Does Air-Pollution Matter in Asset Pricing?

Abstract

Air-pollution affects firms' operating costs, reduces firms' productivity, and future investment opportunities. Therefore, surprises in air-pollution level constitute an added risk factor to individual firms, which will be priced by rational investors. Using the Chinese data, we construct a simple measure of air-pollution risk for individual firms. Cross-sectional evidence suggests that differences in air-pollution betas are related to firms' future fundamentals, including profit margins and investment. More important, future return differences of individual stocks can be explained by the differences in their air-pollution betas, which is consistent with the pricing story of air-pollution risk. In addition, we present natural experiments to account for alternative channels and potential endogeneity issues. Different from the current research on the subject that adopts a behavioral approach, our study provides robust evidence on air-pollution as an independent risk factor that firms should care.

Key Words: AQI, Air-pollution Risk, Beta, Cross-sectional Returns, Natural Experiment, Sentiment Risk

1 Introduction

Most current studies on the impact of climate change to the financial markets focus on either investors' trading behavior affected by climate change or differential valuation of green versus brown firms by investors because of their contribution to the climate change. In this study, we ask a different but equally important question, which is how firms' fundamentals including risks are passively affected by climate change. This is a fairly broad question and is difficult to answer empirically in the mature capital markets, where climate change variations are insufficient that could allow us to isolate significant impacts. Given the rising importance of emerging markets and worsening environment conditions, we study how firms' risks are affected by climate change and the corresponding pricing effect. In particular, we choose the Chinese capital markets as a laboratory to study the issue due to the severe air-pollution and large variations both over time and across regions. Utilizing the special geographic characteristics and unique governmental management of certain events, along with our air-pollution risk measure, we show that air-pollution is an important and independent risk factor that not only affects individual firms' stock prices but also alters their fundamentals.

Due to the poor empirical performance of the CAPM model and the consumption based

CAPM, there is a resurgence in the production based CAPM.[1] Since firms operate in a complex environment, not only the ever-changing business environment, including technological advancement, operating efficiency, new investment opportunities, and changing consumers' preferences will affect firms' performance, but the natural environment will have an impact on their fundamentals and risks as well. For example, worsening air-pollution may increase firms' operating costs in providing a workable environment, deteriorate employees' productivities, and lower the quality of their products. In response, firms will be forced to alter their current investment which will limit their future investment opportunities. When the air-pollution level varies substantially over time, these direct or indirect impacts will be unexpected, which also add uncertainty or risks to firms. Therefore, documenting climate change risks on firms is important in asset pricing studies.

Given the enforcement of relatively strict environmental protection laws and the clean environment, it is difficult to uncover credible evidence when focusing on mature capital markets. In other words, there are insufficient variations in short-term changes in environmental factors that can be linked to variations in firms' economic activities. Capital markets in underdeveloped countries on the other end of the spectrum cannot offer much insight either because of the limited role played by their capital markets or because of environmental issues being largely ignored in these countries. In contrast, the Chinese capital markets are better suited to study these important issues. Over the past thirty years, the Chinese capital markets have played a critical role in the growth of its economy. At the same time, on its path to growth, air-pollution has become a large issue and a major concern of the public. In fact, it has not only become an epidemic health hazard directly affecting the quality of life across major cities in China, but also forced policy maker to rethink about their country's environmental policy seriously. As a result, using the Chinese capital markets to understand the air-pollution risk in particular can offer unique insights. Moreover, it provides investors in the developed market with an important perspective as to what might affect business at home if climate change worsens since all of us living in the global village.

Without detailed information on firms' operating structure, it is challenging to study firms' climate change risks. As an alternative, we try to construct a measure from an investors' perspective. Given the rising adverse impact of climate change including air-pollution on human, consumers (investors), firms, and governments are increasingly conscious about preserving our green environment. As a result, investors will factor in the air-pollution risk into their investment decision on individual stocks. Ultimately, if the air-pollution risk is large enough, it will affect firms' bottom line, and investors should care enough about such a risk that results in a measurable risk premium. Consequently, we propose using a sensitivity measure of an individual stock returns to air-pollution changes as a measure of air-pollution risk. Such a risk factor can be neither diversified away nor simply absorbed into the market factor. Over time, such a risk factor may play an increasingly important role when investors' preferences or environmental consciousness changes. This approach is also in the spirit of the APT model of Ross. One caveat of the proposed measure is the possible reflection of investors' assessment of the externality generated by those "dirty" firms. Therefore, we will try to control firm characteristics such as ESG score and the firm fixed effect.

[1] In fact, one can interpret some of the factors used in the popular Fama and French's (1993) three-factor model as reflecting the production side characteristics. More elaborated and theoretically motived models are summarized in Zhang (2001).

In our quest of establishing the pricing effect of air-pollution risk, we recognize several possible endogeneity issues. First, as mentioned early, some firms may generate air-pollution, which may create positive externality for them. This is especially the case when firms are seeking high growth by ignoring the environmental impact. Such an effect may offset the adverse air pollution risk on firms. As an imperfect measure, we will use the ESG measure as an indirect control. Moreover, as Chinese economy is heavily dependent on manufacture, this factor could alter our estimation of air-pollution risk. We propose a second approach to control. Firm level pollution is likely to affect local air-pollution. Therefore, we decompose our air-pollution risk into systematic versus idiosyncratic measure. It should be the systematic part that affect the pricing of the air-pollution risk. Second, a high growth firm may be more vulnerable to air pollution risk just because of the nature of their business. In this case, it is problematic when the air-pollution risk measure is correlated with the firm growth rate since firm growth has been shown to be related to future returns. To alleviate the concern, we will both directly control for growth and utilize an nature experiment. Finally, the level of air-pollution may be correlated with aggregate consumption. In this case, our air-pollution risk measure may partially reflect the consumption risk as in the consumption CAPM model. Despite this is a less likely scenario given the weak support for the consumption based CAPM in China (see), we show that our air-pollution betas are directly tied to firms' fundamental risks instead of the demand side risks. In addition, we utilize a Hui-river natural experiment where there are air-pollution level differences geographically due to large consumption differences in winter heating. However, there is no significant difference in the air-pollution risk measure.

In addition to the real side effect of air-pollution risk on stock prices, there are demand side impact of air-pollution. First, from a rational perspective, air-pollution can alter investors' attitude toward risk, which cause the risk premia of individual stocks to vary along with air-pollution change. Since this is likely to be an aggregate effect over time, we will control for it in our estimation. Second, there is a behavioral channel, of which air-pollution can bias investors' ability to process information. This is especially a concern when using the Chinese capital market data to study the direct economic impact of air-pollution since majority of investors in the Chinese capital markets are individual investors. Such a feature of the Chinese capital markets is in contrast to that of mature capital markets. When investors experience heavy air pollution, their mood may be depressed, which changes their trading behavior by weighing more on negative news than on positive news. Consequently, current stock prices or returns are low when the air-pollution levels are high (see, for example, **?**, **?**, and **?**). From the perspective of this study, it is important to ask whether the two channels will affect our results. The first channel might enhance our results to some degree, but it should be viewed as part of the evidence we are documenting since if air-pollution risk does not matter, there won't be the corresponding risk premium.

A simple way to differentiate the behavioral channel from the risk channel is to control for the sentiment factor since investors are more likely to downplay the negative news when the sentiment is high. Indeed, we continue to find that the market returns significantly covary with changes in the air-quality index even after controlling for all relevant factors including various measures of the sentiment risk in a time-series setting. Perhaps a more effective way to investigate which channel is more likely to prevail is to compare the impact of air-pollution surrounding a firm's physical location to that of surrounding investors' locations since sentiment risks affect investors' behavior directly. Our panel regression results show that stock returns are insensitive to air pollution changes in investors' locations while sensitive to firms' locations. In addition, if the behavioral efforts are similar across investors in different stocks, it will have a limited effect on our cross-sectional study.

Prior research explores either the contemporaneous relation between stock returns and weather conditions from a behavioral perspective, or how investors price clean versus dirty firms differently. For example, **?**, **?**, **?**, **?**, **?**, **?**, **?**, and **?** have found that stock returns can be affected by cloud coverage, length of days, temperature, snowstorm, and lunar phases. Others, including **?**, **?**, and **?** have focused on specific weather-related trading patterns. In addition, there is 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 **?**, **?**, **?**, **?**, and **?**). Compare to other types of weather related factors, the effects of air-quality on stock returns have received less attention. **?** and **?** have investigated the US markets, and Italy markets, respectively, and found that air pollution is negatively related to market returns, while **?** have explored the Chinese markets with similar conclusions. **?** and **?** find the adverse effect of air pollution on individual trading performance.[2] In contrast, we focus on the risk nature of air-quality, and provide strong evidence to support this view.

Our research contributes to the literature in four important ways. First, we study the economic impact of air pollution from a risk perspective in contrast to the behavioral approach or the perspective of air-pollution externality of firms taking by existing studies on similar topics. In particular, we document that air pollution is a unique risk factor to firms using the Chinese capital markets as a laboratory. Second, we provide a simple way to measure the air-pollution risk which is linked to firm fundamental risks. Third, relying on special institutional features of the Chinese data, we construct natural experiments to tease out confounding factors, such as firm growth, consumption risk, and investors' psychological behavior, in documenting the pricing effect of the air-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 analysis. Due to the potential non-stationarity 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.[3]

The rest of the paper proceeds as follows. In the next section, we discuss our hypothesis related to air-quality risk and the characteristics of the Chinese capital markets. Due to our unique approach used in this study, we provide details on data and variable construction in Section 3. In Section 4, we provide empirical evidence on the pricing effect of the air-quality risk using both two-way sorting and cross-sectional regression approaches. In addition, we disentangle the pricing effect from other potential effects through a natural experiment. In Section 5, we provide evidence on the link between air pollution risk and firm fundamentals. In order to be consistent with the literature, we further investigate whether the air-quality factor is a proxy for risk or a measure of sentiment in Section 6. If air pollution is a fundamental risk to firms, we study the characteristics of firms which has high risk in Section 7. Section 8 provides concluding comments.

[2]Moreover, these studies rely on air pollution data published by the Chinese government.

[3]In fact, if air quality proxy is measured on changes instead of levels, some of the results documented in **?** and **?** disappear.

2 Theory and Institutional Background

In contrast to existing studies that focus on how weather related factors might cause irrational behavior of investors and ultimately affect stock prices or how firms contribute to climate change, we are interested in understanding the risk nature of air-pollution imposed on individual firms' business and determining how it is priced. To build the foundation, we first discuss the related theoretical issues. Since we rely on the Chinese capital markets to uncover the empirical evidence, we will also discuss how the unique institutional features of the Chinese capital markets can help us to identify the independent air pollution risk in this section.

2.1 Air-Quality As A Risk Factor

Although risk can be defined as any uncertainty with a known distribution, it can occur under numerous circumstances. From a firm's perspective, any uncertainties affecting a firm's operation and its bottom line constitute risks. In a perfect market with homogeneous investors, these risks can be aggregated into the market risk. However, firms operate in a complex environment,[4] and investors are not homogeneous in reacting to different type of risks, which gives rise to the pricing of other types of risks. To a large extent, risks rooted from economic and market conditions have been extensively studied in the literature. Despite environmental conditions can also affect firms' operation, which create risks that are common to all firms, such risks are under-explored. This is especially important as we are experiencing significant climate change. To study how the environmental risks affect asset prices, we narrow down to the air-pollution risk as a starting point since it directly affects both firms' business and individual investors' wellbeing simultaneously with substantial time variations.

There are at least three channels that air-pollution could play an important role in asset pricing. First, from a behavioral perspective, investors' mood might be affected when experiencing heavy air-pollution. In this case, they may interpret bad news more negatively than they should, which will result in low current stock prices on average. Second, firms may actively pollute the environment in pursuing their objectives. If investors are conscientious about climate change, they will price price these polluting firms differently. Finally, all firms are operating in a natural environment. As an important case, air-pollution could affect their business in a significant way, which creates an additional risk. Since many studies have exploited the first two channels, we focus on the last channel while controlling for the impacts from the other two channels. For example, since behavioral changes tend to correlate with investors' sentiment changes, we will use several sentiment measures as controls. For firms' environmental externality, it will be controlled by firms' ESG scores.

Air-pollution can deteriorate employees' productivity both voluntarily and involuntarily. Heavy air pollution can reduce employees' urge to work hard and hinder the likelihood of spurring their creative ideas. In fact, **?** finds that air-pollution damages the productivity of workers. Air-pollution may also directly or indirectly affect firms' operations, which increases firms operating costs in short-run in providing a safe working environment. For example, on a heavily polluted day, indoor operated firms may have to spend more on air filtration and

[4]Not only uncertainties from the general economy and markets, but also

lighting, while outdoor operated firms may see an increase in product defection rate, and medical related costs including sick leave. At the same time, investors' risk preferences can also be altered by air-pollution, making them more risk averse when facing heavy air-pollution. In this case, investors' required risk premia for all stocks will increase. Finally, for a polluting firm, air-pollution may feedback to its public image may adversely affect corporate culture, making employees less willing to contribute their efforts in an active way.

Over a long-run, the adverse impacts of environment may force firms to invest in the green technology, which can crowd out investment in their main business in the intermediate-run.[5] Without sufficient investment, firms' business and their competitiveness can be adversely affected. Moreover, long-term climate change may not only cause weather to change more violently but also make air-pollution more variable, which intensifies its real impact on business. No matter whether the effects from air-pollution are short-run or long-run, they adversely impact firms' bottom line in a significant way. When such a risk is real to firms, investors will ultimately demand a premium to compensate their exposure to the air-pollution risk. Therefore, not only the risk should be priced, but the compensation should vary across individual firms depending on how sensitive of their business to air-pollution. This is our different take on this subject that is worth exploring.

Given our unique perspective on the air-pollution risk, it should be measured directly from firms' fundamentals, which is consistent with a production based pricing model. However, without comprehensive information on firms' operation, it is difficult to measure. If air-pollution risk matters and is priced independently, we can measure individual firms' air-pollution risks from the perspective of stock price sensitivities to air-pollution changes as an alternative. As investors live in the same environment as firms, they are exposed to air-pollution concurrently. This means that for rational investors they will change their expectations about firms' future cash flows when there are unexpected changes in the air-pollution level due to the direct and/or indirect impact discussed above. Therefore, air-pollution changes will ultimately influence firms' stock prices. Due to the heterogeneity in different firms' business, such a sensitivity measure can not only capture the cross-sectional dispersion but also time variations in risks. Our measure is also consistent with the spirit of the APT model of **?**.

Although our approach of measuring the supply-side air-pollution risk can also be viewed as a "reduced form" approach, we need to show that such a measure is indeed related to the supply side risk. To establish the link, we will proceed in two ways. First, we will demonstrate that our air-pollution risk measure is positively related to the Coefficient of Variation of ROE or cash flows, which are popular measures of fundamental risks. Second, as air-pollution will affect firms' fundamentals, we can tie our air-pollution risk measure to firms' future investment. In addition, as we will also show that air-pollution risk is independent of the market risk.

There are also some caveats in adopting our measure of the air-pollution risk. First, due to short sample period and allowing time variations, we intend to use daily data in our estimation of air-pollution risk. One may wonder why investors should care about relatively high frequency air-pollution changes in pricing? As discussed earlier, air-pollution can have short-term impact (through direct costs), intermediate-term impact (through productivity variations), and long-term impact (through investment) as well on firms. Daily stock prices

[5]Although investing in the green technology will cost firms, it may positively affect firms' future investment opportunities.

should reflect them all accordingly. Therefore, our measure should be able to capture the fundamental impact of air-pollution given sufficient estimation window. Second, risk only occurs when there are unexpected changes in air-pollution. Since weather related factors exhibit seasonality, we will use seasonality adjusted air-pollution changes in estimation. Third, why is the air-pollution risk systematic instead of idiosyncratic? Air-pollution is pervasive in China across geographic locations. It adversely affects many firms at the same time, if not all. At the same time, such a risk is not diversifiable since Chinese investors have very limited access to foreign capital markets, and the A-share market is not available to foreign investors. Finally, the air-pollution risk should also be an independent risk factor relative to the market risk. This is because exogenous changes in air-pollution are unlikely to covary with the overall stock market movement to be absorbed into the market factor. Moreover, given the different channels of impacts discussed above, air-pollution can ultimately affect investors' utility in different ways.[6]

As worsening air-pollution can affect firms' operating costs, reduce firms' productivity, and limit firms' future investment opportunities, rational investors will thus demand rewards for firms to be exposed to the air-pollution risk. At the same time, firms and government are likely to take different measures to combat air-pollution, which means that the risk will be time varying. In other words, our null hypothesis is that the air-pollution risk is priced. To test the hypothesis, we rely on the popular cross-sectional regression approach, that is regressing future individual stocks' returns on current air-pollution beta measure.[7] The regression coefficient is thus the risk premium of the air-pollution risk, which should be positive if the risk is priced. Due to our indirect measure of air-pollution risk, such a cross-sectional regression may also subject to some compounding effects, which needs to be addressed carefully.

First, it is possible that changes in the air-pollution level are a result of changes in the aggregate consumption of investors, such as, switching from public transportation to personal vehicles, from coal-based heating to gas-based heating, and so on. Consequently, air-pollution betas may be correlated with the consumption risk betas, which might affect a firm's future returns. From an empirical perspective, since there is no empirical support for the consumption based CAPM using the Chinese data, this channel is unlikely to have a real effect. Nevertheless, we will try to evaluate this alternative channel using a nature experiment. From a geographic perspective, the Huai River divides China into north and south. People living in the northern part of China rely heavily on burning coal for the heating purpose during the winter season from November to March of the next year, which is one of the main causes of air-pollution during the heating season in the north. We can thus examine the air-pollution beta differences between firms located in the provinces adjacent to the north of the Huai River and firms located in the provinces adjacent to the south of the Huai River, as well as beta differences between the heating and the non-heating seasons. There should be no systematic difference if our air-pollution risk measure does not apprroxy for the consumption risk. Finally, we will provide additional evidence that ties the air pollution risk to firms' fundamental risks.

Second, the Chinese economy is largely built on manufacture in the past decade. In pursuing high profits, firms are "actively" affecting air-quality across the country to a certain

[6]It is unclear whether individual investors or institutional investors (who represent certain types of individuals) are more conscious of the environmental issues. But the degree of their consciousness about the environment will be distinct from the homogeneous assumption under the CAPM.

[7]Due to relatively short sample period, we use panel regressions instead of the Fama-MacBeth regression.

degree. Although our focus is on how firms are passively affected by air-pollution risk, this factor needs to be controlled for. Otherwise, the adverse impact of air pollution risk on firms will be offset by the positive externality that a firm may enjoy. To rule out this possibility, we will use firms' ESG score as an indirect control. A more direct way to control for such an effect is to decompose the air-pollution change into systematic and idiosyncratic components. Variations in firm level emission of pollution will likely affect local air-pollution level variations. If this is an important channel that affects pricing, the idiosyncratic air pollution risk measure estimated using local AQI should matter instead of the systematic air-pollution risk measure.

Finally, cross-sectional differences in the firm level air-pollution betas may happen to be correlated with the differences in individual firms' growth potential either due to the nature of their business as an example. As a result, high growth firms' stock prices could be more sensitive to air-pollution changes. At the same time, a fast-growth firm tends to be riskier than a low-growth firm, and thus requires a high risk premium. To account for such an effect, we will directly control for firm growth. In addition, we explore a natural experiment, where there is a significant exogenous shock to the air-pollution level unrelated to firms' (growth) decisions. Surrounding the shock, any differences in individual stock returns can only be a result of the air-pollution risk when holding other things constant. In particular, 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. During these events, the Chinese government suspended the production of some heavily polluting factories and controlled traffic to improve air quality. Given these government actions were purely politically motivated and majority firms were still in operation, the related air quality changes are independent of firms' decisions.

In order to validate our air-pollution beta as a risk measure, it is also important to recognize the behavioral channel discussed early. As argued by **?**, weather conditions can affect investors' moods, which leads investors to react differently to different types of news. In particular, heavy air-pollution can depress investors, making them to react to bad news stronger than good news, which implies a negative contemporaneous relation between air-pollution and the stock return on an aggregate level. From a risk perspective, if worsening air-pollution will negatively impact a firm's fundamentals and alter investors' expectations about firms' future cash flows, the current stock prices or returns will be low. Although both effect will point to the same direction, the behavioral effect will be temporary and will not change the expected return, while the risk factor will alter individual firms expected return. To tease out the risk effect from the behavioral differences, we investigate the differential impacts of air-pollution changes surrounding firms versus air-pollution changes surrounding investors in addition to controlling for various sentiment measures. If the risk channel dominates the behavioral channel, air-pollution changes surrounding firms should have a stronger impact on stock returns than those close to investors.

2.2 Air Quality in China

In the past thirty years, China has achieved its amazing economic growth. But at the same time, it has become one of the worst air-polluted countries. In fact, the air quality has deteriorated over time to a point of public health concern. While blue sky is taken for granted in the western countries, it is almost a miracle to see clear sky in large Chinese cities. Instead, major news organizations, such as BBC, CNN, NBC, and others have actively reported this meteorological disaster in the past. The main sources of air pollution are construction and related material industries, automobiles, heating, and others. Despite some variations in the sources of air pollution across geographic locations, for example, burning coal for the heating purpose is important to provinces in the northern part of China, air pollution has severely affected the public health, people's daily life, and business across the country. 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 some firms' production and limited the number of vehicles on roads in Beijing. As a result, the sky suddenly became blue. These two events will be used in our natural experiment.

Due to the social and economic impact of air pollution in China, the U.S. Embassy has constructed Air Quality Indices (AQI) for five major cities in China since 2008.[8] At the same time, the official meteorological services of China also publishes a similar measure for the 31 provinces, municipalities, and autonomous regions, which has much wider coverage and longer sample period than the U.S. Embassy data. As a result, our main results rely on the Chinese government measure. Although, we recognize that the Chinese measure is routinely criticized for under reporting or being smoothed (see **?**), it is not a major concern in our study since it will bias against finding results. Moreover, the U.S. Embassy measure will be used in our robustness study. Both the Chinese government measure and the U.S. Embassy figures are based on pollutant concentration of particulate matter smaller than 2.5 micrometers in diameter, which is known as $PM_{2.5}$.[9]

Insert Table 1 Approximately Here

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. As a result, there is a steady drop in the AQI level over time. However, the situation is still worrisome, especially in the northern region. As shown in Table 1, the air quality in China is unhealthy at a level of 81.47 over our sample period from 2000 to 2018. In comparison, the average of $PM2.54$ level of US is in the upper 30. Moreover, the air quality in northern China is 93.36 on average, which is much higher than that in southern China of 71.93. What is more striking is that there are over three and a half months (or 29% of days) with unhealthy or worse air quality, while the situation is a little better in the southern provinces (15% days). This means that, during these horrible days, everyone should stay indoors and reduce their activity levels, which may severely impact the productivity of firms and the quality of life in China.

Air quality also exhibits strong seasonality over a year as shown in Figure 1. In the winter months from November to March, the average AQIs could be 30% to 40% higher than those in

[8]Different from the Chinese government figures, the U.S. Embassy started disclosing air quality indices for Beijing, Chengdu, Guangzhou, Shanghai, and Shenyang on April 8, 2008, May 14, 2012, November, 21, 2011, December 2, 2011, and April 22, 2013, respectively.

[9]The U.S. Embassy only covers five major cities, including Beijing, Chengdu, Guangzhou, Shanghai, and Shenyang.

the summer months. Therefore, we will either adjust for the seasonality or use the difference measure in our empirical study. However, there are little differences in the level of AQI among different days of a week.

Insert Figure 1 Approximately Here

3 Data Sample and Variable Construction

To be consistent with the existing literature, we first describe the source and characteristics of our sample data. We then provide sufficient details on variable construction so that readers can replicate our results.

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 2000 to December 2018. The choice of our sample period is consistent with existing studies on a similar topic in China and the availability of data. As discussed before, we use the Chinese air quality index data maintained by the Ministry of Environmental Protection of China. For our robustness study, we also use the AQI data published by the U.S. Department of State (http://www.stateair.net/), which are collected 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/). Stock returns and accounting information of individual firms are obtained from the standard $CSMAR$ database (The China Stock Market & Accounting Research Database) and $CSDCC$ (China Securities Depository and Clearing Company Limited). Block trading information is obtained from the $Wind$ database.

Our sample period covers $4,725$ trading days with $214,567$ provincial-day AQI observations. In cross-sectional regression analysis, we restrict our sample to include firms that have data for all variables. As a result, we have $338,404$ and $137,946$ firm-month and firm-quarter observations, respectively. 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 air quality indices in China. Many existing studies on related topics use the level measures on weather related variables, which could be problematic. It is well-known that these measures are very persistent, and could potentially be nonstationary. When the dependent variable is also nonstationary, there could be a spurious regression concern.[10] To avoid such an econometrics issue, especially in time-series analysis,

[10]This is because the realized return is a sum of expected and unexpected return. The expected return tends to be very persistent and close to have a unit root.

we use changes for all weather related variables including the air-quality variable instead of levels.

As discussed in Section 2.1, our main use of the AQI data is to estimate the pollution risk measure from stock returns. Most prior studies use the weather characters of cities where stock exchanges are located (see, for example, **?**; **?**), or cities where the listing firms are located (see, for example, **?**). 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. Moreover, our pollution risk measure is a systematic risk measure. We propose to measure aggregate air quality change used in our time-series regression, $\Delta AAQI_t$, as the average change in the AQIs of all 31 provinces in day t if available. There are two caveats needs to be addressed. First, as we have emphasized that our study focuses on how firms are adversely affected by air pollution risk, it seems that we should use local AQIs of a particular firm. However, since our risk measure is based on sensitivities of stock returns, any risk impact should be factored into stock prices with respect to the market wide air-pollution risk if investors are rational. Second, some firms may have actually contributed to air pollution as the focus of many current studies. Despite this is not our focus, it should be properly controlled for. If a firm is polluting air, it will likely affect local air quality. Therefore, we define the idiosyncratic air quality measure ($\Delta AQI^I_{k,t}$) by subtracting the aggregate air quality measure ($\Delta AAQI_t$) from the local air quality (($\Delta AQI_{k,t}$)).

If the pollution risk is a systematic risk that affects individual firms, we need a corresponding risk measure used in our cross-sectional study. With the two air quality measures and motivated by the APT model, we can estimate the sensitivities of individual stock returns to both $\Delta AAQI_t$ and $\Delta AQI_{k,t}$ as the systematic risk measure and the firm environmental impact measure, respectively, where k represents the location of the firm.[11] There are two issues in estimating the risk measure. First, the AQI level exhibits apparent seasonality as shown in Figure 1. We thus apply $X11$ filter to remove seasonality first.[12] Second, to resolve the issue of relatively short sample period and the ability to measure air-pollution risk level, we use overlapping daily returns over a three-month period to estimate the monthly individual beta.[13] As a robustness check, we also apply overlapping weekly data over past three months.

To estimate the air-pollution risk for the i-th A-share stock in month t, we apply the following two-factor model,

$$r_{i,t(d)} = \alpha_{i,t} + \beta_{i,t} \times (-\Delta AAQI_{t(d)}) + \gamma_{i,t} \times (-\Delta AQI^I_{k,t(d)}) + \varepsilon_{i,t(d)}, \tag{1}$$

where the dependent variable $r_{i,t(d)}$ is the daily return of stock i, while the independent variables $\Delta AAQI_{t(d)}$ and $\Delta AQI^I_{k,t(d)}$ are the aggregate AQI change and the idiosyncratic AQI change in the firm location in the past three months, respectively.[14] We denote the coefficient estimate of $\beta_{i,t}$ as $AQBeta_{it}$, and $\gamma_{i,t}$ as $AQBeta^I_{it}$.[15]

[11] A firm is assigned to one of the 31 provinces (if available) according to the geographical distance. If the distances to two provinces are the same, we will break the tie according to the province that it belongs to.

[12] Since we use changes in AQI, results are not very sensitive to filtering.

[13] Although it will create autocorrelation in the measure, it is less of an issue since we focus on cross-sectional regressions.

[14] Since the air-pollution risk is a negative factor and a large AQI means worse air pollution, we put a negative sign in front of $\Delta AAQI$. As discussed above, the idiosyncratic AQI is used to capture the positive effect, we did not use a negative sign on ΔAQI^I.

[15] To avoid persistent impact of a "influential" observation when using a rolling regression, we weight both

In addition, we construct several fundamental variables. Although we study how firms are affected by the air pollution risk, our risk measure is estimated from investors' side. To show such a measure is indeed tied to fundamental risks that firms are facing, we construct the Coefficient of Variation for ROE ($CV_{i,t}^{ROE}$). In particular, at time t, we first compute the standard deviation ($SD_{i,t}^{ROE}$) and the mean ($MU_{i,t}^{ROE}$) of quarterly ROE in the past three years. The coefficient of variation for ROE is just ($SD_{i,t}^{ROE}/MU_{i,t}^{ROE}$). We also investigate whether pollution risk affect a firm's future profit margin change ($\Delta PM_{i,t+1}$) and investment change in property, plant, and equipment (PPE) in the next six-month ($I/K_{i,t+1}$) scaled by the capital stock. When these accounting variables are used in various empirical settings as the dependent variables, the data frequency is quarterly. Correspondingly, we use $\overline{AQBeta_{it}}$ ($\overline{MktBeta_{it}}$), which are the average of $AQBeta_{it}$ ($MktBeta_{it}$) during the related period.

In our cross-sectional study, we control for individual firms' market capitalizations (ME_{it}) and book-to-market ratios (BM_{it}) following **?**, stock i's return momentum (MOM_{it}) measured as its cumulate returns from month ($t-7$) to month ($t-12$), illiquidity ($ILLIQ_{it}$), the idiosyncratic volatility ($IVOT_{it}$) estimated using daily residual returns in the month with respect to the Carhart four-factor model, stock return skewness ($Skew_{it}$) following **?**, the earnings-price ratio (EP_{it}) and the abnormal turnover (TO_{it}) following **?**, and the natural logarithm of Baidu SME index ($LnBDIndex_{it}$). We also control for cash flow (CF/K_{it}) computed from earnings before interest, taxes, depreciation, and amortization (EBITDA) scaled by the capital stock, the asset-liability ratio ($Leverage_{it}$), the change in asset turnover ($\Delta ATO_{i,t+1}$), the natural logarithm of the total asset ($LnTA_{it}$), operating leverage ($OpLeverage_{it}$), , the share turnover (STO_{it}), and the natural logarithm of economic polity uncertainty index of Chinese Mainland ($LnEPU_{it}$) measured by **?**, the reciprocal of close price ($INVP_{it}$), the labor intensity (LI_{it}) defined as the ratio of the number of employees to total assets (in million yuan), and a dummy variable IND_{it}, which equals 1 if a firm is from the mining and steel industries and 0 otherwise. ESG is a series of dummy variables to control ESG effect. The ESG index is disclosed by Sino-Securities Index Information Service (Shanghai) Co. Ltd.

In the time-series study, we have constructed several meteorological related variables, and common control variables commonly used in other study. The meteorological variables, $\Delta ATEM_t$, $\Delta AHUM_t$, and $\Delta AWIND_t$ are computed as the average 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 return (HML_t), and the momentum factor return (UMD_t), which are estimated following **?** and **?**. To differentiate the behavioral story from the risk story, we also control for investor sentiment ($\Delta SentIndex_t$), which was first developed by **?** for the U.S. capital markets. We also use ΔCCI_t and $\Delta InFlow_t$ as additional sentiment variables used by **?**. In addition, a CSR related measure of sentiment, $PREM_t$, is constructed using the difference between the logs of the top quintile abnormal total CSR firms' performance and the bottom quintile abnormal total CSR firms' performance (see **?**). Due to differences in the characteristics of Chinese investors and the special institutional structure, we measure investor sentiment by the monthly change of the percentage of investment accounts opened during the month t ($\Delta ACCOUNTS_t$) following **?**.[16] Since economic development may also

the dependent and independent variables by weight, $w_{t-l} = 0.8^l$, where l is the lth prior period from time t.

[16] To account for the potential correlation between investor sentiment proxies and economic conditions, all sentiment variables are orthogonalized to annual growth rates of industrial production, durable goods consumption, nondurable goods consumption, and services consumption, employment rate, and the recession indicator

impact both weather conditions and stock returns simultaneously, we use quarterly change in PMI, ΔPMI_t, to control for economic activities.

3.3 Summary Statistics

In order to be consistent with other studies in the literature, we first report summary statistics for variables used in our study in Table 2. In particular, Panel A shows the summary statistics of time series variables, while Panel B reports summary statistics for cross-sectional variables. During our sample period, daily market returns are negatively skewed when comparing mean to median. The average daily change in air quality ($\Delta AAQI_t$) is positive, 0.229, which may seem to be inconsistent with the pattern in Figure 1. This is because the summary statistics reported here are the average across five cities. The distribution of $\Delta AAQI_t$ is also positively skewed, meaning significant worsening days are more likely than improving days in air-pollution. Other weather related variables in Panel A, including daily changes of temperature ($\Delta ATEM_t$), humidity ($\Delta AHUM_t$), and wind speed ($\Delta AWIND_t$), also show increasing trends over our sample period since these increments are positive and significant. As expected, investor sentiment has increased over our sample period as measured by several variables including the sentiment index ($\Delta SenIndex_t$), consumer confidence index (ΔCCI_t), account-opening ($\Delta ACCOUNTS_t$), and quarterly PMI change (ΔPMI_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, despite the mean return is larger than the median returns, most individual stocks' monthly returns tend to be negatively skewed with a large variation. This suggests 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.[17] This negative skewness in monthly return is much weaker than that in daily return, which is why we focus on monthly returns in cross-sectional study. The average monthly return of 1.70% seems to be high over our sample period. This could be a result of the great run up in the Chinese stock market in 2014 and 2015. There are about a quarter of firm-months out of a total of $170,613$ firm-months with CSR reports in our sample. 45.60% of the firms are state-owned enterprises. Observations from mining and steel companies count about 1.50% of the total number of observations. For labor intensity, on average, there are 0.889 employees per million yuan assets. These firms have an asset liability ratio of 0.46, with an average market capital of \$616 million ($= e^{22.22}/6.5$ billion).

4 Empirical Results

To establish the pricing of air pollution risk, we not only provide cross-sectional evidence using popular asset pricing tests, but also propose some natural experiments to support that

constructed by the state information center.

[17] Such an overreaction behavior may explain some of the results found in the literature on a similar topic. To alleviate this effect and to document the pricing effect, we focus on low frequency returns in cross-sectional study.

such a risk is an independent risk factor, not a result of possible correlations with other risk factors. We also present the contemporaneous evidence between stock returns and the air-pollution changes in order to be consistent with the existing literature. Different from existing studies on similar subjects, we also provide evidence suggesting that such a relation is largely driven by the risk nature of air-pollution instead of investors' behavior differences induced by air-pollution.

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

Different from existing studies that either focus on green versus grey firm or the behavior impact of air-pollution, we are interested in the pricing of the air pollution risk in this section. As discussed in 2.1, our main air-pollution risk measure $AQBeta_i^S$ reflects the sensitivity of individual stock i's returns to air-pollution changes in the same spirit as the APT model of **?**. We will also include the $AQBeta_i^I$ measure to assess and control the "grey" effect of firm. If air-pollution is a priced risk factor, our air pollution risk measure itself should not only produce sufficient variations across individual firms, but also be able to differentiate future returns of individual stocks. In other words, we should find a positive risk premium from cross-sectional regressions of future stock returns on $AQBeta^S$s.

To demonstrate the uniformity of a relation between the air-pollution risk measure $AQBeta^S$ and future returns, we first use the double sorting approach. In particular, we follow **?** to first determine the portfolio breakpoints by sorting individual stocks on two dimensions. The portfolio breakpoints are then used to group all A-share stocks simultaneously into 25 portfolios according to their market capitalization ($Size$) and air pollution beta ($AQBeta^S$) in Panel A, and 25 portfolios according to their book-to-market value (BM) and air pollution beta ($AQBeta^S$) in Panel B of Table 3. Numbers reported in the table are the next month equal-weighted portfolio returns as a common practice.

Insert Table 3 Approximately Here

As shown in the Panel A, the portfolio returns decrease with firm size in general, except for a few large portfolios. This is consistent with **?**. More important, there is a clear positive relation between portfolio returns and $AQBeta^S$s within each size group, despite a somewhat "hump" shaped relation occurred in the large size groups when air pollution risks are high.[18] In fact, the return difference between the high $AQBeta^S$ portfolio and the low $AQBeta^S$ portfolio is positive and significant at a 1% level for each size group. For portfolios with relatively low $AQBeta$s, their returns do increase monotonically with their $AQBeta^S$s. Therefore, high level of exposure to the air pollution risk results in a positive premium in returns.

In contrast, when stocks are sorted according to the idiosyncratic air-pollution risk measure $AQBeta^I$ as shown in Panel C of 3, the risk and return relation is rather flat for most portfolios. Despite, the return difference between the high $AQBeta^I$ portfolio and the low $AQBeta^I$ portfolio is significant at a 10% level for the three size group, the sign is negative. These results suggest that the positive externality effect of potential firm air pollution emission is not essential for our sample.

[18]Perhaps, the air pollution also has a high-order effect that has impacted investors' utility directly.

The positive relation between air-pollution risk and return is not an artifact of the particular sorting scheme used. When sorting according to book-to-market and $AQBeta^S$, results shown in Panel B of Table 3 are also consistent with **?** for each of the book-to-market groups. Despite the relation on the $AQBeta^S$ dimension is more "hump" shaped than the size goups, the difference between high $AQBeta^S$ portfolio and low $AQBeta^S$ is still significant at a 1% level within any given book-to-market groups. Similarly, there is no result when the idiosyncratic air pollution risk measure is used. Therefore, no matter whether it is for size or book-to-market sorted portfolios, $AQBeta^S$ has additional explanatory power that can span most of the portfolio returns, suggesting the pricing of the air pollution risk.

The double sorting approach is useful in revealing the pattern of a relation, yet it does not account for other possibilities. For example, variation in the air-pollution risk can be correlated with return reversal, momentum, liquidity, return skewness, and so on. To control for these factors, we perform cross-sectional tests in Table 4. A common practice is to use Fama-MacBeth regression in this case. Given our short sample period of nine years, we use pooled panel regressions instead with adjustment for both firm and year fixed effect. 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.

Insert Table 4 Approximately Here

As hypothesized, the $AQBeta^S$ is significant in explaining future return differences of individual stocks as shown in Model 1 of Table 4. At the same time, the $AQBeta^I$ variable continues to be insignificant.[19] This is consistent with the general pattern in Table 3. Therefore, stock returns are affected by the air pollution risk. The conventional market beta ($MktBeta$) is insignificant as in most cross-sectional regressions. Although the book-to-market variable is significant, the size variable is only significant after adding the illiquidity measure as shown in Model 3. This suggests that both the size variable and illiquidity variable may share common estimation errors. Such estimation errors offset with each other when both variables are used in the regression (see **?**). The coefficient estimate of $AQBeta^S$ is 0.0106, which is also robust to the inclusion of different control variables. For example, adding all the control variables in Model 7 has virtually no effect on $AQBeta^S$, except that the coefficient estimate of BM actually becomes insignificant. One can consider using the BM variable as a way to control for the growth effect, which does not seems to be important in our case. In addition, both the skewness variable and the turnover variable are significant. Therefore, to a large extent, air-pollution risk, measured by $AQBeta$, is an independent factor in explaining the expected return differences of individual stocks.

Despite the idiosyncratic air pollution risk measure is insignificant, suggesting the air pollution externality effect is not important in affect asset prices. As discussed before, a second way to control for such an effect is to include the popular ESG measure directly in the cross-sectional regression. Results are reported in Table 5. Since the structure of Table Table 4 and Table 5 are the same, except the latter with an additional control of ESG, we can compare the two tables directly. Results are virtually the same with slightly smaller estimates

[19] Since both $AQBeta^S$ and $AQBeta^I$ are estimated from the same regression, they are orthogonal to each other.

after controlling for ESG. Therefore, we now have two pieces of evidence all suggesting the externality effect will not affect the pricing of the air pollution risk.

Insert Table 5 Approximately Here

4.2 Natural Experiments

To further isolate the air pollution risk from the potential growth factor and the consumption risk, we utilize two special nature experiments.

4.2.1 The Growth Factor – Special Events

As discussed before, another possible endogeneity channel is related to firm growth. If somehow growth firm are more vulnerable to air pollution, they will have high air-pollution betas. Although a firm's growth has nothing to do with its expected return under a traditional asset pricing model, a high growth firm tends to be more risky than a low growth firm resulting in a high expected return. Such a link between $AQBeta^S$ and future returns through growth indicates a possible endogeneity issue in our regression specification. Our empirical design in Section 2.1 does not rule out this possibility. In order to show that firms are exposed to the air-pollution risks that are independent of growth but influence their future returns, we utilize the events such as the 2014 APEC Economic Leaders' Week (November 5 to 11, 2014) and the commemoration of the 70th anniversary of WWII (August 2 to September 4, 2015) to construct a natural experiment. During these periods, the Chinese government used executive orders to significantly reduce the air pollution level including shutting down some firms in Beijing, which are exogenous to firms remaining open during the period. Since such dramatic changes in air-pollution are unrelated to firm growth, they affect firm returns only if air-pollution matters. 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, not because of a firm's decision to change its investment that affects growth.

There are two caveats needed to be taking care of including 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.[20] To control for economic condition, we also compare firms in Beijing to firms in the rest of the country by using another dummy variable "Beijing." In the final implementation of the "event study," we use cross-sectional pooled regression approach to control for other factors. The key variable of interest is the interaction term of "$Event \times Beijing$," which essentially is a difference-in-difference measure that reflects the impact of air-quality risk. The regression results are reported in Table 6.

Insert Table 6 Approximately here

[20]This is in addition to adjusting seasonality in the AQI measure.

In all the regressions, the dummy variable $Event_t$ equals 1 during the two periods, and 0 during the same periods of the previous years (November 5 to 11 of 2013 and August 20 to September 4 of 2014), while the dummy variable $Beijing_i$ equals 1 if a firm operates in Beijing, and 0 otherwise. Model 1 shows that the daily average abnormal return during the event period actually dropped by 0.06% although insignificant.[21] Moreover, firms operating in Beijing generally have lower returns than those in the rest of the country, which could largely be a result of the air-pollution risk. However, as indicated by the interaction term, there was 0.22% significant daily improvement in return for firms that operate in the Beijing area during the event periods relative to firms operating in the rest of the country. Since this is a difference-in-difference measure that is unlikely related to seasonality and economic conditions, it rather captures the incremental rise in return from the exogenous change in the air-pollution risk.[22] Therefore, we can conclude that the air-pollution risk has a real effect on the expected returns of individual stocks. When controlling for market risk, size, and book-to-market in Model 2, or additional controls of liquidity, return skewness, and idiosyncratic volatility 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 main result.

4.2.2 The Consumption Risk–The Huai River Experiment

The last potential endogeneity issue discussed in Section 2.1 is that the air-pollution risk may be a reflection of the consumption risk. Although the direct consumption risk is very weak to non-existence, some aspect of it may be important. Therefore, explore another natural experiment in our study. Due to the heating practice in the north of the Huai River during the winter season from November to March (a major consumption item), firms located in the north are *passively* exposed to higher levels of air-pollution risk than firms in the south of the river. In contrast, air-pollution risks are similar in the rest of year for the two groups of firms. If the difference is a result of consumption differences, and the consumption risk matters, we should observe difference differences in the air pollution risk measure. In other words, if there is no difference in the $AQBeta$s for firms across the river especially during the *heating* season, it is unlikely that the pricing of air pollution risk is a result of consumption risk. Therefore, examining firm level risk differences around the Huai River constitutes a good experiment that speaks for the endogeneity issue. In some sense, examining firms next to the Huai River bears the idea of regression discontinuity. In implementation, we define a dummy variable ($HUAI_i$) for firm i, which equals one if it is located in Shanxi, Henan, or Shandong provinces, and equals zero if it is located in Hubei, Anhui, or Jiangsu provinces. Using the dummy variable, we examine both the systematic and idiosyncratic air-pollution beta differences between firms located adjacent to the north of the Huai River and firms located in the provinces adjacent to the south of the Huai River. Results are reported in Table 7.

Insert Table 7 Approximately here

As expected, the dummy variable ($HUAI_i$) in the first equation of Table 7 indicates that

[21] This may suggest that hosting these events not only has wasted resources but also negatively affected firms.

[22] Although this is a contemporaneous relation, it implies that the expected return will drop due to increase in the current price, which is consistent with reduction in the air-pollution risk.

the systematic air pollution betas ($AQBeta^S$) are similar across the Hui river for the whole sample year. Therefore, investors do not see the systematic air pollution risks are different for firms across river indicating different levels of consumption risks do not affect the systematic air pollution risk. Moreover, the no difference result carries through both the heating and non-heating season as indicated in equations 3 and 5. It is also interesting to see that the results are different for the idiosyncratic air pollution risk. Despite no difference for the whole year sample, idiosyncratic air pollution risk does seem to be larger for firms located in the north than in the south of the Hui river. This makes sense since firms do subject to elevated level of air pollution during the heating season, which is a unique risk they face.

5 The Air Pollution Risk As a Fundamental Risk to Firms

Our evidence in Section 4.1 on the pricing of air-pollution risk is robust with respect to the possible externality effect of air pollution, firm growth, and the consumption risk. Despite our focus is the impact of the air pollution risk on firm from a pricing perspective, our measure of air-pollution risk is estimated from investors' side, not directly from the perspective of firms. In this section, we intend to show that our air pollution risk measure not only related to firms' fundamental risks but also is independent to market risk. Moreover, our risk measure is also tied to firms' fundamentals.

5.1 Air Pollution Risk and Fundamental Risk

A direct approach to show that our air-pollution risk measure reflects fundamental risk is to tie our $AQBeta$ to fundamental risk measures of a firm. One such a measure is the co-efficient of variation (CV) used in statistics, which measures the dispersion of a sample around the mean. In our application, we will construct the measure from the ratio between the standard deviation of ROE and the mean of ROE, CV^{ROE}.[23] Since we are focusing on the cross-sectional setting, such a measure is useful for comparing the degree of variation of ROE from one firm to another, even if the average ROEs are drastically different from one another. We choose ROE as an example because air pollution will adversely affect firms' ROEs if it is a fundamental risk to firms.

Insert Table 8 Approximately Here

In implementation, we exam a predictive relation of our $AQBeta$ measure both systematic and idiosyncratic components for the Coefficient of Variation of ROE (CV^{ROE}). The pooled cross-sectional regression results are shown in Table 8. As expected, the air-pollution risk is significantly related to a firm's fundamental risk measured by scaled ROE volatility. In particular, when regressing $CV_{i,t+1}^{ROE}$ on $\overline{AQBeta_{it}^S}$ of a firm, the coefficient estimate of 0.148 is statistically significant at a 1% level shown in equation (1). Although the coefficient estimates drop somewhat, it is still significant at the same level shown in equation (2). Therefore,

[23] In finance, investors care about how much volatility, or risk, is assumed in comparison to the amount of expected return from investments, which is the essence of the coefficient of variation measure.

our air pollution risk indeed reflects fundamental risks in certain dimensions. In contrast, the idiosyncratic air pollution risk measure $\overline{AQBeta^I_{it}}$ is unable to predict $CV^{ROE}_{i,t+1}$. It is also interesting to see that $CV^{ROE}_{i,t+1}$ is related to the market beta of individual stocks as shown in equation (2). This piece of evidence can serve as a support for using the coefficient of variation measure as a fundamental risk measure. Our results are robust with controls of related firm characteristics, such as the log total asset ($LnTA_{it}$), the market beta ($MkeBeta_{it}$), change in capital stock scaled investment ($\Delta I/K_{it}$), and the operating leverage ($OpLeverage_{it}$) measured as the PPE divided by total assets.

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

Despite our air pollution risk measure is capable of explaining cross-sectional stock return differences and is associated with individual stocks fundamental risks, it is still possible that such a measure reflects the market risk. In other words, we need to address the question of whether the air-pollution risk is likely to be an independent risk factor with respect to the market risk. From the perspective of our empirical tests, it is indeed independent of the market risk due to our explicit control of the market beta in all the cross-sectional regression specifications. From the perspective of the risk measure itself, even when the air-pollution risk is independent of the market risk, their beta measures could be correlated cross-sectionally. This is because both the systematic risk measure and our $AQBeta^S$ are second moment measures, which could be time-varying affected by common underlying state variables. However, if the two betas are unrelated, the air-pollution risk is likely to be independent of the market risk.

From the perspective of the CAPM model, any priced risks will be captured by the market risk factor, while all unpriced risks are represented by the idiosyncratic volatility ($IVOT$). As we have shown that the $AQBeta^I$ is not priced in Table 4, we can further investigate the relation between $AQBeta^I$ and $IVOT$. If $AQBeta^I$ is indeed irrelevant in pricing, it is likely to be correlated with $IVOT$ rather than the market beta. Therefore, we investigate the contemporaneous relation among market beta, idiosyncratic volatility, $AQBeta^S$ and $AQBeta^I$ in Table 9.

Insert Table 9 Approximately here

In order to be general, we estimate the idiosyncratic volatility of a stock ($IVOT$) from the residual returns with respect to the **?** model. As shown in the first model in Table 9, the coefficient estimate of $AQBeta^S_{it}$ is insignificant, while the coefficient estimate of $AQBeta^I_{it}$ is significantly positive at a 1% level. This indicates that $AQBeta^S_{it}$ is not an "idiosyncratic" risk while $AQBeta^I_{it}$ is likely correlated with the idiosyncratic risk of individual stocks. In contrast, when the dependent variable is the market beta of an individual stock in the second model, both the coefficient estimates of $AQBeta^S_{it}$ and $AQBeta^I_{it}$ are insignificant, which suggests that there is no comovement among $AQBeta$ and market beta. This could at least suggest that the air-pollution risk is an independent risk factor to the market factor. These results hold 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.

5.3 The Importance of Air Pollution Risk to Firms' Fundamentals

If the air-pollution risk is a fundamental risk which is neither part of the consumption risk nor a result of firm growth, it is important to further investigate how such a risk will affect firms' fundamentals. In particular, we intend to study whether air pollution risk will affect firms' investment decision and profit margins. As argued in 2.1, firms with high air-pollution risk may be poorly managed without much investment opportunity. Alternatively, these firms need to devote a large amount of resources to counter the impact of air pollution, which will crowd out investment. Similarly, firms with high air-pollution risks not only have an adverse impact on their productivity, but also potentially increase their operating costs. If such a supply side effect is substantial, firms profit margin will shrink. We first provide evidence through pooled cross-sectional regression in Table **??** on investment. The robust t-statistics with industry clustering effects are in the brackets.

Insert Table 10 Approximately Here

Our dependent variable is the investment change in property, plant, and equipment in the next six-month scaled by the capital stock ($(\Delta I/K)_{i,t+1}$). It is interesting to see that not only the coefficient estimate of $\overline{AQBeta_{it}^S}$ is negative and significantly significant at a 1% level, but $\overline{AQBeta_{it}^I}$ is significant with the right sign as well. Therefore, both the systematic and idiosyncratic air pollution risks matter in affecting firms' future investment. At the same time, firms with low cash flows may be financially constrained, which may be especially important in facing high air pollution risk. In particular, we control for cash flows $(CF/K)_{it}$, measured as earnings before interest, taxes, depreciation, and amortization (EBITDA) scaled by the capital stock, as well as firm and time fixed effect. In general, firms with large cash flows tend to investment more as shown in the first equation in Table 10. When it is used as a proxy for financial constrain, we can interact the cash flow variable with $\overline{AQBeta_{it}^S}$ in the same equation. It is expected that the negative relation between air pollution risk and future investment should be less pronounced when $CF/K_{i,t+1}$ is large. This is exactly the case as shown in the table since the interaction term is significant with a positive sign. Our results may be affected by the fact that both cash flow and investment are persistent. Therefore, we further control for the past investment along with other variables, such as leverage, size, and asset turn-ovrer in the second equation in Table 10. Results are very robust.

We further investigate if a firm's future profit margin is also affected by current air-pollution risk in Table 11. In the first column of the table, we regress changes in the next quarter profit margin ($\Delta PM_{i,t+1}$) of individual firms on the average monthly $AQBeta_{it}^S$ in the current quarter ($\overline{AQBeta_{it}^S}$). The variable is insignificant, indicating that firms' profit margins are not sensitive to air pollution risk. similar results holds true when the idiosyncratic air pollution measure ($\overline{AQBeta_{it}^I}$) is used in the second equation or both systematic and idiosyncratic air pollution risk measures are used in the last equation.

Insert Table 11 Approximately Here

As a general conclusion based on above evidence, air-pollution is a risk factor that affects firms' real activities in an important way. Although it is unlikely to be driven by the demand side, investors price such a risk rationally.

6 Stock Returns and Air Quality: The Contemporaneous Evidence

Despite our effort in linking the effect of air-pollution to stock returns from the supply side rather than the investor behavioral biases in the previous section, a contemporaneous relation does not necessarily imply the pricing of air-pollution risk.

One unpleasant experience for someone who has visited China in recent years is the heavy air-pollution. In fact, the severity of air-pollution has not only directly impacted people's daily life, but also had profound economic consequences. One of the impacts is the stock price change. To demonstrate, we use a difference-in-difference approach by comparing the market reaction around the days with the severe air-quality deterioration relative to that around days with the significant air-quality improvement. The worst (best) air-pollution days are defined as the 1% days with the largest (smallest) changes in air quality, ΔAQI_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 five-day window, [-2, +2], around the worst (best) air-pollution day minus the average daily return of the month. In order to control for other unspecified factors, we implement 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,[24] and are plotted in Figure 2.

Insert Figure 2 Approximately Here

The pattern in Figure 2 clearly shows that the stock market reacts efficiently and negatively when air-pollution worsens dramatically. In particular, the relative cumulative abnormal stock return is almost zero the day before a large air-pollution occurs. The relative CAR drops by close to 2.0% on the event day, and is statistically significant. To a large extent, the relative CAR remains the same on the day after. Therefore, air-pollution seems to have a significant impact on stock returns.

As discussed in Section 2.1, such a negative market reaction pattern does not necessarily suggest that severe air-pollution causes the risk to rise, which in turn drives down stock prices. The behavioral story argues that air-pollution can depress investors' moods such that they react to bad news more actively than good news (see **?** and **?**). More important, a general conclusion can only be reached based on a full sample instead of a partial sample. Therefore, we continue our investigation using both time-series regressions and panel regressions for off-board transactions.

Similar to current studies, we first examine the time-series relation using aggregate data in Table 12. The baseline regression shown in Model 1 is consistent with known results,

[24]It is also well-known that air-pollution is 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.

indicating that the aggregate air-pollution is negatively and statistically related to current return. This negative relation documented in the literature is not a result of seasonality, and is very robust despite the use of the change measure $\Delta AAQI_t$ instead of the air-pollution level measure used in the current literature. To further investigate whether such a negative relation is mainly driven by the air-pollution risk or the behavioral differences caused by air-pollution, we apply two approaches. The most commonly observed behavioral bias is the investor sentiment. As argued earlier, air-pollution will also affect investor sentiment, and in turn change stock prices. That is, controlling for sentiment should result in weak effect of air-pollution, but should still be significant if the air-pollution risk is priced. Alternatively, if the behavioral factor dominates, stock returns should be more sensitive to local air-pollution changes occurred close to investors than to those close to firms.

There are many proxies used in the literature for the investor sentiment. The most popular one is **?**'s sentiment index ($SentIndex_t$) by averaging the six sentiment factors including the closed-end fund discount, the share turnover, the number of IPOs, the first-day returns of IPOs, the equity share in new issues, and the dividend premium.[25] As shown in Model 2, the change in the sentiment index cannot account for the daily change in the aggregate return once the air-pollution measure is used. We have also tried more direct measures of investor sentiment, such as the Consumer Confidence Index (ΔCCI_t) and the aggregate net capital inflow to stocks ($\Delta InFlow_t$)) used by **?** in Model 3. These measures continue to be insignificant. Similarly, the CSR based sentiment measure $Prem_t$ is also insignificant. Due to the special feature of the Chinese markets, a better proxy for investor sentiment is the number of new account opening each month ($\Delta ACCOUNTS_t$) as argued by **?**. Although this measure is significant at a 13%level (see Model 4), there is almost no change for the coefficient estimate of $\Delta AAQI_t$.[26]

Insert Table 12 Approximately Here

In addition, we control for the Fama and French and Carhart factors including the size (SMB_t), book-to-market (HML_t), and momentum (UMD_t) in Model 6 of Table 12. As expected, both the size and book-to-market factors are very significant in addition to our air-pollution factor. It is surprising to see that the momentum factor is insignificant partly due to high correlation with the sentiment factors. Since air pollution level can also change with the weather condition, we account for it by controlling for temperature change ($\Delta ATEM_t$), humidity change ($\Delta AHUM_t$), and wind speed change ($\Delta AWIND_t$) in Model 7. The significance level of the air-pollution variable drop to 10%. Finally air-pollution can increase when industry production increases, which is controlled in Model 8 using PMI (ΔPMI_t). With all the controls in place including seasonal effect using month dummies in Model 8, the coefficient estimates of $\Delta AAQI_t$ continue to be significant at a 10% level. Therefore, air pollution is likely to impose additional risks to firms, which causes current stock prices to change.

Although we have tried to control for investor sentiment, there are other potential be-

[25]Different from **?**, we did not use principal component in order to avoid the forward-looking bias. In fact the first PCA is highly correlated with our average measure. We have also tried these six factors individually. Results are similar.

[26]**?** has proposed to use $\Delta PREM_t$ based on the difference between the top quintile of CSR firms' total abnormal performance and the bottom quintile of CSR firms' total abnormal performance as an investor sentiment measured. It is again insignificant as shown in Model 5 of Table 12.

havioral biases. Instead of trying other factors, we apply a more direct approach. Since the behavioral biases stem from the demand side on individual investors while the risk factor hinges on a firm's operation, we can explore locational differences in air-pollution. In particular, under the behavior story, it is the air-pollution surrounding individual investors' locations that might affect their trading behavior. In contrast, under the risk story, it is the air-pollution in firms' locations that matters. In order to implement the idea we use panel regression across individual stocks. Although we can identify each firm's location and use the AQI data close to the region, we do not know where each investor is trading from. To resolve this issue, we use the off-board transaction data for block-trading, of which we have the brokerage houses' location information. To ensure sufficient local variations, we use the local air quality index published by the China Meteorological Administration. Comparing with the U.S. embassy data, the Chinese figure might subject to some biases. First, for political reasons the overall level tends to be biased down. This may not be a severe issue since we focus on cross-sectional differences, and use the difference measure instead of the level. Second, the Chinese government may engage in manipulating the index level when it was just over the threshold of a different class. To mitigate this bias, we can delete observations corresponding to air-pollution level one unit smaller than a threshold. The regression results are reported in Table 13.

Insert Table 13 Approximately Here

In order to account for the potential price impact of block trading, the dependent variable used here is the block trading premium, which is defined as the difference between trading price and the closing price of the previous trading day divided by the closing price of the previous trading day. When the air-quality is measured close to firms' locations ($\Delta AQI_{i,t}$) as shown in Model 1 of Table 13, it continues to be very significant at a 1% level, and is negatively related to current stock returns. The estimate is obtained after controlling for the Fama and French factors, liquidity factor, return skewness, volatility of individual firms, weather conditions, and other unobserved factors by adopting firm and year fixed effect. In fact, the relation is even stronger comparing with a similar result in Table 12. This means that the impact from variations in air quality on firms is likely to be associated with firms' fundamentals.

If such a negative relation is largely a result of behavioral biases, air-pollution changes in the location of traders will affect the block trading premia. In this case, we construct $\Delta ChinaAQI_t^{Ask}$ and $\Delta ChinaAQI_t^{Bid}$ as daily change in air quality index of where sell orders and buy orders are placed. As reported in Model 2 and Model 3, none of the trader-location air-quality variables ($\Delta ChinaAQI_t^{Ask}$ or $\Delta ChinaAQI_t^{Bid}$) are significant. On the contrary, the air-quality index close to a firm is still significant at a 5% level when all the three local air-quality measures are used in Model 4 of Table **??**, both of the traders' location air-quality variables continue to be insignificant. This is the direct evidence suggesting that the negative relation between air quality and return is unlikely a result of behavioral biases.

7 CSR Disclosure, Ownership Structure, Labor Intensity, and Pollution Sensitive Industries

Although we consider our approach of estimating the air-pollution risk as a reduced form approach in measuring the supply side of risk, we now try to study the pricing issue more directly from a firm's perspective. Utilizing some of the special features of the Chinese capital markets, we can group firms into different subsamples according to their characteristics and exam the differential impact of the air-pollution risk. In particular, we will explore potential difference in the dimension of CSR versus none CSR firms, state-owned versus none state-owned firms, pollution sensitive firms, and labor intensive firms.

Some firms provide CSR report, where they disclose their efforts on social responsibility including addressing the air-pollution issue. Since these firms are more transparent on environmental issues and thus are more conscious on dealing with these issues, their returns should be less sensitive to air-quality risk. In contrast, non-CSR firms may be more vulnerable to air-pollution risk. In this case, we define a dummy variable CSR_{it} which equals one if firm i has disclosed a CSR report in year t, and 0 otherwise. Using the same control variables as in Table 4, we include both CSR_{it} and $CSR_{it} \times AQBeta_{it}$ in the panel regression in the Table 14. All models are adjusted for firm fix-effects and industry clustering.

Insert Table 14 Approximately here

Given that CSR firms are more transparent and may subject less to the air-pollution risk, we test differences between CSR and non-CSR firms. One caveat is that even when CSR firms have significantly lower returns than non-CSR firms, it could be a result of differences in their general social responsibilities, other than air-pollution. Although air-pollution is only one of the items in a CSR report, a social responsibility measure of a firm changes much slower than variations in the air-quality risk. In this case, the 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 0.714, which continues to be significant at 1% level. As expected, the coefficient estimate of -0.383 for the interaction term, $CSR_{it} \times AQBeta_{it}$, is significantly negative at a $1\% level$, suggesting that CSR firms subject to less air-quality risk than non-CSR firms. Moreover, since $AQBeta_{it} + CSR_{it} \times AQBeta_{it}$ of 0.331 is still positive and significant, the air-pollution risk matters for both CSR and non-CSR firms.

We can also group firms into two subsamples according to their ownership structure. In China, many public traded companies have large state ownership, the SOE firms. Although the average state ownership used to be more than 60%, it has dropped substantially to about 30% in recent years. From the ownership perspective, there are two factors that will influence the impact of air-pollution risk on firms. In general, SOE firms are less efficiently run, but are more like to benefit from regulations and government policies protection at the same time. This will make SOE firms more vulnerable to the air-pollution risk than non-SOE firms in China. Because of differences in ownership structure, the pricing effect of air-pollution should be stronger for SOE firms than for non-SOE firms. At the same time, because the ultimate owners of SOEs are governments, the higher is the level of state ownership, the higher is the risk sharing by government, which means the air-pollution risk has less effect for SOE firms than for non-SOEs. Therefore, the net effect of air-quality risk among different types of firms is an empirical issue. We reestimate our main model in Table 4 with an additional dummy variable SOE_{it}, which equals one if the state ownership is more than 30% and zero otherwise.

As shown in the second equation of Table 14, the coefficient estimate of 0.566 for $AQBeta_{it}$ remains to be positive and statistically significant at a 1% level after adding SOE dummy. Although the interaction term of $SOE_{it} \times AQBeta_{it}$ is positive, it is only significant at a 10% level, suggesting that the high risk nature of SOE firms marginally outweighs the risk sharing effect of the air-quality risk.

The effect of air-pollution could also vary substantially across different industries. Some industries may well be the net source of air-pollution rather than the victim of air-pollution. For example, the mining and the steel industries are the two major polluters in China. These firms may enjoy economic externalities from polluting the environment, while society bears the costs. 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 their industry classifications. In particular, we introduce a dummy variable IND_{it}, which equals to 1 if a firm is from one of the polluting industries, and 0 otherwise. Similar cross-sectional regression results are reported in the third column of Table 15. For regular firms, the coefficient estimate of $AQBeta_{it}$ is significant and very similar to our baseline result. However, the coefficient estimate of -0.486 for the interaction term $IND_{it} \times AQBeta_{it}$ is also significant, but is very negative. This suggests that the premium is actually negative for polluters, which is consistent with the economic externality argument.

Insert Table 15 Approximately here

One of the direct impact of air-pollution on firms is through the labor costs and productivity of employees. For labor intensive firms, they are likely to subject to large air-pollution risk because of substantial labor costs. For example, the textile companies, the construction companies, and the assembling lines employ a large number of people in China. Other things being equal, investors will demand large risk premia for these firms. Therefore, we further differentiate the impact of air-pollution in connection to labor intensity by defining a variable LI_{it}, which is the ratio between the number of employees and the firm's total asset. The cross-sectional regression results are shown in the last column of Table 16. It is interesting to see that labor intensity itself is insignificant in explaining cross-sectional return difference, which should be the case in an efficient capital market. The coefficient estimate of $AQBeta_{it}$ is significant and very similar to our baseline result. However, as expected, the coefficient estimate of the interaction term $LI_{it} \times AQBeta_{it}$ is also significant with an estimate of 0.189. This suggests that the premium is actually higher for labor intensive firms.

Insert Table 16 Approximately here

8 Concluding Comments

It is now generally accepted that individual stock returns are determined by multiple risk factors, at least from the perspective of production based pricing models. The success of

Fama and French's three-factor model or the recent five-factor model supports this view. To a large extent, however, these models are based on a "reduced-form" approach since the economic meanings of the underlying factors remain unclear and are subject to interpretation. Moreover, most of these factors are based on firm characteristics, which can only be proxies for fundamental risks. In this study, we take a different approach in identifying one potentially important risk factor–the air-pollution risk.

The impact of climate change has become such an important issue world wide. On the economic side, many studies have documented weather related anomalies on the behavior of investors and how economic activities affects climate change. We approach the issue differently from the firm perspective by arguing that air-pollution is a fundamental risk factor that affects a firm's performance and fundamentals. It is commonly believed that firm operations will pollute air, but is overlooked how air pollution could impact a firm's operate, which will either directly affects its bottom line or make it more prone to demand or supply shocks. This is a source of risk that ultimately affects the firm's performance. In particular, when air-pollution gets worsening, not only a firm's productivity gets depressed, but its operation is more prone to shocks, which generates the air-pollution risk. An increase in the air-pollution risk will thus cause the stock prices to react. We have constructed a unique measure of air-pollution risk and tested these implications on both market level and individual stock level using data from the Chinese capital markets.

Our focus on the Chinese capital markets is a direct result of the severity of air-pollution in China. Indeed, we find that market returns negatively comove with changes in the air-pollution level consistent with our hypothesis. Such a negative relation is largely a result of the risk nature of air-pollution since we control for investor sentiment using various measures. The evidence suggests that the Chinese markets in recent years did react to air-pollution changes. More important, we take a step further by estimating the air-pollution betas for individual stocks. Based on cross-sectional regression results, we show that air-pollution betas can explain future return differences across individual stocks, which indicates the pricing of air pollution risk in the Chinese capital markets. To further show that air-pollution risk is tied to firms' fundamentals, we investigate how changes in air-quality risk affect firms' future fundamentals. In particular, we document that not only firms' fundament risk measures, such as the coefficient of variation, are tied to our air pollution risk, but the firms' future investments are related to their air-pollution betas. In addition, we utilize two nature experiments to show that the air-pollution risk is an independent risk factor that is exogenous to a firm's choice.

Despite our limited focus of the Chinese capital market in study as a starting point, the strong evidence suggests the real effect of air pollution on firms. We hope future studies can propose new measures that are adequate in studying the developed markets. With a much longer sample period and individual firms, we will not only be able to construct more powerful tests but also learn additional insights.

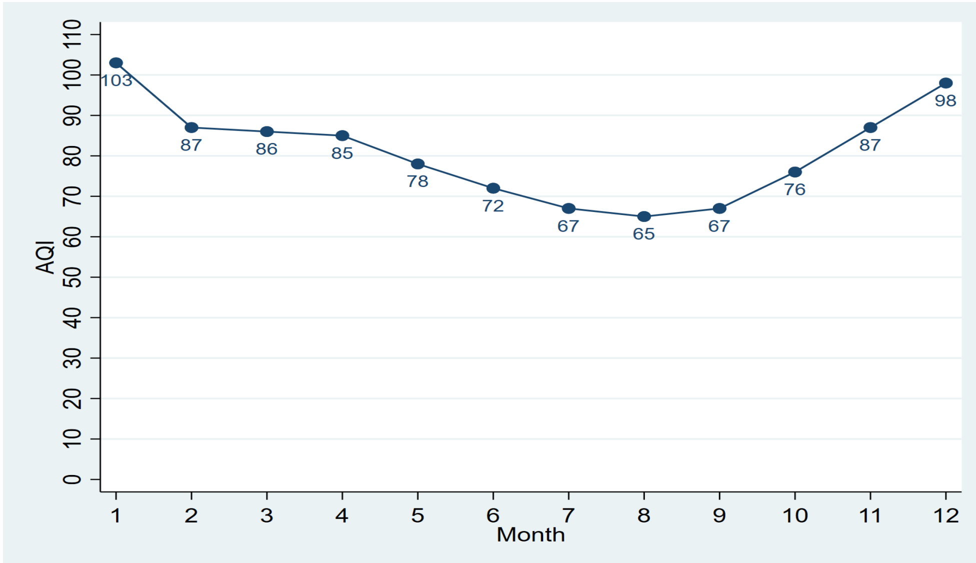

Figure 1: Monthly Distribution of AQI

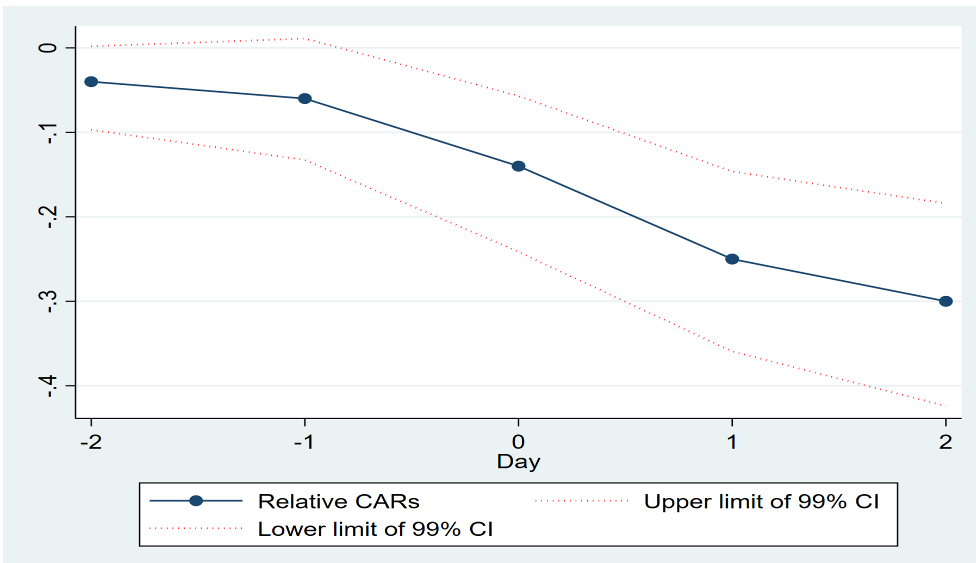

Figure 2: **Relative Market Reaction**

This figure shows the market reaction around the days with large air quality deterioration relative to that around days with large air quality improvement. The worst (best) air-quality days are defined as those days with the largest (smallest) changes in the AQI index that is in the top (bottom) one percentile.

Table 1: **Understanding Air Quality in China**

This table provides air quality index of capital of provinces in mainland China, which are published by the Ministry of Environmental Protection of China. The numbers under "Mean" and "STD" are the mean and standard deviation of AQI level, while those under "[a-b]" denote the percentage of days of which the AQI falls in the interval from "a" to "b". According to the guideline 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] suggests unhealthy air quality for sensitive groups; [151-200] is unhealthy air quality; [201-300] represents very unhealthy air quality; and [>301] is hazardous air quality.

Province	N	Mean	STD	[1-50]	[51-100]	[101-150]	[151-200]	[201-300]	[>300]
Total	228127	81.47	45.19377	18.28	61.10	15.28	3.35	1.36	0.62
Northern China									
Beijing	6919	98.99	59.45	14.13	50.57	22.33	8.24	3.19	1.53
Gansu	6919	105.69	68.80	4.28	59.59	23.96	7.23	2.04	2.91
Hebei	6925	107.68	64.03	5.91	56.65	23.10	7.36	4.62	2.35
Henan	6924	94.68	45.95	4.33	65.50	21.11	5.47	2.90	0.68
Heilongjiang	6922	82.26	48.46	15.57	64.84	13.31	3.28	2.18	0.82
Inner Mongolia	6925	78.89	45.20	20.56	60.97	14.12	2.80	0.92	0.62
Jilin	6924	76.21	37.57	15.08	72.00	9.49	2.04	1.04	0.36
Liaoning	6920	89.82	40.89	8.03	68.66	16.94	4.35	1.62	0.40
Shaanxi	6922	98.08	46.80	4.72	64.10	22.25	5.39	2.77	0.77
Shandong	6923	98.58	43.74	2.66	62.26	25.80	6.28	2.41	0.59
Shanxi	6921	97.86	47.10	7.63	56.25	26.70	5.65	2.88	0.90
Tianjin	6921	91.58	45.82	8.41	63.30	20.16	5.20	2.37	0.56
Average		93.36	49.48	9.28	62.06	19.94	5.27	2.41	1.04
Southern China									
Anhui	6920	83.27	36.81	13.82	64.12	18.02	2.90	0.97	0.17
Chongqiong	6918	82.57	33.92	13.98	63.20	18.53	3.54	0.74	0.01
Fujian	6919	58.29	21.92	35.58	60.92	3.40	0.04	0.03	0.03
Guangdong	6922	67.59	27.32	26.24	63.02	9.38	1.23	0.13	0.01
Guangxi	6922	57.98	24.34	41.23	53.51	4.71	0.45	0.10	0.00
Guizhou	6923	62.95	23.76	30.42	63.53	5.78	0.25	0.01	0.01
Hainan	6924	39.08	16.65	80.60	18.44	0.92	0.03	0.00	0.00
Hubei	6920	88.29	38.14	9.94	61.01	24.13	3.50	1.17	0.25
Hunan	6923	83.54	38.71	14.52	60.83	19.54	3.71	1.13	0.27
Jiangsu	6924	84.63	36.24	12.16	64.05	19.40	3.34	0.91	0.14
Jiangxi	6920	71.84	28.83	19.49	69.13	9.97	1.07	0.25	0.09
Shanghai	6925	72.35	34.99	24.20	60.58	12.27	2.25	0.52	0.17
Sichuan	6919	86.51	37.55	10.32	68.07	16.58	3.31	1.49	0.23
Yunnan	6918	59.34	16.72	29.18	69.83	0.98	0.00	0.00	0.00
Zhejiang	6924	80.80	32.25	13.50	66.45	16.97	2.57	0.45	0.06
Average		71.93	29.88	25.01	60.45	12.04	1.88	0.53	0.10
Other									
Ningxia	6918	81.80	37.35	8.12	73.24	14.86	2.76	0.61	0.40
Qinghai	6920	87.53	48.32	6.94	72.41	16.72	2.20	0.59	1.14
Tibet	6923	53.47	20.93	46.87	50.63	2.25	0.22	0.01	0.01
Xinjiang	6920	102.80	74.12	11.50	56.84	16.72	7.18	4.65	3.11
Average		81.40	45.18	18.36	63.28	12.64	3.09	1.47	1.17

Table 2: **Summary Statistics**

This table provides summary statistics for air quality and other weather characters. The sample period spans from January 2009 to June 2017. Panel A reports the time series summary statistics of the weeky market excess return ($RMRF_{t+1}$), weekly change of national AQI (ΔAQI_t^S), the temperature change (ΔTEM_t^S), the sunshine duration (ΔSSD_t^S), the precipitation (ΔPRE_t^S), the wind speed (ΔWIN_t^S), and the relative humidity (ΔHUM_t^S). SMB_t, HML_t, and UMD_t are common price factors. In addition, investor sentiment and macroeconomic variables are measured monthly. The investor sentiment index $SenIndex_t$ is the average of the six variables, including closed-end fund discount ($CEFD_t$), $TURN_t$ (turnover ratio), the average first-day returns ($RIPO_t$), the number of IPOs ($NIPO_t$), the share of equity issues in total equity and debt issues (S_t), and dividend premium (P_t^{D-ND}). ΔCCI_t is change in Consumer Confidence Index, which is constructed by China Economic Monitoring & Analysis Center. $\Delta InFlow_t$ is the change in the aggregate net capital inflow from investors into listed stocks (see **?**). We also use $\Delta ACCS_t$ as a measure of investor sentiment specially for the Chinese markets. 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 ($RET_{i,t+1}$), air quality beta ($AQBeta_{it}^S$ and $AQBeta_{it}^I$), market beta ($MktBeta_{it}$), natural log of market capitalization ($LnME_{it}$), book-to-market ratio (BM_{it}), momentum (MOM_{it}), market illiquidity ($ILLIQ_{it}$), return skewness ($Skew_{it}$), earnings-price ratio (EP_{it}), abnormal turnover (TO_{it}), idiosyncratic volatility ($IVOT_{it}$), volatility ($VOL_{i,t-1}$), share turnover (STO_{it}), the reciprocal of close price, $INVP_{it}$, labor intensity (LI_{it}), dummy variable (IND_{it}) that equals 1 if a firm is from mining, steel, transport, or construction industries, investment in PPE relative to the capital stock ($I/K_{i,t+1}$), the semiannual EBITDA scaled by the capital stock (CF/K_{it}), asset-liability ratio ($Leverage_{i,t+1}$), natural logarithm of the total asset ($LnTA_{i,t+1}$), change in asset turnover ($\Delta ATO_{i,t+1}$), the coefficient of variation of weighted ROE ($CV_{i,t+1,t+4}^{ROE}$), operating leverage ($OpLeverage_{it}$), share turnover (STO_{it}), natural logarithm of the economic-policy uncertainty index ($LnEPU_{it}$), change in profit margin ($\Delta PM_{i,t+1}$), change in AQI (ΔAQI_{it}), and change in national AQI (ΔAQI_{it}^S). 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
Province-Weekly Variables						
ΔAQI_t^I	11330	-0.580	6.015	-1.300	-0.472	0.388
ΔTEM_t	11330	-0.495	8.215	-1.650	-0.725	0.266
ΔSSD_t	11330	-0.879	8.454	-1.784	-0.833	0.169
ΔPRE_t	11330	-0.805	10.368	-0.933	-0.257	0.746
ΔWIN_t	11330	-0.650	16.270	-1.625	-0.704	0.280
ΔRHU_t	11330	-0.765	8.886	-1.533	-0.617	0.299
Weekly Variables						
$RMRF_{t+1}$	945	0.002	0.034	-0.017	0.002	0.021
SMB_t	945	0.001	0.022	-0.010	0.002	0.013
HML_t	945	0.000	0.013	-0.008	0.000	0.007
UMD_t	945	0.002	0.057	-0.026	0.005	0.037
Monthly Variables						
$\Delta SentIndex_t$	228	-0.186	4.671	-0.722	-0.165	0.275
ΔCCI_t	228	-0.104	1.417	-0.313	-0.001	0.199
$\Delta InFlow_t$	228	-0.685	9.713	-2.091	-1.291	-0.158
$\Delta ACCS_t$	203	0.137	0.623	-0.241	-0.025	0.278
ΔPMI_t	179	0.001	0.051	-0.010	0.000	0.010

Table 2 Cont.

Panel B: Summary Statistics of Cross-Sectional Variables						
	Number	Mean	STD	P25	Median	P75
Monthly Variables						
$RET_{i,t+1}$	388404	0.007	0.129	-0.073	-0.005	0.074
$AQBeta_{it}^S$	388404	-0.001	0.103	-0.047	-0.000	0.043
$AQBeta_{it}^I$	388404	-0.000	0.006	-0.002	-0.000	0.002
$MktBeta_{it}$	388404	1.072	0.890	0.606	1.044	1.496
$LnME_{it}$	388404	21.814	1.286	20.927	21.783	22.597
BM_{it}	388404	0.749	0.665	0.312	0.551	0.956
MOM_{it}	388404	0.057	0.377	-0.184	-0.024	0.197
$ILLIQ_{it}$	388404	-18.879	1.393	-19.730	-18.815	-17.928
$Skew_{it}$	388404	0.007	0.656	-0.393	0.002	0.406
EP_{it}	385346	0.016	0.051	0.004	0.017	0.035
TO_{it}	388404	0.996	0.641	0.531	0.823	1.283
$IVOT_{it}$	388404	0.018	0.009	0.011	0.016	0.023
$VOL_{i,t-1}$	383799	0.027	0.012	0.018	0.025	0.034
STO_{it}	388404	462.957	455.706	151.688	305.560	607.822
$INVP_{it}$	388404	0.127	0.088	0.064	0.104	0.164
LI_{it}	388404	0.363	0.481	0.000	0.000	1.000
IND_{it}	388404	0.098	0.298	0.000	0.000	0.000
Quarterly Variables						
$I/K_{i,t+1}$	137946	0.064	0.270	-0.014	0.002	0.073
CF/K_{it}	137946	0.292	0.504	0.074	0.211	0.430
$Leverage_{i,t+1}$	137946	0.461	0.221	0.294	0.458	0.615
$LnTA_{i,t+1}$	137946	21.943	1.336	21.004	21.778	22.683
$\Delta ATO_{i,t+1}$	137946	0.125	0.671	-0.170	0.011	0.226
$CV_{i,t+1,t+4}^{ROE}$	131550	-0.226	1.143	-1.001	-0.367	0.416
$OpLeverage_{it}$	131550	0.233	0.172	0.098	0.200	0.336
STO_{it}	131550	0.025	0.022	0.009	0.018	0.033
$LnEPU_{it}$	131550	4.801	0.628	4.330	4.767	5.179
$\Delta PM_{i,t+1}$	137946	0.029	5.244	-0.486	-0.018	0.672
ΔAQI_{it}	137946	0.000	0.043	0.000	0.000	0.000
ΔAQI_{it}^S	137946	0.001	0.044	0.000	0.000	0.000

Table 3: **The Cross-Sectional Pricing Effect of the Air-Pollution Risk**

This table presents the monthly mean returns of the 25 Size and $AQBeta^S$ sorted portfolios in Panel A, the monthly mean returns of the 25 Book-to-Market and $AQBeta^S$ sorted portfolios in Panel B, the monthly mean returns of the 25 Size and $AQBeta^I$ sorted portfolios in Panel C, and the monthly mean returns of the 25 Book-to-Market and $AQBeta^I$ sorted portfolios in Panel D. $AQBeta^S$ and $AQBeta^I$ of a stock are estimated using the methodology outlined in Section 3.2. ***, **, and * denote the significance levels of the 1%, 5%, and 10%, respectively.

Panel A: The 25 $Size - AQBeta^S$ Portfolios

	$AQBeta^S$					
$Size$	1(low)	2	3	4	5(high)	5-1
1(small)	0.0116	0.0199	0.0284	0.0267	0.0269	0.0153^{***}
2	-0.0024	0.0060	0.0123	0.0132	0.0102	0.0126^{***}
3	-0.0101	0.0023	0.0074	0.0062	0.0017	0.0118^{***}
4	-0.0128	-0.0002	0.0031	0.0045	0.0031	0.0159^{***}
5(big)	-0.0063	0.0044	0.0048	0.0043	0.0033	0.0096^{***}

Panel B: The 25 $BM - AQBeta^S$ Portfolios

	$AQBeta^S$					
BM	1(low)	2	3	4	5(high)	4-1
1(small)	-0.0114	-0.0047	0.0010	0.0010	0.0004	0.0118^{***}
2	-0.0092	-0.0003	0.0061	0.0052	0.0042	0.0134^{***}
3	-0.0058	0.0050	0.0086	0.0110	0.0096	0.0154^{***}
4	0.0011	0.0101	0.0163	0.0161	0.0139	0.0129^{***}
5(big)	0.0090	0.0203	0.0204	0.0199	0.0205	0.0115^{***}

Panel C: The 25 $Size - AQBeta^I$ Portfolios

	$AQBeta^I$					
$Size$	1(low)	2	3	4	5(high)	5-1
1(small)	0.0226	0.0235	0.0250	0.0236	0.0181	-0.0046^{***}
2	0.0072	0.0091	0.0098	0.0084	0.0046	-0.0026^{*}
3	-0.0006	0.0030	0.0047	0.0011	-0.0006	0.0000
4	0.0000	0.0014	-0.0011	0.0005	-0.0027	-0.0027^{*}
5(big)	0.0007	0.0030	0.0026	0.0045	0.0004	-0.0003

Panel D: The 25 $BM - AQBeta^I$ Portfolios

	$AQBeta^I$					
BM	1(low)	2	3	4	5(high)	4-1
1(small)	-0.0035	-0.0022	-0.0028	-0.0025	-0.0035	0.0001
2	0.0019	0.0012	0.0013	0.0024	-0.0011	-0.0030^{**}
3	0.0052	0.0056	0.0088	0.0061	0.0029	-0.0023
4	0.0118	0.0142	0.0111	0.0123	0.0085	-0.0033^{**}
5(big)	0.0175	0.0198	0.0194	0.0183	0.0158	-0.0016

Table 4: **Cross-Sectional Relation between Stock Returns on Air-Pollution Risks**

This table investigates the pricing effect of air-pollution risk using the air-pollution beta as a risk measure. The dependent variable is the monthly stock return of firm i in month $t+1$ ($RET_{i,t+1}$). In addition to the air-pollution beta, $AQBeta^S_{it}$ and $AQBeta^I_{it}$, as the independent variable, we control for the monthly market beta of firm i, $MktBeta_{it}$, the book-to-market ratio, BM_{it}, the natural log of market capitalization, $LnME_{it}$, stock i's return momentum measured as its cumulate returns from month $(t-7)$ to month $(t-12)$, MOM_{it}, the illiquidity measure, $ILLIQ_{it}$, the skewness of stock return computed following **?**, $Skew_{it}$, the earnings-price ratio, EP_{it}, and the abnormal turnover following **?**, TO_{it}.

	$RET_{i,t+1}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.0428	0.0468	0.0961***	0.0871***	0.0578*	0.0596*	0.0895***
	[1.22]	[1.38]	[2.89]	[2.66]	[1.76]	[1.85]	[2.86]
$AQBeta^S_{it}$	0.0123**	0.0117**	0.0106**	0.0103**	0.0119**	0.0120**	0.0105**
	[2.24]	[2.18]	[2.10]	[2.04]	[2.10]	[2.17]	[2.16]
$AQBeta^I_{it}$	-0.0498	-0.0464	-0.0351	-0.0378	-0.0499	-0.0392	-0.0396
	[-1.10]	[-1.01]	[-0.79]	[-0.85]	[-1.04]	[-0.81]	[-0.82]
$MktBeta_{it}$	-0.0000	0.0001	0.0012	0.0011	0.0002	0.0005	0.0012
	[-0.01]	[0.15]	[1.50]	[1.40]	[0.20]	[0.51]	[1.59]
$LnME_{it}$	-0.0017	-0.0019	-0.0154***	-0.0142***	-0.0023*	-0.0022	-0.0128***
	[-1.11]	[-1.30]	[-5.80]	[-5.29]	[-1.66]	[-1.62]	[-4.94]
BM_{it}	0.0033**	0.0032**	0.0013	0.0013			0.0009
	[2.15]	[2.14]	[1.00]	[0.99]			[0.66]
MOM_{it}		0.0025	0.0019	0.0019			0.0007
		[0.86]	[0.67]	[0.68]			[0.26]
$ILLIQ_{it}$			-0.0131***	-0.0122***			-0.0106***
			[-5.62]	[-5.08]			[-4.64]
$Skew_{it}$				-0.0022**			-0.0025***
				[-2.52]			[-2.99]
EP_{it}					0.0381**	0.0374**	0.0177
					[2.40]	[2.44]	[1.21]
TO_{it}						-0.0041***	-0.0029**
						[-3.24]	[-2.59]
Number	388404	388404	388404	388404	385346	385346	385346

Table 5: **Cross-Sectional Relation between Stock Returns on Air-Pollution Risks after Controlling ESG**

This table investigates the pricing effect of air-pollution risk using the air-pollution beta as a risk measure. The dependent variable is the monthly stock return of firm i in month $t+1$ ($RET_{i,t+1}$). In addition to the air-pollution beta, $AQBeta^S_{it}$ and $AQBeta^I_{it}$, as the independent variable, we control for the monthly market beta of firm i, $MktBeta_{it}$, the book-to-market ratio, BM_{it}, the natural log of market capitalization, $LnME_{it}$, stock i's return momentum measured as its cumulate returns from month $(t-7)$ to month $(t-12)$, MOM_{it}, the illiquidity measure, $ILLIQ_{it}$, the skewness of stock return computed following **?**, $Skew_{it}$, the earnings-price ratio, EP_{it}, and the abnormal turnover following **?**, TO_{it}.

	$RET\_i, t+1$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.0466	0.0502	0.0988***	0.0899***	0.0602*	0.0619*	0.0915***
	[1.33]	[1.49]	[2.98]	[2.75]	[1.84]	[1.93]	[2.93]
$AQBeta^S_{it}$	0.0122**	0.0115**	0.0105**	0.0101**	0.0118**	0.0118**	0.0104**
	[2.22]	[2.16]	[2.08]	[2.03]	[2.09]	[2.17]	[2.15]
$AQBeta^I_{it}$	-0.0538	-0.0503	-0.0397	-0.0423	-0.0541	-0.0434	-0.0440
	[-1.19]	[-1.10]	[-0.90]	[-0.96]	[-1.14]	[-0.90]	[-0.91]
$MktBeta_{it}$	-0.0000	0.0001	0.0012	0.0011	0.0002	0.0005	0.0012
	[-0.03]	[0.13]	[1.48]	[1.38]	[0.18]	[0.49]	[1.57]
$LnME_{it}$	-0.0018	-0.0020	-0.0154***	-0.0143***	-0.0024*	-0.0023*	-0.0129***
	[-1.23]	[-1.41]	[-5.83]	[-5.32]	[-1.74]	[-1.70]	[-4.97]
BM_{it}	0.0032**	0.0030**	0.0012	0.0012			0.0008
	[2.03]	[2.02]	[0.90]	[0.90]			[0.63]
MOM_{it}		0.0023	0.0017	0.0018			0.0006
		[0.80]	[0.62]	[0.63]			[0.24]
$ILLIQ_{it}$			-0.0130***	-0.0122***			-0.0106***
			[-5.60]	[-5.06]			[-4.65]
$Skew_{it}$				-0.0021**			-0.0024***
				[-2.47]			[-2.94]
EP_{it}					0.0343**	0.0337**	0.0149
					[2.20]	[2.24]	[1.03]
TO_{it}						-0.0041***	-0.0029**
						[-3.24]	[-2.59]
ESG controls	YES	YES	YES	YES	YES	YES	YES
Number	388404	388404	388404	388404	385346	385346	385346

Table 6: **Stock Returns During the Special Event Periods**

This table investigates the differential stock returns during the special event periods, when the Chinese government improves air quality using executive orders. The dependent variable is the daily average abnormal return of firm i during the event period. $Event_t$ is a dummy variable which equals to 1 during the 2014 APEC Economic Leaders' Week (November 5 to 11, 2014) or commemoration of the 70th anniversary of victory of China against Japanese aggression and Anti-Fascist war (August 20 to September 4, 2015), and equals to 0 during the related periods from November 5 to 11, 2013 or from August 20 to September 4, 2014. $Beijing_i$ is a dummy variable which equals to 1 if the firm operates around the Beijing area, and 0 otherwise. $MktBeta_{it}$, $BM_{i,t-1}$, $LnME_{i,t-1}$, $ILLIQ_{i,t-1}$, $Skew_{i,t-1}$, $IVOT_{i,t-1}$, and $LnBDIndex_{it}$ are the market beta, the last month book-to-market, log market capitalization, illiquidity, return skewness, idiosyncratic volatility, and the natural logarithm of Baidu SME index, respectively. The regressions are clustered at the stock level.

	(1)	(2)	(3)	(4)
Constant	0.0043***	0.1722**	0.1787**	0.0398
	[4.83]	[2.16]	[2.30]	[0.14]
$Event_{it}$	0.0026*	0.0050**	0.0088***	0.0089***
	[1.81]	[2.41]	[2.92]	[2.96]
$Beijing_i$	-0.0072***	-0.0098***	-0.0048**	-0.0048**
	[-4.85]	[-6.49]	[-2.39]	[-2.39]
$Event_{it} \times Beijing_i$	0.0027*	0.0039**	0.0033**	0.0035**
	[1.74]	[2.55]	[2.22]	[2.11]
$MktBeta_{it}$		0.0017***	0.0018***	0.0017***
		[3.23]	[3.36]	[3.28]
$BM_{i,t-1}$		-0.0054	-0.0054	-0.0054
		[-1.43]	[-1.56]	[-1.56]
$LnME_{i,t-1}$		-0.0072**	-0.0117***	-0.0118***
		[-2.13]	[-3.11]	[-3.11]
$ILLIQ_{i,t-1}$			-0.0044**	-0.0044**
			[-2.51]	[-2.50]
$Skew_{i,t-1}$			-0.0025***	-0.0025***
			[-3.00]	[-2.98]
$IVOT_{i,t-1}$			0.1725**	0.1715**
			[2.42]	[2.40]
$LnBDIndex_{it}$				0.0308
				[0.50]
Month control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Within R^2	0.0570	0.0994	0.1299	0.1304
Number	873	873	873	873

Table 7: **Differences in the Air-Pollution Risk Across the Huai River**

This table presents regression results of RD test to examine the influence of the Huai River policy. The dependent variables of the column (1), column (2) , and column (3) are monthly air-quality index, AQI_{it}, systematic AQI Beta, $AQBeta^S_{it}$, and idiosyncratic AQI Beta, $AQBeta^I_{it}$, respectively. $HUAI_i$ is a dummy variable equal to one if firm i is located north of the Huai River, $Distance_{it}$ represents the degree of northern latitude of firm i relative to that of the Huai River. $LnGDP_{i,t-1}$, $LnPOP_{i,t-1}$, $LnNF_{i,t-1}$, and $LnGR_{i,t-1}$ are log of the last month gross domestic product, log of total population in a region, log of the number of domestic firms, and log of total government revenue at year end in RMB, respectively. Panel A, Panel B, and Panel C present the results for the whole period, heaing period (from December to March of next year), and non-heating period (from April to November). We further require $|Distance_{it}|<5°$ in the test.

	The Whole Period		Heating Period		Non-Heating Period	
	$AQBeta^S_{it}$	$AQBeta^I_{it}$	$AQBeta^S_{it}$	$AQBeta^I_{it}$	$AQBeta^S_{it}$	$AQBeta^I_{it}$
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.0124	-0.0031*	0.0539	0.0054**	-0.0091	-0.0072***
	[0.39]	[-1.90]	[1.29]	[2.07]	[-0.22]	[-3.55]
$HUAI_{it}$	-0.0005	0.0000	0.0004	0.0002*	-0.0009	-0.0000
	[-0.38]	[0.45]	[0.25]	[1.78]	[-0.56]	[-0.58]
$Distance_{it}$	0.0000	0.0000	-0.0002	-0.0000	0.0001	0.0000
	[0.10]	[0.47]	[-0.34]	[-0.92]	[0.27]	[1.13]
$LnGDP_{i,t-1}$	-0.0013	-0.0005*	0.0005	0.0006	-0.0024	-0.0011***
	[-0.24]	[-1.96]	[0.07]	[1.42]	[-0.33]	[-3.21]
$LnPOP_{i,t-1}$	0.0003	0.0000	0.0006	-0.0001	0.0001	0.0001
	[0.13]	[0.26]	[0.23]	[-0.83]	[0.05]	[0.83]
$LnNF_{i,t-1}$	0.0001	-0.0000	0.0014	0.0001	-0.0005	-0.0000
	[0.03]	[-0.02]	[0.51]	[0.36]	[-0.19]	[-0.24]
$LnGR_{i,t-1}$	-0.0003	0.0005**	-0.0045	-0.0007**	0.0019	0.0011***
	[-0.08]	[2.48]	[-0.88]	[-2.09]	[0.37]	[4.25]
Within R^2	0.0002	0.0006	0.0005	0.0014	0.0001	0.0017
Number	24695	24695	8150	8150	16545	16545

Table 8: **Linking Air-Pollution Risk to fundamental Risks**

This table investigates the relation between firms' fundamental risks and AQI betas. The dependent variables is the coefficient of variation (CV) of the next 4 quarters' ROE ($CV^{ROE}_{i,t+1,t+4}$). In addition to the independent variable of maximum air-pollution beta, $\overline{AQBeta^S_{it}}$ and $\overline{AQBeta^I_{it}}$, we include the asset-liability ratio, $Leverage_{it}$, the natural logarithm of the total asset, $LnTA_{it}$, operating leverage $OpLeverage_{it}$, the illiquidity measure, $ILLIQ_{i,t-1}$, , the skewness of stock return, $Skew_{it}$, the share turnover, STO_{it}, and the natural logarithm of economic polity uncertainty index of Chinese Mainland measured by **?**, $LnEPU_{it}$. The regressions are clustered at the firm level.

	$CV^{ROE}_{i,t+1}$	
	(1)	(2)
Constant	-0.1986***	1.9081***
	[-6.74]	[5.58]
$\overline{AQBeta^S_{it}}$	0.1476***	0.1175**
	[2.91]	[2.32]
$\overline{AQBeta^I_{it}}$	-0.6355	-1.0409
	[-0.57]	[-0.93]
$\overline{MktBeta_{it}}$		0.0338***
		[3.84]
$\overline{IVOT_{it}}$		0.0584
		[0.11]
$Leverage_{it}$		0.9430***
		[15.52]
$LnTA_{it}$		-0.0684***
		[-4.07]
$OpLeverage_{it}$		0.3271***
		[4.33]
$ILLIQ_{i,t-1}$		0.0477***
		[4.18]
$Skew_{i,t-1}$		-0.0182***
		[-3.86]
STO_{it}		-1.6816***
		[-5.34]
$LnEPU_{it}$		-0.0662***
		[-4.66]
Quarter control	Yes	Yes
Firm FE	Yes	Yes
Within R^2	0.0208	0.0373
Number	130706	130706

Table 9: **The Cross-Sectional Relation Between Market Beta and Air-Pollution Risk**

This table investigates the relation between market beta and AQI betas. The dependent variables of column (1) and column (2) are the idiosyncratic volatility ($IVOT_{it}$) and market beta ($MktBeta_{it}$), respectively. In addition to the independent variable of air-pollution beta, $AQBeta_{it}^{S}$ and $AQBeta_{it}^{I}$, we include the market beta, $MktBeta_{it}$, the return volatility of prior period, $VOL_{i,t-1}$, the stock return, RET_{it}, the share turnover, STO_{it}, and the reciprocal of close price, $INVP_{it}$.

	(1) $IVOT_{it}$	(2) $MktBeta_{it}$
Constant	0.0098***	0.2093***
	[32.27]	[9.27]
$AQBeta_{it}^{S}$	-0.0006	-0.1691
	[-1.19]	[-0.46]
$AQBeta_{it}^{I}$	0.0095***	-1.0577
	[3.60]	[-0.79]
$VOL_{i,t-1}$	0.1585***	25.9646***
	[28.40]	[29.80]
RET_{it}	0.0227***	0.2771***
	[22.41]	[5.26]
STO_{it}	0.0000***	-0.0001***
	[28.48]	[-6.41]
$INVP_{it}$	-0.0099***	0.5140***
	[-8.74]	[5.43]
Number	383799	383799

Table 10: **Financial Constrain and Air-Pollution Risk**

This table presents the results of cross-sectional regression of air-pollution risk on economic activities. The dependent variable is the investment in property, plant, and equipment (PPE) in the next quarter scaled by the capital stock ($I/K_{i,t+1}$). The independent variable is the maximum air-pollution beta in the quarter, $\overline{AQBeta_{it}^{S}}$ and $\overline{AQBeta_{it}^{I}}$. The control variables include the cash flow, CF/K_{it}, measured by earnings before interest, taxes, depreciation, and amortization (EBITDA) scaled by the capital stock, the asset-liability ratio, $Leverage_{it}$, the natural logarithm of the total asset, $LnTA_{it}$, the investment, I/K_{it}, and the change in asset turnover, $\Delta ATO_{i,t+1}$. The regressions are clustered at the firm level.

	$I/K_{i,t+1}$	
	(1)	(2)
Constant	0.0564***	-0.9569***
	[8.69]	[-17.26]
$\overline{AQBeta_{it}^{S}}$	-0.0288***	-0.0301***
	[-3.29]	[-3.46]
$\overline{AQBeta_{it}^{I}}$	-0.2851**	-0.2808**
	[-2.20]	[-2.15]
CF/K_{it}	0.0082**	0.0042
	[2.18]	[1.14]
$\overline{AQBeta_{it}^{S}} \times CF/K_{it}$	0.0991***	0.1017***
	[3.92]	[4.06]
$\overline{AQBeta_{it}^{I}} \times CF/K_{it}$	-0.3567	-0.3775
	[-0.80]	[-0.86]
$Leverage_{i,t+1}$		-0.0187**
		[-2.06]
$LnTA_{i,t+1}$		0.0502***
		[18.98]
I/K_{it}		-0.1079***
		[-7.77]
$\Delta ATO_{i,t+1}$		0.0067***
		[4.50]
Year control	Yes	Yes
Month control	Yes	Yes
Firm FE	Yes	Yes
Within R^2	0.0366	0.0553
Number	137946	137946

Table 11: **Profit Margin and Risks**

This table investigates the relation between air pollution risk and profit. The dependent variables is the change in profit margin of next period ($\Delta PM_{i,t+1}$). In addition to the change in AQI and national average AQI, ΔAQI_{it} and ΔAQI^S_{it}, as the independent variables, we control for the asset-liability ratio, $Leverage_{it}$, the natural logarithm of the total asset, $LnTA_{it}$, the change in asset turnover, ΔATO_{it}, and the investment scaled by the capital stock, I/K_{it}. The regressions are clustered at the firm level.

	$\Delta PM_{i,t+1}$		
	(1)	(2)	(3)
Constant	-2.4212***	-2.4045***	-2.4225***
	[-3.38]	[-3.36]	[-3.38]
$\overline{AQBeta^S_{it}}$	0.1886		0.1876
	[1.16]		[1.16]
$\overline{AQBeta^I_{it}}$		0.5167	0.4189
		[0.21]	[0.17]
$Leverage_{it}$	-2.3579***	-2.3573***	-2.3581***
	[-16.66]	[-16.65]	[-16.66]
$LnTA_{it}$	0.1678***	0.1679***	0.1678***
	[4.76]	[4.77]	[4.76]
$\Delta AssetTurnover_{it}$	1.0755***	1.0755***	1.0755***
	[32.21]	[32.21]	[32.21]
I/K_{it}	0.2854***	0.2854***	0.2855***
	[4.48]	[4.48]	[4.49]
Quarter control	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Within R^2	0.0194	0.0195	0.0195
Number	137946	137946	137946

Table 12: **Time-Series Regressions of Market Returns on Air-Pollution Changes**

This table presents the time-series regression results. The dependent variable is the next period market excess return ($RMRF_{t+1}$). The independent variables are the weekly changes of national AQI, ΔAQI_t^S, and measures of investor sentiment including the change of investor sentiment index ($\Delta SentIndex_t$) constructed according to **?**, the change of the Consumer Confident Index (ΔCCI_t), inflow ($\Delta InFlow_t$), number of new accounts ($\Delta ACCS_t$). SMB_t, HML_t, UMD_t, and ΔPMI_t are the size factor, the book-to-market factor, the momentum factor, and the change in PMI, respectively. ΔTEM_t^S, ΔSSD_t^S, ΔPRE_t^S, ΔWIN_t^S, and ΔRHN_t^S are national weekly changes in the temperature, the sunshine duration, the precipitation, the wind speed, and the relative humidity, respectively. The MonthControls are a series of dummy variables to control month effects. The Newey West t-statistic is reported in the bracket.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.0022	0.0020	0.0023	0.0022	0.0035	0.0031	0.0009	0.0007
	[0.48]	[0.44]	[0.51]	[0.48]	[0.71]	[0.64]	[0.16]	[0.13]
ΔAQI_t^S	0.0113**	0.0114**	0.0113**	0.0114**	0.0134**	0.0137**	0.0144**	0.0142**
	[2.09]	[2.11]	[2.10]	[2.10]	[2.38]	[2.44]	[2.46]	[2.43]
$\Delta SentIndex_t$		0.0008***				0.0008***	0.0008***	0.0008***
		[2.92]				[2.79]	[2.81]	[2.80]
ΔCCI_t			0.0024***			0.0015*	0.0012	0.0013
			[2.68]			[1.67]	[1.09]	[1.10]
$\Delta InFlow_t$				-0.0001		-0.0001	-0.0001	-0.0001
				[-1.22]		[-0.68]	[-0.79]	[-0.77]
$\Delta ACCS_t$					0.0086***	0.0081***	0.0093***	0.0092***
					[3.37]	[3.28]	[3.32]	[3.28]
SMB_t						-0.0965	-0.0963	-0.0968
						[-1.25]	[-1.20]	[-1.21]
HML_t						-0.0410	-0.0469	-0.0493
						[-0.36]	[-0.39]	[-0.41]
UMD_t						0.0111	0.0232	0.0220
						[0.46]	[0.90]	[0.84]
ΔPMI_t							-0.0149	-0.0162
							[-0.41]	[-0.45]
ΔTEM_t^S								-0.0001
								[-0.46]
ΔSSD_t^S								0.0001
								[0.80]
ΔPRE_t^S								0.0002
								[0.19]
ΔWIN_t^S								0.0000
								[0.25]
ΔRHU_t^S								0.0000
								[0.20]
Month Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number	945	945	945	945	842	842	742	742

Table 13: **Province level regression**

This table presents the time-series regression results. The dependent variable is the value-weighted stock return of each province ($RPRF_{t+1}$). The independent variables are the local weekly changes of AQI, ΔAQI_t^I, and measures of investor sentiment including the change of investor sentiment index ($\Delta SentIndex_t$) constructed according to **?**, the change of the Consumer Confident Index (ΔCCI_t), inflow ($\Delta InFlow_t$), number of new accounts ($\Delta ACCS_t$). SMB_t, HML_t, UMD_t, and ΔPMI_t are the size factor, the book-to-market factor, the momentum factor, and the change in PMI, respectively. ΔTEM_t, ΔSSD_t, ΔPRE_t, ΔWIN_t, and ΔRHN_t are local weekly changes in the temperature, the sunshine duration, the precipitation, the wind speed, and the relative humidity, respectively. The MonthControls are a series of dummy variables to control month effects. The Newey West t-statistic is reported in the bracket.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.0013***	0.0009**	0.0017***	0.0013***	0.0015***	0.0009*	0.0010**	0.0013***
	[3.15]	[2.14]	[3.95]	[3.17]	[3.67]	[2.01]	[2.23]	[3.16]
ΔAQI_{it}^I	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000	0.0000
	[0.19]	[0.18]	[0.18]	[0.18]	[0.05]	[-0.07]	[-0.08]	[0.21]
$\Delta SentIndex_t$		0.0009***				0.0010***	0.0010***	
		[25.33]				[25.45]	[25.50]	
ΔCCI_t			0.0011***			-0.0004***	-0.0004***	
			[10.33]			[-3.11]	[-3.39]	
$\Delta InFlow_t$				-0.0000***		0.0000	0.0000	
				[-3.72]		[0.55]	[0.19]	
$\Delta ACCS_t$					0.0131***	0.0132***	0.0131***	
					[51.11]	[48.97]	[49.09]	
SMB_t						0.0016	0.0008	
						[0.13]	[0.06]	
HML_t						-0.2482***	-0.2507***	
						[-11.79]	[-11.97]	
UMD_t						0.0362***	0.0354***	
						[9.85]	[9.75]	
ΔPMI_t							0.0253***	
							[3.84]	
ΔTEM_t								0.0000
								[0.61]
ΔSSD_t								-0.0000
								[-0.45]
ΔPRE_t								-0.0000
								[-1.17]
ΔWIN_t								0.0000
								[0.19]
ΔRHU_t								-0.0000
								[-0.42]
Month Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number	11330	11330	11330	11330	11330	11330	11330	11330

Table 14: **ESG and the Air-Pollution Risk**

ESG ranking is made by Wind.

Rank	Number	$AQBeta^S$	$AQBeta^I$
AAA	36	-0.0205	0.0004
AA	1,829	-0.0021	-0.0001
A	1,2602	-0.0016	-0.0001
BBB	48,659	0.0001	-0.0001
BB	53,565	0.0014	-0.0001
B	4,998	0.0027	-0.0001
CCC	474	0.0004	0.0009

Table 15: **The Cross-Sectional Relation Between Industry and Response to the Air-Pollution Risk**

This table examines different response to air-pollution risk for firms from different industry. The independent variable, IND_{it}, is a dummy variable which equals 1 if a firm is from the mining, steel, transport, and construction industries, and 0 otherwise. The control variables include the monthly stock return, RET_{it}, the book-to-market ratio, BM_{it}, the natural log of market capitalization, $LnME_{it}$, stock i's return momentum measured as its cumulate returns from month $(t-7)$ to month $(t-12)$, MOM_{it}, the illiquidity measure, $ILLIQ_{it}$, and the skewness of stock return computed following **?**, $Skew_{it}$, the earnings-price ratio, EP_{it}, and the abnormal turnover following **?**, TO_{it}.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-0.0318*	-0.0334*	-0.0201	-0.0167	-0.0310*	-0.0307	-0.0141
	[-1.67]	[-1.81]	[-1.07]	[-0.90]	[-1.66]	[-1.65]	[-0.77]
IND_{it}	0.0022*	0.0021*	0.0021*	0.0022**	0.0025**	0.0023**	0.0026**
	[1.93]	[1.94]	[1.91]	[2.08]	[2.18]	[2.03]	[2.41]
RET_{it}	-0.0062	-0.0064	-0.0026	-0.0039	-0.0047	-0.0027	-0.0001
	[-1.04]	[-1.08]	[-0.40]	[-0.61]	[-0.79]	[-0.46]	[-0.02]
$LnME_{it}$	0.0014*	0.0015*	-0.0016	-0.0021	0.0014*	0.0014*	-0.0026
	[1.73]	[1.86]	[-0.63]	[-0.89]	[1.74]	[1.73]	[-1.08]
BM_{it}	-0.0001	-0.0001	0.0000	0.0000			-0.0004
	[-0.12]	[-0.06]	[0.01]	[0.04]			[-0.48]
MOM_{it}		-0.0005	-0.0007	-0.0008			-0.0011
		[-0.25]	[-0.38]	[-0.43]			[-0.59]
$ILLIQ_{it}$			-0.0027	-0.0032			-0.0036
			[-1.14]	[-1.37]			[-1.57]
$Skew_{it}$				0.0008			0.0008
				[0.88]			[0.86]
EP_{it}					0.0003	-0.0026	-0.0017
					[0.02]	[-0.18]	[-0.13]
TO_{it}						-0.0009	-0.0003
						[-0.63]	[-0.17]
Number	388404	388404	388404	388404	385346	385346	385346

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-0.0247*	-0.0237*	-0.0212	-0.0184	-0.0222	-0.0215	-0.0135
	[-1.70]	[-1.70]	[-1.34]	[-1.19]	[-1.59]	[-1.51]	[-0.87]
IND_{it}	0.0016	0.0016	0.0015	0.0016*	0.0019*	0.0015	0.0019*
	[1.64]	[1.60]	[1.55]	[1.67]	[1.81]	[1.55]	[1.95]
RET_{it}	-0.0069*	-0.0071*	-0.0058	-0.0061	-0.0066	-0.0038	-0.0025
	[-1.65]	[-1.70]	[-1.17]	[-1.23]	[-1.60]	[-0.90]	[-0.48]
$MktBeta_{it}$	-0.0014	-0.0013	-0.0012	-0.0013	-0.0015	-0.0013	-0.0013
	[-0.37]	[-0.36]	[-0.33]	[-0.35]	[-0.41]	[-0.36]	[-0.34]
$LnME_{it}$	0.0012*	0.0011*	0.0004	-0.0001	0.0010*	0.0010	-0.0006
	[1.79]	[1.76]	[0.16]	[-0.03]	[1.68]	[1.57]	[-0.30]
BM_{it}	-0.0002	-0.0002	0.0001	0.0001			-0.0004
	[-0.28]	[-0.21]	[0.15]	[0.13]			[-0.57]
MOM_{it}		0.0011	0.0009	0.0008			0.0004
		[0.66]	[0.59]	[0.53]			[0.27]
$ILLIQ_{it}$			-0.0007	-0.0011			-0.0014
			[-0.32]	[-0.51]			[-0.74]
$Skew_{it}$				0.0008			0.0008
				[1.14]			[1.12]
EP_{it}					-0.0012	-0.0024	-0.0009
					[-0.10]	[-0.19]	[-0.08]
TO_{it}						-0.0006	-0.0003
						[-0.40]	[-0.21]
Number	388404	388404	388404	388404	385346	385346	385346

Table 16: **Different Firm Attributes and Response to the Air-Pollution Risk**

This table examines different response to air-pollution risk for firms with different attributes. The LI_{it} variable is the ratio of the number of employees to total assets (in million yuan). The dependent variable is the monthly stock return of firm i in month $t+1$ ($RET_{i,t+1}$). In addition to the air-pollution beta, $AQBeta^S_{it}$ and $AQBeta^I_{it}$, as the independent variable, we control for the monthly market beta of firm i, $MktBeta_{it}$, the book-to-market ratio, BM_{it}, the natural log of market capitalization, $LnME_{it}$, stock i's return momentum measured as its cumulate returns from month $(t-7)$ to month $(t-12)$, MOM_{it}, the illiquidity measure, $ILLIQ_{it}$, the skewness of stock return computed following **?**, $Skew_{it}$, the earnings-price ratio, EP_{it}, and the abnormal turnover following **?**, TO_{it}.

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.0385	0.0426	0.0926***	0.0835**	0.0541*	0.0559*
	[1.10]	[1.26]	[2.80]	[2.56]	[1.67]	[1.75]
$AQBeta^S_{it}$	0.0087	0.0081	0.0070	0.0068	0.0078	0.0078
	[1.48]	[1.42]	[1.29]	[1.25]	[1.26]	[1.31]
$AQBeta^I_{it}$	-0.0692	-0.0714	-0.0570	-0.0594	-0.0731	-0.0617
	[-1.46]	[-1.50]	[-1.24]	[-1.29]	[-1.48]	[-1.23]
LI_{it}	0.0014**	0.0014**	0.0013**	0.0014**	0.0012*	0.0012*
	[2.29]	[2.35]	[2.21]	[2.22]	[1.69]	[1.79]
$LI_{it} \times AQBeta^S_{it}$	0.0087*	0.0086*	0.0081*	0.0081*	0.0100**	0.0101**
	[1.88]	[1.88]	[1.82]	[1.80]	[2.06]	[2.14]
$LI_{it} \times AQBeta^I_{it}$	0.0337	0.0444	0.0387	0.0379	0.0401	0.0391
	[0.69]	[0.92]	[0.82]	[0.81]	[0.81]	[0.80]
$MktBeta_{it}$	0.0000	0.0001	0.0012	0.0011	0.0002	0.0005
	[0.00]	[0.16]	[1.53]	[1.43]	[0.20]	[0.52]
$LnME_{it}$	-0.0015	-0.0017	-0.0154***	-0.0142***	-0.0022	-0.0021
	[-1.01]	[-1.20]	[-5.82]	[-5.31]	[-1.57]	[-1.53]
BM_{it}	0.0037**	0.0035**	0.0016	0.0016		
	[2.46]	[2.44]	[1.25]	[1.25]		
MOM_{it}		0.0023	0.0017	0.0017		
		[0.80]	[0.61]	[0.62]		
$ILLIQ_{it}$			-0.0132***	-0.0123***		
			[-5.69]	[-5.14]		
$Skew_{it}$				-0.0022**		
				[-2.52]		
EP_{it}					0.0381**	0.0374**
					[2.42]	[2.46]
TO_{it}						-0.0042***
						[-3.36]
Number	388404	388404	388404	388404	385346	385346