Does the Stock Market Influence Investor Everyday Decisions? The Case of Parking Violations

Abstract

We explore in this study whether stock market returns influence investor decisions in their everyday life. We find that past and contemporaneous US stock market returns are related negatively to the registered number of parking violations in New York City between 2014 and 2020. We support as the channel of this relationship the level of investor anxiety. These results support extensions of the utility theory demonstrating the significance of emotions on individuals' decisions. Overall, this study shows evidence of the societal impact of finance.

Keywords: Societal Impact; Utility Theory; Stock Market Returns; Parking Violations

JEL codes: G4; D9; R4; L9

1. Introduction

Numerous studies have established several variables that influence stock market returns. We instead focus in this study on the significance of stock market returns as the main independent variable. This is an interesting inquiry considering that the research undertaken in the field of finance has often received criticism due to the lack of exploring implications to the society (e.g., Zingales, 2015; Brooks et al., 2019).

We explore in this study whether stock market returns are related to parking violations. Theoretically, this study builds on our understanding of individuals' decisions with the use of data from the real world rather than the most often-used experiments. According to the 'classic' utility theory (e.g., Von Neumann and Morgenstern, 1944), people merely make decisions that maximize their utility. Surely, investors are not expected to violate parking rules to avoid financial penalties. The utility theory then suggests that there should be no relationship between returns and parking violations. In the extreme case that investors were to violate the parking rules, this should have been more likely to occur on days that individuals experienced gains from the financial markets since on such "good" days, violating the parking rules would damage their overall wealth to a lower extent.

However, there is plenty of evidence showing that humans often make decisions that contradict utility theory's expectations (e.g., Conlisk, 1989). Studies in psychology (e.g., Loewenstein et al., 2001) have shown that emotions can have an impact on our decisions. Caplin and Leahy (2001) even report theoretically the significance of anticipatory anxiety as an extension of the utility theory, theorizing the need for utility theory to incorporate emotions to understand individuals' decisions. Transportation literature has previously shown that driving behavior is influenced by emotions. For example, Pêcher et al. (2009) offer a comprehensive review in this field, Dula et al. (2010) report empirical evidence showing that drivers with high anxiety drive dangerously, and Roidl et al. (2014) highlight the significance of emotions such as anxiety on the tendency of drivers to break traffic violations. We thus expect that the presence of poor (good) stock market returns would likely be a cause to undertake more (less) parking violations. Investor anxiety is potentially the mechanism driving this relation. Against the no relation expectation based on the ‘classic’ utility theory, we expect that lagged and contemporaneous stock market returns are more likely to be related negatively to the number of parking violations.

To test this, we use a comprehensive dataset available for New York City with all registered parking violations since 2014. The dataset used is extensive, with 86 million rows of data available. The dataset offers details on individual violations that assist us to offer strong support for the relationship. We find that lagged and contemporaneous US stock market returns are related negatively to the number of parking violations in New York City. Not all investors follow closely daily stock market performance with plenty of evidence of investor inattention in financial markets (e.g., Patell and Wolfson 1982; Penman, 1987; Damodaran, 1989). We find that up to four-day lagged stock market returns, and the contemporaneous stock market returns, are related to the number of parking violations. This relation is economically significant showing for example that a 1% decrease of contemporaneous stock market returns is on average related to an increase in parking fines approximately by $3,525 in a day ($920,025 in a year). Our empirical evidence then contradicts the ‘classic’ utility theory by showing that investors are influenced by emotions (generated by stock market returns) when making decisions in their everyday life.

To offer some support behind the channel that drives this relationship, we explore the relations between lagged investor anxiety and stock market returns as well as lagged investor anxiety and parking violations. We find that lagged stock market returns are related to investor anxiety, indicating that stock returns influence investor anxiety. We instead find that lagged investor anxiety is not related to stock market returns, and so the reverse relation is not empirically present. We also find very little evidence that lagged investor anxiety is directly related to parking violations. When we though interact the level of anxiety in the market with stock market returns, we find that the parameter coefficients of the interaction variables are significant. Overall, these results seem to indicate that stock market returns influence investor anxiety that affects the frequency of parking violations.

Similar to other studies in this field (Engelberg and Parsons, 2016; Giulietti et al., 2020; Lin and Pursiainen, 2020; and Wisniewski et al., 2020), we are based on some assumptions considering that it is not possible to know the stock selections of each investor and whether they have undertaken a parking violation to test the relation with the use of direct data. Some investors may trade in passive funds that reflect the whole market and others within different stocks that on average would reflect the market movements. According to Pew Research Centre (2020), more than half of the US households invest in the financial market[1], and so a significant percentage of US citizens are likely investors. One also needs a reasonable financial position to own a car and so some noise is excluded in our setting.

We also report some empirical evidence to indicate that the understudy relationship is likely driven by investor behavior. First, in line with evidence that investor attention is most pronounced early in a week (e.g., Patell and Wolfson 1982; Penman, 1987; Damodaran, 1989), we find that the contemporaneous relation is present using data for Monday & Tuesday but not for Thursday & Friday. Investors respond to contemporaneous stock market returns to the extent they are aware of. There is low investor attention towards the end of the week, and high attention early in a week. It does thus make sense that the understudy relation is most pronounced early rather than late in a week since investors do not necessarily show the same

1 https://www.pewresearch.org/fact-tank/2020/03/25/more-than-half-of-u-s-households-have-some-investment-in-the-stock-market/

level of attention in the financial markets on all days of the week. They would more likely follow stock market returns early rather than late in the week.

Second, the main relation seems to be most pronounced within small investors who more likely have high/low attention early/late in the week. We find that the relationship is most pronounced within violations that took place with drivers in vans or taxis in comparison to expensive cars. It is more likely for small investors to be driving vans and taxis,[2] with more substantial investors driving counterpart expensive cars. Literature (e.g., Lemmon and Portianguina, 2006; Siganos et al., 2017) suggests that small investors are relatively more susceptible to emotions, supporting our empirical finding. Finally, we find that the negative relationship is most pronounced within stock returns of firms headquartered in the New York State in comparison to the full market (S&P500). Due to the home bias (e.g., Coval and Moskowitz, 1999; Griblatt and Keloharju, 2001), local firms' stock returns would influence most of the behavior of investors in New York City.

We undertake several additional tests to support the empirical validity of the main relation. For example, we find that the relationship is present in cars with and without registration from the New York state and thus the relation does not seem to be driven by drivers who were not potentially aware of the local parking rules. The relation also holds after controlling for daily macroeconomic conditions, and the available enforcement force. The relation is present within parking violations that involve cameras showing that is at least partly driven by drivers' rather than traffic wardens' behavior.

We also report that the relationship is not the outcome of autocorrelation or any seasonality patterns in parking violations. Results hold for example after controlling for lagged

[2] An old saying for example states that "When taxi drivers are handing out stock tips, it's time to sell", indicating the interest even of taxi drivers investing in financial markets. This comes as no surprise considering that more than half of the US households invest in stocks (Pew Research Centre, 2020).

parking violations and after estimating parking violations above-average violations or corresponding per year violations. An interesting placebo test is that we explore stock market returns in association with the number of parking violations before the stock market opens at 9.30 am. As expected, we find in this specification that there is no relation. There is only a relationship with stock market returns when using the parking violations after the market opens. We also find that the relationship is most pronounced within high-cost parking violations, indicating further that investors are not fully rational when responding to financial markets.

The studies closest to our work are likely those that explore the significance of stock market returns towards the health of the population. It is found that poor stock returns are related to increases in hospital admissions (Engelberg and Parsons, 2016), fatal accidents (Giulietti et al., 2020), domestic violence (Lin and Pursiainen, 2020), and suicide rates (Wisniewski et al., 2020). These studies follow similar assumptions to our study by using stock market returns. They do not also have access to individual investor transactions and have no information on individual names for example who were admitted in the hospital or who undertook domestic violence. In comparison to these studies, we explore the influence of stock market returns on the behavior of investors in a non-health-related issue. Parking violations also reflect the decisions of a relatively large percentage of investors. According to Gallup Survey (2018), 64% of US adults drive daily their cars, with at least 83% many times a typical week.[3] Even in a big city such as New York City and the existence of a good public transport system, around 45% of people own a car and 27% of them commute daily with their car to work.[4] Previously used contexts instead explore consequences to a very minor percentage of the overall population. For example, Engelberg and Parsons (2016, pp. 1231) state that

[3] https://news.gallup.com/poll/236813/adults-drive-frequently-fewer-enjoy-lot.aspx.
[4] https://edc.nyc/article/new-yorkers-and-their-cars.

"hospitalizations are fairly rare" and Giulietti et al. (2020, pp. 11) that only "0.5% of police-reported crashes [in 2015] are fatal".

The remainder of this paper is structured as follows: Section 2 discusses the data used and the methodology followed. Sections 3 to 5 report the empirical findings. Finally, Section 6 concludes this study.

2. Data and methodology

2.1. Data

We use several data sources to test the relationship. Our data for parking violations arrive from the NYC OpenData[5] that reports all registered violations in New York City between January 2014 and October 2020. The dataset offers detailed information for each parking violation such as the timing, location of the violation, vehicle body type, vehicle make, type of violation, and cars' registration state. The magnitude of the dataset used is extensive. The analysis is based on 86 million rows of data. Daily stock market returns (S&P500) arrive from Datastream. We download daily weather data from NOWData for New York City Central Park; temperature, precipitation, and snow.[6] We download the Federal US holidays from TimeandDate.[7] We add a dummy equal to one for days after the 3rd March 2020, otherwise zero, that was the first recorded covid-19 incident in New York State.[8]

[Please insert Figure 1 around here]

Table 1 offers the descriptive statistics of all the variables used in this study. We find for example that the average number of violations is 39,406, with a significant variation in a

[5] https://opendata.cityofnewyork.us/
[6] https://w2.weather.gov/climate/xmacis.php?wfo=okx
[7] https://www.timeanddate.com/holidays/us/?hol=1
[8] https://en.wikipedia.org/wiki/COVID-19_pandemic_in_New_York_City

day from 774 to 83,163. Figure 1 visualizes the daily number of parking violations undertaken during the sample period. There is evidence of outliers in this dataset. For the main analysis, we winsorize the top and bottom 2% (total 4%).[9] We report the descriptive statistics of the winsorized parking violations. The average and the median of stock market returns is 0%. The maximum daily performance is 9% and the minimum -12%.

[Please insert Table 1 around here]

2.2. Methodology

We undertake the following Poisson estimation for the main analysis since the dependent variable is non-integer and cannot take negative values:

$$ParkingViolations_t = constant + b_1\, S\&P500_t + b_2\, S\&P500_{t-1} + b_3\, S\&P500_{t-2} + b_4\, S\&P500_{t-3} + b_5\, S\&P500_{t-4} + b_6\, S\&P500_{t-5} + b_7\, Temperature_t + b_8\, Precipitation_t + b_9\, NewSnow_t + b_{10}\, Holidays_t + b_{11}\, Covid\text{-}19_t + FEs\ DayoftheWeek + FEs\ Month + FEs\ Year + u_t \quad (1)$$

Our dependent variable is the sum of parking violations per day. The main independent variables for interest are the contemporaneous and the lagged S&P500 daily stock returns.[10] Since investors may not observe everyday stock market performance (e.g., Patell and Wolfson 1982; Penman, 1987; Damodaran, 1989), we expect that there should be a relation starting a few days before a parking violation occurs. As discussed in the Introduction Section, according to the 'classic' utility theory, these parameter coefficients should be insignificant. To the extent investors are humans with biases influencing their decisions, the parameter coefficients on S&P500 are expected to be negative.

[9] For robustness, we also report results without any winsorization later in this study.
[10] In untabulated results, we find that our conclusions are unchanged when using value- and equal-weighted stock market returns.

We control for several variables that may influence the frequency of parking violations (e.g., Fisman and Miguel, 2007; Ackerman and Moustafa, 2011). The weather is expected to have a significant impact on the likelihood of the investors going out or even perhaps the effort by the police to capture unlawful activity. It is expected that there are fewer parking violations on days with low temperatures, and on days with high precipitation and snow. Fewer parking violations are also expected during holidays and since the arrival of covid-19 in New York City. We also add fixed effects per day of the week, month, and year to capture potential seasonal patterns on traffic activity. In line with Petersen (2009), we cluster standard errors on the day of the week.

3. Main empirical results

3.1 Main relationship

We report in this section the main results of this study. As shown in equation (1) earlier, the dependent variable is the daily number of parking violations. The main independent variable is S&P500. Columns (1), (3), (4), and (5) of Table 2 only report the contemporaneous relation. Columns (2), (6), and (7) report results when adding up to five lagged stock market returns. For robustness, we report results with and without the use of fixed effects on the day of the week, month, and year.

We find strong evidence that the lagged and contemporaneous stock market returns are related negatively to the number of parking violations. Apart from the S&P500 parameter coefficient in day -5, the remaining parameter coefficients are significantly negative. Against the utility theory's expectations, we find that poor (strong) stock market returns are related to more (less) parking violations. Investors seem to be influenced by their emotions generated from stock market returns in their everyday life.

[Please insert Table 2 around here]

The economical magnitude of this relationship is strong. As shown in column (7), we find for example that per unit decrease in contemporaneous stock market returns, the expected log count of the number of parking violations increases by 1.05 after controlling for other determinants. The estimated incidence rate ratio decreases by a factor of 0.35 [which is the exponential value of -1.05]. A one-unit decrease of stock market returns is thus linked with a contemporaneous increase of parking violations by 65% [(0.35-1)*100]. In untabulated results, we also re-estimate the Poisson with stock market returns reflecting % i.e. 2.38% rather than 0.0238, and find that a one-unit decrease in stock market returns is linked with a contemporaneous increase of parking violations by 1.04%. In 2019, the total cost for parking violations was for example $23million[11] or $88,123 per working day [$23million / 261 days]. So, a 1% decrease of daily stock market returns is related to an increase in fines approximately by $3,525 [$91,648 - $88,123] or $920,025 in a year. Note that these estimations only reflect the impact of the contemporaneous stock market returns before thus adding the influence of the previous four days' stock market returns.

In columns (4) and (5), we explore the magnitude of the relation separately for days with less than -1% and on days with more than 1% stock market returns. We find later in the study that as expected, small deviations in stock market returns (between -1% and 1%) do not influence investor behavior in association with parking violations (see Table 5), and we so explore here the relation on days with stock market returns experiencing more substantial movements. The extent to which the investors respond to stock market returns is likely to be related to expected gains/losses,[12] the relation is still likely more pronounced within significant

[11] https://www.freightwaves.com/news/ups-hit-with-22m-in-nyc-parking-fines

[12] Some investors may be dissatisfied achieving a small profit if they were used to or/and expected more pronounced gains. In the same spirit, some investors may be happy receiving small losses if they expected significant losses.

negative (rather than positive) stock market returns that would generate bad emotions leading to parking violations. We indeed find that the relation is insignificant on days with over 1% market returns, but significantly negative on days with less than -1% stock market returns.

Note that the parameter coefficients of the control variables are as expected. We find that there are fewer parking violations on days with relatively low temperatures, and on days with high precipitation and snow. We also find that there are fewer parking violations during holidays and in the period after covid-19. Although we do not tabulate the parameter coefficients of the fixed effects for space consideration, we find that they can explain a significant variation of parking violations. The pseudo-R-square is 0.4097 in column (7) versus 0.1293 in column (6). We find that there are more parking violations in recent years, and also towards the end of the week. In the remaining analysis, we use all control variables, but we no longer tabulate them.

3.2 Robustness tests

In this section, we explore several robustness tests of the main relation. We first estimate the cumulative stock market returns over the period -5 to 0 days. In line with the main result of this study, column (1) of Table 3 shows that the magnitude of the cumulative stock market returns is related negatively to the number of parking violations. We further explore the magnitude of the relationship moving to days with more extreme stock market performances. Columns (2) to (7) report results when moving from more than 1% absolute stock market returns to gradually more than 6% absolute stock market returns. As expected, we report that the relationship becomes most pronounced as we move to days with more extreme absolute stock returns. The relevant parameter coefficient is -0.800 (more than 1% absolute stock market returns), -0.816 (2%), -0.813 (3%), -1.218 (4%), -1.683 (5%), and -2.177 (6%). Although only a few observations are available on days with extreme cumulative market performance, those parameter coefficients are all significant at the 1% level.

[Please insert Table 3 around here]

Column (1) of Table 4 further explores the main results if not following any outlier treatment on the number of parking violations. Earlier, we winsorized the number of parking violations at the top and bottom 2%. We find that our results hold without following any winsorization since the parameter coefficients on S&P500 remain significantly negative.

[Please insert Table 4 around here]

Columns (2) and (3) of Table 4 explore results when undertaking additional methodological estimations; negative binomial and OLS regression, respectively. We previously used a Poisson estimation. The negative binomial has one parameter more than the Poisson estimation by adjusting the variance independently from the mean. Once again, we find that the relevant parameter coefficients remain negative with both additional methodological estimations.

Column (4) of Table 4 explores the significance of stock market returns for weekend parking violations. The previous analysis excluded weekend values since the stock market is closed. We note that the number of observations in this estimation is very low for any serious empirical analysis (only 294 observations). Still, we explore whether there is any evidence of a negative relation within this dataset. We indeed find that Thursday's stock market returns are related negatively to the weekend's parking violations. We find that the remaining parameter coefficients are insignificant. The no relation with the use of Friday's stock market returns may make some sense considering that academic literature (e.g., Patell and Wolfson 1982; Penman, 1987; Damodaran, 1989) previously shown that investor inattention is very strong on Fridays. Investors would not respond to Friday's stock market returns to the extent they are not aware of.

3.3 Placebo tests

We undertake several placebo tests. We first report results on the contemporaneous relation before and after the stock market opens at 9.30 am. The expectation is that there should be no relation between the number of parking violations and stock market returns before the market opens. Columns (1) and (2) of Table 5 indeed support these expectations. The parameter coefficient on S&P500 is significantly negative only after the stock market opens.

[Please insert Table 5 around here]

We have tabulated until now the relation with the use of up to five-day lags on stock market returns. 'Old' stock returns are expected not to matter. Indeed, in untabulated results, we find that there are no relations when using lags earlier than a day, -4. Column (3) tabulates for example the results when using lags from day -6 to -10 (weekend values are excluded). All parameter coefficients are insignificant.

Finally, we explore the significance of relatively small changes in stock market returns. Table 3 previously reported that the relationship becomes most pronounced within days with significant movement in the stock market. Instead, we report here results on days with little change in stock market returns that we expect no relation. Column (4) reports results when generating a dummy that takes one if the sum of the five-day lags in the stock market returns is between -1 and 1%, otherwise zero. We also report results in column (5) when we undertake the estimation within days that the absolute cumulative stock market returns are less than 1%. As expected, we find that the relevant parameter coefficients are all insignificant.

4. Some empirical support of the assumptions undertaken

We offer in this section some empirical support to the assumptions we are based on to build our story.

4.1 The relationship reflects investor behavior

We assume that citizens who violate the parking rules are investors. As stated in the Introduction Section, Pew Research Centre (2020) reports that more than half of the US households invest in the financial market, and so a significant percentage of US citizens are likely investors. To own a car, one needs a reasonable financial position and so our setting excludes unnecessary noise offering further assurance that a significant percentage of drivers are likely investors. Still, we are not aware which of the parking violations are from citizens who invest in the financial market. We undertake three tests to offer some empirical evidence that our results likely reflect investor behavior.

First, we know from the academic literature (e.g., Patell and Wolfson 1982; Penman, 1987; Damodaran, 1989) that investor inattention is much stronger towards the end of a week. If the relationship that we study is indeed driven by investor behavior, the contemporaneous relation should be most pronounced early rather than late in a week. Considering that there is low investor attention towards the end of the week, and high attention early in a week, we expect that the understudy relation is most pronounced early rather than late in a week since investors do not necessarily show the same level of attention in the financial markets on all days of the week. They would more likely follow stock market returns early rather than late in the week. To test this, we estimate the relationship using data only for Monday & Tuesday and then only for Thursday & Friday. Columns (1) and (2) of Table 6 indeed report that there is a negative relation using data from Monday & Tuesday, but no relation with data from Thursday

& Friday. Investors who have relatively high attention early in a week, are more likely to be aware of the current stock market returns, and so more likely to respond to such information.

[Please insert Table 6 around here]

Second, we generate a stock return index based on firms headquartered in New York City. Investors who live in New York City are more likely to invest in local stocks due to home bias (e.g., Coval and Moskowitz, 1999; Griblatt and Keloharju, 2001). Stock returns in local firms are more certain to influence their behavior. Column (3) shows that the relationship is indeed most pronounced with the use of NY stock returns. For example, the parameter coefficient of the contemporaneous relation is -1.468 in this table in comparison to -1.050 previously reported in Table 2 for S&P500. Column (4) includes both S&P500 and NYC returns in the same estimation for a direct comparison. Note that there is a high correlation between the two stock return indexes (0.90) and so we need to interpret these results with the appropriate caution. As expected, we find that the negative relation is most pronounced with the use of NYC stock returns potentially due to home bias. These results indicate that the relationship likely reflects investor behavior.

Finally, we test what types of investors may drive this relation. We re-estimate the results only for parking violations in vans or taxis that reflect 14% of all violations. Such drivers are expected, if any, to be small investors. We compare these results in comparison to the relationship for violations that took place by drivers in expensive cars,[13] which is 13% of all violations. Drivers in expensive cars are expected to be relatively more substantial investors. According to the literature (e.g., Lemmon and Portianguina, 2006; Siganos et al., 2017), small investors are influenced the most by emotions, and so the relationship is expected most prominent within vans and taxis. As shown in columns (1) and (2) of Table 7, we find that

[13] Audi, Bentley, BMW, Bugatti, Chevrolet, Chrysler, Ferrari, Jaguar, Lamborghini, Lotus, McLaren, Mercedes, Porsche, and Rolls Royce.

relevant parameter coefficients on S&P500 are negative for both groups. As expected, the magnitude of the relationship is most pronounced for vans&taxis group. For example, the parameter coefficient of the contemporaneous S&P500 is -1.781 and significant at the 1% level for violations by van or taxi drivers, but relatively lower at -0.941 and significant at the 5% level for violations by expensive car drivers.

[Please insert Table 7 around here]

To test empirically whether these differences are statistically significant, we undertake DiD analysis. The dependent variable is the number of parking violations for the two groups. We add a dummy that takes one for parking violations with van or taxis that we interact with stock market returns. The parameter coefficients of the interaction variables capture the difference in parking violations between the two groups as induced by stock market returns. We find that the sign of the parameter coefficients of the interaction variables is all negative, three of them are significant. The F-statistic of the interaction variables is equal to 160.91 and significant at the 1% level. These results indicate that the relationship is most prominent within small investors.

4.2 The mechanism of the relation

We offer here some empirical validity behind the channel of the relation. We expect that investor anxiety is behind this relation. There is plenty of evidence in psychology and transportation literature that emotions such as anxiety can have an impact on our decisions; for example, on our driving behavior (e.g., Loewenstein et al., 2001; Pêcher et al., 2009; Dula et al., 2010; Roidl et al., 2014). The relation is thus expected stronger on days that poor (good) stock market returns are linked with high (low) investor anxiety.

To empirically support this, we get access to a recently developed investor anxiety index[14] that is based on the search activity in millions on the Investopedia website. High values of the investor anxiety index indicate high anxiety. Note that this index is only available since January 2015, and so the number of observations reduces in these estimations. We first explore the relations between lagged investor anxiety and stock market returns as well as lagged investor anxiety and parking violations. As shown in Column (1) of Table 8, we find that lagged stock market returns are related to investor anxiety, indicating that stock market returns influence investor anxiety. We instead find in column (2) that lagged investor anxiety is not related to stock market returns, and so the reverse association is not empirically valid. We also find very little evidence that lagged investor anxiety is related to parking violations since only one out of the five parameter coefficients of the lagged investor anxiety variables is statistically significant. There is thus little evidence that investor anxiety directly influences parking violations.

More importantly, we interact S&P500 with the investor anxiety index. The dependent variable is once again parking violations. Column (4) reports that the sign in all parameter coefficients of the interaction variables is negative. We find that four out of the total six interaction variables are significant. In untabulated results, we find that the F-test that explores the significance of all these parameter coefficients indeed shows significance at the 1% level, offering some support to the suggested mechanism. Overall, these results seem to indicate that stock market returns influence investor anxiety that impacts the frequency of parking violations.

[Please insert Table 8 around here]

[14] https://www.investopedia.com/anxiety-index-explained/

5. Potential alternate explanations of the relationship

We test in this section potential alternative explanations of the main relation that we attempt to invalidate.

5.1 Macroeconomics drive the relation

We first test whether the relation is simply driven by macroeconomics. To test this, we add in the main estimation commonly used macroeconomic variables available in daily frequency. In particular, we add the Aruoba-Diebold-Scotti business conditions,[15] Policy Index,[16] and VIX. A level of multicollinearity is acceptable amongst these macroeconomic variables for this study. We are interested in whether the main relation holds after controlling for these variables rather than whether the economy relates to the number of parking violations.

As shown in Table 9, we find that most of the parameter coefficients of macroeconomic variables are insignificant. Only three out of the total eighteen are significantly negative. More importantly, the parameter coefficients on S&P500 remain significantly negative after relevant macroeconomic controls.

[Please insert Table 9 around here]

5.2 Parking violations reflect genuine errors by non-local drivers

An alternate explanation of the main relation is that drivers may end up violating the parking rules because they simply may not be aware of the parking rules in New York City. The parking violation dataset offers data on the registration state that we use to eliminate such an explanation.

We re-estimate the main association separately for cars with and without registration from the New York State. Columns (1) and (2) of Table 10 report that the magnitude and the

[15] https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/ads
[16] https://www.policyuncertainty.com/us_monthly.html

statistical significance of the relevant parameter coefficients are similar when comparing the two estimations. Our evidence thus indicates that the relationship is not driven by errors of non-local drivers.

[Please insert Table 10 around here]

5.3 Stock market returns only influence parking violations with minimal fines

We have interpreted the main relation as evidence against the 'classic' utility theory according to which investors would not be influenced by emotions regarding violating parking rules. An alternate explanation is that investors may be happy to violate parking rules as long as the fines are minor. We explore here whether the main association differs in comparison to the magnitude of the fine. The parking violation dataset identifies the exact type of violation, and also the cost reflecting each violation.

We re-estimate the main relation separately for high- and lost-cost parking violations. We use the median cost of a violation to differentiate the two groups. The average cost of the high-cost violation group is $155 and of the low-cost violation group $62. For our results to be in line with the utility theory, the relation should be non-present within high-cost violation rules. Investors are potentially aware or have the notion of the potential cost of each violation and so fully rational people would have been careful not to violate parking rules with a relatively high fine. Columns (3) and (4) of Table 10 report the results. We find that the relationship is present in both groups; high- and low-cost violations. If any, the economical significance of the relationship is most pronounced within high-cost violations.

We undertake DiD analysis to explore the statistical difference between the two groups. Our dependent variable is the number of parking violations for high and low-cost fines. We add a dummy for parking violations with high costs, otherwise zero. We interact this dummy variable with stock market returns. Column (5) reports the results. We find that the parameter coefficients of the interaction variables are negative, but only one of them is significant in statistical terms. The F-test of all the interaction variables as a group is significant at the 1% level. These results show that the relationship is actually most pronounced on high-cost parking violations, offering further empirical validation against the ‘classic’ utility theory.

5.4 Reverse relation

We also test whether there is a reverse association. This explores the extent to which investors who violate the parking rules may be influenced emotionally and so their investing behavior may differ after the violation. Theoretically, there is relatively little concern of a reverse relation considering that there are relatively few parking violations in a day to influence enough investors to generate any impact on stock market returns. Still, we explore whether lagged parking violations are related to stock market returns.

As shown in Table 11, we find that all relevant parameter coefficients are insignificant. The reverse relation is thus not likely.

[Please insert Table 11 around here]

5.5 Autocorrelation and seasonality in parking violations drive the relation

We also explore whether autocorrelation or any seasonality trend in parking violations drive the relationship. We previously added the day of the week, month and year fixed effects to adjust for relevant trends. We undertake in this section further tests in this direction. Column (1) of Table 12 adds lagged parking violations at day *t-10* that captures a nearby period of parking violations and re-estimates the main regression. We find that parking violations are as expected positively autocorrelated. Still, the parameter coefficients on SP500 remain significantly negative after the addition of the lagged parking violations variable.

[Please insert Table 12 around here]

Column (2) reports results when using Newey West robust standard errors (Newey and West, 1987) that adjust for autocorrelation (previously used clustered standard errors). Column (3) further shows results when adding a time trend that captures any seasonality in patterns over time. We find that the parameter coefficients on S&P500 remain significantly negative in both columns. Once again, we find that our conclusions are unchanged.

Finally, we estimate the abnormal parking violations that are the daily number of parking violations minus the average parking violations over time, or minus the average violations per corresponding year, month, and day of the week. Results are reported in columns (4) to (7), respectively. We now estimate OLS regressions rather than Poisson since the dependent variable, abnormal parking violations, takes negative values. We find that relevant adjustments on our dependent variable do not influence our conclusions. Overall, we conclude that autocorrelation and seasonality are unlikely sources of the relationship.

5.6 Enforcement drives the relation

We also explore the significance of enforcement on the relation. First, we test whether the observed variation on parking violations simply reflects the available enforcement. We download from NYC OpenData[17] the active employees during the sample period. We only count the employees with the description as 'traffic control inspector', 'traffic enforcement agent', and 'associate traffic enforcement'. We estimate the logarithm of the number of employees that we add as an extra control variable in the main regression. Note that relevant data are only available in annual frequency.

Column (1) of Table 13 reports the results. We find that the relation between traffic control agents and parking violations is indeed positive. More staff is linked with more parking violations. The relevant parameter coefficient is equal to 1.608 and highly significant at the 1%

[17] https://data.cityofnewyork.us/City-Government/Citywide-Payroll-Data-Fiscal-Year-/k397-673e/data

level. More importantly, the parameter coefficients on S&P500 remain significantly negative after controlling for enforcement.

[Please insert Table 13 around here]

We also test whether the main relation is simply the effect of the impact of stock market returns on officers rather than on drivers' behavior. The main relation is likely to be influenced by the impact of stock market returns in both groups. We acknowledge that it is difficult to totally disentangle the relation. Still, we undertake here a test to report that at least part of the relation is indeed driven by drivers' behavior. We have access to the number of parking violations from breaking the speed limit in School areas as captured on camera ('code 36'). If the relation is empirically valid with the use of these violations, this could only be as a result of drivers' behavior due to stock market returns. Since the cameras identify the illegal activity, the anxiety level of officers has very little, if any, to do with these violations.

In this estimation, the dependent variable is the number of parking violations caught in the cameras used in nearby Schools which is 14% of all parking violations. Since Covid had a major impact on School activities, we only report results using data in the period before Covid. As shown in Column (2) of Table 13, we still find that the parameter coefficients on S&P500 tend to be negative indicating evidence that the relationship is due to drivers' response to stock market returns.

5.7 Traffic volume drives the relation

We also test whether traffic may drive the relation. We have previously, amongst others, controlled for time-fixed effects and weather conditions to capture the extent to which variations in traffic volume influence our results. In this section, we use a more direct control for traffic volume to offer further assurance. Unfortunately, we could only find sparse data on a daily variation on traffic volume that could not be used for robust empirical analysis.[18] We instead use the annual average daily traffic volume data developed by the New York State Department of Transportation.[19] Note that this dataset offers data only before 2020. We add this additional control variable and re-estimate the main probit regression.

Column (3) of Table 13 shows that our conclusions remain unchanged. We find that as expected the parameter coefficient on traffic volume is significantly positive indicating that more traffic is related to more parking violations. More importantly, the parameter coefficients on S&P500 tend to remain negative. The use of alternate controls for traffic volume does not change our previous conclusions.

Finally, Column (4) of Table 13 reports results when adding all additional control variables used in this study: traffic warden, traffic volume, trend, macroeconomic within one estimation. Due to space consideration, we do not tabulate the parameter coefficients of the macroeconomic variables in this estimation. We still find that our conclusions remain unchanged even after controlling for a very large number of control variables.

6. Conclusion

Typical studies in the field of finance explore factors that influence stock returns. We explore in this study the influence of stock market returns on the number of parking violations. Using an extensive dataset with parking violations for New York City, we find that lagged and contemporaneous stock market returns are associated negatively with the number of parking violations. We find that the channel of this relationship is investor anxiety. Results are robust within numerous robustness tests. We show for example that the relation is not empirically

[18] NYC Open Data offers daily traffic volume but we could only match at best 18% of the days in our dataset.
[19] https://data.ny.gov/Transportation/Annual-Average-Daily-Traffic-AADT-by-Roadway-Segme/hm9d-9ywu

present when exploring today's stock market returns on the parking violations before the market opened at 9.30 am. Also, the contemporaneous relation is most pronounced on early days in the week when investor attention is relatively strong (e.g., Patell and Wolfson 1982; Penman, 1987; Damodaran, 1989). The relation is present at both high- and low-cost parking rules. If any, the relation is most pronounced within high-cost parking rules. Our results indicate that small investors are influenced the most by stock market returns, larger investors still react to albeit in a smaller magnitude. Overall, our results offer evidence in line with the extension of the utility theory according to which emotions such as anxiety influence individuals' decisions.

We follow some assumptions in this study since we cannot test the relation with direct data. Although not ideal, our assumptions are similar to those used in other studies in this field. For example, one of the main papers is that by Engelberg and Parsons (2016), who published their paper in the *Journal of Finance*, showing that more hospital admissions occur following poor stock market returns. Like our study, Engelberg and Parsons use the stock market returns to test the relation, and they are not aware of any individual names admitted to the hospital for a direct test to be undertaken. We also report empirical relations that support the notion that our main relation captures what we require such as that the relation is most pronounced within stock returns of firms headquartered in New York (investors in New York would likely trade proportionately more in such stocks due to the home bias effect).

There is plenty of research that can still be undertaken to demonstrate the societal impact of finance. Hopefully, this study will offer some contribution to relevant future research work.

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Table 1 Descriptive statistics

	Average	Minimum	Median	Maximum	N
Parking violations (no winsorization)	39406	774	39252	83163	1718
Parking violations	39439	21289	39252	63132	1718
S&P500	0.00	-0.12	0.00	0.09	1718
Temperature	56.90	9.00	58.50	88.00	1718
Precipitation	0.14	0.00	0.00	4.97	1718
New snow	0.09	0.00	0.00	11.00	1718
Holidays	0.01	0.00	0.00	1.00	1718
Covid-19	0.10	0.00	0.00	1.00	1718
Ln investor anxiety index	4.63	4.54	4.62	4.88	1462
Aruoba-Diebold-Scotti business conditions	-0.43	-27.99	-0.12	8.59	1718
Ln policy index	4.43	1.20	4.37	6.69	1718
Ln VIX500	2.75	2.21	2.67	4.42	1718
Ln traffic wardens	7.46	6.21	7.92	8.11	1718
Ln traffic volume	18.37	17.88	18.22	19.61	1510

This table shows the descriptive statistics of the variables used in this study.

Table 2 The relation between stock market returns and the frequency of parking violations

	Parking violations{t}						
				S&P500{t}>1%	S&P500{t}<-1%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
S&P500{t}	-0.944***	-1.071***	-0.921**	-1.782	-1.680*	-1.152**	-1.050***
	(0.002)	(0.004)	(0.026)	(0.233)	(0.081)	(0.037)	(0.008)
S&P500{t-1}		-0.974**				-1.133**	-0.967***
		(0.017)				(0.037)	(0.003)
S&P500{t-2}		-1.157***				-0.982***	-0.911***
		(0.003)				(0.000)	(0.000)
S&P500{t-3}		-0.960***				-1.074***	-0.964***
		(0.000)				(0.000)	(0.000)
S&P500{t-4}		-1.144***				-0.990**	-0.908**
		(0.000)				(0.031)	(0.022)
S&P500{t-5}		-0.62				-0.66	-0.675
		(0.397)				(0.350)	(0.319)
Temperature{t}			0.001***	0.003	0.003	0.001***	0.001***
			(0.002)	(0.176)	(0.161)	(0.000)	(0.003)
Precipitation{t}			-0.136***	-0.167***	-0.210***	-0.137***	-0.137***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
New snow{t}			-0.059***	-0.053***	-0.062**	-0.061***	-0.058***
			(0.000)	(0.001)	(0.025)	(0.000)	(0.000)
Holidays{t}			-0.368***	-0.231***	-0.489***	-0.319***	-0.367***
			(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Covid-19{t}			-0.174***	-0.263***	-0.166*	0.086***	-0.160***
			(0.000)	(0.000)	(0.069)	(0.000)	(0.000)
Constant	10.448***	10.462***	10.417***	10.437***	10.343***	10.544***	10.428***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Day of the week, month, and year FEs	Yes	Yes	Yes	Yes	Yes	No	Yes
Number of observations	1718	1713	1718	197	165	1713	1713
Pseudo R-square	0.2932	0.3026	0.4042	0.4912	0.4952	0.1293	0.4097

This table shows the relation between lagged / contemporaneous stock market returns (S&P500) and the number of parking violations. We undertake Poisson estimations. Our dependent variable is the daily number of parking violations. The main independent variables for interest are the contemporaneous and the lagged S&P500 daily stock returns. All variables are in daily frequency. Further details on the variables used are available in the data and methodology section. P-values are shown in parenthesis. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.

Table 3 The significance of the magnitude of stock market performance

	Parking violations{t}						
	All days	Days with |∑S&P500| >1%	Days with |∑S&P500| >2%	Days with |∑S&P500| >3%	Days with |∑S&P500| >4%	Days with |∑S&P500| >5%	Days with |∑S&P500| >6%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
∑S&P500	-0.910***	-0.800***	-0.816***	-0.813***	-1.218***	-1.683***	-2.177***
	(0.000)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
Constant	10.428***	10.422***	10.318***	10.335***	10.197***	10.057***	9.817***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Previous control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1713	916	462	237	115	65	43
Pseudo R-square	0.4095	0.4489	0.5116	0.6203	0.7697	0.8072	0.8664

This table shows the significance of the magnitude of stock market returns on the main relation. ∑S&P500 indicates the sum of the stock market returns from day -5 to 0. | | is the absolute value. P-values are shown in parenthesis. *** indicates statistical significance at the 1% level.

Table 4 Robustness tests

	Parking violations{t}			Weekend violations{t}
	No winsorization	Negative binomial	OLS	
	(1)	(2)	(3)	(4)
S&P500{t}	-1.074***	-1.076***	-0.045*	
	(0.008)	(0.008)	(0.058)	
S&P500{t-1}	-1.081***	-1.019***	-0.040**	1.128
	(0.001)	(0.004)	(0.050)	(0.361)
S&P500{t-2}	-0.975***	-0.969***	-0.037**	-3.165**
	(0.000)	(0.000)	(0.019)	(0.018)
S&P500{t-3}	-0.998***	-1.037***	-0.039**	1.910
	(0.000)	(0.000)	(0.011)	(0.183)
S&P500{t-4}	-0.894**	-0.962**	-0.037*	-0.466
	(0.035)	(0.026)	(0.078)	(0.762)
S&P500{t-5}	-0.722	-0.663	-0.028	0.859
	(0.332)	(0.384)	(0.395)	(0.398)
Constant	10.435***	10.425***	33.524***	10.506***
	(0.000)	(0.000)	(0.000)	(0.000)
Lnalpha		-3.475***		
		(0.000)		
Previous control variables	Yes	Yes	Yes	Yes
Number of observations	1713	1713	1713	294
Pseudo R-square	0.4263	0.0247		0.4926
R-square			0.4028	

This table shows the results of several robustness tests. All variables are in daily frequency. P-values are shown in parenthesis. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.

Table 5 Placebo tests

	Parking violations{t}				
	Before 9.30 am	After 9.30 am			Days with |∑S&P500|<1%
	(1)	(2)	(3)	(4)	(5)
S&P500{t}	-0.963	-0.911**			
	(0.127)	(0.011)			
Dummy if |∑S&P500|<1				0.007	
				(0.573)	
∑S&P500					1.512
					(0.282)
S&P500{t-6}			-0.046		
			(0.930)		
S&P500{t-7}			-0.11		
			(0.801)		
S&P500{t-8}			-0.114		
			(0.841)		
S&P500{t-9}			0.313		
			(0.581)		
S&P500{t-10}			0.397		
			(0.597)		
Constant	8.969***	10.144***	10.425***	10.413***	10.449***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Previous control variables	Yes	Yes	Yes	Yes	Yes
Number of observations	1718	1718	1708	1718	797
Pseudo R-square	0.2162	0.4242	0.4003	0.4022	0.4241

This table shows the results of several placebo tests. ∑S&P500 indicates the cumulative stock market returns from day -5 to 0. | | is the absolute value. P-values are shown in parenthesis. **, and *** indicate statistical significance at the 5, and 1% levels, respectively.

Table 6 Does the main relation reflect investor behavior?

	Parking violations{t}			
	Mon&Tue	Thu&Fri	All days	All days
	(1)	(2)	(3)	(4)
S&P500{t}	-1.675***	-0.489		1.137
	(0.000)	(0.572)		(0.146)
S&P500{t-1}				1.361***
				(0.000)
S&P500{t-2}				1.467***
				(0.002)
S&P500{t-3}				-0.039
				(0.958)
S&P500{t-4}				-0.054
				(0.962)
S&P500{t-5}				0.37
				(0.454)
NYCReturns{t}			-1.468***	-2.618**
			(0.002)	(0.013)
NYCReturns{t-1}			-1.371***	-2.590***
			(0.002)	(0.000)
NYCReturns{t-2}			-1.172***	-2.524***
			(0.007)	(0.000)
NYCReturns{t-3}			-0.944**	-0.698
			(0.025)	(0.539)
NYCReturns{t-4}			-0.865	-0.710
			(0.145)	(0.650)
NYCReturns{t-5}			-0.749	-1.114
			(0.406)	(0.363)
Constant	10.428***	10.487***	10.430***	10.430***
	(0.000)	(0.000)	(0.000)	(0.000)
Previous control variables	Yes$	Yes$	Yes	Yes
F test of S&P500 variables				
F test of interaction variables				
Number of observations	676	691	1713	1713
Pseudo R-square	0.3935	0.4189	0.4157	0.4178

This table offers some support for the assumption taken whether the relationship reflects investor behavior. NYCReturns shows the average stock returns of firms headquartered in New York City. All variables are in daily frequency. $ day of the week fixed effects are not added in this estimation. P-values are shown in parenthesis. **, and *** indicate statistical significance at the 5, and 1% levels, respectively.

Table 7 The relation for different types of investors

	Parking violations{t}		
	in van or taxis	in expensive cars	DiD
	(1)	(2)	(3)
S&P500{t}	-1.781***	-0.941**	-1.038***
	(0.009)	(0.014)	(0.002)
S&P500{t-1}	-1.748***	-0.860***	-0.780*
	(0.000)	(0.008)	(0.074)
S&P500{t-2}	-1.344***	-0.836***	-0.631
	(0.000)	(0.005)	(0.134)
S&P500{t-3}	-1.692***	-0.907***	-0.752*
	(0.002)	(0.000)	(0.051)
S&P500{t-4}	-1.587**	-0.903**	-0.825*
	(0.023)	(0.015)	(0.055)
S&P500{t-5}	-1.285	-0.648	-0.619
	(0.241)	(0.371)	(0.374)
Dummy for van or taxis {t} (1)			0.153***
			(0.000)
Dummy for van or taxis {t-1} (2)			0.262***
			(0.000)
Dummy for van or taxis {t-2} (3)			-0.089**
			(0.032)
Dummy for van or taxis {t-3} (4)			0.214***
			(0.000)
Dummy for van or taxis {t-4} (5)			-0.312***
			(0.000)
Dummy for van or taxis {t-5} (6)			-0.098***
			(0.000)
Interaction; S&P500{t} * (1)			-0.594
			(0.141)
Interaction; S&P500{t-1} * (2)			-1.005**
			(0.041)
Interaction; S&P500{t-2} * (3)			-0.860
			(0.101)
Interaction; S&P500{t-3} * (4)			-1.000***
			(0.000)
Interaction; S&P500{t-4} * (5)			-0.775**
			(0.023)
Interaction; S&P500{t-5} * (6)			-0.632
			(0.200)
Constant	8.577***	8.484***	8.464***
	(0.000)	(0.000)	(0.000)
Previous control variables	Yes	Yes	Yes
F test of interaction variables			160.91***
			(0.000)
Number of observations	1713	1713	3431
Pseudo R-square	0.4638	0.3546	0.3634

This table shows the relation separately for parking violations in van or taxi and expensive cars. Small investors are more likely to be the drivers of vans or taxis, while more substantial investors drive expensive cars. All variables are in daily frequency. P-values are shown in parenthesis. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.

Table 8 The significance of investor anxiety on the relation

	Ln investor anxiety index{t} (1)	S&P500{t} (2)	Parking violations{t} (3)	Parking violations{t} (4)
S&P500{t}				1.960
				(0.116)
S&P500{t-1}	-0.047*	-0.203*	-0.610**	4.096***
	(0.050)	(0.075)	(0.012)	(0.003)
S&P500{t-2}	-0.049*	0.107	-0.862***	2.081
	(0.090)	(0.297)	(0.000)	(0.142)
S&P500{t-3}	-0.043	0.01	-0.855***	3.468***
	(0.113)	(0.889)	(0.000)	(0.000)
S&P500{t-4}	-0.051**	-0.115**	-0.881***	4.105***
	(0.034)	(0.025)	(0.000)	(0.000)
S&P500{t-5}	-0.056	0.03	-0.720*	3.046
	(0.181)	(0.553)	(0.059)	(0.164)
Ln investor anxiety index{t}				-0.639
				(0.219)
Ln investor anxiety index{t-1}	1.302***	0.063	-0.132	0.654
	(0.000)	(0.571)	(0.840)	(0.397)
Ln investor anxiety index{t-2}	-0.283**	-0.032	-2.331**	-2.434**
	(0.022)	(0.801)	(0.025)	(0.012)
Ln investor anxiety index{t-3}	-0.037	-0.076	1.217	1.075
	(0.462)	(0.495)	(0.195)	(0.226)
Ln investor anxiety index{t-4}	0.048	0.042	-0.225	-0.096
	(0.419)	(0.726)	(0.726)	(0.849)
Ln investor anxiety index{t-5}	-0.043	0.018	0.043	0.081
	(0.222)	(0.784)	(0.897)	(0.791)
S&P500{t} * Ln investor anxiety index{t}				-4.387*
				(0.098)
S&P500{t-1} * Ln investor anxiety index{t-1}				-8.931***
				(0.002)
S&P500{t-2} * Ln investor anxiety index{t-2}				-4.621
				(0.125)
S&P500{t-3} * Ln investor anxiety index{t-3}				-7.576***
				(0.000)
S&P500{t-4} * Ln investor anxiety index{t-4}				-9.001***
				(0.000)
S&P500{t-5} * Ln investor anxiety index{t-5}				-6.667
				(0.152)
Constant	0.057**	-0.067	17.166***	16.846***
	(0.025)	(0.107)	(0.000)	(0.000)
Previous control variables	Yes	Yes	Yes	Yes
Number of observations	1452	1453	1453	1452
R-square	0.9895	0.0862		
Pseudo R-square			0.4796	0.4845

This table offers some support for the mechanism behind the relation highlighting the significance of investor anxiety. All variables are in daily frequency. P-values are shown in parenthesis. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.

Table 9 To invalidate alternate explanations I: Controlling for macroeconomic conditions

	Parking violations{t}		
S&P500{t}	-1.227*		
	(0.061)		
S&P500{t-1}	-1.334**		
	(0.042)		
S&P500{t-2}	-1.281*		
	(0.068)		
S&P500{t-3}	-1.024**		
	(0.013)	Ln policy index {t-3}	-0.006
S&P500{t-4}	-0.653		(0.540)
	(0.268)	Ln policy index {t-4}	0.000
S&P500{t-5}	-0.581		(0.965)
	(0.296)	Ln policy index {t-5}	-0.001
ADS{t}	-0.036***		(0.932)
	(0.001)	Ln VIX500{t}	-0.122**
ADS{t-1}	-0.008		(0.016)
	(0.601)	Ln VIX500{t-1}	-0.030
ADS{t-2}	-0.022		(0.813)
	(0.322)	Ln VIX500{t-2}	-0.013
ADS{t-3}	-0.006		(0.934)
	(0.780)	Ln VIX500{t-3}	0.022
ADS{t-4}	0.016		(0.892)
	(0.502)	Ln VIX500{t-4}	0.049
ADS{t-5}	0.068***		(0.680)
	(0.000)	Ln VIX500{t-5}	-0.028
Ln policy index{t}	0.001		(0.701)
	(0.926)	Constant	10.808***
Ln policy index {t-1}	-0.001		(0.000)
	(0.948)	Previous control variables	Yes
Ln policy index {t-2}	0.001	Number of observations	1713
	(0.945)	Pseudo R-square	0.4958

This table explores the relation after controlling for macroeconomic conditions. The tabulated results are the outcome of one estimation. P-values are shown in parenthesis. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.

Table 10 To invalidate alternate explanations II

	Parking violations with NY plates {t} (1)	Parking violations without NY plates {t} (2)	High-cost parking violations {t} (3)	Low-cost parking violations {t} (4)	DiD (3) - (4) (5)
S&P500{t}	-1.016***	-1.171***	-1.483***	-0.857**	-0.910***
	(0.007)	(0.009)	(0.004)	(0.032)	(0.008)
S&P500{t-1}	-0.941***	-1.028**	-1.722***	-0.683**	-0.657*
	(0.002)	(0.012)	(0.000)	(0.023)	(0.075)
S&P500{t-2}	-0.908***	-0.906***	-1.290***	-0.817**	-0.729*
	(0.000)	(0.005)	(0.000)	(0.018)	(0.088)
S&P500{t-3}	-0.958***	-0.995***	-1.420***	-0.833***	-0.745***
	(0.000)	(0.000)	(0.008)	(0.000)	(0.002)
S&P500{t-4}	-0.904***	-0.974	-1.412**	-0.721*	-0.667*
	(0.008)	(0.114)	(0.043)	(0.063)	(0.079)
S&P500{t-5}	-0.684	-0.621	-1.188	-0.475	-0.445
	(0.254)	(0.513)	(0.304)	(0.384)	(0.393)
Dummy for high-cost violation {t} (1)					-0.779***
					(0.000)
Dummy for high-cost violation {t-1} (2)					0.269***
					(0.000)
Dummy for high-cost violation {t-2} (3)					-0.135***
					(0.000)
Dummy for high-cost violation {t-3} (4)					0.243***
					(0.000)
Dummy for high-cost violation {t-4} (5)					-0.382***
					(0.000)
Dummy for high-cost violation {t-4} (6)					-0.077***
					(0.000)
Interaction; S&P500{t} * (1)					-0.392
					(0.368)
Interaction; S&P500{t-1} * (2)					-1.056*
					(0.068)
Interaction; S&P500{t-2} * (3)					-0.73
					(0.301)
Interaction; S&P500{t-3} * (4)					-0.785
					(0.102)
Interaction; S&P500{t-4} * (5)					-0.794
					(0.127)

Interaction; S&P500{t-5} * (6)					-0.73
					(0.353)
Constant	10.176***	8.918***	9.257***	10.053***	10.075***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Previous control variables	Yes	Yes	Yes	Yes	Yes
F test of interaction variables					138.17***
					(0.000)
Number of observations	1713	1713	1713	1713	3431
Pseudo R-square	0.4097	0.4023	0.3772	0.4187	0.8062

This table explores alternate explanations of the relation. Columns (1) and (2) explore the significance, if any, of the parking violations with cars registered or not registered in the New York state. Columns (3) and (5) explore the significance of the magnitude of the fine. High-cost parking violations are those with at least the median cost, while those in the bottom parking violations are considered low-cost. P-values are shown in parenthesis. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.

Table 11 To invalidate alternate explanation III; Reverse relation

	S&P500{t}
Parking violations{t-1}	-0.023
	(0.723)
Parking violations{t-2}	0.019
	(0.507)
Parking violations{t-3}	-0.039
	(0.538)
Parking violations{t-4}	-0.014
	(0.771)
Parking violations{t-5}	-0.067
	(0.251)
Constant	4.847*
	(0.077)
Previous control variables	Yes
Number of observations	1713
R-square	0.0124

This table explores whether there is a reverse association in the reported relation. All variables are in daily frequency. P-values are shown in parenthesis. * indicates statistical significance at the 10% level.

Table 12 To invalidate alternate explanation IV; Autocorrelation and seasonality

	Parking violations{t}			Abnormal parking violations {t} that is daily violations minus			
	Add lagged parking violations	Newey West robust standard errors	Add time trend	a. average violations	b. corresponding year violations	c. corresponding month violations	d. corresponding day of the week violations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
S&P500{t}	-0.903**	-1.050**	-1.060***	-4.452*	-4.441*	-4.475*	-4.371*
	(0.020)	(0.013)	(0.007)	(0.058)	(0.057)	(0.052)	(0.058)
S&P500{t-1}	-0.809**	-0.967**	-0.965***	-4.036**	-4.021**	-4.062**	-4.012**
	(0.010)	(0.029)	(0.004)	(0.050)	(0.048)	(0.042)	(0.049)
S&P500{t-2}	-0.758***	-0.911**	-0.911***	-3.719**	-3.650**	-3.710**	-3.715**
	(0.006)	(0.038)	(0.000)	(0.019)	(0.022)	(0.022)	(0.022)
S&P500{t-3}	-0.771***	-0.964**	-0.974***	-3.943**	-3.934**	-3.883**	-3.852**
	(0.001)	(0.029)	(0.000)	(0.011)	(0.013)	(0.012)	(0.012)
S&P500{t-4}	-0.664	-0.908**	-0.955**	-3.726*	-3.685*	-3.860*	-3.760*
	(0.116)	(0.038)	(0.016)	(0.078)	(0.076)	(0.071)	(0.076)
S&P500{t-5}	-0.265	-0.675	-0.696	-2.760	-2.777	-2.717	-2.763
	(0.722)	(0.166)	(0.303)	(0.395)	(0.387)	(0.393)	(0.393)
Parking violations{t-10}	0.000***						
	(0.000)						
Trend			-0.002**				
			(0.049)				
Constant	10.186***	10.428***	10.447***	1.242***	4.428***	1.230***	9.933***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Previous control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1708	1713	1713	1713	1713	1713	1713
Pseudo R-square	0.4842	0.4097	0.4117				
R-square				0.4028	0.3162	0.3445	0.3894

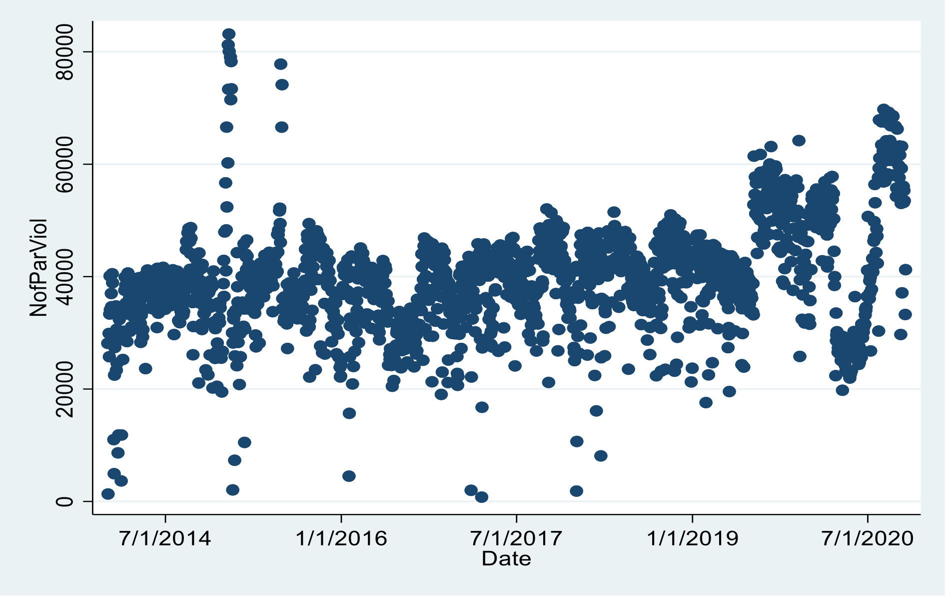
This table explores whether autocorrelation and seasonality are behind the relationship. All variables are in daily frequency. P-values are shown in parenthesis. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.

Table 13 To invalidate alternate explanations V; Controlling for enforcement, traffic volume, and all additional control variables

	Parking violations{t}	Parking violations on School cameras{t}	Parking violations{t}	Parking violations{t}
	Add traffic wardens	Pre-covid period	Add traffic volume	Add all additional control variables: traffic warden, traffic volume, trend, macroeconomic
	(1)	(2)	(3)	(4)
S&P500{t}	-1.050***	-3.310*	-0.944	-2.091*
	(0.008)	(0.081)	(0.178)	(0.076)
S&P500{t-1}	-0.967***	-2.316*	-0.580***	-1.704
	(0.003)	(0.073)	(0.003)	(0.229)
S&P500{t-2}	-0.911***	-2.071	-0.793**	-1.979***
	(0.000)	(0.206)	(0.027)	(0.005)
S&P500{t-3}	-0.964***	-1.922*	-0.882***	-1.649*
	(0.000)	(0.063)	(0.000)	(0.099)
S&P500{t-4}	-0.908**	-1.671	-0.484	-0.410
	(0.022)	(0.194)	(0.135)	(0.695)
S&P500{t-5}	-0.675	-3.123***	-0.642	-0.743
	(0.319)	(0.007)	(0.140)	(0.163)
Ln traffic wardens{t}	1.608***			-1.017*
	(0.000)			(0.070)
Ln traffic volume{t}			0.128***	0.312**
			(0.000)	(0.020)
Trend				-0.002*
				(0.091)
Constant	-2.276***	7.533***	8.164***	13.030***
	(0.000)	(0.000)	(0.000)	(0.000)
Previous control variables	Yes	Yes	Yes	Yes
Macroeconomic variables	No	No	No	Yes
Number of observations	1713	1546	1505	1505
Pseudo R-square	0.4097	0.4254	0.4306	0.4478

This table explores the relation after controlling for additional control variables. P-values are shown in parenthesis. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.

Figure 1 The number of parking violations during the sample period



This figure shows the daily number of parking violations over time before winsorization.