When Paper Losses Get Physical: Domestic Violence and Stock Returns*

Tse-Chun Lin† and Vesa Pursiainen‡

May 2020

Abstract

We find a significant negative relationship between stock returns during the week and the reported incidence of domestic violence during the weekend. Our findings suggest that wealth shocks caused by the stock market can affect stress levels within families, escalate arguments, and trigger violence. The effect of stock returns on reported domestic violence is primarily attributable to negative returns, and the incidence of domestic violence increases with the magnitude of loss. The effect also increases with local stock market participation. Using Google search volumes as an alternative proxy for the incidence of domestic violence yields similar results.

JEL classification: D03, D14, D62, J12

Keywords: domestic violence, intimate partner violence, stress, household, behavior

*We appreciate the helpful comments from Sumit Agarwal, Utpal Bhattacharya, Tzu-Chang Cheng, Lauren Cohen, Mikael Homanen, Matti Keloharju, Lisa Kramer, Alan Kwan, Kai Li, Chen Lin, Albert Menkveld, Ville Rantala, Elias Rantapuska, David Reeb, Ryan Riordan, Hannes Schwandt, David Solomon, Xuan Tian, Tzu-Ting Yang, Jeffrey Zwiebel, the conference participants at American Finance Association (AFA) Annual Meeting 2019, Barcelona GSE Summer Forum 2019, Helsinki Finance Summit 2018, Research in Behavioral Finance Conference 2018, EEA-ESEM 2018, ESPE 2018, AFFI 2018, SSES Annual Congress 2018, TER 2018, TFA 2018, 2018 NCCU Symposium of Finance, European Retail Investment Conference (ERIC) 2019 Doctoral Consortium, and FMA Asia/Pacific 2018 Doctoral Student Consortium, as well as the seminar participants at the University of New South Wales, Hong Kong University of Science and Technology, Hong Kong Baptist University and the University of Hong Kong. Tse-Chun Lin gratefully acknowledges research support from the Faculty of Business and Economics at the University of Hong Kong. All errors remain the responsibility of the authors.

†The University of Hong Kong. E-mail: tsechunlin@hku.hk

‡University of St. Gallen. E-mail: vesa.pursiainen@unisg.ch

1 Introduction

Domestic violence is one of the most common types of crime, as well as a substantial public health problem. Nearly a third of women and more than a quarter of men in the U.S. experience physical violence by an intimate partner in their lifetime, while the estimated annual cost of domestic violence against women alone is more than $5.8 billion.[1] Economic models of household bargaining that incorporate domestic violence typically suggest that violence may arise because it provides positive utility to the perpetrator, while the victims' outside options determine their willingness to suffer domestic violence.[2] In addition, Card and Dahl (2011) develop a loss-of-control model to analyse how domestic violence can be triggered unintentionally when an argument escalates out of control. Their model provides similar predictions to a household bargaining one in which preferences are affected by emotional cues from a gain-loss function. They also find compelling evidence of domestic violence being triggered by emotional shocks related to losses in football when the home team was predicted to win.

Our paper is the first attempt to study a negative externality of the stock market affecting the incidence of domestic violence. Money is one of the most common sources of stress generally and in intimate relationships in particular.[3] There is also empirical evidence suggesting a link between economic stress and domestic violence.[4] Stock price movements represent shocks to wealth and may either exacerbate or relieve economic stress levels. Engelberg and Parsons (2016) find evidence of stock market having a meaningful impact on the stress levels of individuals, reflected in a significant negative relationship between lo-

[1]Estimates by Centers for Disease Control and Prevention (2003, 2011)

[2]See, e.g., Tauchen, Witte, and Long (1991); Aizer (2010); Anderberg, Rainer, Wadsworth, and Wilson (2016)

[3]For example, in the latest annual "Stress in America" survey conducted by the American Psychological Association (APA) (2017), 62% of respondents report money as a source of stress. In a survey conducted in the U.S. by Harris Poll on behalf of SunTrust Bank in 2015, respondents reported finances to be the most common cause of stress in their relationship, cited by 35% of respondents, followed by annoying habits (25%). A summary of the survey findings is available online at: https://www.prnewswire.com/news-releases/love-and-money-people-say-they-save-partner-spends-according-to-suntrust-survey-300030921.html.

[4]See, e.g., Benson, Fox, DeMaris, and Van Wyk (2003); Schwab-Reese, Peek-Asa, and Parker (2016).

cal stock market returns and hospital admissions for psychological conditions. Schwandt (2018) shows that wealth shocks caused by the stock market predict wealth changes and strongly affect health outcomes, including physical health, mental health, and even survival rates. In our context, we hypothesize that stock returns might affect stress levels within families and intimate relationships. The increased stress level could potentially trigger and escalate arguments, resulting in increased incidence of domestic violence. Intuitively, the stress levels required to escalate arguments are likely to be less drastic than those requiring hospitalization.

To formalize our hypothesis, we construct a simple loss-of-control model adapted from that of Card and Dahl (2011).[5] In addition to predicting the negative link between stock market returns and the incidence of domestic violence, the illustrative model highlights the importance of reference points in the form of expected stock returns and predicts that stock market losses should have a stronger effect than stock market gains.

To test our hypothesis, we construct a large sample of incidents of domestic violence in the U.S., using data from the National Incident Based Reporting System (NIBRS), which includes all reports of crime by city/county for the participating police agencies. The agencies in our data cover a population of 39 million in 2001, the first year of our sample. The coverage grows to 86 million in 2016, as more agencies gradually join the system. We calculate daily and weekly incident rates, defined as the number of reported incidents per 100,000 capita, at the level of individual police agencies. In our analysis, we define domestic violence as reported incidents of assault, aggravated assault, or intimidation by a spouse, partner, or boyfriend/girlfriend.[6]

We then construct a local stock market index for each U.S. state, calculated as the market-cap-weighted average return of all stocks headquartered in the state. Similar to

[5]The model is included in Appendix A.1.

[6]When discussing the existing literature, we use the term *domestic violence* interchangeably with the terms *intimate partner violence* and *family violence* to refer to various types of violence perpetrated within the family, without specifying the exact definition in each case. We generally focus on violence against intimate partners, although the term domestic violence could in other contexts include other forms of violence as well, e.g., parent-to-child violence or sibling violence.

Engelberg and Parsons (2016), our methodology utilizes the well-documented tendency of investors to overweight local stocks in their portfolios. Hence, our state-level stock index is likely to be a good proxy for the returns to investors in the same state.[7] This setup allows us to exploit the cross-sectional variation between states for each time period, in addition to variation across time within the state, which increases the robustness of our analysis.[8] While not all families participate in the stock market, more than 20% of U.S. households do have direct investments in stocks, and approximately 50% have direct or indirect stock investments (Bricker, Dettling, Henriques, Hsu, Moore, John Sabelhaus, and Windle, 2014; Bricker and Li, 2017). As discussed below, our estimates of stock market participation in our data are consistent with these figures. These ratios clearly indicate that a sufficient share of the population are exposed to stock market movements to have a noticeable impact on their stress levels and consequent domestic violence incidents.

We perform our main analysis at the weekly level. In order to study the relationship between weekly stock market returns and levels of domestic violence, for each week, we only include the incidents taking place during the weekend between Friday 4pm (stock market closing) and Sunday 12 pm (midnight), while the weekly stock returns are calculated from Monday to Friday. We choose the weekly frequency because weekly stock market returns represent larger and more meaningful wealth shocks from market movements than daily returns, while still allowing us to capture the relatively instantaneous effect of return shocks for a causal interpretation. Moreover, as shown in Figure 1, the rates of domestic violence are higher during the weekend, when stock markets are closed, than during weekdays. Based on our hypothesis, we anticipate that negative stock market returns should increase stress levels within families, trigger and escalate arguments, and result in higher levels of domestic violence.

[7]French and Poterba (1991) document this "home bias" phenomenon in the international context, while Coval and Moskowitz (1999) show it also applies in domestic investments. Seasholes and Zhu (2010) provide evidence of local bias by individual investors.

[8]As we show in our robustness checks in Section 5.3, our findings are also robust to using the S&P 500 as a proxy for stock market return.

To illustrate this relationship, in Figure 2, we plot the seasonally adjusted average level of domestic violence and stock market returns around the week of October 6-12, 2008, the largest weekly stock market drop in our data. This figure suggests a visible negative association between domestic violence and stock returns. During the week of the main stock market crash, there is a pronounced increase in domestic violence, while the following week experiences both strongly positive stock returns and significantly reduced levels of domestic violence.

Our regression results provide more general support for the hypothesis. We find a significant negative relationship between state-level stock market returns and rates of domestic violence. This relationship is robust to controlling for police agency-month joint fixed effects, holiday fixed effects, and week-of-the-year fixed effects capturing conceivable seasonality within the year. We also control for state-level weekly insured unemployment rate, which is the only relevant macroeconomic variable available at weekly intervals. Utilizing the cross-sectional dimension of the data, we also show that the result holds when including week fixed effects, thus capturing only the cross-sectional variation between agencies for each week. This provides further comfort in the identification, in addition to the time series correlation that, e.g., the analysis of Engelberg and Parsons (2016) relies on.[9]

Furthermore, the significant negative relationship between local stock returns and levels of domestic violence only holds for the concurrent week, while lagged or forward stock returns have no significant predictive power over domestic violence. This finding further supports a causal interpretation of the negative correlation. We also find that the relationship between stock returns and domestic violence is larger in magnitude and statistically more significant for negative stock returns. Consistently, exceptionally large negative weekly returns are associated with significantly higher levels of domestic violence. For example, the effect of a 13% drop in weekly return on domestic violence is nearly four times as big as that of a 7%

[9] Engelberg and Parsons (2016) perform a time-series regression with hospitalization due to psychological conditions in California as the dependent variable and stock returns of firms headquartered in California as the independent variable.

drop in weekly return.

Consistent with Card and Dahl (2011), our results suggest that unexpected losses are associated with stronger emotional cues and hence a larger effect on the incidence of domestic violence. The results of Da, Huang, and Jin (2019) suggest that investors' return expectations are significantly affected by recent past returns, with the most recent four weeks being the most influential for extrapolative beliefs. Hence, we perform the same analysis using returns relative to last four weeks' average return and find that the magnitude of the effect is more stable across different model specifications. We also find that the directionality of the relationship is much clearer when controlling for reference points. When using returns relative to four-week average, only losses appear to have a significant negative relationship with domestic violence. Furthermore, the effect of such losses increases in a monotone fashion with the magnitude of the loss.

A clear interpretation of the relationship between stock returns and domestic violence requires that an adequate number of households are exposed to the stock market. We construct a location-based measure stock market participation using the Individual Income Tax Return Statistics from the IRS and divide the agencies in our sample into three categories each year, based on the level of stock market participation at the agency location. We find that the effect of stock returns on the incidence of domestic violence is strongest in areas with the highest stock market participation, consistent with our hypothesis.[10][11]

A potential concern related to data on domestic violence based on incidents reported to police agencies is that not all incidents get reported. This may lead to understating true incidence levels of domestic violence, and possibly result in a bias in the results, in case there are systematic differences in the propensity to report. To mitigate this concern, we construct an alternative proxy for the incidence of domestic violence based on Google search

[10]The average stock market participation rate for households across the police agency locations in our data is 19.7%, with standard deviation of 7.0%.

[11]In the Internet Appendix, we perform a similar analysis differentiating by income levels. We find that the relationship between stock returns and rates of domestic violence is negative for all income levels, but the middle tertile exhibits the strongest and statistically most significant relationship between stock returns and domestic violence.

volumes for the keyword "domestic violence" for each U.S. state. It seems plausible that victims (or perpetrators) of domestic violence might conduct online searches involving these keywords following incidents of domestic violence. Unlike with reported incidents, there is no reason why this indicator would understate the incidence of domestic violence, especially for wealthy households. This methodology provides us with a state-level daily panel dataset of search volumes. Consistent with our main results using reported incidents of domestic violence, we find a statistically significant negative relationship between the weekly stock return and google search volume for domestic violence during the weekend.

Another potential concern is that our findings might be driven by local firm events, such as layoffs or plant closures, that may also be also correlated with negative local stock returns. This would mean that the channel is not stock-market-related financial stress but the associated economic stress. To address this issue, we use three alternative proxides for stock market that are unlikely to be significantly correlated with local economic events. First, we construct a state-level stock index for each police agency, excluding the companies based in any county which the police agency covers. We then perform our baseline regression analysis using these indices. The results are consistent with the main results, suggesting that our findings are not driven by very local economic factors. Second, we show that the results are robust to using the S&P 500 index returns instead of state-level stock returns, further alleviating the concern that local firm events might affect the findings. Finally, we construct a national stock index excluding the firms headquartered in the same state where the agency is located. The results remain qualitatively similar when using this index. In addition, the findings are robust to using to non-logarithmic form of the domestic violence rate or a dummy indicating non-zero number of incidents as the dependent variable for the extensive margin analysis.

To verify that our findings are specific to domestic violence and not a reflection of other general patterns in crime rates, we construct similar incidence rates for other offenses that might conceivably be correlated with stock returns. These include assaults where the victim is unknown to the perpetrator, murders, sex offenses, robberies, and drug offenses. We show that none of these other types of crime exhibit a similar significant relationship. This finding further alleviates the concern that our results are driven by local economic conditions, as no other crimes are significantly affected by the local stock market movements.

Our estimates also suggest that the the economic magnitude of the effect of stock returns on domestic violence is not trivial. A 13-percentage-point decrease in weekly stock return relative to four-week average leads to an estimated 2.7% increase in domestic violence around the average rate.[12] The coefficient we estimate for a dummy indicating a local stock market drop of at least 13% relative to four-week average suggests an increase in domestic violence of 4.6% from the average rate. Interestingly, in terms of economic magnitude, the relationship between stock return and domestic violence based on Google search volume is much stronger than that based on reported incidents. The estimated coefficient in Table 8 Panel B (Model 4) suggests that a 13%-point decrease in stock return would result in 15% increase in domestic violence around the mean rate. For comparison, Card and Dahl (2011) estimate that "upset losses" in professional football by the home team lead to a roughly 10% increase in at-home male-on-female intimate partner violence on Sundays during the season. Engelberg and Parsons (2016) report an increase of more than 5% in hospital admissions associated with the Black Monday stock market fall of almost 25%.

We perform a number of robustness checks to validate our results. These include different specifications of the domestic violence (LHS) variable, different definitions of weekend and different stock return periods, different stock return reference points, analyses excluding states with the most listed companies, and analyses controlling for firm news, Google search volumes for "unemployment", and stock return volatility. Our findings on the negative relationship between stock returns and the incidence of domestic violence remain robust to all these alternative specifications.

Our paper contributes to the literature by providing the first link between the stock

[12]This estimate is based on Model 4 in Table 5.

market and domestic violence. Domestic violence triggered this way could be viewed as a negative externality of stock market movements that affects household utility beyond the shock to financial wealth. Such externalities might, in part, help explain some of the implied high risk aversion or the limited stock market participation of households.[13] We also add to the literature on the economic causes of domestic violence and provide additional evidence of both the effect of economic stress as well as the effect of emotional cues on the incidence of domestic violence.

2 Literature review and hypothesis development

2.1 Domestic violence in the economic literature

Economic theories incorporating domestic violence can be broadly divided into two categories. The first includes economic models of household bargaining that suggest that domestic violence arises because it provides positive utility to the perpetrator.[14] The victims' willingness to suffer violence is determined by their outside options. Early non-cooperative models of the family including domestic violence as a source of gratification and instrument of control include Tauchen et al. (1991) and Farmer and Tiefenthaler (1997). In related work, Pollak (2004) develops a model in which children adopt behavioral patterns with respect to domestic violence from their parents.

In the empirical literature following this framework, Aizer (2010) shows that decreases in the male-female wage gap reduce violence against women. Anderberg et al. (2016) show that an increase in male unemployment decreases the incidence of domestic violence, while an increase in female unemployment does the opposite. Bloch and Rao (2002) find evidence

[13] Mehra and Prescott (1985) observed that historical stock returns are much higher than could be rationalized by standard intertemporal economic models, given the realized return volatility. This has been dubbed the "equity premium puzzle" in the literature.

[14] It is common in the literature to focus on domestic violence perpetrated by men, although there is obviously also a significant amount of domestic violence perpetrated by women. We adhere to this convention in referring to the perpetrator with masculine and to the victim with feminine pronouns.

of men using domestic violence as a bargaining tool to extract transfers from the wife's family in the context of rural India.

The second strand of literature suggests that domestic violence can be triggered unintentionally when an argument escalates out of control. This channel is highlighted by Gelles and Straus (1989) and Kelly and Johnson (2008), among others. Card and Dahl (2011) develop a more formal loss-of-control model to study the link between family violence and the emotional cues associated with unexpected wins and losses by professional football home teams. In their empirical analysis, they find that upset losses lead to significant increases in at-home violence by men against their wives and girlfriends. Similarly, Beland and Brent (2018) show that extreme traffic congestion is associated with significant increases in domestic violence.

There is also a substantial body of literature linking domestic violence to economic hardship. Conger, Elder, Jr., Lorenz, Conger, Simons, Whitbeck, Huck, and Melby (1990) study the negative impact of economic hardship on marital quality. Gelles and Straus (1989) describe the "typical wife beater" as someone worrying about economic security and dissatisfied with his standard of living. Benson et al. (2003) find evidence of financial strain and employment instability being related to domestic violence.

Another notable strand of literature focuses on the link between domestic violence and substance abuse. de Bruijn and de Graaf (2016) review the literature on the role of substance abuse in domestic violence and conclude that there is robust evidence of alcohol use increasing the likelihood of physical violence. There is also some evidence of cocaine use increasing women's risk of becoming a victim of domestic violence. Luca, Owens, and Sharma (2015) study the impact of alcohol prohibition in India and find evidence that restricting access to alcohol may help reduce domestic violence. There is evidence that treatment for substance abuse can help reduce domestic violence as well (e.g., Murphy and Ting, 2010).

Finally, Moffitt, Krueger, Caspi, and Fagan (2000) study to what extent perpetrators of domestic violence are the same as or similar to the perpetrators of other crime. They find that domestic violence and general crime represent different constructs that are moderately related; they are not two expressions of the same underlying antisocial propensity. In contrast to our study, Huck (2015) finds a positive relationship between stock returns and general crime rates, arguing that this is consistent with envy models, i.e., individuals see their own position as relatively worse following gains by others. In particular, he argues that low-income individuals who hold less (or no) stocks feel worse off relative to high income individuals on days with high stock returns, resulting in increase of crime rates for low-income individuals.

2.2 Domestic violence and stock market returns

We argue that large stock market movements may also have an immediate effect on the stress levels of individuals and hence trigger and escalate arguments, similar to the impact of unexpected football losses documented by Card and Dahl (2011). This argument is in line with the results of Engelberg and Parsons (2016), who find a connection between stock market and hospital admissions for psychological conditions. Schwandt (2018) finds more direct evidence shows that wealth shocks caused by the stock market can have detrimental effects. His results suggest that such shocks predict wealth changes and have an adverse effect on a number of health outcomes, including physical health, mental health and survival rates. Lin, Chen, and Liu (2015) also find a connection between mental disorders and stock market fluctuations in Taiwan. The medical literature provides further indirect support. Chen, Chen, Liu, and Lin (2012) find that daily falls in the stock market index are associated with higher incidence of stroke in Taiwan. Similarly, two studies using data from China find that stock market volatility is associated with higher levels of deaths due to coronary heart disease (Ma, Chen, Jiang, Song, and Kan, 2011) and higher cardiovascular mortality (Lin, Zhang, Xu, Liu, Xiao, Luo, Xu, He, and Ma, 2013).

A necessary condition for stock returns to have an effect on the level of domestic violence is that a substantial number of people hold stocks. Reassuringly, the literature shows that more than 20% of U.S. households have direct investments in stocks, while approximately

50% have direct or indirect stock investments (Bricker et al., 2014; Bricker and Li, 2017). In our domestic violence data, we do not observe what stocks perpetrators are holding. Hence, we follow Engelberg and Parsons (2016) to exploit the tendency of investors to overweight local stocks (home bias) to identify the relevant stock returns that induce domestic violence.[15]

In the Appendix A.1, we follow the approach in Card and Dahl (2011) to construct a simple loss-of-control model for the incidence of domestic violence. This model suggests a negative relationship between the stock return and the likelihood of domestic violence. As in Card and Dahl (2011), the gains and losses are measured relative to expectations, i.e., the reference point also matters. For example, Da et al. (2019) and Greenwood and Shleifer (2014) show evidence that investors extrapolate from stocks' recent past returns, with more weight on more recent returns, and that such extrapolative beliefs are stronger among non-professionals. This means that recent past returns should represent a good proxy for individual investors' expectations of future returns.

Based on these observations, we formulate our main hypothesis as follows:

Hypothesis: *The incidence of domestic violence is negatively related to the difference between the realized local stock market returns and the investors' expectations.*

3 Data and methodology

3.1 Domestic violence data

We obtain data on reported incidents of intimate partner violence from the National Incident Based Reporting System (NIBRS), which includes all reports of crime filed by individual police agencies. The number of agencies increases over time, as more agencies join the

[15]French and Poterba (1991) document this "home bias" phenomenon in the international context, while Coval and Moskowitz (1999) show it also applies in domestic investments. Seasholes and Zhu (2010) provide evidence of local bias by individual investors.

NIBRS.[16] The NIBRS data include a large number of small agencies, which have many weekly observations with zero incidents reported. To improve the consistency of the agencies in our sample, and to reduce the noise introduced by large number of zero observations, we only include agencies covering populations of at least 10,000. The NIBRS database is available from 1991 onward, but its coverage in the early years is very low, which could lead to poor representativeness of the data for these years. Hence, we cut our sample period from 2001 onward. This is the first yera when there are more than 1,000 agencies covering a population of above 10,000. Table 1 shows the number of agencies in our sample in each year. The agencies included cover a population of 86.2 million in 2016, the last year in our data, compared with 39.0 million in 2001, the first year.

The incident reports include the date and the time (by the hour) of the incident, as well as a number of other details. It is important to note that the incidents do not necesarily result in arrests, so the coverage of the data is broader than arrested or prosecuted cases. Similar to Card and Dahl (2011), we define domestic violence as a reported incident of assault, aggravated assault, or intimidation by a spouse, partner, or boyfriend/girlfriend. For calculating incident rates, we include all incidents satisfying these criteria, which means that our definition is less restrictive than that adopted by Card and Dahl (2011), who focus on male-on-female domestic violence occurring at home only.

We construct domestic violence rates, defined as number of reported incidents per 100,000 capita, at the level of individual police agencies. Our main analysis is performed on the basis of weekly observations. In order to establish a relationship between weekly stock market returns and levels of domestic violence, for each week, we only include the incidents taking place during the weekend, between Friday 4pm (stock market closing) and Sunday 12am (midnight), while the weekly stock returns are calculated from Monday to Friday. Compared with daily returns, the weekly stock return is more likely to generate a meaningful wealth shock to households, while still allowing us to capture the instantaneous effect of return

[16] There are also agencies leaving the system, but generally the number of agencies grows every year in our sample period.

shocks for a causal interpretation. Moreover, as incidents of domestic violence happen much more often on Friday, Saturday, and Sunday, than on other weekdays (as shown in Figure 1), we focus on the relationship between weekly stock returns and the domestic violence during these three days.

3.2 Local stock market returns

We obtain stock market data from the Center for Research in Security Prices (CRSP) for all U.S. stocks listed on NYSE, NASDAQ, and AMEX. We combine the stock data with company location data from Compustat. As an additional source of location data, we download all 10-K reports available in electronic format in the EDGAR database and add locations missing in Compustat based on these reports. This yields approximately 90% of the stock-day observations in CRSP during our sample period of 1996-2015. We then construct weekly state-level stock market index returns as market-cap-weighted average returns of all listed companies headquartered in each state. We use these state-level indices as a proxy for local stock returns for our analysis.

4 Main results

4.1 Description of the data

Table 2 shows summary statistics for the observations in our sample. The unit of observation is individual police agency on a weekly basis. The average domestic violence rate (DV rate) is 2.5 incidents per 100,000 capita.[17] For comparison, we include offense rates for other offense categories. Drug offense is the most common type of assault, with an average rate of 3.0 incidents per 100,000 capita.

The average weekly stock return at the state-level is 0.2%, with 55% of weekly obser-

[17] This rate is broadly consistent with the average male-on-female rate of 1.28 per Sunday from noon to midnight, as reported by Card and Dahl (2011).

vations involving positive and 45% negative returns. 4.0% of weekly observations involve negative returns of 5% or more, and 1.8% of 7% or more, while 0.9% involve losses of at least 9% and 0.2% losses of at least 13%. We also include the same statistics for stock returns relative to last for weeks' average return. Unsurprisingly, the average difference to four-week rolling average is very close to zero. In 48% of the weekly observations, the return is higher than the four-week average, and in 52% lower.

The average agency in our data covers a population of approximately 41,700. We only include agencies covering at least 10,000 people, which thus represents the minimum, while the largest agency in our data covers a population of 1.1 million. The average stock market participation rate across the police agency locations in our data is 19.7% with a standard deviation 7.0%. The wealth level of agency locations, as measured by county-level personal income (PI) per capita, varies substantially from $12,000 to more than $100,000. The average state-level weekly insured unemployment (IU) rate is 2.4%, with weekly values ranging from 0.2% to 11.5%.

4.2 Stock market returns and incidence of domestic violence

Our hypothesis predicts a negative relationship between stock market gains or losses and domestic violence. To test this, we use regressions of the following form:

$$ln(1 + DV\ rate)_{i,s,t} = \alpha_0 + \alpha_1 \times Return_{s,t} + \beta \times X_{i,s,t} + \epsilon_{i,t} \quad (1)$$

where $ln(1 + DV\ rate)_{i,s,t}$ is the natural logarithm of one plus the domestic violence rate (*DV rate*) of agency i, located in state s, during week t. $Return_{s,t}$ is the return of the stock market index for state s during week t, and $X_{i,s,t}$ is a vector of controls, including the weekly *insured unemployment (IU) rate*, and depending on the specification, *agency fixed effects* (2,139 agencies), *agency-year joint fixed effects*, *agency-quarter joint fixed effects*, or *agency-month joint fixed effects*to capture time-variant factors like local economic conditions at the state level, *holiday fixed effects* with dummies for major holidays taking place during the week t (19 different holidays), and *week-of-year fixed effects* (52 weeks) to capture any seasonal effects.[18] In all regressions, we cluster standard errors by agency.

The results, shown in Panel A of Table 3, are consistent with our hypothesis. In all model specifications, the incidence of domestic violence during weekends is significantly negatively related to stock market returns during the same week. As shown by Model 4, the result is robust to including agency-month joint fixed effects that capture all local economic factors at monthly frequency. This mitigates the potential concern that our results are driven by other economic factors that are correlated with stock returns. For example, during economic downturns, stock returns are likely to be lower, while the economic hardship could plausibly cause increased levels of domestic violence, independent of stock returns. In addition, we control for weekly insured unemployment rate, reported at the state level, which is the only macroeconomic variable available at weekly intervals. Finally, as shown by Model 5, the result also holds when including week fixed effects, capturing essentially only cross-sectional differences across agencies for any given week.

To explore the impact of reference points, we also include a specification using weekly return relative to the rolling four-week average stock return:

$$ln(1 + DV\ rate)_{i,s,t} = \alpha_0 + \alpha_1 \times \Delta Return_{s,t} + \beta \times X_{i,s,t} + \epsilon_{i,t} \qquad (2)$$

where $\Delta Return_{s,t}$ is the current week stock return less the average weekly return of the last four weeks. This specification thus uses the rolling four-week average return as a time-variant reference point, against which current week's gains or losses are measured.[19]

The results, shown in Panel B of Table 3, also show a consistently negative and sta-

[18] The holidays and other major celebration days we include for holiday fixed effects are New Year's Eve, New Year's Day, Martin Luther King, Jr. Day, George Washingtons Birthday, Easter Day, 2nd Easter Day, Good Friday, Ascension Day, Whit Sunday, Memorial Day, Independence Day, Labor Day, Columbus Day, Veterans Day, Thanksgiving Day, Christmas Eve, Christmas Day, Valentines Day, and Halloween.

[19] Empirically, we cannot observe the expected stock return and hence cannot tell whether four weeks is the right period for calibrating expectations. In the Internet Appendix (Table A.9), however, we show that using alternative reference periods yields similar results.

tistically significant relationship between stock returns relative to recent past returns and domestic violence. The most striking difference between the results for raw stock returns, reported in Panel A, and reference-dependent stock returns in Panel B, is the consistency of the magnitude of the estimated effect. In Panel A, the estimated coefficients are substantially higher for the models with a smaller number of fixed effects and decrease when including agency-time fixed effects at shorter intervals. In contrast, the estimated coefficient for reference-dependent stock returns are remarkably stable across all model specifications. This suggests that the regression model shown in Panel B appears to fit our model in Section A.1 better than the regression using raw stock returns. In other words, reference point in the form of expected stock returns does matter for the impact of current stock return.

In Table 4, we perform the same regressions including lagged and forward returns. We see that only concurrent week returns are statistically significantly related to levels of domestic violence, while the coefficients estimated for neither lagged nor forward returns are statistically significant. This result gives strong support for a causal interpretation of the same-week effect, as it is unlikely that the relevant economic factors that might be correlated with stock returns would change rapidly enough to not be reflected in the surrounding weeks' stock returns. This result holds for both raw stock market returns, as well as returns relative to four-week average.

To better understand the nature of the relationship between stock returns and domestic violence, we perform an analysis with returns separated into positive and negative ones. The results, shown in Table 5, indicate that the effect of stock returns is stronger for negative stock returns. This is consistent with our model predictions.

For raw stock market return, the estimated coefficient for positive returns is also negative, suggesting that higher returns are associated with lower levels of domestic violence, but this relationship for positive returns is weaker in both magnitude and statistical significance. Interestingly, when using returns relative to four-week average, the directionality of the result becomes significantly stronger. The estimated coefficient for positive returns is entirely insignificant, while the coefficient for negative returns is large and highly statistically significant. At the bottom of the table, we also report p-values from an F-test of the difference between the positive and negative coefficients. For the specifications including a reference point (Models 3 and 4), the coefficients are significantly different, with p-values below one percent.

To further explore the relationship between exceptionally low stock returns and domestic violence, we include an analysis with dummies for weeks where the state-level stock market exhibits negative returns of at least a given magnitude. For example, the variable *Drop 7%* takes the value one if the weekly stock market return is negative 7% or lower. We include several different magnitudes of negative returns. We also perform this analysis using drops relative to four-week average to investigate the impact of having a reference point.

The results are shown in Table 6. For raw stock market returns, the estimated coefficients for the drop dummies increase in an almost monotone fashion with the magnitude of loss. This means that the larger the loss, the larger an increase in domestic violence it is associated with. For instance, the effect of a 13% drop in weekly return on domestic violence is nearly four times as big as that of a 7% drop in weekly return. This relationship becomes even clearer when using returns relative to four-week average. The estimated coefficients for stock market drops relative to past returns increase in perfectly monotone fashion, and all of the estimates are statistically significant. These results suggest that the main driver of the negative relatinship between stock returns and domestic violence are extreme negative return events.[20] In the Internet Appendix (Table A.8), we also include a model specification controlling for stock volatility, finding that it does not change our results.

Finally, the documented relationship between domestic violence and stock returns could be due to increased alcohol consumption after experiencing a bad stock return week. In that case, domestic violence would be just a by-product of excessive alcohol use amid emotional cues. However, our results in Internet Appendix (Table A.10) show that, although the

[20] This conclusion is further supported by additional analysis not reported here, using more granular return magnitude dummies.

correlation between the fraction of domestic violence incidents that involve the use of alcohol and stock returns is negative, it is not statistically significant. The results mitigate the potential concern that alcohol would be the main driver of our findings.

5 Additional analysis

5.1 Stock returns and stock market participation

As we discuss in Section 2.2, a causal interpretation of the relationship between stock returns and domestic violence is only plausible if an adequate number of households are exposed to the stock market. To study the role of stock market participation, we construct a location-based measure of stock market participation using the Individual Income Tax Return (Form 1040) Statistics from the IRS. These data include zipcode-level data of types of income and households. We define stock market participation as the proportion of households in a given zipcode that report dividend income during the year. We then calculate population-weighted average level of stock market participation for each county and match those to agency locations. The tax data are available from 2004 onward, so the sample period for this analysis is 2004-2016.

The average stock market participation rate across the police agency locations in our data is 19.7% and standard deviation 7.0%. Figures 3 and 4 show the distribution of stock market participation in our sample both unconditionally, as well as plotted against the income level. From these we see that i) there is clearly an adequate amount of stock market participation in our sample generally, and ii) there is substantial variation in the stock market participation between different locations, even at similar income levels. Hence, we can exploit the variation in stock market participation to provide further evidence that the negative relationship between stock returns and the incidence of domestic violence is due to the wealth shocks caused by the stock market and not due to other, unobserved, events.

We divide the agencies in our sample into three categories each year, based on the level of stock market participation at the agency location, and then include dummies indicating these wealth categories in our regressions. Table 7 shows the results of these regressions including interactions of stock returns with dummies indicating the stock market participation level of the agency location. The estimated coefficients are negative for all stock market participation levels, but economically smallest and statistically insignificant for the lowest stock market participation category across all model specifications. In the most robust specification, including agency-month fixed effects, the magnitude of the estimated coefficients increases monotonically with stock market participation, and the estimates are statistically significant only for the highest stock market participation category. This finding might even be underestimated given that the reported incidence of domestic violence is generally substantially lower in areas with high stock market participation, as illustrated in Figure 5.

In the Internet Appendix A.4, we also explore the effect depending on income level, using similar methodology to divide the locations into three categories based on personal income per capita. We find that the relationship between stock returns and rates of domestic violence are negative for all income levels, but the middle tertile exhibits the strongest and statistically most significant relationship between stock returns and domestic violence. The relationship is not statistically significant in the top tertile, and the estimated coefficients are also substantially smaller in magnitude. This provides an interesting contrast to our stock market participation results. This makes sense intuitively, as stock market participation tends to increase with income, while reported rates of domestic violence decrease with income. Hence, in the middle part of the income distribution households are likely to have a large enough exposure to the stock market and the reported rates of domestic violence are high enough to generate substantial aggregate effects.

5.2 Google search volume as an alternative indicator of domestic violence

A potential concern related to data on domestic violence bases on incidents reported to police agencies is that not all incidents get reported. This may lead to understating true incidence levels of domestic violence, and possibly result in a bias in the results, in case there are systematic differences in the propensity to report. To mitigate this concern, we construct an alternative proxy for the incidence of domestic violence based on Google search volumes. We obtain an index of daily search volumes from Google Trends for the keyword "domestic violence" for each U.S. state. It seems plausible that victims (or perpetrators) of domestic violence might conduct online searches involving this phrase following incidents of domestic violence. Unlike with reporting to police, there is no reason why this indicator would understate the incidence of domestic violence. Also, while reporting incidents to the police may be less likely in the case of wealthier households, such households are more likely to have access to the internet and to actively use it to search for information. Hence, the search volume is likely to capture some part of the domestic violence within the wealthier population that may be missing in the police report data.

This methodology provides us with a state-level daily panel dataset of search volumes. Google Trends data is available from 2004 onward, but the quality of the daily state-level data appears to be weaker within the earliest periods, with a large number of zero values. To mitigate this issue, we begin our search volume sample from 2005, and in cases where there are periods of at least 30 consecutive days with only zero values, we exclude all data for the given state prior to such periods. This means that for a few states the sample begins later than 2005.

For our analysis, we then construct a weekly panel dataset that includes the combined Google search volume for Friday, Saturday, and Sunday, of each week. As we collect the search volume data state by state, the basis of the index for each state is arbitrary and does not enable comparing the levels of domestic violence between states. Hence, we rescale each weekly state-level index to have a mean value of 100 over the sample period. We then perform regressions of the following form:

$$ln(1 + Google\ volume)_{s,t} = \alpha_0 + \alpha_1 \times Return_{s,t} + \beta \times X_{s,t} + \epsilon_{i,t} \quad (3)$$

where $ln(1 + Google\ volume)_{i,s,t}$ is the natural logarithm of one plus the Google search volume index ($Google\ volume$) in state s during week t.

The results, shown in Panel A of Table 8, show a statistically significant negative relationship between the weekly stock return and google search volume for "domestic violence" during the weekend. This finding is consistent with our main results using reported incidents of domestic violence. In terms of economic magnitude, the relationship between stock return and domestic violence based on Google search volume is much stronger than that based on reported incidents. The estimated coefficient (Model 4) suggests that a 13%-point decrease in stock return would result in 15% increase in domestic violence around the mean rate. Panel B of Table 8 shows the results using stock return relative to the four-week average, instead of raw stock return, as the explaining variable. The estimated coefficients also indicate a significant negative relationship between stock return relative to past average and the incidence of domestic violence.

5.3 Confounding local economic factors and variable specification

It could be possible that our results are driven by unobserved factors that simultaneously affect local communities and stock prices. The most obvious candidates would be layoffs or facility closures by firms, which might potentially result in increased levels of domestic violence and negative stock price reactions. This would mean that the channel is not stock-market-related financial stress but other economic stress. To address this concern, we first note that the results in the literature on layoff announcement returns are mixed. For example, Blackwell, Marr, and Spivey (1990) find a negative stock-market reaction to plant-closing announcements, while Palmon, Sun, and Tang (1997) find that the direction of announcement returns depends on the reason cited for the layoffs. Furthermore, the magnitude of announcement returns is relatively modest. Chalos and Chen (2003) find a positive market reaction to layoff announcements related to revenue refocusing, insignificant reaction to layoffs involving cost cutting, and weak evidence of a negative market reaction to layoffs related to plant closings.

To address the issue empirically, we perform an analysis with alternative proxies for stock market return that are not likely to be affected by such local economic events. First, we construct a state-level stock index for each police agency, excluding the companies based in any county which the police agency covers. We then perform our baseline regression analysis using these indices excluding local companies as the proxy for stock market return. Second, we perform the same analysis using the S&P 500 as the proxy for stock returns. These alternative proxies for stock returns are unlikely to be significantly affected by local economic events. Third, for each agency, we construct a national value-weighted stock market index excluding the firms headquartered in the same state where the agency is located.

The results, shown in Panel A of Table 9, are consistent with the main results, shown for comparison in column 1. These results suggests that our findings are not driven by local economic factors, but remain consistent with our hypothesis that negative stock returns can trigger incidents of domestic violence via increased stress levels.

Finally, to make sure that the results are not sensitive to the specification of the dependent variable, in Panel B, we show the same analysis using non-logarithmic form of the domestic violence rate (columns 1-4) and a dummy taking the value one if there is a non-zero number of incidents (columns 5-8). The latter can be thought of as an extensive margin analysis. The results remain statistically significant across all model specifications.[21]

[21] The results remain qualitatively similar when using Poisson regressions with the number of incidents as the dependent variable, including agency-quarter fixed effects, where we are able to get a converged estimation.

5.4 Other offense rates

As discussed above, we find a significant negative relationship between weekly stock returns and domestic violence during the weekend. To verify that our findings are specific to domestic violence and not a reflection of other general patterns in crime rates, we construct similar incidence rates for other offenses that might conceivably be correlated with stock returns. We include analysis on (i) *assaults*, defined as aggravated assault, assault, or intimidation, where the victim is unknown to the perpetrator, (ii) *murders*, (iii) *sex offenses*, including rape, sodomy, sexual assault with an object, and fondling, (iv) *robberies*, and (v) *drug offenses*, including drug/narcotic violations and drug equipment violations.

The results, shown in Table 10, provide no evidence of a similar significant relationship between weekly stock returns and offense rates during the weekend for any of the other types of offense. These results support our hypothesis that stock returns are relevant due to the stress they induce in relationships and hence trigger incidents of domestic violence. Such changes in stress levels do not appear to translate into differences in the other offense rates we analyze.

5.5 Other robustness checks

We perform a number of additional robustness checks with results reported in the Internet Appendix. To make sure that our results are not driven by the choice of weekend period or weekly stock returns, we perform a regression analysis using different weekend periods for the *DV rate*, as well as different period lengths for stock returns (Internet Appendix Table A.4). We find that our results are robust to various definitions of weekend, whether or not we include Monday morning until 9am (stock market opening) and whether we begin the weekend on Thursday or Friday. Across all of these various specifications, we find a statistically significant negative relationship between the weekly stock return and the incidence of domestic violence during the weekend. Similarly, when using the stock returns for any period between one and five most recent trading days before the weekend, this negative relationship remains statistically significant. Taken together, these results suggest that our findings are not driven by the choice of variable definitions.

We also perform an analysis excluding states with the largest number of listed companies in our data, namely Illinois, Massachusetts, and Texas (Internet Appendix Table A.5). The states with generally the largest number of listed companies in the U.S., New York and California, are not included in our data. The results remain similar when excluding any or all of the states with the largest number of listed companies.

To further check that our findings relate to wealth shocks caused by the stock market, instead of other economic hardship, such as company layoffs, we perform an analysis controlling for weekly Google search volume for "unemployment" (Internet Appendix Table A.7). This variable is likely to capture weekly changes in worries related to employment. The Google search volume index is at the state level. The estimated coefficients for stock returns remain negative and statistically significant. The magnitude is somewhat larger than in our main results, driven by the different sample selection subject to Google data availability.

6 Conclusion

We find a significant negative relationship between weekly local stock returns and the incidence of domestic violence from Friday to Sunday in the same week. This effect is significant only for the concurrent week stock returns, meaning that lagged or forward stock returns have no significant correlation with the level of domestic violence. It is also robust to controlling for local economic conditions. These findings support a causal interpretation of the effect, i.e., stock market movements triggering incidents of domestic violence.

Stock market movements, especially large ones, represent both financial and emotional shocks, which can affect stress levels within families and trigger and escalate arguments. This represents a very specific externality of stock investments. However, the finding may have broader significance. When stock returns also trigger incidents of domestic violence, they also affect household utility beyond the financial shock. If externalities of this type abound, they could help explain the seemingly high risk aversion implied by the realized stock market returns and return volatility, often referred to as the equity premium puzzle (Mehra and Prescott, 1985). If the volatility of the stock market causes variation in utility that is larger than that caused by the purely financial component of utility, then standard economic models measuring utility only by wealth might underestimate the total "risk" of stock investments.

References

Aizer, Anna, 2010, The gender wage gap and domestic violence, *American Economic Review* 100, 1847–59.

American Psychological Association, 2017, Stress in america: The state of our nation, *Annual survey* .

Anderberg, Dan, Helmut Rainer, Jonathan Wadsworth, and Tanya Wilson, 2016, Unemployment and domestic violence: Theory and evidence, *The Economic Journal* 126, 1947–1979.

Beland, Louis-Philippe, and Daniel A. Brent, 2018, Traffic and crime, *Journal of Public Economics* 160.

Benson, Michael L., Greer L. Fox, Alfred DeMaris, and Judy Van Wyk, 2003, Neighborhood disadvantage, individual economic distress and violence against women in intimate relationships, *Journal of Quantitative Criminology* 19, 207–235.

Blackwell, David W., M. Wayne Marr, and Michael F. Spivey, 1990, Plant-closing decisions and the market value of the firm, *Journal of Financial Economics* .

Bloch, Francis, and Vijayendra Rao, 2002, Terror as a bargaining instrument: A case study of dowry violence in rural india, *The American Economic Review* 92, 1029–1043.

Bricker, Jesse, Lisa J. Dettling, Alice Henriques, Joanne W. Hsu, Kevin B. Moore, Jeffrey Thompson John Sabelhaus, and Richard A. Windle, 2014, Changes in u.s. family finances from 2010 to 2013: Evidence from the survey of consumer finances, *Federal Reserve Bulletin* 100, 1–40.

Bricker, Jesse, and Geng Li, 2017, Credit scores, social capital, and stock market participation, *Finance and Economics Discussion Series 2017-008. Washington: Board of Governors of the Federal Reserve System* .

Card, David, and Gordon B. Dahl, 2011, Family violence and football: The effect of unexpected emotional cues on violent behavior, *The Quarterly Journal of Economics* 126, 103–143.

Centers for Disease Control and Prevention, 2003, Costs of intimate partner violence against women in the united states, *Department of Health and Human Services* .

Centers for Disease Control and Prevention, 2011, National intimate partner and sexual violence survey - 2010 summary report, *National Center for Injury Prevention and Control* .

Chalos, Peter, and Charles J. P. Chen, 2003, Employee downsizing strategies: Market reaction and post announcement financial performance, *Journal of Business Finance and Accounting* 29, 847–870.

Chen, Chun-Chih, Chin-Shyan Chen, Tsai-Ching Liu, and Ying-Tzu Lin, 2012, Stock or stroke? stock market movement and stroke incidence in taiwan, *Social Science & Medicine* 75, 1974–1980.

Chien, YiLi, and Paul Morris, 2017, Household participation in stock market varies widely by state, *The Regional Economist* 3, 4–5.

Conger, Rand D., Glen H. Elder, Jr., Frederick O. Lorenz, Katherine J. Conger, Ronald L. Simons, Les B. Whitbeck, Shirley Huck, and Janet N. Melby, 1990, Linking economic hardship to marital quality and instability, *Journal of Marriage and Family* 52, 643–656.

Coval, Joshua D., and Tobias J. Moskowitz, 1999, Home bias at home: Local equity preference in domestic portfolios, *The Journal of Finance* 54, 2045–2073.

Da, Zhi, Xing Huang, and Lawrence J. Jin, 2019, Extrapolative beliefs in the cross-section: What can we learn from the crowds?, *Working paper* .

de Bruijn, Dorien Maria, and Ireen Maria de Graaf, 2016, The role of substance use in same-day intimate partner violence: A review of the literature, *Aggression and Violent Behavior* 27, 142–151.

Di Noia, Jennifer, 2002, Indicators of gender equality for american states and regions: An update, *Social Indicators Research* 59, 35–77.

Engelberg, Joseph, and Christopher A. Parsons, 2016, Worrying about the stock market: Evidence from hospital admissions, *The Journal of Finance* 71, 1227–1250.

Farmer, Amy, and Jill Tiefenthaler, 1997, An economic analysis of domestic violence, *Review of Social Economy* 55, 337–358.

French, Kenneth R., and James M. Poterba, 1991, Investor diversification and international equity markets, *The American Economic Review* 81, 222–226.

Gelles, Richard J., and Murray A. Straus, 1989, *Intimate Violence: The Causes and Consequences of Abuse in the American Family* (Touchstone, New York).

Greenwood, Robin, and Andrei Shleifer, 2014, Expectations of returns and expected returns, *The Review of Financial Studies* 27, 714–746.

Heath, Chip, Steven Huddart, and Mark Lang, 1999, Psychological factors and stock option exercise, *The Quarterly Journal of Economics* 114, 601627.

Huck, John R., 2015, Taking a beating on the stock market: Crime and stock returns, *Working paper* .

Kelly, Joan B., and Michael P. Johnson, 2008, Differentiation among types of intimate partner violence: Research update and implications for interventions, *Family Court Review* 46, 476–499.

Lin, Chung-Liang, Chin-Shyan Chen, and Tsai-Ching Liu, 2015, Do stock prices drive people crazy?, *Health Policy and Planning* 30, 206214.

Lin, Hualiang, Yonghui Zhang, Yanjun Xu, Tao Liu, Jianpeng Xiao, Yuan Luo, Xiaojun Xu, Yanhui He, and Wenjun Ma, 2013, Large daily stock variation is associated with cardiovascular mortality in two cities of guangdong, china, *PLoS ONE* 8.

Luca, Dara Lee, Emily Owens, and Gunjan Sharma, 2015, Can alcohol prohibition reduce violence against women?, *American Economic Review* 105, 625–29.

Ma, Wenjuan, Honglei Chen, Lili Jiang, Guixiang Song, and Haidong Kan, 2011, Stock volatility as a risk factor for coronary heart disease death, *European Heart Journal* 32, 1006–1011.

Mehra, Rajnish, and Edward C. Prescott, 1985, The equity premium: A puzzle, *Journal of Monetary Economics* 15, 145–161.

Moffitt, Terrie E., Robert F. Krueger, Avshalom Caspi, and Jeff Fagan, 2000, Partner abuse and general crime: How are they the same? how are they different?, *Criminology* 38, 199–232.

Murphy, Christopher M., and Laura Ting, 2010, The effects of treatment for substance use problems on intimate partner violence: A review of empirical data, *Aggression and Violent Behavior* 15, 325–333.

Odean, Terrance, 1998, Are investors reluctant to realize their losses?, *The Journal of Finance* 53, 1775–1798.

Palmon, Oded, Huey-Lian Sun, and Alex P. Tang, 1997, Layoff announcements: Stock market impact and financial performance, *Financial Management* 26, 54–68.

Pollak, Robert A., 2004, An intergenerational model of domestic violence, *Journal of Population Economics* 17, 311–329.

Schwab-Reese, Laura M., Corinne Peek-Asa, and Edith Parker, 2016, Associations of financial stressors and physical intimate partner violence perpetration, *Injury Epidemiology* 3.

Schwandt, Hannes, 2018, Wealth shocks and health outcomes: Evidence from stock market fluctuations, *American Economic Journal: Applied Economics* 10, 349–77.

Seasholes, Mark S., and Ning Zhu, 2010, Individual investors and local bias, *The Journal of Finance* 65, 1987–2010.

Sugarman, David B., and Murray A. Straus, 1988, Indicators of gender equality for american states and regions, *Social Indicators Research* 20, 229–270.

Tauchen, Helen V., Ann Dryden Witte, and Sharon K. Long, 1991, Domestic violence: A nonrandom affair, *International Economic Review* 32, 491–511.

Figure 1: Number of incidents by weekday and hour

Shows the number of incidents in our data by incident weekday and hour. The weekly *DV rate* we use in our analysis includes the incidents taking place between Friday, 4pm, and Sunday, 12pm (midnight), highlighted in the chart.

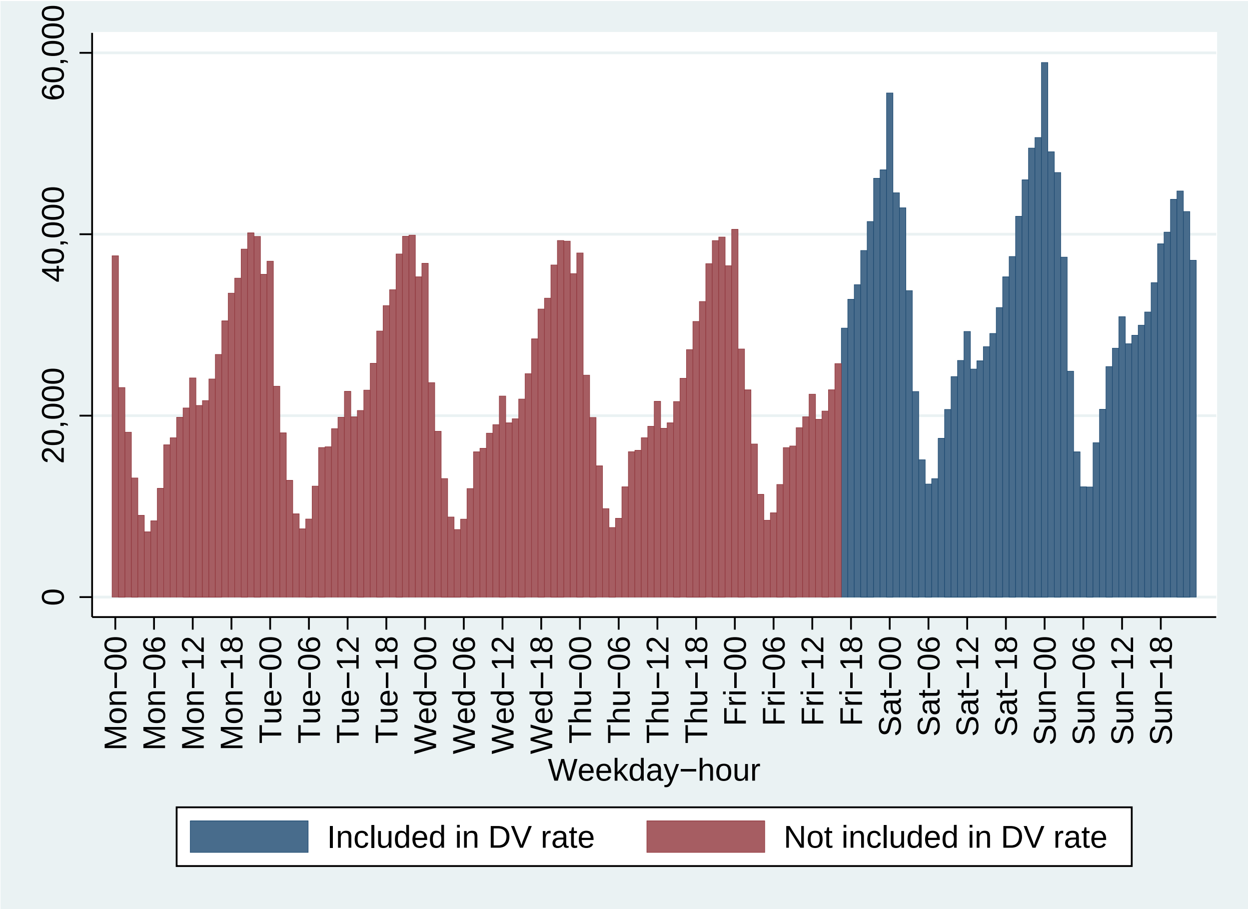

Figure 2: October 2008 stock market crash and domestic violence

The weekly average residual from a regression of observations of *ln(1+DV rate)* on agency-year fixed effects, week-of-year fixed effects, and holidays fixed effects, plotted against the weekly return of the S&P 500 index around the week October 6-12. This week experienced the largest weekly stock market drop in our data.

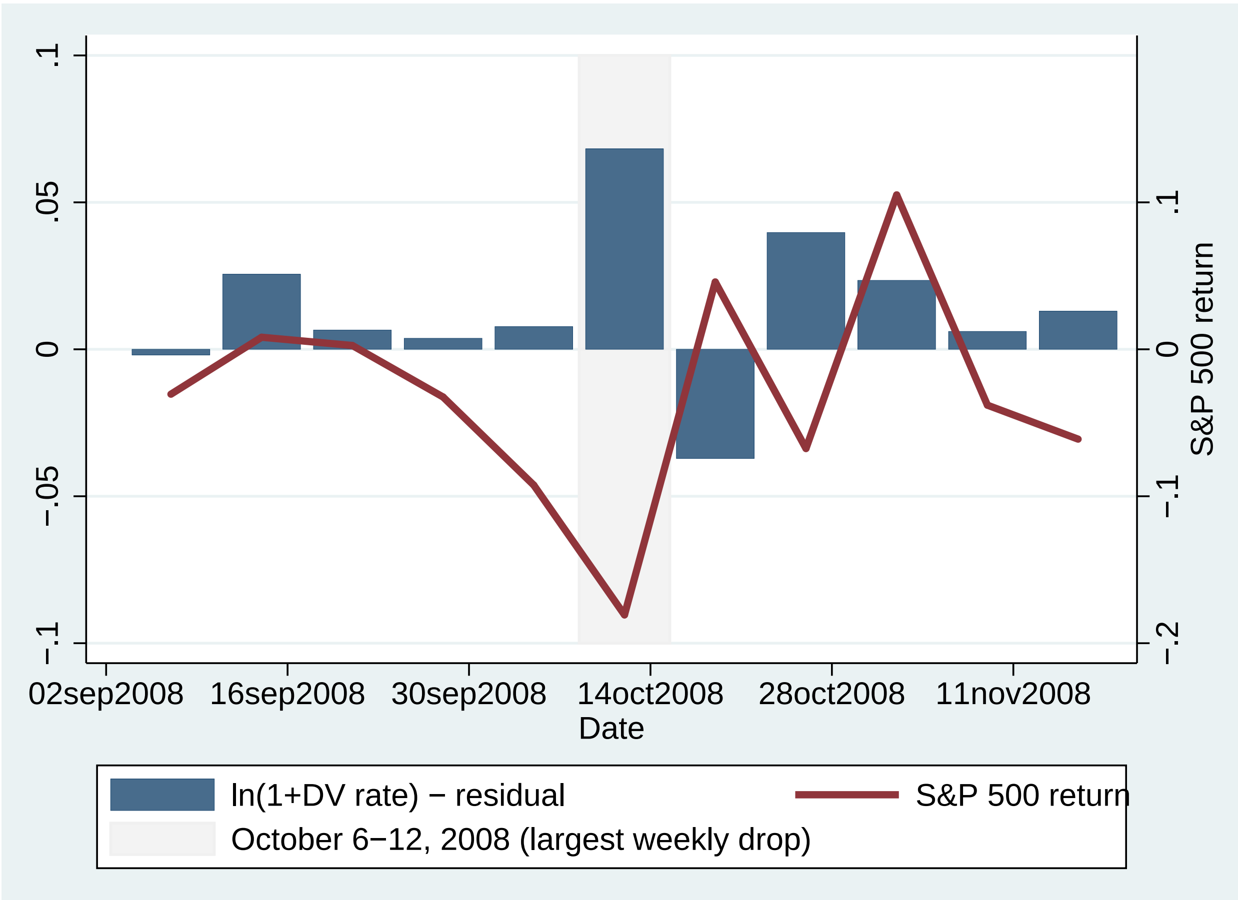

Figure 3: Distribution of stock market participation

Distribution of agency-week observations by the average stock market participation at the agency location. Stock market participation is calculated as the proportion of households reporting dividend income in their tax filings by zipcode and aggregated to county level as the population-weighted average. For agencies covering areas within multiple counties, stock market participation is calculated as the covered-population-weighted average of the counties.

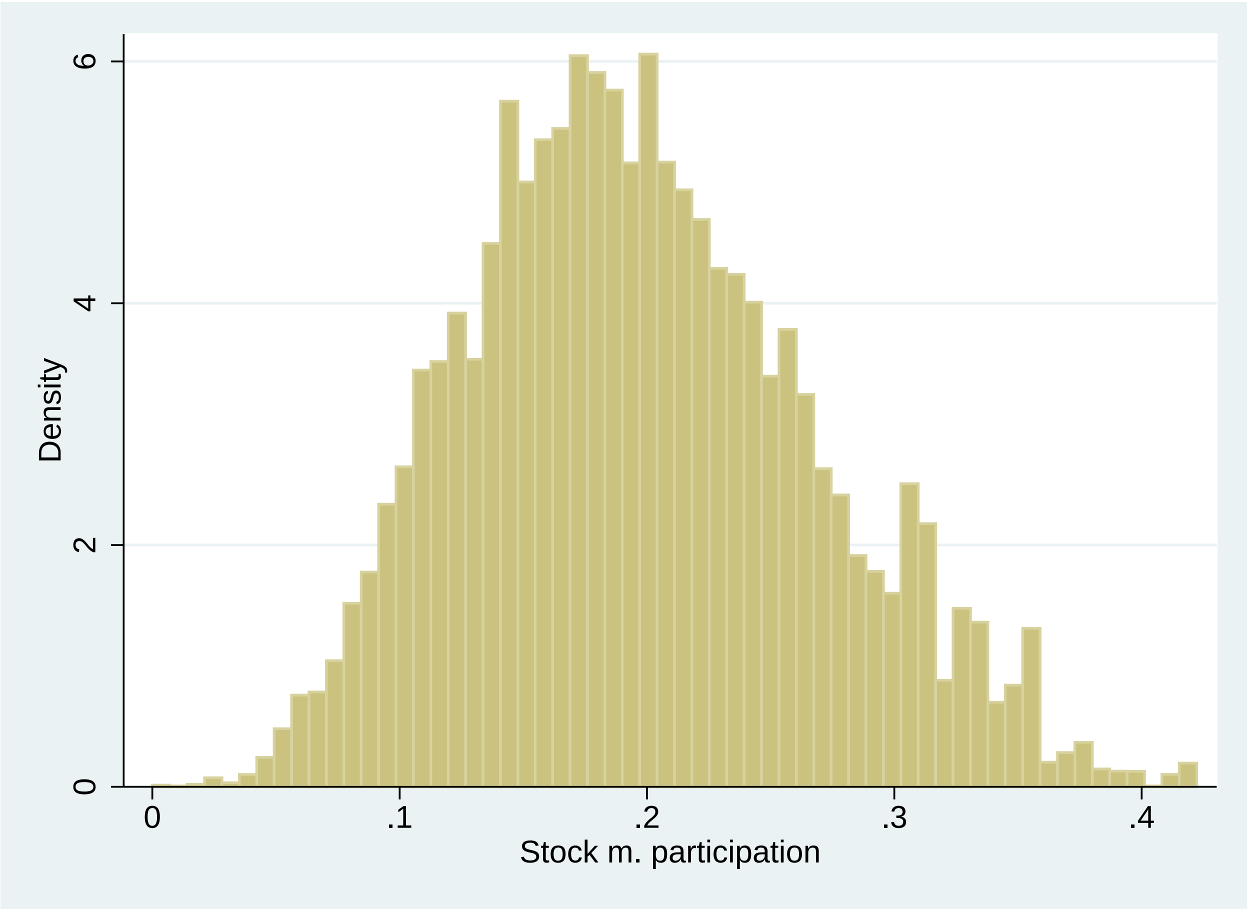

Figure 4: Stock market participation vs. income level

Distribution of agency-week observations by the average stock market participation at the agency location. Stock market participation is calculated as the proportion of households reporting dividend income in their tax filings by zipcode and aggregated to county level as the population-weighted average. Personal Income (PI) per capita is measured at the county level. For agencies covering areas within multiple counties, stock market participation and PI per capital are calculated as the covered-population-weighted average of the counties.

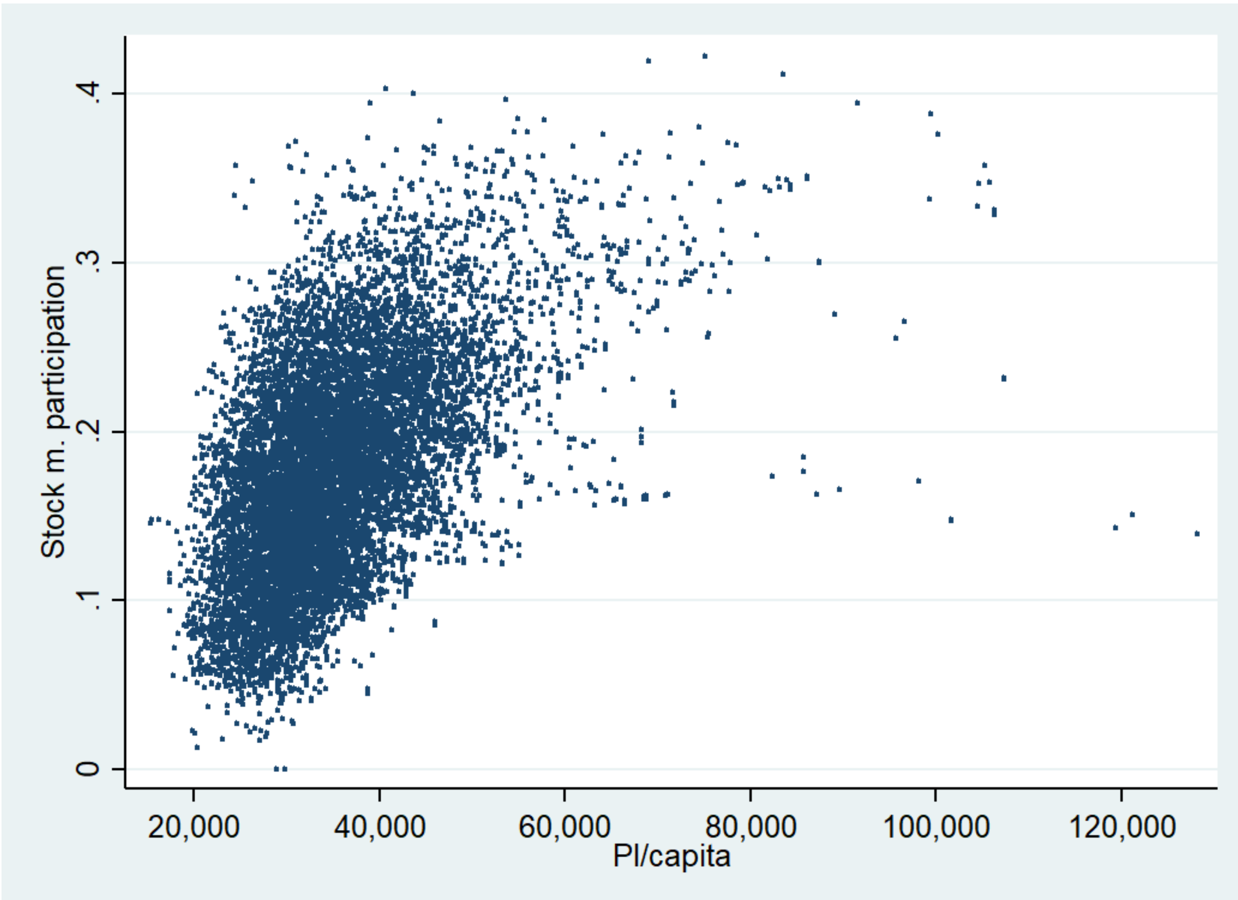

Figure 5: Average domestic violence rate vs. stock market participation

A binscatter chart of agency-week observations plotted based on the rate of domestic violence, calculated as the weekly number of incidents per 100,000 persons for each agency location occurring between Friday 4pm and Sunday 12am (midnight) of each week, against the agency location average stock market participation. Stock market participation is calculated as the proportion of households reporting dividend income in their tax filings by zipcode and aggregated to county level as the population-weighted average. For agencies covering areas within multiple counties, stock market participation is calculated as the covered-population-weighted average of the counties.

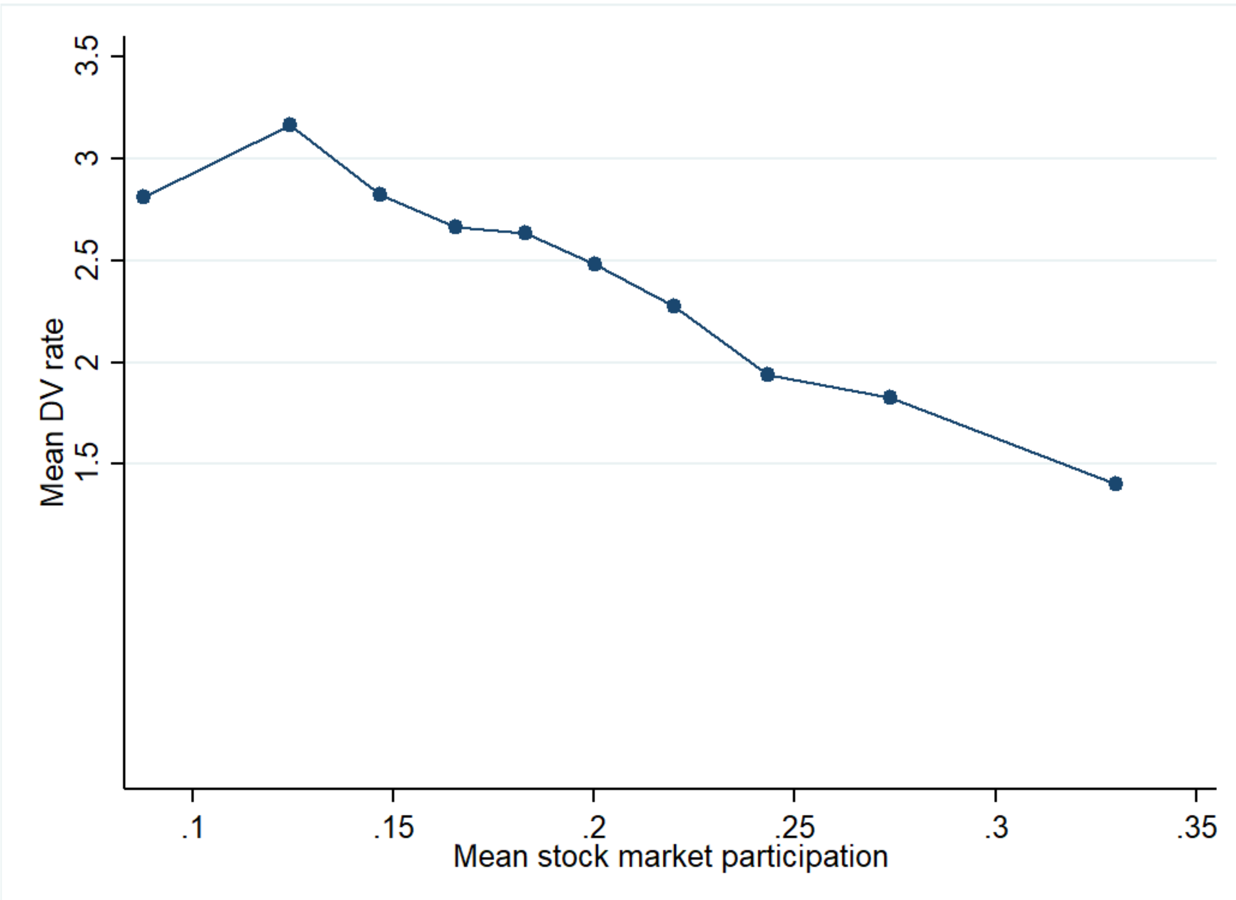

Table 1
Number of police agencies

This table shows the number of police agencies included in our sample for each year, and the population covered by them. Number of states is the number of distinct states in which we have police agencies in our data.

Year	Population covered	Number of agencies	Average population	Number of states
2001	39,038,231	1,005	38,844	20
2002	42,316,107	1,066	39,696	21
2003	45,700,878	1,173	38,961	23
2004	50,203,468	1,254	40,035	25
2005	55,875,711	1,354	41,267	28
2006	59,243,478	1,401	42,287	32
2007	61,376,689	1,449	42,358	33
2008	64,198,753	1,524	42,125	33
2009	68,180,681	1,647	41,397	34
2010	70,135,954	1,664	42,149	34
2011	72,237,565	1,730	41,756	34
2012	75,658,735	1,807	41,870	34
2013	77,793,671	1,835	42,394	34
2014	79,589,803	1,868	42,607	35
2015	80,689,280	1,890	42,693	34
2016	86,201,011	1,993	43,252	35

Table 2
Summary statistics - weekly observations

Domestic violence (DV) rate and other offense rates rates are calculated as the number of incidents occurring between Friday 4pm and Sunday 12am (midnight) of each week. Stock market return variables are calculated on a weekly basis. *Population* is the population covered by the given police agency. *Stock market participation* is the average proportion of households with dividend income at the agency location. *PI per capita* is the average Personal Income per capita at the agency location. *IU rate* is the weekly insured unemployment rate measured at the state level.

	Mean	Std	p10	p50	p90
Incidents (per 100,000)					
DV rate	2.523	4.072	0.000	0.000	7.872
Assault rate	0.605	1.808	0.000	0.000	2.255
Murder rate	0.019	0.279	0.000	0.000	0.000
Sex offense rate	0.395	1.390	0.000	0.000	1.106
Robbery rate	0.346	1.294	0.000	0.000	0.838
Drug offense rate	3.024	5.087	0.000	0.000	8.830
Raw stock return					
Return	0.002	0.030	-0.031	0.003	0.033
Return ex. county	0.002	0.030	-0.031	0.003	0.033
Positive	0.555	0.497	0.000	1.000	1.000
Negative	0.445	0.497	0.000	0.000	1.000
Drop 5%	0.040	0.195	0.000	0.000	0.000
Drop 7%	0.018	0.133	0.000	0.000	0.000
Drop 9%	0.009	0.094	0.000	0.000	0.000
Drop 11%	0.004	0.065	0.000	0.000	0.000
Drop 13%	0.002	0.050	0.000	0.000	0.000
Relative to 4-week avg					
Δ Return	0.000	0.034	-0.035	-0.001	0.036
Positive	0.481	0.500	0.000	0.000	1.000
Negative	0.519	0.500	0.000	1.000	1.000
Drop 5%	0.048	0.214	0.000	0.000	0.000
Drop 7%	0.020	0.139	0.000	0.000	0.000
Drop 9%	0.009	0.092	0.000	0.000	0.000
Drop 11%	0.005	0.068	0.000	0.000	0.000
Drop 13%	0.003	0.053	0.000	0.000	0.000
Agency variables					
Population ('000)	41.706	68.949	11.636	23.104	78.832
Stock m. participation	0.197	0.070	0.111	0.191	0.296
PI/capita ('000)	38.173	12.340	25.862	35.689	52.641
IU rate (%)	2.367	1.152	1.090	2.190	3.940
N	1,296,975				

Table 3
Domestic violence and state-level stock returns

The dependent variable is $ln(1 + DV\ rate)$, where $DV\ rate$ is calculated as the weekly number of incidents per 100,000 persons for each agency location occurring between Friday 4pm and Sunday 12am (midnight) of each week. *Weekly IU control* is the state-level weekly insured unemployment rate. We include *Agency fixed effects*, *Agency-Year*, *Agency-Quarter*, or *Agency-Month joint fixed effects*, to capture any differences in local economic and other conditions, as well as any other location-specific factors, *Holidays fixed effects*, including a set of dummies for major holidays in case they take place during the week, and *Week of Year fixed effects* (52 weeks). Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

Panel A: Raw state-level stock market return

	(1)	(2)	(3)	(4)	(5)
Return	−0.0948***	−0.0673***	−0.0702***	−0.0646***	−0.0778**
	(0.0135)	(0.0149)	(0.0154)	(0.0198)	(0.0368)
Weekly IU control	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No
Agency FE	Yes	No	No	No	No
Agency-Year FE	No	Yes	No	No	No
Agency-Quarter FE	No	No	Yes	No	Yes
Agency-Month FE	No	No	No	Yes	No
Week of Year FE	No	Yes	Yes	Yes	No
Week FE	No	No	No	No	Yes
Holidays FE	No	Yes	Yes	Yes	No
N	1,296,975	1,296,975	1,296,975	1,296,975	1,296,975
R^2	0.287	0.330	0.376	0.483	0.377

Panel B: Relative to 4-week-average return

	(1)	(2)	(3)	(4)	(5)
Δ Return	−0.0488***	−0.0594***	−0.0557***	−0.0582***	−0.0540*
	(0.0103)	(0.0126)	(0.0138)	(0.0179)	(0.0311)
Weekly IU control	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No
Agency FE	Yes	No	No	No	No
Agency-Year FE	No	Yes	No	No	No
Agency-Quarter FE	No	No	Yes	No	Yes
Agency-Month FE	No	No	No	Yes	No
Week of Year FE	No	Yes	Yes	Yes	No
Week FE	No	No	No	No	Yes
Holidays FE	No	Yes	Yes	Yes	No
N	1,296,975	1,296,975	1,296,975	1,296,975	1,296,975
R^2	0.287	0.330	0.376	0.483	0.377

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 4
Domestic violence vs. lagged and forward stock returns

The dependent variable is $ln(1 + DV\ rate)$, where $DV\ rate$ is calculated as the weekly number of incidents per 100,000 persons for each agency location occurring between Friday 4pm and Sunday 12am (midnight) of each week. *Weekly IU control* is the state-level weekly insured unemployment rate. We include *Agency-Month joint fixed effects* to capture any differences in local economic and other conditions, as well as any other location-specific factors, *Holidays fixed effects*, including a set of dummies for major holidays in case they take place during the week, and *Week of Year fixed effects* (52 weeks). Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

	Raw stock market return			Relative to 4-week average		
	(1)	(2)	(3)	(4)	(5)	(6)
Return	−0.0646***	−0.0663***	−0.0644***			
	(0.0198)	(0.0211)	(0.0210)			
Return (t-1)		−0.0064	−0.0052			
		(0.0309)	(0.0312)			
Return (t+1)			0.0070			
			(0.0241)			
Δ Return				−0.0582***	−0.0602***	−0.0556***
				(0.0179)	(0.0185)	(0.0180)
Δ Return (t-1)					−0.0111	−0.0079
					(0.0260)	(0.0258)
Δ Return (t+1)						0.0232
						(0.0208)
Weekly IU control	Yes	Yes	Yes	Yes	Yes	Yes
Agency-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Week of Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,296,975	1,296,975	1,296,975	1,296,975	1,296,975	1,296,975
R^2	0.483	0.483	0.483	0.483	0.483	0.483

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 5
Domestic violence and directional state-level stock returns

The dependent variable is $ln(1 + DV\ rate)$, where *DV rate* is calculated as the weekly number of incidents per 100,000 persons for each agency location occurring between Friday 4pm and Sunday 12am (midnight) of each week. *Weekly IU control* is the state-level weekly insured unemployment rate. We include *Agency-Quarter joint fixed effects* to capture any differences in local economic and other conditions, as well as any other location-specific factors, *Holidays fixed effects*, including a set of dummies for major holidays in case they take place during the week, and *Week of Year fixed effects* (52 weeks). Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

	Raw stock market return		Relative to 4-week average	
	(1)	(2)	(3)	(4)
Return x Positive	−0.0537*	−0.0633*		
	(0.0317)	(0.0328)		
Return x Negative	−0.0805***	−0.0774**		
	(0.0295)	(0.0327)		
Δ Return x Positive			0.0096	0.0198
			(0.0293)	(0.0312)
Δ Return x Negative			−0.1443***	−0.1475***
			(0.0311)	(0.0328)
Weekly IU control	Yes	Yes	Yes	Yes
Agency-Year FE	Yes	No	Yes	No
Agency-Quarter FE	No	Yes	No	No
Week of Year FE	Yes	Yes	Yes	No
Holidays FE	Yes	Yes	Yes	Yes
F-test: Positive-Negative, p-value	0.620	0.808	0.008	0.007
N	1,296,975	1,296,975	1,296,975	1,296,975
R^2	0.330	0.376	0.330	0.376

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 6
Domestic violence and weekly drops in state stock market index

The dependent variable is $ln(1 + DV\ rate)$, where $DV\ rate$ is calculated as the weekly number of incidents per 100,000 persons for each agency location occurring between Friday 4pm and Sunday 12am (midnight) of each week. *Weekly IU control* is the state-level weekly insured unemployment rate. We include *Agency-Month joint fixed effects* to capture any differences in local economic and other conditions, as well as any other location-specific factors, *Holidays fixed effects*, including a set of dummies for major holidays in case they take place during the week, and *Week of Year fixed effects* (52 weeks). Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

	Raw stock market return					Relative to 4-week average				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Drop 5%	0.0018					0.0093**				
	(0.0046)					(0.0039)				
Drop 7%		0.0125**					0.0178***			
		(0.0057)					(0.0044)			
Drop 9%			0.0192**					0.0220***		
			(0.0086)					(0.0072)		
Drop 11%				0.0356***					0.0255**	
				(0.0126)					(0.0111)	
Drop 13%					0.0448**					0.0324**
					(0.0168)					(0.0155)
Weekly IU control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agency-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week of Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,296,975	1,296,975	1,296,975	1,296,975	1,296,975	1,296,975	1,296,975	1,296,975	1,296,975	1,296,975
R^2	0.483	0.483	0.483	0.483	0.483	0.483	0.483	0.483	0.483	0.483

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 7
Domestic violence and stock returns vs. stock market participation

The dependent variable is $ln(1 + DV\ rate)$, where $DV\ rate$ is calculated as the weekly number of incidents per 100,000 persons for each agency location occurring between Friday 4pm and Sunday 12am (midnight) of each week. *Weekly IU control* is the state-level weekly insured unemployment rate. We include *Agency-Month joint fixed effects* to capture any differences in local economic and other conditions, as well as any other location-specific factors, *Holidays fixed effects*, including a set of dummies for major holidays in case they take place during the week, and *Week of Year fixed effects* (52 weeks). Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

	Raw stock market return			Relative to 4-week average		
	(1)	(2)	(3)	(4)	(5)	(6)
High SMP x Return	−0.0857***	−0.0941***	−0.0709**			
	(0.0256)	(0.0253)	(0.0270)			
Medium SMP x Return	−0.0830**	−0.1059***	−0.0589			
	(0.0376)	(0.0363)	(0.0425)			
Low SMP x Return	−0.0403	−0.0313	−0.0295			
	(0.0333)	(0.0300)	(0.0336)			
High SMP x Δ Return				−0.0717***	−0.0772***	−0.0620**
				(0.0262)	(0.0265)	(0.0274)
Medium SMP x Δ Return				−0.0800**	−0.0793**	−0.0584
				(0.0335)	(0.0315)	(0.0350)
Low SMP x Δ Return				−0.0487*	−0.0400	−0.0314
				(0.0256)	(0.0263)	(0.0327)
Weekly IU control	Yes	Yes	Yes	Yes	Yes	Yes
Agency-Year FE	Yes	No	No	Yes	No	No
Agency-Quarter FE	No	Yes	No	No	Yes	No
Agency-Month FE	No	No	Yes	No	No	Yes
Week of Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,103,052	1,103,052	1,103,052	1,103,052	1,103,052	1,103,052
R^2	0.319	0.365	0.474	0.319	0.365	0.474

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 8
Google search volume for "domestic violence" by state

The dependent variable is $ln(1 + Google\ volume)$, where *Google volume* is calculated as the weekly state-level index of Google search volume index for the keyword "domestic violence" during Friday, Saturday, and Sunday of each week, and scaled to have a mean of 100 for each state during the sample period of 2005-2016. In cases where the state has at least 30 consecutive days of zero search volume, we exclude any period prior to such zero periods from the data. Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

Panel A: Raw state-level stock market return

	(1)	(2)	(3)	(4)
Return	−0.9860**	−1.0181**	−0.9507**	−1.2056**
	(0.4102)	(0.4127)	(0.4102)	(0.5201)
Weekly IU control	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No
State FE	Yes	No	No	No
State-Year FE	No	Yes	No	No
State-Quarter FE	No	No	Yes	No
State-Month FE	No	No	No	Yes
Week of Year FE	No	Yes	Yes	Yes
Holidays FE	No	Yes	Yes	Yes
N	23,978	23,977	23,977	23,974
R^2	0.165	0.225	0.271	0.387

Panel B: Relative to 4-week-average return

	(1)	(2)	(3)	(4)
Δ Return	−0.8240**	−0.8323**	−0.8259**	−1.0521**
	(0.3753)	(0.3852)	(0.3825)	(0.4465)
Weekly IU control	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No
State FE	Yes	No	No	No
State-Year FE	No	Yes	No	No
State-Quarter FE	No	No	Yes	No
State-Month FE	No	No	No	Yes
Week of Year FE	No	Yes	Yes	Yes
Holidays FE	No	Yes	Yes	Yes
N	23,978	23,977	23,977	23,974
R^2	0.165	0.225	0.271	0.387

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 9
Robustness check - alternative LHS and RHS variables

The dependent variable is shown above each column. *DV rate* is calculated as the weekly number of incidents per 100,000 persons for each agency location occurring between Friday 4pm and Sunday 12am (midnight) of each week. *DV dummy* is a dummy taking the value one if there is a non-zero number of incidents. *Weekly IU control* is the state-level weekly insured unemployment rate. We include *Agency-Month joint fixed effects* to capture any differences in local economic and other conditions, as well as any other location-specific factors, *Holidays fixed effects*, including a set of dummies for major holidays in case they take place during the week, and *Week of Year fixed effects* (52 weeks). Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

Panel A: Alternative stock market indices

	ln(1+DV rate)			
	(1)	(2)	(3)	(4)
Return	−0.0646***			
	(0.0198)			
Return ex. county		−0.0747***		
		(0.0218)		
S&P 500 return			−0.0709**	
			(0.0325)	
Return ex. state				−0.0885***
				(0.0289)
Weekly IU control	Yes	Yes	Yes	Yes
Agency-Month FE	Yes	Yes	Yes	Yes
Week of Year FE	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes
N	1,296,975	1,285,735	1,296,975	1,296,975
R^2	0.483	0.483	0.483	0.483

Significance levels: * 0.1, ** 0.05, * 0.01.**

Panel B: Alternative LHS variables

	DV rate				DV dummy			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Return	−0.2852***				−0.0302***			
	(0.0915)				(0.0107)			
Return ex. county		−0.3311***				−0.0352***		
		(0.0973)				(0.0116)		
S&P 500 return			−0.2635*				−0.0404**	
			(0.1430)				(0.0175)	
Return ex. state				−0.3433**				−0.0469***
				(0.1352)				(0.0149)
Weekly IU control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agency-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week of Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,296,975	1,285,735	1,296,975	1,296,975	1,296,975	1,285,735	1,296,975	1,296,975
R^2	0.469	0.469	0.469	0.469	0.515	0.515	0.515	0.515

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 10
Other offense rates vs. stock returns

The dependent variable is *ln(1+Offense rate)*, where *Offense rate* is calculated as the weekly number of incidents of the specified offense type per 100,000 persons for each agency location occurring between Friday 4pm and Sunday 12am (midnight) of each week. *Weekly IU control* is the state-level weekly insured unemployment rate. We include *Agency fixed effects* to capture any agency- and location-specific factors, *Holidays fixed effects*, including a set of dummies for major holidays in case they take place during the week, *State-Month joint fixed effects*, and *Week of Year fixed effects* (52 weeks). Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

	(1) Assault	(2) Murder	(3) Sex offense	(4) Robbery	(5) Drug offense
Return	0.0079	0.0007	−0.0236	0.0023	0.0167
	(0.0199)	(0.0039)	(0.0154)	(0.0104)	(0.0250)
Weekly IU control	Yes	Yes	Yes	Yes	Yes
Agency-Month FE	Yes	Yes	Yes	Yes	Yes
Week of Year FE	Yes	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes	Yes
N	1,296,975	1,296,975	1,296,975	1,296,975	1,296,975
R^2	0.418	0.248	0.301	0.459	0.492

Significance levels: * 0.1, ** 0.05, * 0.01.**

A Internet Appendix

A.1 Illustrative loss-of-control model

We follow the approach in Card and Dahl (2011) to construct a simple loss-of-control model for the incidence of domestic violence. We write the basic relationship between the likelihood of an argument escalating to violence and stock returns as:

$$h_t = h^0 - \mu(R_t - E_{t-1}[R_t]) \tag{4}$$

where h is the likelihood of an interaction escalating to violence. R_t is the stock market return in period t. μ is the gain-loss utility function associated with the stock market return. As in Card and Dahl (2011), the gains and losses are measured relative to expectations, i.e., the reference point matters. In our context, this setup is supported by a large number of studies suggesting that reference points matter in stock investments. For example, Odean (1998) shows that investors exhibit a strong preference for realizing winning rather than losing investments, while Heath, Huddart, and Lang (1999) show that past stock returns and reference prices matter for stock option exercise.

If we assume that μ is piecewise linear, similar to Card and Dahl (2011), we have:

$$\begin{aligned} \mu(R_t - E_{t-1}[R_t]) &= \alpha(R_t - E_{t-1}[R_t]), \quad R_t - E_{t-1}[R_t] < 0 \\ &= \beta(R_t - E_{t-1}[R_t]), \quad R_t - E_{t-1}[R_t] > 0, \end{aligned}$$

where α and β are positive constants. In this case, loss aversion implies that $\alpha > \beta$. From (4) we then have:

$$\begin{aligned} h^L(R_t) &= h^0 - \alpha(R_t - E_{t-1}[R_t]), \quad R_t - E_{t-1}[R_t] < 0 \\ h^G(R_t) &= h^0 - \beta(R_t - E_{t-1}[R_t]), \quad R_t - E_{t-1}[R_t] > 0. \end{aligned} \tag{5}$$

In the special case where $E_{t-1}[R_t] = 0$, the model simplifies into:[22]

[22] An average annual stock return of 10% would imply a weekly compounding return of 0.18%.

$$h^L(R_t) = h^0 - \alpha R_t, \quad \text{for losses}$$
$$h^G(R_t) = h^0 - \beta R_t, \quad \text{for gains.} \tag{6}$$

One challenge for testing our model empirically is that we cannot observe the expected stock return for the relevant investors. Therefore, we perform our main analysis for both raw stock returns, i.e., implicitly assuming a zero expected stock return, as well as for stock returns relative to last four weeks' average weekly stock return.

As an illustration of the model predictions and the impact of the different parameters, let us assume $\alpha = 0.1$ and expected stock return $E_{t-1}[R_t] = 2\%$. In this case, a negative stock return of 10% increases the likelihood of domestic violence by $-0.1 \times (-10\% - 2\%) = 1.2\%$. If the expected stock return is lower, say, $E_{t-1}[R_t] = -1\%$, the same 10% loss will increase the likelihood of domestic violence by only $-0.1 \times (-10\% - (-1)\%) = 0.9\%$.[23] In other words, larger losses increase the likelihood of domestic violence more, and the effect is larger when the expected return is higher.

A.2 The role of gender and gender inequality

As Card and Dahl (2011) focus on male-on-female domestic violence occurring on an unexpected football home team loss day, we further explore the role of gender and gender inequality in our context. Panel A of Table A.1 shows a regression analysis with the dependent variable *DV rate* calculated separately for each gender. We see that the negative relationship between stock market returns and domestic violence holds for both genders, although the statistical significance is weaker for female perpetrators. This may be due to the substantially lower number of incidents of domestic violence perpetrated by women in our data.[24]

It seems plausible that the relationship between stock market returns and domestic violence depends on the cultural context. As discussed in Section 2.1, a number of studies

[23] The increase in the likelihood of domestic violence here is measured in percentage points, not in percent.
[24] Less than 20% of the incidents in our data are committed by women.

suggest that the incidence of domestic violence is related to the relative economic power between men and women in families. Therefore, in states where gender inequality is higher, we might expect the dynamics of domestic violence to be different as well. We test this prediction using the updated version of the Gender Equality Index provided by Di Noia (2002), based on the methodology originally developed by Sugarman and Straus (1988). The index is available for each U.S. state. We include a *High inequality* dummy variable for each state, which takes value one if the state has a below-median index value, zero otherwise.

Panel B of Table A.1 shows a regression analysis including interaction terms between stock returns and the High inequality dummy separately for domestic violence perpetrated by men and women. This analysis shows some interesting differences between genders. From Models 3 and 4, we see that the negative relationship between stock market returns and domestic violence perpetrated women exists only in states with relatively low gender inequality. The relationship is highly statistically significant. In the above-median-inequality states, this relationship appears to completely disappear, as can be seen by comparing the coefficients of the *Return* variable and its interaction with the *High inequality* dummy. These coefficients are similar in magnitude and have the opposite signs, effectively offsetting each other for the high-inequality states. For men, no such distinction between high- and low-inequality states seems to exist. The estimated coefficients for the interaction term are negative and not statistically significant.

A.3 Other determinants of domestic violence

To facilitate comparisons of our data with earlier studies of domestic violence, we include an additional regression analysis of other determinants of domestic violence. Table A.2 shows the results of this analysis. Panel A includes all domestic violence perpetrated by both genders. Model 1 does not control for agency fixed effects (or any other fixed effects), and therefore represents largely a cross-sectional comparison of different locations and their characteristics, showing their correlations with the incidence of domestic violence within them.

We see that locations with low male unemployment and high female uneployment tend to experience higher levels of domestic violence. This result is consistent with the findings of Anderberg et al. (2016), who use regional data from the United Kingdom. Controlling for agency fixed effects, higher male unemployment is still associated with lower levels of domestic violence, suggesting that increases in male unemployment tend to decrease domestic violence. Changes in female unemployment do not appear to have a statistically significant effect on domestic violence.

Poorer places, as measured by average personal income per capita at the county level, tend to experience higher levels of domestic violence, consistent with the findings of Benson et al. (2003). Larger cities, as measured by population, tend to have higher levels of domestic violence. On the other hand, when controlling for agency fixed effects, the estimated coefficient for population becomes negative, suggesting that population growth within a location is actually associated with decreasing levels of domestic violence.

As might be expected by both economic models of household bargaining, as well as general intuition, states with higher gender equality tend to have lower levels of domestic violence. Decreases in the wage gap between genders seem to be associated with decreases in domestic violence, a finding that is consistent with the results of Aizer (2010). Times of higher investor sentiment appear to be associated with higher levels of domestic violence, a finding that is somewhat counter-intuitive and perhaps worth exploring in future research.

A.4 Stock returns and regional income level

The rate of stock market participation is positively correlated with income level, as shown by, e.g., Chien and Morris (2017). Conversely, domestic violence is more prevalent among households at lower income levels, as discussed by, e.g., Benson et al. (2003). Our data confirm the latter observation, as shown in Figure A.1, which plots the monthly observations of the rate of domestic violence against the average personal income level.

Given these opposite correlations of domestic violence and stock market participation with income level, it seems logical to ask from which income groups the relationship between stock returns and reported domestic violence comes from. Intuitively, we expect the strongest relationship in the middle part of the income distribution, where households are likely to have a large enough exposure to the stock market, and where they also represent a high enough proportion of the reported rates of domestic violence. It should also be noted that domestic violence exists even in the highest income categories. Furthermore, even in the lowest income categories, a meaningful proportion of households have some stock investments.

To test for the role of income level, we first divide the agencies in our sample into three categories each year, based on the average personal income per capita at the agency location, and then include dummies indicating these wealth categories in our regressions. Table A.3 shows the results of these regressions including interactions of stock returns with dummies indicating the income level of the agency location. The estimated coefficients are negative for all income levels, but the middle tertile exhibits the strongest and statistically most significant relationship between stock returns and domestic violence. The relationship is not statistically significant in the top tertile, and the estimated coefficients are also substantially smaller in magnitude.

A.5 Robustness check – LHS and RHS periods

To make sure that our results are not driven by the choice of weekend period or weekly stock returns, we perform a regression analysis using different weekend periods for the *DV rate*. The results are shown in Panel A of Table A.4. The first column shows the results using our main definition, from Friday 4pm until Sunday midnight. Column 2 includes the Monday morning until 9am (stock market opening) in addition. Column 3 defines weekend beginning from Thursday 4pm (stock market close), including all of Friday. In this specification, the weekly stock return overlaps with the DV rate period by one day, as Friday returns are included in the stock market return. Column 4 only includes Friday and Saturday, ending at

9am on Sunday morning. Across all specifications, the estimated coefficients remain negative and statistically significant.

Panel B shows the results using different periods for stock returns, and our main definition of DV rate (Friday 4pm - Sunday midnight). For example, *Return (3d)* is the stock market return over the last three trading days before the weekend. This differs somewhat from our main analysis that uses weekly returns, as the weekly return contains weeks that have fewer than five trading days. Here as well, the estimated coefficients are negative and statistically significant for all specifications. Taken together, these results suggest that our findings are not driven by the choice of variable definitions.

A.6 Robustness check – Excluding states with many listed companies

To assess the robustness of our findings, we perform an analysis excluding states with the largest number of listed companies in our data, namely Illinois, Massachusetts, and Texas. The states with generally the largest number of listed companies in the U.S., New York and California, are not included in our data.

The results are shown in Table A.5. The estimated coefficient for stock return remains negative and statistically significant when excluding any or all of the states with the largest number of listed companies.

A.7 Robustness check – Controlling for firm news

Above, we show plenty of evidence suggesting that the relationship between stock returns and the incidence of domestic violence is unlikely to be driven by local firm-specific events that are unrelated to stock returns (such as layoffs and other potentially negative firm events). To provide further comfort that the results are driven by the wealth shocks instead of other channels, we perform a regression analysis specifically controlling for firm-related news. To do this, we construct a firm-level news sentiment index using RavenPack News Analytics (RPNA) data.

The data include details of each news article mentioning the firm from a large number of sources, including Dow Jones Newswires, Barrons, the Wall Street Journal, and over 22,000 other traditional and social media sites. The data also include measures of structured sentiment, relevance, and novelty. We include only highly relevant (relevance of 100) and novel (ens_similarity_gap of at least 90) news articles. We exclude news of the content groups "technical-analysis", "stock-prices", and "order-imbalances", because these news are directly reporting the stock market performance of the firm and hence clearly not relevant for our attempt to exclude the firm-events that might affect domestic violence through other channels.

For each firm, we calculate the weekly number of articles and their average composite sentiment score (CSS). We then calculate two weekly indices of news sentiment for each state. *News index (mcap-N-news)* is a state-level firm-news sentiment index calculated as the average news sentiment weighted by market cap and the number of news articles. *News index (N-news)* is a state-level firm-news sentiment index calculated as the average news sentiment weighted by the number of news articles only. We then perform a regression analysis controlling for these news sentiment indices.

The results are shown in Table A.6. The negative relationship between stock returns and the incidence of domestic violence remains statistically significant and virtually unchanged compared to our main results. This further suggests that our results are not driven by other firm-specific events.

A.8 Robustness check – Controlling for Google search volume for "unemployment"

To further check that our findings relate to wealth shocks caused by the stock market, instead of other economic hardship, such as company layoffs, we perform an analysis controlling for weekly Google search volume for "unemployment". This variable is likely to capture weekly changes in worries related to employment. The Google search volume index is at the state level. We scale the mean of the index to be one for each state over the sample period. This reduces the sample size, as google search volume is only available from 2005 onward (we ecxlude 2004 due to poor data quality). We further exclude periods of more than 30 consecutive days of zero search volume in the state.

The results are shown in Table A.7. The estimated coefficients for stock returns remain negative and statistically significant across all specifications. The magnitude is somewhat larger than in our main results, driven by the different sample selection.

A.9 Robustness check – Controlling for stock volatility

To explore whether the volatility of stock returns matters as well, we conduct an analysis controlling for the volatility of daily stock returns during the week. The results are shown in Table A.8. The estimated coefficients for volatility are not statistically significant in any of the model specifications, including or excluding the weekly stock return, while the estimated coefficients for stock returns remain negative and statistically significant across all specifications. Hence, volatility during the week does not appear to have a significant effect on the incidence of domestic violence.

A.10 Robustness check – Different reference points

In our main analysis, we use the last four weeks' average stock return as a reference point and estimate the effect of current stock return relative to this reference point. To make sure that our results are not driven by the choice of reference period, we replicate our main regression analysis using different period lengths for the reference stock return, ranging from the last two weeks to the last six months. We also include an exponential decay model, with declining weights for further past returns, using decay estimates from Da et al. (2019).

The results are shown in Table A.9. The estimated coefficients remain statistically significant across all specifications. The magnitude is smaller for the two and three weeks refrence points, but appears more stable for four weeks and longer periods.

A.11 Incident composition – alcohol

In this section, we study whether the composition of incidents changes conditional on stock returns, focusing on the role of alcohol use. Specifically, we look at the fraction of weekly incidents at police agency level that involve the use of alcohol. The results are reported in Table A.10. We find no significant relationship between the proportion of incidents involving alcohol and weekly stock returns, although the estimated coefficients for stock return are negative.

Figure A.1: Average domestic violence rate vs. PI per capita

Simple agency-week observations plotted based on the rate of domestic violence, calculated as the weekly number of incidents per 100,000 persons for each agency location occurring between Friday 4pm and Sunday 12am (midnight) of each week, against the agency location average Personal Income (PI) per capita. PI per capita is measured at the county level. For agencies covering areas within multiple counties, the PI per capita is calculated as the covered-population-weighted average of the counties.

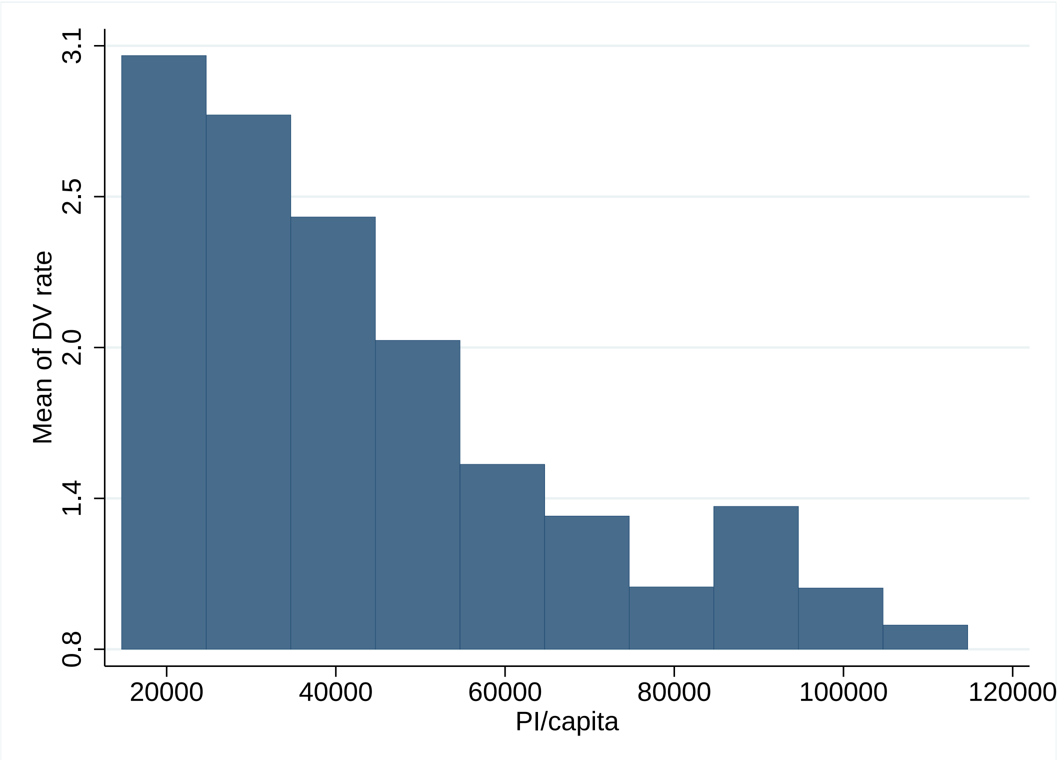

Table A.1
Domestic violence by gender and state-level stock returns

The dependent variable is $ln(1 + DV\ rate)$, where $DV\ rate$ is calculated as the weekly number of incidents per 100,000 persons for each agency location occurring between Friday 4pm and Sunday 12am (midnight) of each week. We include *Agency fixed effects* to capture any agency- and location-specific factors, *Holidays fixed effects*, including a set of dummies for major holidays in case they take place during the week, *State-Quarter or State-Month joint fixed effects*, and *Week of Year fixed effects* (52 weeks) to control for timing. Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

Panel A: Domestic violence by gender of perpetrator

	Male		Female	
	(1)	(2)	(3)	(4)
Return	−0.0532***	−0.0544***	−0.0327*	−0.0336*
	(0.0147)	(0.0144)	(0.0164)	(0.0169)
Weekly IU control	Yes	Yes	Yes	Yes
Agency-Year FE	Yes	No	Yes	No
Agency-Quarter FE	No	Yes	No	Yes
Week of Year FE	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes
N	1,296,975	1,296,975	1,296,975	1,296,975
R^2	0.311	0.358	0.149	0.202

Panel B: Domestic violence vs. gender inequality

	Male		Female	
	(1)	(2)	(3)	(4)
High inequality x Return	−0.0562**	−0.0332	0.0426	0.0608*
	(0.0234)	(0.0279)	(0.0336)	(0.0315)
Return	−0.0309*	−0.0412**	−0.0496***	−0.0578***
	(0.0168)	(0.0173)	(0.0141)	(0.0141)
Weekly IU control	Yes	Yes	Yes	Yes
Agency-Year FE	Yes	No	Yes	No
Agency-Quarter FE	No	Yes	No	Yes
Week of Year FE	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes
N	1,296,975	1,296,975	1,296,975	1,296,975
R^2	0.311	0.358	0.149	0.202

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table A.2
Other determinants of domestic violence

The dependent variable is $ln(1 + DV\ rate)$, where $DV\ rate$ is calculated as the weekly number of incidents per 100,000 persons for each agency location during Friday, Saturday, and Sunday of each week. *Unemployment (male)* and *Unemployment (female)* are the state-level unemployment rates for each gender. *Unemployment gap (M-F)* is the difference in unemployment between men and women at the state level. *Female/male wage* is the median wage for women divided the median wage for men at the state level. *Gender equality* is the Gender Equality Index calculated by Di Noia (2002). We include *Agency fixed effects* to capture any agency- and location-specific factors, *Year fixed effects*, *Week of Year fixed effects* (52 weeks), and *Holiday fixed effects*, including a set of dummies for major holidays in case they take place during the week. Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

Panel A: All domestic violence

	(1)	(2)	(3)	(4)
Return	−0.1735***	−0.0884***	−0.0742***	−0.0578***
	(0.0338)	(0.0151)	(0.0162)	(0.0173)
Unempl. (male) (%)	−0.0550***	−0.0012	−0.0057	−0.0057
	(0.0198)	(0.0031)	(0.0044)	(0.0044)
Unempl. (female) (%)	0.0873**	−0.0024	0.0000	0.0000
	(0.0334)	(0.0061)	(0.0074)	(0.0074)
ln(PI/capita)	−0.3191***	−0.1759***	0.2359**	0.2359**
	(0.0912)	(0.0594)	(0.0934)	(0.0934)
ln(Population)	0.3217***	−0.0848	−0.0552	−0.0551
	(0.0229)	(0.0729)	(0.0676)	(0.0675)
Gender equality	−0.0070			
	(0.0089)			
Female/male wage (%)	0.0061	−0.0049**	−0.0019	−0.0019
	(0.0075)	(0.0019)	(0.0017)	(0.0017)
Sentiment	0.0383**	0.0062	0.0180*	0.0061
	(0.0162)	(0.0058)	(0.0095)	(0.0088)
Agency FE	No	Yes	Yes	Yes
Holidays FE	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Week of Year FE	No	No	No	Yes
N	1,122,485	1,122,485	1,122,485	1,122,485
R^2	0.085	0.287	0.288	0.289

Significance levels: * 0.1, ** 0.05, * 0.01.**

Panel B: Domestic violence by gender

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
Return	−0.1474***	−0.0711***	−0.0571***	−0.0563***	−0.0363**	−0.0341**
	(0.0326)	(0.0151)	(0.0165)	(0.0187)	(0.0155)	(0.0157)
Unempl. (male) (%)	−0.0478**	−0.0016	−0.0057	−0.0207***	0.0007	−0.0010
	(0.0181)	(0.0028)	(0.0041)	(0.0062)	(0.0011)	(0.0015)
Unempl. (female) (%)	0.0761**	−0.0019	0.0004	0.0307***	−0.0007	−0.0008
	(0.0307)	(0.0056)	(0.0068)	(0.0109)	(0.0019)	(0.0022)
ln(PI/capita)	−0.3086***	−0.2031***	0.2311**	−0.0648**	−0.0084	0.0362
	(0.0832)	(0.0547)	(0.0896)	(0.0266)	(0.0164)	(0.0254)
ln(Population)	0.2979***	−0.0968	−0.0652	0.1191***	−0.0041	−0.0018
	(0.0215)	(0.0693)	(0.0630)	(0.0093)	(0.0157)	(0.0158)
Gender equality	−0.0079			−0.0022		
	(0.0082)			(0.0030)		
Female/male wage (%)	0.0056	−0.0049***	−0.0018	0.0016	−0.0008	−0.0005
	(0.0069)	(0.0018)	(0.0015)	(0.0025)	(0.0005)	(0.0006)
Sentiment	0.0378**	0.0060	0.0155	0.0086	0.0034**	0.0090**
	(0.0150)	(0.0056)	(0.0094)	(0.0068)	(0.0013)	(0.0036)
Agency FE	No	Yes	Yes	No	Yes	Yes
Holidays FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	No	Yes	No	No	Yes
N	1,122,485	1,122,485	1,122,485	1,122,485	1,122,485	1,122,485
R^2	0.084	0.271	0.272	0.035	0.115	0.115

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table A.3
Domestic violence and stock returns vs. income level

The dependent variable is $ln(1 + DV\ rate)$, where *DV rate* is calculated as the weekly number of incidents per 100,000 persons for each agency location occurring between Friday 4pm and Sunday 12am (midnight) of each week. *Weekly IU control* is the state-level weekly insured unemployment rate. We include *Agency-Quarter joint fixed effects* to capture any differences in local economic and other conditions, as well as any other location-specific factors, *Holidays fixed effects*, including a set of dummies for major holidays in case they take place during the week, and *Week of Year fixed effects* (52 weeks). Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

	Raw stock market return		Relative to 4-week average	
	(1)	(2)	(3)	(4)
High PI/capita x Return	−0.0263	−0.0396		
	(0.0400)	(0.0416)		
Medium PI/capita x Return	−0.0836**	−0.0870**		
	(0.0407)	(0.0368)		
Low PI/capita x Return	−0.0687*	−0.0611*		
	(0.0359)	(0.0359)		
High PI/capita x Δ Return			−0.0180	−0.0187
			(0.0366)	(0.0376)
Medium PI/capita x Δ Return			−0.0854***	−0.0789**
			(0.0298)	(0.0310)
Low PI/capita x Δ Return			−0.0610**	−0.0540**
			(0.0230)	(0.0254)
Weekly IU control	Yes	Yes	Yes	Yes
Agency-Year FE	Yes	No	Yes	No
Agency-Quarter FE	No	Yes	No	Yes
Week of Year FE	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes
N	1,246,726	1,246,726	1,246,726	1,246,726
R^2	0.326	0.373	0.326	0.373

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table A.4
Robustness check – sensitivity to LHS and RHS periods

The dependent variable is $ln(1 + DV\ rate)$, where $DV\ rate$ is calculated as the daily number of incidents per 100,000 persons for each agency location. Panel A shows the results calculating DV rate for different periods. Panel B shows the results using the main definition of DV rate (Friday 4pm - Sunday midnight), using stock returns for different period lengths before the weekend. Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

Panel A: Different definitions of weekend for DV rate (LHS variable)

	(1) Fri 16-Sun 24	(2) Fri 16-Mon 9	(3) Thu 16-Sun 24	(4) Fri 16-Sun 9
Return	−0.0646***	−0.0577***	−0.0810***	−0.0546**
	(0.0198)	(0.0209)	(0.0190)	(0.0202)
Weekly IU control	Yes	Yes	Yes	Yes
Agency-Month FE	Yes	Yes	Yes	Yes
Week of Year FE	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes
N	1,296,975	1,296,975	1,296,975	1,296,975
R^2	0.483	0.491	0.515	0.451

Panel B: Different cumulative return periods (RHS variable)

	(1)	(2)	(3)	(4)	(5)
Return (1d)	−0.1415**				
	(0.0624)				
Return (2d)		−0.0929***			
		(0.0235)			
Return (3d)			−0.0636***		
			(0.0223)		
Return (4d)				−0.0580***	
				(0.0206)	
Return (5d)					−0.0503**
					(0.0198)
Weekly IU control	Yes	Yes	Yes	Yes	Yes
Agency-Month FE	Yes	Yes	Yes	Yes	Yes
Week of Year FE	Yes	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes	Yes
N	1,296,975	1,296,975	1,296,975	1,296,975	1,296,975
R^2	0.483	0.483	0.483	0.483	0.483

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table A.5
Robustness check – excluding states with most listed companies

The dependent variable is $ln(1 + DV\ rate)$, where $DV\ rate$ is calculated as the weekly number of incidents per 100,000 persons for each agency location occurring between Friday 4pm and Sunday 12am (midnight) of each week. *Weekly IU control* is the state-level weekly insured unemployment rate. We include *Agency-Month joint fixed effects* to capture any differences in local economic and other conditions, as well as any other location-specific factors, *Holidays fixed effects*, including a set of dummies for major holidays in case they take place during the week, and *Week of Year fixed effects* (52 weeks). Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

	(1) ex. IL	(2) ex. MA	(3) ex. TX	(4) ex. IL, MA, TX
Return	−0.0646***	−0.0578***	−0.0605***	−0.0532**
	(0.0198)	(0.0202)	(0.0198)	(0.0200)
Weekly IU control	Yes	Yes	Yes	Yes
Agency-Month FE	Yes	Yes	Yes	Yes
Week of Year FE	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes
N	1,296,397	1,170,149	1,263,423	1,136,019
R^2	0.483	0.485	0.482	0.482

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table A.6
State-level stock returns and news

The dependent variable is $ln(1 + DV\ rate)$, where *DV rate* is calculated as the weekly number of incidents per 100,000 persons for each agency location occurring between Friday 4pm and Sunday 12am (midnight) of each week. *News index (mcap-N-news* is a state-level firm-news sentiment index weighted by market cap and the number of news articles. *News index (N-news* is a state-level firm-news sentiment index weighted by the number of news articles. *Weekly IU control* is the state-level weekly insured unemployment rate. We include *Agency-Month joint fixed effects* to capture any differences in local economic and other conditions, as well as any other location-specific factors, *Holidays fixed effects*, including a set of dummies for major holidays in case they take place during the week, and *Week of Year fixed effects* (52 weeks). Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

	Raw stock market return		Relative to 4-week average	
	(1)	(2)	(3)	(4)
Return	−0.0641***	−0.0647***		
	(0.0202)	(0.0199)		
Δ Return			−0.0577***	−0.0583***
			(0.0183)	(0.0181)
News index (mcap-N-news)	−0.0001		−0.0001	
	(0.0003)		(0.0003)	
News index (N-news)		0.0001		0.0001
		(0.0004)		(0.0004)
Weekly IU control	Yes	Yes	Yes	Yes
Agency-Month FE	Yes	Yes	Yes	Yes
Week of Year FE	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes
N	1,296,975	1,296,975	1,296,975	1,296,975
R^2	0.483	0.483	0.483	0.483

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table A.7
Robustness check – controlling for Google "unemployment"

The dependent variable is $ln(1 + DV\ rate)$, where *DV rate* is calculated as the weekly number of incidents per 100,000 persons for each agency location occurring between Friday 4pm and Sunday 12am (midnight) of each week. *Weekly IU control* is the state-level weekly insured unemployment rate. We include *Agency-Month joint fixed effects* to capture any differences in local economic and other conditions, as well as any other location-specific factors, *Holidays fixed effects*, including a set of dummies for major holidays in case they take place during the week, and *Week of Year fixed effects* (52 weeks). Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

	(1)	(2)	(3)	(4)
Return	−0.1073***	−0.1036***	−0.1133***	−0.1048***
	(0.0215)	(0.0257)	(0.0236)	(0.0344)
Google Unemployment	−0.0045*	−0.0002	−0.0007	−0.0013
	(0.0025)	(0.0011)	(0.0012)	(0.0013)
Weekly IU control	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No
Agency FE	Yes	No	No	No
Agency-Year FE	No	Yes	No	No
Agency-Quarter FE	No	No	Yes	No
Agency-Month FE	No	No	No	Yes
Week of Year FE	No	Yes	Yes	Yes
Holidays FE	No	Yes	Yes	Yes
N	914,155	914,155	914,142	913,904
R^2	0.286	0.319	0.364	0.473

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table A.8
State-level stock returns and volatility

The dependent variable is $ln(1 + DV\ rate)$, where $DV\ rate$ is calculated as the weekly number of incidents per 100,000 persons for each agency location occurring between Friday 4pm and Sunday 12am (midnight) of each week. *Weekly IU control* is the state-level weekly insured unemployment rate. We include *Agency fixed effects*, *Agency-Year*, *Agency-Quarter*, or *Agency-Month joint fixed effects*, to capture any differences in local economic and other conditions, as well as any other location-specific factors, *Holidays fixed effects*, including a set of dummies for major holidays in case they take place during the week, and *Week of Year fixed effects* (52 weeks). Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

Panel A: Raw state-level stock market return

	(1)	(2)	(3)	(4)
Return	−0.0646***		−0.0639***	−0.0895**
	(0.0198)		(0.0198)	(0.0377)
Volatility		−0.0939	−0.0899	−0.0951
		(0.1575)	(0.1594)	(0.1575)
Return x Volatility				1.0374
				(1.0239)
Weekly IU control	Yes	Yes	Yes	Yes
Agency-Month FE	Yes	Yes	Yes	Yes
Week of Year FE	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes
N	1,296,975	1,295,970	1,295,970	1,295,970
R^2	0.483	0.484	0.484	0.484

Panel B: Relative to 4-week-average return

	(1)	(2)	(3)	(4)
Δ Return	−0.0582***		−0.0574***	−0.0748*
	(0.0179)		(0.0181)	(0.0377)
Volatility		−0.0939	−0.0753	−0.0842
		(0.1575)	(0.1599)	(0.1565)
Δ Return x Volatility				0.7006
				(1.0559)
Weekly IU control	Yes	Yes	Yes	Yes
Agency-Month FE	Yes	Yes	Yes	Yes
Week of Year FE	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes
N	1,296,975	1,295,970	1,295,970	1,295,970
R^2	0.483	0.484	0.484	0.484

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table A.9
Different reference points

The dependent variable is $ln(1 + DV\ rate)$, where $DV\ rate$ is calculated as the weekly number of incidents per 100,000 persons for each agency location occurring between Friday 4pm and Sunday 12am (midnight) of each week. *Weekly IU control* is the state-level weekly insured unemployment rate. We include *Agency-Month joint fixed effects* to capture any differences in local economic and other conditions, as well as any other location-specific factors, *Holidays fixed effects*, including a set of dummies for major holidays in case they take place during the week, and *Week of Year fixed effects* (52 weeks). Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

	(1) 2 weeks	(2) 3 weeks	(3) 4 weeks	(4) 5 weeks	(5) 6 weeks	(6) 6 months	(7) Exp. decay
Δ Return	−0.0316**	−0.0351**	−0.0582***	−0.0595***	−0.0572***	−0.0649***	−0.0460**
	(0.0153)	(0.0161)	(0.0179)	(0.0181)	(0.0180)	(0.0191)	(0.0169)
Weekly IU control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agency-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week of Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,296,975	1,296,975	1,296,975	1,296,975	1,296,975	1,296,975	1,296,975
R^2	0.483	0.483	0.483	0.483	0.483	0.483	0.483

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table A.10
Incident composition analysis – alcohol

The dependent variable, *Fraction alcohol*, is the fraction of incidents that involved the use of alcohol. *Weekly IU control* is the state-level weekly insured unemployment rate. We include *Agency-Month joint fixed effects* to capture any differences in local economic and other conditions, as well as any other location-specific factors, *Holidays fixed effects*, including a set of dummies for major holidays in case they take place during the week, and *Week of Year fixed effects* (52 weeks). Heteroscedasticity-consistent standard errors, clustered by state, are shown in parentheses.

	(1)	(2)
Return	−0.0206	−0.0084
	(0.0147)	(0.0174)
Weekly IU control	Yes	Yes
Agency-Quarter FE	Yes	No
Agency-Month FE	No	Yes
Week of Year FE	Yes	Yes
Holidays FE	Yes	Yes
N	542,867	487,074
R^2	0.342	0.489

Significance levels: * 0.1, ** 0.05, * 0.01.**