0.329**	–0.267***	–0.274***	–0.263***	–0.257***
	(0.129)	(0.096)	(0.095)	(0.095)	(0.096)
Holiday interval (D)			3.284***	3.265***	3.229***
			(0.626)	(0.625)	(0.623)
Rain				0.309***	0.307***
				(0.066)	(0.066)
Wind				–0.015	–0.014
				(0.015)	(0.015)
CO emissions				–0.386	–0.456
				(1.101)	(1.103)
VIX					0.001
					(0.019)
EPU index					–0.510***
					(0.184)
Time trend	Y	Y	Y	Y	Y
Year, month & day of the week F.E.	N	Y	Y	Y	Y
R^2	0.380	0.668	0.670	0.671	0.671
N	6550	6550	6550	6550	6550

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.
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 linear and quadratic time trends. Holiday interval 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. Rain refers to the mean level of rain in millimeters calculated by averaging the amount of daily rain measured at available weather stations in the United States. Wind refers to the vectorial average of all wind directions and speeds across the U.S.. 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. EPU index obtained from http://www.policyuncertainty.com/us_daily.html. VIX obtained from http://www.cboe.com The period covers all days from 01/01/1990 to 31/12/2015 for which car accidents and financial data are observed.

Table A3: Alternative stock market returns measure

	Dow Jones	Value weighted	Returns not std.	No extreme returns
Daily returns	–0.210**	–0.246**	–0.242***	–0.238**
	(0.096)	(0.096)	(0.094)	(0.112)
R^2	0.671	0.671	0.671	0.671
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 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 % change in the Value weighted index between the day the index is observed and the previous day, 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 A4: Alternative outcomes

	Log accidents	# fatalities	# vehicles	# persons
Daily returns	–0.005**	–0.270**	–0.577***	–0.837***
	(0.002)	(0.116)	(0.185)	(0.323)
R^2	0.678	0.667	0.607	0.653
N	6550	6550	6550	6550
$\bar{Y}$	4.03	58.87	89.86	147.60

Robust standard errors in parentheses. **/*** indicates significance at the 0.05/0.01 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. Number of fatalities: the dependent variable is the daily number of fatalities in crashes involving at least one car. Number of vehicles: the dependent variable is the daily number of vehicles in crashes involving at least one car. Number of persons: the dependent variable is the daily number of persons in crashes involving at least one car.