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ABSTRACT

We provide detailed empirical evidence of a direct effect of air pollution on the efficient operation of the New York Stock Exchange, linking short-term variations in fine particulate matter (PM2.5) in Manhattan to movements in the S&P 500. The effects are substantial – a one standard deviation increases in ambient PM2.5 reduces same-day returns by 11.9% in our preferred specification – and remarkably robust to a variety of specifications and a battery of robustness and falsification checks. Furthermore, the intra-day effects that we observe are difficult to reconcile with competing hypotheses. Despite investors being dispersed geographically we find strong evidence that the effect is strictly local in nature, consistent with the high concentration of market influencers in New York. While we are agnostic as to the underlying mechanism, we provide evidence suggestive of the role of decreased risk tolerance operating through pollution-induced changes in mood or cognitive function.

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1. Introduction

Despite the long-standing theoretical appeal of the efficient market hypothesis (Fama, 1965), researchers have uncovered significant empirical deviations from it. Findings have included unexplained movements in aggregate prices, such as excessive price volatility (Shiller, 1981) and the equity premium puzzle (Mehra and Prescott, 1985), inadequate incorporation of new information (Roll, 1984), the inexplicable role of location specific factors (Froot and Dabora, 1999), and the influence of trader emotions due to external stimuli (Saunders, 1993; Kamstra et al., 2003; Cueva at al., 2015). Building on emerging economic evidence that links air pollution with a wide range of human impacts, including cognition, mood and worker productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016; Lavy et al., 2014), we push this one step further by looking at the effect of local air pollution on stock market returns. While we remain largely agnostic on the precise mechanisms at play, we hypothesize that pollution decreases the risk attitudes of investors via short-term changes in brain and/or physical health.

Specifically, we estimate the effect of plausibly exogenous short-run changes in fine particulate matter ($PM_{2.5}$) in Manhattan over a 15 year period on daily returns of the S&P 500, one of the most commonly used benchmarks for the overall New York Stock Exchange (NYSE).[2] The stocks quoted on the S&P 500 come from firms widely differentiated by activity and geography, making it unlikely that daily variations in the fundamentals that determine the fair value of those firms could be correlated with daily

[2] Some recent correlational studies on air pollution and investor behavior include Lepori (2016), Li and Peng (2016), and Demir and Ersan (2016). Our analysis extends on this research through extensive attention to potential sources of confouding.

variations in air quality in the vicinity of Wall Street. We control flexibly for a wide range of potentially-confounding meteorological considerations and other air pollutants to isolate the effect of $PM_{2.5}$ from competing environmental factors. Furthermore, by controlling for time-specific factors using day of week fixed effects and year-by-week fixed effects, our analysis excludes many additional potential confounding factors, such as the well-established effect of length of day on investor mood (Kamstra et al., 2003).

We find a significant negative effect of $PM_{2.5}$ on S&P 500 returns. In our preferred specification, a one standard deviation increase in daily ambient $PM_{2.5}$ concentrations causes a statistically significant 11.9% reduction in daily percentage returns. The magnitude is comparable to estimates of the effect of variations in daily weather conditions on returns (Goetzmann and Zhu, 2005; Hirshleifer et al., 2003). The result proves remarkably robust to a variety of different assumptions about confounding and a variety of falsification checks. We drill further into the data by conducting an intra-day analysis. We find that $PM_{2.5}$ concentrations throughout the day, but not the other environmental variables, affect returns; this pattern is consistent with $PM_{2.5}$ having indoor penetration rates of over 90%, making it difficult to reconcile with competing hypotheses.

Critics of such local-based effects point out that any inefficient behavior by Manhattan-based investors creates arbitrage opportunities for those located elsewhere. This would imply our results are spurious, and air quality in New York City serves as a proxy for more general changes in the fundamental value of stocks traded in the S&P 500. Since these stocks come from firms whose activities are widely dispersed across the country and beyond, we can explore this threat by testing specifically for a local effect. Using data from all pollution monitors across the U.S., we find that pollution in New

York City has by far the largest effect and is the only significant one. This makes it implausible that unobserved variations in macroeconomic conditions – which could in theory influence air quality and stock price movements simultaneously – are driving the results. This points to the primacy of the attitudes of Manhattan-based market-makers, or the particular concentration of investors and those exercising discretion in investment decisions who work in and around Wall Street, in influencing price movements (consistent with Goetzmann and Zhu, 2005).

Although several candidate mechanisms may explain the results, we investigate the potential role that pollution-induced changes in risk aversion may play by examining the effects of $PM_{2.5}$ on movements in the volatility index (VIX). The VIX, which measures the expected stock market volatility, is widely considered a measure of fear amongst traders. We find that increases in $PM_{2.5}$ lead to increases in the VIX. Furthermore, decomposing the VIX into its risk and uncertainty elements, we find that the effects only exist for the 'pure' risk aversion component. These findings suggest that pollution-induced changes in risk appetite may be an important part of the story.

The results are important for at least two reasons. First, recent research on the effect of pollution on worker productivity has focused either on work in outdoor settings and/or in low skilled occupations (Graff Zivin and Neidell, 2012; Chang et al., 2016). As such, the existing results are only pertinent for a small subset of employment in the U.S. and comparably developed economies. By focusing on financial market professionals, we extend this to include a set of indoor workers in a highly-skilled, cognitively-demanding occupation, suggesting the detrimental effect of pollution on workplace performance is even more widespread than previously believed.

Second, at a macroeconomic level, an effect of pollution on stock returns points to another channel through which a polluted natural environment undermines the efficient operation of a modern economy. Stock price variations send investment signals across the whole of the U.S. and international economy - that is their purpose - and a well-functioning stock market is a fundamental foundation for the efficiency claims made for market-based economies. Thus, a significant impact of pollution upon daily returns implies departure from the efficient markets hypothesis. In short, variations in air quality in Manhattan – by affecting the investment sentiments of NYSE-based traders – causes inefficient price signals rippling out across the wider economy.

The rest of the paper is laid out as follows. In Section 2 we review the evidence that points to a link from individual exposure to $PM_{2.5}$ to stock market returns. In Section 3 we outline data sources. In Section 4 we set out our empirical strategy. Section 5 presents the main results and those from a series of robustness checks. Section 6 concludes.

2. Pollution Exposure and Stock Market Returns

In order for daily local pollution levels to influence stock market returns on the same day, a link from local pollution to an aspect of decision making relevant for stock market returns must exist. In this section, we describe several mechanisms that might underpin such a link. Though later we will have something to say about the possible role of risk appetite, the contribution of this paper is *not* to choose between mechanisms, as a number of the candidates might sensibly be expected to work in the same direction.

In brief, we posit that changes in air pollution have a variety of well-established impacts on the human body and mind. These changes can affect investor decision making via changes in factors such as risk appetite, choice bracketing behavior and mood. Such changes in decisions by marginal investors or market-makers – physically located in New York – affect movements in prices on the NYSE.

2.1. Pollution and health

We focus on fine particulate matter ($PM_{2.5}$), which consists of solid and liquid particles in the air less than 2.5 micrometers in diameter. Although natural sources, such as forest fires, contribute to $PM_{2.5}$ levels in New York City, the bulk of $PM_{2.5}$ comes from anthropogenic sources resulting from fossil fuel combustion by automobiles, industry, and commercial and residential heat sources. According to the United States Environmental Protection Agency, about 70% of $PM_{2.5}$ in the city comes from sources outside the urban area (US EPA 2004a, Figure 5), transported by wind and air movements from the surrounding region.

Wall Street traders face $PM_{2.5}$ exposure at various times during the day. Although spending time outdoors, such as when traveling to work, is one important period of exposure, indoor time is also pertinent. Given its diminutive size, $PM_{2.5}$ easily enters buildings, with penetration ranging from 70–100 percent (Thatcher and Layton, 1995; Ozkaynak et al., 1996; Vette et al., 2001). Unlike other common air pollutants - which either remain outside or break down very rapidly once indoors - going inside reduces one's exposure to $PM_{2.5}$ only minimally.

The tiny sizes of the particles that make up $PM_{2.5}$ also make this pollutant particularly pernicious. It penetrates deep into human lungs and passes beyond into the circulatory system to induce both respiratory and cardiovascular effects (Seaton et al., 1995). A large body of toxicological and epidemiological evidence suggests that exposure to $PM_{2.5}$ harms a range of health outcomes (see US EPA 2004b for a review). These risks may manifest themselves in clearly defined episodes, such as asthma attacks and heart attacks, which lead to hospitalizations and mortality (Dockery and Pope, 1994; Pope, 2000). They also lead to more subtle effects, such as changes in blood pressure, irritation in the ear, nose, throat, and lungs, and mild headaches (Pope, 2000; Sorenson et al., 2003); Ghio et al., 2000). These milder effects, which arise from exposure to lower levels of $PM_{2.5}$, are generally unobserved by the econometrician – they typically do not lead to healthcare encounters – and in some cases may be largely unnoticed even by the individual experiencing them. These more subtle effects may instead show up in, for example, diminished work performance (Chang et al., 2016).

Symptoms from $PM_{2.5}$ exposure can arise soon after exposure, but can also sustain for hours and even days afterwards. This points to the need the need to allow for contemporaneous and lagged effects of pollution in our analysis.

More recent evidence also links $PM_{2.5}$ with cognitive effects. While cognitive effects may arise indirectly through impaired respiratory functioning, a direct route exists through changes in blood flow and circulation (Pope and Dockery, 2006). For example, since the brain consumes a large fraction of the oxygen needs of the body, any deterioration in blood supply can affect cognitive output (Clarke et al., 1999).

Furthermore, unlike other pollutants, the size of $PM_{2.5}$ also allows it to travel up the olfactory axon and enter the brain directly (Wang et al., 2007).

Empirical evidence documents cognitive effects on humans shortly after exposure. Lavy et al. (2014) show that increased same-day $PM_{2.5}$ in the vicinity of an exam venue significantly decreases exam scores of Israeli students in the standardized national Bagrut test. Archsmith et al. (2016) show that the decision-making accuracy of Major League Baseball umpires falls as ambient $PM_{2.5}$ in the vicinity of the baseball stadium increases on game-day. In recent experimental evidence, Allen et al. (2016) randomly assigned professional-grade employees to work in simulated office environments with artificially manipulated indoor air quality.[3] They found that cognitive scores - particularly in the domains of 'strategy' and 'information usage' - declined significantly on days with worse indoor air quality.

2.2. Health and decision making

The changes in health of the body and brain induced by pollution exposure can affect decision-making in various ways. Indirectly, health can affect decision-making through changes in resource allocation (Grossman, 1972). More directly, health can affects one's mood and emotions through the physical discomfort caused by the onset of illness, which can affect decision making.

While the effects of cognition on some dimensions of decision-making are self-evident – decision-making is in itself a cognitive function – there are additional channels relevant for investor behavior. Dohmen et al. (2010) elicited measures of risk appetite

[3] The study did not investigate $PM_{2.5}$ directly but instead studied volatile organic compounds - a key precursor for $PM_{2.5}$ in urban centers - and carbon dioxide.

and time preference, finding that risk appetite and degree of patience were increasing in how well a subject scored in a cognitive task administered on the same day. While they offer the theory of ‘choice bracketing’ – making decisions by comparing choices in isolation rather than as a group – as an explanation for this effect (Tversky and Kahneman, 1981), bracketing may also be part of the change in decision-making induced by diminished cognition. For example, Rabin and Weizsacker (2010) and Abeler and Marklein (2016) show that improved math performance, an important part of an investor’s toolkit, reduces narrow bracketing.

2.3. Decision making and stock market returns

There is a well-established link from changes in risk aversion to financial decision making. Increased risk aversion leads investors to shift away from risky assets such as stocks, which lowers the returns on the market. An exogenous increase in risk aversion among a subset of investors would be expected to reduce same-day return. This occurs as the newly more risk averse investors move to reduce their risk exposure. Patience is also long viewed as an essential ingredient in stock choices; it enables investors to focus on the long term and ride out the short-run ups and downs. Similarly, choice bracketing can also affect the type of stocks chosen as traders shift away from more complex choices into simpler choices with lower returns.

More generally much of the recent behavioral finance literature focuses on the emotional and visceral influences on financial behavior - how trading is influenced by “how people are feeling.” The link from mood to stock returns has been the subject of a large and robust literature; see Saunders (1993) and the subsequent studies. Central to these articles is the notion that changes in mood induced by the weather affect the decisions of investors, in particular inducing them to shift to safer bets. Again, the effect of mood is conjectured to work through induced increases in risk aversion (see, for example, Kamstra (2003)).

Last, it is worth making explicit that the proposed link hinges on the existence of a *local* effect from air quality. Although many traders are physically present at the NYSE, others are located elsewhere and trade electronically. Moreover, even those physically present on the trading floor might be receiving instructions from people located anywhere in the world. Consistent with Saunders (1993), we assume that the marginal investors trade in New York, such that traders physically present can be expected to significantly influence stock prices. In addition, even those geographically dispersed investors need to contract with a physically present trader, and traders seek to affect prices in favor of their investors (Hirshleifer et al., 2003).

A counter-acting effect is that the inefficient behavior of local investors creates an arbitrage opportunity for investors outside the city (Goetzmann and Zhu, 2005; Loughran and Schultz, 2004; Jacobsen and Marquering, 2008; Chang et al., 2008; Cao and Wei, 2005). To the extent that this counter-action were perfect we would see no net effect of local air quality on aggregate returns, suggesting that the null hypothesis would prevail. We will take great care to build a convincing case for a local effect of $PM_{2.5}$ concentrations on stock market returns in the same location.

3. Data

The central part of our analysis exploits daily level data from a variety of sources.

3.1 Stock market returns

The main dependent variable of interest is the daily percentage returns on the U.S. S&P 500. The S&P 500 index, the most widely-cited NYSE index, is designed to measure performance of the broad domestic economy through changes in the aggregate market value of 500 stocks representing all major industries.

We use the value-weighted daily records from January 2000 through November 2014 to compute the daily returns.[4] We obtain the data on the S&P 500 from Datastream (https://forms.thomsonreuters.com/datastream/). Table 1 shows the daily percentage return of .025 over the sample period, a value comparable to previous estimates.

In our investigation of risk aversion as a potential mechanism we use the Chicago Board Options Exchange (CBOE) Volatility Index (VIX). The VIX represents the expected range of movement in the S&P 500 index over the next year. It is a widely used proxy for market risk aversion, popularly referred to as the “fear index” or the “investor fear gauge” (Coudert and Gex, 2008; Whaley, 2009). The daily VIX index data is obtained from Factset (http://www.factset.com/) for the same dates as the S&P 500. Table 1 also reports the daily mean VIX of 21.22.

Given the time-series nature of the data we first seek to verify the stationarity of each series to rule out the possibility of spurious results due to time trends. We begin with a graphical analysis. Figure 1 plots the daily percentage return of the S&P 500 for the study period. Although the plot shows significant activity around major stock events,

[4] We begin our analysis in 2000 because this is when $PM_{2.5}$ became routinely reported on a daily basis from the pollution monitor we use.

it appears stationary in pattern, a finding consistent with previous studies.[5] The results of a Dickey-Fuller test presented in Table 1 indicate that we can formally reject the null hypothesis of the existence of a unit root. Likewise, Figure 2 plots the daily VIX price for the study period. The increase in VIX around the financial crisis supports the construct validity of this measure. Again there is no obvious drift present, a finding also supported by the results of a Dickey-Fuller test presented in Table 1.

3.2 Air quality and weather

Air quality data is obtained from the New York State monitoring network designed to comply with the federal regulations set forth by the US Environmental Protection Agency. We collect hourly measures of $PM_{2.5}$, carbon monoxide, and ozone at the Division Street monitoring station in Lower Manhattan (monitor number 36-061-0134), the station closest to the NYSE (located only 0.72 miles away).[6]

Weather data is obtained from two sources. Hourly observations for air temperature, dew point, air pressure and wind speed are retrieved from the Air Quality System (AQS) of the US Environmental Protection Agency. They are drawn from the weather monitoring station at Susan Wagner High School, Staten Island (monitor number 36-085-0067), which is the closest station to the NYSE with consistent data throughout our study period. Data for cloud cover and precipitation come from LaGuardia airport

[5] We performed an analysis omitting the period of the financial crisis (October to December 2008 inclusive) and estimates were largely undisturbed.

[6] In a robustness check instead of using the pollution measure from the closest air quality monitoring station we use a measure of Manhattan-average pollution levels by constructing an inverse distance-weighted average level of $PM_{2.5}$ records at the three monitoring stations within 10 miles of the NYSE (until December, 2006, there were only two monitoring stations within 10 miles of the NYSE). Results using the Manhattan average were very close to those presented here.

monitoring station (monitor number USW00014732) of the Quality Controlled Local Climatological Database of the National Oceanic and Atmospheric Administration (NOAA).

For all environmental variables, we compute the daily average as the twenty-four hour period from 4:00 PM to 3:59 PM to match the end of the NYSE trading day. Rather than start the daily measure when the NYSE opens, we allow for the possible delay in effects within a day from $PM_{2.5}$ exposure, as the effects of $PM_{2.5}$ take some time before manifesting. This definition also excludes concentrations that arise after trading closes, which logically can have no effect. In addition we perform a more flexible analysis by using all environmental variables in two-hour blocks.

Table 1 presents summary statistics for all environmental variables. Air quality has improved greatly in New York over time. The mean daily $PM_{2.5}$ over the time period is 11.53, below the annual air quality standards of 15 that applied at this time.[7] The maximum $PM_{2.5}$ during this period is 75.86, with 66 days where daily values exceeded the daily air quality standard of 35.

4. Econometric Model

To investigate the effect of $PM_{2.5}$ levels on daily returns, we estimate the following equation via ordinary least squares (OLS):

$$(1) \qquad r_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 r_{t-2} + \beta_3 PM_{2.5t} + W_t\beta_4 + P_t\beta_5 + \Phi_t + \varepsilon_t.$$

[7] The current annual standard is 12.0.

The variable r_t is the S&P 500 percent return on date t. Following standard practice, we include two lags of the dependent variables (r_{t-1} and r_{t-2}) to control for any residual auto-correlation.[8] The independent variable of interest is the daily measure of fine particulate matter, $PM_{2.5}$. Our main interest lies in the parameter β_3, which relates daily $PM_{2.5}$ to daily stock market returns.

Weather conditions are known to influence stock market returns. We control for them in the vector W_t which contains temperature, dew point, precipitation, wind speed, air pressure and cloud cover. The vector P_t contains measures of other pollutants that might have an independent effect on returns: daily mean measures of 1-hour ozone and 8-hour carbon monoxide.

The vector Φ_t contains various time fixed-effects. It includes day of the week dummy variables to flexibly allow for different returns throughout the week. It also includes a "tax dummy" that indicates the first five trading days and the last trading day of the tax year to account for tax-loss selling.[9] Moreover, it includes year-by-week dummy variables to capture seasonality and other temporal patterns.[10] Amongst other things, the year-by-week dummy variables serve to control fully for any possible impact of length of day on returns, of the sort studied by Kamstra et al. (2003) and pursuant

[8] For examples see Goetzmann and Zhu, 2005; Loughran and Schultz, 2004; Jacobsen and Marquering, 2008; Chang et al., 2008; Kamstra et al., 2003; Saunders, 1993; Hirshleifer et al., 2003.
[9] Consistent with the tax-loss selling hypothesis, US firms have been show to experience higher returns during the first few trading days of January (Reinganum, 1983).
[10] The seasonality of stock market returns is well-established (Kamstra et al., 2012; Heston and Sadka, 2008; Wang et al., 1997; and Kohers and Patel, 1999). However, the results of Levy and Yagil, 2012; Brusa and Liu (2004) point to year-by-week dummies as the most appropriate controls in this setting.

literature. Finally, ε_t is an error term that allows for arbitrary serial correlation within a week using Newey-West standard errors.[11]

Our main assumption for identifying β_3 is that $PM_{2.5}$ is uncorrelated with ε conditional on the covariates included. One potential threat is that stock market returns are driven by the fundamentals of a firm – none of which we observe – and environmental policy affects these fundamentals (as well as $PM_{2.5}$). For example, complying with environmental policy might raise the general operating costs to a firm, leading to worker layoffs and plant closure, but also lower pollution levels. While such an argument might have credibility if we were studying annualized or other lower frequency data, our focus on high-frequency (daily and even hourly) variation in $PM_{2.5}$ eliminates this concern. Also note that the firms that comprise the S&P500 have headquarters and operations all over the country and the wider world. What we identify is a specifically *local* effect, as we link air quality particular to New York to stock price movements, and not air quality at other locations.

A second concern is that $PM_{2.5}$ is correlated with other local environmental influences that vary on a daily basis, such as weather and other pollutants. As already noted, weather has a well-known relationship with stock returns. It is also seems plausible that other pollutants might affect returns through similar mechanisms as $PM_{2.5}$. To limit this concern, we control directly for weather and co-pollutants in equation (1). Furthermore, for temperature and humidity - which we expect to be the most likely confounders - we control flexibly by way of a series of indicator 'bins' of width 2.5 degrees. This allows for possible threshold effects and other non-linearity in impacts.

[11] Using different lengths of time for the Newey-West correction had a minimal impact on our standard errors.

Moreover, the year-by-week indicators also further control for weather to the extent that it is constant within a week. For example, weather is highly serially correlated over a few days, so controlling for the year-week allows us to compare different $PM_{2.5}$ levels within that small time period where weather remains stable. To further challenge the specification we conduct a pair of further tests. First, a sensitivity analysis where we exclude all meteorological variables and co-pollutant controls. Second, to further probe the possibility that we are failing to adequately capture the effect of rain we re-estimate our preferred specification on that subsample of days where realized precipitation was zero.

We further isolate the role of $PM_{2.5,}$ as opposed to other daily varying confounders, by performing intra-day analysis using hourly data. The advantage of this specification is that, because the NYSE is a climate controlled environment, most environmental factors do not penetrate indoors. Of the environmental factors we consider, $PM_{2.5}$ is the only one that penetrates effectively. Therefore, we would expect weather and co-pollutant conditions at, say, 10am to have no effect on returns, whereas $PM_{2.5}$ levels at 10am should have an effect on returns, if it has an effect at all.[12]

The upper panel in Figure 3 plots daily $PM_{2.5}$ levels and the lower panel the daily $PM_{2.5}$ residuals after controlling for weather controls and time dummies. The lower panel makes clear that there is plenty of variation in pollution levels that is independent of weather conditions. It is this variation that underpins our identification.

[12] Our continued focus on daily returns is inconsequential for the hourly analysis: any effect on hourly returns should be reflected in daily returns. Note that we cannot predict the differential magnitude of the hourly effects since this would require us to know the speed at which exposure translates into changes in decision making.

5. Results

5.1 Main Results

Table 2 contains our main results, with the estimates in column 1 corresponding with equation (1). The coefficient on $PM_{2.5}$ of -.0171 is statistically significant at the 1% level. This estimate indicates that a one unit increase in $PM_{2.5}$ decreases the daily percentage returns by 1.7%. Put differently, a one standard deviation increase in $PM_{2.5}$ decreases the daily percentage returns by 11.9%, a substantial effect on daily NYSE returns.

As $PM_{2.5}$ can remain in the body for several days and may have a delayed effect on health, in columns two and three we include one and two lags of $PM_{2.5}$, respectively. Since we are already controlling for lagged returns, this specification will capture any cumulative effects to the extent they exist. Although the lags are also negative in direction, they do not obtain statistical significance at conventional levels. Furthermore, the contemporaneous effect remains more or less unchanged, suggesting the immediacy of the effects of $PM_{2.5}$ on returns.

As a falsification test, we add one and two leads of $PM_{2.5}$. Pollution in the future should not affect returns today, so finding an effect from future returns would suggest model misspecification. Shown in columns four and five, we find that the coefficients on the leads are small in size, mixed in sign, and never statistically significant. Again the coefficient on contemporaneous $PM_{2.5}$ remains more or less unchanged.

5.2 Sensitivity analysis

A concern already noted is the possible confounding role played by weather variables and other pollutants. We already include a wide suite of controls (including flexible controls for temperature and dew point) in the main specification, but to further probe this issue we conduct three robustness checks, with the results summarized in Table 3.

First, we exclude all weather variables entirely. If weather variables correlated with $PM_{2.5}$ are important confounders then omitting them should appreciably change our results. The results of this exercise, summarized in column 1, shows minimal changes in our estimates, from -.0171 to -.0178. This suggests that although weather may have an influence on returns it is *not* in a way that is correlated with $PM_{2.5}$.[13] While we cannot rule out some other unobserved meteorological confounder, the fact that omitting the six major meteorological factors does not disturb our result limits this concern.

Second, we dig deeper into the possible confounding role of precipitation. Precipitation may impact mood directly, and also plays an important role in influencing $PM_{2.5}$ levels. As a further check we conduct a sub-sample analysis by limiting ourselves to days on which no precipitation occurred.[14] The results, shown in column three, provide an estimate of -.0145, again quite close to our original estimate. This suggests that precipitation is unlikely to be a major source of confounding.

In column 3 we present the results of a third exercise, similar to the first except now focusing on the role of co-pollutants. Since many pollutants have short-term health impacts, and fossil fuels contribute to their formation, it is possible that we are falsely

[13] We present the coefficients for weather in the appendix table and the hourly analysis.
[14] Recall that we have defined a day not by the calendar but as the twenty four hour block of time from 4 PM one day to 4 PM the next.

attributing some of the effect of those to $PM_{2.5}$. Again, although we cannot test whether other, unobserved pollutants confound this relationship, we can test the extent to which the pollutants we do observe confound this relationship. Excluding the co-pollutant controls from the regression causes the estimate on our coefficient of interest to rise from -.0171 to -.0205. This rather minimal change suggests that other pollutants are unlikely to represent a source of omitted variable bias.

Another potential concern is the role of traffic; traffic increases pollution, but can also lead to stress, which may affect returns. To assess this, we add to our regression daily traffic data, obtained from the 3 traffic monitors located in Manhattan.[15] Shown in column (4) of Table 3, adding traffic scarcely affects the coefficient on $PM_{2.5}$, suggesting traffic is not a source of confounding.

An additional concern in interpreting our results is that the volume of stocks traded may also change as a result of in response to pollution, potentially conflating our estimates as both a volume and a price effect. To assess this possibility, we re-estimate equation (1) using the volume of stocks traded as the dependent variable. Shown in column (5) of Table 3, we find a small, statistically insignificant relationship between $PM_{2.5}$ and trade volume. Furthermore, if we include trade volume as a covariate in our main specification, the coefficient on $PM_{2.5}$ remains largely similar (not shown). These results suggest that our results are capturing a pure price effect.

[15] Continuous volume traffic data is obtained from the Department of Transportation (DOT) for the New York Metropolitan Transportation Council (NYMTC), available at https://www.dot.ny.gov/divisions/engineering/technical-services/highway-data-services/hdsb. The traffic monitors are Manhattan Span (id: 040920), Exit 29A Manhattan Bridge (id: 104745), and Manhattan Bridge Over (id: 127951).

Although we hypothesize that $PM_{2.5}$ affects stocks prices through investor behavior, the fundamental value of each stock has not changed. Therefore, stock prices should recover in the days after an increase in pollution occurs. To assess this, we replace the dependent variable in equation (1) with future S&P 500 returns. If the stock market recovers, then we expect pollution today to have a positive effect on returns in the future. Table 4 presents results consistent with this. Returns on day t+1 are positive and statistically significant, and completely offset the negative effect from day t. As we move further into the future the coefficients are all statistically insignificant, and become increasingly smaller in magnitude.

5.3 Placebo tests

A potential challenge to our inference is that unobserved macroeconomic changes may impact both $PM_{2.5}$ levels in New York and NYSE price movements. Exogenously occurring positive macroeconomic news today might lead to both a rise in the price of stocks and at the same time an increase in pollution in urban centers as real economic activity expands. Failing to account for such news in our regression could lead us to claim a spurious causal relationship from air pollution to stock price movements. Although this seems unlikely given the high frequency of data used, to further limit any such concerns we execute two placebo checks.[16]

First, we re-estimate our preferred specification 43 times, in each case replacing the New York $PM_{2.5}$ series with the analogous series from each of 43 other US cities. We

[16] Note that macroeconomic fluctuations, to the extent they might bias our results, would likely bias them downward. Insofar as the story just told was to pass muster, it would imply a positive association between daily $PM_{2.5}$ and stock price movements, whereas our analysis generates negative coefficients throughout.

chose those cities that (a) were over 250 miles from New York City and (b) were such that data was available to provide daily measures for 80% of days in our study period.[17] Insofar as macroeconomic variations mattered, we would expect these to be reflected in air quality in cities across the country, not just in New York, and so would expect to detect pollution levels in other locations affecting S&P 500 returns. The upper panel in Figure 4 plots the estimated coefficients on the respective $PM_{2.5}$ placebo series by city. 28 of the placebo series generate a positive coefficient, 15 negative. In terms of size all are much smaller than the baseline estimate using the New York series – the next largest coefficient is -.00646, which is a third of the size of our main estimate. The lower panel plots the associated p-values for the placebo $PM_{2.5}$ coefficients and show that none obtain significance at the 10% level, and only a small number at the 20% level. Together this leads us to conclude that the effect we identify is indeed a local one.

As a second test, we conduct a similar exercise by replacing the same-day New York $PM_{2.5}$ series with the series taken from that same city but on 1,000 different, randomly-selected dates. We do this by randomly re-ordering the $PM_{2.5}$ values within New York, and re-estimating the preferred version of the model but using the falsely assigned $PM_{2.5}$ levels. Insofar as our claim of a contemporaneous effect of air quality on investor behavior and stock market outcomes is valid, we would not expect this placebo series to have significant explanatory power. Figure 5 confirms that this is indeed the case. The upper panel plots the estimated coefficients on the placebo series, ordered by magnitude. It can be seen that roughly half generate positive coefficients, half negative.

[17] Some locations monitor $PM_{2.5}$ every 3 or 6 days. We excluded cities less than 250 miles from New York because they could reasonably be affected by New York activity. Nonetheless, the estimates using data from these closer cities also supported our results (available upon request).

The lower panel again plots the associated p-values, and we observe that in 40 out of 1,000 cases the placebo series prove significant at the 5% level. This is roughly what we would expect of the coefficient estimates obtained for a series of irrelevant regressors inserted in turn into the regression.

5.4 Non-linear estimates

In our baseline specification we have assumed a linear relationship between $PM_{2.5}$ and investor behavior. We probe for possible non-linearity by including separate indicators for every 5 μg/m^3 of $PM_{2.5}$ (with > 25 as the highest bin). In addition to enabling us to test for any non-linearity, such as threshold effects, this also serves as a robustness check: if $PM_{2.5}$ affects returns, then higher levels of $PM_{2.5}$ should have larger effects. The results from this analysis, shown in Figure 6, while somewhat noisy, generally support a linear effect of $PM_{2.5}$ as the coefficients are nearly monotonically increasing in $PM_{2.5}$. Only estimates from the two highest bins are statistically significant, though both are below the current daily air quality standard of 35 μg/m^3. This suggests that effects arise even when $PM_{2.5}$ complies with environmental regulations.

5.5 Intra-day analysis

While the central results thus far presented rely on daily variations in pollution and weather, the fine-grained nature of the data gives us the opportunity to explore intra-day effects. Since exposure to the elements can have nearly immediate effects, we investigate this by constructing average pollution and weather measures over two-hour time blocks. Using these measures, we modify equation (1) as follows:

(2) $r_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 r_{t-2} + \sum_j \beta_{3j} PM_{2.5tj} + \sum_j W_{tj}\beta_{4j} + \sum_j P_{tj}\beta_{5j} + \Phi_t + \varepsilon_t.$

In this equation, we enter $PM_{2.5}$, weather (W), and other pollutants (P) in two-hour blocks, ranging from j = 12:00 AM – 1:59 AM to 10:00 PM to 11:59 AM.[18]

The key feature of this analysis is the difference in the ability of environmental variables to penetrate indoors. Investors are largely outdoors when traveling to work at the NYSE and thus exposed to all elements at that time. Once on the trading floor, the climate-controlled environment in the NYSE significantly reduces exposure though does not eliminate all sources. In fact, of the variables considered we only expect $PM_{2.5}$ to have an effect during the day because of its high indoor penetration rates.[19] Therefore, we only expect weather to affect traders during commuting hours while $PM_{2.5}$ might affect traders even once indoors.

One concern with this analysis is whether there is sufficient independent variation in hourly pollution. Figure 7 plots average hourly $PM_{2.5}$, both for the entire year and only for the summer months (July and August). Two immediate patterns suggest ample variation in $PM_{2.5}$. First, $PM_{2.5}$ peaks at 8 AM and at 7 PM, a very different pattern from temperature, which peaks midday. Second, $PM_{2.5}$ levels decrease in the summer, again very different from temperature, which increases in the summer.

[18] To keep the number of coefficients feasible, we restrict all environmental variables to enter linearly. Note that solar radiation is entered daily rather than hourly.
[19] For example, imagine a day that has a constant temperature of 85F and constant $PM_{2.5}$ level of 10 µg/m3 every. As workers travel to the office they are exposed to both this temperature and $PM_{2.5}$ level. Once workers reach the NYSE, the temperature to which they are exposed changes to that indoors at the climate-controlled exchange, while the $PM_{2.5}$ to which they are exposed remains approximately unchanged.

Note that we cannot predict the relative magnitudes of the hourly $PM_{2.5}$ responses for three reasons. One, penetration rates are not 100%, and we do not have measures of indoor $PM_{2.5}$ at the exchange. Two, although the effects from $PM_{2.5}$ can be expected to reveal themselves in the first few hours after exposure, we cannot pinpoint the exact time at which it affects workers. Three, there may be cumulative effects from $PM_{2.5}$ exposure within the day that we cannot disentangle with an additively separable model.[20]

In Figure 8 we display estimates from equation 2 for the hourly measures of $PM_{2.5}$, temperature and ozone.[21] Several findings stand out. First, consistent with prior literature, temperature has a significant and positive effect, but only from 8 – 10 AM, prime commuting hours. Warmer temperature on the journey to work - the usual story would say - improves mood, reduces risk aversion and so in turn increases daily returns. Second, ozone, a pollutant that does not penetrate indoors (and is not generally believed to have cognitive effects) is never statistically significant. Third, $PM_{2.5}$ has a statistically significant effect from 6 – 8 AM, 8 – 10 AM, and 10 AM – 12 PM, which include a period after traders and most other financial professionals are at work. The effect becomes considerably smaller throughout the afternoon, possibly reflecting the delay with which $PM_{2.5}$ affects the body. Last, as expected we do not see effects in the evening hours after the exchange has closed, a finding consistent with our lead tests from Table 2. These hourly results further support our contention that $PM_{2.5}$ has a causal effect on stock market returns.

[20] A richer model with interactions terms is not feasible given the number of additional variables and the correlation in PM2.5 through the day.
[21] Intra-day results for all environmental variables are available upon request.

5.6 Exploring risk aversion as mechanism

In Section 2 we summarized research that potentially links human exposure to $PM_{2.5}$ to decreased returns via increased risk aversion. Though we recognize the possibility of other mechanisms - and indeed it may be that several mechanisms are at work simultaneously - in this section we probe the idea that pollution-induced changes in risk appetite may be playing a role by using data on the VIX index, a widely used proxy for market risk aversion (Coudert and Gex, 2008); Whaley, 2009).

We estimate our main regressions using the VIX index as the dependent variable. Our hypothesis of risk aversion as a potential mechanism underpinning our central results would imply a positive coefficient on $PM_{2.5}$. Table 5 reports the results from this analysis, repeating the structure in Table 2. Consistent with our hypothesis, we find that $PM_{2.5}$ has a statistically significant positive relationship with the VIX. It implies that a one unit increase in $PM_{2.5}$ concentration increases the value of VIX by 1.9%. Similar to our previous results, we find that adding leads and lags of $PM_{2.5}$ does not substantially alter our findings.

While the VIX is commonly used as a proxy for risk aversion, it reflects both changes in taste for risk and in anticipated market volatility. We decompose the overall measure into these two elements, referred to as the 'risk aversion' and 'uncertainty' components, respectively (Bekaert et al., 2013).[22] The results of re-estimation using each of those components as dependent variables in turn are presented in Table 6. They indicate that $PM_{2.5}$ significantly increases the pure risk aversion component, but is

[22] Following Bekeart et al (2013) we regress realized variance (computed using daily percentage returns) on the 22-day lagged squared VIX and realized variance. The fitted value from this regression is the estimated measure of 'uncertainty' and the residual is our 'risk aversion' proxy.

statistically unrelated to the uncertainty component. Sensitivity analyses including leads and lags (not shown) mirror previous results that only contemporaneous $PM_{2.5}$ matters.[23] While not definitive, these results support pollution-induced risk aversion as a possible mechanism linking changes in $PM_{2.5}$ to changes in stock market returns.

6. Conclusion

The efficient markets hypothesis is a central tenet of neoclassical economics. We provide the first empirical evidence of a causal link from air quality and the efficient operation of financial markets. In particular, poor air quality in the city in which a stock-market is based causes market prices to diverge from prices based on fundamentals. When Manhattan-based traders are exposed to higher levels of $PM_{2.5}$, the return on the S&P 500 on that day is lowered. This is consistent with an induced fall in risk appetite among a subset of traders, plausible given existing research on the role short-term exposure to air pollution can have on brain health, cognition and risk attitude. The effects are economically significant - a one standard deviation increases in ambient $PM_{2.5}$ concentrations reduces same-day returns by 11.9% in our preferred specification - and prove robust to a variety of specifications and a battery of robustness and falsification checks. In the daily analysis which is central in the paper we take particular care to isolate the role of pollution from weather factors - already known to affect mood and trading behavior - using a variety of methods. Furthermore, the intra-day effects that we observe are difficult to reconcile with competing hypotheses.

[23] Results are also robust to the confounding sensitivity analysis done in Table 3.

Investors are widely dispersed. There is however a very strong concentration of those who exercise financial discretion working in offices in New York - not just those trading at the NYSE but wealth managers and other market-influencers more generally (for example Blackrock, the world's largest wealth management company is Manhattan-based). Furthermore the market-making activities are largely New York based. As such we were particularly careful to investigate the geography of the effect. The results point to a strictly *local* effect, as pollution levels in a wide set of other American cities are unrelated to S&P 500 returns. This also rules out that the analysis is picking up unaccounted for variations in macroeconomic circumstances that contemporaneously influence stock market and pollution levels across cities.

The results can be seen as interesting on a number of levels. First, they provide further evidence of the ubiquitous influence that the natural environment has on important social and economic outcomes. Variations in the quality of air in Manhattan systematically distort investment signals being sent out across the whole economy. Second, if we consider returns as a metric for the productivity of an NYSE trader, the results point to a detrimental effect of diminished air quality on the work performance of this class of employee, so significantly extending the insight of recent research showing similar impacts on the productivity of low-skilled workers.

7. Bibliography

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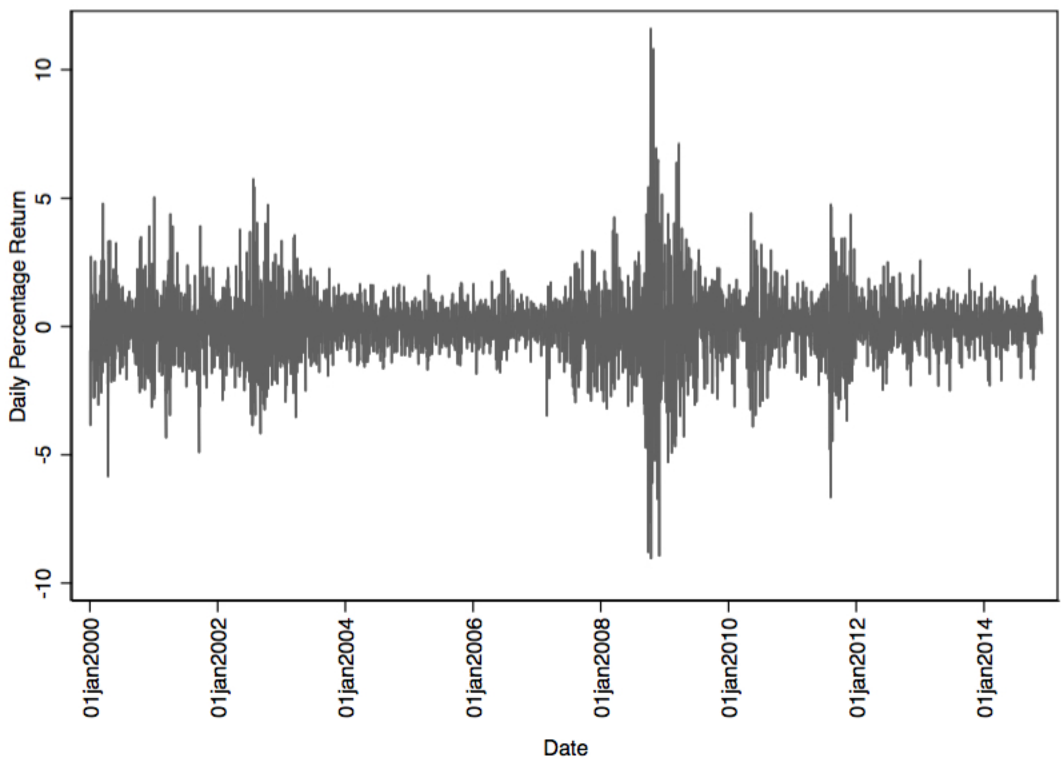
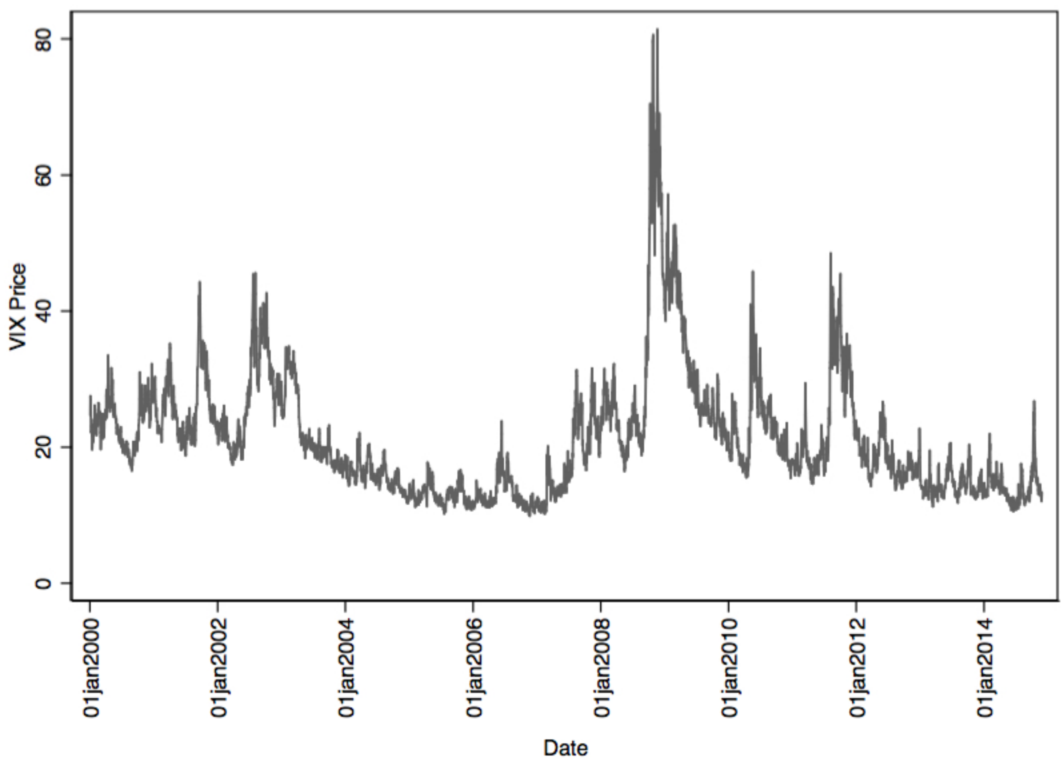
Figure 1: Daily Variation in S&P 500



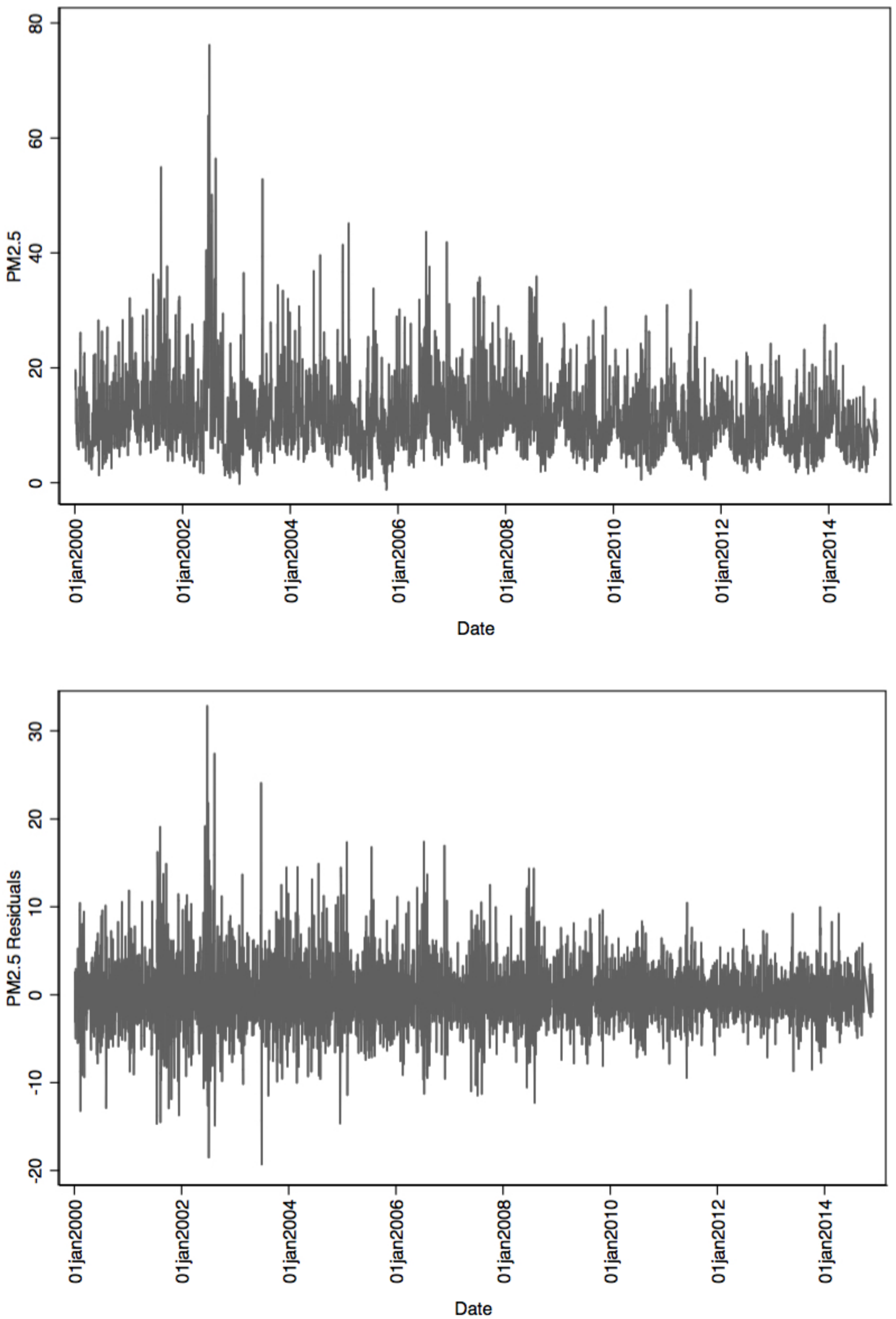
Notes: This plot shows the daily percentage return in the S&P 500 over time.

Figure 2: Daily Variation in VIX



Notes: This plot shows the daily VIX price over time.

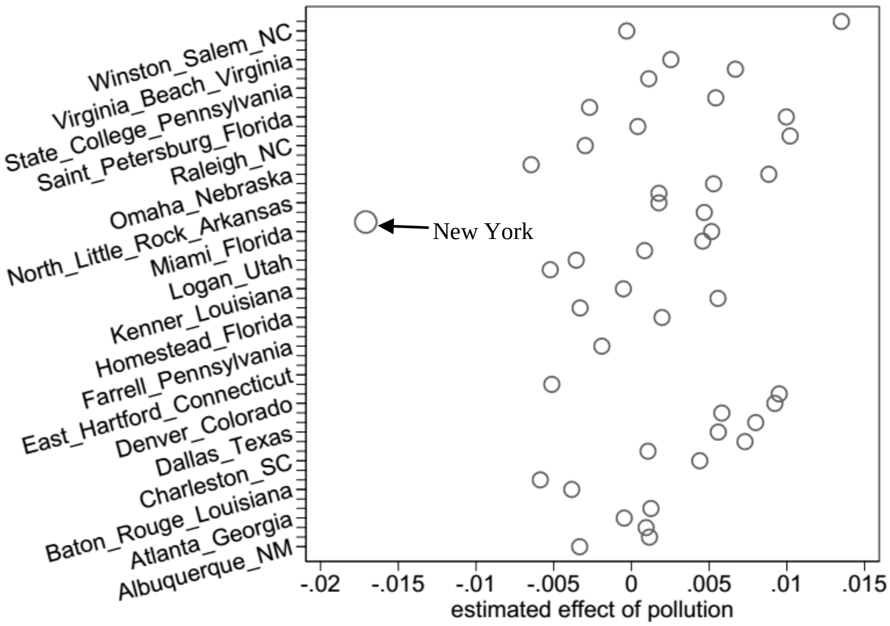
Figure 3: Daily Variation in $PM_{2.5}$



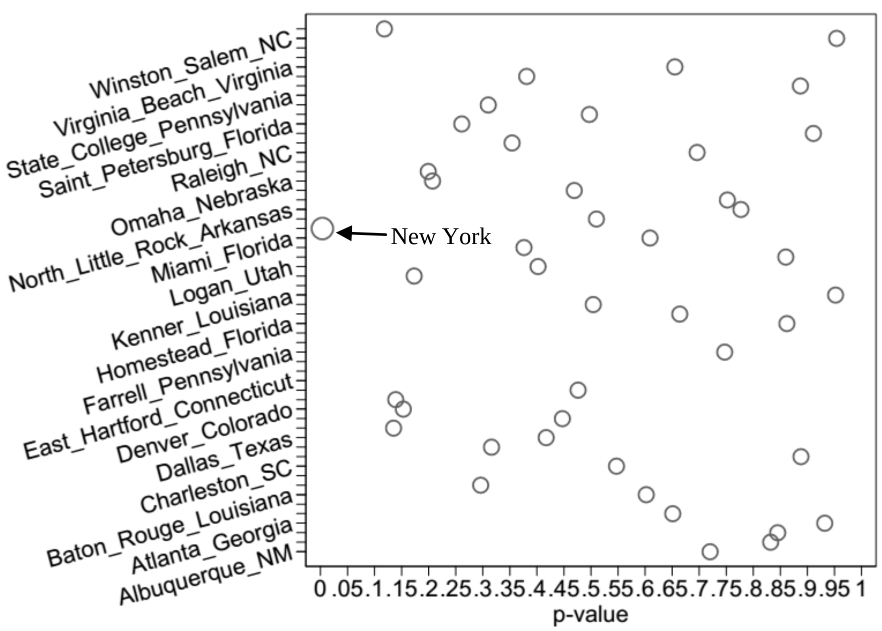
Notes: The upper panel plots unadjusted daily $PM_{2.5.}$ The bottom panel plots $PM_{2.5}$ adjusted for temperature (2.5 degree indicators), dew point (2.5 degree indicators), air pressure, wind speed, precipitation, cloud cover, ozone, carbon monoxide, day of week indicators, year-week indicators, and a tax dummy.

Figure 4: Falsely Assigned Pollution by City

A. Coefficients



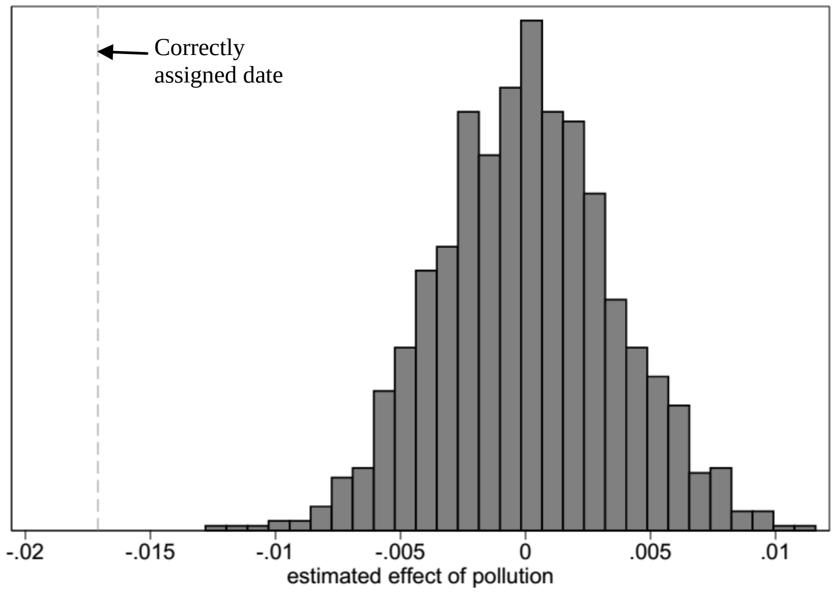
B. P-values



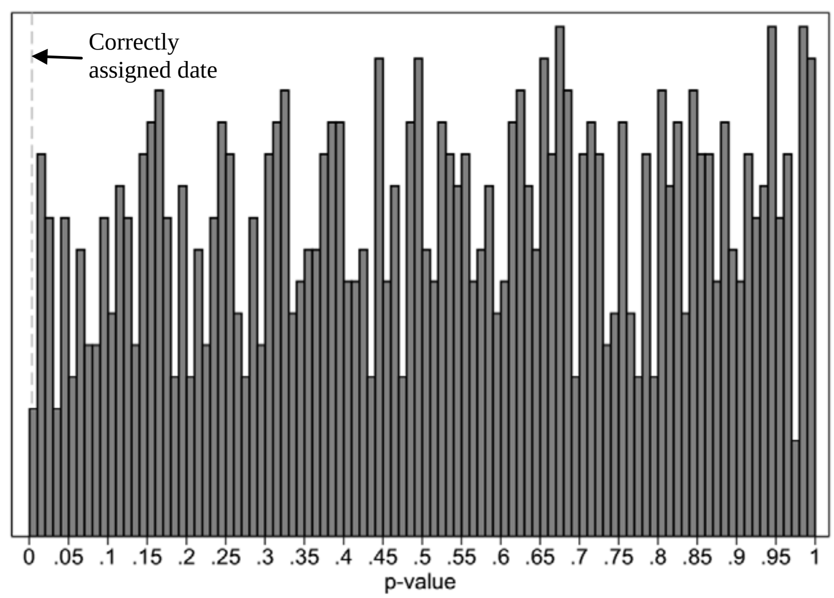
Notes: Each circle represents the coefficient (panel A) or p-value (panel B) from a regression of that city's pollution on S&P 500 returns, controlling for one and two lagged returns, temperature (2.5 degree indicators), dew point (2.5 degree indicators), air pressure, wind speed, precipitation, cloud cover, ozone, carbon monoxide, day of week indicators, year-week indicators, and a tax dummy.

Figure 5: Falsely Assigned Pollution by Date

A. Coefficients

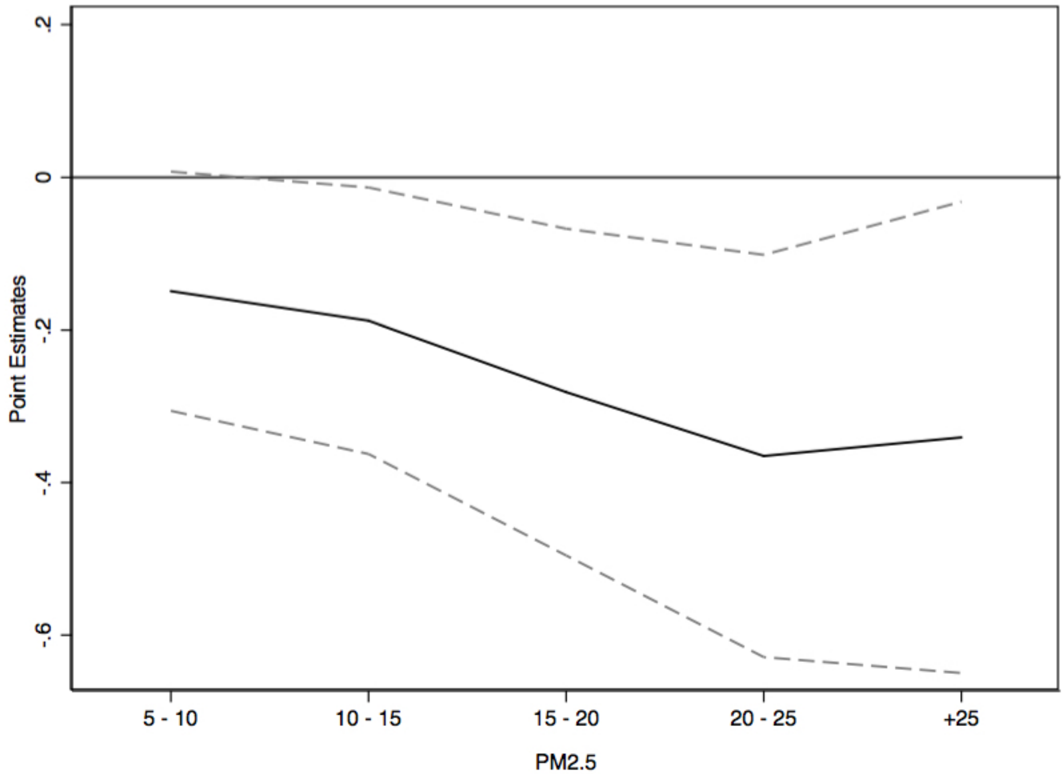


B. P-values



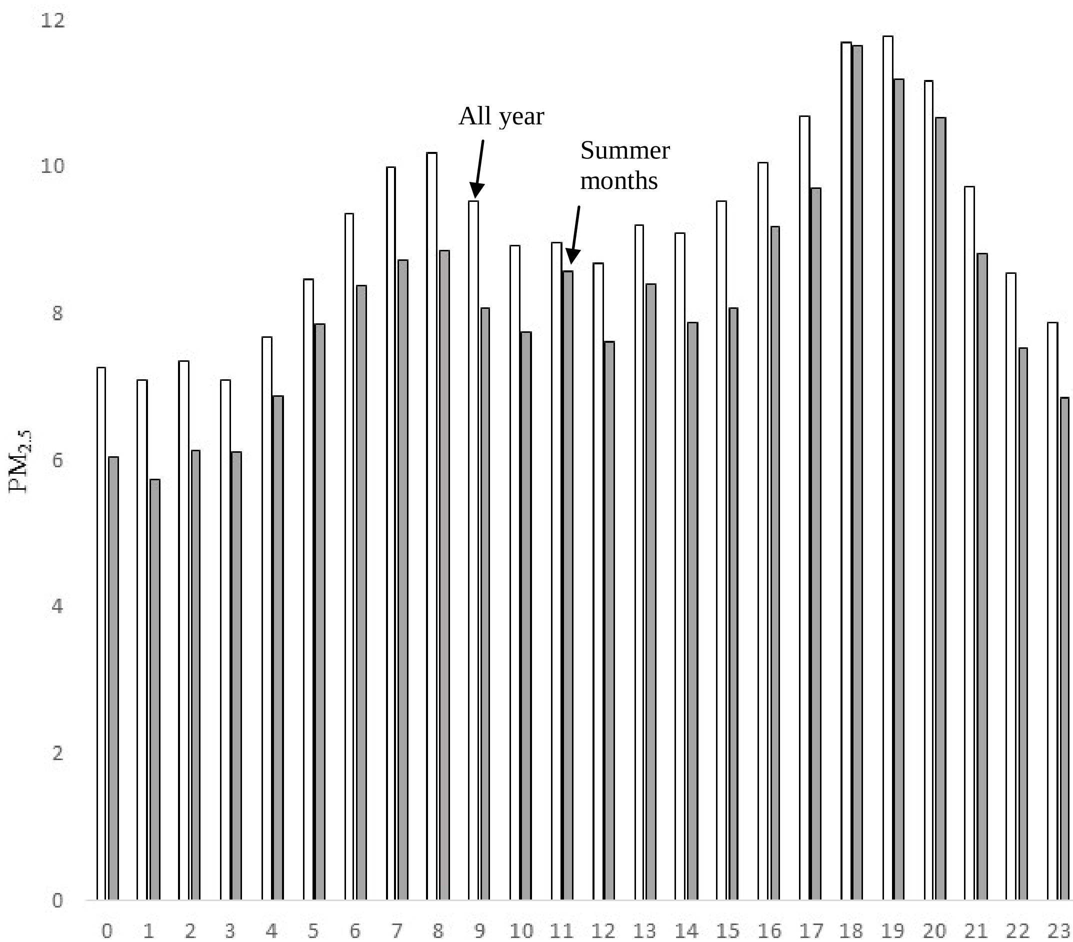
Notes: Each plot represents the coefficient (panel A) or p-value (panel B) from a regression of pollution on S&P 500 returns, randomly re-assigning dates 1,000 times. The dashed line represents the estimated effect from the correctly assigned dates. Regressions control for one and two lagged returns, temperature (2.5 degree indicators), dew point (2.5 degree indicators), air pressure, wind speed, precipitation, cloud cover, ozone, carbon monoxide, day of week indicators, year-week indicators, and a tax dummy.

Figure 6: Non-linear Results



Notes: this figure plots the coefficients for $PM_{2.5}$ indicator variables for each 5 units, with 0-5 as the reference category. Gray dash lines represent the 95 percent confidence interval based on standard errors clustered on week. The dependent variable is daily percentage stock market return. The regression includes controls for temperature (2.5 degree indicators), solar radiation, dew point (2.5 degree indicators), air pressure, wind speed, precipitation, ozone, carbon monoxide, tax dummy, day of week dummies and week-year dummies.

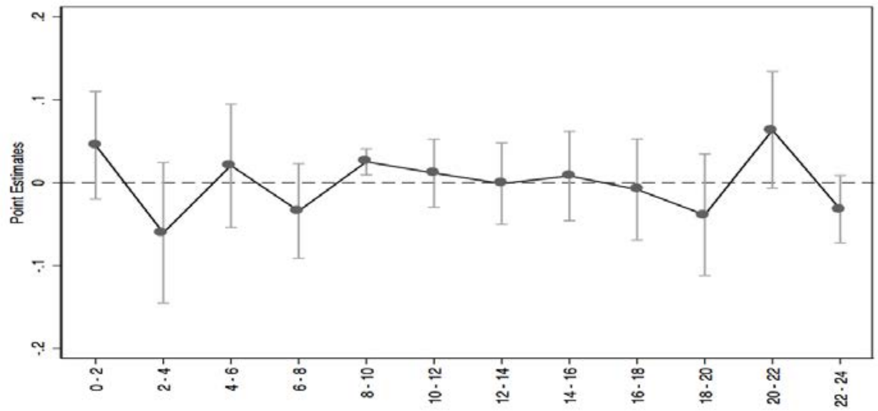
Figure 7: Hourly $PM_{2.5}$



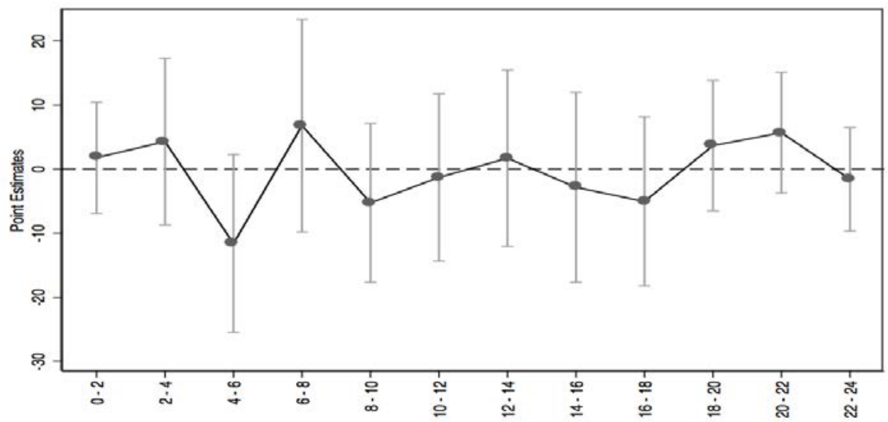
Notes: This figure plots the average $PM_{2.5}$ levels by hour of day using all days in the year (white bars) and all days in the summer months only (gray bars).

Figure 8: Hourly Effects of Temperature, Ozone and $PM_{2.5}$

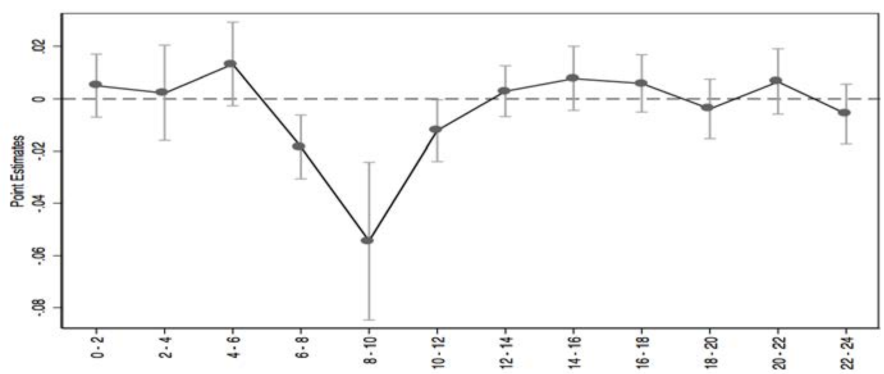
a. Temperature



b. Ozone



c. $PM_{2.5}$



Notes: These graphs plot coefficients for each two-hour block of temperature, $PM_{2.5}$, and ozone based on results from one regression. The dependent variable is daily percentage stock market return. The regression includes controls for solar radiation (daily), dew point (hourly), air pressure (hourly), wind speed (hourly), precipitation (hourly), carbon monoxide (hourly), tax dummy, day of week dummies and week-year dummies. Gray whiskers denote 95 percent confidence intervals.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.
Daily percentage return	0.02	1.28
Dicky-Fuller test statistic for unit root	-64.08	
VIX price	21.22	9.04
Dicky-Fuller test statistic for unit root	-5.936	
$PM_{2.5}$ (μ/m^3)	11.53	6.97
Carbon monoxide 8-hour (ppm)	0.84	0.40
Ozone 8-hour (ppm)	0.02	0.01
Air pressure (pa)	1006.54	9.20
Wind speed (km/h)	99.51	110.70
Average temperature (°F)	55.58	17.32
Precipitation (mm)	31.74	90.85
Dew Point (°F)	82.06	14.54
Cloud cover from sunrise to sunset (percent)	64.15	16.78

Notes: Critical values for the Dickey-Fuller test statistic are -3.43 (1%), -2.86 (5%), and -2.57 (10%).

Table 2: Main Regression Results for the Effect of Pollution on S&P 500 Returns

	(1) Daily	(2) 1-Day Lag	(3) 2-Day Lag	(4) 1-Day Lead	(5) 2-Day Lead
$PM_{2.5,t}$	-0.0168***	-0.0166***	-0.0180***	-0.0174***	-0.0178***
	[0.0055]	[0.0055]	[0.0054]	[0.0055]	[0.0055]
$PM_{2.5,t-1}$	-	-0.0042	-0.0033	-	-
	-	[0.0047]	[0.0044]	-	-
$PM_{2.5,t-2}$	-	-	-0.0044	-	-
	-	-	[0.0053]	-	-
$PM_{2.5,t+1}$	-	-	-	0.0028	0.0033
	-	-	-	[0.0045]	[0.0046]
$PM_{2.5,t+2}$	-	-	-	-	-0.0021
	-	-	-	-	[0.0043]
Observations	3722	3722	3722	3722	3722
Time Dummies	Y	Y	Y	Y	Y
Weather	Y	Y	Y	Y	Y
Co-pollutants	Y	Y	Y	Y	Y

Notes: The dependent variable is daily percentage return of the S&P500 index. Newey-West standard errors allowing for arbitrary serial correlation within a week in brackets. Weather covariates include temperature (2.5 degree indicators), dew point (2.5 degree indicators), air pressure, wind speed, precipitation and cloud cover. Co-pollutant covariates include ozone and carbon monoxide. Time dummies include day of week, year-week and tax dummy. All environmental variables are the mean of daily values. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 3: Sensitivity Analyses

	(1) No Weather Controls	(2) Zero Precip.	(3) No Co-pollutants	(4) Traffic Inclusion	(5) Volume as Outcome
$PM_{2.5,t}$	-0.0178***	-0.0142*	-0.0140***	-0.0167***	-2.573
	[0.0051]	[0.0075]	[0.0053]	[0.0055]	[5.877]
Observations	3722	2492	3722	3722	3722

Notes: The dependent variable in columns (1)-(4) is daily percentage return of the S&P500 index and the volume of trades in column (5). Newey-West standard errors allowing for arbitrary serial correlation within a week in brackets. See notes to Table 2 for full list of covariates included. Column (1) omits all weather controls from the regression. Column (2) limits the sample to days when no precipitation occurred over the 24-hour time period. Column (3) excludes all co-pollutants from the regression. Column (4) includes daily traffic as a regressor. Column (5) uses the volume of stocks traded as the dependent variable. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 4: Recovery Analysis

	(1) 1-Day	(2) 2-Day	(3) 3-Day	(4) 4-Day	(5) 5-Day	(6) 6-Day	(7) 7-Day
$PM_{2.5,t}$	0.0150*	0.0122	-0.0121	-0.00323	0.00512	0.000016	0.00669
	[0.0083]	[0.0080]	[0.0082]	[0.0084]	[0.0084]	[0.0085]	[0.0088]
Obs.	3722	3722	3722	3722	3722	3722	3722

Notes: The dependent variable in Column (1) is S&P500 returns on day (t+1) – returns on day (t), column (2) is returns on day (t+2) – returns on day (t+1), etc. Newey-West standard errors allowing for arbitrary serial correlation within a week in brackets. Weather covariates include temperature (2.5 degree indicators), dew point (2.5 degree indicators), air pressure, wind speed, precipitation and cloud cover. Co-pollutant covariates include ozone and carbon monoxide. Time dummies include day of week, year-week and tax dummy. All environmental variables are the mean of daily values. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 5: The Effect of Pollution on the Volatility Index

	(1) Daily	(2) 1-Day Lag	(3) 2-Day Lag	(4) 1-Day Lead	(5) 2-Day Lead
$PM_{2.5,t}$	0.0198**	0.0202**	0.0209**	0.0207**	0.0218**
	[0.0056]	[0.0057]	[0.0057]	[0.0056]	[0.0058]
$PM_{2.5,t-1}$	-	-0.0075	-0.0079	-	-
	-	[0.0051]	[0.0051]	-	-
$PM_{2.5,t-2}$	-	-	0.0021	-	-
	-	-	[0.0051]	-	-
$PM_{2.5,t+1}$	-	-	-	-0.0042	-0.0067
	-	-	-	[0.0049]	[0.0048]
$PM_{2.5,t+2}$	-	-	-	-	-0.0094
	-	-	-	-	[0.0048]
Observations	3722	3722	3722	3722	3722
Time Dummies	Y	Y	Y	Y	Y
Weather	Y	Y	Y	Y	Y
Co-pollutants	Y	Y	Y	Y	Y

Notes: The dependent variable is daily volatility index (VIX). Newey-West standard errors allowing for arbitrary serial correlation within a week in brackets. Weather covariates include temperature (2.5 degree indicators), dew point (2.5 degree indicators), air pressure, wind speed, precipitation and cloud cover. Co-pollutant covariates include ozone and carbon monoxide. Time dummies include day of week, year-week and tax dummy. All environmental variables are the mean of daily values. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 6: Pollution and the VIX Components: Risk Aversion and Uncertainty

	(1) Daily	(2) 1-Day Lag	(3) 2-Day Lag	(4) Daily	(5) 1-Day Lag	(6) 2-Day Lag
		Risk Aversion			**Uncertainty**	
$PM_{2.5,t}$	0.0870***	0.0873***	0.0911***	-0.0062	-0.0061	-0.0059
	[0.0263]	[0.0267]	[0.0271]	[0.0046]	[0.0046]	[0.0047]
$PM_{2.5,t-1}$	-	-0.00585	-0.00813	-	-0.0027	-0.0028
	-	[0.0281]	[0.0281]	-	[0.0046]	[0.0047]
$PM_{2.5,t-2}$	-	-	0.0116	-	-	0.00037
	-	-	[0.0249]	-	-	[0.0039]
Obs.	3700	3700	3700	3700	3700	3700
Time Dummies	Y	Y	Y	Y	Y	Y
Weather	Y	Y	Y	Y	Y	Y
Co-pollutants	Y	Y	Y	Y	Y	Y

Notes: The dependent variable is VIX separated into risk aversion (column 1-3) and uncertainty (column 4-6) components. Newey-West standard errors allowing for arbitrary serial correlation within a week in brackets. Weather covariates include temperature (2.5 degree indicators), dew point (2.5 degree indicators), air pressure, wind speed, precipitation and cloud cover. Co-pollutant covariates include ozone and carbon monoxide. Time dummies include day of week, year-week and tax dummy. All environmental variables are the mean of daily values. * significant at 10%, ** significant at 5%, *** significant at 1%.