Particles, Pollutions and Prices

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Abstract

We investigate whether a sentiment effect arising from poor air quality negatively affects stock prices. We find little evidence suggesting that local air quality directly affects stock prices. However, we show that the local air quality index (which is increasing in air pollution) relative to that of Beijing negatively affects stock prices. We apply a discontinuity design that focuses on observations with the relative air quality index falling in the narrow band around zero and find a consistent result. Additional analysis unveils a subsequent reversal in stock prices in response to the relative air quality. Further, the relative air quality index also negatively affects trading volume. Finally, we show that the negative association between stock prices and the relative air quality index is not influenced by economic fundamentals or investor sophistication. In sum, our findings suggest that poor air quality negatively affects stock prices and investor trading activities.

Keywords: *air pollution, air quality index, stock prices, China*

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1. Introduction

A debate has been going on on whether environmental conditions affect stock prices. The pioneering work by Saunders (1993) starts a strand of literature that investigates whether weather and other environmental factors affect people's mood and thereby their trading behaviors. He documents a significant association between the New York Stock Exchange's daily returns and weather conditions in the New York City. Along the same line, Hirshleifer and Shumway (2003) extend Saunders (1993) by looking into 26 stock exchanges worldwide and find similar results. Other studies show that environmental factors such as temperature, the length of sunshine, daylight saving time changes, and lunar cycles also affect stock prices (Cao and Wei, 2005; Kamstra, Kramer and Levi, 2003; Kamstra, Kramer and Levi, 2000; Garrett, Kamstra and Kramer, 2005; Yuan, Zheng and Zhu, 2006). In contrast, Jacobsen and Marquering (2008) cast doubt on whether patterns in stock returns are affected by the weather. In particular, they find that results in Kamstra, Kramer and Levi (2003) and Cao and Wei (2005) can be also explained by other variables with strong seasonal patterns such as the sell-in-May effect and the Halloween effect. Kelly and Meschke (2010) further argue that there is no evidence in the psychological literature which directly relates changes in depression to changes in risk aversion. As such, a causal link between the weather and stock returns is far from being conclusive.

We carry on this stream of research and investigate whether there is a causal link between environmental conditions and stock prices in China. In particular, we test whether air pollution negatively affects stock returns through its impact on investors' mood. There are several advantages of our setting over those employed in prior studies. First, the link between air pollution and people's mood is less ambiguous that between weather and mood. Clinical and psychological research documents that exposure to air pollution or an awareness of harmful environments can cause negative moods such as anxiety, depression and apathy (Evans, Jacobs, Dooley and Catalano, 1987; Evans, Colome and Shearer 1988; Jones, 1978). Second, artificial classifications of various regions of air quality based on the Air Quality Index (AQI) can provide a unique opportunity to test for a causal link from air quality to stock prices if investor preferences are affected by these artificial classifications. We conduct a discontinuity design that focuses on observations with AQI values falling in the narrow band around artificial cutoffs. Given that the distribution of observations lying just above or below the cutoffs can be random, a difference regression can shed light on a causal effect from air quality to stock prices.[1] Third, in prior studies, capital markets investigated are more mature markets dominated by sophisticated investors less likely to be affected by behavioral biases. In contrast, the equity market in China is dominated by less sophisticated individual investors, who are more likely to succumb to behavioral biases. Therefore, findings in China can potentially shed light on the upper bound of the impact of unfavorable environments on stock prices.

We summarize our findings as follows. First, using the raw and de-seasoned air quality indices following Saunders (1993) and Hirshleifer and Shumway (2003), we find that the level of AQI has little impact on stock returns. To the extent that an AQI value of 100 is artificially classified as a cutoff between unhealthy and healthy regions by the Chinese government, we restrict our sample to observations with AQI lying just below or above 100 and re-examine the impact of AQI on stock prices. Again, we do not find any significant effect caused by different regions of AQI. We note that there is a discontinuity in the distribution of AQI around the value of 100. This phenomenon is consistent with the conjecture that government can manipulate the AQI slightly down to

[1] Note that such a test is a joint test of 1) whether there is a causal effect from air quality to stock prices and 2) the investors care about the range to which the AQI level belongs. Given that the government provides different classifications based on various cutoffs, it is reasonable to assume that these cutoffs should matter for investors. In a subsequent section, we provide more evidence showing that the cutoffs are important and that the government manipulates the AQI reporting to avoid unfavourable regions.

reduce the percentage of days that are considered polluted. Therefore, the insignificant discontinuity test result could be due to this manipulation.

We further explore other air quality measures to determine whether the insignificant association between air quality and stock prices is due to the failure in adequately capturing how people perceive air quality. As the AQI of Beijing attracts wide attention from the media, we argue that the AQI of Beijing can be a reference point for investors to define relative air quality. Although such a reference point is arbitrary, it is not without rationale. First of all, Beijing, the capital city of China, is located in a region with the most serious air pollution problem. Its pollution problem attracts most attention from foreign and domestic media. Beijing is perhaps the world's worst polluted national capital. Second, such a comparison approach is consistent with the social comparison theory which suggests that people form subjective feelings of happiness by comparing personal status with that of other people while evaluating their own status or welfare. Third, the comparison approach is easy to implement and does not require sophisticated knowledge about the distribution of the air quality index. As such, it is reasonable to believe that Beijing can serve as a reference point for investors to evaluate their relative air quality.

We find that stock returns are significantly negatively affected by the difference in AQI between a stock exchange and Beijing. We further restrict observations to those with AQI lying just below or above the AQI of Beijing and estimate a discontinuity model. We find a significant negative stock return around the cutoff where local AQI exceeds Beijing AQI. This finding supports the joint argument that Beijing is the reference point for investors to evaluate their local air quality, and that the perceived air quality based on this reference point negatively affects stock prices. Further analysis shows a reversal in returns in response to relative air quality (AQI of a stock exchange minus that of Beijing) in a subsequent period. In addition, we present evidence that daily stock trading volume is negatively associated with the relative air quality. This finding further supports the argument that relative AQI matters for stock prices and investors' trading activities. To rule out the possibility that AQI and stock returns are jointly determined by economic conditions, we test whether there is any discontinuity in firm performance around the dates when local AQI is just below or just above Beijing AQI. Our result suggests that the association between relative AQI and stock returns is not driven by changes in economic fundamentals. Therefore, we attribute the observed effect to investors' behavioral bias caused by the perceived air quality.

We make the following contributions. First, we contribute to the literature on behavioural biases due to environmental factors (Saunders, 1993; Cao and Wei, 2005; Kamstra, Kramer and Levi, 2003; Garrett, Kamstra and Kramer, 2005; Yuan, Zheng and Zhu, 2006). Our results support a causal link between the perceived air quality and stock prices. Second, we contribute to the psychology literature on reference points. The finding that relative AQI, instead of raw AQI, affects stock prices adds empirical evidence to the comparison theory of happiness (Veenhoven and Ehrhardt, 1995; Schyns, 1998), especially its social comparison variant (Festinger, 1954; Corcoran, Crusius and Mussweiler, 2011; Easterlin, 1974). Third, we contribute to the political science literature. We confirm evidence of data manipulation in AQI around the cutoff between healthy and unhealthy regions of AQI as in prior studies (Andrews, 2008, Chen, Jin, Kunar and Shi, 2012, Ghanem and Zhang, 2014) and consolidate the manipulation conjecture by shedding light on the real distribution of air quality.

This paper proceeds as follows. Section 2 discusses China's air pollution problem, reviews the literature and proposes our research question. Section 3 presents statistics of China's air quality index. Section 4 provides evidence of a negative association between poor air quality and stock prices. Section 5 summarizes and concludes.

2. Background, literature review and research question

2.1. Background

Currently in China, one of the hottest environment-related words is PM2.5, which measures the density of a specific air pollutant which is inhalable and very harmful to people's health. PM stands for particulate matter, which is a complex mixture of extremely small particles and liquid droplets, such as acids (nitrates and sulphates), organic chemicals, metals and soil or dust particles. The US Environmental Protection Agency (EPA) groups particle pollution into two categories. Inhalable coarse particles, such as those found near roadways and dusty industries, are larger than 2.5 micrometers and smaller than 10 micrometers in diameter. Fine particles, such as those found in smoke and haze, are 2.5 micrometers or smaller in diameter. These particles can be directly emitted from sources such as forest fires, or they can form when gases emitted from power plants, industries and automobiles react in the air. Once inhaled, these particles can affect a person's heart and lungs and cause serious health problems.

Air pollution in China is very serious. Transformed into a non-unit index which usually ranges from 0 to 500, the concentration of PM2.5 in some Chinese cities often exceeds the threshold separating healthy and unhealthy regions, and sometimes even reaches extreme values higher than 500 (though reporting is truncated at 500). The topic of air pollution often occupies newspaper pages and social media. Frequent haze not only attracts attention from traditional media and social networks, but also disrupts people's daily life. When the concentration of pollutant particles in the air exceeds certain levels, people's respiratory and cardiovascular systems are exposed to health hazards. In addition, many pollutant particles are opaque and when they cumulate, the atmosphere becomes murky and visibility decreases, even causing traffic problems. Among all forms of pollutions, air pollution is the most difficult for people to escape from.

Air pollution also affects people's feelings and emotions. Clinical and psychological studies document that exposure to air pollution or an awareness of harmful environment can cause negative moods such as anxiety, depression and apathy (Evans, Jacobs, Dooley and Catalano, 1987, Evans, Colome and Shearer, 1988, Jones, 1978). In an experimental research, Rotton (1983) finds that people report a lower level of happiness and well-being and even give lower values for paintings they are asked to evaluate, when exposed to air pollution.

2.2. Environmental factors and stock prices

With clinical and psychological evidence that bright, sunny days or rainy and overcast days affect people's mood differently (Persinger, 1975, Cunningham, 1979), Saunders (1993) first establishes a link between the sunshine/cloudiness of the New York City and the New York Stock Exchange's stock returns. He finds that the New York Stock Exchange Index is systematically negatively correlated with the cloudiness of the New York City. Hirshleifer and Shumway (2003) extend Saunders's (1993) work to 26 major stock exchanges around the world and find that a positive association between sunshine and stock returns exists internationally. Chang, Chen, Chou and Lin (2008) take a more careful look at this sunshine-stock price association by using intraday trading data. They find that the New York City cloud cover only affects stock returns during the opening period of NYSE trading days. Loughran and Schultz (2004) find that though NYSE stock returns are significantly associated with the weather conditions in the New York City, portfolio returns of firms located in the same city is not significantly associated with weather conditions of that city. Goetzmann and Zhu (2005) also fail to document such an association when using trading records of private investors in five US cities.

While Hirshleifer and Shumway (2003) use de-seasoned daily cloud cover and link it to the daily change in stock prices, Kamstra, Kramer and Levi (2003) use a more regular and better determined environmental factor, hours of sunshine, and its clinical negative mood effect on people, seasonal affective disorder, to explain stock market cycles. They use data from countries at various latitudes and at both hemispheres to capture the influence of daylight and find significant and substantial effect of seasonal affective disorder on stock returns. Their results also show that the impact of seasonal affective disorder is more pronounced in countries at higher latitudes, where short daylight during the winter is more severe. Garrett, Kamstra and Kramer (2005) further find that using a conditional CAPM which allows the price of risk to vary according to hours of daylight can capture the effect of seasonal affective disorder. Apart from the impact of daylight and sunshine, research also exists on the associations between daylight saving disruption (Kamstra, Kramer and Levi, 2000), temperature (Cao and Wei, 2005) and lunar cycles (Yuan, Zheng and Zhu, 2006) and stock prices.

A study relevant to our research is Levy and Yagil (2011). They use an indicator variable which equals one when the air quality of the New York City is classified as "unhealthy" and find that stock returns on unhealthy days are lower than those on healthy days. However, out of the 2,594 trading days they examine, less than 2% are classified as unhealthy. The large size difference between the "healthy" and "unhealthy" samples can weaken the validity of their results.

There is also evidence against the impact of environmental factors on stock prices, especially the impact of seasonal affective disorder. Jacobsen and Marquering (2008, 2009) argue that variables associated with seasonal affective disorder can simply capture some seasonal patterns such as the Sell-in-May effect, the Halloween effect or even ice cream consumptions, and that Kamstra, Kramer and Levi's (2003) causal association between the effect of seasonal affective disorder and stock prices is spurious.

Kelly and Meschke (2010) cast doubt on the theoretical causal link between seasonal affective disorder and trading behaviors. They show that the seasonal pattern of stock returns in Kamstra, Kramer and Levi (2003) does not match the result of a survey conducted by Kasper, Roger, Yancey, Schultz, Skwerer and Rosenthal (1989).

2.3. Air pollution: psychological impact and cognition of air pollution

While the impact of air pollution on physical health has been confirmed by clinical and medical research (Evans and Jacobs, 1981), there is also survey and experimental evidence that air pollution psychologically affects people's mood, causing anxiety, depression and stress (Evans, Jacobs, Dooley and Catalano, 1987). For example, Evans, Colome and Shearer (1988) conduct a survey on the impact of air pollution on people and document a positive association between air pollution and the feeling of anxiety. Jones (1978) and Stone, Breidenbach and Heimstra (1979) find that exposure to cigarette smoke causes annoyance (Evans, Jacobs, Dooley and Catalano, 1987). Rotton (1983) uses two experiments to study how air pollution affects people's feelings and other psychological behaviors. In his research, people exposed to malodorous pollution report a reduced level of happiness and well-being. Further, they attach lower values to paintings they are asked to evaluate.

The psychology literature not only documents the consequence of air pollution, but also explores people's cognitive assessment of air quality. Indeed, it is sometimes not the severity of air pollution itself, but people's perceived severity of air pollution, that matters (Zeidner and Shechter, 1988). Several studies use surveys to investigate whether and to what extent the public is aware of the air pollution problem (Rankin, 1969; Evans and Jacobs, 1981; Evans, Colome and Shearer, 1988). Other researchers try to identify factors that affect the public's awareness and evaluation of the air pollution problem. On the one hand, the natural level of air pollution and the publicity of air quality information matter. On the other hand, demographic factors such as education, age and health status affect people's cognitive process (Bickerstaff and Walker, 2001). This literature also documents an interesting "neighborhood-halo-effect" (Hall, Brajer and Lurmann, 2010), which suggests that people tend to over-evaluate the air quality in the neighborhood they live in (Rankin, 1969).

As discussed above, real air pollution as well as perceived air pollution negatively affect people's mood. People in bad mood are usually more pessimistic and more likely to reduce their valuation of things (Wright and Bower, 1992). In this paper, we try to find evidence that air pollution has a negative impact on stock prices.

3. Air pollution: data and summary statistics

3.1. Data and sample period

To determine whether and how air pollution affects stock prices, we need to obtain air quality data and stock market information. We obtain stock market trading data from CSMAR and the registered addresses of A-share listed firms from CCER. Harmful content in the air includes SO_2, NO_2, CO, O_3 and particulate matters. Particulate matters, known as PM, refer to dust, smoke, liquid drops, dirt and other particles in the air. They are harmful to health when they are small enough to be inhalable. PM 2.5, also known as "fine" particles, are those particles less than 2.5 micrometers in diameter and can be extremely harmful as they can deposit in people's lungs and pose grave health risks.

Before 2013, PM 2.5 concentration is not reported separately in China. Starting in January, 2013, China adopted a new set of air quality standards, which include the level of PM2.5 as a part of its air quality index. The new standards were first tried out in some big cities such as Beijing, Shanghai and Guangzhou, and were subsequently adopted by other cities. The website of Ministry of Environmental Protection of the

People's Republic of China (MEPC) now provides the following three sets of air quality data: 1) Hourly real time concentration of air pollutants under the new standards for 161 cities; 2) Historical daily Air Quality Index (AQI) under the new standards for 161 cities starting from January 1, 2014; and 3) Historical daily AQI under the old standards from June 5, 2000 to December 31, 2013.[2] The hourly air quality data set provides detailed information on the concentrations of different air pollutants from several monitoring points in each city. For each type of air pollutant, an average concentration is calculated and then transformed into a non-unit Air Quality Index ranging from 0 to 500. In the two historical daily Air Quality Index datasets, daily Complex Air Quality Index and the types of main air pollutants are reported.

Table 1 shows MEPC's classification of Air Quality Index. The air quality is good (healthy) when AQI is below 100, is polluted (unhealthy) when AQI is above 100, and is severely polluted when AQI exceeds 300. Table 2 reports the periods and the number of cities covered by the three datasets. In 2000, AQIs of only 42 cities were reported and most of these cities are provincial capitals. From 2000 to 2011, the number of cities with available AQI data increased gradually and reached 120 in 2011. However, this number decreased by almost one half in 2013, as many big cities (Beijing, Shanghai and Guangzhou) began to switch to the new air quality standards.

Though PM 2.5 is currently the focus of attention, we mainly use the daily Complex Air Quality Index based on the old air quality standards (before PM 2.5 was separately measured and reported) as the period for the new-standard-based AQI data is too short. While the old-standard-based AQI dataset contains AQI from June 5, 2000 to December 31, 2013, our sample period starts from January 1, 2001 to December 31, 2012. Observations in 2000 are dropped to ensure complete fiscal years. Observations in 2013

[2] In the old standards, PM 2.5 is not measured separately. Only the concentration of "Inhalable Particles" is included in the calculation of AQI. Also note that the daily AQI reported is measured for a period from 12:00pm on Day t-1 to 12:00pm on Day t.

are dropped as many main cities, such as Beijing, Shanghai and Guangzhou, began to adopt the new air quality standards and data for these cities are not available in 2013.

3.2. Summary statistics

We manually collect AQI data from the MEPC's website. We choose the capital city of each province and report summary statistics of daily AQI for these cities to form a general picture of air quality across China. We also report descriptive statistics of Shenzhen where the Shenzhen Stock Exchange is located even though it is not a provincial capital. These 32 cities are sufficiently representative of different regions in China. Further, they are all among those cities where daily AQI information is available as early as 2000.

Panel A, Table 3 reports the mean, standard deviation, minimum and maximum of daily AQI of each city during 2001-2012. We sort these cities by their geographic locations. The means of daily AQI in southern and southwestern China are lower than those in other regions. Standard deviations of AQI are also lower in these two regions and their maximum AQIs seldom reach 500.[3] We notice that the daily AQI of Haikou, capital of Hainan Province (an island below the southern tip of the mainland), never exceeds 100, the cutoff point between healthy and unhealthy regions of the air quality index. Air quality in northern China and northwestern China, however, are the worst with the highest daily AQI means, standard deviations and maximums. Panel B, Table 3 reports the mean and maximum of daily AQI of each city in four quarters. AQI readings are usually higher in the first and fourth quarters and lower in the second and third quarters. However, we note that Beijing is somehow different from other cities in the quarterly pattern. The mean of AQI readings in the second quarter is a little higher than that in the first quarter while the third quarter has the best air quality.

[3] 500 is the maximum reading in this dataset.

We present Pearson correlations of daily AQI of these cities with that of Beijing, Shanghai and Shenzhen in Table 4. Beijing is the capital of China and its air pollution problem attracts worldwide attention. Shanghai and Shenzhen are cities where the two A-Share Stock Exchanges in China are located. The Pearson correlation between the AQIs of any two cities is positive and significant, except that between Beijing and Wulumuqi. Six correlation coefficients are larger than 0.5, and the paired cities are all located close to each other (Beijing and Shijiazhuang, Beijing and Tianjin, Shanghai and Nanjing, Shanghai and Hangzhou, Shenzhen and Guangzhou, Shenzhen and Haikou).

3.3. Time-series patterns in air quality

We first determine how air quality in China changes overtime. We partition our data into two periods (2001-2006 and 2007-2012) and compare the means of daily AQI between these two periods for Beijing, Shanghai and Shenzhen. Table 5 shows that the means of daily AQI during 2007-2012 are significantly lower than those during 2001-2006 for all three cities. The difference in the means is large for Beijing. We also use a t-test to determine the significance level of the change in air quality in other capital cities. Untabulated results show that 30 out of the 32 cities in Table 3 experienced a significant reduction in daily AQI during the period 2007-2012. The two exceptions are Haikou and Hefei, with the mean of daily AQI increasing by 3.52 in Haikou and by 4.81 in Hefei. Figure 1-1 shows the means of daily AQI each year from 2001 to 2012 for Beijing, Shanghai and Shenzhen and Figure 1-2 presents the percentage of days when AQI exceeds 100, the cutoff point between healthy and unhealthy air quality, each year. Though a time-series trend in mean daily AQI is not obvious, the percentage of unhealthy days (AQI > 100) generally declines for Shanghai and Beijing.

Next, we check the predictability of AQI by using the following autoregressive model:

$$AQI_{it} = \alpha_0 + \sum_{j=1}^{q} \alpha_j AQI_{i,t-j} + \varepsilon_i, \quad (1)$$

where AQI_{it} is the AQI of City i during Period t. We use q = 1, 2, 3 to examine the predictability of AQI based on its lagged values. We estimate this autoregressive model using daily, weekly and monthly data.

As stated earlier, we focus on Beijing, Shanghai and Shenzhen and report results for these three cities in Table 6. Panel A presents daily results. For all three cities, one-day lagged AQI is significantly positively associated with current period AQI. For Beijing and Shanghai, the coefficients on the two-day lagged and three-day lagged AQIs are not significant. For Shenzhen, the coefficient on the two-day lagged AQI is significantly negative and the coefficient on the three-day lagged AQI is significantly positive. Panel B presents weekly autoregressive results. We calculate the weekly average AQI for each city and estimate Model (1). It is not surprising that most of the coefficients on lagged 1, lagged 2 and lagged 3 AQIs are significantly positive as taking weekly average absorbs the volatility of daily AQI and a 7-day period is not long enough to exhibit a potential periodic reversal pattern. Monthly autoregressive results are presented in Panel C. Results are similar to those in Panel A except that the coefficient on lagged 2 AQI is significantly positive and the coefficient on lagged 3 AQI is significantly negative for Shenzhen.

3.4. Manipulation in AQI reporting

Prior studies show that regional decentralization and personnel control system are crucial for the economic growth of China (Qian and Weingast, 1997, Li and Zhou, 2005, Jin, Qian and Weingast, 2005, Zhou, 2007). Such a mechanism motivates government officials to meet or exceed economic and noneconomic goals. These officials can devote real resources and efforts to achieve these goals. However, they can also achieve these goals by manipulating statistics (Merli and Raftery, 2000). As environmental protection has become more important in China, it is possible that government officials manipulate the reporting of AQI. Indeed, several studies have shown some evidence of AQI manipulation around healthy and unhealthy regions of the index (Andrews, 2008, Chen, Jin, Kunar and Shi, 2012, Ghanem and Zhang, 2014). Though these studies show consistent results of downward manipulation around critical points, we find it still necessary to conduct our own test of the manipulation. First, Andrews (2008) and Ghanem and Zhang (2014) mainly focus on the manipulation of PM10 instead of the complex AQI used in our paper. Second, though Chen, Jin, Kunar and Shi (2012) examine the manipulation of complex AQI, the sample period is only from 2000 to 2009. As the public's attention toward China's air quality is increasing fast in recent years, we want to determine if government manipulation is changing in recent years. Fourth and more importantly, US consulates in five Chinese cities started releasing their recording of PM 2.5 in recent years. This provides us a chance to potentially obtain a benchmark for the disclosure of air quality by the Chinese government.

To determine whether there is manipulation in AQI reporting, we draw the distribution of MEPC reported daily AQI. We mainly focus on Beijing. We first partition the distribution of AQI into the following intervals: [1, 5], [6, 10], …, [96, 100], [101, 105], [106, 110], …, [296, 300], [300, 500] and obtain the frequency of reported days in each interval. We then draw a histogram. Figure 2-1 shows the daily AQI distribution based on MEPC data from 2001 to 2012. The grey bar is the frequency of AQI in the interval [96, 100] and the white bar is the frequency of AQI in the interval [101, 105]. We find that there is a dip in the interval [101, 105] and the frequency of AQI in [96, 100] is much higher than that in [101, 105]. This pattern is consistent with those in prior studies. However, the dip itself still cannot completely rule out the possibility that the discontinuity just appear by chance if there is no benchmark. The website of US Embassy in Beijing released their historical records of hourly PM2.5 concentration starting from April 8, 2008. These PM2.5 readings are recorded by the US Embassy independently and are transformed into a non-unit index based on US standards. The US-standard based index also use 100 as a cut-off point between healthy and unhealthy regions. We understand that the MEPC AQI is based on a combination of air pollutants while the US-index is based on PM 2.5 concentration only and that the MEPC AQI is daily based while the US-index is hourly based. However, we believe that the US Embassy data can still provide some insight on how the true distribution of air quality is. To match the recording periods, we use both MEPC AQI and US Embassy AQI between April 8, 2008 and December 31, 2012 to draw their respective distributions. Figure 2-2 is the histogram of the US index. We can see that the shape of the bars is smooth for intervals falling into [26, 300]. There is no dip at [101, 106]. When we draw the histogram of MEPC AQI for the same period in Figure 2-3, we continue to observe a dip just above AQI of 100. The combination of air quality distributions from these two sources further confirms possible AQI reporting manipulation by MEPC.

We also use MEPC data to calculate a "Manipulation Index" defined as (Frequency of AQI in [96,100]) / (Frequency of AQI in [101,105]). Figure 2-4 shows the trend of this manipulation index. The imbalance between the adjacent intervals around AQI of 100 is generally higher after 2006.

4. Air quality and stock prices

4.1. Air quality and stock prices

Following prior studies (Saunders, 1993; Hirshleifer and Shumway, 2003; Kamstra, Kramer and Levi, 2003), we first exam whether daily stock market returns are associated with air quality in cities where stock exchanges are located. To gauge air quality of stock exchanges, we consider two measures. Saunders (1993) use a categorical variable to capture different levels of cloud cover and Hirshleifer and Shumway (2003) use a de-seasoned daily cloud cover when estimating the effect of weather. Loughran and Schultz (2004) argue that the de-seasoned approach can be problematic. Apart from the fact that the calculation itself uses future information to adjust for current data, the assumption that people actually do such a comparison is doubtful as the calculation is complex. Indeed, Loughran and Schultz (2004) use the raw cloud cover data and obtain results similar to those in Hirshleifer and Shumway (2003). As there is no direct evidence on whether people use the de-seasoned approach, we use both the raw AQI and the de-seasoned AQI to determine whether and how air quality affects stock prices.

Specifically, we use the following two measures: 1) *AQI_Raw*: raw value of AQI, as reported by MEPC; and 2) *AQI_deseasoned*: de-seasoned AQI calculated as:

$$AQI\_deseaoned_{tw} = AQI\_Raw_{tw} - MeanAQI\_Raw_{w},$$

where t indexes a day, w indexes a calendar week during a year Day t belongs to and $MeanAQI\_Raw_{w}$ is the average of raw AQI during Week w for the period 2001-2012. This air quality measure compares the daily air quality level with the normal level during the same period during a year.

We first perform a univariate analysis to determine whether there is any pattern in market returns associated with air quality. We partition daily returns into groups based on the level of air quality index. Observations with air quality index higher than the 90^{th} (75^{th}) percentile are grouped as the "Bad Air Quality" group. Observations with air quality index lower than the 10^{th} (25^{th}) percentile are grouped as the "Good Air Quality" group. We calculate the sample means of daily stock market returns and perform a t-test to determine whether stock market returns are significantly different between the "Good Air Quality" group and the "Bad Air Quality" group. Results are reported in Panel A and Panel B, Table 7. The mean daily return for the full sample is 0.0003. When we use *AQI_Raw* to measure air quality, the differences in value weighted average daily stock market returns are negative but not significant (diff. = -0.0004, t = -0.3923, for 10^{th} – 90^{th}; diff. = -0.0002, t = -0.2632, for 25^{th} – 75^{th}). When *AQI_deseasoned* is used as the air quality measure, the differences are positive but not significant (diff. = 0.0006, t = 0.6279, for $10^{th} - 90^{th}$; diff. = 0.0001, t = 0.1797 for $25^{th} - 75^{th}$).

We then use multivariate regressions to determine whether air quality affects stock returns. Specifically, we estimate the following model:

$$R_t = \alpha_0 + \alpha_1 AQI_t + \varepsilon_t, \tag{2}$$

where R_t is the daily value-weighted return of Shanghai or Shenzhen A-Share Exchange on Day t, AQI_t is the air quality based on MEPC data on Day t. We expect α_1 to be negative.[4]

We estimate the coefficients on *AQI_Raw* and *AQI_deseasoned* using Model (2). As people's mood can be affected by the current day air quality as well as the change in air quality, we also use the change in air quality from the previous day as another dependent variable. Hirshleifer and Shumway (2003) also estimate a logit model with the dependent variable being an indicator for positive daily stock market returns. We follow their method and estimate a logit model in addition to an OLS model. To make our results more readable, we divided each air quality measure by 100.

Panel A, Table 8 reports results when *AQI_Raw* is used as an air quality measure. Column (1) presents results when *AQI_Raw* is used and Column (2) presents results using *Change_AQI_Raw*. None of the coefficients on *AQI_Raw* (or *Change_AQI_Raw*) are significant (0.00066, t = 0.84 for *AQI_Raw*; and -0.00090, t = -1.10 for *Change_AQI_Raw*). Columns (3) and (4) present results for the Logit model. Still, none of the coefficients on air quality measures are significant (0.11307, z = 1.16 for *AQI_Raw*; and -0.05088, z = -0.50 for *Change_AQI_Raw*).

In Panel B results are based on *AQI_deseasoned*. None of the coefficients on *AQI_deseasoned* or *Change_AQI_de_seasoned* are significant (0.00042, t = 0.53 in

[4] When equal weighted average daily stock market returns are used as an alternative, results are qualitatively the same.

Column (1); -0.00116, t = -1.40 in Column (2); 0.08372, z = 0.84 in Column (3) and -0.07462, z = -0.72 in Column (4)).

Both univariate and regression results suggest that there is no systematic association between local air quality and stock market returns. We further applied a discontinuity analysis to determine whether air quality classifications affect stock prices. Levy and Yagil (2011) use an indicator variable that equals one when the air quality of the New York City is classified as "unhealthy" to determine whether this has a negative impact on stock prices. Artificial classification itself can influence the stock market if people's attitudes toward different air quality index regions are different. For example, for *AQI_Raw*, a value of 100 can be a critical point. AQI higher than 100 is classified as "unhealthy" and AQI lower than 100 is classified as "healthy". Though the difference in air quality between a day with an AQI of 100 and a day with an AQI of 101 is small, people can still feel differently if they take the 1-point difference as a jump from "healthy" to "unhealthy" regions. As using such an indicator to capture the level of air quality can be rough because it ignores the variation in air quality within healthy/unhealthy regions, we restrict our sample to observations just below or above the cutoff between unhealthy and healthy regions and re-examine the impact of air quality on stock prices. Specifically, we use three subsamples when daily *AQI_Raw* falls into the following three regions: [85, 115], [80, 120] and [75, 125], and estimate the following model:

$$R_t = a_0 + a_1 Poor1 + a_2 AQI\_Raw_t + a_3 AQI\_Raw_t^2 + \varepsilon_t, \qquad (3)$$

where *Poor1* is an indicator that equals 1 when *AQI_Raw* exceeds 100, and 0 otherwise. We also add to Model (3) a quadratic term of air quality measure in case that the association between air quality and stock market returns is not linear within small intervals. If investors react differently when the air quality is slightly above or slightly below the critical point, we would find a_1 to be negative in the sub-sample regression.

Table 9 presents regression results. Column (1) presents regression results using Model (2) and the full sample. We then estimate Model (3) for the three subsamples. In Columns (2) to (4), we exclude the quadratic term of *AQI_Raw*, and in Columns (5) to (7) we use the full model. In Columns (2) to (4), the coefficients on *Poor1* are negative but not significant (-0.00443, t = -1.63 for [85, 115]; -0.00336, t = -1.36 for [80, 120] and -0.00347, t = -1.56 for [75, 125]). In Columns (5) to (7), the coefficient on *Poor1* are negative and marginally significant for [75, 125] (-0.00417, t = -1.69) and negative but insignificant for [85, 115] (-0.00478, t = -1.54) and [80, 120] (-0.00373, t = -1.33). Results in Table 9 show little evidence supporting a significant impact of *AQI_Raw* on stock prices.

Andrews (2008), Ghanem and Zhang (2014) and Chen, Jin, Kunar and Shi (2012) and our summary statistics show evidence of AQI manipulation around AQI of 100. Such manipulation could be an explanation for the insignificant coefficients on *Poor1*. For example, if investors know that AQI is manipulated, especially when it is close to 100, they will not take the value of 100 as a real cutoff point between healthy and unhealthy regions even if the official classification suggests so. As a result, our discontinuity identification can lose validity for its crucial assumption.

4.2. Relative air quality and stock prices

So far, we have found no evidence that local air quality directly affects stock prices. It could be the case that investors are not influenced by air quality while making trading decisions. However, it is also possible that the measures we use (*AQI_Raw* and *AQI_de_seasoned*) do not correctly reflect how people perceive air quality. In this section, we determine whether people rely on alternative measures of air quality. Zeidner and Shechter (1988) point out that sometimes it is people's perceived severity of air pollution that matters. The comparison theory of happiness (Veenhoven and Ehrhardt, 1995, Schyns, 1998) states that, the subjective feeling of happiness is based on the people's evaluation of "how life is" compared with "how life should be" (or some standards). While such standards can change, there are mainly two variants of this comparison theory. One is "lifetime comparison", which suggests that people evaluate their situations with their past experiences. For example, Brickman, Coates and Janoff-Bulman (1978) show that extreme experience of happiness (winning a lottery) or pains (suffering from an accident) affect people's future judgment of happiness. The other is "social comparison", which suggests that people compare their personal status with that of other people. Festinger (1954) first comes up with the notion of social comparison. He argues that people turn to social evaluation when there is no objective way of evaluation. Further studies on this topic propose other incentives for social comparison such as self-satisfaction, effective social communication and efficient cognition (Corcoran, Crusius and Mussweiler, 2011). The idea of social comparison has been applied in many economic and social topics, such as consumer behaviour (Argo, White and Dahl, 2006) and organizational decision making (Damisch, Mussweiler and Plessner, 2006).

The social comparison theory can work in our case. Specifically, investors can compare local AQI with that of other cities when evaluating air quality. Indeed, *AQI_deseasoned* and *Poor1* we use earlier already involve some comparison. The de-seasoned approach assumes that people compare the daily local air quality with a "normal level" while *Poor1* suggests that people compare the air quality with some pre-determined standards. Both procedures are based on local air quality data alone and do not reflect potential social comparison. Comparing local air quality with that of other cities is reasonable for two reasons. First, such a comparison follows the approach suggested by the social comparison theory. Second, it is easy to conduct such a comparison as the data needed are easy to obtain. Specifically, we propose the following two relative air quality measures.

First, we define *AQI_de_overall* which is the difference between local AQI and a weighted average AQI of 31 provincial capital cities. This measure compares local air quality with the general level of air quality across the whole country. Our earlier descriptive results show that the correlation coefficients of AQIs between two closely located cities are high. Therefore, the AQI of a provincial capital city can be a reasonable proxy for the air quality of that province. While there is theoretical and empirical evidence to social comparison theory, there is no universal conclusion on proper comparison groups. Berkowitz (1972) points out that the intimacy of the association with the reference group, the similarity of oneself to the reference group and the attractiveness of the reference groups are the main determinants of the choice of to whom people compare their own status. In accordance with Berkowitz (1972), we use an attention-based weighted average AQI instead of a simple average. The idea is that, when people are evaluating the general level of air quality of the whole country, they pay different attention to different cities. We use Baidu Search Index to proxy for the attention paid to air quality in various cities. Specifically, we obtain the Baidu Search Index of the key word "Air Quality" in each of the 31 provincial capital cities. The search index is available from January, 2011. Table 10 shows the percentage of Baidu Search Index for "Air Quality". We can see that the percentage of search index is generally higher for more developed cities (Beijing, Shanghai, Guangzhou, Xi'an) and lower for less developed cities (Xining, Lasa, Yinchuan). As our sample period is from 2001 to 2012, we used the average percentage of Baidu Search Index as the weights to calculate the overall air quality index.

Second, we define *AQI_de_Beijing* which is the difference between the local AQI and the AQI of Beijing. This measure compares local air quality with that of a single city, Beijing. *AQI_de_Beijing* can be seen as a special case of *AQI_de_overall*, which puts 100% weight on the AQI of Beijing. Using Beijing as a reference point is arbitrary but has some merits. First of all, it is simple and workable to compare local air quality with that of a target city. Indeed, Beijing is usually listed first in many weather/ environmental reports. Second, it is reasonable to use Beijing as the reference point because, as the capital of China, Beijing receives the most attention from both domestic and international media. From Table 10, we can see that the percentage of Search Index for "Air Quality" is the highest for Beijing and has grown even higher in 2013 and 2014. Third, according to an earlier analysis (Table 3), Beijing is located in the region with the most serious air pollution problem, which can further increase the attention people pay to the air quality of Beijing.

Table 3, Figures 1-1 and 1-2 show that the air quality in Beijing is worse than that of Shanghai and Shenzhen in general, however, *AQI_de_Beijing* is not always negative. Table 11 presents descriptive statistics of *AQI_de_Beijing*. Indeed, 29.26% of trading days in Shanghai and 16.74% of trading days in Shenzhen experience air quality worse than that of Beijing. We present in Figures 3-1 and 3-2 histograms of the percentage of days with positive *AQI_de_Beijing* each year and find that there is no declining trend.

We then conduct a joint test of whether people use relative air quality measures to form their perceived air quality, and whether the perceived air quality affects investors' trading decisions and therefore stock prices. Using *AQI_de_overall* and *AQI_de_Beijing* as our new air quality measures, we perform univariate and multivariate regression analyses. Results are reported in Table 12 and Table 13.

Panel A, Table 12 is based on *AQI_de_overall*. We can see that the differences in value weighted average daily stock market returns are both positive but only significant for $10^{th} - 90^{th}$ (diff. = 0.0020, t = 1.8545, for $10^{th} - 90^{th}$; diff. = 0.0006, t = 0.869 for $25^{th} - 75^{th}$). When we partition the sample according to *AQI_de_Beijing* (Panel B, Table 12), the differences are positive and significant in both. Specifically, the mean market returns when *AQI_de_Beijing* is lower than the 10^{th} percentile is 0.0026 (t = 2.3706), higher than the mean when *AQI_de_Beijing* is higher than the 90th percentile. The difference is eight times the full sample mean. Even when we compare stock market returns between less extreme air quality groups (25th and 75th percentiles), the difference is still significant (0.0014, t = 2.0760).

Multivariate regression results are consistent with univariate analysis. Panel A, Table 13 reports results when *AQI_de_overall* is used as the air quality measure. In the OLS model, the coefficient on *Change_AQI_de_overall* is negative and significant (-0.00138, t = -1.67) but the coefficient on *AQI_de_overall* is insignificant(-0.00085, t = -0.94). In the Logit model, the coefficients on *AQI_de_overall* and *Change_AQI_de_overall* are both negative but not significant (-0.15888 and z = -1.48 for *AQI_de_overall* and -0.14641, z = -1.41 for *Change_AQI_de_overall*).

Panel B presents coefficients on *AQI_de_Beijing*. The coefficients on *AQI_de_Beijing* and *Change_AQI_de_Beijing* are both negative and significant in the OLS model (-0.00084, t = -2.19 for *AQI_de_Beijing* and -0.00075, t = -2.32 for *Change-_AQI_de_Beijing*). When we estimate the Logit model, the coefficients are also negative and significant (-0.14381, z = -3.12 for *AQI_de_Beijing* and -0.08313, z = -1.96 for *Change_AQI_de_Beijing*).

We also perform OLS and Logit regressions using *AQI_de_Beijing* on weekly and monthly basis and the results are reported in Table 14. The coefficients on *AQI_de_Beijing* are significantly negative while *Change_AQI_de_Beijing* is not significantly associated with stock market returns on weekly and monthly basis.

The impact of *AQI_de_Beijing* is economically significant. We know from Table 12 that the mean daily stock market returns for our whole sample is 0.03%. Base on the coefficient in Column (1) of Panel B, Table 13, when *AQI_de_Beijing* increases by 10 points (before being scaled by 100), the weighted average daily stock market return decreases by 0.0084% on average, which is about a fourth of the of sample mean. The market value of Shanghai (Shenzhen) A-Share Stock Exchange is about RMB 15,000 (3,500) billion at the end of 2013. A 0.0084% reduction in the daily stock market return translates into a reduction in market capitalization of RMB 1.26 (0.3) billion in the Shanghai (Shenzhen) A-Share Stock Exchange.

Earlier, we have used a discontinuity design to determine whether the market reacts to *AQI_raw* differently around artificial cutoff points. Given that the value of 0 for *AQI_de_Beijing* can serve as a critical point which affects people's attitudes toward air quality, we use *AQI_de_Beijing* = 0 as a cutoff. As air pollution in Beijing is usually severe, seeing a local AQI even higher than that of Beijing can make people feel bad. If this is the case, then stock market returns can be different within a narrow band just above or below *AQI_de_Beijing* of 0. Accordingly, we apply the discontinuity model and set *Poor2* to 1 when *AQI_de_Beijing* is positive and 0 otherwise. We also control for Month and Year effects and the Market Type.

Results are presented in Table 15. We first estimate Model (2) using the full sample in Column (1). The coefficient of *AQI_de_Beijing* is negative and significant (-0.00084, t = -2.19). Then we use subsamples where the air quality measure falls into small intervals around the critical point of 0 ([-15, 15], [-20, 20] and [-25, 25]) and estimate Model (3). In Columns (2) to (4), we exclude *AQI_de_Beijing*^{2} and the coefficients on *Poor2* are negative and significant (-0.00467, t = -2.31 for [-15, 15]; -0.00330, t = -1.90 for [-20, 20] and -0.00319, t = -2.04 for [-25, 25]). Columns (5) to (8) present results for the quadratic model. The coefficients on *Poor2* are negative and significant for all subsamples (-0.00497, t = -2.45 for [-15, 15]; -0.00392, t = -2.22 for [-20, 20] and -0.00360, t = -2.26 for [-25, 25]).

Results in Table 15 suggest that there exists a reduction in daily stock market returns when the local AQI goes from a level that is a little lower than that of Beijing to a level that is a little higher than that of Beijing. The impact of the jump in relative AQI around 0 on stock prices is economically significant. Using Column (2) for example, the coefficient on *Poor2* in Column (2) is -0.00467, while the mean of the value-weighted average stock market returns in this AQI region is about -0.00056. Therefore, the reduction in stock prices due to the AQI jump around the critical point is more than eight times the mean sample stock return. Using the market value of Shanghai (Shenzhen) A-Share Stock Exchanges at the end of 2013 of RMB 15,000 (3,500) billion, a -0.467% change in stock market returns translates into a reduction in market capitalization of RMB 70 (16.4) billion in Shanghai (Shenzhen) A-Share Stock Exchange.

Results in Table 15 are consistent with our findings in Table 13 and Table 14. On the one hand, these results support that *AQI_de_Beijing* is a reasonable measure which captures how people evaluate air quality. On the other hand, the reduction stock market returns within small intervals around the critical point further confirms that it is the relative air quality (relative to Beijing) that affects stock prices.

4.3. Further evidence

4.3.1. Reversal of market returns

Tetlock (2007) investigate the predictability of pessimistic information on the Dow Jones returns. He finds that lagged-one-day negative media pessimism is associated with lower market prices, but the influence reverses to fundamentals in the following trading week. If the association between air quality and stock prices comes from a sentiment effect that air quality has on investors, it would be important to find out whether the market can shed some of the negative impact of air quality in earlier periods and adjust for the mispricing in subsequent periods. Following Tetlock (2007), we estimate the following model to determine whether the impact of air quality on stock market returns reverses in subsequent periods:

$$R_t = a_0 + a_1 AQI_t + a_2 Lag1\_AQI + a_3 Lag2\_AQI + a_4 Lag3\_AQI + a_5 Lag4\_AQI \\ + a_6 Lag1\_R + a_7 Lag2\_R + a_8 Lag3\_R + a_9 Lag4\_R + a_{10} Lag1\_Vol$$

$$+ a_{11}Lag2\_Vol + a_{12}Lag3\_Vol + a_{13}Lag4\_Vol + \varepsilon_t. \quad (4)$$

In Model (4), R_t is the weighted average stock market return in Period t and AQI_t is the air quality measure in Period t. *LagN_AQI* is the Nth lag of *AQI*, *LagN_R* is the Nth lag of weighted average stock market return and *LagN_Vol* is the Nth lag of total number of shares traded on the stock exchange. We estimate Model (4) on daily, weekly and monthly basis and the coefficients are reported in Table 16. In Column (1), we include only AQI_t and lags of *AQI*. In Column (2), the full model is used.

In Table 16, the coefficients on lagged *AQI_de_Beijing* are not significant in the daily and weekly regressions. The coefficient on *AQI_de_Beijing* in the weekly model becomes insignificant when lagged variables are added. However, when we estimate the model on a monthly basis, Panel C, Table 16 shows that the coefficients on lagged 3 *AQI_de_Beijing* are significantly positive in both model specifications (0.06402, t = 2.26 in Column (1) and 0.07373, t = 2.87 for Column (2)).

To conclude, results of the reversal model suggest that, the impact of air quality on stock prices do not reverse in the short run. In the long run, however, there is some evidence that the impact reverses in about three months.

4.3.2. Air quality and trading volume

Prior studies in this strand of literature also explore the impact of environmental conditions on trading volume. Loughran and Schultz (2004) use extreme weather conditions and trading volume of stocks in different areas to provide evidence of localized trading behavior. They show that when there is some extreme weather (such as a blizzard), trading volume of local stocks decreases significantly. Chang, Chen, Chou and Lin (2008) use TAQ data to investigate the intraday trading pattern of the association between NYSE and cloud cover in the New York City. They find that in the first 15 minutes of a trading day, order imbalance is significantly positively correlated with cloud cover, suggesting that investors are more likely to sell when there lacks sunshine. However, the influence only lasts for a short period after the opening of trading. Goetzmann and Zhu (2005) use a special database which gives them access to individual investors' trades in five major US cities. They find that there is no significant association between individual investors' net buy volume or shares traded and the local weather condition.

As further understanding of the association between investors' trading behavior and air quality requires trading data, we use the daily total trading volume of Shanghai or Shenzhen A-share market to examine how air quality affects trading volume. Specifically, we estimate the following model:

$$\begin{aligned} Ln(Vol)_t \text{ or } Ln(Shares)_t = {} & a_0 + a_1 AQI + a_2 AbsR_t + a_3 Lnsize_t + a_4 BV \\ & + a_5 Lqvol_t + a_6\, L5dvol_t + a_7\, LMR_t + \mathcal{E}_t, \end{aligned} \tag{5}$$

where $Ln(Vol)_t$ is the natural logarithm of total trading volume in Shanghai or Shenzhen Stock Exchange on Day t and $Ln(Shares)_t$ is the natural logarithm of total traded shares on Day t. We use *AQI_de_Beijing* as the air quality measure. We control for the absolute value of daily stock market return $AbsR_t$, the natural logarithm of total market value of all stocks in the stock exchange $Lnsize_t$ and the total book value of all firms BV_t. We also include some liquidity related variables (Gao, Li and Yeung, 2012; Chordia, Roll and Subrahmanyam, 2001). $Lqvol_t$ is the volatility of stock market returns during the preceding quarter, $L5dvol_t$ is the volatility of stock market returns during the preceding 5 days, and LMR_t is the stock market return during the preceding month.

Table 17 shows the results of estimating Model (5). Column (1) uses $Ln(Vol)$ as the dependent variable and the coefficient on *AQI_de_Beijing* is negative and significant (-0.02112, t = -2.48). When $Ln(Shares)$ is used as the dependent variable, the coefficient on *AQI_de_Beijing* is also negative and significant in Column (2) (-0.01780, t = -2.22). To conclude, it appears that the total stock market trading volume is negatively associated with air quality measured as *AQI_de_Beijing*.

4.4. Economic condition?

Our previous empirical results support that *AQI_de_Beijing* can be a good measure for perceived air quality and that the perceived AQI is negatively associated with the stock prices. However, before we conclude that the association is caused by a sentiment effect of perceived air quality, we need to rule out the possibility that it is caused by changes in economic fundamentals due to air quality. If, for example, heavily polluted air prevents people from going out and conducting economic activities, the performance of the retail industry can be negatively affected and the association between air quality and stock market returns can then reflect the impact of air quality on cash flows, instead of a behavior bias. Though the reduction in stock market returns we find in Table 15 suggests that market reacts differently to the signs of *AQI_de_Beijing* within a small region around *AQI_de_Beijing* of 0, it does not directly support our mood-based story unless it is accompanied by evidence that other firm-value related factors are continuous around the critical point. Here, we show evidence that the reduction stock market returns in Table 15 is not caused by fundamentals.

We conduct the following test. First, for every quarter, we calculate an accounting performance based ratio for each stock exchange as follows:

$$Ratio_q = \sum_{i=1}^{n} Performance_{iq} / \sum_{i=1}^{n} Totalassets_{iq},$$

where $Performance_{it}$ is the performance-based accounting number of Firm i in Quarter q. We use the following four performance-related accounting measures: total profit, operating revenue, operating expense, and operating profit. Then we estimate the following model:

$$Ratio_t = a_0 + a_1 AQI_t + a_2 Poor2 + a_3 AQI_t^2 + \varepsilon t, \quad (6)$$

which is similar to Model (3) except that we use $Ratio_t$ to replace the daily stock market return R_t. Note that $Ratio_t$ is quarterly based while *AQI* and *Poor2* are daily based.

Table 18 presents results when we use the ratio of total profit to total assets as the performance measure. Other three performance measures produce similar results. We observe that none of the coefficients on *Poor2* are significantly negative, and many of these coefficients are even positive (though not significant) (-0.00002, t = -0.01 for [-15, 15], excluding $AQI\_de\_Beijing^2$; 0.00020, t = 0.12 for [-20, 20], excluding $AQI\_de\_Beijing^2$; 0.00108, t = 0.73 for [-25, 25], excluding $AQI\_de\_Beijing^2$; 0.00019, t = 0.09 for [-15, 15]; -0.00011, t = -0.07 for [-20, 20] and 0.00070, t = 0.48 for [-25, 25]). These results suggest that the reduction in stock prices due to local AQI exceeding Beijing AQI (Table 15) is unlikely to be caused by some air quality related jump in economic fundamentals. Based on results in Table 15 and Table 18, we attribute the association between relative air quality and stock prices to the sentiment effect and behavior bias proposed in Saunders (1993).

4.5. Additional tests

4.5.1. Are institutional investors less affected?

Institutional investors, often seen as sophisticated investors, could be less affected by air pollutions. CSMAR provides information on the top-10 tradable-share shareholders and the numbers of shares they hold for each listed firm. We calculate the ratio of the number of shares held by institutional investors divided by the number of tradable shares outstanding and use this ratio as a rough estimate of institutional ownership of tradable shares.[5] We then construct two portfolios based on the institutional ownership ratio. If a firm's institutional ownership ratio is larger than the sample median, it is partitioned into the "High institutional ownership" group. Otherwise, it is in the "Low institutional ownership" group. We rebalance at the beginning of each quarter as the top-10 tradable-share shareholders' information is released quarterly. The basic idea for

[5] We use tradable shares instead of all shares outstanding because before the "Tradable Share Reform" there are a large number non-tradable shares for Chinese listed companies.

this partitioning is that the higher the level of institutional ownership, the more likely that the marginal investor is an institutional investor. To the extent that institutional investors are more sophisticated, the association between stock prices and air quality should be lower for the "High institutional ownership" group. We calculate market value-weighted daily portfolio returns, *Vwdreturn*, for both portfolios and re-estimate Model (2) for the "High institutional ownership" group and the "Low institutional ownership" group, respectively. Note that the sample period starts from 2012, when the top-10 tradable-share shareholder information was first available.

Results are reported in Table 19. The coefficients on air quality measures are significantly negative in all model specifications (-0.00100, t = -2.13 in Column (1), -0.00191, t = -2.28 in Column (2), -0.00095, t = -2.37 in Column (3) and -0.00195, t = -2.65 in Column (4)). Though the magnitudes of the coefficients on air quality measures for the "High institutional ownership" group are smaller than those for the "Low institutional ownership" group (about one half in magnitude), F-tests show that the coefficients on air quality measures between two portfolios are not significantly different (0.89, p = 0.3455 for Column (1) versus Column (2) and 1.41, p = 0.2352 for Column (3) versus Column (4)). Therefore, institutional investors also appear to be affected by air quality while making investment and trading decisions.

4.5.2. Other tests

We divide our sample into two periods, 2001 – 2005 and 2006-2012, and re-estimate Model (2) to determine how the association between air quality and stock market returns changes over time. In un-tabulated analysis, we find that the coefficients on *AQI_de_Beijing* are not significantly different between these two periods.

Table 3, Panel B suggests that the seasonal pattern of *AQI_raw* for Beijing is a little different from other cities. Our relative air quality measure *AQI_de_Beijing* may be affected by a difference in seasonal patterns. To determine whether the negative association between stock market returns and *AQI_de_Beijing* is sensitive to this potential problem, we adjust *AQI_de_Beijing* for the sample mean of all observations in the same week across 12 years and re-estimate model (2) using the de-seasoned *AQI_de_Beijing*. Un-tabulated results are qualitatively the same and the magnitudes of the coefficients are similar.

5. Summary and conclusion

We examine whether and to what extent air quality affects stock prices in China, where the air pollution problem attracts worldwide attention. We first use the raw and de-seasoned air quality index as air quality measures but find that AQI has little impact on stock returns. We further conduct a discontinuity research design which restricts our sample to observations of AQI lying just below or above the critical point of air quality classification and re-examine the impact of AQI on stock prices. Again, we find limited evidence that AQI classification affects stock prices.

We then use some relative air quality measures based on the social comparison theory to determine if these measures catch investors' perceived air quality. We find that the difference in local AQI and Beijing AQI best captures how people digest and evaluate air quality information. Our results show that a positive difference between local and Beijing AQIs is associated with a lower stock market return and a lower possibility of positive stock market return. Our further discontinuity test suggests that there is a reduction in stock market returns when local AQI goes from slightly below to slightly above AQI of Beijing. The reduction in stock prices due to the jump in relative AQI is more than eight times that of the sample mean stock returns which translates into billions of yens worth of losses on the Shanghai and Shenzhen Stock Exchanges on a single day.

We also find a reversal in returns in the long run. In addition, we discover that daily trading volume is negatively associated with the relative AQI. These findings further support the argument that the relative AQI matters for stock prices and investor trading behavior. We also show that the association between the relative AQI and stock returns is unlikely to be driven by economic fundamentals. Therefore, we attribute the air pollution effect on stock return, if any, to investors' behavioral bias associated with the *perceived* air quality.

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Appendix: Variable definitions

Variables	**Definition**
AQI_Raw	MEPC reported local Air Quality Index
AQI_deseasonal	MEPC reported local Air Quality Index minus the mean of AQI for the same week in a year
AQI_de_overall	MEPC reported local Air Quality Index minus the attention weighted average AQI of 31 capital cities
AQI_de_Beijing	MEPC reported local Air Quality Index minus AQI of Beijing
AQI_Raw^2	the square term of *AQI_Raw*
$AQI\_de\_Beijing^2$	the square term of *AQI_de_Beijing*
Change_AQI_Raw	*AQI_Raw* on day *t* minus *AQI_Raw* on day *t*-1
Change_AQI_deseasoned	*AQI_deseasoned* on day *t* minus *AQI_deseasoned* on day *t*-1
Change AQI_de_overall	*AQI_de_overall* on day t minus *AQI_de_overall* on day *t*-1
Change AQI_de_Beijing	*AQI_de_Beijing* on day *t* minus *AQI_de_Beijing* on day *t*-1
Dretwdtl	Daily market value weighted average stock return of a stock exchange
Dpos	Indicator variable that equals 1 if *Dretwdtl* > 0 and 0 otherwise
Wretwdtl	Weekly market value weighted average stock return of a stock exchange
Wpos	Indicator variable that equals 1 if *Wretwdtl* > 0 and 0 otherwise
Mretwdtl	Monthly market value weighted average stock return of a stock exchange
Mpos	Indicator variable that 1 if *Mretwdtl* > 0 and 0 otherwise
Dnshrtrdtl	Daily total number of shares traded on a stock exchange
Wnshrtrdtl	Weekly total number of shares traded on a stock exchange
Mnshrtrdtl	Monthly total number of shares traded on a stock exchange
Lag n Variable	Lagged n period value of a certain variable
Poor1	Indicator variable that equals 1 if *AQI_Raw* > 100 and 0 otherwise
Poor2	Indicator variable that equals 1 if *AQI_de_Beijing* > 0 and 0 otherwise
Profit Ratio	Total profits of all firms on a stock market divided by total assets of all these firms
$AbsR_t$	Absolute value of *dretwdtl*
Lnsize	Natural logarithm of total market value of all stocks in a stock exchange
BV	Total book value of all firms in a stock exchange
$Lqvol_t$	Volatility of stock market returns during the preceding quarter
$L5dvol_t$	Volatility of stock market returns during the preceding 5 days
LMR_t	Stock market return of the previous month
Ln(Vol)	Natural logarithm of total trading volume
Ln(Shares)	Natural logarithm of total trading shares

Figure 1-1: Yearly mean of AQI in three cities from 2001 to 2012

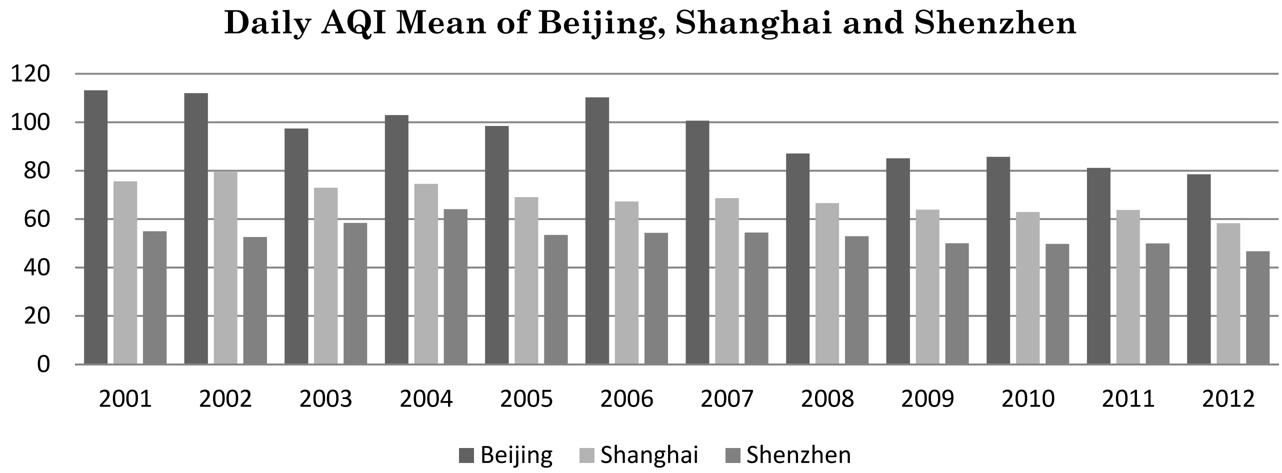


Figure 1-2: Yearly percentage of days when AQI is larger than 100 (classified as unhealthy) from 2001 to 2012

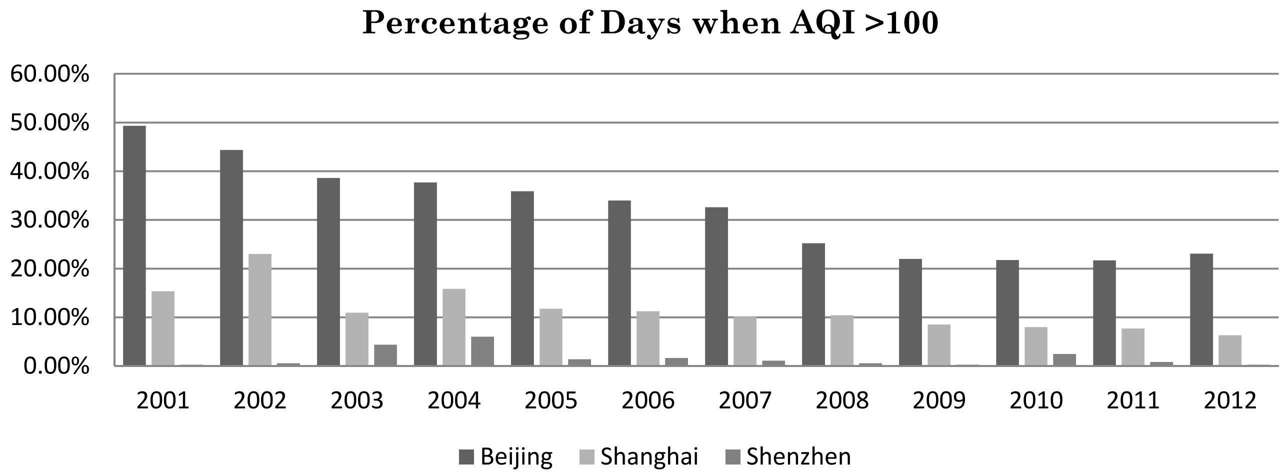


Figure 2-1: Daily AQI distribution of Beijing from 2001.1.1 to 2012.12.31, based on MEPC data.

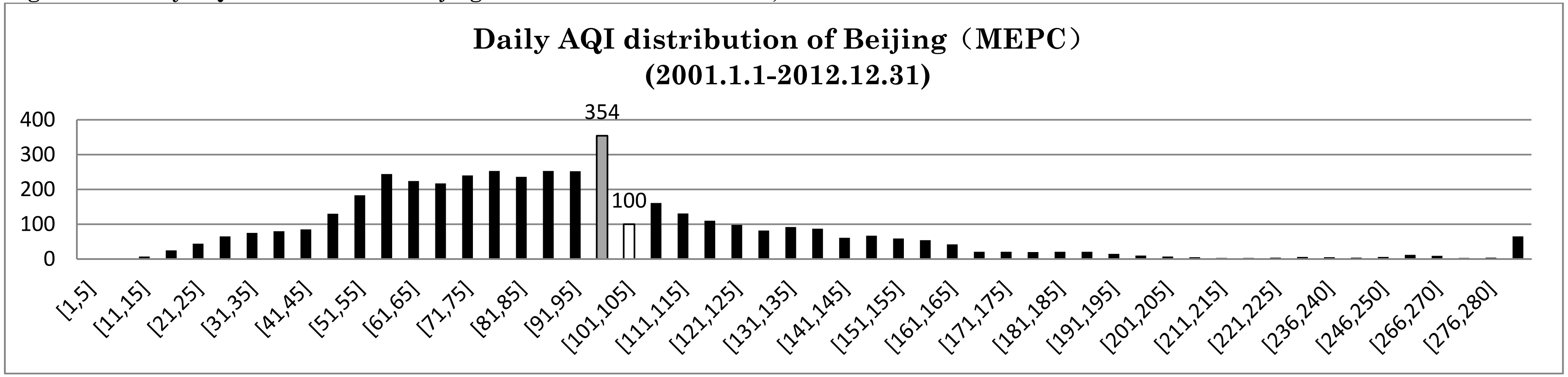


Figure 2-2: Hourly AQI distribution of Beijing from 2008.4.8 to 2012.12.31, based on US Embassy data.

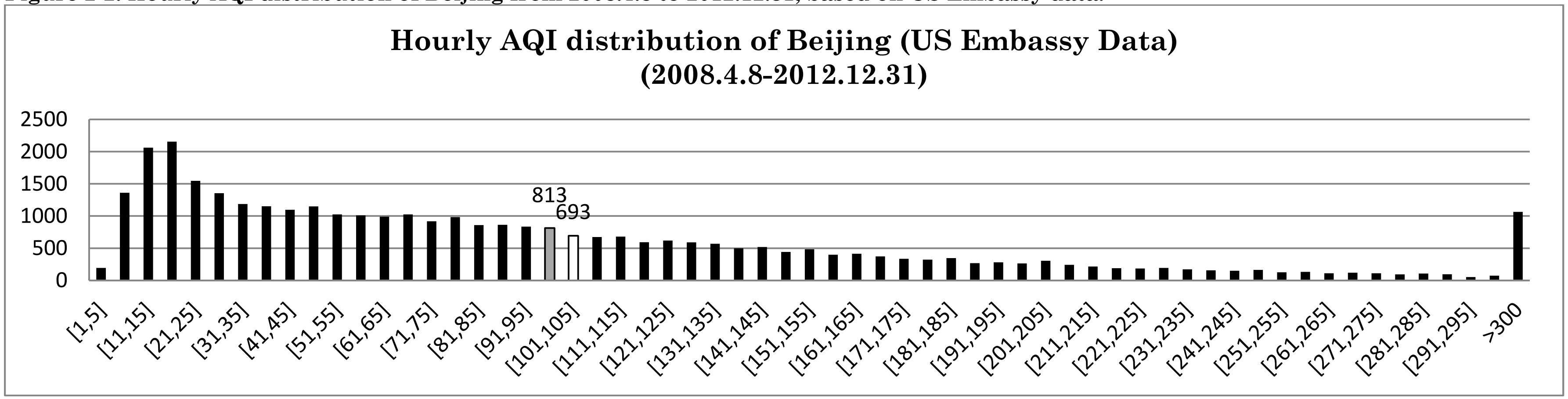


Figure 2-3: Daily AQI distribution of Beijing from 2008.4.8 to 2012.12.31, based on MEPC data.

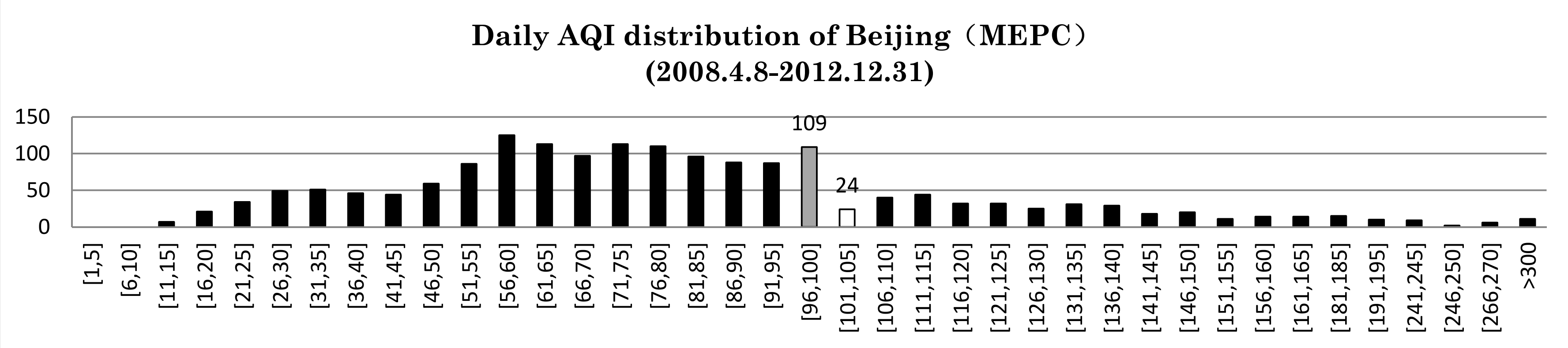
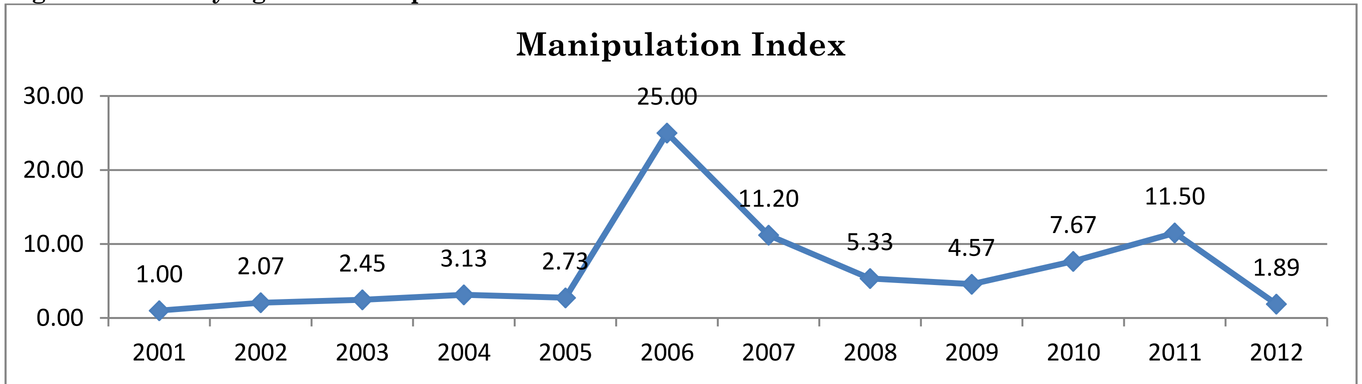


Figure 2-4: Yearly figure of Manipulation Index.



*Manipulation Index is calculated as the frequency of AQI in [96,100] divided by the frequency of AQI in [101,105]

Figure 3-1: The percentage of days with positive *AQI_de_Beijing* each year in Shanghai

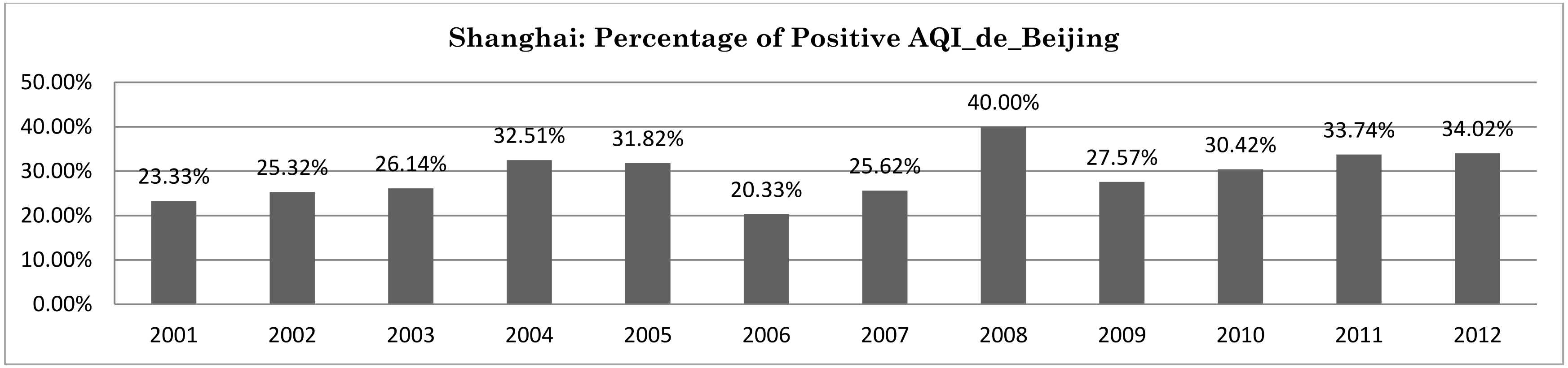


Figure 3-2: The percentage of days with positive *AQI_de_Beijing* each year in Shenzhen

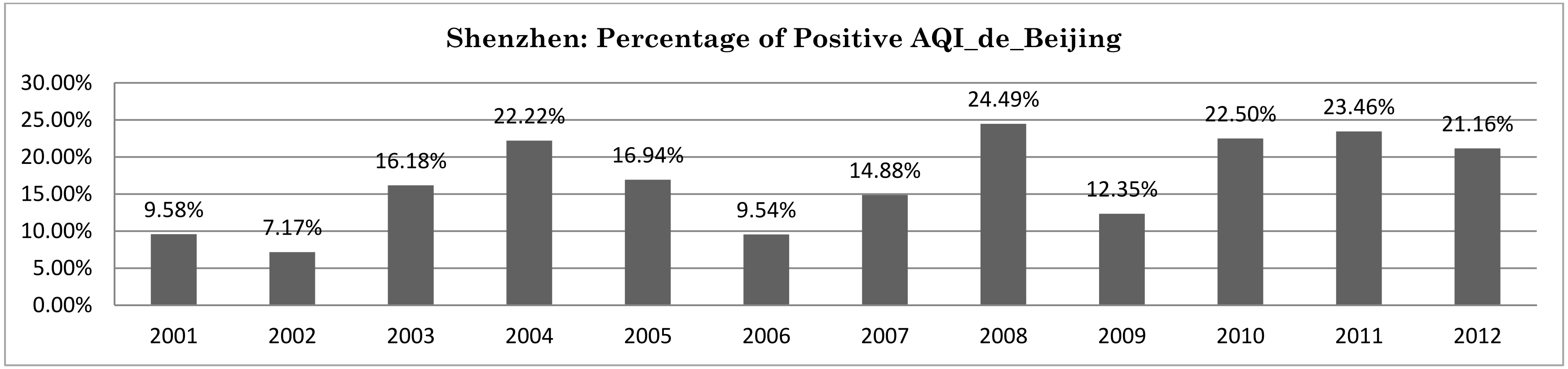


Table 1: MEPC classification of Air Quality Index
This table presents MEPC's classification of AQI Quality Index based on the old criteria we use in this paper. When AQI is higher than 100, the air quality is labelled as "unhealthy".

Range	Class
0-50	Excellent
51-100	Good
101-150	Slightly polluted (unhealthy)
151-200	Lightly polluted
201-250	Moderately Polluted
251-300	Heavily Polluted
300+	Severely Polluted

Table 2: Number of Cities available in the MEPC Air Quality Index database

	Periods	Number of Cities
Hourly Air Quality Data under New Standards	Real Time	161
Daily Air Quality Data under New Standards	2014.1.1 - now	161
Daily Air Quality Data under Old Standards	2000.6.5 - 2001.6.4	42
	2001.6.5 - 2004.6.3	47
	2004.6.4 - 2005.12.31	84
	2006.1.1 - 2011.2.10	86
	2011.2.11 - 2013.1.14	120
	2013.1.15 - 2013.3.26	68
	2013.3.27 - 2013.4.19	64
	2013.4.20 - 2013.12.31	62

*Number of cities covered by the old standards in 2013 decreased because some main cities switched to the new standards which include PM 2.5 starting from January, 2013.

Table 3: Summary statistics of Air Quality Index in major cities

In this table we present the summary statistics of Air Quality Index (old criteria) of 32 main cities (capital cities of each province plus Shenzhen, where one of the stock market exchanges is located) from 2001.1.1 to 2012.12.31. We divide the 32 cities into 7 geographic regions. Panel A reports the number of observations, mean, standard deviation, minimum and maximum number of AQI for each city. Panel B reports the mean and maximum value of AQI in four quarters for each city.

		PanelA:2001-2012					PanelB:QuarterFeatures							
							Quarter1		Quarter2		Quarter3		Quarter4	
District		Obs	Mean	STD	Min	Max	Mean	Max	Mean	Max	Mean	Max	Mean	Max
NorthEast	Changchun	4371	72.5548	26.9367	13	500	82.7250	405	70.5221	500	58.5050	124	78.6682	280
	Haerbin	4371	79.8749	35.6634	20	500	91.3630	500	76.3428	500	63.8141	132	88.1936	308
	Shenyang	4371	88.7483	35.5493	13	500	100.3407	500	87.0129	500	76.8141	196	91.0500	299
North	Beijing	4371	96.1272	55.4143	12	500	99.6528	500	104.3722	500	80.4452	197	100.2355	500
	Huhehaote	4371	74.4750	43.9040	12	500	87.3982	500	74.7721	500	56.7171	216	79.2991	500
	Shijiazhuang	4371	94.2462	45.2747	12	500	104.9889	413	90.3511	500	76.2131	166	105.6336	500
	Taiyuan	4371	94.1698	45.8173	11	457	106.7380	397	89.0515	457	75.2729	181	105.8409	400
	Tianjin	4371	84.2713	37.4551	14	500	91.5083	500	85.8897	500	69.3155	138	90.5618	407
NorthWest	Lanzhou	4371	113.0631	77.3662	12	500	142.4861	500	104.5735	500	76.0481	495	129.6882	500
	Wulumuqi	4371	103.0668	78.5995	14	500	154.4519	500	72.4090	500	63.2647	136	122.8500	500
	Xian	4371	91.9122	34.6759	24	500	103.2222	462	84.6268	500	76.4207	255	103.5473	443
	Xining	4371	90.7021	51.5007	20	500	110.2926	500	93.3520	500	68.6437	500	90.9655	304
	Yinchuan	4371	77.3677	34.8630	22	500	91.6185	500	79.7151	500	59.7171	203	78.7527	169
East	Fuzhou	4371	58.6099	22.6311	0	500	63.7556	500	62.0257	140	49.7035	107	59.1100	139
	Hangzhou	4371	79.2796	30.7032	18	500	84.1213	500	78.2840	259	65.7525	150	89.0746	370
	Hefei	4371	79.5418	32.9254	9	500	81.7361	500	81.6011	500	65.1532	158	89.7782	385
	Jinan	4371	88.8538	33.9048	23	435	98.9778	435	89.0984	358	74.9393	218	92.6246	402
	Nanchang	4371	71.9973	27.7055	15	500	77.2315	500	67.6048	249	62.2611	131	80.9655	236
	Nanjing	4371	81.9012	33.6650	14	500	85.6370	500	86.4936	414	68.0553	173	87.5746	319
	Shanghai	4371	68.6131	34.4195	16	500	73.9750	500	69.9476	500	55.4116	155	75.2664	370
Mid	Changsha	4371	82.6543	35.5881	11	453	90.2787	453	78.0625	443	71.2276	189	91.1682	373
	Wuhan	4371	85.4448	32.5814	14	500	93.4741	500	83.9936	466	67.5431	154	96.9473	273
	Zhengzhou	4371	80.5974	26.6175	21	357	88.1657	318	79.5910	357	68.4433	142	86.3491	233
South	Shenzhen	4371	53.5207	21.2597	13	289	58.6750	289	45.3061	121	44.5032	118	65.6273	176
	Guangzhou	4371	64.3997	24.4994	14	303	69.9398	228	59.1682	167	57.8858	116	70.6664	303
	Haikou	4371	36.3079	13.2548	6	99	40.9852	84	31.9596	75	28.6800	95	43.6655	99
	Nanning	4371	56.8529	21.7501	12	174	61.9056	174	48.0689	116	47.6818	111	69.7764	133
SouthWest	Chengdu	4371	82.6280	30.3587	18	500	91.0028	282	79.7528	500	71.4479	168	88.4600	500
	Guizhou	4371	66.4793	22.7047	11	308	71.9907	187	63.6241	141	58.6183	144	71.7746	308
	Kunming	4371	61.7348	15.7581	19	146	66.1056	112	58.2960	108	56.7770	112	65.8164	146
	Lasa	4371	49.4955	21.3817	9	368	59.5111	242	50.6517	368	34.9991	81	53.0546	140
	Chongqing	4371	84.4786	31.4798	11	340	95.0815	300	83.5285	232	69.9048	162	89.6218	340

Table 4: Pearson correlations of AQI in difference cities

In this table we report the Pearson correlations of AQI of 32 cities with that of Beijing, Shanghai and Shenzhen. Correlations that are significant at 1% level are marked with *.

Cities	Beijing	Shanghai	Shenzhen
Shanghai	0.0992*		
Shenzhen	0.1280*	0.2612*	
Changchun	0.3545*	0.1500*	0.1695*
Haerbin	0.3078*	0.1425*	0.1713*
Shenyang	0.3719*	0.2081*	0.1543*
Huhehaote	0.4557*	0.2052*	0.1822*
Shijiazhua	0.5345*	0.1514*	0.2197*
Taiyuan	0.4658*	0.1994*	0.2888*
Tianjin	0.7009*	0.2143*	0.1857*
Lanzhou	0.2141*	0.2758*	0.2594*
Wulumuqi	0.0103	0.1503*	0.2211*
Xian	0.2914*	0.1827*	0.2626*
Xining	0.1799*	0.1929*	0.1625*
Yinchuan	0.2869*	0.1884*	0.1746*
Fuzhou	0.1543*	0.3244*	0.3913*
Hangzhou	0.1987*	0.6577*	0.4114*
Hefei	0.1527*	0.4777*	0.3162*
Jinan	0.3118*	0.2471*	0.2106*
Nanchang	0.1928*	0.4493*	0.4627*
Nanjing	0.2226*	0.6170*	0.2989*
Changsha	0.2170*	0.3960*	0.4402*
Wuhan	0.2178*	0.4492*	0.4590*
Zhengzhou	0.3576*	0.2592*	0.2572*
Guangzhou	0.1656*	0.1791*	0.6144*
Haikou	0.0740*	0.1749*	0.5381*
Nanning	0.1361*	0.2068*	0.6035*
Chengdu	0.1545*	0.2269*	0.2999*
Guizhou	0.1659*	0.2530*	0.4074*
Kunming	0.1154*	0.1604*	0.3284*
Lasa	0.1185*	0.1415*	0.1302*
Chongqing	0.1933*	0.3223*	0.4105*

Table 5: Comparison of AQI for different periods for Beijing, Shanghai and Shenzhen

In this table, we calculate and compare the sample means of AQI for two sub-periods.

		Beijing	Shanghai	Shenzhen
	2001-2012	96.13	68.61	53.52
Daily AQI Mean	Period 1:2001-2006	105.75	73.17	56.34
	Period 2:2007-2012	86.40	64.04	50.65
Difference		19.35	9.12	5.68
t-value		11.73	8.84	8.92
p-value		< 0.0001	< 0.0001	< 0.0001

Table 6: Predictability of AQI, auto-regression

Table 6 shows the results of auto-regression of AQI in Beijing, Shanghai and Shenzhen. Panel A shows the results based on daily AQI, Panel B uses weekly average of AQI and Panel C uses monthly average AQI. *t*-values reported in parentheses are based on standard errors that are heteroskedasticity-robust. *, **, *** stand for significance at the 10%, 5% and 1% levels, respectively.

Panel A: Daily Autoregression									
	Beijing			Shanghai			Shenzhen		
Day t	AQI	AQI	AQI	AQI	AQI	AQI	AQI	AQI	AQI
Lag 1 AQI	0.49413	0.49410	0.49410	0.56702	0.57115	0.57135	0.72414	0.70784	0.70558
	(16.08)***	(14.56)***	(14.55)***	(14.51)***	(11.29)***	(11.29)***	(49.89)***	(33.50)***	(33.27)***
Lag 2 AQI		0.00005	-0.00799		-0.00728	-0.02279		0.02250	-0.04897
		(0.00)	(-0.32)		(-0.24)	(-0.69)		(0.99)	(-1.70)*
Lag 3 AQI			0.01627			0.02715			0.10090
			(0.90)			(1.36)			(4.72)***
_cons	0.49413	0.49410	0.49410	0.56702	0.57115	0.57135	0.72414	0.70784	0.70558
	(16.08)***	(14.56)***	(14.55)***	(14.51)***	(11.29)***	(11.29)***	(49.89)***	(33.50)***	(33.27)***
N	4376	4376	4376	4376	4376	4376	4376	4376	4376
adj. R-sq	0.244	0.244	0.244	0.321	0.321	0.322	0.524	0.525	0.529
Panel B: Weekly Autoregression									
Week t	AQI	AQI	AQI	AQI	AQI	AQI	AQI	AQI	AQI
Lag 1 AQI	0.34648	0.29252	0.25874	0.39621	0.35415	0.34527	0.61381	0.51275	0.50665
	(7.69)***	(6.32)***	(6.00)***	(7.65)***	(6.18)***	(6.12)***	(19.08)***	(12.61)***	(12.23)***
Lag 2 AQI		0.15657	0.09429		0.10590	0.07613		0.16337	0.14368
		(3.64)***	(2.15)**		(2.08)**	(1.43)		(3.92)***	(3.13)***
Lag 3 AQI			0.21466			0.08378			0.03788
			(4.75)***			(1.88)*			(0.90)
_cons	62.75002	52.87532	41.45506	41.57063	37.16665	34.05046	20.72974	17.37200	16.71937
	(15.56)***	(11.16)***	(7.74)***	(12.55)***	(10.81)***	(9.08)***	(12.26)***	(9.19)***	(8.23)***
N	636	636	636	636	636	636	636	636	636
adj. R-sq	0.119	0.139	0.177	0.156	0.164	0.168	0.377	0.393	0.393
Panel C: Monthly Autoregression									
Month t	AQI	AQI	AQI	AQI	AQI	AQI	AQI	AQI	AQI
Lag 1 AQI	0.45019	0.42793	0.43024	0.44013	0.45205	0.45020	0.58959	0.56387	0.57346
	(4.75)***	(4.04)***	(4.04)***	(6.55)***	(6.78)***	(6.70)***	(8.81)***	(6.99)***	(7.36)***
Lag 2 AQI		0.04970	0.07009		-0.02700	-0.00069		0.04312	0.18775
		(0.53)	(0.66)		(-0.29)	(-0.01)		(0.56)	(2.03)**
Lag 3 AQI			-0.04907			-0.05786			-0.25373
			(-0.62)			(-0.68)			(-3.09)***
_cons	52.73582	50.07482	52.62928	38.33057	39.36700	41.66390	21.86836	20.93376	26.24799
	(6.15)***	(5.20)***	(5.11)***	(8.28)***	(5.85)***	(6.11)***	(6.26)***	(5.49)***	(7.07)***
N	144	144	144	144	144	144	144	144	144
adj. R-sq	0.196	0.193	0.189	0.190	0.185	0.182	0.347	0.344	0.382

Table 7: Univariate analysis

This table shows the univariate analysis of daily stock market returns. We compare the sample mean of stock market returns when the air quality is in the top 10% (25%) percentiles with the sample mean of stock market returns when the air quality is in the bottom 10% (25%) percentiles. In Panel A, air quality is measured by *AQI_Raw*, In Panel B, air quality is measured by *AQI_deseasoned*.

Panel A: Univariate analysis based on *AQI_Raw*				
		Value-Weighted Average Full Sample Mean:0.0003		
Good Air Quality	*AQI_Raw* <= p10	0.0003	*AQI_Raw* <= p25	0.0001
Bad Air Quality	*AQI_Raw* >= p90	0.0007	*AQI_Raw* >= p75	0.0002
	dif	-0.0004	dif	-0.0002
	t	-0.3923	*t*	-0.2632
	p	0.6949	*p*	0.7924
Panel B: Univariate analysis based on *AQI_deseasoned*				
Good Air Quality	*AQI_deseasoned* <= p10	0.0003	*AQI_deseasoned* <= p25	0.0004
Bad Air Quality	*AQI_deseasoned* >= p90	-0.0003	*AQI_deseasoned* >= p75	0.0003
	dif	0.0006	dif	0.0001
	t	0.6279	*t*	0.1797
	p	0.5302	*p*	0.8574

Table 8: Air quality measures and daily stock market returns

Table 8 presents the regression results of model (2). Columns (1) and (2) present results for the OLS Model. Columns (3) and (4) present results for the logit model where the dependent variable is an indicator for positive stock market returns. We regress the stock market returns on air quality measures (Columns (1), (3)) and on change in air quality measures (Column (2), (4)). *t*-values reported in parentheses are based on standard errors that are heteroskedasticity-robust. *, **, *** stand for significance at the 10%, 5% and 1% levels, respectively. Air quality is measured by *AQI_Raw* and *AQI_deseasoned* in Panel A and B respectively.

Panel A: Stock Market Daily Return and *AQI_Raw*				
	OLS Model		Logit Model	
	(1)	(2)	(3)	(4)
VARIABLES	*Dretwdtl*	*Dretwdtl*	*Dpos*	*Dpos*
AQI_Raw	0.00066		0.11307	
	(0.84)		(1.16)	
Change_AQI_Raw		-0.00090		-0.05088
		(-1.10)		(-0.50)
Weekday Effect	Yes	Yes	Yes	Yes
Month Effect	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes
Market Indicator	Yes	Yes	Yes	Yes
Constant	-0.00072	-0.00015	0.03137	0.12743
	(-0.48)	(-0.11)	(0.19)	(0.87)
Observations	5796	5788	5796	5788
Adjusted R-squared	0.017	0.017		
pseudo R-sq			0.022	0.022

Panel B: Stock Market Daily Return and *AQI_deseasoned*				
	OLS Model		Logit Model	
	(1)	(2)	(3)	(4)
VARIABLES	*Dretwdtl*	*Dretwdtl*	*Dpos*	*Dpos*
AQI_deseasoned	0.00042		0.08372	
	(0.53)		(0.84)	
Change_ AQI_deseasoned		-0.00116		-0.07462
		(-1.40)		(-0.72)
Weekday Effect	Yes	Yes	Yes	Yes
Month Effect	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes
Market Indicator	Yes	Yes	Yes	Yes
Constant	-0.00019	-0.00014	0.12125	0.12821
	(-0.14)	(-0.10)	(0.83)	(0.88)
Observations	5796	5796	5796	5796
adj. R-sq	0.017	0.017		
pseudo R-sq			0.022	0.022

Table 9: Stock market returns around critical points

This table reports the results of model (3). Column (1) is based on model (2) and the full sample. Columns (2), (3) and (4) are based on model (3) while Columns (5), (6) and (7) contain a quadratic term of air quality measure. *t*-values reported in parentheses are based on standard errors that are heteroskedasticity-robust. *, **, *** stand for significance at the 10%, 5% and 1% levels, respectively. *AQI_Raw* is used as air quality measure. *AQI_Raw* = 100 is used as the critical point. *Poor1* equals 1 when *AQI_Raw* exceeds 100 and equals 0 otherwise. We use ±15, ±20, and ±20 around the *AQI_Raw* = 100 respectively to construct the subsamples

Stock market returns around critical points, based on *AQI_Raw*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dretwdtl	*Dretwdtl*	*Dretwdtl*	*Dretwdtl*	*Dretwdtl*	*Dretwdtl*	*Dretwdtl*
	Full Sample	[85,115]	[80,120]	[75,125]	[85,115]	[80,120]	[75,125]
Poor1		-0.00443	-0.00336	-0.00347	-0.00478	-0.00373	-0.00417
		(-1.63)	(-1.36)	(-1.56)	(-1.54)	(-1.33)	(-1.69)*
AQI_Raw	0.00063	0.02011	0.01300	0.01328	-0.03441	-0.01767	-0.02584
	(0.80)	(1.45)	(1.26)	(1.67)*	(-0.15)	(-0.15)	(-0.37)
AQI_Raw2					0.02842	0.01644	0.02123
					(0.24)	(0.26)	(0.57)
Year Effect				Controlled			
Month Effect				Controlled			
Market Indicator				Controlled			
Constant	-0.00143	-0.01777	-0.00979	-0.01036	0.00828	0.00443	0.00750
	(-1.04)	(-1.40)	(-1.00)	(-1.33)	(0.08)	(0.08)	(0.23)
Observation	5796	652	889	1131	652	889	1131
Adjusted R-square	0.015	0.014	0.009	0.012	0.018	0.010	0.010

Table 10: Percentage of Baidu Search Index from each city

Table 10 presents the percentage of Baidu Search Index for the key words "Air Quality" from 31 capital cities. For each city, the percentage is calculated as local search index divided by the sum of search index of 31 cities. Columns (1) to (4) report the percentage of search index for each year from 2011 to 2014. Column (5) reports the results based on data from 2011 to 2012.

		(1) 2011	(2) 2012	(3) 2013	(4) 2014 1.1-5.31	(5) 2011-2012
North East	Changchun	2.20%	2.18%	1.85%	1.76%	2.19%
	Haerbin	2.23%	2.12%	1.98%	1.77%	2.17%
	Shenyang	2.49%	2.57%	2.13%	2.17%	2.53%
North	**Beijing**	**11.63%**	**11.04%**	**20.46%**	**32.21%**	**11.33%**
	Huhehaote	1.23%	0.72%	1.24%	1.17%	0.98%
	Shijiazhuang	3.15%	2.40%	3.63%	2.87%	2.78%
	Taiyuan	2.97%	3.18%	2.16%	1.76%	3.08%
	Tianjin	4.95%	6.12%	4.16%	4.73%	5.53%
North West	Lanzhou	1.71%	1.99%	1.74%	1.45%	1.85%
	Wulumuqi	1.99%	2.46%	1.40%	1.41%	2.22%
	Xian	4.60%	4.58%	3.57%	2.48%	4.59%
	Xining	0.31%	0.25%	0.37%	0.47%	0.28%
	Yinchuan	0.35%	0.55%	0.64%	0.49%	0.45%
East	Fuzhou	2.28%	2.76%	2.09%	1.81%	2.52%
	Hangzhou	4.72%	4.81%	3.70%	2.89%	4.76%
	Hefei	2.61%	2.18%	2.28%	1.90%	2.39%
	Jinan	3.63%	3.36%	3.13%	2.60%	3.50%
	Nanchang	1.57%	1.78%	1.61%	1.47%	1.68%
	Nanjing	5.09%	4.46%	3.48%	2.45%	4.77%
	Shanghai	**10.14%**	**8.89%**	**14.12%**	**13.30%**	**9.52%**
Mid	Changsha	2.76%	2.69%	2.43%	2.02%	2.72%
	Wuhan	4.16%	4.30%	3.08%	2.21%	4.23%
	Zhengzhou	4.12%	3.75%	3.25%	2.17%	3.93%
South	Guangzhou	5.16%	5.29%	3.05%	2.49%	5.22%
	Haikou	1.04%	0.96%	1.44%	1.18%	1.00%
	Nanning	1.78%	3.45%	1.36%	1.29%	2.62%
South West	Chengdu	4.25%	4.62%	3.78%	2.92%	4.43%
	Guiyang	1.44%	1.52%	1.45%	1.15%	1.48%
	Kunming	1.89%	1.82%	1.72%	1.40%	1.85%
	Lasa	0.11%	0.06%	0.14%	0.11%	0.08%
	Chongqing	3.45%	3.14%	2.56%	1.89%	3.29%

Table 11: Summary statistics of the difference between local AQI and AQI of Beijing for Shanghai and Shenzhen

Table 11 reports the summary statistics of difference between local AQI and AQI of Beijing for Shanghai and Shenzhen. We group the daily difference of AQI into positive and negative groups in each city and calculate the mean, standard deviation and median of the difference.

		Obs	Percentage	Mean	Sd	Median
Shanghai	Local AQI > Beijing AQI	848	29.26%	32.66	38.03	24
	Local AQI < Beijing AQI	2050	70.74%	-52.25	52.89	-40
Shenzhen	Local AQI > Beijing AQI	485	16.74%	21.64	17.78	17
	Local AQI < Beijing AQI	2413	83.26%	-55.16	53.69	-44

Table 12 : Univariate analysis

This table shows the univariate analysis of daily stock market returns. We compare the sample mean of stock market returns when the air quality is in the top 10% (25%) percentiles with the sample mean of stock market returns when the air quality is in the bottom 10% (25%) percentiles. In Panel A, air quality is measured by *AQI_de_overall*. In Panel B, air quality is measured by *AQI_de_Beijing*.

		Value-Weighted Average Full Sample Mean:0.0003		
Panel A: Univariate analysis based on *AQI_de_overall*				
Good Air Quality	*AQI_de_overall* <= p10	0.0016	*AQI_de_overall* <= p25	0.0006
Bad Air Quality	*AQI_de_overall* >= p90	-0.0004	*AQI_de_overall* >= p75	0.0001
	dif	0.002	dif	0.0006
	t	1.8545*	*t*	0.869
	p	0.0639	*p*	0.3849
Panel B: Univariate analysis based on *AQI_de_Beijing*				
Good Air Quality	*AQI_de_Beijing* <= p10	0.0024	*AQI_de_Beijing* <= p25	0.0012
Bad Air Quality	*AQI_de_Beijing* >= p90	-0.0002	*AQI_de_Beijing* >= p75	-0.0003
	dif	0.0026	dif	0.0014
	t	2.3706**	*t*	2.0760**
	p	0.0179	*p*	0.038

Table 13: Air quality measures and daily stock market returns

Table 13 presents the regression results of model (2). Columns (1) and (2) present results for the OLS Model. Columns (3) and (4) present results for the logit model where the dependent variable is an indicator for positive stock market returns. We regress the stock market returns on air quality measures (Columns (1), (3)) and on change in air quality measures (Column (2), (4)). *t*-values reported in parentheses are based on standard errors that are heteroskedasticity-robust. *, **, *** stand for significance at the 10%, 5% and 1% levels, respectively. Air quality is measured by *AQI_de_overall* and *AQI_de_Beijing* in Panel A and B respectively.

Panel A: Stock Market Daily Return and *AQI_de_overall*

	OLS Model		Logit Model	
	(1)	(2)	(3)	(4)
VARIABLES	*Dretwdtl*	*Dretwdtl*	*Dpos*	*Dpos*
AQI_de_overall	-0.00085		-0.15888	
	(-0.94)		(-1.48)	
Change_ AQI_de_overall		-0.00138		-0.14641
		(-1.67)*		(-1.41)
Weekday Effect	Yes	Yes	Yes	Yes
Month Effect	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes
Market Indicator	Yes	Yes	Yes	Yes
Constant	-0.00040	-0.00017	0.08450	0.12480
	(-0.29)	(-0.13)	(0.57)	(0.86)
Observations	5794	5792	5794	5792
adj. R-sq	0.017	0.017		
pseudo R-sq			0.022	0.022

Panel B: Stock Market Daily Return and *AQI_de_Beijing*

	OLS Model		Logit Model	
	(1)	(2)	(3)	(4)
VARIABLES	*Dretwdtl*	*Dretwdtl*	*Dpos*	*Dpos*
AQI_de_Beijing	-0.00084		-0.14381	
	(-2.19)**		(-3.12)***	
Change_ AQI_de_Beijing		-0.00075		-0.08313
		(-2.32)**		(-1.96)*
Weekday Effect	Yes	Yes	Yes	Yes
Month Effect	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes
Market Indicator	Yes	Yes	Yes	Yes
Constant	-0.00038	-0.00018	0.09105	0.12550
	(-0.28)	(-0.13)	(0.62)	(0.86)
Observations	5796	5796	5796	5796
Adjusted R-squared	0.018	0.018		
pseudo R-sq			0.023	0.022

Table 14: Stock market returns and *AQI_de_Beijing*: weekly and monthly results

Table 14 reports regression results of model (2) on weekly and monthly basis. Month and market fixed effects are controlled. Air quality is measured by *AQI_de_Beijing*. Columns (1), (2), (5) and (6) present results of the OLS Model. Columns (3), (4), (7) and (8) present results of the logit Model where the dependent variable is an indicator for positive stock market returns. We regress stock market returns on air quality measurements (Columns (1), (3), (5), (7)) and change in air quality measures (Column (2), (4), (6), (8)). *t*-values reported in parentheses are based on standard errors that are heteroskedasticity-robust. *, **, *** stand for significance at the 10%, 5% and 1% levels, respectively.

	Panel A: Stock Market Weekly Return				Panel B: Stock Market Monthly Return			
	OLS Model		Logit Model		OLS Model		Logit Model	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	*Wretwdtl*	*Wretwdtl*	*Wpos*	*Wpos*	*Mretwdtl*	*Mretwdtl*	*Mpos*	*Mpos*
AQI_de_Beijing	-0.00560*		-0.378**		-0.0549**		-1.653**	
	(-1.77)		(-2.12)		(-2.14)		(-2.47)	
Change_AQI_de_Beijing		-0.00159		-0.219		-0.00606		-0.193
		(-0.61)		(-1.57)		(-0.27)		(-0.37)
Month Effect Market Effect	Controlled				Controlled			
Constant	0.00299	0.00372	0.307	0.350	-0.00172	0.00695	-0.389	-0.125
	(0.74)	(0.93)	(1.37)	(1.57)	(-0.09)	(0.36)	(-0.87)	(-0.29)
Observations	1212	1212	1212	1212	288	288	288	288
Adjusted R-square	0.008	0.006			0.015	0.002		
pseudo R-sq			0.017	0.015			0.070	0.055

Table 15: Stock market returns around critical points

This table reports the results of model (3). Column (1) is based on model (2) and the full sample. Columns (2), (3) and (4) are based on model (3) while Columns (5), (6) and (7) contain a quadratic term of air quality measure. *t*-values reported in parentheses are based on standard errors that are heteroskedasticity-robust. *, **, *** stand for significance at the 10%, 5% and 1% levels, respectively. *AQI_de_Beijing* is used as air quality measure. *AQI_de_Beijing* = 0 is used as the critical point. *Poor2* equals 1 when *AQI_de_Beijing* exceeds 0 and equals 0 otherwise. We use ±15, ±20, and ±20 around the *AQI_de_Beijing* =0 respectively to construct subsamples.

Stock market returns around critical points, based on *AQI_de_Beijing*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dretwdtl	Dretwdtl	Dretwdtl	Dretwdtl	Dretwdtl	Dretwdtl	Dretwdtl
	Full Sample	[-15,15]	[-20,20]	[-25,25]	[-15,15]	[-20,20]	[-25,25]
Poor2		-0.00467	-0.00330	-0.00319	-0.00497	-0.00392	-0.00360
		(-2.31)**	(-1.90)*	(-2.04)**	(-2.45)**	(-2.22)**	(-2.26)**
AQI_de_Beijing	-0.00084	0.01973	0.00740	0.00691	0.02186	0.01138	0.00910
	(-2.19)**	(1.62)	(0.96)	(1.23)	(1.78)*	(1.42)	(1.53)
AQI_de_Beijing²					0.00001	0.00001	0.00000
					(0.75)	(1.59)	(1.25)
Year Effect				Controlled			
Month Effect				Controlled			
Market Indicator				Controlled			
Constant	-0.00110	0.00116	0.00103	0.00013	0.00085	0.00059	-0.00110
	(-0.92)	(0.43)	(0.45)	(0.06)	(0.31)	(0.25)	(-0.92)
Observation	5796	1201	1608	1996	1201	1608	1996
Adjusted R-square	0.016	0.022	0.015	0.012	0.022	0.016	0.013

Table 16: Stock market returns and *AQI_de_Beijing*: the reversal model

This table shows results of the reversal model. We regress stock market returns on current and lagged *AQI_de_Beijing*. We also controlled for lagged stock market returns and lagged trading volumes in Column(2). *t*-values reported in parentheses are based on standard errors that are heteroskedasticity-robust. *, **, *** stand for significance at the 10%, 5% and1% levels, respectively. Panel A presents results on a daily basis, Panel B on a weekly basis and Panel C on a monthly basis.

Panel A: Reversal model on daily basis

	(1) *Dretwdtl*	(2) *Dretwdtl*
AQI_de_Beijing	-0.00121	-0.00123
	(-3.01)***	(-3.02)***
Lag 1 AQI_de_Beijing	0.00038	0.00040
	(0.90)	(0.95)
Lag2 AQI_de_Beijing	0.00032	0.00021
	(0.76)	(0.51)
Lag3 AQI_de_Beijing	-0.00073	-0.00073
	(-1.56)	(-1.57)
Lag4 AQI_de_Beijing	-0.00037	-0.00038
	(-0.95)	(-0.99)
Lag 1 dretwdtl		0.02729
		(1.48)
Lag2 dretwdtl		-0.04251
		(-2.32)**
Lag3 dretwdtl		0.03865
		(2.00)**
Lag4 dretwdtl		0.03922
		(2.16)**
Lag 1 dnshrtrdtl		0.00000
		(3.67)***
Lag2 dnshrtrdtl		-0.00000
		(-1.53)
Lag3 dnshrtrdtl		-0.00000
		(-0.16)
Lag4 dnshrtrdtl		-0.00000
		(-0.96)
Weekday Effect	Yes	Yes
Month Effect	Yes	Yes
Market Indicator	Yes	Yes
Constant	0.00093	0.00013
	(0.75)	(0.10)
N	5796	5790
adj. R-sq	0.005	0.012

Panel B: Reversal model on weekly basis

	(1) *Wretwdtl*	(2) *Wretwdtl*
AQI_de_Beijing	-0.00485	-0.00445
	(-1.47)	(-1.36)
Lag 1 AQI_de_Beijing	-0.00262	-0.00216
	(-0.77)	(-0.64)
Lag 2 AQI_de_Beijing	0.00115	0.00188
	(0.27)	(0.44)
Lag 3AQI_de_Beijing	-0.00524	-0.00474
	(-1.25)	(-1.15)
Lag 4 AQI_de_Beijing	0.00323	0.00376
	(0.82)	(0.96)
Lag 1 wretwdtl		0.06236
		(1.63)
Lag 2 wretwdtl		0.10166
		(2.75)***
Lag 3 wretwdtl		0.07911
		(2.00)**
Lag 4 wretwdtl		-0.00386
		(-0.10)
Lag 1 wnshrtrdtl		-0.00000

		(-2.50)**
Lag 2 wnshrtrdtl		0.00000
		(1.13)
Lag 3 wnshrtrdtl		-0.00000
		(-0.15)
Lag 4 wnshrtrdtl		0.00000
		(1.27)
Month Effect	Yes	Yes
Market Indicator	Yes	Yes
Constant	0.00297	0.00172
	(0.71)	(0.39)
N	1207	1206
adj. R-sq	0.008	0.023

Panel C: Reversal model on monthly basis

	(1) Mretwdtl	(2) Mretwdtl
AQI_de_Beijing	-0.04757	-0.04282
	(-1.77)*	(-1.64)
Lag 1 AQI_de_Beijing	-0.03947	-0.03769
	(-1.14)	(-1.13)
Lag 2 AQI_de_Beijing	-0.03390	-0.02865
	(-1.10)	(-0.91)
Lag 3 AQI_de_Beijing	0.06402	0.07373
	(2.26)**	(2.87)***
Lag 4 AQI_de_Beijing	-0.02436	-0.00576
	(-0.85)	(-0.20)
Lag 1 mretwdtl		0.06457
		(1.00)
Lag 2 mretwdtl		0.17010
		(2.46)**
Lag 3 mretwdtl		0.05280
		(0.66)
Lag 4 mretwdtl		0.22982
		(3.52)***
Lag 1 mnshrtrdtl		-0.00000
		(-0.70)
Lag 2 mnshrtrdtl		0.00000
		(0.06)
Lag 3 mnshrtrdtl		0.00000
		(1.36)
Lag 4 mnshrtrdtl		-0.00000
		(-0.71)
Month Effect	Yes	Yes
Market Indicator	Yes	Yes
Constant	-0.00335	0.00617
	(-0.14)	(0.21)
N	283	282
adj. R-sq	0.032	0.136

Table 17: Daily trading volume and *AQI_de_Beijing*

This table presents results of model (5). Column (1) measures trading volume as the natural logarithm of traded value and Column (2) measures trading volume as the natural logarithm of total number of traded shares. *t*-values based on standard errors that are heteroskedasticity-robust in parentheses are reported. *, **, *** stand for significance at the 10%, 5% and 1% levels, respectively.

	(1) *Ln*(*Vol*)	(2) *Ln*(*Shares*)
AQI_de_Beijing	-0.02112	-0.01780
	(-2.48)**	(-2.22)**
$AbsR_t$	6.30982	6.85332
	(12.51)***	(14.26)***
Lnsize	0.64161	0.09850
	(28.65)***	(4.52)***
BV	-0.00000	-0.00000
	(-24.17)***	(-0.18)
$Lqvol_t$	4.05997	6.05342
	(3.12)***	(4.95)***
$L5dvol_t$	4.16161	5.12646
	(5.57)***	(7.21)***
lMR_t	1.65221	1.60248
	(25.06)***	(25.24)***
Weekday Effect	Yes	Yes
Month Effect	Yes	Yes
Year Effect	Yes	Yes
Market Indicator	Yes	Yes
Constant	8.58821	17.83044
	(17.51)***	(37.39)***
Observations	5796	5796
Adjusted R-square	0.921	0.910

Table 18: Performance related accounting numbers around critical points

This table reports results of model (6) and the dependent variable is the ratio of total profit/total assets. *t*-values reported in parentheses are based on standard errors that are heteroskedasticity-robust and month, year and market fixed effects controlled. *, **, *** stand for significance at the 10%, 5% and 1% levels, respectively. *Poor2* equals 1 when *AQI_de_beijing* is positive and equals 0 otherwise. We use ±15, ±20, and ±20 around the critical points respectively to construct the subsamples.

	Total Profit						
	(1) Profit Ratio Full Sample	(2) Profit Ratio [-15,15]	(3) Profit Ratio [-20,20]	(4) Profit Ratio [-25,25]	(5) Profit Ratio [-15,15]	(6) Profit Ratio [-20,20]	(7) Profit Ratio [-25,25]
Poor2		-0.00002	0.00020	0.00108	0.00019	-0.00011	0.00070
		(-0.01)	(0.12)	(0.73)	(0.09)	(-0.07)	(0.48)
AQI_de_Beijing	0.00067	0.00787	0.00759	0.00200	0.00639	0.00952	0.00401
	(1.23)	(0.60)	(1.02)	(0.38)	(0.50)	(1.31)	(0.76)
AQI_de_Beijing^2					-0.04324	0.03530	0.02819
					(-0.49)	(1.03)	(1.36)
Year Effect				Controlled			
Month Effect				Controlled			
Market Indicator				Controlled			
Constant	-0.02527	-0.02319	-0.01942	-0.01769	-0.02294	-0.01972	-0.01803
	(-9.04)***	(-3.51)***	(-3.55)***	(-3.65)***	(-3.48)***	(-3.58)***	(-3.69)***
Observations	8022	1705	2268	2807	1705	2268	2807
Adjusted R-square	0.272	0.232	0.215	0.203	0.232	0.215	0.204

Table 19: Impact of institutional ownership

This table presents subsample regression results of model (2). We partition firms into two portfolios according to the level of institutional ownership. If the level of institutional ownership is higher than median, then a firm is classified into the "High institutional ownership" group. If the level of institutional ownership is lower than median, then a firm is classified into the "Low institutional ownership" group. *Vwdreturn* is the market value-weighted average daily portfolio return. We regress *Vwdreturn* on *AQI_de_Beijing* /*Change_AQI_de_Beijing*. *t*-values reported in parentheses are based on standard errors that are heteroskedasticity-robust. *, **, *** stand for significance at the 10%, 5% and 1% levels, respectively. F-test compares the coefficients on *AQI_de_Beijing* / *Change_AQI_de_Beijing* in the two subsamples.

	(1)	(2)	(3)	(4)
	High Institutions	Low Institutions	High Institutions	Low Institutions
	Vwdreturn	*Vwdreturn*	*Vwdreturn*	*Vwdreturn*
AQI_de_Beijing	-0.00100	-0.00191		
	(-2.13)**	(-2.28)**		
Change_AQI_de_Beijing			-0.00095	-0.00195
			(-2.37)**	(-2.65)***
Weekday Effect	Yes	Yes	Yes	Yes
Month Effect	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes
Market Indicator	Yes	Yes	Yes	Yes
Constant	0.00095	0.00283	0.00109	0.00309
	(0.63)	(1.11)	(0.72)	(1.22)
F-test	0.89		1.41	
	0.3455		0.2352	
Observations	4360	4360	4360	4360
Adjusted R-square	0.025	0.017	0.025	0.018