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# Stock Market Reaction on Air Polluted Days: The Case of China

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**ABSTRACT**

This study examines the Chinese stock market reaction to 22 smog events between 2012 and 2015. Two possible mechanisms, a 'rational' reaction based on value relevance and an 'irrational' reaction based on psychological bias, are recognized to explain the interrelationship between smog events and a potential market reaction. Using event study methodology, we find results supporting the 'rational' reaction, suggesting that, at least in the short term, firms in the polluting industries are punished by the stock market during events, while environmentally protective companies are rewarded. When investigating the 'irrational' reaction, we find no support of a negative effect for the stock market as a whole during events, but some results indicate that firms located in a province experiencing smog perform worse during events than they do otherwise. However, these results are economically insignificant and we therefore suggest other possible explanations. In addition, we do not find the issuance of CSR reports to mitigate some of the negative effects seen for companies in the polluting industries.

**Keywords:** Chinese stock market, Market efficiency, Mood effect, Smog, CSR reporting

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# INTRODUCTION

Smog, an adverse weather phenomenon closely associated with air pollution, has become a serious environmental issue in China in recent years, ever since an outbreak that affected 20 provinces in January 2013. Since it causes negative health effects, economic damage and attracts both public and governmental attention, we expect to observe a stock market reaction to the smog issue. A number of previous studies use event study methodology to examine the stock market reaction to the announcement of company specific environmental news. Results suggest that stock returns are negatively affected by bad news (see, e.g., Hamilton, 1995; Cohen and Konar, 1997) and positively affected by good news (see, e.g., Klassen and McLaughlin, 1996; Dasgupta et al. 2001), while some find weaker results in different settings (see, e.g., Tam et al., 2012). However, the severe air pollution problem in China cannot be attributed to one specific company, meaning that there is a gap between our setting and these studies. To cover the gap, we identify a link between smog and firm value through two possible explanations; (1) a cash flow effect caused by governmental intervention and an increased demand for environmentally protective products or services (these companies are mainly related to pollution control and monitoring technologies, but also, for example, dust collection), and (2) a cost of capital effect. As this side of the mechanism is value relevant and supports market efficiency, we regard it as a rational reaction of investors.

On the other hand, smog could also cause a mood effect resulting in investor bias. Previous studies investigating a relationship between weather and financial markets are motivated by findings in psychology that show how emotions and mood can influence human decision making. In general, we make more optimistic decisions and have more positive evaluations when we are in good mood. Several studies examining the connection between weather and the stock market (see, e.g., Hirshleifer and Shumway, 2003; Saunders, 1993) argue that people become more optimistic when the sun shines, and thus they may be more inclined to buy stocks. They hypothesize that people may incorrectly attribute their good mood to positive economic prospects rather than good weather, as emotions have been found to affect both our judgment (see, e.g., Clore and Schwartz, 1983) and risk assessment (see, e.g., Johnson and Tervsky, 1983). Support for this hypothesis of weather affecting stock market returns is found for several markets around the world by Hirshleifer and Shumway (2003). As this side of the mechanism is based upon psychological bias, we regard it as an irrational reaction of investors.

Two previous studies exploring the relationship between mood and financial markets in a Chinese setting investigate the effect of air pollution on stock market returns, using a linear regression model (Hu et al., 2014; Li and Peng, 2016). However, one limitation in these papers is that the effect of air pollution on people's mood, and in turn on stock returns, may not be linear. To address this problem, we use event study methodology instead of linear regression to observe the market reaction only on infrequent severe events. In our research, we attempt to develop a value-based model to explain how smog could affect the stock returns of certain industries, while acknowledging the possibility of a mood effect at the same time. To test the stock market reaction to smog, we first investigate investors' reaction towards certain industries. We find that several of the polluting industries blamed for causing smog have significantly lower abnormal returns during events than during other dates, while companies in the environmentally protective business show significantly higher abnormal returns during events. These results support our argument of a rational market reaction during smog, at least in the short term. However, at the end of the event window two industries show large abnormal returns of the opposite sign that erase most of the accumulated abnormal returns.

In a next step, we try to capture any mood effects during these events and find no support for smog causing a negative overall market reaction. Furthermore, we investigate how firms located in a province experiencing smog compare to other firms at the same time, as well as to themselves during other dates. Some mild support is found in favor of a local mood effect. However, the difference between events and other dates is economically small enough to be explained by other factors, such as actual economic damage from the smog. As a final step, we estimate a linear regression model to explore whether the issuance of CSR reports could influence how investors react to firms in the polluting industries at event dates. Results do not support our hypothesis that CSR reporting can mitigate some of the negative event date abnormal returns for companies in the polluting industries.

Our study contributes to the field of studies investigating the stock market reaction to adverse weather effects and pollution. Also, we provide some new findings regarding the link between air pollution, mood and the stock market in a Chinese setting. Last but not least, our study could shed some light on market efficiency in China since investors appear to be value conscious in response to smog events.

The rest of the paper will be structured as follows: (1) we provide some background information about the severity of smog in China, its harmful effects and social impact; (2)

hypotheses are developed based on two different stock market mechanisms; (3) an empirical framework is provided; (4) data and empirical results from a series of statistical tests are presented; (5) conclusions and limitations are discussed.

# SMOG: HARMFUL EFFECTS, SOURCES AND SOCIAL IMPACT

In spite of its rapid economic development, China has not given enough attention to environmental protection historically. Pollution has become a serious problem in China, among which air pollution is especially critical due to the heavy dependence on coal and other fossil fuels for electricity and heating. Smog, a joint effect of meteorological factors and air pollution, has been around for a long time, but during recent years it has become gradually worse as proved by serious deterioration in visibility ever since the 1980s (Gong et al., 2012). The average number of yearly smog dates among Chinese cities reached 35.9, a record high since 1961 (Ministry of Environment Protection of People's Republic of China, 2014). In Beijing, out of 695 days since January 2014, 375 days are classified as 'polluted' and 297 days have PM 2.5 as the primary pollutant .

According to China Meteorological Administration, smog in China is featured with high levels of PM 2.5. PM 2.5 is fine particulate matter with a diameter of 2.5 mm or less, and is more harmful to human health than larger particles because it's small enough to invade the respiratory system, bring toxic substances into lungs and may even penetrate into blood circulation. In medical research, smog has been found to increase the risk of a number of health problems, such as lung cancer (Fu et al., 2015), cardiovascular diseases (Lu et al., 2015) and even premature death (Chowdhury and Dey, 2016). A study based on observations from Hong Kong finds that in the long term, for every 10 microgram per cubic meter (μg/m3) of increased exposure to PM 2.5, the risk of dying from any cancer increases by 22%. More specifically, the risk of mortality from cancer in the upper digestive tract rises by 42%, cancer in the digestive organs by 35%, breast cancer in females by 80% and lung cancer in males by 36% (Wong et al., 2016). PM 2.5 might even be associated with defects in DNA repair.

Apart from the health effects, smog is also causing economic damage. The low visibility brings much inconvenience and considerable risk to daily life and urban operation. For example, the economic loss on transportation was estimated to around 500 million CNY (approximately 78 million USD) during a severe smog event that affected 20 provinces in China in January 2013 (Mu and Zhang, 2013). The harmful effect on human health also incurs considerable health care costs; the increased short-term health care costs amounted to about 22.6 billion CNY during the same event (Mu and Zhang, 2013).

It is believed that the smog in China is mainly caused by coal burning, transportation emission, industrial emission and construction dust. Coal produces hundreds of times more particulate matter than natural gas for the same amount of energy delivered (US Energy Information Administration, 1999). However, it is still the most widely used fuel for electricity generation, especially in northern China. Smog also demonstrates a strong seasonal pattern, being more frequent and serious during winter, since northern China heavily relies on coal for heating. Steel manufacturing, non-ferrous metal producers and the oil industry are explicitly blamed for industrial emission in the Law of Air Pollution Control. Transportation emission concentrates mainly in large cities with heavy traffic. Beijing’s local government has therefore implemented rules to restrict private vehicles during heavy air pollution to control this source of pollution. The rapid growth in infrastructure and real estate also brings serious dust pollution at construction sites and during the transportation of construction materials. Among the sources of particulate pollution mentioned above, we focus on coal producers, steel producers, non-ferrous metal producers and the oil industry as the emission can be more directly traced to these specific industries, whereas it is hard to tell who to blame for transportation emission and construction dust.

Although the smog issue has been around for long, it was not until 2013 when it received wide media coverage and public attention. There were about 300 news articles about smog published in Chinese during 2012, but the number rocketed to around 10,000 in 2013 (retrieved from Factiva). Another evidence of public awareness is the rise of the topic ‘雾霾’ (Chinese for smog) in Google Trends, which first started in early 2013. The popularity of the topic also demonstrates a seasonal pattern, with increased popularity during winter time and peaks on major smog events, indicating that people are more concerned about the smog issue when smog happens. Noticeably, a documentary independently produced by journalist Jing Chai, Under the Dome, received over 200 million views in five days after its publication (Gardner, 2015). It attributed the smog problem to certain industries, namely coal power plants, steel manufacturing and oil products. This is deemed as a milestone event that aroused enormous public awareness. Stocks in the environmental protection business rose significantly, while CNPC and Sinopec's (the two largest state-owned oil companies in China that were criticized in the documentary) stock prices decreased on the trading day immediately after the documentary was published (Noble, 2015). The effect of public awareness can also be observed in Li and Peng's (2016) results, which are further mentioned below.

In response to the rising public attention and the negative economic effects, the Chinese government has taken actions to carefully monitor air pollution. First, a new air quality index that includes the PM 2.5 level was introduced in 74 cities as a pilot program, allowing PM 2.5 levels to be officially monitored for the first time in China. In the following year, 87 more cities applied the new index. Second, a new smog alert system which is divided into three levels has been set up. The PM 2.5 level, together with visibility and humidity, are considered as criteria for issuing a smog alert (as can be seen in Table B1 in Appendix B). Because of a closely inverse correlation between PM 2.5 concentration and visibility (Chai et al., 2013), smog alerts are highly dependent on PM 2.5 levels.

Besides the monitoring and alert systems, regulations were revised and the Chinese government demonstrated an assertive attitude to deal with the smog issue. Keqiang Li, Premier of China, expressed that "all acts of illegal production and emissions will be brought to justice and held accountable" and promised a strict enforcement of the environmental protection law in 2015 (Buckley and Wong, 2015). A new version of the Air Pollution Prevention and Control Law was issued in 2015, which targets fossil fuel burning, industrial production, vehicle emission and airborne dust as the major sources of air pollution. The law describes rules for monitoring pollution and emergency management during heavily polluted days. It suggests to encourage cleaner fuels, coal processing and toxic filtering technology through economic incentives, and indicates penalties for companies that fail to meet emission standards. There were 135,059 cases of penalties related to environmental issues and a total of 149.78 billion CNY (approximately 23 billion USD) was invested into air pollution control devices in 2013 (Ministry of Environment Protection of People's Republic of China, 2014). The government's efforts to control the air pollution issue may give rise to significant contingent liabilities and higher risks for polluting companies, while benefitting more sustainable companies or companies that work within the environmental technology business.

# LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

In light of the harmful effects on human health, the economy and the resulting social impacts, we would expect smog to have some kind of influence on the stock market as well. As we explore the stock market reaction to smog, we also make an attempt to construct a theoretical framework and to rationalize our expectations. Two mechanisms on how smog could affect the stock market are suggested based on previous literature and theories, and we predict the two mechanisms to be differently reflected in the stock market.

## A Relatively 'Rational' Mechanism Behind the Stock Market Reaction

*In this mechanism to explain a market reaction to smog, we ask ourselves two questions: (1) is environmental performance valued by investors; (2) how is smog associated with certain companies?*

Plenty of event studies have been conducted to observe the stock market reaction in response to environmental news with the aim of investigating whether environmental performance is valued by investors or not. Hamilton (1995) finds significant negative abnormal returns on the day toxic release inventory emission data is first announced. Klassen and McLaughlin (1996) test the stock price reaction to environmental news of listed US firms in manufacturing, utilities and oil & gas extraction. A CAR of 0.63% is observed for positive news (environmental awards) during the 3-day event window and a CAR of –0.82% is observed for negative news (chemical and oil spills, gas leaks or explosions). Dasgupta et al. (2001) perform an event study in the context of four developing countries and also document significant results for both positive and negative news. However, the magnitude of reaction is rather high, with as much as a 20% increase for positive news and a 4%-15% decrease for negative news, which might be partly attributed to the small sample size. Notably, they find that firm values decrease most severely in response to citizen complaints and government action. More specifically in a Chinese setting, Tam et al. (2011) find that the adverse stock market reaction towards negative environmental events is weaker than the reactions previously observed in studies conducted in the US, Canada and a variety of developing countries. All these studies indicate that investors do react to environmental news and value the environmental performance of a firm. The value relevance of environmental performance can be explained in two ways from a valuation point of view. It can be (1) a cash flow effect, meaning that a future cost is expected for polluting companies and increased revenues and/or subsidies are expected for environmentally protective companies, or (2) a cost of capital effect, which may be caused by a growing preference for 'green investment' (Ambec and Lanoie, 2008). As this side of research is based on market efficiency and valuation theory, we regard it as a 'rational' reaction of investors and it serves as a theoretical foundation for our hypothesis. Since smog is closely associated with air pollution, we expect smog to serve as a form of negative environmental news and thus to have some effect on investors.

However, a noticeable gap still exists since the aforementioned event studies all investigate company specific news, while smog as a weather phenomenon is not. How could investors link smog to some consequences for certain companies? Blacconiere and Patten (1994) document that following a chemical leak event, companies within the chemical industry reported a negative CAR and companies with a larger portion of their revenue in the chemical segment were even more negatively affected, even though these companies were not responsible for the disaster. A possible explanation for such findings is through governmental policy enforcement. Because of the externality of pollutant emission, firms tend to produce pollution regardless of the social impact, while the government needs to take action to internalize the cost of the polluting behavior to avoid over pollution (Cornes and Sandler, 1986). A number of studies have been conducted to investigate the impact of pollution control approaches and determinants of government policy implementation, both in developing and developed countries. Dasgupta et al. (2001) find that more inspections would contribute to reduce the pollution emission in China and a number of other studies report similar results, i.e. that government enforcement and regulation help improve the pollution condition (Doonan et al., 2005; Féres and Reynaud, 2011).

Regarding the determinants of government policy enforcement, a number of factors have been examined, including firm characteristics, the social impact of pollutant emission and local environmental damage. Studies in both developed and developing countries find that public complaints and community pressure serve as a major source of pressure for local governments to have higher levels of regulation enforcement in terms of effective levy rates and number of inspections (Dasgupta et al., 2003; Doonan et al., 2005; Féres and Reynaud, 2011). Further supportive evidence shows that the negative impact on stock prices from bad environmental news becomes even stronger when public complaints are reported (Dasgupta et al., 2001). Dion et al. (1998) point out that higher local environmental damages will prompt more inspections and more inspection effort is allocated to firms that are likely to generate larger damages because of pollutant emission. These findings are in line with public interest theory regarding regulations, which holds that "regulation is supplied in response to the demand of the public for the correction of inefficient and inequitable market practices" and predicts that regulations should primarily be imposed for industries that generate substantial external costs (Posner, 1974).

In the case of smog, we argue that the social damage and community pressure of the smog issue should have an effect in prompting the government to enforce environmental regulations. According to public interest theory, it is likely that the Chinese government would focus on highly-polluting industries in their regulation enforcement, through an increased number of inspections, higher effective levy rates and by urging investments in cleaner energy. Future costs would harm firm value in the polluting industries. Even though environmental performance differentiates between companies and not all companies in polluting industries are to be equally blamed, we argue that the pollution issue is more of a general problem on an industry level in China. Therefore, we expect to observe a negative stock market reaction for the polluting industries on average.

On the other hand, the cash inflow prospects of environmentally protective companies would improve based on expectations of government subsidies and an increased demand for their products or services. In fact, government investment in pollution control grew around 900% from 2000 to 2013[1], and even further investments can be foreseen in response to the smog issue. On the consumer side, the demand for certain air pollution related products, such as air purifiers and anti-pollution masks, is also predicted to experience a large growth. As such, we expect a positive market reaction for firms within the environmental protection business at smog events.

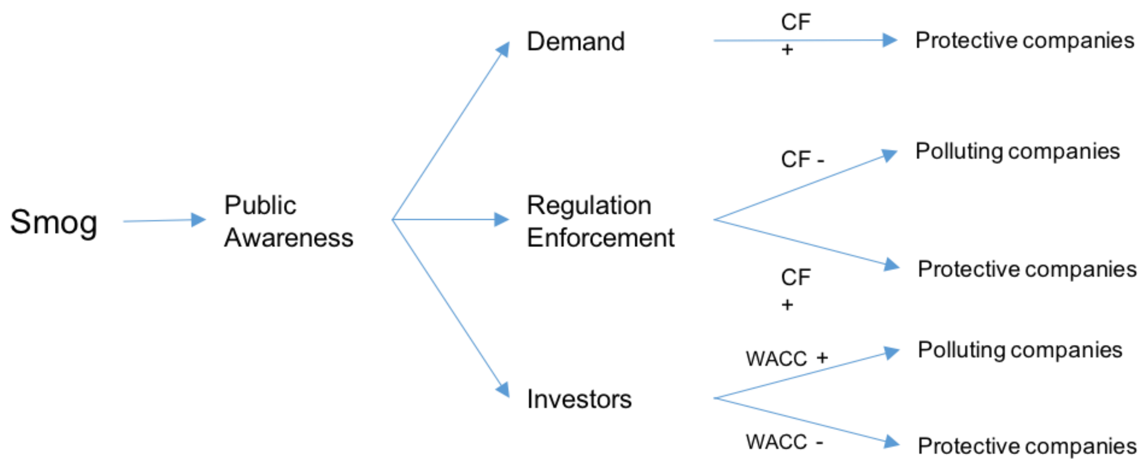
Meanwhile, the value change in response to smog could also be attributed to a change in the cost of capital as 'green companies' may enjoy better access to capital markets and banks (Ambec and Lanoie, 2008). The increasing portion of green investors may result in a lack of risk sharing in polluting firms and a higher cost of capital, until a reform is performed to address the green preference of investors (Heinkel et al., 2001). Government policy may also play a part by holding lower debt rates for the environmental protective business, either through local

[1] Based on data from National Bureau of Statistics of the People's Republic of China. Retrieved from: http://www.stats.gov.cn/ztjc/ztsj/hjtjzl/2013/201412/t20141226_659969.html

government investment or national banks, which lowers the cost of capital for these companies. As the public awareness of air pollution is accumulating through repetitive occurrences of smog, the cost of capital for firms in polluting industries may increase while the environmental protective business receives a more favorable required return from investors.

To summarize the factors that may affect firm value in the polluting industries and environmental protective business, we illustrate the 'rational' mechanism of smog affecting the stock market and state our first two hypotheses.

*Figure 1 - Model of the Rational Mechanism*




$H_1$: *Firms in what are considered polluting industries are punished by the stock market during events.*

$H_2$: *Firms considered environmentally protective are rewarded by the stock market during events.*

## A Less 'Rational' Mechanism Behind the Stock Market Reaction

*We regard this mechanism as irrational because this strand of research is based on the existence of psychological bias and breach the efficient market hypothesis.*

In the mood effect mechanism, our theory is built upon the link between environmental factors (weather) and mood, leading to irrationality in decision making and investor behavior through the effect mood has on our assessments of the future (Hirshleifer and Shumway, 2003). A number of studies in behavioral finance have explored the effect of weather on stock markets. Saunders (1993) focuses on New York City for the period of 1927-1989 and was the first to link weather conditions to investment behavior in financial markets. His study shows that less cloud coverage is associated with higher returns, and that the return difference between the most and least cloudy days is statistically significant. These results support the hypothesis that investors are more optimistic on sunny days and more pessimistic on cloudy days and that this in turn has an effect on the stock market. Hirshleifer and Shumway (2003) confirm these findings when examining 26 stock market indices around the globe for the period of 1982-1997. They find a highly significant negative relationship between cloud cover and returns. After controlling for sunshine, they find that other weather conditions such as rain or snow seem unrelated to stock returns. More specifically related to smog, psychology articles have shown an association between air pollution and annoyance (Forsberg et al., 1997) and anxiety (Colome et al., 1986). Bad mood, in turn, may influence people's judgment (Clore and Schwartz, 1983) and risk assessment (Johnson and Tervsky, 1983).

Following this strand of research, two recent papers cover the relationship between the stock market and air pollution in China (Hu et al., 2014; Li and Peng, 2016). Both papers embrace the mood effect to hypothesize a negative correlation between stock market returns and air pollution levels. Hu et al. (2014) report weaker results as they find that only the relative air pollution level compared to Beijing has a significant negative impact on the stock market. On the other hand, Li and Peng (2016) state that "environmental awareness plays a significant role in affecting investors' moods and behaviour", based on the fact that the negative relationship between air pollution levels and stock market returns is not found before the period 2010-2014. However, the mechanism of public awareness fitting into mood effect is not clearly explained in the article.

As we try to explore the rationale of smog causing fluctuations in the stock market, we design further tests to approximately capture the mood effect of smog. First, we are curious about whether the stock market as a whole is generally underperforming on smog dates. If there is a mood effect, we expect the returns of market indices to be lower during events. Hypothesis 3 is stated as follows:

$H_3$: *Market index returns are lower during events.*

Secondly, as smog is a regional weather phenomenon, only people experiencing it should have their mood directly affected. Levy and Yagil (2011) observe that air pollution has a larger effect on investors close to the polluted area. The same pattern should apply to our subject of smog. As previous research suggests that investors tend to prefer stocks close to home even in portfolios of domestic stocks (Coval and Moskowitz, 1999), we use company location as an approximation of investor location. Thus, we would expect firms located in a province experiencing smog to be the more affected by the mood effect than those firms located in other provinces. Hypothesis 4 is therefore stated as follows:

$H_4$: *Firms located in a province experiencing smog have lower abnormal returns than other firms during events.*

However, as we are not able to account for possible differences in the normal level of returns between provinces (e.g. due to certain industries being located in certain provinces), it is possible that the tests related to Hypothesis 4 do not tell the truth. We therefore also compare firms in a province experiencing smog to themselves outside events and it leads us to Hypothesis 5.

$H_5$: *Firms located in a province experiencing smog have lower returns and abnormal returns than they have outside events.*

## Mitigating Factor to the Stock Market Reaction

As a final step of our research, we also want to see if there is any factor that can mitigate the negative impact of smog for companies within polluting industries. The specific emission data for firms are hard to access and might be inaccurate, as suggested by Lin (2012) and Chen and Huang (2015). Instead, we choose the issuance of CSR reports as a possible mitigating factor that may reflect the environmental performance of a company and also be easily accessible to the public. Blacconiere and Patten (1994) report that chemical companies with more extensive environmental disclosure are less punished by the market after the Bhopal chemical leakage. Nowadays, an increasing number of companies are investing millions of dollars in CSR activities, no matter size and ownership organizations, and they proclaim their credentials by producing CSR reports (KPMG, 2011). Malik (2015) argues that we wouldn’t see such a growing trend in CSR reporting if it creates no value for companies. The literature on CSR reporting in China, and perhaps even internationally, is still premature, so it is not yet clear whether CSR reporting could be a factor. In fact, there are contradicting theories regarding the correlation between environmental performance and environmental disclosure. Social Political theories, such as the legitimacy theory, predict that firms with poor environmental performance will have a higher level of discretionary disclosure in an attempt to gain legitimacy (Gray et al., 1995), while economic disclosure theory holds that firms with better environmental performance are motivated to disclose more to inform investors about their performance (Li et al., 1997). As such, a CSR report may not be enough to deliver sufficient information on environmental performance to affect firm value. Secondly, 'green investors' may not be convinced by a CSR report. However, if investors do buy this information, it is likely that the polluting companies issuing CSR reports would perform better than their industry peers during smog. We therefore make an attempt to examine its possible mitigation effect under the smog setting and propose Hypothesis 6 as follows:

$H_6$: *Firms in the polluting industries that issue CSR reports show more positive abnormal returns than their industry peers at event dates.*

# EMPIRICAL FRAMEWORK

To investigate the stock price impact of a certain event, the event study methodology is commonly used. In capital market research, event studies serve an important purpose by being able to test market efficiency as well as the effect of an unanticipated event on share prices (Kothari and Warner, 2004). Finance theories often suggest that share prices immediately reflect all the information available to the market. Given this assumption, the value relevance of a particular event can be investigated by its impact on the share price. Thus, the first task is to define the event that is of interest and then the time period over which the returns of the firms experiencing this event will be studied. An event study can look at firms experiencing a certain event either at the same calendar time (event clustering) or at separate calendar times.

To understand the impact of an event, the abnormal return of a share has to be calculated. This is done by separating the observed returns into two parts; the normal returns expected to take place had the event not happened, and the abnormal returns caused by the event (Schimmer, Levchenko, and Müller, 2014). Thus, to estimate the abnormal return a benchmark model has to be used to determine the expected return for each share and date. The abnormal return (AR) is then the difference between the observed return and the expected return. For firm $i$ and date $t$ the abnormal return is

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|X_t)$$

where $AR_{i,t}$, $R_{i,t}$ and $E(R_{i,t}|X_t)$ are the abnormal, observed, and expected returns respectively for time period $t$. $X_t$ is the conditioning information for the expected return model.

The cumulative average abnormal return ($CAR$) can then be calculated for a single firm as

$$CAR_{i,T} = \sum_{t}^{T} AR_{i,t}$$

Based on the individual stock abnormal returns, the average abnormal return ($AAR$) can be calculated for each day $t$ of the event window. This aggregates the abnormal returns for all $N_m$ stocks from a certain industry experiencing the event $m$ across all $M$ events to find the average abnormal return at each day during the event windows.

$$AAR_t = \frac{1}{M} \cdot \sum_{m=1}^{M} \left( \frac{1}{N_m} \cdot \sum_{i=1}^{N_m} AR_{i,t,m} \right)$$

The cumulative average abnormal return ($CAAR$) is then the sum of the average abnormal returns over $T$ days in the event window.

$$CAAR_T = \sum_{t=1}^{T} AAR_t$$

The typical null hypothesis to be tested is whether the event on average is associated with a change in share price, that is if the average abnormal return during the event window is equal to zero. It is usually also of interest to study if the average abnormal returns for some period around the event are equal to zero. First, if the event is partially anticipated by the market we would expect some of the abnormal return to show up in the pre-event window. Second, the study of the post-event returns provides information regarding market efficiency (Kothari and Warner, 2004).

However, one has to be aware that an event study is a joint test of the underlying assumptions that abnormal returns are zero and that the assumed model of expected returns is correct (Schimmer et al., 2014; Kothari and Warner, 2004). McWilliams and Siegel (1997) add that for the results of an event study to be valid, the event has to be unanticipated and there can be no confounding events during the event window, such as the announcement of unexpected earnings, which distort the effect of the event.

Although the event study method seems straightforward, there are some areas that warrant further attention. These areas are further explained below.

## What is Considered an Event

We define an event date as a day where the maximum PM 2.5 level is over 500 in any of the five major cities covered by our data. Another requirement is that the PM 2.5 level has not been over 500 for the particular city during the past nine days. There are three reasons for classifying levels over 500 as an event; the first reason is the smog alert system used in China. A warning is issued if one of several combinations of humidity, visibility and PM 2.5 levels are expected to be reached within the next couple of days. However, there is one type of warning based almost solely on the PM 2.5 level which is issued if the level is expected to exceed 500. As we are unable to obtain data of humidity and visibility levels, as well as the actual forecasts, we have to rely on the actual PM 2.5 measurement. When searching for news coverage on Factiva, we find considerably more news reports regarding smog during dates identified as event dates than on other dates. The second reason for using this level is the US Embassy in China's description of the health effects related to different levels of PM 2.5. Levels between 300 and 500 are considered "hazardous" and come with a serious risk of respiratory effects for the general population. The health effects from levels exceeding 500 are not even mentioned, thus PM 2.5 levels over 500 should be considered extreme. The third reason for using this level is that we only want to capture infrequent and more extreme events.

If the date identified as an event date is not a trading day, the next day that is a trading day is set as the event date. This date is considered an event date no matter if the firm is located in the province experiencing smog or not. However, in our province tests we do make a distinction between the firms located in a province experiencing smog and those that are not.

## Event-Date Clustering and Portfolio Creation

The normal procedure of analyzing aggregated abnormal returns assumes that the event windows of the sample do not overlap in calendar time. If this assumption is true, the variance of the aggregated cumulative abnormal returns can be calculated without thinking about covariances across shares as the covariances are zero. However, when event dates are clustered the covariances between abnormal returns across shares will not be zero. This leads to a downward bias of the standard deviation, which results in an overstated t-statistic and overrejection of the null hypothesis (Bernard, 1987). A method used in previous studies to by-pass this is to construct a value-weighted return portfolio for every single event date where all firms experiencing this event are included (see, e.g., Armstrong et al., 2010). The portfolio is created by value-weighting the abnormal returns of all firms experiencing the event based on the daily market value of equity as can be seen in the equation below:

$$AR_{p,t} = \sum_{i=1}^{N} \frac{AR_{i,t} \cdot (Shares_{i,q} \cdot P_{i,t})}{\sum_{i=1}^{N}(Shares_{i,q} \cdot P_{i,t})}$$

Where $Shares_{i,q}$ is the number of shares for firm $i$ at quarter $q$, and $P_{i,t}$ is the stock price for firm $i$ at time $t$.

We create a value-weighted portfolio for each of the industries of interest; coal producers, steel producers, non-ferrous metal producers, oil refiners & distributors, and environmentally protective companies. For our province tests, we construct portfolios in a similar manner but based on firm location rather than industry group (if the firm is located in a province that is experiencing smog it is included in one portfolio, if it's located outside the province experiencing smog it is included in another). Test statistics are then based on portfolio returns since this will allow for cross correlation of abnormal returns (Sefcik and Thompson, 1986; MacKinlay, 1997). However, as our non-parametric test, the Wilcoxon rank-sum test, does not incorporate the standard deviation we can use it to test the individual stock abnormal returns of all firms belonging to a certain portfolio.

For our portfolio analysis, the $AAR$ at each event day $t$ for portfolio $p$ is calculated as

$$AAR_{p,t} = \frac{1}{M} \cdot \sum_{m=1}^{M} AR_{p,t,m}$$

Where $M$ is the total number of events. The portfolio $CAAR$ over $T$ days in the event window is then

$$CAAR_{p,T} = \sum_{t=1}^{T} AAR_{p,t}$$

T-tests are based on $AAR$ and $CAAR$, while Wilcoxon rank-sum tests are based on $AR$ and $CAR$. For $CAR$ and $CAAR$, two different periods are tested. One stretching from one day before the event date until one day after, denoted [-1, 1], and one stretching from two days before the event date until two days after, denoted [-2, 2].

## Event Windows and Estimation Windows

According to Kothari and Warner (2004) there are some serious limitations in regard to long-horizon methods. However, in general short-horizon methods are quite powerful as long as the abnormal performance is concentrated to the event window. Short-horizon methods also have the advantage of the test specification not being very sensitive to assumptions about the cross-sectional and time-series dependence of abnormal returns or the choice of expected return measure. Another benefit of using shorter event windows is the difficulty of controlling for confounding events when long windows are used (McWilliams and Siegel, 1997). Thus, the window should be short enough to minimize the amount of confounding events, but long enough to capture the significant impact of the event. Event windows used in previous studies typically range from 1 to 11 days and center symmetrically around the event date (Schimmer et al., 2014). Oler, Harrison, and Alen (2007) find that 76% of the reviewed studies in their paper use event windows that close within five days after the event date. Our event window spans over five trading days, starting two days before the event date and ending two days after the event date. This allows us to capture possible effects from smog forecasts being released before the event date and also any effects occurring during the days right after the event, while keeping the number of confounding events down.

In many of our tests we compare event days to non-event days. A non-event day is simply a day that is not part of an event window. The non-event cumulative abnormal returns are calculated for each non-event day.

Estimation windows, usually ending just before the event window, are commonly used to predict expected returns. Previous studies indicate that results are not sensitive to the choice of estimation window length as long as the window exceeds 100 days (Park, 2004). It is of importance that no events occur during the estimation window. Events occurring during this window could have a substantial impact on the expected return measure. This would lead to both the normal returns as well as the abnormal returns capturing the effect of the event, which is problematic since the methodology assumes that effect is captured only by the abnormal returns (MacKinlay, 1997).

In our sample most events (20 out of 22) occur during the period between October and April. Thus, only summers have over 100 trading days in a row without an event occurring. This affects our choice of expected return model.

## Expected Return Models

Brown and Warner (1980, 1985) find that simple prediction models often yield results similar to those of more advanced models. This can be explained by the fact that the variance of abnormal returns is generally not affected much by the model used (MacKinlay, 1997).

Due to events occurring during the estimation window it is not always possible to use a regression based expected return model. We therefore use the 'market adjusted model' as our main model. This model has been used in several previous event studies (see, e.g., Faccio, 2006; Faccio and Parsley, 2009; Armstrong, Barth, Jagolinzer, and Riedl, 2010). The market adjusted model deducts the reference market return $R_{m,t}$ on date *t* from the observed return $R_{i,t}$ for firm *i* at date *t* (Schimmer et al., 2014).

$$AR_{i,t} = R_{i,t} - R_{m,t}$$

As a robustness check we also include the results obtained from the 'market model' in all of our statistical tests. This model considers a firm's individual risk by multiplying the market return, $R_{m,t}$, with a firm individual $\beta$ factor while assuming the risk-free rate to be a constant included in the $\alpha$ factor (Schimmer et al, 2014). The return of firm *i* at date *t* is thus estimated as

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}$$

And the abnormal return for firm *i* at date *t*, $AR_{i,t}$, is then calculated as

$$AR_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i R_{m,t})$$

The regression coefficients are estimated yearly for each firm during summers as this period is free from events every year except for 2014. Although this does not follow recommendations from previous literature regarding estimation window placement relative to the event window, it should still serve as a decent robustness check due to the additional risk adjustment.

For both models we use value-weighted indices as a proxy for the market return. Stocks listed on the Shenzhen Stock Exchange use the return of the Shenzhen Stock Exchange A Share Index as the reference market return, while stocks listed on the Shanghai Stock Exchange use the return of the Shanghai Stock Exchange A Share Index.

## Controlling for Confounding Events

McWilliams and Siegel (1997) argue that for the results of an event study to be valid, firms for which other financially relevant events occur during the event window will have to be excluded from analysis. If not excluded, the abnormal returns caused by these other events will be attributed to the event we are studying. Due to the amount of events and number of firms in our industry portfolios we are not able to control for confounding events at a detailed level. However, for each event window, as well as for the day(s) just before the event window, we look for the release of quarterly and annual reports for each firm included in our portfolios. If a report is released during an event window we remove the firm from the analysis during that event. We also look for major industry news, large changes in commodity prices (e.g. copper for the copper producers included in the non-ferrous metal industry portfolio) and news regarding new regulation affecting a certain industry. If an event of this type occurs during an event window we exclude all industry observations during that particular event.

## Statistical Testing

Previous studies claim that there are several potential problems in regards to hypothesis testing when using the event study method. Parametric tests are commonly employed in hypothesis testing, but these tests make assumptions about the population the sample is drawn from that may not always be true. According to Corrado (2011) several studies have found non-normality to be an issue with returns data from many different stock exchanges. Other potential problems are that abnormal return estimators are cross-sectionally (in event time) correlated, heteroscedastic, or auto-correlated for a given firm (Binder, 1998). Therefore, alternative approaches using non-parametric tests, such as variations of the sign test and the rank test, are often employed as they are free of specific assumptions about the distribution of returns (MacKinlay, 1997).

We use Student's t-test to test if abnormal returns are different from zero ($\mu = 0$) during events, but use Welch's t-test and Wilcoxon rank-sum test for other statistical tests. The former allows us to test whether the mean of event returns is equal to the mean of non-event returns ($\mu_x = \mu_y$), while the latter allows us to test whether event returns and non-event returns follow the same distribution ($X_1 \sim X_2$) without the assumption of normality that is required for t-tests. Previous studies, such as Binder (1998) and Corrado (2011), claim that daily stock returns often are non-normally distributed. We also include a bootstrap test statistic to test equality of means, this allows us to estimate the probability of obtaining a t-statistic more extreme than the one observed in our t-tests given that the null hypothesis of $\mu_x = \mu_y$ is true.

Welch's t-test is recommended to be used whenever the variances of the two groups tested are believed to be unequal. Zimmermann (2004) suggests using Welch's t-test over Student's t-test for "optimum protection" whenever the two groups compared are of unequal size. Welch's t-test is more robust than Student's t-test for unequal variances and unequal sample sizes, and comes close to the power of Student's t-test when the two groups have equal variance (Ruxton, 2006).

The highest weight is put on the test results obtained from the rank-sum tests as the samples tested are larger and due to the common problem with non-normality. Also, some of the industry portfolios include companies that constitute a large portion of the industry's total market value of equity which could distort results.

### *T-Tests*

Using Student's t-test, we test whether event abnormal returns are equal to zero. The test statistic for $\mu = \mu_0$ with an unknown standard deviation is given by

$$t = \frac{(\bar{x} - \mu_0)\sqrt{n}}{s}$$

Where $\bar{x}$ is the sample mean, $n$ is the sample size, and $s$ is the sample standard deviation. The statistic is distributed as Student's $t$ with $n - 1$ degrees of freedom.

When testing if event returns are equal to non-event returns, the test statistic when the standard deviations of the two groups are unknown, but we know that they are not equal to each other, is given by

$$t = \frac{(\bar{x} - \bar{y})}{\sqrt{(s_x^2/n_x + s_y^2/n_y)}}$$

Where $s_x$ is the standard deviation of group $x$, $s_y$ is the standard deviation of group $y$, $n_x$ is the size of group $x$, and $n_y$ is the size of group $y$.

Using Welch's formula, the degrees of freedom are given by

$$-2 + \frac{(s_x^2/n_x + s_y^2/n_y)^2}{\frac{(s_x^2/n_x)^2}{n_x + 1} + \frac{(s_y^2/n_y)^2}{n_y + 1}}$$

## *Wilcoxon Rank-Sum Test*

The Wilcoxon rank-sum test tests the null hypothesis that event returns ($X_1$) are drawn from the same distribution as non-event returns ($X_2$). Our sample consists of $n_1$ observations of $X_1$ and $n_2$ observations of $X_2$, adding up to a total of $n$ observations. These $n$ observations are then ranked without regard to the group they belong to. For ties the averaged rank is used. Wilcoxon's test statistic is the sum of ranks for the observations in the first group:

$$T = \sum_{i=1}^{n_1} R_{1i}$$

The expected value of $T$ can be calculated as

$$E(T) = \frac{n_1(n+1)}{2}$$

And the variance of $T$ as

$$Var(T) = \frac{n_1 n_2 s^2}{n}$$

Where $s$ is the standard deviation of the combined ranks, $r_i$, of both groups.

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(r_i - \bar{r})^2$$

Using a normal approximation, we calculate the test statistic $z$ as

$$z = \frac{T - E(T)}{\sqrt{Var(T)}}$$

### *Bootstrap Test Statistic to Test Equality of Means*

Using a bootstrap, the probability mechanism under the null hypothesis of equal means between two groups is estimated by transforming the empirical distributions so that the null is true while allowing the variance to be unequal. This cannot be interpreted as an exact probability, as it is guaranteed to be accurate only when the sample size goes to infinity (Efron and Tibshirani, 1993).

Suppose that we have a sample, $x$, consisting of two groups, $y$ and $z$ (which in our case represent event observations and non-event observations). $\bar{y}$ and $\bar{z}$ are the groups' mean returns and $\bar{x}$ is the mean return of the combined sample. The data can then be transformed so that the mean returns of the two groups are equal, while allowing for unequal variance. This is done by subtracting the group mean and adding the sample mean to all observations for each group so that $\tilde{y}_i = y_i - \bar{y} + \bar{x}$ for $i = 1, 2, \ldots, n_y$ and $\tilde{z}_i = z_i - \bar{z} + \bar{x}$ for $i = 1, 2, \ldots, n_z$. Then, $B$ bootstrap data sets are formed ($y^{*b}$, $z^{*b}$) where $y^{*b}$ is sampled with replacement from $\tilde{y}_1$, $\tilde{y}_2$,…, $\tilde{y}_{n_y}$ and $z^{*b}$ is sampled with replacement from $\tilde{z}_1$, $\tilde{z}_2$,…, $\tilde{z}_{n_z}$.

For each bootstrap data set, the t-statistic is calculated as

$$t(x^{*b}) = \frac{(\bar{y}^{*b} - \bar{z}^{*b})}{\sqrt{(s_y^{2*b}/n_y + s_z^{2*b}/n_z)}}, \qquad b = 1,2, \ldots, B$$

The achieved significance level is then calculated as

$$P_{bstrap} = \#\{t(x^{*b}) \geq t_{obs}\}/B$$

when we expect positive t-statistics and

$$P_{bstrap} = \#\{t(x^{*b}) \leq t_{obs}\}/B$$

when we expect negative t-statistics. $B$ is the total number of bootstrap replications and $t_{obs}$ is the observed t-statistic

## The Rational Market Reaction

To test our two hypotheses that

$H_1$: *Firms in what are considered polluting industries are punished by the stock market during events*

$H_2$: *Firms considered environmentally protective are rewarded by the stock market during events*

we provide four different tests for each of our industries of interest. T-tests and bootstraps are based on industry portfolio $AAR$ and $CAAR$, while Wilcoxon rank-sum tests are based on individual stock $AR$ and $CAR$ of the firms belonging to that industry. All tests mentioned in this section are done industry by industry.

The first test is a one-tailed Student's t-test of whether the mean of an industry portfolio's event abnormal returns is equal to zero. We expect the polluting companies to have negative abnormal returns and the environmentally protective companies to have positive abnormal returns. However, for these results to be valid an assumption that our market adjustment is the proper benchmark has to be made. We do not expect this to be the case and therefore complement this with other tests. Therefore, the tests mentioned below compare an industry's event abnormal returns to the abnormal returns of the same industry during non-events.

The second test is a one-tailed Welch's t-test of whether the average industry portfolio abnormal return is equal between events and non-events. We expect polluting companies to have a lower mean during event windows and environmentally protective companies to have a higher mean during event windows.

The third test is a one-tailed Wilcoxon rank-sum test of whether event abnormal returns come from the same distribution as non-event abnormal returns. We expect the polluting industries to have their abnormal returns drawn from a separate distribution during event windows, resulting in a lower than expected rank. We expect the opposite to be true for environmentally protective companies.

The fourth test is a bootstrap test of the equality of means. This computes the probability of obtaining a t-value more extreme than the one observed in the second test given that the null hypothesis of $\mu_x = \mu_y$ is true. For each industry portfolio, abnormal returns are transformed so that the mean of event and non-event abnormal returns are equal, but the variance is kept intact.

This is done separately for the event date $AAR$ and the two different $CAAR$ tested. For the polluting industries, we estimate the probability of obtaining a t-value larger than or equal to the observed t-value. For the environmentally protective companies, we estimate the probability of obtaining a t-value smaller than or equal to the observed t-value. The bootstraps are performed with replacement for 5,000 repetitions. The number of observations drawn are based on the original sample sizes.

### *Event Date Abnormal Returns when Controlling for Size and Book-to-Market*

We also check the results obtained from a linear regression model estimated using OLS with $AR_{i,t}$ as the dependent variable. Only observations during 2012-2014 are included as data is missing for book equity during 2015. This allows us to control for size and book-to market as they have not been previously controlled for when estimating the expected return. Fama and French (1992) find these variables to capture some of the cross-sectional variation in stock returns.

We estimate the following equation:

$$\begin{aligned} AR_{i,t} = \alpha_0 + \beta_1 Size_{i,t} + \beta_2 BM_{i,t} + \sum_{j=3}^{7} \beta_j Industry\ dummies_{i,t} + \beta_8 Event\ date_{i,t} \\ + \sum_{j=9}^{13} \beta_j Industry\ dummies_{i,t} \cdot Event\ date_{i,t} + \sum_{j=14}^{24} \beta_j Month\ dummies_{i,t} \\ + \sum_{j=25}^{26} \beta_j Year\ dummies_{i,t} + \varepsilon_{i,t} \end{aligned}$$

Where $\alpha_0$ is the intercept, $\varepsilon_{i,t}$ is the error term, $Size_{i,t}$ is the natural logarithm of market value of equity, $BM_{i,t}$ is the book-to-market ratio, $Event\ date_{i,t}$ is an event date dummy, $Month\ dummies_{i,t}$ indicates dummies for months January to November, $Year\ dummies_{i,t}$ indicates dummies for years 2012 and 2013, and $Industry\ dummies_{i,t}$ indicates dummies for our industries of interest, namely $Coal_{i,t}$, $Steel_{i,t}$, $Non\text{-}ferrous_{i,t}$ $Oil_{i,t}$, and $Env.prot._{i,t}$. A detailed table of variable definitions can be found in Table A1 in Appendix A.

This regression is also repeated with some variables winsorized at the 5% and 95% level to make sure that the results are not driven by outliers. $Size_{i,t}$ and $BM_{i,t}$ are winsorized by year and $AR_{i,t}$ is winsorized by year and industry group.

We expect the polluting industries to have lower abnormal returns compared to the rest of the market at event dates and therefore their $Industry\ dummy_{i,t} * Event\ date_{i,t}$ variables to have negative coefficients. We expect the opposite to be true for environmentally protective companies.

We investigate the underlying assumptions of no multicollinearity, normality of residuals, and a linear relationship between the dependent and each of the independent variables, while we let the robust regression option in STATA take care of any autocorrelation and heteroscedasticity. The variance inflation factor (VIF) is used to detect possible multicollinearity. According to Wooldridge (2009), setting a cutoff value for VIF above which we suspect multicollinearity is somewhat arbitrary. However, a VIF value of 10 is often used as a cutoff point to indicate multicollinearity even if the measure is of limited use.

Note that this regression, and the CSR regression mentioned below, will have the significance of the regression coefficients overstated due to event date clustering. It would however not be possible to run these regressions with portfolio abnormal returns as the dependent variable since this would not allow us to control for firm-specific factors.

## The Irrational Market Reaction

To test the hypothesis that

$H_3$: *Market index returns are lower during events*

we use three different tests, each done separately for the Shenzhen and Shanghai indices.

The first test is a one-tailed Welch's t-test of whether the mean of event market returns is equal to the mean of non-event market returns. We expect event market returns to be somewhat lower than non-event market returns.

The second test is a one-tailed Wilcoxon rank-sum test of whether event market returns are drawn from the same distribution as non-event market returns. We expect event market returns to be drawn from a different distribution, resulting in a lower than expected rank.

The third test is a bootstrap test of the equality of means. This computes the probability of obtaining a t-value larger than or equal to the one observed in the first test given that the null hypothesis of $\mu_x = \mu_y$ is true. Market index returns are transformed so that the mean of event and non-event returns are equal, but the variance is kept intact. The bootstraps are performed with replacement for 5,000 repetitions. The number of observations drawn are based on the original sample sizes.

To test our hypothesis that

$H_4$: *Firms located in a province experiencing smog have lower abnormal returns than other firms during events*

we provide two tests.

T-tests are based on province portfolios constructed in a similar manner to our industry portfolios. One value-weighted portfolio is created where all companies located in a province experiencing smog are included (the "smog province portfolio") and one portfolio is created where all other companies are included (the "non-smog province portfolio"). These portfolios are only created during events. When using Wilcoxon rank-sum test we instead base the test on individual stocks, but the grouping is done in the same way.

The first test is a one-tailed Welch's t-test of whether the smog province portfolio's average abnormal returns are equal to the non-smog province portfolio's average abnormal returns. We expect the smog province portfolio to have lower average abnormal returns than the non-smog province portfolio.

The second test is a one-tailed Wilcoxon rank-sum test of whether the firms located in a province experiencing smog have their individual stock abnormal returns drawn from the same distribution as firms located in other provinces. We expect firms located in a province experiencing smog to have their abnormal returns drawn from a different distribution than other firms, resulting in a lower than expected rank.

However, this hypothesis and the two tests just described do not account for the possibility that there is a difference in the level of abnormal returns between provinces (e.g. due to certain industries being concentrated to certain provinces). We therefore also test a fifth hypothesis that

$H_5$: *Firms located in a province experiencing smog have lower returns and abnormal returns than they have outside events* using two different tests. Each test is done province by province. When testing this hypothesis, only smog in the province tested is considered an event. Non-events on the other hand are based on dates where there is no province at all experiencing smog. Note that when testing this hypothesis we test both returns and abnormal returns since if there is an overall market effect the test results based on abnormal returns might not detect any differences between events and non-events.

The first test is a one-tailed Welch's t-test of whether the mean of value-weighted returns and abnormal returns of firms located in a certain province are equal between events and non-events. We expect the mean event returns and abnormal returns to be lower than the non-event means.

The second test is a one-tailed Wilcoxon rank-sum test of whether the individual stock returns and abnormal returns of firms located in a certain province are drawn from the same distribution during events and non-events. We expect event returns and abnormal returns to be drawn from a different distribution than non-event returns and abnormal returns, resulting in a lower than expected rank.

## Can CSR Reporting Affect Event Date Abnormal Returns?

To test our sixth hypothesis that

$H_6$: *Firms in the polluting industries that issue CSR reports show more positive abnormal returns than their industry peers at event dates*

we use OLS to estimate the linear regression model

$$AR_{i,t} = \alpha_0 + \beta_1 Size_{i,t} + \beta_2 BM_{i,t} + \sum_{j=3}^{7} \beta_j Industry\ dummies_{i,t} + \beta_8 Event\ date_{i,t} + \sum_{j=9}^{13} \beta_j Industry\ dummies_{i,t} \cdot Event\ date_{i,t} + \beta_{14} CSR_{i,t} + \beta_{15} CSR_{i,t} \cdot Event\ date_{i,t} + \sum_{j=17}^{21} \beta_j Industry\ dummies_{i,t} \cdot CSR_{i,t} + \sum_{j=22}^{26} \beta_j Industry\ dummies_{i,t} \cdot CSR_{i,t} \cdot Event\ date_{i,t} + \sum_{j=14}^{24} \beta_j Month\ dummies_{i,t} + \sum_{j=25}^{26} \beta_j Year\ dummies_{i,t} + \varepsilon_{i,t}$$

Where $CSR_{i,t}$ is a CSR reporting dummy. A detailed table of variable definitions can be found in Table A1 in Appendix A. This allows us to separate the effect of CSR reporting on event dates from the effect during other dates. We expect CSR reporting to have a mediating effect for companies in the polluting industries, whereas the effect for the environmentally protective companies is uncertain.

Only observations during 2012 to 2014 are included in the regression as book equity and CSR reporting data is missing for 2015. This regression is also repeated with some variables winsorized at the 5% and 95% level to make sure that the results are not driven by outliers. $Size_{i,t}$ and $BM_{i,t}$ are winsorized by year and $AR_{i,t}$ is winsorized by year and industry group.

# STOCK MARKET REACTION TO SMOG

## Data

We use Thomson Reuters Datastream to collect daily stock prices as well as quarterly total number of shares, quarterly book equity and industry group classification for all firms listed on the Shenzhen and Shanghai Stock Exchanges. Daily prices for the Shenzhen Stock Exchange A Share Index and the Shanghai Stock Exchange A Share Index are also obtained. This data is collected for the period between 2012 and 2015 and is then combined with CSR reporting data from CSMAR, company location data and a list of what firms are considered environmentally protective.

Hourly levels of PM 2.5 for five of the major cities in China (Beijing, Chengdu, Guangzhou, Shanghai, and Shenyang) are collected from the US Embassy in China. Using this data, 23 event dates are identified during the period between 2012 and 2015. However, there is one event where no price changes occur for any firm or index, this event is excluded. Thus, our analysis consists of 22 events.

Some shares have had their trading permanently suspended but are still included after that point in the data obtained from Datastream. All observations for these firms are dropped after the date of suspension. There are no missing values for price, but the stock prices of some firms sometimes do not change for several weeks or even months. We believe that these observations are really missing values and therefore exclude some observations from our analysis where the stock price has not changed for over five trading days.

In total, our sample consists of 2,801 firms and 2,629,345 observations. The number of observations per industry and event, as well as the total number of firms in each industry and how many of those that issue CSR reporting, can be found in Table 1. The total number of firms located in each province can be found in Table 2. The number of events per major city can be found in Table B2 in Appendix B.

**TABLE 1**

**Firms per industry and event**

This table presents the number of firms per industry and event, as well as the total number of different firms in each industry. "N-f metals" is short for non-ferrous metals.

| **Event date** | **Coal** | **Steel** | **N-f metals** | **Oil** | **Env. Prot.** |
|---|---|---|---|---|---|
| 2012-01-10 | 25 | 33 | 56 | 7 | 34 |
| 2012-02-20 | 25 | 33 | 57 | 7 | 32 |
| 2013-01-14 | 26 | 33 | 61 | 8 | 37 |
| 2013-01-28 | 25 | 33 | 61 | 8 | 37 |
| 2013-02-11 | 25 | 33 | 60 | 8 | 37 |
| 2013-02-25 | 25 | 33 | 63 | 8 | 36 |
| 2013-03-18 | 21 | 32 | 58 | 8 | 35 |
| 2013-12-06 | 26 | 31 | 62 | 7 | 35 |
| 2013-12-23 | 26 | 30 | 61 | 7 | 33 |
| 2014-01-15 | 25 | 31 | 62 | 7 | 33 |
| 2014-01-31 | 26 | 31 | 58 | 7 | 33 |
| 2014-02-14 | 26 | 31 | 61 | 7 | 33 |
| 2014-02-25 | 25 | 30 | 61 | 7 | 32 |

| | | | | | |
|---|---|---|---|---|---|
| 2014-04-09 | 27 | 30 | 59 | 7 | 30 |
| 2014-06-11 | 27 | 32 | 56 | 8 | 36 |
| 2014-06-23 | 27 | Excluded | 56 | 8 | 35 |
| 2014-10-31 | Excluded | 24 | 38 | 8 | 29 |
| 2014-11-26 | 28 | 32 | 59 | 8 | 31 |
| 2015-01-15 | 27 | Excluded | 54 | 6 | 31 |
| 2015-04-15 | 27 | 30 | 57 | 8 | 32 |
| 2015-11-09 | 27 | 30 | 52 | 9 | 29 |
| 2015-11-30 | 28 | 33 | 50 | 9 | 34 |
| Total number of firms | 28 | 33 | 67 | 9 | 38 |
| Of which issue CSR reports | 14 | 13 | 33 | 3 | 8 |

**TABLE 2**

**Firms per province**

This table presents the number of firms located in the same provinces as the cities we have collected PM 2.5 data for.

| **Province (major city)** | **Number of firms** |
|---|---|
| Hebei (Beijing) | 311 |
| Sichuan (Chengdu) | 90 |
| Guangdong (Guangzhou) | 383 |
| Jiangsu (Shanghai) | 471 |
| Liaoning (Shenyang) | 70 |
| Other | 1,476 |
| Total number of firms | 2,801 |

## Tests of the Rational Market Reaction

### *Does Smog Lead to Negative Abnormal Returns for Firms in Polluting Industries and Positive Abnormal Returns for Environmentally Protective Companies?*

Day-by-day descriptive statistics including the individual stocks for each industry can be found in Table B3 in Appendix B. Table 3 presents the results from one-tailed Student's t-tests of whether event abnormal returns are equal to zero for each industry portfolio. Our hypotheses suggest that firms in polluting industries have negative abnormal returns during events, while environmentally protective companies have positive abnormal returns. Our two expected return models, the market adjusted model (MAM) and the market model (MM), generally seem to produce abnormal returns that are quite similar. However, for the oil industry there is a noticeable difference.

The event date AAR for the coal and steel producers are significantly negative, at the 10% level for coal producers and at the 1% level for steel producers. Non-ferrous metal producers show negative event date AAR, although this is outside the significance threshold. Environmentally protective companies show a positive event date AAR that is significant at the 5% level. Contrary to our expectations, the oil industry has a positive event date AAR.

**TABLE 3**

**T-tests of whether the average abnormal returns are equal to zero**

This table presents the results from one-tailed t-tests of whether the average abnormal returns of our value-weighted industry portfolios are equal to zero. All abnormal returns are expressed in percentage terms. Both the abnormal returns obtained from the market adjusted model (MAM) and the market model (MM) are tested, but only the test results for the MAM abnormal returns are presented. For the polluting industries, the probability of abnormal returns being negative are tested. For the environmentally protective companies, the probability of abnormal returns being positive are tested. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

| | **Coal** | | **Steel** | | **N-f metals** | | **Oil** | | **Env. protective** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Portfolio* | | *Portfolio* | | *Portfolio* | | *Portfolio* | | *Portfolio* | |
| | ***N*** | **MAM** | ***N*** | **MAM** | ***N*** | **MAM** | ***N*** | **MAM** | ***N*** | **MAM** |
| Event date AAR | 21 | -0.1909* | 20 | -0.4030*** | 22 | -0.1895 | 22 | 0.1927 | 22 | 0.5498* |
| CAAR [-1. 1] | 21 | -0.2832 | 20 | -0.4835** | 22 | 0.2678 | 22 | -0.1804 | 22 | 1.0731*** |
| CAAR [-2. 2] | 21 | -0.9314** | 20 | -0.0296 | 22 | 0.0679 | 22 | -0.1083 | 22 | 0.5219 |

CAAR [-2, 2] is significantly negative for coal producers at the 5% level. CAAR [-1, 1] is significantly negative for steel producers at the 5% level. Also, CAAR [-1, 1] is significantly positive for environmentally protective companies at the 1% level. No support is found for our hypothesis that the oil industry is punished.

Overall, event abnormal returns seem to point in the predicted direction. But as we do not know how event abnormal returns compare to non-event abnormal returns for each industry we can’t tell the market reaction simply based on these tests.

### *Does Smog Have an Impact on the Size of Abnormal Returns for Firms in Polluting Industries and Environmentally Protective Companies?*

Table 4 presents the results from one-tailed Welch’s t-tests of whether event abnormal returns are equal to non-event abnormal returns for each industry portfolio. Our hypotheses suggest that firms in polluting industries have more negative abnormal returns during events than during non-events, while environmentally protective companies have more positive abnormal returns during events than during non-events. Results from Wilcoxon rank-sum tests, which are based on individual stock abnormal returns of the firms in each industry, are also presented. Our hypotheses suggest that firms in polluting industries have their event abnormal returns drawn from another distribution than their non-event abnormal returns, resulting in a lower than expected rank. The opposite is expected for environmentally protective companies, resulting in a higher than expected rank during events. Bootstrapped probabilities of equality of means in Table 5 show the achieved significance level of the t-tests in Table 4.

Coal producers have lower average abnormal returns during events than they do during non-events. However, t-tests do not find any significance. Meanwhile, rank-sum tests show significance at the 1% level for all test specifications. Bootstrapped probabilities of equality of means in Table 5 show that the event date AAR and CAAR [-2, 2] are significant at the 10% level, based on the probability of obtaining a t-value more extreme than the one observed given that the mean is equal between events and non-events. When testing the MM, significance is found in close to all test for coal producers. These results support our first hypothesis and suggest that coal producers are punished by the stock market during events. The event date average abnormal return of the individual stocks, as seen in Table B3 in Appendix B, is 0.22 (0.39) percentage points lower than the average abnormal return outside events when using the

MAM (MM). Individual stock CAAR [-2, 2] is 0.84 (1.14) percentage points lower than the average 5-day CAR outside event windows.

All three tests show similar results for steel producers. CAR [-2, 2] is not found to be significantly different from non-event 5-day CAR using any test or expected return model. Significance is found at the 1% level in all three tests when testing the equality of event date AR and non-event AR. CAR [-1, 1] is significant at the 1% to the 5% level in our different tests. Similar results are found when testing the abnormal returns obtained from the MM. These results are consistent with our first hypothesis that steel producers are punished during events. Based on the abnormal returns of individual stocks obtained from the MAM (MM) found in Table B3 in Appendix B, the average abnormal return at event dates is 0.26 (0.27) percentage points lower than the average during non-events and CAAR [-1, 1] is 0.30 (0.34) percentage points lower than the average non-event 3-day CAR.

The event abnormal returns of non-ferrous metal producers are not found to be significantly different from non-event abnormal returns. However, when testing the abnormal returns obtained from the MM all three tests find significance at the event date. Thus, it seems as if non-ferrous metal producers might be punished by the stock market at event dates, but over the span of the whole event window this effect is neutralized or diluted so that the cumulative abnormal returns are not significantly different from non-event cumulative abnormal returns. Based on these results, we do find some support of our first hypothesis that non-ferrous metal producers are punished by the stock market during events. However, this effect seems to be concentrated to the event date where the average event date abnormal return obtained by the MAM (MM), as seen in Table B3 in Appendix B, is 0.16 (0.30) percentage points lower than the average non-event abnormal return for individual stocks.

The oil industry does not follow the predicted pattern and exhibits a higher AAR at event dates than during non-events. In fact, event date AR and CAR [-2, 2] are far from significant in any test, no matter the expected return model used. Consequently, we fail to find any support for our first hypothesis that event abnormal returns are lower than non-event abnormal returns for the oil industry. We believe that these results are due to two state-owned companies, CNPC (constituting 70-81.5% of the total market equity of the oil industry) and Sinopec (constituting 17.6-28% of the total market equity of the oil industry), dominating the industry. State-owned companies tend to have higher bargaining powers when it comes to levy charges (Dasgupta et al., 2003) and have been accused of having a strong influence over environmental policymaking

**TABLE 4**
**Tests of whether event abnormal returns are different from non-event abnormal returns**

This table presents the test results of both one-tailed Welch's t-tests and Wilcoxon rank-sum tests. Abnormal returns obtained from the market adjusted model (MAM) as well as the market model (MM) are tested, but only the test results for the MAM abnormal returns are presented. T-tests are based on value-weighted industry portfolio average abnormal returns, while rank-sum tests are based on individual stock abnormal returns. Panel A shows the test results for event day abnormal returns, Panel B shows the test results for cumulative abnormal returns over event days [-1, 1], and Panel C shows the test results for cumulative abnormal returns over event days [-2, 2]. P-values are based on our hypotheses that non-event abnormal returns are higher than event abnormal returns for the polluting industries and that non-event abnormal returns are lower than event abnormal returns for the environmentally protective companies.

| | | **Coal** | **Steel** | **N-f metals** | **Oil** | **Env. protective** |
|---|---|---|---|---|---|---|
| | | | Panel A: Event date AR | | | |
| T-test | T-statistic | 0.86 | 2.65 | 0.96 | -0.90 | -1.42 |
| | P-value | 0.200 | **0.008** | 0.173 | 0.811 | **0.085** |
| Rank-sum | Z-statistic | 3.72 | 3.86 | 3.42 | -0.63 | -2.87 |
| | P-value | **0.000** | **0.000** | **0.000** | 0.736 | **0.002** |
| | | | Panel B: CAR [-1. 1] | | | |
| T-test | T-statistic | 0.19 | 1.86 | -0.78 | 0.08 | -2.30 |
| | P-value | 0.427 | **0.038** | 0.778 | 0.469 | **0.016** |
| Rank-sum | Z-statistic | 2.97 | 3.60 | -2.22 | 0.50 | -4.66 |
| | P-value | **0.002** | **0.000** | 0.987 | 0.310 | **0.000** |

**TABLE 4 CONTINUED**

| | | **Coal** | **Steel** | **N-f metals** | **Oil** | **Env. protective** |
|---|---|---|---|---|---|---|
| Panel C: CAR [-2. 2] | | | | | | |
| T-test | T-statistic | 1.22 | 0.23 | -0.26 | -0.40 | -0.49 |
| | P-value | 0.118 | 0.410 | 0.601 | 0.653 | 0.314 |
| Rank-sum | Z-statistic | 6.27 | 0.21 | -0.11 | 0.64 | -1.22 |
| | P-value | **0.000** | 0.415 | 0.542 | 0.262 | 0.112 |

**TABLE 5**
**Bootstrap test of equality of means**

This table presents the bootstrapped probabilities to obtain a t-value more extreme than the ones observed in Table 4 given that the null hypothesis of $\mu_{non-event} = \mu_{event}$ is true. 5,000 bootstrap replications with replacement are performed for each industry portfolio. Data is transformed so that for each industry the mean abnormal return is equal between the two groups being tested, but the original variance in each group is kept. For the polluting industries, $P_{bstrap}$ the probability of bootstrapped t-values to be equal to or larger than the observed t-value in Table 4, $T_{obs}$, is calculated. For environmentally protective companies, the probability of bootstrapped t-values to be equal to or smaller than the observed t-value is calculated. Panel A shows the test results for event date AAR, Panel B shows the test results for CAAR [-1, 1] and Panel C shows the test results for CAAR [-2, 2].

| | **Coal** | **Steel** | **N-f metals** | **Oil** | **Env. protective** |
|---|---|---|---|---|---|
| Panel A: Event date AAR | | | | | |
| $T_{obs}$ | 0.86 | 2.65 | 0.96 | -0.90 | -1.42 |
| $P_{bstrap}$ | **0.069** | **0.002** | 0.141 | 0.835 | 0.166 |
| Panel B: CAAR [-1. 1] | | | | | |
| $T_{obs}$ | 0.19 | 1.86 | -0.78 | 0.08 | -2.30 |
| $P_{bstrap}$ | 0.463 | **0.005** | 0.757 | 0.447 | **0.016** |
| Panel C: CAAR [-2. 2] | | | | | |
| $T_{obs}$ | 1.22 | 0.23 | -0.26 | -0.40 | -0.49 |
| $P_{bstrap}$ | **0.083** | 0.416 | 0.611 | 0.734 | 0.308 |

in China (Spegele and Wong, 2015).

For environmentally protective companies, CAR [-2, 2] is not found to be significantly different from non-event 5-day CAR in any of our three tests. The reason for this is the negative abnormal returns observed on the last day of the event window (see Panel A in Table B3 in Appendix B), which erase a large part of the positive abnormal returns accumulated during the rest of the event window. The event date AAR is about 10 (18) times as large as the non-event AAR when using the MAM (MM). The event date AAR is found to be significantly different from non-event AAR at the 10% level when using a t-test. However, the bootstrap test of equality of means does not find any significance when testing the event date AAR. On the other hand, the rank-sum test finds that the distribution of event date AR is significantly different from the distribution of non-event AR at the 1% level. The results are less dispersed when looking at CAR [-1, 1]. The t-test and bootstrap test show significance at the 5% level, while the rank-sum test finds the distribution of CAR [-1, 1] significantly different from the distribution of non-event 3-day CAR at the 1% level. Similar results are obtained when using the abnormal returns from the MM. These results are consistent with our second hypothesis and suggest that environmentally protective companies are rewarded by the stock market at the day of the smog as well as the day before and the day after smog.

In unreported tests, we also check if rank-sum test results of individual stocks are affected by using non-overlapping 3-day CAR and 5-day CAR during non-events (i.e. the 3-day CAR and 5-day CAR are only calculated every third and fifth trading day respectively, instead of being calculated every trading day as in our reported test results). The only difference found is that CAR [-2, 2] becomes significantly higher than non-event 5-day CAR at the 10% level for environmentally protective companies when using the MAM.

### *Controlling Event Date Abnormal Returns for Size and Book-to-Market*

To control for size and book-to-market, we use OLS to estimate a linear regression model with the individual stock abnormal returns based on the MAM, $AR_{i,t}$, as the dependent variable. Note that the significance of the coefficients of all variables involving the $Event\ date_{i,t}$ variable could be overstated due to event date clustering. However, this has no effect on the coefficient estimates. Also, the residuals are not normally distributed which has an effect on hypothesis testing. The results of this regression are shown in Table 6. The results are robust to other test specifications and also to winsorization of some variables (see Table C1 in Appendix C, only the event date coefficient for the oil industry loses significance while the coefficients of the other polluting industries at event dates become more significant).

Opposite to our expectations, $Size_{i,t}$ is found to have a positive relationship with $AR_{i,t}$ and $BM_{i,t}$ is found to have a negative relationship with $AR_{i,t}$. The coefficients of the industry dummies by themselves are not of interest in our analysis, they are only there to separate the "everyday effect" from the event date effect. The event date effect for the average firm is found to be positive and significantly different from zero at the 1% level. However, no interpretation of this can be done in relation to our irrational market reaction tests as abnormal returns can only be used to detect an irrational market reaction when compared to other abnormal returns, either to those of firms not experiencing smog or to the firms themselves but during dates when there is no smog (assuming that firms close to the smog are more affected than the rest of the market).

Our $Industry\ dummy_{i,t} \cdot Event\ date_{i,t}$ coefficients all display the predicted sign; negative coefficients for the polluting industries and a positive coefficient for environmentally protective companies. The event date coefficients for the environmentally protective companies and the steel industry are significant at the 1% level. For non-ferrous metal producers, the event date coefficient is significant at the 5% level. Meanwhile, the event date coefficients of coal producers and the oil industry are significant at the 10% level. The marginally significant negative event date coefficient for the oil industry is surprising considering our previous test results. Since the $Size_{i,t}$ coefficient is positive and two of the largest companies in China are oil companies it could be that the reverse size effect is what results in positive event date abnormal returns when not controlling for size. However, this is still inconsistent with the results obtained when comparing event abnormal returns to non-event abnormal returns. Also, removing $Size_{i,t}$ and $BM_{i,t}$ from the regression does not change the significance. In an unreported regression we therefore also include observations from 2015. The negative event date coefficient found for the oil industry becomes positive and is not found to be significantly different from zero (p-value = 0.574). Thus, it seems as if the oil industry might have been punished by the stock market up until 2014, but after that the relationship has changed. Other than for the oil industry, these results confirm the findings from previous tests.

**TABLE 6**

**Linear regression including control variables with $AR_{i,t}$ as the dependent variable**

This table presents the results from a linear regression model estimated using OLS with individual stock abnormal returns as the dependent variable. For a closer description of the variables included, see Table A1 in Appendix A. This regression allows us to control for size and book-to-market. The coefficients are based on abnormal return expressed in percentage terms. The presented p-values are based on the predicted sign. Month and year dummies are included in the regression but are not presented.

| Variable | Predicted sign | Coefficient | T-statistic | P-value |
|---|---|---|---|---|
| $\alpha_0$ | +/- | **-0.2341** | -10.91 | 0.000 |
| $Size_{i,t}$ | - | 0.0063 | 4.71 | 1.000 |
| $BM_{i,t}$ | + | -0.0196 | -12.96 | 1.000 |
| $Coal_{i,t}$ | +/- | **-0.1142** | -8.81 | 0.000 |
| $Steel_{i,t}$ | +/- | -0.0189 | -1.58 | 0.114 |
| $Non\text{-}ferrous_{i,t}$ | +/- | **-0.0286** | -3.05 | 0.002 |
| $Oil_{i,t}$ | +/- | 0.0003 | 0.01 | 0.991 |
| $Env.prot._{i,t}$ | +/- | 0.0166 | 1.25 | 0.212 |
| $Event\ date_{i,t}$ | +/- | **0.0473** | 4.45 | 0.000 |
| $Coal_{i,t} \cdot Event\ date_{i,t}$ | - | **-0.1299** | -1.56 | 0.059 |
| $Steel_{i,t} \cdot Event\ date_{i,t}$ | - | **-0.2650** | -4.07 | 0.000 |
| $Non\text{-}ferrous_{i,t} \cdot Event\ date_{i,t}$ | - | **-0.1208** | -2.02 | 0.022 |
| $Oil_{i,t} \cdot Event\ date_{i,t}$ | - | **-0.2494** | -1.53 | 0.064 |
| $Env.prot._{i,t} \cdot Event\ date_{i,t}$ | + | **0.3970** | 3.70 | 0.000 |

$Adj.R^2 = 0.0013$

Observations = 1,910,255

## Tests of the Irrational Market Reaction

### *Overall Market Reaction*

Table 7 presents descriptive statistics for market index returns during events and non-events. The mean return of the Shenzhen index is about 5.5 times higher at event dates than during non-events and 2.7 times higher during the average event window day. For the Shanghai index, the mean event date return is about 16 times higher at event dates than during non-events and about 6.6 times as high during the average event window day.

**TABLE 7**
**Descriptive statistics of market index returns**

This table presents the number of observations and the observed mean market index returns during event dates, event windows and non-events. The mean returns are expressed in percentage terms.

| | Event dates | | Event windows | | Non-events | |
|---|---|---|---|---|---|---|
| **Index** | ***N*** | **Mean return** | ***N*** | **Mean return** | ***N*** | **Mean return** |
| Shenzhen | 22 | 0.5128 | 110 | 0.2513 | 932 | 0.0922 |
| Shanghai | 22 | 0.5814 | 110 | 0.2355 | 932 | 0.0359 |

Table 8 presents the results from t-tests, rank-sum tests and bootstrapped test statistics. None of the tests for the Shenzhen index find that event returns are significantly lower than non-event returns (p-values range between 0.841 and 0.932). Tests of the Shanghai index returns show similar results, with p-values ranging between 0.906 and 0.988. Some of the difference is likely due to market returns, on average, being higher during winter months than summer months and events occurring mostly during winter. When dropping all observations during January most of the difference between event and non-event market returns is eliminated. However, unreported tests still do not find event returns to be significantly lower than non-event returns. As we fail to reject the null hypotheses that event date and event window returns are equal to non-event returns we do not find support for our third hypothesis that market returns are lower during events.

**TABLE 8**
**Tests of market index returns**

This table presents the test results of one-tailed Welch's t-tests, Wilcoxon rank-sum tests and bootstrapped tests of equality of means. 5,000 bootstrap replications with replacement are performed for each market index. Data is transformed so that for each index the mean return is equal between the two groups being tested, but the original variance in each group is kept. The probability of obtaining a t-value larger than or equal to the observed t-value is estimated. Panel A shows the results of tests that event window returns are equal to non-event returns. Panel B shows the results of tests that event date returns are equal to non-event returns. P-values are based on our hypothesis that event returns are lower than non-event returns.

| | | **Shenzhen** | **Shanghai** |
|---|---|---|---|
| Panel A: Event window index returns | | | |
| T-test | T-value | -1.05 | -1.32 |
| | P-value | 0.853 | 0.906 |
| | $P_{bstrap}$ | 0.892 | 0.913 |
| Rank-sum | Z-value | -1.00 | -2.24 |
| | P-value | 0.841 | 0.988 |
| Panel B: Event date index returns | | | |
| T-test | T-value | -1.06 | -1.75 |
| | P-value | 0.849 | 0.953 |
| | $P_{bstrap}$ | 0.853 | 0.964 |
| Rank-sum | Z-value | -1.49 | -1.71 |
| | P-value | 0.932 | 0.956 |

### *Do Firms Located in a Province Experiencing Smog Have Lower Returns than Other Firms at the Same Time?*

Table 9 presents descriptive statistics for the comparison of firms located in the province(s) experiencing smog to those firms that are located in other provinces during events. Panel B shows that the mean event date abnormal returns based on both the MAM and the MM are somewhat higher for the smog province portfolio than for non-smog province portfolio. The mean event date abnormal returns of individual stocks are also slightly higher for the firms in the smog province portfolio. No matter if looking at the portfolios or the individual stocks in Panel A and no matter the expected return model used, the mean event window abnormal return is higher for the firms in the smog province portfolio than for the firms in the non-smog province portfolio.

**TABLE 9**

**Descriptive statistics of firms located in the province(s) experiencing smog and firms located in other provinces**

This table presents the number of observations (*N*), mean returns and abnormal returns during event windows and event dates for firms in the smog province portfolio and firms in the non-smog province portfolio. Abnormal returns obtained from the market adjusted model (MAM) as well as the market model (MM) are presented. These statistics are shown for two groups; value-weighted province portfolios and individual stocks. All returns are expressed in percentage terms. Panel A presents event window returns and Panel B presents event date returns.

| | **Smog portfolio** | | | | **Non-smog portfolio** | | | |
|---|---|---|---|---|---|---|---|---|
| | ***N*** | **MAM** | **MM** | **Return** | ***N*** | **MAM** | **MM** | **Return** |
| Panel A: Event windows | | | | | | | | |
| Portfolio | 110 | 0.1137 | 0.1230 | 0.3616 | 110 | 0.0232 | -0.0124 | 0.2553 |
| Individual stocks | 27,619 | 0.1116 | 0.0068 | 0.3328 | 229,766 | 0.0720 | -0.0289 | 0.3145 |
| Panel B: Event dates | | | | | | | | |
| Portfolio | 22 | 0.0607 | 0.1255 | 0.6378 | 22 | 0.0189 | -0.0481 | 0.5612 |
| Individual stocks | 5,524 | 0.0008 | -0.1290 | 0.4535 | 45,956 | -0.0071 | -0.1356 | 0.5406 |

Table 10 presents the test results of t-tests and rank-sum tests. Neither t-tests nor rank-sum tests find that the abnormal returns of firms in the smog province portfolio are lower than the abnormal returns of firms in the non-smog province portfolio, neither at event dates nor during event windows. Event date p-values range between 0.617 and 0.989 and event window p-values range between 0.960 and 1.000. Similar results are obtained when testing the MM abnormal returns. We fail to reject the null hypotheses that the event date and event window abnormal returns of firms in the smog province portfolio are equal to the abnormal returns of firms in the non-smog province portfolio. Consequently, no support is found for our fourth hypothesis that firms located in a province experiencing smog have lower abnormal returns than other firms. Instead, these results suggest that there is no mood effect. There is however a possibility that there is normally a difference in the level of abnormal returns between provinces. If there is, the tests just discussed would not allow us to draw any inferences about the existence of mood effects.

**TABLE 10**

**Tests of whether abnormal returns in the province experiencing smog are different from abnormal returns in other provinces at the same time**

This table presents the test results of both one-tailed Welch's t-tests and Wilcoxon rank-sum tests. Abnormal returns obtained from the market adjusted model (MAM) as well as the market model (MM) are tested, but only the test results for the MAM abnormal returns are presented. T-tests are based on the average abnormal returns of value-weighted portfolios, while rank-sum tests are based on individual stock abnormal returns. Two value-weighted portfolios are created; one containing the firms located in the province(s) experiencing smog and one containing firms located in other provinces. P-values are based on our hypothesis that the returns and abnormal returns of firms located in the province(s) experiencing smog are lower than the returns and abnormal returns of firms located in other provinces.

| | | Event window | Event date |
|---|---|---|---|
| T-test | T-value | -1.75 | -0.30 |
| | P-value | 0.960 | 0.617 |
| Rank-sum | Z-value | -5.75 | -2.31 |
| | P-value | 1.000 | 0.989 |

### *Do Firms Located in a Province Experiencing Smog Have Lower Returns than They Have Outside Events?*

Table 11 presents the results from province-by-province t-tests testing the equality of means between event portfolios and non-event portfolios for each province. As can be seen, Chengdu and Guangzhou only experience one event each, which prevents t-tests from being used to test event date returns. Shanghai and Shenyang only experience three and five events respectively. This will make it hard to draw any generalized conclusions based on our results as there might be other effects in play during those few days. In all tests, results are similar no matter the expected return model used.

Portfolio t-tests do not find the returns and abnormal returns of firms located around Beijing to be lower during events than during non-events. The rank-sum test finds that event date abnormal returns are significantly lower than non-event abnormal returns at the 5% level. At event dates the mean individual stock abnormal return is 0.07 percentage points lower than during non-events. Still, consistent with our results when testing market index returns, the null hypothesis that event stock returns are lower than non-event stock returns for the same firms cannot be rejected based on the results for Beijing. For firms located around Beijing the mean stock return is 0.48 percentage points higher at event dates. During the event window, the rank-sum test of the firms located around Beijing finds that abnormal returns are significantly lower at the 10% level. However, the mean is only about 0.003 percentage points lower during event windows.

For firms located around Shanghai, the rank-sum test does not find event date abnormal returns to be significantly lower than non-event abnormal returns. The t-test of the event date AAR finds significance at the 10% significance level. The mean event date abnormal return is 0.22 percentage points lower than the mean non-event abnormal return. The rank-sum test of event date stock returns finds that they are significantly lower at the 1% level, with the mean event date stock return being 0.19 percentage points lower than the mean non-event stock return. None of the event window tests find any support for rejecting the null hypotheses of event window returns and abnormal returns being equal to non-event returns and abnormal returns. Actually, during the average event window day firms located around Shanghai have abnormal returns that are 0.16 percentage points higher than during the average non-event day. The difference in average stock returns is as high as 0.43 percentage points.

**TABLE 11**

**Province-by-province t-tests of whether event returns are different from non-event returns**

This table presents the results of Welch's t-tests performed province-by-province, testing whether the mean value-weighted returns of firms located in a certain province are equal between periods when the province is experiencing smog and periods when none of the five major cities are experiencing smog. Tests are based on value-weighted portfolios, one is created each day for each province. Abnormal returns obtained from the market adjusted model (MAM) and the market model (MM) are tested, as well as stock returns. The test results for the MM abnormal returns are not presented. All returns are expressed in percentage terms. The p-values presented are based on our hypothesis that event returns are lower than non-event returns. For Chengdu and Guangzhou there is only one event date observation, thus t-tests can't be used.

| | **Non-event** | | **Event date** | | | | **Event window** | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Major city** | ***N*** | **Mean** | ***N*** | **Mean** | **T-value** | **P-value** | ***N*** | **Mean** | **T-value** | **P-value** |
| Beijing - MAM | 933 | 0.0069 | 14 | 0.1317 | -0.66 | 0.739 | 70 | 0.0842 | -1.23 | 0.888 |
| Beijing - Return | 933 | 0.0526 | 14 | 0.8136 | -1.68 | 0.942 | 70 | 0.2942 | -1.09 | 0.860 |
| Shanghai - MAM | 934 | 0.0730 | 3 | -0.1485 | 1.99 | **0.089** | 15 | 0.2136 | -1.42 | 0.911 |
| Shanghai - Return | 934 | 0.1333 | 3 | -0.0634 | 0.52 | 0.327 | 15 | 0.4310 | -1.32 | 0.898 |
| Shenyang - MAM | 934 | 0.0445 | 5 | -0.0932 | 1.33 | 0.124 | 25 | 0.0958 | -0.51 | 0.694 |
| Shenyang - Return | 934 | 0.1145 | 5 | 0.4826 | -1.19 | 0.853 | 25 | 0.3962 | -1.20 | 0.880 |
| Chengdu - MAM | 933 | 0.0221 | 1 | - | - | - | 5 | -0.0673 | 1.71 | **0.068** |
| Chengdu - Return | 933 | 0.0895 | 1 | - | - | - | 5 | -0.0751 | 0.61 | 0.286 |
| Guangzhou - MAM | 935 | 0.0566 | 1 | - | - | - | 5 | 0.0122 | 0.37 | 0.365 |
| Guangzhou - Return | 935 | 0.1291 | 1 | - | - | - | 5 | 0.4462 | -0.77 | 0.759 |

**TABLE 12**

**Province-by-province rank-sum tests of whether event and non-event returns are drawn from the same distribution**

This table presents the results of Wilcoxon rank-sum tests performed province-by-province, testing whether the returns of firms located in a certain province are drawn from the same distribution during periods when the province is experiencing smog and periods when none of the five major cities are experiencing smog. Abnormal returns obtained from the market adjusted model (MAM) and the market model (MM) are tested, as well as stock returns. The test results for the MM abnormal returns are not presented. All returns are expressed in percentage terms. The p-values presented are based on our hypothesis that event returns are lower than non-event returns.

| | Non-event | | Event date | | | | Event window | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Major city** | ***N*** | **Mean** | ***N*** | **Mean** | **Z-value** | **P-value** | ***N*** | **Mean** | **Z-value** | **P-value** |
| Beijing - MAM | 256,813 | 0.0741 | 3,582 | 0.0021 | 1.76 | **0.040** | 18,144 | 0.0715 | 1.43 | **0.076** |
| Beijing - Return | 256,813 | 0.1441 | 3,582 | 0.6221 | -13.43 | 1.000 | 18,144 | 0.2487 | -6.41 | 1.000 |
| Shanghai - MAM | 408,829 | 0.0717 | 1,219 | -0.0176 | -0.72 | 0.763 | 6,133 | 0.2454 | -10.30 | 1.000 |
| Shanghai - Return | 408,829 | 0.1447 | 1,219 | -0.0439 | 4.14 | **0.000** | 6,133 | 0.5750 | -11.61 | 1.000 |
| Shenyang - MAM | 62,630 | 0.0369 | 304 | -0.2308 | 2.24 | **0.013** | 1,551 | 0.0764 | -1.11 | 0.867 |
| Shenyang - Return | 62,630 | 0.1136 | 304 | 0.3469 | -1.05 | 0.854 | 1,551 | 0.3933 | -3.53 | 1.000 |
| Chengdu - MAM | 82,598 | 0.0303 | 84 | 0.1881 | -0.868 | 0.807 | 426 | 0.0423 | -2.10 | 0.982 |
| Chengdu - Return | 82,598 | 0.1043 | 84 | -0.5711 | 3.567 | **0.000** | 426 | 0.0375 | 1.38 | **0.084** |
| Guangzhou - MAM | 339,898 | 0.0581 | 335 | 0.2381 | -1.712 | 0.957 | 1,708 | 0.0575 | -0.64 | 0.738 |
| Guangzhou - Return | 339,898 | 0.1475 | 335 | 0.6704 | -4.141 | 1.000 | 1,708 | 0.5024 | -6.46 | 1.000 |

Firms located around Shenyang exhibit significantly lower event abnormal returns only in the rank-sum test (at the 5% level), but no test finds a significant difference between event windows and non-events. The mean abnormal return is 0.27 percentage points lower at event dates (though the median is about 0.03 percentage points higher at event dates).

For firms located around Chengdu, the t-test finds event abnormal returns to be lower than non-event abnormal returns at the 10% level. The rank-sum test finds that the event date returns of the individual firms located around Chengdu are significantly lower than non-event returns at the 1% level. However, as this test only involves one event it is hard to draw any inferences. For firms located around Guangzhou no significant difference is found between events and non-events.

Overall, some mild support is found in favor of our fifth hypothesis and a local mood effect. Several of the tests show that firms located around Beijing and Shenyang (together they have a total of 19 events) have lower abnormal returns at event dates. The rank-sum test also suggests that firms located around Beijing have lower abnormal returns during event windows than they do during non-event days. However, another possible explanation of these negative abnormal returns is that there is a temporary operational effect during smog (e.g. workers not being able to get to work), which actually has a very small effect on the fundamental value of companies.

## Can CSR Reporting Affect Event Date Abnormal Returns?

To test if CSR reporting has an effect on event date abnormal returns we use OLS to estimate a linear regression model with the individual stock abnormal returns based on the MAM, $AR_{i,t}$, as the dependent variable. Mainly, we would expect CSR reporting, as a proxy for environmental disclosure, to have a mitigating effect for the polluting industries. Note that the significance of all coefficients of variables involving the $Event\ date_{i,t}$ variable could be overstated due to event date clustering. However, this has no effect on the coefficient estimates. Also, the residuals are not normally distributed which has an effect on hypothesis testing. The results of this regression are shown in Table 13. The results are similar when using other test specifications and also when winsorizing some variables at the 5% and 95% level (see Table C2 in Appendix C for results after winsorizing, the main difference is that the $Coal_{i,t} * Event\ date_{i,t} \cdot CSR_{i,t}$ coefficient loses significance).

The everyday effect found for CSR reporting is negative and significantly different from zero at the 1% level. For the coal industry, CSR reporting overall has an additional negative effect significant at the 10% level. For steel and non-ferrous metal producers CSR reporting has a negative relationship to abnormal returns that is significantly different from zero at the 5% level. No effect significantly different from zero is found for the oil industry. Environmentally protective companies on the other hand have a positive CSR reporting coefficient which is significantly different from zero at the 10% level.

At event dates, a positive effect from CSR reporting is found for environmentally protective companies, but this is not significantly different from zero. Coal producers are the only polluters with a positive coefficient for CSR reporting at event dates, however the coefficient is not found to be significantly different from zero for any of the polluting industries.

For companies in the polluting industries there is mild significance found for a negative everyday effect of CSR reporting. However, there is no effect significantly different from zero from CSR reporting at event dates and no support for our hypothesis that CSR reporting can mitigate some of the negative effects observed on event dates.

**TABLE 13**

**Linear regression including control variables and CSR dummies with $AR_{i,t}$ as the dependent variable**

This table presents the results from a linear regression estimated using OLS with individual stock abnormal returns as the dependent variable. For a closer description of the variables included, see Table A1 in Appendix A. We are interested in whether CSR reporting can mitigate some of the negative effect seen on event dates for the polluting industries. The coefficients are based on abnormal return expressed in percentage terms. The presented p-values are based on the predicted sign. Month and year dummies, as well as the intercept, industry dummies, event date dummies, size and book-to-market, are included in the regression but are not presented.

| **Variable** | **Predicted sign** | **Coefficient** | **T-statistic** | **P-value** |
|---|---|---|---|---|
| $CSR_{i,t}$ | +/- | **-0.0234** | -5.38 | 0.000 |
| $Coal_{i,t} * CSR_{i,t}$ | +/- | **-0.0451** | -1.77 | 0.077 |
| $Steel_{i,t} * CSR_{i,t}$ | +/- | **-0.0546** | -2.29 | 0.022 |
| $Non\text{-}ferrous_{i,t} \cdot CSR_{i,t}$ | +/- | **-0.0446** | -2.39 | 0.017 |
| $Oil_{i,t} \cdot CSR_{i,t}$ | +/- | -0.0558 | -1.19 | 0.232 |
| $Env.prot._{i,t} \cdot CSR_{i,t}$ | +/- | **0.0631** | 1.73 | 0.083 |
| $Event\ date_{i,t} \cdot CSR_{i,t}$ | +/- | 0.0203 | 0.77 | 0.443 |
| $Coal_{i,t} \cdot Event\ date_{i,t} \cdot CSR_{i,t}$ | + | 0.0936 | 0.55 | 0.292 |
| $Steel_{i,t} \cdot Event\ date_{i,t} \cdot CSR_{i,t}$ | + | -0.0196 | -0.16 | 0.564 |
| $Non\text{-}ferrous_{i,t} \cdot Event\ date_{i,t} * CSR_{i,t}$ | + | -0.0594 | -0.50 | 0.698 |
| $Oil_{i,t} \cdot Event\ date_{i,t} \cdot CSR_{i,t}$ | + | -0.2333 | -0.82 | 0.793 |
| $Env.prot._{i,t} \cdot Event\ date_{i,t} \cdot CSR_{i,t}$ | +/- | 0.5268 | 1.49 | 0.137 |

$Adj.R^2 = 0.0014$

Observations = 1,910,255

# CONCLUSIONS

The objective of this paper was to investigate how the Chinese stock market reacts to 22 smog events in five of the major cities. Six different hypotheses were developed; two related to rational market reactions, three related to mood effects and one related to the effect of CSR reporting.

Our first and second hypotheses were that the polluting industries blamed for the smog are punished by the stock market during events, while firms considered environmentally protective are rewarded. Results supporting the punishment hypothesis were found for coal, steel and non-ferrous metal producers. For the oil industry, no support in favor of our hypothesis was found. However, the industry is dominated by state-owned companies that have been blamed for having a large influence over environmental policymaking. Regarding our second hypothesis, we find that environmental protective companies have significantly higher abnormal returns during events than during non-events. Overall, support is found for our theory that investors take into account possible effects from smog on future cash flows or the cost of capital. However, for both the non-ferrous metal producers and the environmentally protective companies there is a reversal toward the end of the event window. We cannot exclude the probability that perhaps the first reaction was an overreaction or just a result of investors punishing some firms for being “bad” and rewarding other firms for being “good”, without any underlying rational explanations.

Our third hypothesis was that stock market returns are lower during events due to the mood effect. Our test results do not support this. In fact, the average event date market return over the 22 events in our sample is 5.6 times higher than the average non-event return for the Shenzhen exchange and 16.2 times higher for the Shanghai exchange. However, most of this effect is likely due to the “January effect” (see, e.g., Haugen and Jorion, 1996), and when all January observations are excluded most of the difference between event and non-event market returns is eliminated. Still, event returns are not found to be significantly lower than non-event returns.

Our fourth hypothesis was that firms located in a province experiencing smog have lower abnormal returns than firms located in other provinces. No significant results to support this hypothesis were found in any of our tests. In fact, all of the eight different event abnormal returns found in Table 9 are on average higher for firms located in the province experiencing smog.

Our fifth hypothesis was that firms located in a province experiencing smog have lower returns and abnormal returns during events than they do during non-events. When looking at Beijing and Shenyang, the two cities where a large majority of events take place, some tests find that the abnormal returns of firms around these cities are significantly lower when the province is experiencing smog, suggesting that provinces experiencing smog more frequently may be more affected by the mood effect. However, the size of this effect is small and it is unclear whether this is a result of mood or just due to actual economic damage caused by the smog.

Our sixth hypothesis was that CSR reporting can be seen as a proxy for environmental disclosure, and therefore that companies in the polluting industries could use CSR reporting to mitigate some of the negative abnormal returns seen on event dates. No effect significantly different from zero is found at event dates. It could be that 'bad' firms are more likely to issue CSR reports in an attempt to gain legitimacy, as suggested by the legitimacy theory (Gray et al., 1995), but that investors do not buy this. Also, Chinese firms have been accused of not realizing the importance of communication with stakeholders, leading to a corporate image that is ineffectively promoted and CSR reports that are lacking in quality (Shin, 2014).

Overall, our findings support that there is a rational market reaction to smog, where, at least in the short term, polluting companies are punished and environmentally protective companies are rewarded. Weak support is found in favor of an irrational market reaction in some tests, but there are other possible explanations.

## Limitations and Further Work

In our study we compare days with PM 2.5 levels over 500 to all other days, which also includes days just below 500. This could be problematic in our tests of the irrational market reaction, because it is possible that the mood effect is present already at much lower levels and therefore we are unable to see it when we compare event days to non-event days. Also, we do not make any distinctions based on the severeness of smog. There is a possibility that people only react during the most extreme events in our sample, and not during all events as is assumed in our testing.

For the test of 'rational' market reaction toward different industries, it could be interesting to use a longer event window in future study. As we could see that non-ferrous metal producers and environmentally protective companies have a large portion of their accumulated abnormal returns erased toward the end of the event window, there might be something going on just outside event windows that we fail to capture. However, using longer event windows would also decrease the power of tests and increase the number of possible confounding events.

Another aspect that could be improved upon is investor location when examining the mood effect. In our paper, we use firm location as a proxy for investor location, which may not be always accurate. It would be valuable to test more directly how the traders located in a smog-covered area are affected by smog.

Regarding our investigation of a possible mitigating effect from CSR reporting, there could be a problem with endogeneity. It is likely that firms with more resources are more probable to issue CSR reports, but at the same time they also have the resources to handle their pollution more carefully.

Some further effort could be made to investigate the effect of environmental performance or environmental disclosure for polluting firms during smog days. In particular, since actual environmental performance may substantially determine the regulatory risk for companies in the polluting industries, cross sectional analysis on firm characteristics related to environmental performance could provide more insight on the reasons why polluting firms are negatively affected by smog. Regarding the impact of environmental disclosure, more criteria could be used to measure the quality of CSR report, in order to observe whether a CSR report of higher quality could better convince investors about their environmental performance and thus mitigate the negative market reaction caused by smog.

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Data collected from:

CSMAR

Factiva

Thomson Reuters Datastream

US Embassy in China

# APPENDIX A

## Abnormal Returns and Cumulative Abnormal Returns

### *Abnormal Return*

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|X_t)$$

where $AR_{i,t}$, $R_{i,t}$ and $E(R_{i,t}|X_t)$ are the abnormal, observed, and expected returns respectively for firm $i$ at time period $t$. $X_t$ is the conditioning information for the expected return model.

### *Cumulative Abnormal Return*

$$CAR_{i,T} = \sum_{t}^{T} AR_{i,t}$$

### *Average Abnormal Return*

$$AAR_t = \frac{1}{M}\sum_{m=1}^{M}\left(\frac{1}{N_m}\sum_{i=1}^{N_m} AR_{i,t,m}\right)$$

Where $M$ is the total number of events and $N_m$ the number of firms experiencing event $m$.

### *Cumulative Average Abnormal Return*

$$CAAR_T = \sum_{t=1}^{T} AAR_t$$

### *Portfolio Abnormal Return*

$$AR_{p,t} = \sum_{i=1}^{N} \frac{AR_{i,t} * (Shares_{i,q} * P_{i,t})}{\sum_{i=1}^{N}(Shares_{i,q} * P_{i,t})}$$

Where $P_{i,t}$ is the price of firm $i$'s stock at time $t$ and $Shares_{i,q}$ is the total number of shares for firm $i$ at quarter $q$.

The above formulas for calculating $AAR_t$ and $CAAR_T$ are also applicable for portfolio abnormal returns.

## Regression Variables

**TABLE A1**

**Regression variables**

This table presents and defines all variables used in our regressions.

| **Variable** | **Definition** |
|---|---|
| $Size_{i,t}$ | $\ln(Market\ value\ of\ equity_{i,t_{i,t}})$ |
| $BM_{i,t}$ | $\frac{Book\ value\ of\ equity_{i,t}}{Market\ value\ of\ equity_{i,t}}$ |
| $Month\ dummies_{i,t}$ | Eleven dummies for the months January-November (i.e. December is the "base case"), equal to 1 if the month is the same as the dummy month. |
| $Year_{i,t}$ | Two year dummies for the years 2012 and 2013 (i.e. 2014 is the "base case"), equal to 1 if the year is the same as the dummy year. |
| $Coal_{i,t}$ | Dummy equal to 1 if the firm is a coal producer, 0 otherwise. |
| $Steel_{i,t}$ | Dummy equal to 1 if the firm is a steel producer, 0 otherwise. |
| $Non\text{-}ferrous_{i,t}$ | Dummy equal to 1 if the firm is a non-ferrous metal producer, 0 otherwise. |
| $Oil_{i,t}$ | Dummy equal to 1 if the firm is an oil refiner or distributor, 0 otherwise. |
| $Env.prot._{i,t}$ | Dummy equal to 1 if the firm is considered environmentally protective, 0 otherwise. |
| $Event\ date_{i,t}$ | Dummy equal to 1 if the date is an event date, 0 otherwise. |
| $Coal_{i,t} \cdot Event\ date_{i,t}$ | Interaction variable equal to 1 if the firm is a coal producer and the date is an event date, 0 otherwise. |

**TABLE A1 CONTINUED**

| | |
|---|---|
| $Steel_{i,t} \cdot Event\ date_{i,t}$ | Interaction variable equal to 1 if the firm is a steel producer and the date is an event date, 0 otherwise. |
| $Non\text{-}ferrous_{i,t} \cdot Event\ date_{i,t}$ | Interaction variable equal to 1 if the firm is a non-ferrous metal producer and the date is an event date, 0 otherwise. |
| $Oil_{i,t} \cdot Event\ date_{i,t}$ | Interaction variable equal to 1 if the firm is an oil refiner or distributor and the date is an event date, 0 otherwise. |
| $Env.prot._{i,t} \cdot Event\ date_{i,t}$ | Interaction variable equal to 1 if the firm is considered environmentally protective and the date is an event date, 0 otherwise. |
| $CSR_{i,t}$ | Dummy equal to 1 if the firm issues CSR reporting, 0 otherwise. |
| $CSR_{i,t} \cdot Event\ date_{i,t}$ | Interaction variable equal to 1 if the firm issues CSR reporting and the date is an event date, 0 otherwise. |
| $Coal_{i,t} \cdot CSR_{i,t}$ | Interaction variable equal to 1 if the firm is a coal producer and issues CSR reporting, 0 otherwise. |
| $Steel_{i,t} \cdot CSR_{i,t}$ | Interaction variable equal to 1 if the firm is a steel producer and issues CSR reporting, 0 otherwise. |
| $Non\text{-}ferrous_{i,t} \cdot CSR_{i,t}$ | Interaction variable equal to 1 if the firm is a non-ferrous metal producer and issues CSR reporting, 0 otherwise. |
| $Oil_{i,t} \cdot CSR_{i,t}$ | Interaction variable equal to 1 if the firm is an oil refiner or distributor and issues CSR reporting, 0 otherwise. |

**TABLE A1 CONTINUED**

| | |
|---|---|
| $Env.prot._{i,t} \cdot CSR_{i,t}$ | Interaction variable equal to 1 if the firm is considered environmentally protective and issues CSR reporting, 0 otherwise. |
| $Coal_{i,t} \cdot CSR_{i,t} \cdot Event\ date_{i,t}$ | Interaction variable equal to 1 if the firm is a coal producer and issues CSR reporting, and the date is an event date, 0 otherwise. |
| $Steel_{i,t} \cdot CSR_{i,t} \cdot Event\ date_{i,t}$ | Interaction variable equal to 1 if the firm is a steel producer and issues CSR reporting, and the date is an event date, 0 otherwise. |
| $Non\text{-}ferrous_{i,t} \cdot CSR_{i,t} \cdot Event\ date_{i,t}$ | Interaction variable equal to 1 if the firm is a non-ferrous metal producer and issues CSR reporting, and the date is an event date, 0 otherwise. |
| $Oil_{i,t} \cdot CSR_{i,t} \cdot Event\ date_{i,t}$ | Interaction variable equal to 1 if the firm is an oil refiner or distributor and issues CSR reporting, and the date is an event date, 0 otherwise. |
| $Env.prot._{i,t} \cdot CSR_{i,t} \cdot Event\ date_{i,t}$ | Interaction variable equal to 1 if the firm is considered environmentally protective and issues CSR reporting, and the date is an event date, 0 otherwise. |

# APPENDIX B

**TABLE B1**

This table presents the three different criteria for issuing yellow, orange and red smog alerts.

| | 1 | | 2 | | | 3 | |
|---|---|---|---|---|---|---|---|
| | **Visibility** | **Humidity** | **Visibility** | **Humidity** | **PM2.5** | **Visibility** | **PM2.5** |
| Yellow | <3 | <80% | <3 | >80% | 115-150 | <5 | 150-250 |
| Orange | <2 | <80% | <2 | >80% | 150-250 | <5 | 250-500 |
| Red | <1 | <80% | <1 | >80% | 250-500 | <5 | >500 |

**TABLE B2**
**Number of events per major city**

This table presents the number of events per major city.

| **City** | **Number of events** |
|---|---|
| Beijing | 14 |
| Chengdu | 1 |
| Guangzhou | 1 |
| Shanghai | 3 |
| Shenyang | 5 |

**TABLE B3**

This table presents the number of observations (*N*), the average abnormal return (in %) obtained from the market adjusted model (MAM) and the average abnormal return obtained from the market model (MM). These statistics are shown for each industry, both for the value-weighted portfolios and for the individual stocks. Abnormal returns are expressed in percentage terms. Panel A shows the average abnormal return of each event window day (the number within brackets indicates the day relative to the event date), as well as the average during the whole event window and outside event windows. Panel B shows cumulative average abnormal return over event window days [-1, 1] and [-2, 2], as well as the average three and five-day CAAR outside event windows.

| | **Coal** | | | | | | **Steel** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Portfolio* | | | *Individual stocks* | | | *Portfolio* | | | *Individual stocks* | | |
| | ***N*** | **MAM** | **MM** | ***N*** | **MAM** | **MM** | ***N*** | **MAM** | **MM** | ***N*** | **MAM** | **MM** |
| Panel A: Average abnormal return (%) | | | | | | | | | | | | |
| AAR [-2] | 21 | -0.1625 | -0.1115 | 544 | -0.3351 | -0.2770 | 20 | 0.3321 | 0.2937 | 625 | 0.2454 | 0.2059 |
| AAR [-1] | 21 | -0.2110 | -0.1730 | 544 | -0.2906 | -0.2897 | 20 | -0.1367 | -0.1097 | 625 | -0.1139 | -0.1478 |
| AAR [0] | 21 | -0.1909 | -0.2876 | 544 | -0.2736 | -0.4347 | 20 | -0.4030 | -0.3420 | 625 | -0.2464 | -0.2550 |
| AAR [1] | 21 | 0.1187 | 0.0647 | 544 | 0.2033 | 0.0802 | 20 | 0.0562 | 0.0793 | 625 | 0.0932 | 0.1003 |
| AAR [2] | 21 | -0.4857 | -0.4789 | 544 | -0.4556 | -0.4885 | 20 | 0.1218 | 0.1167 | 625 | 0.0729 | 0.0385 |
| Event window AAR | 105 | -0.1863 | -0.1973 | 2,720 | -0.2303 | -0.2819 | 100 | -0.0059 | 0.0076 | 3,125 | 0.0102 | -0.0116 |
| Non-event AAR | 933 | -0.0642 | -0.0369 | 24,849 | -0.0569 | -0.0435 | 933 | 0.0103 | 0.0128 | 30,637 | 0.0111 | 0.0116 |
| Panel B: Cumulative average abnormal return (%) | | | | | | | | | | | | |
| 3-day CAAR [-1, 1] | 21 | -0.2832 | -0.3959 | 544 | -0.3609 | -0.6442 | 20 | -0.4835 | -0.3724 | 625 | -0.2671 | -0.3025 |
| 3-day CAAR (non-event) | 931 | -0.2047 | -0.1268 | 24,795 | -0.1851 | -0.1497 | 930 | 0.0339 | 0.0435 | 30,571 | 0.0368 | 0.0374 |
| 5-day CAAR [-2, 2] | 21 | -0.9314 | -0.9863 | 544 | -1.1516 | -1.4097 | 20 | -0.0296 | 0.0380 | 625 | 0.0512 | -0.0581 |
| 5-day CAAR (non-event) | 929 | -0.3274 | -0.2119 | 24,767 | -0.3119 | -0.2681 | 929 | 0.0498 | 0.0702 | 30,538 | 0.0569 | 0.0584 |

**TABLE B3 CONTINUED**

| | Non-ferrous metals | | | | | | Oil | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Portfolio* | | | *Individual stocks* | | | *Portfolio* | | | *Individual stocks* | | |
| | ***N*** | **MAM** | **MM** | ***N*** | **MAM** | **MM** | ***N*** | **MAM** | **MM** | ***N*** | **MAM** | **MM** |
| Panel A: Average abnormal return (%) | | | | | | | | | | | | |
| AAR [-2] | 22 | -0.0523 | -0.0479 | 1,262 | -0.0667 | -0.0837 | 22 | -0.0772 | -0.0023 | 167 | -0.1347 | -0.1978 |
| AAR [-1] | 22 | 0.0296 | 0.0554 | 1,262 | 0.0503 | 0.0109 | 22 | -0.2529 | -0.1995 | 167 | -0.1544 | -0.1474 |
| AAR [0] | 22 | -0.1895 | -0.3282 | 1,262 | -0.1675 | -0.3271 | 22 | 0.1927 | 0.4430 | 167 | 0.0114 | 0.0206 |
| AAR [1] | 22 | 0.4277 | 0.3619 | 1,262 | 0.3767 | 0.2808 | 22 | -0.1202 | 0.0838 | 167 | 0.1984 | 0.1760 |
| AAR [2] | 22 | -0.1476 | -0.1877 | 1,262 | -0.1108 | -0.1714 | 22 | 0.1493 | 0.2887 | 167 | 0.2319 | 0.2347 |
| Event window AAR | 110 | 0.0136 | -0.0293 | 6,310 | 0.0164 | -0.0581 | 110 | -0.0217 | 0.1227 | 835 | 0.0305 | 0.0172 |
| Non-event AAR | 933 | -0.0086 | -0.0262 | 59,297 | -0.0072 | -0.0224 | 929 | -0.0529 | 0.0313 | 7,491 | 0.0491 | 0.0085 |
| Panel B: Cumulative average abnormal return (%) | | | | | | | | | | | | |
| 3-day CAAR [-1, 1] | 22 | 0.2678 | 0.0891 | 1,262 | 0.2593 | -0.0354 | 22 | -0.1804 | 0.3273 | 167 | 0.0554 | 0.0492 |
| 3-day CAAR (non-event) | 930 | -0.0343 | -0.0903 | 59,167 | 0.0161 | -0.0752 | 925 | -0.1556 | 0.1002 | 7,473 | 0.1354 | 0.0173 |
| 5-day CAAR [-2, 2] | 22 | 0.0679 | -0.1465 | 1,262 | 0.0818 | -0.2904 | 22 | -0.1083 | 0.6137 | 167 | 0.1526 | 0.0861 |
| 5-day CAAR (non-event) | 929 | -0.0454 | -0.1536 | 59,097 | 0.0230 | -0.1314 | 923 | -0.2676 | 0.1729 | 7,462 | 0.1919 | 0.0007 |

**TABLE B3 CONTINUED**

| | Environmentally protective | | | | | |
|---|---|---|---|---|---|---|
| | *Portfolio* | | | *Individual stocks* | | |
| | ***N*** | **MAM** | **MM** | ***N*** | **MAM** | **MM** |
| Panel A: Average abnormal return (%) | | | | | | |
| AAR [-2] | 22 | -0.0044 | -0.0045 | 734 | 0.0351 | 0.0065 |
| AAR [-1] | 22 | 0.1836 | 0.1895 | 734 | 0.15 | 0.0875 |
| AAR [0] | 22 | 0.5498 | 0.4474 | 734 | 0.4251 | 0.2845 |
| AAR [1] | 22 | 0.3397 | 0.2659 | 734 | 0.3396 | 0.2423 |
| AAR [2] | 22 | -0.5468 | -0.6032 | 734 | -0.4898 | -0.6088 |
| Event window AAR | 110 | 0.1044 | 0.0590 | 3,670 | 0.0920 | 0.0024 |
| Non-event AAR | 933 | 0.0533 | 0.0247 | 34,472 | 0.0541 | -0.0118 |
| Panel B: Cumulative average abnormal return (%) | | | | | | |
| 3-day CAAR [-1, 1] | 22 | 1.0731 | 0.9028 | 734 | 0.9147 | 0.6143 |
| 3-day CAAR (non-event) | 931 | 0.1453 | 0.0550 | 34,396 | 0.1532 | -0.0487 |
| 5-day CAAR [-2, 2] | 22 | 0.5219 | 0.2951 | 734 | 0.4600 | 0.0120 |
| 5-day CAAR (non-event) | 930 | 0.2608 | 0.1050 | 34,355 | 0.2655 | -0.0782 |

# APPENDIX C

**TABLE C1**

**Abnormal return regression with some variables winsorized**

This table presents the results from a linear regression estimated using OLS with individual stock abnormal returns as the dependent variable. This regression allows us to control for size and book-to-market. Three of the variables have been winsorized at the 5% and 95% level; size (by year), BM (by year) and AR (by industry and year). The coefficients are based on abnormal return expressed in percentage terms. The presented p-values are based on the predicted sign. Month and year dummies are included in the regression but are not presented.

| Variable | Predicted sign | Coefficient | T-statistic | P-value |
|---|---|---|---|---|
| $\alpha_0$ | +/- | **-0.2085** | -10.44 | 0.000 |
| $Size_{i,t}$ | - | 0.0044 | 3.55 | 1.000 |
| $BM_{i,t}$ | + | -0.0289 | -11.15 | 1.000 |
| $Coal_{i,t}$ | +/- | **-0.1118** | -11.52 | 0.000 |
| $Steel_{i,t}$ | +/- | **-0.0200** | -2.32 | 0.021 |
| $Non\text{-}ferrous\ metals_{i,t}$ | +/- | **-0.0375** | -5.33 | 0.000 |
| $Oil_{i,t}$ | +/- | -0.0097 | -0.53 | 0.596 |
| $Env.prot._{i,t}$ | +/- | 0.0089 | 0.88 | 0.381 |
| $Event\ date_{i,t}$ | +/- | **0.0420** | 5.03 | 0.000 |
| $Coal_{i,t} * Event\ date_{i,t}$ | - | **-0.1554** | -2.63 | 0.004 |
| $Steel_{i,t} * Event\ date_{i,t}$ | - | **-0.2141** | -3.91 | 0.000 |
| $Non\text{-}ferrous\ metals_{i,t} * Event\ date_{i,t}$ | - | **-0.0947** | -1.99 | 0.023 |
| $Oil_{i,t} * Event\ date_{i,t}$ | - | -0.1217 | -0.99 | 0.161 |
| $Env.prot._{i,t} * Event\ date_{i,t}$ | + | **0.2587** | 3.37 | 0.001 |

$Adj. R^2 = 0.0013$

Observations = 1,910,255

## TABLE C2
## CSR regression with some variables winsorized

This table presents the results from a linear regression estimated using OLS with individual stock abnormal returns as the dependent variable. We are interested in whether CSR reporting can mitigate some of the negative effect seen on event dates for the polluting industries. Three of the variables have been winsorized at the 5% and 95% level; size (by year), BM (by year) and AR (by industry and year). The coefficients are based on abnormal return expressed in percentage terms. The presented p-values are based on the predicted sign. Month and year dummies, as well as the intercept, industry dummies, event date dummies, size and book-to-market, are included in the regression but are not presented.

| **Variable** | **Predicted sign** | **Coefficient** | **T-statistic** | **P-value** |
|---|---|---|---|---|
| $CSR_{i,t}$ | +/- | **-0.0073** | -2.17 | 0.030 |
| $Coal_{i,t} * CSR_{i,t}$ | +/- | **-0.0339** | -1.74 | 0.082 |
| $Steel_{i,t} * CSR_{i,t}$ | +/- | **-0.0523** | -3.00 | 0.003 |
| $Non\text{-}ferrous\ metals_i * CSR_{i,t}$ | +/- | **-0.0401** | -2.82 | 0.005 |
| $Oil_{i,t} * CSR_{i,t}$ | +/- | -0.0065 | -0.19 | 0.847 |
| $Env.prot._{i,t} * CSR_{i,t}$ | +/- | **0.0547** | 1.92 | 0.055 |
| $Event\ date_{i,t} * CSR_{i,t}$ | +/- | 0.0145 | 0.70 | 0.487 |
| $Coal_{i,t} * Event\ date_{i,t} * CSR_{i,t}$ | + | 0.1228 | 0.97 | 0.165 |
| $Steel_{i,t} * Event\ date_{i,t} * CSR_{i,t}$ | + | -0.0254 | -0.23 | 0.591 |
| $Non\text{-}ferrous\ metals_{i,t} * Event\ date_{i,t} * CSR_{i,t}$ | + | -0.0315 | -0.32 | 0.627 |
| $Oil_{i,t} * Event\ date_{i,t} * CSR_{i,t}$ | + | -0.3396 | -1.34 | 0.909 |
| $Env.prot._{i,t} * Event\ date_{i,t} * CSR_{i,t}$ | +/- | 0.3159 | 1.37 | 0.172 |

$Adj.R^2 = 0.0013$
Observations = 1,910,255