Is Air-Quality a Risk Factor that Affects Stock Returns? *

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Key Words: AQI, Air Quality Beta, CSR, Pollution Risk, Cross-sectional Returns

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1 Introduction

In efficient capital markets, investors make decision based on all available information. Some are easy to quantify while others are difficult to measure, especially on the soft information that may have direct and immediate effect, for example, changes in our green environment. In recent years, such information has captured increasing attention not only because of its direct impact on the quality of our life but also due to its possible impact on the real economy, including individual firms' performance and risks. However, most current studies have overlooked the economic impact of the green environment because of the difficulty in measuring its direct impact, especially in mature capital markets where there is sufficient effort and progress in environment protection. Therefore, in this study we focus our attention on the Chinese capital markets where environmental issues are a major concern nowadays. This allows us to document the economic impact of air quality from the perspective of risk instead of behavioral differences as approached in the current literature. Using a unique measure, we show that air-quality is a unique risk factor that not only affects individual firms' fundamentals but also determines their expected returns.

Firms operate in a complex environment. Not only the ever changing market conditions, including technology advancement, operation efficiency, investment opportunities, and consumers preferences will affect the risks of firms, but also the way that firms interact with the environment will feed back to impact their risks and performance. Given the limited natural resources in the world and the adverse impact of climate change on our life, investors, consumers, firms, and governments are increasingly conscious about preserving our gree environment. Certainly, being green and being environmentally responsible may improve a firm's bottom line in a long-run, but it is also costly in a short-run. Therefore, it is important to know how sensitive that a firm's decisions or fundamentals are affected by the environmental risk factor and whether investors care enough about such a factor that will influence the firm's expected return in a significant way.

Despite the importance of environmental issues, both the general public and firms operating in the developed countries may not perceive the imminent impact of environmental changes because of the strict regulations and the sufficient efforts taken by the public. Consequently, it may be difficult to document the direct economic impact of the environmental risk in mature capital markets. At the same time, capital markets in under developed countries cannot offer much insight either because of the limited role played by their capital markets or environmental issues being largely ignored in these countries. In contrast, the Chinese capital markets are better suited for studying these important issues. In fact, Chinese capital markets have not only played a critical role in the growth of its economy, but also have become the second largest one in the world. As a result, using the Chinese capital markets to understand the environmental risks offers unique perspectives. First, air quality has been worsening since the end of last century in China. In fact, it has become an epidemic health hazard that directly impact people's quality of life across major cities in China. Second, majority investors in the Chinese capital markets are individual investors. Such a composition is in contrast to that of mature capital markets, where institutional investors dominate. Individual investors can be more conscious on the environmental issues than institutions because they care about the air they breath and the food they eat. Thus, the economic impact can be significant enough to document. Lastly, it is a top health issue that forces government to take action on certain firms. These factors make Chinese markets an ideal place to study the differential impact of air-quality risk.

From an asset pricing perspective, the uncertainty associated with changing environmental conditions can be a systematic risk factor that affects the performance of all firms. For example, a firm's performance can be sensitive to environment changes because of its direct investment exposure to environmental risks or due to the environmental impact from its operating costs. At the same time, heavy polluting firms are damaging their public image, causing consumers reluctant to use their products. Moreover, such irresponsible firm behaviors toward environment may deteriorate corporate culture, making employees less willing to contribute their efforts. The government is more likely to enforce strict environmental regulations, which increases costs to firms. These effects are especially important to firms when pollution is worsening, but the degree of impacts is difference across firms. Therefore, the environmental risk is a systematic risk that can play an important role in affecting firms' performance and stock prices. It is also an independent risk factor with respect to the market risk since it can ultimately affect investors' utility in a different dimension. In this study, we focus particularly on air-quality in China because of its importance and the availability of data.

To investigate whether air-quality in China is a unique risk factor that affects Chinese stock returns, we construct a unique proxy for air pollution risk using the Air Quality Index (AQI) published by US consulates across China. Changes in AQI should be negatively correlated with asset returns. In general, worsening air pollution limits firms' future investment opportunities, which leads to lower current asset prices or returns. From an empirical perspective, however, such a negative relation between increasing pollution level and low stock returns is also consistent with a behavioral story. For example, it is argued that bad weather may depress investors' mood and in turn change their trading behavior by weighing more on negative news than on positive news. As a result, such a weather-induced unpleasant mood will be associated with low current stock prices or returns (see, for example, Saunders, 1993; Kamstra et al., 2003, and so on). In this study, we propose different approaches to tease out the pricing effect of air pollution risk.

The simplest way to differentiate the two channels is to control for the sentiment factor since investors are more likely to down play the negative news when the sentiment is high. Indeed, we find that the market returns significantly covariate with changes in the air quality index even after controlling for all relevant factors including the sentiment factor. Perhaps a more effective way to investigate which channel is more likely to prevail is to utilize a special information about Chinese firms. About 30% of firms issue special reports (the CSR report) on their social responsibility, in which information about environment protection and pollution is disclosed. Presumably, if the comovement between air quality change and stock prices is mainly driven by the behavioral reason, such a negative relation should be similar among both CSR firms and non-CSR firms after controlling for firm characteristics because it is the investors' mood that is affected by air-quality, not the types of firms. Under the alternative risk story, however, CSR firms' returns should react to air pollution changes less negatively than that of non-CSR firms since the disclosure firms are more transparent and are subject to less information asymmetry. Our panel regression results shows that both the stock returns and volatilities of CSR firms are less sensitive to air pollution changes than the non-CSR firms are.

Time-series correlation does not necessarily imply pricing. A factor is a pricing risk factor only if it rewards investors with a risk premium, which can be estimated from a cross-sectional regression. According to the APT model of Ross [1976], if air pollution is a systematic risk factor, individual stock returns should covary sufficiently with the pollution risk factor such that the corresponding sensitivity estimates (the pollution beta) will differ significantly across individual stocks. Moreover, the cross-sectional return differences should be explained by the cross-sectional differences in the air-quality betas. Using both the two-way sorting approach and the cross-sectional regression approach, we show that future stock return differences are indeed related to the dispersion of pollution betas. Therefore, air-quality is likely to be a priced risk factor.

There are two caveats need further investigation in order to claim air-quality to be a unique risk factor. First, the level of air pollution may be correlated with aggregate consumption. In this case, our air-quality beta might serve as a proxy for the consumption beta. Despite this is a less likely scenario given the weak evidence of the consumption based CAPM, we will show that our pollution betas are directly tied to firms' fundamentals. After all, the cross-sectional differences in consumption betas are related to the demand side, while the differences in pollution betas are more related to the supply side, more specifically firms' fundamentals. We find that stocks with large pollution risk tend to have low future profit margins and output. Second, air pollution can also be correlated with the growth of firms. This is especially the case for an economy that heavily relies on manufacture. A simple way to tease out the growth factor is to control for firm growth in cross-sectional regressions. In addition, we rely on a natural experiment where a shock is independent of firms' investment decisions, which helps to isolate the effect of pollution risk on firms. Our difference-in-difference results from the event study again support the hypothesis that air-quality is a priced risk factor.

As mentioned earier, prior research explores the contemporaneous relation between stock returns and weather conditions from a behavioral perspective. For example, Saunders [1993], Kamstra et al. [2003], Hirshleifer and Shumway [2003], Loughran and Schultz [2004], Cao and Wei [2005], Garrett et al. [2005], Yuan et al. [2006], and Chang et al. [2008] have found that stock returns can be affected by cloud coverage, length of days, temperature, snowstorm, and lunar phases. Others, including Chang et al. [2008], Lu and Chou [2012], and Kaustia and Rantapuska [2016] have focused on specific weather-related trading patterns. In addition, there are evidence suggesting that, not only individual investors, but also professional market participants including institutional investors, analysts, market makers, trading floor communities, and professional managers can be influenced by weather conditions (see Goetzmann et al., 2015, deHaan et al., 2015, Goetzmann and Zhu, 2005, Lepori, 2016, and Chhaochharia et al., 2015). Compare to other types of weather related factors, the effects of air-quality on stock returns have received less attention. Levy and Yagil [2011] have investigated the US markets, and found that air pollution is negatively related to market returns, while Li and Peng [2016] have explored the Chinese markets with similar conclusions. In contrast, we focus on the risk nature of air-quality and document that it is a risk factor and its beta loadings explain cross-sectional return differences of Chinese stocks.

Our research contributes to the literature in four important ways. First, we study the important economic impact of environmental issues from a risk perspective in contrast to the behavior approach taking by existing studies on similar topics. In particular, we provide strong evidence supporting air pollution being a unique risk factor using the Chinese capital markets as a laboratory. For example, we construct pollution betas of individual stocks and further show that these betas explain future cross-sectional return differences of individual stocks. Given the severity of air pollution in China, this is unlikely to be a short-term trivial factor. Second, we provide evidence from the supply side by linking pollution risk to firms fundamentals. Third, relying on special institutional feature of the Chinese data, we construct a natural experiment to tease out confounding factors, such as firm growth and investors' psychological behavior, in documenting the pricing effect of pollution risk. Finally, from an econometrics perspective, existing studies suffer a potential spurious regression effect when the level of weather related variables are used as independent variables in time-series regressions. Due to the potential nonstationarity of air quality index, we construct our pollution risk proxy based on changes, instead of levels, which makes our empirical results more reliable and robust.

The rest of the paper proceeds as follows. In the next section, we discuss our hypothesis related to air-quality risk and unique characteristics of the Chinese capital markets. Due to the unique approach adopted in this paper, we provide details on data and variable construction in Section 3. In Section 4, we first investigate whether the air-quality factor is a proxy for risk or a measure of sentiment. We then provide empirical evidence on the pricing effect of the air-quality risk using both two-way sorting and cross-sectional regression. Robustness studies and additional tests are shown in Section 5. Section 6 provides concluding comments.

2 Theory and Institutional Background

Different from existing studies that focus on the behavioral relation between weather related factors and stock returns, we investigate the risk nature of air-quality in affecting firm performance. It is thus important to understand the related theoretical issues first. Since we rely on data from the Chinese capital markets in empirical tests, we also discuss the unique institutional features in this section.

2.1 The Impact of the Air-Quality Risk

From a supply side, firms operate in a complex environment. In general, firms' investment decisions are influenced by the general economic, market, or even environmental conditions, creating risks that are common to all firms. In particular, environment conditions could affect investors attitude towards green technology, which in turn affects future investment opportunities. Depending on firms characteristics and investor preferences, firms will react differently when making investment decisions. In this sense, the changing environment itself is a risk factor facing individual firms. One such potential risk factor is the air-quality risk, which will ultimately affect stock prices of individual firms. In the framework of the APT model, individual stock returns will load differently on the air-quality factor. If air-quality is indeed a priced risk factor, the cross-sectional difference in these pollution betas should explain the return differences of individual firms. This is the main test that we will carry out in this study.

Even when the null hypothesis of no pricing effect of the air-quality risk is rejected, it does not necessarily mean that the observed relation is entirely driven by the pollution risk. On the aggregate level, changes in the pollution level may be a result of changes in the consumption pattern of investors, for example, switching from public transportation to the use of personal vehicle, from coal based heating to gas heating, etc. In other words, the pollution index serves as a proxy for aggregate consumption. To isolate this possible channel, we will tie a firm's sensitivity to air-quality changes to the firm's fundamentals, such as the profit margin, if the pollution risk we have in mind arises from the supply side. In particular, we will investigate whether cross-sectional differences in future profit margin, investment, and output are inversely related to differences in the pollution risk of individual firms (discussed in Section 3.2).

Another possible interpretation of our results is related to the growth of economy. A severe consequence of a fast growing economy is its adverse impact on the environment, including air pollution. This is especially an important factor for an emerging economy. In this case, air pollution level may have been served as a proxy for growth. To account for this possibility, we will explicitly control for firm level growth. To further show that the pricing effect is not related to growth, we perform a natural experiment. When there is a significant shock to air pollution level unrelated to firms' operating decisions, any differences in returns are largely a result of changes in risks instead of growth. We study the return behavior during the 2014 APEC meeting (November 5-11, 2014) and the Commemoration of the 70th Anniversary of WWII (August 20-September 4, 2015) using the difference-in-difference approach.

From a demand side, especially on an aggregate level, it is the investors that ultimately determine the rewards for exposing firms to such risk factors in equilibrium. When air pollution worsens, investment opportunities will be limited, which will cause asset prices to drop. In other words, there is a negative contemporaneous relation between the air pollution level and equity prices on an aggregate level. Again, a rejection of the null hypothesis that pollution is *not* a risk factor in this framework could also be consistent with a behavioral story.

As argued by Saunders [1993], weather conditions can affect investors' moods, which leads investors to react differently to different types of news. For example, heavy air pollution can depress investors, making them to react to bad news stronger than good news. Under such a mechanism, an increase in the pollution level will be associated with a lower stock return contemporaneously, especially on the aggregate level. To separate the two possibilities, we can use the sentiment factor to control for the behavioral story. Another way to separate the two stories is to investigate if there are differential reactions to pollution changes for firms with different "exogenous" pollution risks. For example, some firms are more socially responsible. For those firms, the negative relation should be weaker if it is a risk story, and there should be no difference if it is the behavioral story.

2.2 Air Quality in China

China is probably a country with heaviest air pollution in the world. As a byproduct of the fast growing economy in the past thirty years, the air quality has deteriorated over the years to a point that the air pollution has become a major public health hazard. On the global level, major news organizations, such as BBC, CNN, NBC, and others have actively reported this meteorological disaster in China. The main sources of air pollution are construction itself and related industries, automobiles, heating, and other industries. Although there are some degree of variations of the contributing sources of air pollution across geographic locations, for example, burning coal for heating purpose is important to provinces in the northern part of China, air pollution has severely affected the general health of the public. No doubt, air pollution is man made in China. This is evident during two important events in our sample–the 2014 APEC meeting (November 5-11, 2014) and Commemoration of the 70th Anniversary of WWII (August 20-September 4, 2015), where the government ordered halting most production and limited the number of cars in Beijing. Consequently, the sky suddenly become blue. These two events will be used as nature experiments in our study.

Due to the social and economic importance of air pollution in China, the U.S. Embassy has constructed Air Quality Indices (AQI) for major cities in China since 2008, long before the publication of a similar measure by the official meteorological service of China. Since it is criticized that the government figures are biased for political reason, we rely on the U.S. Embassy data in this study. In particular, such an air quality index is measured based on pollutant concentration of particulate matter smaller than 2.5 micrometers in diameter, which is known as $PM_{2.5}$. The details about AQIs among five major cities, including Beijing, Chengdu, Guangzhou, Shanghai, and Shenyang that are compiled by the U.S. Embassy, are reported in the Table 1.

Insert Table 1 Approximately Here

On average, the air quality in China is "unhealthy for sensitive groups" during our sample period from 2009 to 2015 as shown in the Table 1. There are about two months (or 17.96% of the days) each year with good air quality (i.e. the PM2.5 level under 50), and over three months in a year with "unhealthy or worse air quality." Among the five major cities, the air quality of Beijing, Chengdu, and Shenyang are especially bad. For example, in Beijing, there are more than 42 days in a year with "hazardous air quality," which means that, during these terrible days, everyone should stay indoors and reduce their activity levels. As a result, air pollution could severely impact the productivity of firms and the quality of life in China.

Because of the adverse impact of air pollution in China and the pressure from general public, the government has taken certain measures to reduce pollution emission, including upgrading heating systems and reducing the number of new vehicle licenses each year. In Panel A of Figure 1, we plot the average AQI over year for the five major cities across China. Overall the air quality has improved to some degree in recent years. The average AQI of Beijing in 2006 is 177, while the index level went down to 136 in 2015. The AQI levels of Chengdu, Guangzhou and Shanghai have also decreased during the period. The air quality levels also exhibit strong seasonality over a year as shown in Panel B of Figure 1. In the later months and early months of a year (largely in winter), the air pollution is the worst, the average AQIs of January, February, November, and December are always greater than 100. However, there are little differences among different days of a week.

Insert Figure 1 Approximately Here

2.3 Corporate Social Responsibility in China

There is another institutional feature that is important in our study. Due to the mounting environmental issues in China, the Ministry of Environmental Protection of China (hereinafter referred to as MEP) released the *Guide to Strengthen Environmental Regulation on Listed Companies* in the Feb. 25, 2008. The China Securities Regulatory Commission (hereinafter referred to as CSRC) worked with MEP to established a reporting system thereafter. The two independent stock exchanges in China–Shanghai Stock Exchange (hereinafter referred to as SSE) and Shenzhen Stock Exchange (hereinafter referred to as SZSE) began to ask certain companies listed at their exchanges to provide CSR reports, which include information about environmental protection and sustained environmental development.[1]

According to the requirement of Shanghai Stock Exchange, those companies that are the constituents of SSE Corporate Governance index, or have issued their equity shares on one or more foreign stock exchanges, or belong to financial industry must disclose their CSR reports since 2008. Shenzhen Stock Exchange also demand the constituent firms of SZSE 100 index to disclose CSR reports since 2008. Both of these two stock exchanges encourage other listed companies to disclose information on CSR. As a result, over one third of CSR disclosure firms voluntary provide CSR reports.

3 Data Sample and Variable Construction

In this section, we first describe the source of our sample data. We then provide detailed information on variable construction. Summary statistics is discussed at the end.

3.1 Data Sample

The sample used in this study covers all listed stocks on both Shanghai Stock Exchange and Shenzhen Stock Exchange over the period from January 2009 to December 2015. The choice of our sample period reflects the availability of CSR data, which is disclosed start-

[1] In addition to the environmental protect, the CSR reports also include information about sustained social and economic development, such as employee health, product quality, public relations, and social services.

ing at the end of 2008 year. Most of prior studies on this topic use an air quality measure maintained by the Ministry of Environmental Protection of China. However, Hu et al. [2014] have documented that the Chinese government tends to manipulate the published air quality data. As an independent party, U.S. Embassy data may provide more accurate information. Therefore, we use the air quality indices published by the U.S. Department of State (http://www.stateair.net/) that are provided by the U.S. Embassy in China. Other meteorological data, such as temperature, humidity, and wind speed, are taken from Weather Underground Organization (https://www.wunderground.com/). The market information and accounting information of individual firms are obtained from $CSMAR$ database (The China Stock Market & Accounting Research Database) and $CSDCC$ (China Securities Depository and Clearing Company Limited).

Our sample period covers $1,700$ trading days. Due to the 50 days of missing the air quality data, our final sample period contains $1,650$ trading days. In cross-sectional regression analysis, we further restrict our sample to include firms that have data for all variables. In order to reduce the effect of possible outliers or influential observations on the coefficient estimates, we also winsorize all continuous variables at the 0.5% and 99.5% levels.

3.2 Variables

The main variable of interest in this study is the aggregate air quality change in China. Many existing studies on related topics use the level measures on weather related variables. Since it is wellknown that these measures are very persistent, and could potentially be nonstationary, there is a spurious regression concern if the dependent variable might also be nonstationary. To avoid such an econometrics issue, especially in time-series analysis, we use changes for all weather related variables including air quality instead of levels.

China is a vast country, air quality may vary sufficiently across provinces at any point of time, which could raise an issue of aggregation. Most prior studies uses the weather characters of cities where stock exchanges are located (see, for example, Saunders, 1993; Hirshleifer and Shumway, 2003), or cities where the listing firms are located (see, for example, Loughran and

Schultz, 2004). However, nowadays trading on individual stocks occurs at every corner and news about severe pollution levels in different cities is available to all investors quickly. What resonates with investors is the overall pollution across country at any given point of time. Therefore, given our focus on the risk nature of air pollution and its effect on stock returns, we propose a special aggregation method for air quality. In order to ensure sufficient variations over time, we measure aggregate air quality change, $\Delta MAQI_t$, as the average change in the average AQIs of the five major cities (Beijing, Chengdu, Guangzhou, Shanghai, and Shenyang) in day t. One may also argue that as long as pollution causes serious consequences, not only the air quality of stock exchange locations or the physical locations of firms, but also the air quality of major cities that investors are resided in will all influence investors decision. We also use alternative aggregation methods, such as the median or the maximum AQIs of Beijing, Chengdu, Guangzhou, Shanghai, and Shenyang in robustness section.

Since $\Delta MAQI_t$ is a proxy for market wide measure of pollution risk, we need a corresponding risk measure for individual stocks in cross-sectional study. According to the APT model, we can estimate the sensitivities of individual stock returns to $\Delta MAQI_t$ as a systematic risk measure, which is the second key variables used in our study. In particular, we estimate the rolling air-quality beta ($AQBeta_{it}$) for each available A-share stock over our sample period according to the following model,

$$RET_{it} = \alpha_{it} + \beta_{it} \times (-\Delta MAQI_t) + \varepsilon_{it}, \tag{1}$$

where the dependent variable RET_{it} is the daily return of stock i in the past three months, and the coefficient estimate of β_{it} is denoted as $AQBeta_{it}$ since pollution is a negative factor and a large AQI means worse pollution.[2]

In addition, we construct several meteorological related variables, and common control variables use in our study. The meteorological variables, ΔTEM_t, ΔHUM_t, and $\Delta WIND_t$ are computed as the maximum change in temperature, humidity, and the speed of wind among the five major cities mentioned above. The dependent variable and common control variables are market excess return ($RMRF_t$), the size factor return (SMB_t), the book-to-market factor

[2]To avoid persistent impact of a "influential" observation when using a rolling regression, we weight both the dependent and independent variables by weight, $w_{t-l} = 0.9^l$

return (HML_t), and the momentum factor return (UMD_t), which are estimated following Fama and French [1993] and Carhart [1997]. To differentiate the behavioral story from the risk story, we also control for investor sentiment, which was firstly developed by Baker and Wurgler [2006] for the U.S. capital markets. Due to differences in the characteristics of Chinese capital markets and institutional structure, we measures investor sentiment (ΔSEN_t) by following Han and Wu [2007] instead, which is the monthly change of the percentage of investment accounts opened during the month t. Moreover, economic development may impact both stock returns and weather conditions simultaneously. Therefore, we uses quarterly change in PMI, ΔPMI_t, to control for economic activities.

As shown by Fama and French [1992], firm characteristics help to explain the cross-sectional expected return differences. We also construct the market capitalization (ME_{it}) and the book-to-market ratio (BM_{it}) for each firm by following Fama and French [1992]. Other cross-sectional control variables include CSR_{it}, which is a dummy variable that equals 1 if a firm i has disclosed a CSR report last year and 0 otherwise, V_{it}, which is a dummy variable that equals 1 if a firm has voluntarily disclosed a CSR report last year and 0 otherwise, SOE_{it}, which is a dummy variable that equals 1 if a firm is state-owned enterprise and 0 otherwise.

Finally, we also investigate how pollution risk affects other stock return volatility of a firm. For example, we compute the idiosyncratic volatility ($IVOL_{it}$) using daily residual returns from the Carhart four factor model each month. The additional controls include the market illiquidity ($ILLIQ_{it}$) and skewness of stock return ($Skew_{it}$) that are obtained following Hou and Loh [2016].

3.3 Summary Statistics

The summary statistics for variables used in our study are reported in Table 2. Panel A shows the summary statistics of time series variables. During our sample period. The average change in air quality ($\Delta MAQI_t$) is positive, 0.238, which may seem to be inconsistent to the pattern in Figure 1. However, $\Delta MAQI_t$ measures the average case scenarios, instead of the average shown in the graph. Other weather related variables in Panel A, including daily changes of temperature (ΔTEM_t), humidity (ΔHUM_t), and wind speed ($\Delta WIND_t$), also show increasing trends over our sample period. As expected, monthly investor sentiment change (ΔSEN_t) and quarterly PMI change (ΔGDP_t) are all positive.

Insert Table 2 Approximately Here

Given the focus of this paper, it is important to examine the cross-sectional characteristics of individual stocks in Panel B. First of all, returns of individual stocks tend to be positively skewed when comparing mean to median. This is in contrast to that of aggregate daily returns shown in Panel A, suggesting that a large drop in daily return tends to follow by small rises in returns, while a large rise in daily return is not fully reversed.[3] There are 3407 firm years out of a total of 14963 firm years (or 22.77%) that disclosed CSR reports in our sample. Among them, over a third voluntarily disclose their CSR reports since the mean value of V_{it} is 0.36, indicating that about 15% ($= 64\% * 22.77\%$) of all firms are required to disclose CSR reports according to the regulation. Given the uneven distribution among the two types of firms, we will use matching approach to reduce possible biase in regressions that are related to CSR. When comparing the two types of firms, we see that CSR firms are little larger in size with high book-to-market value (or low growth) than the non-CSR firms. This is consistent with the fact that CSR firms are more likely to be state-owned with an average SOE_{it} of 63% versus an average SOE_{it} of 44% for non-CSR firms. The idiosyncratic volatility of CSR firms is also lower than that of the non-CSR firms, which is consistent with the well-documented evidence that smaller and high growth firms tend to carry high firm specific risks.

4 Empirical Results

To be consistent with the current literature, we first investigate whether air quality matters in the equity markets by focusing on the time-series evidence. We then present evidence suggesting that such a relation is largely driven by the risk nature of air-quality instead of

[3] Such an overreaction behavior may explain some of the results found in the literature on a similar topic. In contrast, to document the pricing effect, we focus on low frequency returns.

investors' behavior. In particular, we provide both cross-sectional evidence and tie the air-quality risk beta to firms' fundamentals as well as implementing a nature experiment.

4.1 Stock Returns and Air Quality: Time-Series Effects

One unpleasant experience for any one who has visited China in recent years is the heavy air pollution. In fact, such an air pollution level has severely affected people's daily life, which should also have had profound economic impacts. One such impact is the stock market reaction. As a initial evidence, we use a difference-in-difference approach by comparing the market reaction around the days with serious air quality deterioration relative to that around days with significant air quality improvement. The worst (best) air-quality days are defined as those days with the largest (smallest) changes in $\Delta MAQI_t$, that is the top (bottom) one percentile of $\Delta MAQI_t$. To avoid cancellation effect, we exclude those days that the best and the worst days occurred within five days. The market reaction (CAR_t) is measured as the cumulative market returns of A-share stocks during the three-day window, [-2, +2], around the worst (best) air-quality day minus the average daily return of the month. We also try to control for other unspecified factors by implementing a difference-in-difference approach. In particular, we subtract CARs around the best air quality day from those around the worst air quality day, and call these CARs as the relative CARs,[4] and are plotted in Figure 2.

Insert Figure 2 Approximately Here

The pattern in Figure 2 clearly shows that the stock market react efficiently and negatively when air quality worsens most dramatically. In particular, the relative cumulative abnormal stock return is almost zero the day before large air pollution occurs. The relative CAR drops by more than 2.2% on the event day. To a large extend, the relative CAR remains the same on the day after.

As dicussed in Section 2.1, such a negative market reaction pattern does not necessarily suggest that severe air pollution cause risk to rise, which in turn drives down stock prices.

[4]It is also well-known that air pollution are affected by weather conditions, which may contribute to our findings. However, large temperature changes only weakly correlated with large air-quality change. In our regression analysis, we will explicitly control for weather conditions.

The behavioral finance literature has been arguing that air pollution can depress investors such that they react to bad news more actively than good news (see Levy and Yagil, 2011 and Goetzmann et al., 2015). In addition, a general condition can only be reached based on full sample instead of a partial sample. Therefore, we further investigate the issue using time-series regressions on the market level but with different controls in Table 3.

Insert Table 3 Approximately Here

The dependent variable of all models used in Table 3 is the daily market excess returns measured as the differences between daily index returns of A share stocks and risk-free interest rate on day t. Without any controls, Model 1 suggests that market excess returns are indeed negatively correlated with the air quality. The coefficient of -0.0015 for one unit air quality change ($\Delta MAQI_t$) is negative and significant at a 5% level. This result is consistent with the current literature despite of using a more accurate measure of air-quality that is based on a difference measure. To see whether such a negative relation is a result of weather-induced mood of investors, we control for investors' sentiment in Model 2. To our surprise, the sentiment factor is insignificant and has no effect on our air quality measure. Only after further controlling for the Fama and French and Carhart factors, that is SMB_t, HML_t, and UMD_t in Model 3, the sentiment factor becomes significant now, suggesting that the original sentiment factor is very noisy (see, Ruan et al., 2010). Despite the magnitude of the coefficient reduces to some degree, it is still significant at a level close to 5%. Therefore the effect of air-quality on stock return observed in Figure 2 is not due to a behavioral reason.

Air pollution level can change with the weather condition, we also control for temperature change (ΔTEM_t), humidity change (ΔHUM_t), and wind speed change ($\Delta WIND_t$) in Model 4, which has no effect. In addition, pollution can increase when industry production increase, which is controlled in Model 5 using PMI (ΔPMI_t). Finally, we control for seasonal effect using month dummies in Model 6. As shown, the coefficient estimates of $\Delta MAQI_t$ only drops slightly and continue to be significant at a 5% level. Therefore, air pollution likely produces additional risk to firms, which affects stock returns.

As discussed in Section 2.1, our alternative strategy to separate the risk impact from the behaviorial effect of air pollution is to investigate the potential differences between firms that disclose CSR report and firms that do not disclose. In this case, we utilize the cross-sectional pooled regression with the CSR dummy variable in Table 4. In contrast to constructing CSR portfolio and non-CSR portfolio and then run time-series regression, this approach allows us to control for heterogeneity on firm level. The interaction term of $CSR_{it} \times \overline{\Delta MAQI_t}$ in the first equation of Table 4 measures the differential effect of CSR discloure. In particular, the estimate of 0.0066 is positive and significant at a 1%, suggesting that changes in air pollution have very different effect on stock returns. Since there is not much time variation in the dummy variable, such an estimate reflects time-series effect. Because of the positive difference, the effect of air pollution is unlikely to be behaviorial.

Insert Table 4 Approximately Here

Worsening air pollution may also deteriate firms' operating environment, which may increase their uncertainty. Consequently, both their systematic and idiosyncratic risks will increase. This hypothesis is tested in the second equation of Table 4 for idiosyncratic volatility and in the third equation for market beta. The significant coefficient estimate of 0.0040 of $\overline{\Delta MAQI_t}$ suggests that idiosyncratic risk indeed increases with air pollution level. Similarly, the overall level of systematic risk increase with air pollution level with a coefficient estimate of 0.045. It is also interesting to see that CSR disclosure substantially reduces the impact of air pollution on systematic risk, but has little effect on idiosyncratic risk.

4.2 The Cross-sectional Evidence on the Pricing of Air-Quality Risk

Despite the fact that we control for sentiment factor, such a control can be imperfect in teasing out the behavioral effect from the risk nature of air pollution. Different from existing studies, we focusing on cross-sectional evidence in this paper. According to the APT model of Ross [1976], if air-quality is a risk factor, it should load on individual stock return differently. As proposed in Section 3.2, such a difference in sensitivity produces a cross-sectional risk measure $AQBeta_i$. Moreover, if investors price the air-quality risk rationally, we should find a positive risk premium from cross-sectional regressions of future stock returns on $AQBeta_i$.

Before discussing the cross-sectional regression result, we first take a close look at the relationship between $AQBeta$ and future returns using the double sorting approach. When forming sorting portfolios, following Fama and French [1993], all SSE stocks are ranked on size. The quintiles are then used to splite SZSE stocks into five groups. Following Fama and French [1992], we sort all A-share stocks simultaneously into 25 portfolios according to their market capitalization ($Size$) and air pollution beta ($AQBeta$) in Panel A, as well as 25 portfolios according to their book-to-market value (BM) and air pollution beta ($AQBeta$) in Panel B of Table 5. Numbers reported in the table are average monthly portfolio returns.

Insert Table 5 Approximately Here

As shown in the Panel A, the portfolio returns decrease with firm size, consistent with Fama and French [1992]. Although the relation between portfolio returns and $AQBeta$s is somewhat "check" shaped, the return difference between the high $AQBeta$ portfolio and the low $AQBeta$ portfolio is positive and significant at any size level. For portofolios with high $AQBeta$s, their returns do increase monotionlly with their $AQBeta$. Therefore, high level of expossure to the air-quality risk results in high future returns.

When sorting according to book-to-market and $AQBeta$, results shown in Panel B of Table 5 is also consistent with Fama and French [1992] on the book-to-market dimension. Although the relation on the $AQBeta$ dimension is a little stronger than those reported in Panel A, it is still non-monotonic for low $AQBeta$ portfolios, especially when book-to-market is low. However, the difference between high $AQBeta$ portfolio and low $AQBeta$ is significant at a 1% level for any given book-to-market level. Therefore, no matter whether it is for size or book-to-market sorted portfolios, $AQBeta$s do span most of the portfolio returns, suggesting the pricing of the air-quality risk.

To control for other factors, such as return reversal, momentum, liquidity, and return skewness, we perform cross-sectional tests in Table 6. A common practice is to use Fama-MacBeth regression in this case. Given our short sample period of seven years, we use pooled regressions instead with adjustment for both firm and year fixed effect in this paper. An advantage of using pooled regression is to control for the possible clustering effect since the air-quality risk might affect certain industries more than others. As hypothesized and consistent with Table 5, ($AQBeta$) is significant in explaining future return differences of individual stocks as shown in Model 1. Despite the conventional market beta to be insignificant in cross-sectional regression, it is actually significant when it is used with our ($AQBeta$s) as shown in Model 2. However, it has a negative sign, suggesting that both market beta and ($AQBeta$) may share common estimation noise (see Ruan et al., 2010).

Insert Table 6 Approximately Here

Although the coefficient estimate for $AQBeta$ remains at 0.49 robust to different additional control variables used. For example, controlling for both size and book-to-market in Model 3 has virtually no effect on $AQBeta$, except that the BM actually becomes negative. In addition, the momentum effect in Model 4 is also significant, while there is no return reversal on monthly frequency shown in Model 5 in the Chinese market. As shown in Model 5, liquidity is indeed important in affecting stock returns, but return skewness measure is unimportant in Model 6. With all the controlling variables, the coefficient estimate of $AQBeta_{it}$ is 0.50, and is significant at a 1% level. Therefore, air-quality risk, measured by $AQBeta$, is important in explaining the expected return differences of individual stocks.

4.3 Does Air-Quality Beta Reflect Fundamental Risks

As argued in Section 2.1, one possible interpretation for the cross-sectional explanatory power of air-quality beta is that air-quality risk reflects consumption risk. In order to show that this is not the case and air pollution is an independent risk factor to firms, we will show that air-quality beta affects firm's future fundamentals. In particular, we study whether individual firms' future profit margins, investment, and per capita output are affected by their ($AQBeta$s). The pooled cross-sectional regression results are reported in Table 7. The robust t-statistics with industry clustering effect are in the brackets.

Insert Table 7 Approximately Here

In the first column of the table, we regress change in profit margin next quarter ($\Delta PM_{i,t+1}$) of individual firms on the average monthly $AQBeta$ in the current quarter ($\overline{AQBeta_{it}}$). As expected, a high air-quality risk adversely affects the firm's future profit margin with a significant coefficient estimate of -0.31. This is with controlling for market risk ($MktBeta_{it}$), book leverage ($Leverage_{it}$), Tobin's Q (Q_{it}) measured as the sum of the book value of debt and the market value of equity divided by the book value of assets, natural log of firm's market capitalization ($LnME_{it}$), and annual observation dummy ($Anual_{it}$).

We further investigate if a firm's future investment is also affected by the air-quality risk in the second column of the table. The dependent variable is change in investment in property, plant, and equipment in the next six-month scaled by the capital stock ($(\Delta I/K)_{i,t+1}$). The coefficient estimate of $\overline{AQBeta_{it}}$ also has the right sign, but is only significant at a 10% level. In addition to control for the above mentioned factors, we also control for cash flows $(CF/K)_{i,t+1}$, measured as earnings before interest, taxes, depreciation, and amortization (EBITDA) scaled by the capital stock) as well as the persistence in investment by including the lagged investment.

It is also interesting to see if air-quality risk affects a firm's per capita output in the last column of the Table 7. In particular, we regress changes in the a firm's per capita output in the next quarter ($\Delta Output_{i,t+1}$) scaled by the number of employees) on the average monthly $\overline{AQBeta_{it}}$ in the current quarter, where a firm's output is measured as its sales plus changes in inventories. In this case, the coefficient estimate of $\overline{AQBeta_{it}}$ is also negative and statistically significant at a 1% level. We also control for related firm characteristics, such as the natural log of the number of employees last quarter ($LnEmployee_{i,t-1}$), the natural log of asset intensity ($LnIntensity_{it}$) measured as the total assets divided by the number of employees, the natural log of the number of quarters that the firm has been in business ($LnAge_{it}$), and the operating leverage ($OpLeverage_{it}$) measured as the PPE divided by total assets. In addition, we use the Herfindahl Index (HHI_{it}) as a control for competition.

In summary, all three regressions suggests that air-quality is a risk that affects firms' real activities in the future in an important way.

4.4 A Natural Experiment

The significant cross-sectional results between future return and air-quality risk could also be due to the fact that high growth firm is more sensitive to air-quality risk (see Section 2.1) if pollution is a result of high growth. In order to show that air-quality is a risk that affects firms' fundamentals and ultimately influence firms' future returns, we design a natural experiment by utilizing two important events– the 2014 APEC Economic Leaders' Week (November 5-11, 2014) and the commemoration of 70th anniversary of WWII (Aug. 20-Sep. 4, 2015), where the Chinese government used executive orders to significantly reduce the air pollution level. During these periods, there are no investment changes initiated by firms that will affect growth and no consumption changes demanded by investors due to the exogenous nature of these events. The only change occurred is the reduction in the air pollution level (risk). Therefore, if stock returns of firms that are operated in Beijing are affected by the events, it is most likely a result of changing in air-quality risk.

Two caveats needed to be taking care of are the general economic conditions and seasonality surrounding the two special events. To take into account the seasonality of air pollution, we compare firm performance during the period with that during the same time periods but in the previous year by introducing a dummy variable "Event." By doing so, the dummy variable also captures the incremental effect of the events. We also compare firms in Beijing to firms in the rest of the country by using the dummy variable "Beijing." To implement this "event study," we use cross-sectional pooled regression. Specifically, we consider the interaction term of "$Event \times Beijing$," which essentially is a difference-in-difference measure that reflects the impact of air-quality risk. These regression results are reported in Table 8.

Insert Table 8 Approximately here

In all the regressions, the dummy variable $Event_{it}$ equals 1 during the two periods from November 5th to the 11th of 2014 and from August 20th to Sepember 4th of 2015, and 0 during the same periods of the previous years (November 5th to the 11th of 2013 and August 20th to Sepember 4th of 2014), while the dummy variable $Beijing_{it}$ equals 1 if a firm operates around Beijing, and 0 otherwise. Model 1 shows that the daily average abnormal return during the event period actually droped by 0.06% although insignificant.[5] In general, firms operate around Beijing generally have lower returns than those firms in the rest of the country, which could largely be a result of air pollution risk. However, the negative impact has dropped significantly for firms that operates in Beijing area during the event period relative to firms operated in the rest of the country as shown by the interaction term with a significant coefficient estimate of 0.22% per day. Since this difference-in-difference measure captures the most important difference arises during the special event for firms that do not subject to air-quality risk, we can conclude that it is the air-quality risk has the real effect on stock returns. When controlling for market risk, size, and book-to-market in Model 2, or additional controls of liquidity, return skewness, and turnover in Model 3, the interaction term that reflects difference-in-difference continues to be significant with a similar coefficient estimate. Adding weather related controls in Model 4 even strengthens our our main result.

4.5 Differential Air-Quality Risk for CSR versus non-CSR Firms

As discussed in Section 2.3, some firms provide CSR report, where they disclose their efforts on social responsibility including dealing with the air pollution issue. Since these firms are more transparent on environment issues and thus are more conscious on dealing with these issues, their returns should be less sensitive to air-quality risk. In contrast, if reaction to air quality change is behavioral, the return sensitivities should not be different across the two groups of firms. In this section, we utilize this special feature to perform additional tests. As in Table 6, we perform panel regression of individual stocks' future returns on air $AQBeta$ in the Table 9. All models are adjusted for firm fix-effects and industry clustering.

Insert Table 9 Approximately here

Given that CSR firms are more transparent and may less subject to the air-quality risk, we test differences between CSR and non-CSR firms. The dependent variable of the first two models in the Table 9 are future monthly returns of individual firms. First of all, CSR

[5] This may suggest that hosting these events not only wasted resources but also negatively affects firms.

firms seem to enjoy significantly lower return than non-CSR firms. This could be a result of differences in their general social responsibilities, other than air pollution. Although air pollution is only one of the item in a CSR report, social responsibility measures of a firm changes much slower than changes in air-quality risk. Therefore, CSR dummy can still be a good measure to capture differential impact of air-quality risk when used interactively with other variables. For non-CSR firms, the coefficient estimate of $AQBeta_{it}$ is 0.557, which continues to be significant at 1% level consistent with the results shown in the Table 6. As expected, the coefficient for the interaction term, $CSR_{it} \times AQBeta_{it}$, of -0.238 is significantly negative at a $1\% level$, suggesting that CSR firms subject to less air-quality risk than non-CSR firms. Therefore, it is unlikely that the effect of air-quality on stock return is due to the behavioral effect. Morover, since $AQBeta_{it} + CSR_{it} \times AQBeta_{it}$ of 0.319 is still positive and significant, air-quality risk matters for both CSR and non-CSR firms. This conclusion is robust with controlling for all popular factors, such as market beta, book-to-market, size, momentum, return reversal, liquidity, and return skewness.

In addition, as described in the Section 2.3, some firms are required by the government to disclose CSR reports, while others voluntarily disclose their CSR reports. We further study if there are differences between these two types of CSR firms by adding a second dummy variable, V_{it}, which equals 1 if firms voluntarily disclose a CSR report last year, and 0 otherwise. Because V_{it} always equals $CSR_{it} \times V_{it}$, there is no V_{it} in Model 2 of Table 9. As shown in the regression, the coefficient of $AQBeta_{it}$ for non-CSR firms continues to be similar and significant as before. For none voluntarily CSR disclosing firms, the coefficient of $AQBeta_{it} + CSR_{it} \times AQBeta_{it}$ (0.178) is smaller but still significant, indicating that air-quality risk matters despite their effort. The coefficient of $CSR_{it} \times AQBeta_{it} + CSR_{it} \times AQBeta_{it} \times V_{it}$ is almost zero, which means that, there is almost no difference between the impact of air quality on non-CSR firms and those on the CSR firms who have voluntarily disclosed their reports. This may suggest that the voluntary disclosures have less to do with air pollution for firms in our sample.

4.6 Comovement Among Market Risk, Idiosyncratic Risk, and Air-Quality Risk

It is well documented that both the systematic risk measure beta and idiosyncratic volatility vary over time since these second moment measures are affected by the underlying state variables. Therefore, if $AQBeta$ also measures a type of fundamental risks, it will vary with with the underlying state variables since it is a second moment based risk measure, which will lead to comovement with the market beta and idiosyncratic volatility. We investigate the contemporaneous relation between market beta and $AQBeta$, and between idiosyncratic volatility and $AQBeta$ in Table 10.

Insert Table 10 Approximately here

The dependent variable of the first model in Table 10 is the idiosyncratic volatility of a stock, which is calculated from the residual returns with respect to the Fama and French [1993] model. As shown, the coefficient estimate of $AQBeta_{it}$ is 0.0085, which is significantly positive at a 1% level. This indicates that when firms face higher air-quality risks their idiosyncratic risks are also likely to increase, which will make investors even harder to diversify their risks. Similarly, when the dependent variable is the market beta in the second model, the coefficient estimate of $AQBeta_{it}$ is also significant at a 1% level, which suggests that there is a comovement among $AQBeta$ and market beta. Since market beta does not have cross-sectional explanatory power for return differences as well-documented while $AQBeta$s do explain cross-sectional return differences, such a comovement more like reflect common time variations. These results holds after controlling for firm level characteristics. Therefore, from the perspective of comovement in the risk structure, our measure of air-quality risk does seem to capture an additional dimension of priced risk.

5 Robustness Study

Empirical studies are prone to the data-snooping bias or sample selection issues. Given the short sample nature of Chinese capital market and the available data, it is especially important to perform robustness tests. Although we cannot split our sample over time, we utilizing a special feature of the Chinese data to separate sample into state-owned versus non-state firm samples. In addition, we investigate different estimates of $AQBeta$ since it is the most important variable in our study

5.1 The Ownership Structure and Pollution Sensitive Industries

A common approach to deal with data-snooping issue is to use a different sample or subsample periods. Since dividing into subsample periods is not possible, we will first group firms into two subsample according to their ownership structure. In China, many public traded companies have large state ownership. The state ownership used to be over 60%. The average state ownership has dropped substantially to about 30% in recent years, which is the threshold to classify firms into State-Owned Enterprises (SOE) and non-SOE groups. There are two factors that will influence the impact of air-quality risk on firms. Because of differences in ownership structure, non-SOE firms are more profit driven than SOE firms in China, which may make them more vulnerable to pollution risk, which will make these firms more sensitive to pollution risk. At the same time, because the ultimate owners of SOEs are governments, and the separation between government influence and independent business decision is weak, regulations and government policies protect SOEs more than non-SOEs. Therefore, SOEs are less likely to face the same air-quality risk as non-SOEs. We reestimate the main model in Table 6 with an addition dummy variable SOE_{it}. Results are reported in Table 11.

Insert Table 11 Approximately here

As shown, the coefficient estimate of $AQBeta_{it}$ of 0.597 remains to be positive and statistically significant at a 1% level after adding SOE as a control. More important, the interaction term of $SOE_{it} \times AQBeta_{it}$ is also significant but negative at a 1% level, suggesting that the air-quality risk affect non-SEO firms in a more significant way than SEO firms as we expected. Despite that, air-quality risk still affects SEO firm since the coefficient estimate of $AQBeta_{it} + SOE_{it} \times AQB_{it}$ (0.359) is significantly different from 0. Overall, air-quality risk matters to both SEO and non-SEO firms with non-SOEs being exposed more to air-quality risk.

The effect of air pollution could also vary substantially across different industries. Some industry may well be the net source of air pollution rather than the victim of pollution. For example, the mining and the steel industries are the two major polluter in China. To further test the differential impact of air-quality, we further separate our sample into the "polluting" firm group and the regular firm group according to industry by introducing a dummy variable IND_{it}, which equals to 1 if a firm is from polluting industries, such as mining or steel industries, and 0 otherwise. Similar cross-sectional regression results are reported in the column 2 of Table 11. For regular firms, the coefficient estimate of $AQBeta_{it}$ is significant and very similar to our baseline result. However, the interaction term $IND_{it} \times AQBeta_{it}$ is significant but very negative. In fact, the coefficient estimate of $AQBeta_{it} + IND_{it} \times AQBeta_{it}$ (-0.21) is negative and statistically significant at a 1% level. This suggests that the premium is actually negative for polluters.

5.2 Alternative Estimates of Key Variables

The most important variable in our study is the air-quality beta ($AQBeta$) of individual stocks. In order to make sure that our results are not sensitive to the particular way of constructing such measure, we will use alternative approaches to construct the measure. Instead of using the average change rate of PM2.5 of across the five cities (namely, Beijing, Chengdu, Guangzhou, Shanghai, and Shenyang) to construct our $\Delta MAQI$ measure, we can use the median value or the maximum values. We then reestimate the $AQBeta$ for individual stocks and redo the main cross-sectional regression in Table 6. Regression results are reported in Table 12.

Insert Table 12 Approximately here

Although the coefficient estimate of $AQBeta$ drops somewhat from 0.498 to 0.440 and 0.421 when using measures based on median and maximum, respectively, they are all significant at a 1% level. Since we focus on cross-sectional regressions across all firms that are located all over the country, we present our main results based on the mean measure. We have also explored the window length to estimate $AQBeta$. Perhaps, the beta estimate is more accurate when using one month of daily returns instead of three months. As shown in Table 12, the corresponding coefficient estimate are even larger and very significant ranging from 0.468 to 0.785. Therefore, our results are very robust with respect to the estimates of air-quality risk beta.

For the contemporaneous time-series regressions reported in Table 3, we can also use alternative measures of $\Delta MAQI$ based on median and maximum values. Results are reported in Table 13. In the first two regressions, the dependent variable is still the equal-weight return of individual stocks. The coefficient estimates of $\Delta MAQI$ not only are negative and significant but also have the similar magnitude. In the last regression, we use the value-weighted market return as the dependent variable but the same $\Delta MAQI$ measure as before. Despite smaller coefficient estimate in this case, it is still significant at a 1% level. Therefore, no matter how to estimate air quality and market returns, market returns are always negatively related to air quality changes, which means that the market does seem to be efficent in reacting to changes in air quality.

Insert Table 13 Approximately here

5.3 Another Look at the Event Study

Most studies rely on nature experiments to draw causality implications. Using special events of the 2014 APEC Economic Leaders' Week (Nov. 5-11, 2014) and the commemoration of 70th anniversary of victory of WWII (Aug. 20-Sep. 4, 2015) in Table 8, we conclude that air-quality is a unique risk in the Chinese market that affects equity returns. However, event study results may be sensitive to the choice of comparison sample group. In this section, we expand the base sample to previous three years of compariable periods. In particular, the dummy variable, *Event* equals to 0 during the periods of November 5th to 11th, 2013, November 5th to 11th, 2012, November 5th to 11th, 2011, or August 20th to September 4th, 2014, August 20th to September 4th, 2013, and August 20th to September 4th, 2012. Table 14 repeats exercise in Table 8 but using the new *Event* dummy variable.

Insert Table 14 Approximately here

Comparing the interaction term of $Event \times Beijing$ in Model 1 of Table 14 to that of Table 8, it is still significant at a 1% level despite the estimate has reduced from 0.0022 to 0.0018. Different from Table 8, the dummy variable *Beijing* is no longer significant in Model 1. However, when all the control variables are used in Model 4, the dummy variable *Beijing* continues to be significant with a similar magnitude. At the same time, the estimate for the interaction term increase to 0.0020. Therefore, our event study results are also robust and strong.

6 Concluding Comments

It is now commonly accepted that individual stock returns are determined by multiple risk factors. The success of Fama and French's three-factor model or five-factor model supports this view. However, what are economic meanings of these factors or what are the underlying fundamental risk factors remain to be unclear or subject to interpretation since all these factors are based on firm characteristics. In this study, we take a different approach in identifying one possible underlying risk factor–air-quality risk.

Different from current studies that document weather related anomalies and offer explanations from behavial perspective, we argue that air-pollution is a fundamental risk factor that affects firm's performance. Changing air-quality will affect the environment that a firm operates, which will make the firm more prone to demand or supply shocks, which ultimately will affect the firm's performance. Therefore, when air-quality gets worsening, risk increases, causing its stock price to drop contemporaneously, or low current return. At the same time, future returns will increase due to rise in its expected return. We test these implications on both market level and from the cross-sectional perspective.

We find that market returns negatively comove with air-pulltion level change consistent with our hypothesis. Since we control for investor's sentiment, the evidence suggests that the Chinese markets in recent years are efficient in reacting to air pollution changes. We take a step further by estimating the air-quality risk betas for individual stocks. From cross-sectional regressions, we show that these air-quality betas can explain future return differences across individual stocks, which indicates the pricing of air-quality risk. To further show that air-quality risk is tied to firms' fundamentals, we investigate how changes in air-quality risk affect firms' future fundamentals. In particular, we document that firms' profit margins and per capita changes in the future are positively related to their air-quality betas. In addition, we utilize a nature experiemnt to show that the explanatory power of air-quality beta is unlikely a result of proxy for consumption risk or growth factor.

In addition to control for commonly used factors in our empirical studies, we perform several robustness tests. Based on the special feature of Chinese firms, we split sample into state-owned versus non-state-owned firms. We also construct different air-quality beta measures used in the corresponding tests. All robustness tests continue to support our main conclusion that air-quality is a risk factor that is priced in the Chinese equity market.

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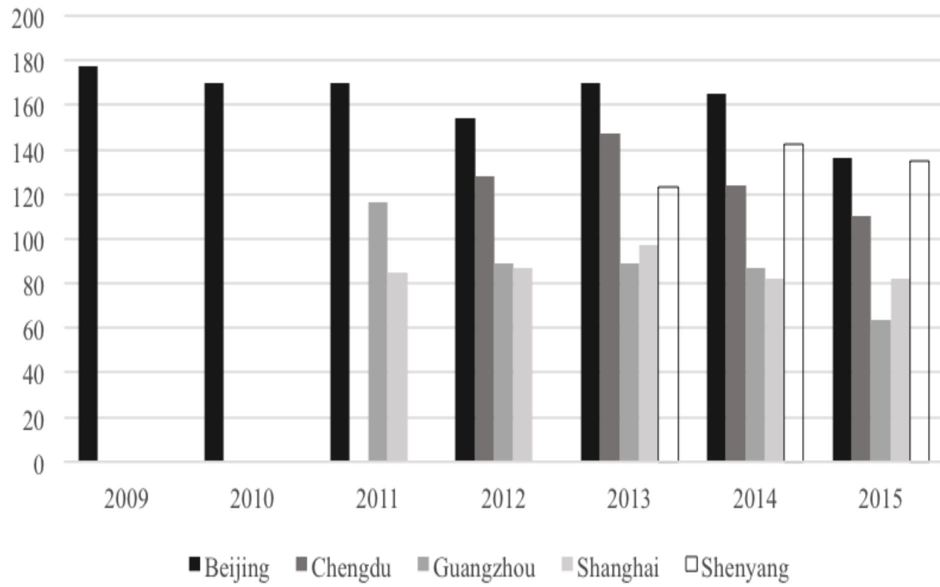
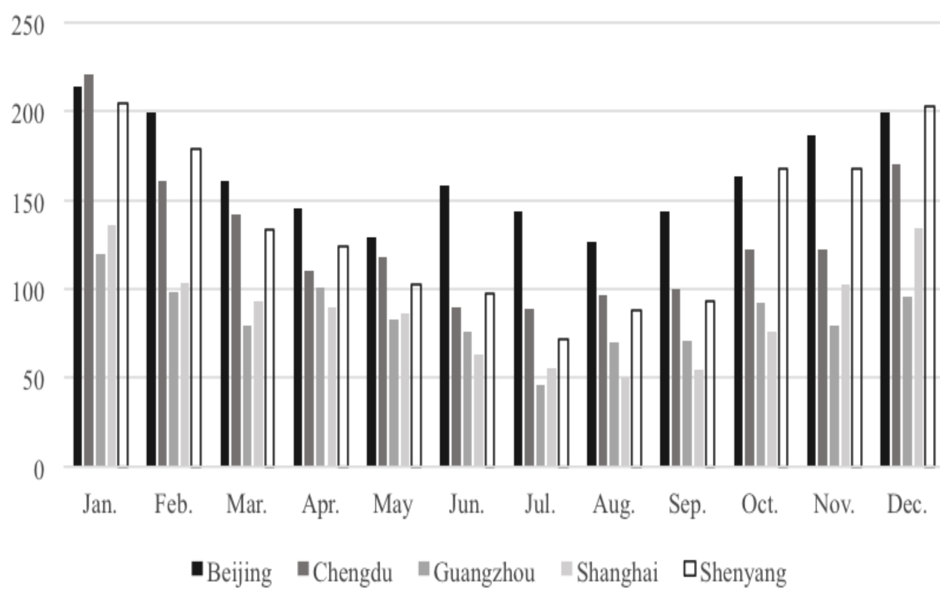


Panel A: Year Distribution



Panel B: Month Distribution

Figure 1: Distribution of PM 2.5

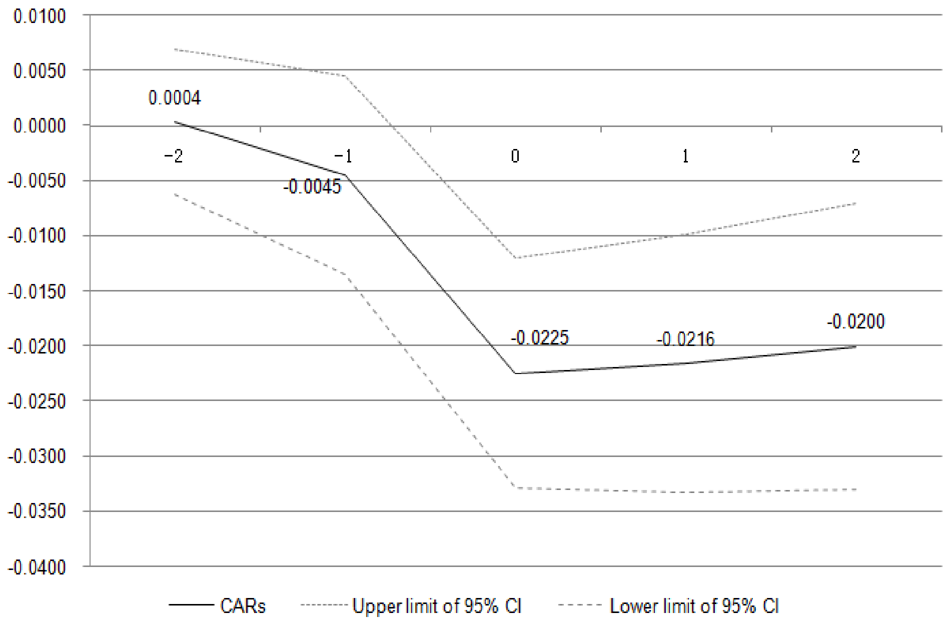


Figure 2: Relative Market Reaction Around Great Change in Air Quality

Table 1: **PM2.5 in China**

This table provides statistics for PM2.5 of five major cities, Beijing, Chengdu, Guangzhou, Shanghai, and Shenyang, which are followed by the U.S. Embassy. The numbers under "mean" and "Std" are the mean and standard deviation of PM 2.5 index level, while "[a-b]" denotes the percentage of days of which the PM 2.5 index falls in the interval from "a" to "b". According to the guidance for PM2.5 of the U.S. Embassy, an index level in the range of [0-50] indicates good air quality; [51-100] is moderate air quality; [101-150] is unhealthy air quality for sensitive groups; [151-200] is unhealthy air quality; [201-300] is very unhealthy air quality; and [>301] is hazardous air quality.

	Number	Mean	Std	[0-50]	[51-100]	[101-150]	[151-200]	[201-300]	[>301]
Total	4999	123.58	92.71	17.96	32.89	22.50	10.88	10.62	5.14
Beijing	1644	162.83	116.20	14.11	19.59	22.32	14.84	17.58	11.56
Chengdu	831	126.30	68.85	6.02	37.30	30.32	11.67	11.91	2.77
Guangzhou	937	82.64	50.84	29.14	41.52	20.28	6.19	2.45	0.43
Shanghai	965	86.90	61.23	29.95	41.24	16.99	6.42	4.56	0.83
Shenyang	622	134.80	92.52	8.68	36.17	24.44	13.34	12.22	5.14

Table 2: **Summary Statistics**

This table provides summary statistics for air quality and other weather characters. The sample period spans from January 2009 to December 2015. Panel A reports the time series summary statistics of the *daily* market return (RET_t), daily maximum change of PM2.5 ($\Delta MAQI_t$), the temperature change (ΔTEM_t), the humidity change (ΔHUM_t), and the wind speed change ($\Delta WIND_t$) of the five major cities, including Beijing, Chengdu, Guangzhou, Shanghai, and Shenyang. In addition, ΔSEN_t is the monthly change in the percentage of investment accounts opened, and ΔPMI_t is measured as the quarterly change in PMI growth. $P25$ and $P75$ represent the $25th$ and the $75th$ percentiles, respectively. Panel B reports the cross-sectional summary statistics of the *monthly* stock return ($StockRET_{it}$), air quality beta ($AQBeta_{it}$), market beta ($MktBeta_{it}$), book-to-market ratio (BM_{it}), natural log of market capitalization ($LnME_{it}$), momentum (MOM_{it}), dummy variable (V_{it}) that equals 1 if a firm has voluntarily disclosed a CSR report last year, dummy variable (SOE_{it}) that equals 1 if a firm is state-owned enterprise, dummy variable (IND_{it}) that equals 1 if a firm is from mining or steel industries, *idiosyncratic volatility* ($IVOL_{it}$), market illiquidity ($ILLIQ_{it}$), return skewness ($Skew_{it}$), change in quarterly profit margin ($\Delta PM_{i,t}$), change in quarterly per capita output ($\Delta Output_{i,t}$), asset-liability ratio ($Leverage_{it}$), Tobin's Q (Q_{it}), natural logarithm of the total assets ($LnAsset_{it}$), natural logarithm of the number of employees ($LnEmployee_{it}$), natural logarithm of asset intensity ($LnIntensity_{it}$), natural logarithm of the age of a firm in quarters ($LnAge_{it}$), operating leverage ($OpLeverage_{it}$), Herfindahl Index (HHI_{it}), change in investment in PPE in the next semi-annual scaled by the capital stock ($\Delta I/K_{it}$), the EBITDA scaled by the capital stock (CF/K_{it}). All continuous variables are winsorized at the 0.5% and 99.5% levels.

Panel A: Summary Statistics of Time Series Variables						
	Number	Mean	STD	P25	Median	P75
RET_t	1650	0.0015	0.0206	-0.0076	0.0033	0.0129
$\Delta MAQI_t$	1650	0.2378	0.7732	-0.1299	0.1048	0.4248
ΔTEM_t	1650	0.0036	0.2524	-0.0556	0.0059	0.0730
ΔHUM_t	1650	0.0215	0.1126	-0.0435	0.0156	0.0850
$\Delta WIND_t$	1650	0.0928	0.2704	-0.0926	0.0554	0.2201
ΔSEN_t	1650	0.0108	0.4733	-0.1554	-0.0029	0.1031
ΔPMI_t	1650	0.0011	0.0200	-0.0060	0.0019	0.0080

Panel B: Summary Statistics of Cross-Sectional Variables									
	Total sample			CSR_{it}=0			CSR_{it}=1		
	Mean	Median	STD	Mean	Median	STD	Mean	Median	STD
Monthly Variables									
$StockRET_{it}$	0.022	0.012	0.145	0.024	0.014	0.148	0.017	0.005	0.136
$AQBeta_{it}$	0.002	0.001	0.017	0.002	0.001	0.017	0.002	0.001	0.017
$MktBeta_{it}$	1.053	1.045	0.264	1.055	1.046	0.252	1.048	1.042	0.297
BM_{it}	0.680	0.510	0.579	0.650	0.486	0.562	0.777	0.588	0.622
$LnME_{it}$	22.03	21.90	1.14	21.77	21.71	0.95	22.87	22.76	1.27
MOM_{it}	0.096	0.062	0.308	0.101	0.069	0.314	0.079	0.042	0.286
V_{it}	0.086	0.000	0.280	0.000	0.000	0.000	0.358	0.000	0.479
SOE_{it}	0.488	0.000	0.500	0.444	0.000	0.497	0.627	1.000	0.483
IND_{it}	0.038	0.000	0.192	0.030	0.000	0.170	0.064	0.000	0.245
$IVOL_{it}$	0.018	0.016	0.008	0.018	0.017	0.008	0.016	0.014	0.008
$ILLIQ_{it}$	-19.04	-18.91	1.19	-18.75	-18.70	0.99	-19.94	-19.84	1.31
$Skew_{it}$	0.002	-0.023	0.608	-0.013	-0.038	0.606	0.050	0.027	0.612
Quarterly Variables									
$\Delta PM_{i,t+1}$	-0.002	-0.001	0.232	-0.001	-0.001	0.247	-0.003	-0.001	0.173
$\Delta Output_{i,t+1}$	0.003	0.004	0.244	0.003	0.004	0.248	0.001	0.004	0.229
$Leverage_{it}$	0.457	0.452	0.234	0.444	0.431	0.238	0.499	0.508	0.218
Q_{it}	2.117	1.590	1.731	2.211	1.657	1.834	1.803	1.400	1.287
$LnAsset_{it}$	21.94	21.72	1.39	21.61	21.49	1.12	23.03	22.78	1.63
$LnEmployee_{it}$	7.640	7.570	1.313	7.392	7.375	1.186	8.463	8.336	1.375
$LnIntensity_{it}$	14.30	14.17	0.99	14.22	14.10	0.95	14.58	14.42	1.09
$LnAge_{it}$	4.112	4.143	0.310	4.100	4.127	0.308	4.151	4.174	0.315
$OpLeverage_{it}$	0.243	0.208	0.170	0.243	0.209	0.165	0.246	0.202	0.183
HHI_{it}	0.144	0.072	0.171	0.145	0.072	0.173	0.139	0.073	0.162
Semi-annual Variables									
$\Delta I/K_{i,t+1}$	-0.012	-0.001	0.556	-0.010	-0.001	0.555	-0.016	-0.003	0.560
$CF/K_{i,t+1}$	0.293	0.255	0.654	0.264	0.235	0.592	0.390	0.347	0.822
	Total			Total	Percentage		Total	Percentage	
No. of Firm Years	14963			11556	77.23		3407	22.77	

Table 3: **The Time-Series Relation between Market Returns and Air Quality**

This table presents the time-series regression results of market excess returns on the air quality. The dependent variable is excess market return, which is measured by subtracting the daily risk-free rate from the daily market return of A shares stocks; $\Delta MAQI_t$ is the maximum change of PM2.5 in day t of the five major cities–Beijing, Chengdu, Guangzhou, Shanghai, and Shenyang; ΔSEN_t is the monthly change of the percentage of investment accounts opened; SMB_t, HML_t, and UMD_t are the mimicking factor-portfolio returns for size, book-to-market equity, and one-year momentum in stock returns, respectively; ΔTEM_t, ΔHUM_t, and $\Delta WIND_t$ are the daily maximum change in the temperature, humidity, and the wind speed of five major cities in day t, respectively; and ΔPMI_t is the quarterly PMI change. The robust Newey West t-statistic is reported in the bracket.

	intercept	$\Delta MAQI_t$	ΔSEN_t	SMB_t	HML_t	UMD_t	ΔTEM_t	ΔHUM_t	$\Delta WIND_t$	ΔPMI_t	Month Control	Adj. R^2
Model1	-0.0056	-0.0015										0.0024
	[-9.53]	[-2.34]										
Model2	-0.0056	-0.0015	0.0016									0.0031
	[-9.50]	[-2.41]	[0.87]									
Model3	-0.0101	-0.0012	0.0024	1.0827	-0.3010	-0.0036						0.3065
	[-8.85]	[-2.26]	[2.15]	[14.24]	[-2.72]	[-2.61]						
Model4	-0.0101	-0.0012	0.0023	1.0827	-0.3011	-0.0036	0.0002	0.0005	0.0002			0.3052
	[-8.95]	[-2.16]	[2.14]	[14.25]	[-2.72]	[-2.61]	[0.13]	[0.13]	[0.10]			
Model5	-0.0101	-0.0012	0.0023	1.0829	-0.3009	-0.0036	0.0002	0.0004	0.0002	0.0105		0.3049
	[-8.99]	[-2.18]	[2.02]	[14.24]	[-2.72]	[-2.62]	[0.10]	[0.12]	[0.10]	[0.48]		
Model6	-0.0101	-0.0012	0.0030	1.0917	-0.3081	-0.0035	0.0004	0.0000	-0.0002	0.0092	Yes	0.3075
	[-5.18]	[-2.29]	[2.18]	[14.31]	[-2.78]	[-2.62]	[0.21]	[-0.00]	[-0.12]	[0.33]		

Table 4: **The Cross-Sectional Relation between Market Returns and Air Quality**

This table presents the panel regression results. The dependent variables of models 1 and 2 are the monthly stock returns ($StockRET_{it}$) of firm i in the month t; the dependent variables of models 3 and 4 are the idiosyncratic volatility, $IVOL_{it}$, which is measured as the standard deviation of the stock returns; and the dependent variables of models 5 and 6 are the market beta ($MktBeta_{it}$). The CSR_{it} is a dummy variable which equals 1 if firms i has disclosed a CSR report last year, and 0 otherwise; $\overline{\Delta MAQI_t}$, $\overline{\Delta TEM_t}$, $\overline{\Delta HUM_t}$, and $\overline{\Delta WIND_t}$ are the monthly average of the maximum change in PM2.5, the temperature, the humidity, and the wind speed, respectively. Market illiquidity ($ILLIQ_{it}$), and skewness of stock return ($Skew_{it}$) are obtained following Hou and Loh [2016]. The robust t-statistics are reported in the bracket.

	$StockRET_{it}$	$IVOL_{it}$	$MktBeta_{it}$
	Model 1	Model 2	Model 3
intercept	-0.5592	-0.0010	-2.6319
	[-25.14]	[-0.65]	[-11.44]
CSR_{it}	-0.0054	0.0003	0.0208
	[-3.05]	[3.24]	[1.48]
$\overline{\Delta MAQI_t}$	-0.0061	0.0040	0.0450
	[-4.88]	[56.26]	[11.74]
$CSR_{it} \times \overline{\Delta MAQI_t}$	0.0066	-0.0003	-0.0471
	[4.52]	[-3.56]	[-3.77]
$MktBeta_{it}$	-0.0084		
	[-8.12]		
BM_{it}	-0.0067	0.0006	-0.1238
	[-6.01]	[8.26]	[-10.89]
$LnME_{it}$	0.1717	0.0145	0.1225
	[95.28]	[161.26]	[12.05]
$ILLLIQ_{it}$	0.1548	0.0148	-0.0436
	[101.16]	[250.36]	[-11.62]
$Skew_{it}$	0.0535	-0.0029	-0.0078
	[42.48]	[-49.84]	[-2.49]
VOL_{it}	-3.8311		0.7402
	[-57.24]		[4.26]
$\overline{\Delta TEM_t}$	0.0448	0.0021	-0.0138
	[28.59]	[26.71]	[-4.61]
$\overline{\Delta HUM_t}$	-0.023	-0.0026	-0.0428
	[-6.97]	[-14.50]	[-5.14]
$\overline{\Delta WIND_t}$	-0.0442	-0.0050	-0.0116
	[-15.40]	[-34.46]	[-1.91]
Year control	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Within R^2	0.2737	0.6038	0.2674
Number	149090	149090	149090

Table 5: **The Cross-Sectional Pricing Effect of the Pollution Risk**

This table presents the monthly mean returns of the 25 Size and AQBeta sorted portfolios and the 25 Book-to-Market and AQBeta sorted portfolios. $AQBeta$ of a stock is estimated by regressing daily returns of an individual stock on the corresponding $-\Delta MAQI$ in the past three months since AQI is a negative factor. ***, **, and * denote the significance levels of the 1%, 5%, and 10%, respectively.

Panel A: The 25 size-AQBeta Portfolios							
		$AQBeta$					
		1(low)	2	3	4	5(high)	5-1
$Size$:	1 (small)	0.0153	0.0133	0.0048	0.0297	0.0754	0.0600***
	2	0.0116	0.0039	0.0008	0.0228	0.0613	0.0498***
	3	0.0069	0.0016	-0.0036	0.0202	0.0483	0.0414***
	4	0.0011	-0.0039	-0.0097	0.0107	0.0282	0.0270***
	5 (big)	-0.0087	-0.0031	-0.0116	0.0061	0.0125	0.0212***
Panel B: The 25 B/M-AQBeta Portfolios							
		$AQBeta$					
		1(low)	2	3	4	5(high)	5-1
BM:	1 (small)	-0.0086	-0.0094	-0.0121	0.0091	0.0263	0.0348***
	2	0.0055	-0.0020	-0.0051	0.0188	0.0452	0.0397***
	3	0.0137	0.0051	0.0016	0.0235	0.0580	0.0443***
	4	0.0135	0.0133	0.0025	0.0274	0.0627	0.0492***
	5 (big)	0.0127	0.0144	0.0029	0.0233	0.0649	0.0521***

Table 6: **Cross-Sectional Relation between Stock Returns on Pollution Risk**

This table investigates the pricing effect of pollution risk using the air-quality beta as a risk measure. The dependent variable is the monthly stock return of firm i in month $t+1$ ($StockRET_{i,t+1}$); $AQBeta_{it}$ is the air quality beta; $MktBeta_{it}$ is the monthly market beta of firm i; BM_{it} is the book-to-market ratio; $LnME_{it}$ is the natural log of market capitalization; MOM_{it} is stock i's return momentum measured as its cumulate returns from month $(t-7)$ to month $(t-12)$; $ILLIQ_{it}$ is the illiquidity measure. The skewness of stock return ($Skew_{it}$) is computed following Hou and Loh [2016]. The robust t-statistics are reported in the bracket.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
intercept	0.0441	0.0535	1.3575	1.3923	1.3887	1.3891	1.3878
	[31.72]	[14.50]	[16.65]	[17.48]	[16.24]	[16.13]	[16.22]
$AQBeta_{it}$	0.4929	0.4944	0.4922	0.4946	0.4898	0.4993	0.4981
	[7.46]	[7.51]	[7.92]	[7.87]	[9.12]	[9.34]	[9.38]
$MktBeta_{it}$		-0.0089	-0.0046	-0.0051	-0.0051	-0.0041	-0.0041
		[-2.77]	[-1.39]	[-1.57]	[-1.57]	[-1.28]	[-1.29]
BM_{it}			-0.0120	-0.0120	-0.0120	-0.0124	-0.0124
			[-4.86]	[-4.80]	[-4.80]	[-4.95]	[-4.96]
$LnME_{it}$			-0.0603	-0.0620	-0.0618	-0.0709	-0.0707
			[-16.40]	[-17.22]	[-15.93]	[-15.43]	[-15.71]
MOM_{it}				0.0119	0.0119	0.0115	0.0115
				[2.79]	[2.78]	[2.68]	[2.67]
$StockRET_{it}$					-0.0027	0.0021	0.0031
					[-0.34]	[0.26]	[0.38]
$ILLIQ_{it}$						-0.0105	-0.0104
						[-6.46]	[-6.57]
$Skew_{it}$							-0.0011
							[-0.79]
Year control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.0229	0.0230	0.0487	0.0492	0.0492	0.0499	0.0499
Number	147191	147191	147191	147191	147191	147191	147191

Table 7: **The Cross-Sectional Relation between Economic Activities and Pollution Risk**

This table presents the results of cross-sectional regression of economic activities on pollution risk. The dependent variable of column A is the change in profit margin in the next quarter ($\Delta PM_{i,t+1}$); the dependent variable of column B is the change in investment in property, plant, and equipment (PPE) in the next six-month scaled by the capital stock ($\Delta I/K_{i,t+1}$); the column C is the change in the ratio of firm output to the number of employees in the next quarter ($\Delta Output_{i,t+1}$), firm's output is measured as sales plus changes in inventories. $\overline{AQBeta_{it}}$ ($\overline{MktBeta_{it}}$) is the average of $AQBeta_{it}$ ($MktBeta_{it}$) during the related period. For the column 1 and column 3, the period is a quarter; for the column 2, it is a semi-annual. $Leverage_{it}$ is the asset-liability ratio. Q_{it} is Tobin's Q, measured by the sum of the book value of debt and the market value of equity divided by the book value of assets. $LnAsset_{it}$ is the natural logarithm of the total assets. $CF/K_{i,t+1}$ is the earnings before interest, taxes, depreciation, and amortization (EBITDA), scaled by the capital stock. $LnEmployee_{it}$ is the natural logarithm of the number of employees. $LnIntensity_{it}$ is the natural logarithm of asset intensity, which measured as the total assets divided by the number of employees. $LnAge_{it}$ is the natural logarithm of the number of quarter the firm has been established. $OpLeverage_{it}$ is the operating leverage, measured as the PPE divided by total assets. HHI_{it} is the Herfindahl Index. $Anual_{it}$ is a dummy variable, which equals to 1 if it is a annual report, and otherwise 0. The robust t-statistic is reported in the bracket.

	$\Delta PM_{i,t+1}$	$\Delta I/K_{i,t+1}$	$\Delta Output_{i,t+1}$
intercept	0.7722	7.9974	1.8321
	[6.72]	[14.42]	[10.56]
$\overline{AQBeta_{it}}$	-0.3074	-0.9227	-0.3891
	[-2.89]	[-1.74]	[-2.27]
$Leverage_{it}$	0.2067	-0.1374	
	[13.38]	[-3.25]	
Q_{it}	0.0013	-0.0118	
	[1.26]	[-2.60]	
$LnAsset_{it}$	-0.0397	-0.3714	
	[-7.31]	[-14.60]	
$\overline{MktBeta_{it}}$	-0.0131	0.0492	
	[-2.22]	[3.28]	
$CF/K_{i,t+1}$		0.1983	
		[11.71]	
$LnEmployee_{it}$			-0.0527
			[-9.64]
$LnIntensity_{it}$			-0.1127
			[-16.65]
$LnAge_{it}$			0.0507
			[1.59]
$OpLeverage_{it}$			-0.0151
			[-0.83]
HHI_{it}			0.0197
			[0.90]
$Anual_{it}$	0.0136	-0.1256	-0.1157
	[1.75]	[-6.81]	[-8.90]
Year	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Within R^2	0.0097	0.0976	0.0694
Number	53253	26938	53253

Table 8: **Stock Returns during Special Event Periods**

This table investigates the stock returns during the event periods, when the government improves air quality to a extreme higher level for special purpose. The dependent variable is the daily average abnormal return of firm i during the event period. $Event_{it}$ is a dummy variable which equals to 1 during the 2014 APEC Economic Leaders' Week (Nov. 5-11, 2014) or commemoration of 70th anniversary of victory of China against Japanese aggression and Anti-Fascist war (Aug. 20-Sep. 4, 2015), and equals to 0 during the related periods, Nov. 5-11, 2013 or Aug. 20-Sep. 4, 2014. $Beijing_{it}$ is a dummy variable which equals to 1 if firms operate around Beijing, and 0 otherwise. The robust t-statistic is reported in the bracket.

	Model 1	Model 2	Model 3	Model 4
intercept	0.0107	0.0918	0.1244	0.1720
	[2.35]	[2.90]	[3.94]	[4.59]
$Event_{it}$	-0.0006	0.0006	0.0006	0.0010
	[-0.86]	[0.75]	[0.74]	[1.10]
$Beijing_{it}$	-0.0149	-0.0223	-0.0284	-0.0369
	[-3.21]	[-3.24]	[-3.65]	[-4.74]
$Event_{it} \times Beijing_{it}$	0.0022	0.0021	0.0021	0.0033
	[2.83]	[2.78]	[2.91]	[3.56]
$MktBeta_{i,t-1}$		-0.0048	-0.0043	-0.0036
		[-3.88]	[-3.49]	[-2.94]
$BM_{i,t-1}$		-0.0023	-0.0027	-0.0033
		[-1.65]	[-2.11]	[-2.60]
$LnMV_{i,t-1}$		-0.0030	-0.0039	-0.0060
		[-2.58]	[-3.03]	[-3.88]
$ILLLIQ_{i,t-1}$			-0.0009	-0.0011
			[-1.81]	[-2.38]
$Skew_{i,t-1}$			0.0004	0.0001
			[0.72]	[0.17]
$VOL_{i,t-1}$			0.0760	0.0933
			[2.13]	[2.62]
ΔTEM_t				-0.0009
				[-0.98]
ΔHUM_t				0.0576
				[3.88]
$\Delta WIND_t$				-0.0179
				[-4.21]
Firm FE	Yes	Yes	Yes	Yes
Adj. R^2	0.0289	0.0419	0.0518	0.0619
Number	7480	7480	7480	7480

Table 9: **Air-Quality Risk for CSR and non-CSR Firms**

This table exams difference between CSR firms and non-CSR firms using pooled regression approach. The dependent variables are the monthly stock returns ($StockRET_{i,t+1}$) of firm i in the month $t+1$. The CSR_{it} variable is a dummy variable which equals 1 if firms i has disclosed a CSR report last year, and 0 otherwise. $AQBeta_{it}$ is the air quality beta; $MktBeta_{it}$ is the monthly market beta of firm i; BM_{it} is the book-to-market ratio; $LnME_{it}$ is the natural log of market capitalization; MOM_{it} is stock i's return momentum measured as its cumulate returns from month $(t-7)$ to month $(t-12)$; Market illiquidity ($ILLIQ_{it}$), and skewness of stock return ($Skew_{it}$) are obtained following Hou and Loh [2016]. The robust t-statistics are reported in the bracket.

	$StockRET_{i,t+1}$	
	Model 1	Model 2
intercept	1.3927	1.3947
	[16.53]	[16.62]
$AQBeta_{it}$	0.5565	0.5566
	[9.92]	[9.92]
CSR_{it}	-0.0084	-0.0075
	[-3.93]	[-3.12]
$CSR_{it} \times AQBeta_{it}$	-0.2380	-0.3788
	[-3.24]	[-3.45]
$CSR_{it} \times V_{it}$		-0.0027
		[-0.96]
$CSR_{it} \times V_{it} \times AQBeta_{it}$		0.3451
		[2.90]
$MktBeta_{it}$	-0.0040	-0.0040
	[-1.26]	[-1.28]
BM_{it}	-0.0126	-0.0127
	[-5.08]	[-5.08]
$LnME_{it}$	-0.0710	-0.0711
	[-16.03]	[-16.13]
MOM_{it}	0.0116	0.0117
	[2.71]	[2.72]
$StockRET_{it}$	0.0030	0.0032
	[0.37]	[0.39]
$ILLLIQ_{it}$	-0.0105	-0.0105
	[-6.65]	[-6.68]
$Skew_{it}$	-0.0011	-0.0011
	[-0.78]	[-0.79]]
Year control	Yes	Yes
Firm FE	Yes	Yes
Within R^2	0.0503	0.0504
Number	147191	147191

Table 10: **Comovement among Air-Quality Risk, Market Risk, and Idiosyncratic Risk**

This table presents the pooled regression results on different measures of risk. The dependent variables of models 1 and 2 are the market beta ($MktBeta_{i,t+1}$), and the dependent variables of models 3 and 4 are the idiosyncratic volatility, $IVOL_{i,t+1}$, which is measured as the standard deviation of the stock i's residual returns with respect to Fama and French's (1993) model. $AQBeta_{it}$ is the air quality beta; $MktBeta_{it}$ is the monthly market beta of firm i; BM_{it} is the book-to-market ratio; $LnME_{it}$ is the natural log of market capitalization; MOM_{it} is stock i's return momentum measured as its cumulate returns from month $(t-7)$ to month $(t-12)$; Market illiquidity ($ILLIQ_{it}$), and skewness of stock return ($Skew_{it}$) are obtained following Hou and Loh [2016]. The robust t-statistics are reported in the bracket.

	$IVOL_{i,t}$	$MktBeta_{i,t}$
	Model 1	Model 2
intercept	-0.0165	1.0399
	[-5.76]	[5.23]
$AQBeta_{it}$	0.0085	0.2309
	[4.27]	[4.42]
BM_{it}	-0.0001	0.0014
	[-0.76]	[0.11]
$LnME_{it}$	0.0061	0.0262
	[32.86]	[2.80]
MOM_{it}	-0.0008	0.0147
	[-5.38]	[2.68]
$StockRET_{it}$	0.0070	0.0500
	[22.84]	[10.13]
$ILLLIQ_{it}$	0.0052	0.0298
	[35.29]	[8.29]
$Skew_{it}$	0.0001	-0.0023
	[1.32]	[-3.21]
Year control	Yes	Yes
Firm FE	Yes	Yes
Within R^2	0.2096	0.0118
Number	147191	147191

Table 11: **Cross-Sectional Regression: Ownership and Industry**

This table presents the cross-sectional regression results. SOE_{it} is a dummy variable which equals 1 if a firm is state-owned enterprise, and 0 otherwise; IND_{it} is a dummy variable which equals 1 if a firm is from the mining and steel industries, and 0 otherwise. $AQBeta_{it}$ is the air quality beta; $MktBeta_{it}$ is the monthly market beta of firm i; BM_{it} is the book-to-market ratio; $LnME_{it}$ is the natural log of market capitalization; MOM_{it} is stock i's return momentum measured as its cumulate returns from month $(t-7)$ to month $(t-12)$; Market illiquidity ($ILLIQ_{it}$), and skewness of stock return ($Skew_{it}$) are obtained following Hou and Loh [2016]. The robust t-statistic is reported.

	Ownership	Industry
intercept	1.3928	1.3895
	[16.31]	[16.30]
$AQBeta_{it}$	0.5965	0.5202
	[11.61]	[9.73]
SOE_{it}	-0.0001	
	[-0.01]	
$SOE_{it} \times AQBeta_{it}$	-0.2376	
	[-3.93]	
IND_{it}		-0.0076
		[-1.71]
$IND_{it} \times AQBeta_{it}$		-0.7305
		[-7.09]
$MktBeta_{it}$	-0.0043	-0.0041
	[-1.35]	[-1.28]
BM_{it}	-0.0125	-0.0124
	[-4.98]	[-4.93]
$LnME_{it}$	-0.0709	-0.0708
	[-15.79]	[-15.79]
MOM_{it}	0.0117	0.0116
	[2.73]	[2.72]
$StockRET_{it}$	0.0036	0.0032
	[0.44]	[0.39]
$ILLLIQ_{it}$	-0.0104	-0.0104
	[-6.55]	[-6.59]
$Skew_{it}$	-0.0012	-0.0011
	[-0.84]	[-0.80]
Year control	Yes	Yes
Firm fixed effects	Yes	Yes
Within R^2	0.0501	0.0502
Number	147191	147191

Table 12: **Alternative Estimation of AQBeta**

This table presents the results of regression listed in the Table 6. The $AQBeta_{it}$ of column 1 (column 2) is extimated using the median (maximum) change of PM 2.5 among Beijing, Chengdu, Guangzhou, Shanghai, and Shenyang in the past one month, while the $AQBeta_{it}$ of column 3, column 4, and column 5 are extimated using the mean, median, and maximum change of PM 2.5 among Beijing, Chengdu, Guangzhou, Shanghai, and Shenyang in the past three months. The robust Newey West t-statistic is reported in the bracket.

	Past 1 Month		Past 3 Months		
	Median	Maximum	Mean	Median	Maximum
$AQBeta_{it}$	0.4402	0.4213	0.6949	0.4675	0.7849
	[10.58]	[2.69]	[22.70]	[14.49]	[9.44]
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Within R^2	0.0504	0.0468	0.0555	0.0516	0.0491
Number	147191	147191	147163	147163	147163

Table 13: **Alternative Estimation of Other Variables**

This table presents the regression results using the same full model listed in the Table 3 but with different air pollution measures. The $\Delta MAQI_t$ of line 1 (line 2) is measured as the median (maximum) change of PM 2.5 among Beijing, Chengdu, Guangzhou, Shanghai, and Shenyang. The dependent variable of line 3 is value-weighted average returns of A shares. The robust Newey West t-statistic is reported in the bracket.

	$\Delta MAQI_t$	Controls	Adj. R^2
Median change of PM 2.5	-0.0011	Yes	0.3071
	[-2.13]	Yes	
Maximum change of PM 2.5	-0.0008	Yes	0.3078
	[-2.26]	Yes	
VW average returns	-0.0012	Yes	0.0481
	[-2.31]	Yes	

Table 14: **Alternative Definition of Event Periods**

This table presents the regression results with alternative definition of event. $Event_{it}$ is a dummy variable which equals to 1 during the 2014 APEC Economic Leaders' Week (Nov. 5-11, 2014) or commemoration of 70th anniversary of victory of China against Japanese aggression and Anti-Fascist war (Aug. 20-Sep. 4, 2015), and equals to 0 during the related periods, Nov. 5-11, 2013, Nov. 5-11, 2012, Nov. 5-11, 2011 or Aug. 20-Sep. 4, 2014, Aug. 20-Sep. 4, 2013, Aug. 20-Sep. 4, 2012.

	Model 1	Model 2	Model 3	Model 4
intercept	0.0126	0.0972	0.1231	0.1356
	[1.08]	[3.81]	[4.91]	[5.27]
$Event_{it}$	-0.0011	0.0009	0.0012	0.0012
	[-1.64]	[1.09]	[1.41]	[1.37]
$Beijing_{it}$	-0.0166	-0.0254	-0.0306	-0.0323
	[-1.43]	[-2.15]	[-2.45]	[-2.60]
$Event_{it} \times Beijing_{it}$	0.0018	0.0018	0.0017	0.0020
	[2.61]	[2.77]	[2.79]	[3.22]
$MktBeta_{i,t-1}$		-0.0034	-0.0031	-0.0030
		[-2.90]	[-2.68]	[-2.64]
$BM_{i,t-1}$		-0.0021	-0.0023	-0.0025
		[-3.92]	[-4.54]	[-5.42]
$LnME_{i,t-1}$		-0.0032	-0.0036	-0.0044
		[-3.51]	[-3.79]	[-4.24]
$ILLLIQ_{i,t-1}$			-0.0013	-0.0013
			[-2.59]	[-2.55]
$Skew_{i,t-1}$			0.0007	0.0003
			[1.20]	[0.50]
$IVOL_{i,t-1}$			0.0526	0.0527
			[1.94]	[1.97]
ΔTEM_t				0.0001
				[0.17]
ΔHUM_t				0.0176
				[0.87]
$\Delta WIND_t$				-0.0098
				[-2.21]
Industry control	Yes	Yes	Yes	Yes
Adj. R^2	0.0276	0.0442	0.0519	0.0543
Number	9038	9038	9038	9038