Air pollution and mergers and acquisitions: Evidence from China

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Abstract:

This paper investigates the impact of air pollution on corporate mergers and acquisitions (M&As) activities for acquiring firms based on their headquarters location. Using a comprehensive sample of Chinese listing firms, we find that air pollution decreases local firms' M&A activities, and they decrease M&A activities through tightened firms' financial constraints and increase environmental governance costs. Furthermore, we show that the negative influence of air pollution on M&A activities is more pronounced in firms located in more developed regions, less polluted regions, and firms with environmental information disclosure. Our results are robust to a series of tests. We also find that acquirers in heavy air pollution areas create less shareholder wealth, take longer to complete acquisitions, and suffer from declining performance in the long-term.

JEL code: G18, G34, Q53, Q56

Key words: mergers and acquisitions, air pollution, financial constraints, environmental cost

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1. Introduction

A growing body of environmental issue research has linked air pollution with various adverse impacts on human health, economic development, and firms' operations. Medical experts stress the harm that pollution does to human health, psychologists highlight several detrimental mental effects for people who live in polluted environments, and economists report the negative effects of pollution on individuals, firms, and the economy as a whole (Jung, Herbohn, & Clarkson, 2018)[2].

An emerging body of literature documents the adverse effect of air pollution on firms' operations; in addition, some papers study the influence of air pollution on decision makings for firms' policies and activities, such as worsened cost of debt financing (Tan, Chan, & Chen, 2022), higher discounts on equity offerings (Han, Cheng, Chan, & Gao, 2022), lower corporate innovation (Tan & Yan, 2021), more conservative accounting policies (Wu, Liu, Chang, & Chan, 2022), among others. However, to our best knowledge, there is still a lack of studies examining whether and how air pollution impacts corporate mergers and acquisitions (M&As), which is one of the largest and most readily observable corporate investments and also crucial for corporate development and reallocation of capital (Gokkaya, Liu, & Stulz, 2021). A growing number of studies that investigate the determinants of M&As have shifted their focus from firm-level characteristics to some external factors. For instance, recent studies document that managers' overconfidence and narcissism (Goel & Thakor, 2010), compensation contracts (Yim, 2013), networks and social ties (Fracassi, 2017; Wu, 2011), board composition (Huang & Kisgen, 2013), ownership structure (Bauguess & Stegemoller, 2008), corporate policies/cultures/types/values (Bonaime, Gulen, & Ion, 2018; Shleifer & Vishny, 2003;

[2] For instance, Jung et al. (2018) put the risk of air pollution into three distinct categories to firms: (1) physical damage to operations caused by worsening environmental conditions; (2) loss of financial viability due to increasingly restrictive climate policy; and (3) costs of litigation and reputational damage due to potential breach of climate policy.

Teerikangas & Very, 2006; Zhang, 2022), business cycle (Maksimovic & Phillips, 2001), political influence (Yang, Zhang, Zhao, & Wang, 2022), and geographical distance between bidder and target (Li, Li, & Zhao, 2022) are significantly associated with M&As. In this paper we investigate whether and how air pollution, as one of the most critical environmental issues affects M&As in China's listed firms.

To fill this gap, we use the annual air quality index measure as a proxy for air pollution (Dong, Fisman, Wang, & Xu, 2021; Wang, Dai, & Kong, 2021), which is obtained from the China Stock Market & Accounting Research Database (CSMAR). We then match the air pollution data and the M&A sample based on the firm headquarters location. We use each firm's headquarter location as the identifier since it is where the majority of plants and operations of a firm are presumably based (Bai, Chu, Shen, & Wan, 2021). In our paper, we examine the Chinese market for three reasons. First, air pollution is among the most challenging environmental problems facing developing countries such as China and India (WHO, 2021). While economic development might cause pollution, particularly in emerging markets, how pollution impacts corporate decision-making processes or activities at the firm levels, is less clear. Thus, properly assessing this issue could have both academic value and critical normative implications. Second, since 2012, the Chinese government has attached great importance to environmental governance, stressed the principle of sustainable development, and introduced a series of policies to adjust the economic structure (CBRC, 2014B)[3]. It is useful to investigate the impact of these policy changes. Third, China began disclosing the daily city-level air pollution from 2000. This provides us with quantifiable and widely distributed air quality measures across China to gauge the impact of air pollution on firms' activities and

[3] China Banking Regulatory Commission (CBRC), 2014b, No. 40 Document General Office of the China Banking Regulatory Commission, Options on Green Credit Implementation. Available at: http://www.cbrc.gov.cn/EngdocView.do?docID= C5AE0DDAFB3E43DF85DC12DD6840244A

behaviours.

We study the impact of air pollution on Mergers & Acquisitions (M&A, hereafter) activities by examining its influence through two channels, namely financial constraints and environmental governance costs. Financial constraints generate negative cash flow shocks and may lead to under-investment (Bond & Van Reenen, 2007; Carpenter & Guariglia, 2008; Guariglia & Yang, 2016). Due to higher environmental governance costs, many firms prefer to hold more cash and decrease investment activities (Tan, Tan, & Chan, 2021; Tan & Yan, 2021). This is also consistent with the resource-based theory, which suggests that the firm's resources are rare and unreplicable, and these resources can help the firm maintain long-term competitive advantages among all firms (Hart, 1995; Kozlenkova, Samaha, & Palmatier, 2014). However, worse air pollution drains a firm's resources toward tackling compliance with local environmental regulations, so a firm has fewer resources to support other firm activities like M&As.

Using a sample that includes 22,327 firm-year observations of 3,564 unique firms in mainland China from 2010 to 2020, we find that air pollution is negatively related to corporate M&As. Since air pollution and corporate investments, including M&As, might be correlated with local economic conditions, we control for state Gross Domestic Product (GDP) growth and GDP per capita in our analysis. Still, our findings are insensitive to these controls. The results are robust to a series of tests and after accounting for endogeneity using a two-stage least squares (2SLS) instrumental variable (IV) approach and Propensity Score Matching (PSM) approach. Our channel analysis shows that severe air pollution is associated with tighter financial constraints and higher environmental governance costs measured by the SA index and the firm's environmental governance investments. Such tighter financial constraints and higher environmental governance costs lead to reduced M&A activities. We also explore the heterogeneity of the effects of air pollution on M&As, which shows that the negative effect of air pollution on M&As is more pronounced in firms located in more developed and less polluted regions, and firms with environmental information disclosure, suggesting that the firms in these regions and with environmental information disclosure pay more attention to the air pollution issues. Lastly, we provide evidence of a negative (positive) relation between the air pollution levels in the acquirer areas and the likelihood of all-cash (stock) payment. The results are consistent with our channel test, which indicates that firms in air pollution areas are more likely to face financial constraints and prefer to use stock payment in M&As. We also find that acquirers in heavy air pollution areas take a longer time to complete acquisitions. Using two-day cumulative abnormal stock returns (CAR) following the M&A deal announcements as a proxy for shareholder value, we find that air pollution is negatively related to acquirer shareholder value. There is also a negative relation between air pollution and a firm's long-term performance following the M&As in subsequent years.

Our paper makes several contributions. First, we advance the literature on the effect of air pollution on corporate policies and activities. While there is a large body of literature on the public health and psychological effects of air pollution, some literature study the impact of air pollution on stock prices, firm operations, and corporate policies and activities(Ai et al., 2020). To our best knowledge, we provide a novel finding for the adverse impact of air pollution on M&As and complement the emerging literature on the impact of climate change on a firm's general business strategy (Amran et al., 2016). Second, given the importance of M&As to countries and firms, the literature examines various determinants of M&As[4]. To our best knowledge, we document a new determinant of M&As - air pollution - thereby complementing

[4] More details for M&As determinants we mentioned before, such as executives' overconfidence and narcissism (Goel & Thakor, 2010), executives' compensation contracts (Yim, 2013), executives' networks and social ties (Fracassi, 2017; Wu, 2011), board composition (Huang & Kisgen, 2013), ownership structure (Bauguess & Stegemoller, 2008), corporate policies/cultures/types/values (Bonaime et al., 2018; Shleifer & Vishny, 2003; Teerikangas & Very, 2006; Zhang, 2022), business cycle (Maksimovic & Phillips, 2001), political influence (Yang et al., 2022), and geographical distance between bidder and target (Li et al., 2022) among others.,

the literature. Third, our findings have important policy implications. Current literature generally motivates the urgency of managing air pollution through the lens of public health. Our new results suggest that air pollution deteriorates M&As, which is an important asset reallocation activity of a firm impacting the capital market (Andrade & Stafford, 2004; Jovanovic & Rousseau, 2008; Martynova & Renneboog, 2008). This would urge policy makers to pay more attention to environmental issues, as there is a broader economic benefit to lowering air pollution in the context of firm-level investment efficiency and shareholder value enhancement. In other words, mitigating air pollution could stimulate economic growth through firm M&As.

The paper is structured as follows. We review the background and literature on air pollution and M&As and propose the hypotheses in Section 2. We then describe the dataset, variable construction, and descriptive statistics in Section 3. We present and discuss our main results and report some robustness tests in Section 4, and we conclude in Section 5.

2. Literature review

2.1. Merger and Acquisitions

Mergers and acquisitions (M&As) are among the most important events in a company's lifecycle and significantly impact the firm's operations and activities. They are considered one of the business strategies for enriched financial performance and growth (Anthony, 2017; Sahu & Agarwal, 2017). M&A transactions enable firms to perform business diversification (Levine, 2017), foreign market entry (Xu, 2017), accessing resources (Ahuja & Katila, 2001), deliberate learning (Zollo & Singh, 2004) and reinforcing market power (Hossain, 2021).

Regarding the determinants for mergers and acquisitions, the research has exploded since the 1970s (DePamphilis, 2019; Feldman & Hernandez, 2021; Fuller & Pusateri, 2018). We mainly focus on finance studies published after 2005 and zoom in on several important internal and external determinants related to acquirers' incentives to engage in M&As. The internal factors that determine M&As include, firstly, the CEOs/managers' characteristics and preferences, such as CEOs' overconfidence and narcissism (Goel & Thakor, 2010), CEOs' compensation contracts (Yim, 2013), top managers' and directors' networks and social ties (Fracassi, 2017; Wu, 2011). The second factor is corporate characteristics, such as board composition (Huang & Kisgen, 2013), ownership structure (Bauguess & Stegemoller, 2008), corporate policies (Bonaime et al., 2018), corporate cultures between targets and bidders (Teerikangas & Very, 2006), corporate types (Zhang, 2022), and corporate values (Shleifer & Vishny, 2003).

More recent literature focus on the external factors that determine M&As, which mainly include political influence (Yang et al., 2022), geographical distance between bidder and target (Li et al., 2022), and the business cycle (Maksimovic & Phillips, 2001). For example, based on a global sample of politically connected firms in 22 countries, Brockman, Rui, and Zou (2013) show that important political factors that determine the M&As are the strength of the legal system and the level of corruption: politically connected bidders conduct more M&A activities relative to unconnected bidders when the corruption level is low and a strong legal system is in place. Uysal, Kedia, and Panchapagesan (2008) find that geographic proximity can increase acquisition activities. Maksimovic and Phillips (2001) find an active market for corporate assets, with close to seven percent of plants changing ownership annually through mergers, acquisitions, and asset sales in the peak of the expansionary periods.

In recent years, green development has become a critical issue for enterprises. Polluters begin to obtain green resources, technology, or management experience through green merger and acquisition (GMA) to meet the requirements of green development. GMA refers to the acquisition, merger, and other economic activities of enterprises to acquire green resources and develop green technology (Salvi, Petruzzella, & Giakoumelou, 2018). Li, Liu, Liu, and Liu (2020) find that GMA helps these polluters access to more resources, alleviate financing constraints, and reduce tax liabilities, implying improved organisational legitimacy, and providing increased capacity for greater risk-taking by these firms. Zhao and Jia (2022) find that GMA positively impacts corporate environmental management. In line with the above studies, Li, Xu, McIver, Wu, and Pan (2020) also find that GMA can provide legitimacy for heavily polluting enterprises to survive and develop further, improving their sustainable development ability significantly.

2.2. Air pollution

Air pollution is one of the heaviest environmental risks worldwide, killing an estimated seven million people worldwide every year (WHO 2022). WHO data show that almost 99% of global population breathes air that exceeds WHO guideline limits containing high levels of pollutants, with low- and middle-income countries suffering from the highest exposures (WHO 2022). The early studies pay more attention to the impact of air pollution on individual health and sentiments/moods (Bakian et al., 2015; Chen, Ebenstein, Greenstone, & Li, 2013; Graff Zivin & Neidell, 2013).

In recent years, literature has begun to link air pollution to a wide range of macroeconomic activities increasingly (Chay & Greenstone, 2005; Chen et al., 2013; Ebenstein et al., 2015; Ebenstein, Fan, Greenstone, He, & Zhou, 2017). For example, previous studies find that air pollution leads to the decline of urban housing prices (Chay & Greenstone, 2005; Zheng, Cao, Kahn, & Sun, 2014), causing an increase in the replacement costs and unemployment in the labour market (Walker, 2013), and decrease in firm productivity, especially in service and manufacturing industries (Adhvaryu, Kala, & Nyshadham, 2014; Chang, Graff Zivin, Gross, & Neidell, 2016; Graff Zivin & Neidell, 2013).

Research exploring the influence of air pollution at the firm-level, have also generated some momentum in recent years. A body of literature details how air pollution affects firms' performance and how it affects firms' decisions and policies. Broadly, two theories regarding the impact of air pollution on firms' performance have been forwarded. The environmental stress theory which suggests that stressors found in the environment, such as radiation, physical structure, non-ergonomic furniture, natural disasters, pollution, illnesses, and climate change, significantly affect the health and sentiments of individuals and social groups (Lazarus & Cohen, 1977). This theory has been tied to the human capital effect to determine whether the environment stresses out people, impacting decision-making process. Air pollution induces negative moods and risk-aversion behaviours among investors, leading to a negative relationship between air pollution and stock returns (Levy & Yagil, 2011). Dong et al. (2021) show that analysts experiencing severe air pollution within a firm's operating environment during visits to the firm produce lower subsequent earnings forecasts. Tan, Tan, et al. (2021) find that air pollution drives a pessimistic mood and/or weakens the cognitive ability of management, leading to poor operation and increase in precautionary needs for more cash due to pollution abatement or decrease in availability of bank loans. Tan and Yan (2021) and Wang, Xing, Yu, and Dai (2021) find that air pollution adversely affect psychology of the executives, affecting decision-making poorly regarding innovation, which ultimately reduces corporate innovation and investment. He and Lin (2022) also find the similar adverse impact on managers' mood that reduces the investment efficiency of firms.

The resource-based theory suggests that firms' resources are rare and challenging for other firms to duplicate. For enterprises, long-lasting competitive advantages come from these unique resources (Peteraf, 1993; Wernerfelt, 1984). However, air pollution drains a firm's financial resources because it requires firms to spend money to comply with environmental regulations (Tan, Tan, et al., 2021; Tan & Yan, 2021). Under a resource-based theory, a firm has fewer resources to support other firm activities. For example, Tan and Yan (2021) find that air pollution reduces corporate innovation investment because it drains financial resources, constraining firms even more and increasing environmental governance costs. Tan, Tan, et al. (2021) find that firms in high-air-pollution cities are subject to higher financial constraints and operating risks than those in low-air-pollution cities. Zhang, Tan, and Chan (2021) find that initial public offerings (IPOs) are under-priced for firms located in areas with severe air pollution compared to firms located in areas with less air pollution. And firms located in cities with severe air pollution have high crash risk, tightened financial conditions, and higher environmental investments.

A number of studies focus on the effects of air pollution on the firm's accounting policies, financial report quality, and internal control quality. For example, Wu et al. (2022) find that increased air pollution induces firms to follow more conservative accounting practices and utilize more conservative estimates in their reporting. Jiang, Li, Shen, and Yu (2022) find that higher air pollution encourages firms to earnings management. Liu, Yang, Liu, and Liu (2019) and Hu, Xue, and Liu (2022) find that firms' internal control quality and financial reporting quality are significantly and negatively associated with the severity of air pollution in their home cities. Another strand of literature focuses on the impacts of air pollution on the corporate capital structure and corporate financing. Liu, Wu, and Chan (2021) show that firms respond to increased air pollution by using more capital and less labour to remain competitive. In addition, Tan, Tan, et al. (2021) establish that air pollution in the firms' operating environment increases the cost of debt financing. Hu and Chang (2022) find that firms in cities with poor air quality pay lower amounts of cash dividends than those in cities with better air quality because those firms increase environment expenditures on anti-pollution measurements, such as purchasing and installing environmentally friendly and efficient equipment, keeping more cash holdings, but these firms face more uncertainty about future earnings. Gan, Li, and Jiang (2022) find that start-up firms suffering severe air pollution receive less investment from venture capital and experience a lower probability of being financed by venture capitalists. Furthermore, Wang et al. (2021) highlight that air pollution is an important noneconomic factor driving firms' human capital and employee treatment strategy. They find that firms in air pollution areas enhance employee treatment through monetary compensation, safety security, and career training.

To manage air pollution, central government and local governments make many environmental regulations. Some of these regulations include limiting firms' business activities or compelling firms to increase spending on pollution abatement, which in effect leads to a reduction in firms' operating and business income (Tan, Zhang, Zhang, & Chan, 2021; Tan & Yan, 2021). In addition, governments impose restrictions on banks and supply chain partners to tighten their credit terms to firms located in high-pollution cities due to the additional credit risk leading to external financing challenges (Tan et al., 2022; Tan, Zhang, et al., 2021). Most current environmental regulation documents of local governments located in severe air pollution require local firms to "stop production" or "suspend operation," etc. urging firms to conduct clean production and environmental investment (Berman & Bui, 2001; Greenstone, 2002).

2.3. Hypothesis development

Although previous research has provided evidence of the impact of air pollution on firms' performance and decision-makings, there is no study investigating the influence of air pollution on firms' M&A decisions or market reactions to such M&As. Why would air pollution have an impact on M&A activities? On the one hand, heavy-polluting enterprises begin to obtain green resources, technology, or management experience through green merger and acquisition (GMA) to meet the requirements of green development. This process is expected to bring many benefits for these firms, such as completing the green transformation, developing green technology, accessing more resources, alleviating financing constraints, and reducing tax liabilities (Li, Liu, Liu, & Liu, 2020; Salvi et al., 2018). If a firm faces more climate/environmental risk, they may try to diversify or manage this risk. Bai et al. (2021) show that firms exposed to high sea level risk (SLR) have a higher probability of becoming acquirers, which is consistent with the notion that the market rewards firms for diversifying away their SLR risk and there is also a significant and positive relationship between the acquirers' cumulative announcement return and pre-merger SLR risk. SLR is one type of environmental risks that has a positive impact on mergers and acquisitions. It is reasonable to expect that air pollution may also promote local firms to conduct M&A activities in order to gain benefits and diversify risk through the M&A deals.

On the other hand, air pollution generates environmental risks, which poses a unique challenge for firms. It can also increase the operational and financial risks of firms affecting firms' performance negatively, which might lead to changes in the firm's policies and decisions, and firms may be forced to more conservative decisions (Liu et al., 2021; Tan, Tan, et al., 2021; Tan & Yan, 2021). Furthermore, under government policies and regulations, firms in areas with severe air pollution may face operating difficulties and financing challenges (Tan et al., 2022; Tan, Zhang, et al., 2021). Therefore, we expect that air pollution is negatively associated with firms' M&A activities, given the financial and operational challenges that air pollution causes. Therefore, it is an empirical question of how air pollution would impact M&A decisions and the performance of the firms. Based on our discussion, we forward the following hypotheses:

Hypothesis 1a (H1a): Air pollution is positively associated with M&A activities of the firms.

Hypothesis 1b (H1b): Air pollution is negatively associated with M&A activities of the firms.

3. Sample, variables construction, and descriptive statistics

3.1. Sample selection

The initial sample consists of all acquiring firms with all A-shares listed on China's two mainland stock exchanges, the Shanghai Stock Exchange, and the Shenzhen Stock Exchange. The data on M&A announcements data and transaction-related party details, stock returns, company locations, and financial information are from the China Stock Market and Accounting Research (CSMAR) database. For some of the missing target firms' locations, we hand collect from Google Engine. Following Erel, Liao, and Weisbach (2012) and Nguyen, Phan, and Simpson (2020), we exclude Leveraged Buyouts (LBOs), spinoffs, recapitalizations, self-tender offers, exchange offers, repurchases, partial equity stake purchases, acquisitions of remaining interest, and privatizations, as well as deals disclosed with less than 1 million RMB. Moreover, we exclude firms from the financial industry. We require the firms to take over control of the targets and exclude gradual acquisitions. Then, we merge the M&A and CSMAR data to retain firm-year observations and form the full sample. The whole matching process results in a final sample containing 22,327 firm-year observations, 3,564 unique acquiring firms located in 31 provincial-level regions in mainland China from 2010 to 2020[5]. All continuous variables are winsorized at the top and bottom 1% to mitigate the concern of outliers. The definitions of the variables are provided in Appendix A. Appendix B presents the number of M&A deals over the sample period, distributed by year in Panel A and by industry using the Industry Classification of Listed Companies issued by the CSRC in 2012 in Panel B. In Panel A of Appendix B, the annual number of M&As deals increased over the period 2010–2016. We notice a sharp increase of acquisitions in 2015 and 2016, with 18.44% and 15.62% of the acquisitions in our sample. In Panel B, we find that industries experience high frequency of M&As include computer equipment, information technology service, chemicals and allied products, electronic and other electrical equipment, and medicine manufacturing.

[5] In our sample, all target firms are non-listed firms in China.

3.2. Air pollution variables

For each city in China, we obtain the monthly air quality index (AQI) between 2013 and 2020 from the CSMAR database. We calculate the annual average AQI of each acquirer's city (AAQI) and target firms city (TAQI). The AQI is constructed based on the levels of six atmospheric pollutants: sulfur dioxide (SO2), nitrogen dioxide (NO2), suspended particulates smaller than 10 μm in aero- dynamic diameter (PM10), suspended particulates smaller than 2.5 μm in aerodynamic diameter (PM2.5), carbon monoxide (CO), and ozone (O3). Prior to 2013, the Chinese government monitored only SO2, NO2, and PM10, which was used to construct the air pollution index (API) that served as a summary measure of air quality. While the API and AQI are not directly comparable, they are highly correlated (Zheng, Cao, & Singh, 2014). Similar to Dong et al. (2021), we use API index before 2013 and AQI index after 2013 in our sample, for notational simplicity we refer to both as AQI in what follows. We do a robustness check using the period from 2013 to 2020 and during this sample period, our independent variable is pure AQI, our baseline results are still existing. For a small number of cities, the AQI index is unavailable via the CSMAR, we can fill in some of the missing data from the Qingyue Open Environment Data Center website, which obtains pollution data directly from local governments[6]. We divide AQI by 1000 for ease of interpretation of the regression coefficients (Dong et al., 2021).

The Ministry of Environmental Protection of China (MEPC) distinguishes among six categories of AQI: I-excellent (AQI $\leq$50), II-good (50 < AQI $\leq$100), III- lightly polluted (100 < AQI $\leq$150), IV-moderately polluted (150 < AQI $\leq$200), V-heavily polluted (200 < AQI $\leq$300) and VI-severely polluted (AQI > 300)[7]. A high AQI means bad air pollution. Appendix C

[6] The Qingyue Open Environment Data Center (https://data.epmap.org) is an organization which compiles environmental data from government sources and provides them freely to the public in standard data formats.
[7] The same six classifications were used both pre- and post-2014, though based on only three pollutants in the earlier period (Dong et al., 2021).

provides summary statistics for air pollution for each city, we can see that the five heaviest pollution regions are Hebei, Henan, Xinjiang, Tianjin, and Shanxi, and the five least pollution regions are Hainan, Tibet, Fujian, Yunnan, and Guangdong.

3.3. Descriptive statistics

We report the summary statistics of the full sample and the M&A subsample in Panels A and B, respectively, of Table 1. The full sample includes 22,327 firm-year observations of 3,564 firms while the M&A subsample consists of 3,541 firm-year observations of 1,600 firms. The mean and median of M&A are 0.120 and 0.000, respectively, and the mean and median of the average air pollution (AQI) are 0.082 and 0.079, respectively. The mean and median of the acquirer's air pollution, AAQI (target's air pollution, TAQI) in the M&A subsample are 0.083 (0.085) and 0.081 (0.082), respectively. These are in line with with previous studies, such as Li, Massa, Zhang, and Zhang (2021). The mean of State-owned enterprise (SOE) is 0.353, indicating that 35.3% of the observations in our sample are SOEs. The descriptive statistics of other variables are also in line with prior studies (Bonaime et al., 2018; Yang et al., 2022). We report the correlation coefficients among all variables specified in Appendix D. We notice that the correlation coefficients among all independent variables and control variables are all smaller than 0.6, indicating that multi-collinearity issue is not a serious concern in our study.

[Insert Table 1 here]

Following Nguyen et al. (2020), we divide the cities in two ways (quartile and bisection) based on the median level of AQI in each year. The univariate results presented in Table 2 provide preliminary evidence that firms headquartered in higher levels of air pollution conduct less M&A activities. For instance, when our sample is divided into high and low quartile subsamples based on the quartile level of air quality index, we find that the mean acquisitiveness for firms located in cities with high air quality index is 3.78% lower than their firms located in cities with low air quality index. And when our sample is divided into high and low two subsamples based on the median level of air quality index, we find that the mean acquisitiveness for firms located in cities with high air quality index is 1.38%, which is lower than their counterparts (Panels A and B in Table 2).

[Insert Table 2 here]

4. Empirical results

4.1. Baseline regression

We examine the effect of air pollution on firm acquisitiveness using the following logit model:

$$M\&A\ dummy_{i,t} = \alpha_0 + \beta_1 \times AQI/1000_{i,t} + \gamma \times Controls_{i,t} + \text{Year} + \text{Industry} + \varepsilon_{i,t} \qquad (1)$$

where M&A dummy is an indicator variable that takes a value of 1 if firm *i* makes at least one acquisition announcement in year *t*, and 0 otherwise. Air pollution is measured by the level of air quality index (AQI) of the city in which firm *i*'s headquarter is located. Following the M&A literature (Erel et al., 2012; Nguyen et al., 2020), we control for several firm characteristics which have power in explaining firm acquisitiveness, including size, leverage, sales growth, ROA, BM, cash holding, firm age, capital expenditure ratio, Institutional ownership, Top 5 concentration ratio, board size and independent director ratio (Dong, Hirshleifer, Richardson, & Teoh, 2006; Faccio & Masulis, 2005; Phan, 2014). Following Yang et al. (2022), we control for province Gross Domestic Product (GDP) growth and GDP per capita in our partial analysis, since corporate M&As might be correlated with local economic conditions. We additionally control for industry and year fixed effects in our M&A linear probability model and also cluster at the firm-level. The definition of all variables are presented in Appndix A.

Columns 1-2 of Table 3 reports the M&A linear probability model results. The coefficients of air pollution are negative (-6.009 and -4.323) and highly significant at 1% level. These results indicate that firms headquartered in more air pollution areas are less likely to pursue M&As. Since both the air pollution level and M&A activities could be correlated with the economic conditions of the firms' headquarters province, we further control for the natural logarithm of the province GDP per capita and province GDP growth rate in the M&A linear probability model and report the results in Column 3 of Table 3. We find that the coefficient of air pollution remains negative (-4.249) and statistically significant at the 1% level. Using the coefficient estimates of air pollution in Column 3, we illustrate the economic economic significance of the effect of air pollution: holding other variables unchanged at their sample means, a 1-standard-deviation increase in air pollution above its sample mean is associated with 11.47% (0.027 × -4.249 = -0.1147) decrease in acquisition probability[8].

[Insert Table 3 here]

4.2. Endogeneity tests

Our baseline regression results may suffer from potential endogeneity issues, such as omitted variables and reverse causality. In order to address these issues, we explore two methods: (1) instrumental variable (IV), and (2) quasi-experiment with propensity score matching.

4.2.1. Instrumental variable (IV) approach

We first explore exogenous variations of air pollution, building on knowledge obtained from the atmospheric environment literature. Following existing studies (Arceo, Hanna, & Oliva, 2016; Chen, Oliva, & Zhang, 2022), we introduce thermal inversions as the exogenous instrument variable (IV) for air pollution. A valid instrument should satisfy two conditions. First, the instrument should be strongly correlated with the variable of interest, that is, air pollution. Second, the instrument should not directly affect firms' M&A activities. Thermal

[8] Here, the number of 0.027 can be found in Table 1, which is the standard deviation of the air pollution variable.

inversions are a common exogenous meteorological phenomenon that leads to high concentrations of air pollutants near the ground level, thereby inducing severe air pollution[9]. Therefore, thermal inversions should be positively correlated with local air pollution and satisfy the relevant condition. Moreover, no existing theories or empirical evidence suggest that firms' M&A activities are driven by thermal inversions. Thus, thermal inversions should also satisfy the exclusion condition and serve as an appropriate instrument for local air pollution measures. We collect the calculated thermal inversions data from the WeChat Description Account. Following Wang et al. (2021),[10] we use the *Thermal_Inversion_Dummy* to represent whether the thermal inversions exist in the city in a given year, and the dummy variable equals one means there exists the thermal inversions in the city in a given year, and 0 otherwise.

Table 4 reports the IV test results. In the first stage result, the coefficients on *Thermal_Inversion_Dummy* is positive and significant at the 1% level, indicating that our instrumental variables are highly correlated with air pollution. The value of *F*-statistics indicates that our instrumental variable is valid and not weak. In the second stage analysis, the coefficient of M&A dummy is negatively and significantly related to air pollution at the 1% level, suggesting that our results are not influenced by potential endogeneity concerns such as omitted variables and reverse causality.

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[9] The underlying mechanism behind thermal inversions is as follows. Under normal conditions, temperature decreases as altitude increases. Given that air moves from hot to cool regions, air pollutants can circulate vertically, thereby decreasing air pollution concentrations near the ground. However, under certain meteorological circumstances (Arceo et al., 2016), the temperature of a layer of air above the ground can be higher than that at low altitudes, which leads to an inversion in the temperature/height gradient of thermal inversion. When this condition occurs, air pollutants are trapped near the ground level, thereby leading to high air pollution concentrations (Chen et al., 2022).

[10] Original data on thermal inversions are from MERRA-2, which divides the Earth into 0.5-degree × 0.625-degree (approximately 50 km×60 km) grids and records 6-h air temperature at 42 layers ranging from the surface to 36,000 m. Next, the temperature difference can be calculated through using the temperature in the second layer (320 m) minus the temperature in the first layer (110 m) within each 6-h period. Then, we can get the average temperature difference from the grid to the city level in a given year. If the difference is positive, then thermal inversions exist, and the dummy variable Thermal_Inversion_Dummy equals one. However, if the difference is negative, then such a condition is normal, and Thermal_Inversion_Dummy equals zero (Wang et al., 2021).

[Insert Table 4 here]

4.2.2. Quasi-experiment with propensity score matching

To substantiate the observed effects of air pollution on M&A activities, we introduce the quasi-experiment of the "Qinling-Huai River policy". As noted by Chen et al. (2013) and Li et al. (2019), the Huai River splits China into northern and southern parts, and China's central government provides free winter heating only in cities north of the Huai River. Because the centralized winter heating system rests on the use of inefficient coal-based hot water boilers, it leads to substantial energy loss and releases a significant amount of air pollutants. Such policy has uninteneded consequences worsening air quality in northern regions, and creating a discontinuity in terms of AQI for cities across the two sides of the Huai River (Lepori, 2016; Li et al., 2021). Thus, there may be observable differences between cities where firms are headquartered with and without central free heating. We use the propensity score matching approach to resolve this issue.

The results from the pre-matched logistic model are presented in column (1), Panel A of Table 5. Then, by applying one-to-one nearest-neighbour propensity score approach, each headquarter city with free heating is matched with the most similar firm that headquarter city without free heating. To improve the matching accuracy, we exclude the pairs with a propensity score difference larger than 1%. We conduct two diagnostic tests to ensure the matching accuracy. First, we re-conduct the logistic analysis using the propensity score-matched sample. The results are reported in column (2), Panel A of Table 5. All coefficients on independent variables in the post-matched logistic model become much smaller and insignificant, suggesting no observable difference between treatment and control after matching. Second, we compare each of the characteristics of firms with and without free heating using *t*-tests. The pre-matched *t*-tests results are reported in Panel B of Table 5, which reveals that firms are significantly different in their characteristics depending on whether they have free heating. The post-matched *t*-tests results are reported in Panel C of Table 5, which show no significant difference between firms with and without free heating in the propensity score-matched sample.

We then re-estimate the baseline regression controlling for industry and year fixed effects using the propensity score-matched sample. The results are reported in Panel D of Table 5, which shows that the coefficients on air pollution remain negative and statistically significant at 1% level. In general, the results of the propensity score matching analysis confirm that the results of Table 3 are robust.

[Insert Table 5 here]

4.3. Channel tests

4.3.1. Environmental governance cost

As discussed in Section 2, a negative association between air pollution and M&A activities may be driven by the positive impact of air pollution on firm environmental governance costs. Therefore, in this section, we analyse if improved environmental governance costs are indeed a channel through which air pollution reduces the firm's M&A activities. We construct firm's environmental investment (*En-Investment*) to proxy firm's environmental governance costs. The data for *En-Investment* is also from the CSMAR database. We utilize a two-stage least square (2SLS) approach to examine our the channel.

In the first stage, we examine if severe air pollution is associated with higher firm's environmental governance costs. The predicted values from the first stage regressions are then used as the independent variable in the second stage analysis. Results of the 2SLS channel analysis are shown in Panel A of Table 6. In column (1) of Panel A, we observe a positive and significant (at the 5% significance level) association between air pollution and *En-Investment*, indicating that severe air pollution is associated with higher firm's environmental governance costs. In columns (2) of Panel A, *Fitted_En-Investment* is negatively related to M&A activities and the result is statistically significant. Overall, our results are consistent with the argument that environmental governance cost is a channel through which air pollution reduces firm's M&A activities.

4.3.2. Financial constraints

Bond and Van Reenen (2007) argue that when firms face financial constraints, the negative cash flow shocks may lead to under-investment. We adopt two measures of financial constraints, namely net operating cash flow (CF) and SA index (SA)[11]. Results of the 2SLS channel analysis are reported in Panel B of Table 6. In columns (1) and (3), air pollution is negatively associated with *CF* and positively associated with *SA*, and the results are statistically significant at the 5% and 1% level respectively, indicating that air pollution is associated with lower net operating cash flow and higher financial constraints. In columns (2) and (4) of Panel B, *Fitted_CF* and *Fitted_SA* are both negatively and significantly associated with M&A activities, suggesting that financial constraint is indeed a channel through which air pollution reduces firm's M&A activities.

[Insert Table 6 here]

4.4. Further analysis

Until now, the results have presented whether and how the air pollution affect M&A decisions. In this section, we further examine the effect of air pollution on M&A payments choice, completion days, shareholder wealth creation, and the firm's long-term performance after the completion of M&As.

[11] SA index is an index reflecting the degree of financing constraint of a company. We obtain the SA index from the CSMAR database. The index is calculated as: (-0.737×Size) + (0.043×$Size^2$) – (0.040×Age), where size is the natural logarithm of total assets of firms, and age is the number of years between the observation year (current accounting period) and the firm establishment date (year). Regardless of absolute value, the larger the SA is (the closer it is to 0), the greater the financing constraint (Hadlock & Pierce, 2010).

4.4.1. Air pollution and M&A payments

The choice of payment method for M&A is a critical aspect of the M&A deal. Beyond the significant potential financial implications of this choice for the merging parties, this issue carry importance in firms' risk management strategy (Faccio & Masulis, 2005; Rhodes-Kropf & Viswanathan, 2004; Shleifer & Vishny, 2003). According to Ray (2022) and DePamphilis (2019), the payment methods of M&A can be divided into three types: cash payment method, stock payment method and, mixed payment method. Cash payment method is the simplest method of making the payment of M&A deals. Cash used in M&A transactions may be arranged by the acquiring company from internal sources or through additional debt. The main advantage of the cash payment method is that it keeps corporate identity and ownership structure remain unchanged (de Bodt, Cousin, & Officer, 2022; Sankar & Leepsa, 2018). Tan, Tan, et al. (2021) show that firms in higher air pollution areas are more likely to hold more cash to face pollution abatement and fewer bank loans. Stock payment method is a non-cash payment method in which acquiring companies issue their own equity shares to the target company as to seal the deal. Under this method, both the acquirer and target company share post-M&A deal outcomes and risks (Alshwer, Sibilkov, & Zaiats, 2011; Faccio & Masulis, 2005). Faccio and Masulis (2005) and Alshwer et al. (2011) develop a financial constraints hypothesis which explains that financially constrained firms are more likely to use stock payment method in a M&A deal. These findings suggest that acquirers in highly air pollution areas are more (less) likely to use stock (cash) as a medium of payment for acquisition deals. The mixed payment method is the combination of both cash and non-cash payment method. In this payment method, the purchase consideration is discharged through a mixture of cash, stock, and debt (DePamphilis, 2019)[12].

[12] An extensive literature review of this field is beyond the scope of our work.

We use the following linear probability model to examine the relation between air pollution and payment consideration:

$$Cash\ dummy_{i,j} = \alpha + \beta \times AAQI/1000_{i,t} + \gamma \times TAQI/1000_{i,t} + \lambda \times Controls_{i,t} + \text{Year} + \text{Industry} + \varepsilon_{i,j,t} \quad (2)$$

$$Stock\ dummy_{i,j} = \alpha + \beta \times AAQI/1000_{i,t} + \gamma \times TAQI/1000_{i,t} + \lambda \times Controls_{i,t} + \text{Year} + \text{Industry} + \varepsilon_{i,j,t} \quad (3)$$

where cash (stock) dummy is an indicator variable that takes a value of 1 if the payment for M&A deal *j* of firm *i* is fully in cash (stock), and 0 otherwise. AAQI (TAQI) is the level of air pollution in the acquirer (target) headquarter city. Following previous studies (Dong et al., 2006; Faccio & Masulis, 2005; Phan, 2014), we control for firm and deal characteristics such as size, BM, sales growth, leverage, cash holdings, capital expense, firm age, deal ratio, diversifying dummy, Intellectual Property dummy, etc. In addition, we also control the industry and year fixed effects. Appendix A provides the description of the variables.

The results of the payment consideration regression reported in Table 7 indicate that, on average, the level of air pollution in an acquirer area is negatively (positively) related to the likelihood of cash (stock) payment. The results are also robust when we add four dummy variables (Deal ratio, Diversifying dummy, Intellectual Property dummy, and Cross-city dummy) as controls. These results are consistent with our predictions that high air pollution in the city where the firm is located drives higher financial constraints, higher environmental investment, and lower operating cash flow. As a result, when a firm pays for deals of M&A, it prefers to use stock as payment method.

[Insert Table 7 here]

4.4.2. Air pollution and completion days

In this section, we examine the effect of air pollution on the number of days the M&A is completed. The literature on mergers and acquisitions (M&As) to date has primarily focused on the motivations for M&As, the realization of synergies, the implications on stock prices, and post-M&A integration. Few studies examine fundamental factors that affect the time interval between acquisition announcements and effective completion, such as the deal duration or completion time. (Luypaert & De Maeseneire, 2015; Thompson & Kim, 2020).

Ekelund Jr, Ford, and Thornton (2001) find that more complex deals evidently result in longer completion times. For example, stock offers require much more administrative burden than cash transactions. Similar to tender offers, mergers frequently take longer to complete compared to tender offers since shareholders must provide their approval. Hostile bids also take longer time because target shareholders must be convinced of the deal's appeal while potential acquirers may also need to fend off any takeover defence mechanisms. Likewise, acquisitions of large companies are likely to increase deal complexity given that they consist of multiple business units and are better armed to resist a hostile bid. Luypaert and De Maeseneire (2015) find the evidence that deal complexity critically affects the time to completion. Stock offers, deal hostility, mergers and larger deals are characterized by a lengthier acquisition duration. This demonstrates that longer completion durations are caused by the complexity of the deal itself. We explore whether as an external factor, air pollution has any bearing on how quickly M&A agreements are reached. Given that these exists a negative association between air pollution and M&A announcements and cash payments, and there are direct and indirect costs for firms involving air pollution, we predict a significant negatively relation between air pollution and the completion days of M&A deals.

The results are reported in Table 8 indicate that, on average, the level of air pollution in an acquirer area is positively related to the completion days of M&A deals, this means that M&A

deals take longer to complete in areas with higher levels of air pollution for acquirers. The results are also robust when we add four variables (Deal ratio, Diversifying dummy, Intellectual Property dummy, and Cross-city dummy) which are related to the M&A characteristics as controls. Our results, thus, confirms that firms take longer to complete acquisitions as a result of excessive air pollution.

[Insert Table 8 here]

4.4.3. Air pollution and firm's performance

In this section, we examine, first, whether air pollution affect shareholder wealth of acquiring firms around the announcements of M&As. and second, the long-term performance of the firms after the M&A deals. To check the welth effect, we calculate the Cumulative Average abnormal returns (CAARs) of the acquiring firms. CAARs around the merger announcement periods provide a clean estimation of the market's reception of the news announcement and the underlying wealth effects (Rahayu & Wardana, 2021). We expect the level of air pollution in an acquirer headquarter city to be negatively related to its shareholder wealth due to the direct and indirect costs associated with air pollution.

Panels A and B of Table 9 report the Average Abnormal Return (AAR) and Cumulative Average Abnormal Return (CAAR) summary statistics for acquire firms. Using the CSI300 index returns as the market returns, we estimate the market model to calculate two-day CARs of the acquiring firms. The length of the estimation window covers 250 trading days prior to each M&A announcement event till the day before each announcement (Meyer, Gremler, & Hogreve, 2014). The event date refers to the announcement date of each M&A. We delete multiple M&As for each firm within 250 trading days and only keep the earliest one. The means of the average abnormal returns (AARs) five days before and after the announcement event reported in Panel A are significant different from zero. Similarly, the means of CAARs reported in Panel B for different windows ranging from [-5, 0] to [-5, +5] are statistically significantly different from zero. However, the cross-sectional regressions of CAARs on AAQI, TAQI, and other firm and deal characteristics reported in Panel C only for the two-day abnormal stock returns, CAAR [-1, 0]. The coefficient on AAQI is negative and statistically significant ($p < 0.05$) which is consistent with our expectations. Such results are also economically significant. One-standard-deviation increase in AAQI above its sample mean is associated with 22 basis points (i.e., 0.22%) decrease in acquirer shareholder value holding other variables fixed at their sample means

Since air pollution is related to environmental issues/risks posing unique challenges for firms, it may raise their operational and financial risks affecting their long-run performance, and lead to changes in their policies and behaviour (Liu et al., 2021; Tan, Tan, et al., 2021; Tan & Yan, 2021). To check the long-run performance, we run regressions of ROA and Growth rate of acquiring firms one year after M&A deals on AAQI, TAQI, and other firms and deals charatictistics. We report the results in Panels A and B of Table 10. We find that the coessicient estimates of AAQI negative at 5% signifance level, irrepspective of models. Thus, the the results imply that that air pollution is negatively affect the long-term performance of the aquiring forms.

[Insert Table 9 here]

[Insert Table 10 here]

4.5. Heterogeneity tests

Our findings thus far support the hypothesis that air pollution is negatively associated with firm's M&A activities. Firms located in areas with high levels of air pollution experience operational and financial issues as a result of government rules and restrictions (Tan et al., 2022; Tan, Zhang, et al., 2021). Internal characteristics and external support characteristics may moderate the impacts of such rules and restrictions. According to Lin, Huang, and Yao (2021), firms with environmental information disclosure are more likely to be impacted by air pollution. Bao and Liu (2022) finds that environmental attention in developed provinces such as southern regions is higher compared with the northern regions. And the governments in southern regions pay more attention to environmental issues and deal with air pollution issues positively. In addition, due to the Qinling-Huai River policy[13] the average air quality in these southern provinces is better than the northern provinces. Thus, a natural question arises whether our baseline results are more pronounced for acquiring firms with environmental information disclosures, firms located in well-developed provinces, and less polluted provinces.

According to Solikhah and Maulina (2021), environmental disclosures by firms represents a form of corporate responsibility to society as they inform people about firm-level activities which have resulted in negative impact on the environment. Zhang, Zhang, Qiao, Li, and Li (2022) find that environmental information disclosures significantly boosts and encourages green innovation. Thus, we expect that the impact of air pollution on firm's M&A activities is more salient for firms with environmental disclosures. According to Huang, Ding, and Failler (2022), the improvement of government environmental attention inhibits ambient pollution through green development and industrial upgrading, however, this phenomenon generally more pronounced in developed countries. White and Hunter (2009) find that balancing environmental quality with economic growth in less developed settings is clearly a challenge. Thus, we expect that firms are more likely to pay more attention to environmental issues if they are located in well-developed provinces and also in less polluted provinces. In other words, the impact of air pollution on M&A activities is more salient for firms located in more developed

[13] The Huai River splits China into northern and southern parts, and China's central government provides free winter heating only in cities north of the Huai River. Because the centralized winter heating system rests on the use of inefficiently coal-based hot water boilers, which leads to substantial energy loss and releases a significant amount of air pollutants. This policy has unintentionally worsened air quality in northern regions, creating a discontinuity in terms of AQI for cities across the two sides of the Huai River (Lepori, 2016; Li et al., 2021).

and less pollured provinces.

We identify firms with environmental disclosures by checking whether information on the environment is included in the listed firms' annual reports. The we divide samples in two groups. We also divide sample firms located in developed or developing provinces based on the Fan-Gang index[14]. Finally, we divide the sample into more polluted and less polluted provinces based on the median level of the air quality index of acquirers' location.

All regreesion results are reported in Table 10, where each regression includes GDP growth and per capita GPD of provinces as addiotional controls along with other firm-level charactarestics. Columns (1), (3) and (5) show that the estimated coefficients of AQI are -4.687, -5.377, and -8.340 for firms with environmental information disclosures, firms located in developed provinces, and firms located in less polluted provinces, respectively, with signicance level at 1%. The findings are consistent with our conjectures.

[Insert Table 11 here]

4.6. Robustness checks

We conduct a series of robustness checks on the baseline results. Firstly, we add more fixed effects and use the alternative model with high frequency fixed effects, and seasonal effect to verify our results again. We then change the dependent and independent variables' measurements as well as the sample's time period to conduct the robustness checks. The models include all the controls present in the baseline tests. For brevity, we do not present the coefficients of control variables.

The findings for the first part are presented in Panels A–C of Table 12. In Panel A, we add the

[14] Fan-Gang index, also known as the marketization index, is an index system that measures the relative progress of marketization in provinces, autonomous regions, and municipalities across the country in the form of indexes. The larger the index, the higher the degree of marketization. The data from the China Market Index Database.

province fixed effect based on our model in Eq. (1). The coefficients in Panel A are negative and significant at the 10% levels across all columns. In Panel B, we run the relationship between air pollution and M&As using the alternative model with high-density fixed effects in Eq. (4)[15]. We use the following year's M&A announcements as our dependent variable and control the firm, year, industry, and province's four fixed effects. The coefficients in panel B are still negative and significant at the 5% and 10% levels across all columns. The findings support our baseline results. Thus, using the alternative model or different fixed effects do not change the baseline findings.

$$M\&A\ dummy_{i,t+1} = \alpha_0 + \beta_1 \times AQI/1000_{i,t} + \gamma \times Controls_{i,t} + \text{Firm} + \text{Year} + \text{Industry} + \text{province} + \varepsilon_{i,t} \quad (4)$$

According to the Qinling-Huai River policy discussed above, China's central government provides free winter heating. As the centralized winter heating system rests on the use of inefficiently coal-based hot water boilers, free winter heating would cause air pollution in winter worse than in other seasons. In Panel C, we choose the monthly average AQI during the winter season (November to January) and other seasons (February to October) of the city where the firm *i*'s headquarters located as our main independent variables, to see if our results are only driven by air pollution in winter. This helps us control the seasonal influence and examine if winter is the only driving factor for our baseline results. The coefficients in Panel C are still negative and significant at the 1% and 5% levels across all columns, which robust our baseline results and demonstrate that the winter season is not a driving factor for the relationship between air pollution and M&A deals.

[Insert Table 12 here]

The findings for the second part are presented in Panels A–D of Table 13. In Panel A, we use

[15] Here, we also check all our results in this paper using the new model, the results are quantitatively similar.

the expense value of the M&A paid by acquirers as the proxy for the M&A dummy in Eq. (1). In Panels B and C, we use PM2.5, which is the logarithm value of the average yearly level of PM2.5 in each acquirer's city obtained from CSMAR, and the natural logarithm of the yearly average AQI in each acquirer's city, as the proxy for AQI (air pollution) in Eq. (1). In panel D, we run the baseline results using the sample period from 2013 to 2020 as a robustness check. The coefficients in both panels are still negative and significant at the 1% level across columns (1)–(3). The findings support those in Table 3. Thus, using an alternative metrics for M&A and air pollution do not change the baseline findings.

[Insert Table 13 here]

5. Conclusion

This paper examines the impact of air pollution on corporate M&A activities in China. We find that there is a negative impact between air pollution and the firm's M&A activities. The results remain robust after mitigating endogeneity concerns and using alternative measures of air pollution and M&A happened. More importantly, we discover that more environmental governance costs and tightened financial constraint is a channel through which air pollution reduces M&A activities. We also find that the negative impact of air pollution on M&A activities is more pronounced in firms located in more developed regions, less polluted provinces, and firms with environmental disclosure, suggesting that the less polluted provinces, developed regions and firms with environmental information disclosure pay more attention to the air pollution issues. Furthermore, we did some tests to show if air pollution impacts the M&A deals' payment consideration. The results are also consistent with our channel test, which indicates that there is a negative (positive) relation between the air pollution levels in the acquirer areas and the likelihood of all-cash (stock) payment. It shows that firms in air pollution areas are more likely to face financial constraints and prefer to use stock payment in M&A

deals.

Table 1. Summary statistics

This table presents the summary statistics for the sample: mean, median, minimum, maximum, standard deviation, 25%,75%, and skewness of variables. In panel A, the M&A dummy is an indicator variable that takes a value of 1 if firm *i* makes at least one acquisition announcement in year *t*, and 0 otherwise. Air pollution is the yearly average Air Quality Index (AQI) in which a firm is headquartered. AAQI is the yearly average Air Quality Index (AQI) of each acquirer's city. In Panel B, TAQI is the yearly average Air Quality Index (AQI) of each target. We divide AAQI (TAQI) by 1000 for ease of interpretation of the regression coefficients. The definitions of the variables are provided in Appendix A. We winsorize the data at the 1% and 99% levels.

Panel A: Full Sample									
Variable	N	Mean	Median	Min	Max	STD	Q1	Q3	Skew.
M&A	22,327	0.120	0.000	0.000	1.000	0.325	0.000	0.000	2.338
Air pollution	22,327	0.082	0.079	1.25e-4	0.251	0.027	0.066	0.091	1.900
Size	22,327	22.142	21.947	19.673	26.161	1.323	21.187	22.889	0.754
Lev	22,327	0.423	0.414	0.053	0.922	0.211	0.252	0.580	0.241
ROA	22,327	0.038	0.039	-0.278	0.192	0.062	0.015	0.068	-1.793
Growth	22,327	0.177	0.096	-0.570	2.923	0.448	-0.013	0.262	3.422
BM	22,327	0.612	0.611	0.102	1.143	0.249	0.423	0.800	0.012
CH/at	22,327	0.017	0.004	-0.229	0.472	0.098	-0.022	0.039	1.784
List age	22,327	2.031	2.197	0.000	3.296	0.910	1.386	2.833	-0.629
Capex/at	22,327	0.048	0.034	2.1e-4	0.222	0.046	0.014	0.067	1.560
INST	22,327	0.063	0.064	3.2e-4	0.147	0.040	0.027	0.095	-0.105
Top 5	22,327	0.545	0.547	0.197	0.892	0.152	0.431	0.658	-0.056
BoardSize	22,327	2.128	2.197	1.609	2.708	0.200	1.946	2.197	-0.284
IndepR	22,327	0.376	0.364	0.125	0.571	0.053	0.333	0.429	1.306
Dual	22,327	0.281	0.000	0.000	1.000	0.449	0.000	1.000	0.974
SOE	22,327	0.353	0.000	0.000	1.000	0.478	0.000	1.000	0.616
Polluter	22,327	0.264	0.000	0.000	1.000	0.441	0.000	1.000	1.069
Panel B: M&A Subsample of acquisitions									
Variable	N	Mean	Median	Min	Max	STD	Q1	Q3	Skew.
AAQI	3,541	0.083	0.081	0.045	0.177	0.025	0.065	0.096	1.067
TAQI	3,541	0.085	0.082	0.045	0.179	0.025	0.069	0.098	1.070
Deal ratio	3,541	0.285	0.068	1e-4	5.767	0.764	0.016	0.219	5.415
Size	3,541	21.985	21.881	19.658	23.309	1.086	21.250	22.667	0.529
Lev	3,541	0.412	0.400	0.057	0.884	0.192	0.261	0.552	0.279
ROA	3,541	0.035	0.037	-0.216	0.173	0.053	0.015	0.062	-1.509
Growth	3,541	0.317	0.192	-0.631	4.330	0.645	0.025	0.411	3.654
BM	3,541	0.521	0.517	0.000	1.060	0.254	0.339	0.712	0.020
CH/at	3,541	0.011	0.002	-0.243	0.414	0.094	-0.028	0.038	1.245
List age	3,541	2.038	1.946	0.693	3.296	0.737	1.386	2.708	0.049
Capex/at	3,541	0.043	0.030	2.4e-4	0.209	0.042	0.012	0.058	1.701

Continue

INST	3,541	0.060	0.059	8.2e-5	0.140	0.037	0.028	0.089	0.144
Top 5	3,541	0.525	0.529	0.200	0.832	0.141	0.423	0.628	-0.070
BoardSize	3,541	2.102	2.197	1.609	2.565	0.188	1.946	2.197	-0.529
IndepR	3,541	0.376	0.333	0.215	0.571	0.052	0.312	0.429	1.171
Dual	3,541	0.329	0.000	0.000	1.000	0.470	0.000	1.000	0.728
SOE	3,541	0.198	0.000	0.000	1.000	0.399	0.000	0.000	1.514
Polluter	3,541	0.246	0.000	0.000	1.000	0.431	0.000	0.000	1.176

Table 2. Univariate results

The table reports the results of univariate analysis on the quartile and bisection differences of M&A decisions between low and high air quality index regions. The value for differences is based on *t*-test. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Four quartiles						
	Bottom Quartile		Top Quartile		Diff	T-value
	N	Mean	N	Mean		
M&A decisions	5,689	14.80%	5,381	11.02%	3.78%**	5.92

Panel B: Median						
	Below Median		Above Median		Diff	T-value
	N	Mean	N	Mean		
M&A decisions	11,364	12.68%	10,963	11.30%	1.38%***	3.17

Table 3. Baseline regression
Air pollution and firm acquisitiveness.

This table reports the results of baseline regressions. It shows the impact of air quality in acquirers' city on the M&A deals' decisions. The dependent variable is the M&A dummy that takes a value of 1 if firm *i* makes at least one acquisition announcement in year t, and 0 otherwise. The main independent variable is Air pollution, measured by the level of air quality index of the city where firm *i*'s headquarters located. Definitions of variables are presented in Appendix A. The *t*-statistics are reported in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	M&A	M&A	M&A
	(1)	(2)	(3)
Air pollution	-6.009***	-4.323***	-4.249***
	(-5.82)	(-4.00)	(-3.87)
Size		0.025	0.025
		(0.82)	(0.81)
Lev		0.285**	0.284**
		(2.07)	(2.06)
ROA		-0.939	-0.943
		(-1.27)	(-1.28)
Growth		0.387***	0.387***
		(9.15)	(9.16)
BM		-0.808***	-0.805***
		(-5.19)	(-5.15)
CH/at		0.166	0.171
		(0.69)	(0.71)
Capex/at		-1.900***	-1.904***
		(-3.49)	(-3.50)
INST		-0.123	-0.120
		(-0.16)	(-0.15)
Top 5		0.017	0.018
		(0.09)	(0.10)
ListAge		0.205***	0.207***
		(5.28)	(5.28)
BoardSize		-0.554***	-0.554***
		(-4.03)	(-4.03)
IndepR		-0.981**	-0.983*
		(-1.96)	(-1.96)
Dual		0.047	0.048
		(0.97)	(0.98)
SOE		-0.889***	-0.890***
		(-13.84)	(-13.86)
Polluter		-0.074	-0.075

Continue

		(-1.29)	(-1.30)
GDP growth			0.183
			(0.12)
GDP per capita			0.795
			(0.62)
Constant	-3.628***	-2.485***	-2.650***
	(-12.00)	(-3.47)	(-3.60)
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
N	22,327	22,327	22,327
Pseudo R-squared	0.061	0.095	0.095

Table 4. Instrumental variable tests

Table 4 reports the results of 2SLS instrumental variable analysis, consisting of 22,327 firm-year observations. The dependent variable is the M&A dummy, which takes a value of 1 if firm *i* makes at least one acquisition announcement in year *t*, and 0 otherwise. The main independent variable is air pollution, which is measured by the level of air quality index of the city where firm *i*'s headquarters located. The instrumental variable is thermal inversion in each city. Definitions of variables are presented in Appendix Table 1. The *t*-statistics are reported in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	First Stage	Second Stage
Dependent Variable	Air pollution	M&A
	(1)	(3)
Air pollution		-0.824**
		(-2.45)
Thermal_Inversion_Dummy*t*	0.004***	
	(13.57)	
Size	0.003	0.003
	(0.12)	(1.22)
Lev	0.042***	0.019
	(3.27)	(1.35)
ROA	-0.001	-0.186
	(-0.31)	(-4.63)
Growth	0.004	0.057***
	(1.27)	(11.34)
BM	0.003***	-0.076***
	(4.11)	(-5.60)
CH/at	0.002	0.005
	(0.24)	(0.27)
Capex/at	-0.019***	-0.213***
	(-5.94)	(-4.04)
INST	0.015***	-0.039
	(3.24)	(-0.51)
Top 5	-0.004***	0.002
	(-3.87)	(0.12)
ListAge	-0.001***	0.020***
	(-4.55)	(5.38)
BoardSize	-0.003	-0.050***
	(-0.32)	(-3.52)
IndepR	-0.013***	-0.072*
	(-4.40)	(-1.45)
Dual	-0.002***	0.005
	(-5.08)	(0.93)
SOE	0.004***	-0.080***
	(10.98)	(-12.43)

Continue

Polluter	0.001***	-0.009
	(2.88)	(-1.55)
Industry	Yes	Yes
Year	Yes	Yes
N	22,327	22,327
Adj R-squared	0.173	0.061
Cragg-Donald Wald F statistic	967.603	-
	(0.00)	

Table 5. Propensity scores matching analysis

Table 5 presents the results of a propensity score matching analysis. Panel A reports the parameter estimates from the logit model used to estimate propensity scores. Free heating (FH) cities are the independent variable, which is a dummy variable that equals 1 if the city is provided with free heating during the winter by the government under the Qinling-Huai River (QH) heating policy, and 0 otherwise. Panels B and C present the differences in characteristics between with free heating cities and without free heating cities and the corresponding t-values in both pre- and post-match samples. Panel D reports the results of re-estimating the regression in Table 3 using the propensity score-matched sample. The dependent variable is the M&A dummy that takes a value of 1 if firm *i* makes at least one acquisition announcement in year *t*, and 0 otherwise. The main independent variable is Free heating (FH) cities, which is a dummy variable that equals 1 if the city is provided with free heating during the winter by the government under the QH heating policy, and 0 otherwise. Definitions of variables are in Appendix Table 1. *z*-statistics (*t*-statistics) are calculated based on robust standard errors and are reported in parentheses. The superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Pre-matched propensity score regression and post-matched regression

	Dependent Variable: *M&A*	
	Pre-match	Post-match
	(1)	(2)
Size	0.163***	-0.022
	(9.34)	(-1.00)
Lev	-0.082***	0.113
	(-0.92)	(1.01)
ROA	-1.318***	0.318
	(-4.78)	(0.90)
Growth	0.084**	-0.013
	(2.53)	(-0.31)
BM	-0.260***	0.072
	(-3.33)	(0.73)
CH/at	0.117	0.053
	(1.25)	(0.18)
Capex/at	-1.937***	0.149
	(-5.26)	(0.34)
INST	0.064	0.421
	(0.12)	(0.64)
Top 5	-0.569***	0.053
	(-4.63)	(0.34)
ListAge	-0.120	-0.023
	(-0.497)	(-0.75)
BoardSize	0.395***	-0.059
	(4.23)	(-0.51)
IndepR	0.520	0.182
	(1.59)	(0.44)
Dual	-0.161***	0.035

Continue

	(-4.51)	(0.74)
SOE	0.612***	0.088*
	(16.67)	(1.93)
Polluter	0.217***	0.008
	(6.56)	(0.20)
Constant	-4.697***	0.254
	(-11.96)	(0.51)
Industry	Yes	Yes
Year	Yes	Yes
Observations	22,327	11,958
Pseudo R^2	0.033	0.001

Panel B. Pre-matched differences in characteristics between with free heating cities and without free heating cities

Variables	No. of observations if *FH cities*= 1	Mean if *FH cities* =1	No. of observations if *FH cities* = 0	Mean if *FH cities* = 0	Mean Difference	*t*-value
Size	7,465	22.233	14,862	22.037	0.196***	10.17
Lev	7,465	0.438	14,862	0.418	0.020***	6.59
ROA	7,465	0.036	14,862	0.040	-0.004***	-5.06
Growth	7,465	0.186	14,862	0.194	0.003	-1.10
BM	7,465	0.630	14,862	0.596	0.034***	9.19
CHTA	7,465	0.015	14,862	0.018	-0.003	-1.61
Capex/at	7,465	0.047	14,862	0.050	-0.003***	-4.08
INST	7,465	0.065	14,862	0.062	0.003***	4.52
Top 5	7,465	0.544	14,862	0.543	0.001	0.86
ListAge	7,465	2.045	14,862	2.026	0.019	1.47
BoardSize	7,465	2.139	14,862	2.128	0.011***	3.78
IndepR	7,465	0.374	14,862	0.376	-0.002	-1.45
Dual	7,465	0.246	14,862	0.292	-0.046***	-7.11
SOE	7,465	0.412	14,862	0.332	0.080***	11.42
Polluter	7,465	0.292	14,862	0.246	0.046***	7.10

Panel C. Post-matched differences in characteristics between with free heating cities and without free heating cities

Variables	No. of observations if *FH cities* =1	Mean if *FH cities* =1	No. of observations if *FH cities* =0	Mean if *FH cities* =0	Mean Difference	*t*-value
Size	5,979	22.313	5,979	22.307	0.006	0.23
Lev	5,979	0.447	5,979	0.446	0.001	0.13
ROA	5,979	0.035	5,979	0.035	0.000	0.15
Growth	5,979	0.177	5,979	0.176	0.001	0.07
BM	5,979	0.632	5,979	0.633	-0.001	-0.19

Continue

CHTA	5,979	0.015	5,979	0.017	-0.002	-1.11
Capex/at	5,979	0.045	5,979	0.045	0.000	0.16
INST	5,979	0.068	5,979	0.067	0.001	0.44
Top 5	5,979	0.540	5,979	0.539	-0.001	-0.35
ListAge	5,979	2.156	5,979	2.157	-0.001	-0.06
BoardSize	5,979	2.145	5,979	2.143	0.002	0.69
IndepR	5,979	0.375	5,979	0.374	0.001	0.01
Dual	5,979	0.226	5,979	0.231	-0.005	-0.54
SOE	5,979	0.480	5,979	0.472	0.008	0.85
Polluter	5,979	0.287	5,979	0.289	-0.002	-0.25

Panel D. Matched sample regression analysis

Variables	M&A
Air pollution (Free heating cities)	-4.582***
	(-3.17)
Size	0.021
	(0.52)
Lev	0.137
	(0.73)
ROA	-0.951
	(-0.77)
Growth	0.435***
	(8.07)
BM	-0.841***
	(-4.41)
CH/at	-0.028
	(-0.90)
Capex/at	-1.967**
	(-2.43)
INST	-0.565*
	(-0.52)
Top 5	-0.067
	(-0.26)
ListAge	0.170***
	(3.23)
BoardSize	-0.518**
	(-2.57)
IndepR	-1.173*
	(-1.65)

Continue

Dual	0.067
	(0.93)
SOE	-0.794***
	(-9.90)
Polluter	-0.090
	(-1.16)
Constant	-2.097**
	(-2.13)
Industry	Yes
Year	Yes
Observations	11,958
Pseudo R^2	0.089

Table 6. Channel tests

This table the results of channel analysis on firm's environmental governance costs and financial constraints. Panel A presents the results of environmental governance costs. Panel B presents the results of financial constraints. The first stage results are reported in column 1 of Panel A and columns (1) and (3) of panel B. Results of the second stage regressions are shown in column (2) of Panel A and columns (2) and (4) of Panel B. Detailed definitions of variables are given in Appendix A. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Environmental governance costs		
Variables	(1)	(2)
	En-Investment	M&A
Air pollution	1.966**	
	(2.02)	
Fit_ En-Investment		-0.015***
		(-2.92)
Constant	0.175	-2.929***
	(0.24)	(-3.46)
Controls	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
N	22,327	22,327
Adj/ Pseudo R-squared	0.000	0.094

Panel B: Financial constraints				
Variables	(1)	(2)	(3)	(4)
	CF	M&A	SA	M&A
Air pollution	-0.739**		0.459***	
	(-2.39)		(6.95)	
Fit_CF		-0.049*		
		(-1.81)		
Fit_SA				-2.196***
				(-3.99)
Constant	3.834***	-2.916**	-4.490***	-2.159**
	(16.75)	(-3.30)	(-79.30)	(-2.46)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	22,327	22,327	22,327	22,327
Adj/ Pseudo R-squared	0.324	0.096	0.378	0.095

Table 7. Air pollution and M&A payments

This Table reports the results of the payment consideration linear logit models. The dependent variable in columns (1) and (2) is cash dummy that equals 1 if the payment for an M&A deal is fully in cash, and 0 otherwise, which in columns (3) and (4) is stock dummy that equals 1 if the payment for an M&A deal is fully in stock, and 0 otherwise. AAQI (TAQI) is the yearly average Air Quality Index (AQI) divide 1000 of each acquirer's (target's) city. Other variables are defined in Appendix A. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	Cash dummy	Cash dummy	Stock dummy	Stock dummy
	(1)	(2)	(3)	(4)
AAQI	-4.004**	-4.345**	7.212***	7.093***
	(-2.19)	(-2.36)	(2.85)	(2.78)
TAQI	2.158	2.081	2.924	2.919
	(1.19)	(1.14)	(1.16)	(1.15)
Deal ratio		-1.343***		0.157***
		(-9.54)		(4.04)
Diversifying dummy		-0.383***		0.105
		(-3.01)		(0.59)
Cross-city dummy		0.002		-0.304**
		(0.02)		(-2.37)
Intellectual Property dummy		-1.128		0.771
		(-0.90)		(0.78)
Constant	2.589	3.532**	-0.196	-0.167
	(1.59)	(2.13)	(-0.09)	(-0.08)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	3,541	3,541	3,541	3,541
Pseudo R-squared	0.186	0.190	0.120	0.123

Table 8. Air pollution and completion days

This table reports the relationship between AAQI, TAQI and completion days for M&A deals. The dependent variable is completion days, which is measured as the natural log of finish declare date minus first declare date, log (finish declare date - first declare date). AAQI (TAQI) is the yearly average Air Quality Index (AQI) divide 1000 of each acquirer's (target's) city. Other variables are defined in Appendix A. *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	Completion days	Completion days
	(1)	(2)
AAQI	2.437**	2.516**
	(2.42)	(2.50)
TAQI	0.537	0.593
	(0.53)	(0.59)
Deal ratio		0.006**
		(2.10)
Diversifying dummy		0.110
		(1.79)
Cross-city dummy		-0.045
		(-0.88)
Intellectual Property dummy		0.619
		(1.39)
Constant	5.129***	4.939***
	(6.44)	(6.14)
Controls	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
N	2,736	2,736
Adj R-squared	0.010	0.100

Table 9. Air pollution and shareholder value

This table reports results of the acquirer CAR cross-sectional regressions. Panels A and B show the summary statistics of Average Abnormal Return (AAR) and Cumulative Average Abnormal Return (CAAR) of Acquire Firms. In panel C, the dependent variable CAR [-1, 0] is acquirer two-day CARs centred on the M&A announcement days. AAQI (TAQI) is the yearly average Air Quality Index (AQI) divide 1000 of each acquirer's (target's) city. Other variables are defined in Appendix A. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Average Abnormal Return (AAR) of Acquire Firms

Event Day	N	Mean	Median	Min	Max	STD	Q1	Q3	Skew.
-5	3,273	0.001**	-0.001	-0.061	0.086	0.024	-0.013	0.011	0.774
-4	3,273	0.001***	-0.001	-0.060	0.083	0.025	-0.012	0.012	0.665
-3	3,273	0.001***	-0.001	-0.067	0.096	0.026	-0.013	0.013	0.786
-2	3,273	0.002***	-0.001	-0.073	0.087	0.026	-0.012	0.013	0.520
-1	3,273	0.005***	0.001	-0.081	0.099	0.031	-0.012	0.018	0.626
0	3,273	0.017***	0.011	-0.128	0.153	0.065	-0.016	0.080	0.193
1	3,273	0.010***	-0.000	-0.119	0.136	0.057	-0.022	0.047	0.170
2	3,273	0.006***	-0.003	-0.106	0.129	0.050	-0.020	0.024	0.503
3	3,273	0.003***	-0.003	-0.105	0.132	0.045	-0.021	0.018	0.634
4	3,273	0.002***	-0.002	-0.099	0.115	0.040	-0.019	0.016	0.674
5	3,273	0.000**	-0.004	-0.095	0.116	0.037	-0.018	0.011	0.797

Panel B: Cumulative Average Abnormal Return (CAAR) of Acquire Firms

Event Window	N	Mean	Median	Min	Max	STD	Q1	Q3	Skew.
CAAR [-5, 0]	3,273	0.005***	0.004	-0.034	0.048	0.015	-0.004	0.014	0.221
CAAR [-3, 0]	3,273	0.007***	0.005	-0.047	0.065	0.021	-0.006	0.020	0.173
CAAR [-1, 0]	3,273	0.012***	0.008	-0.081	0.098	0.036	-0.008	0.040	0.067
CAAR [0, +1]	3,273	0.014***	0.005	-0.114	0.131	0.055	-0.013	0.051	0.005
CAAR [0, +3]	3,273	0.009***	0.002	-0.097	0.112	0.042	-0.010	0.025	0.403
CAAR [0, +5]	3,273	0.007***	0.001	-0.081	0.102	0.034	-0.008	0.016	0.735
CAAR [-1, +1]	3,273	0.012***	0.005	-0.079	0.097	0.038	-0.009	0.037	0.091
CAAR [-3, +3]	3,273	0.007***	0.002	-0.057	0.071	0.025	-0.006	0.016	0.483
CAAR [-5, +5]	3,273	0.005***	0.001	-0.043	0.062	0.019	-0.005	0.011	0.787

Panel C: Air pollution and acquirer's CAAR

Variables	CAAR [-1, 0]	CAAR [-1, 0]	CAAR [0, 1]	CAAR [0, 1]
	(1)	(2)	(3)	(4)
AAQI	-0.063**	-0.062**	0.008	-0.002
	(-2.09)	(-2.06)	(0.17)	(-0.03)
TAQI	0.045	0.042	-0.023	-0.023
	(1.47)	(1.39)	(-0.50)	(-0.49)
Deal ratio		-0.000		-0.000
		(-0.71)		(-1.31)

Continue

Diversifying dummy		0.004**		0.007**
		(2.03)		(2.33)
Cross-city dummy		0.003*		0003
		(1.84)		(1.42)
Intellectual Property dummy		0.021		0.045*
		(1.31)		(1.90)
Constant	0.118***	0.111***	0.027**	0.133***
	(5.23)	(4.92)	(2.01)	(3.88)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	3,273	3,273	3,273	3,273
Adj R-squared	0.075	0.077	0.086	0.095

Table 10. Air pollution and long-term benefits

This table reports the results of the acquirer's ROA and Growth in one year after M&A deals happened. AAQI (TAQI) is the yearly average Air Quality Index (AQI) divide 1000 of each acquirer's (target's) city. Other variables are defined in Appendix A. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	ROA_{t+1}	ROA_{t+1}	$Growth_{t+1}$	$Growth_{t+1}$
	(1)	(2)	(3)	(4)
AAQI	-0.142**	-0.141**	-1.837**	-1.754*
	(-2.55)	(-2.55)	(-1.82)	(-1.74)
TAQI	0.068	0.065	0.391	0.414
	(1.22)	(1.16)	(0.39)	(0.41)
Deal ratio		-0.000		0.035
		(-1.11)		(12.02)
Diversifying dummy		0.000		-0.002
		(0.08)		(-0.03)
Cross-city dummy		-0.004		0.014
		(-1.16)		(0.26)
Intellectual Property dummy		0.026		1.326**
		(0.89)		(2.54)
Constant	0.015***	0.022	6.393***	6.244***
	(0.31)	(0.43)	(7.13)	(6.93)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	2,092	2,092	2,092	2,092
Adj R-squared	0.265	0.268	0.116	0.118

Table 11. Heterogeneity tests

This table reports the results of heterogeneity tests. To examine the impact of air pollution and firm acquisitiveness, we explore four such variables: (a) Influence of Environmental disclosure; (b) Influence of well-developed provinces and others, we measure the development degree of the provinces using the Fan-Gang index; (c) Influence of the acquirer's air pollution level, we divide the sample into more polluted and less polluted provinces based on the Acquirer's AQI median level. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	(1)	(2)	(3)	(4)	(7)	(8)
	Environmental disclosure	Non-Environmental disclosure	Well-developed provinces	Developing provinces	Less polluted provinces	More polluted provinces
Air pollution	-4.687***	-3.064	-5.377***	-3.367	-8.340***	-1.976
	(-3.77)	(-1.33)	(-3.94)	(-1.52)	(-3.59)	(-1.05)
GDP growth	-1.364	10.607**	2.347	1.272	-2.057	3.393
	(-0.82)	(2.36)	(1.02)	(0.41)	(-1.09)	(0.88)
GDP per capita	1.652	-6.356	0.355	-1.353	1.121	-1.174
	(1.24)	(-1.59)	(0.21)	(-0.46)	(0.76)	(-0.33)
Constant	-1.363	-6.557	-4.459***	-0.834	-1.390	-3.642**
	(-1.39)	(-3.38)	(-5.47)	(-0.63)	(-1.52)	(-2.45)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	17,645	4,682	16,538	5,789	15,681	6,646
Pseudo R-squared	0.089	0.143	0.092	0.119	0.104	0.085

Table 12. Robustness checks

This table reports the results of further robustness checks on the baseline results. In panel A, we add the province fixed effect based on Eq. (1). In panel B, we run the baseline results using alternative model with high-density fixed effects in Eq. (4). In panel C, we control the seasonal influence and use the monthly average AQI during the winter season (November to January) and other seasons (February to October) of the city where the firm i's headquarters located as our main independent variables. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Alternative fixed effect

Variables	M&A	M&A	M&A
	(1)	(2)	(3)
Air pollution	-2.836*	-2.227*	-2.201*
	(-1.79)	(-1.89)	(-1.86)
GDP growth			-1.763
			(-0.92)
GDP per capita			2.061
			(1.48)
Constant	-4.165***	-2.327***	-2.316***
	(-12.76)	(-2.71)	(-2.60)
Controls	No	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
Province	Yes	Yes	Yes
N	22,327	22,327	22,327
Adj R-squared	0.067	0.098	0.099

Panel B: Alternative model with High-density fixed effects

Variables	$M\&A_{t+1}$	$M\&A_{t+1}$	$M\&A_{t+1}$	$M\&A_{t+1}$	$M\&A_{t+1}$	$M\&A_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
Air pollution	-0.391*	-0.390*	-0.443**	-0.442**	-0.444**	-0.443**
	(-1.92)	(-1.92)	(-2.16)	(-2.16)	(-2.16)	(-2.16)
GDP growth		-0.018		-0.002		-0.007
		(-0.05)		(-0.01)		(-0.02)
GDP per capita		-0.076		-0.079		-0.073
		(-0.25)		(-0.26)		(-0.24)
Constant	0.981***	0.988***	1.006***	1.013***	1.039***	1.045***
	(5.53)	(5.56)	(5.64)	(5.67)	(5.79)	(5.82)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	No	No	No	No	Yes	Yes

Continue

Province	No	No	Yes	Yes	Yes	Yes
N	18,062	18,062	18,062	18,062	18,062	18,062
Adj R-squared	0.107	0.107	0.107	0.107	0.107	0.106

Panel C: Seasonal influence

Variables	M&A	M&A	M&A	M&A	M&A	M&A
	(1)	(2)	(3)	(4)	(5)	(6)
$Air\ pollution_{Nov-Jan}$	-4.122***	-2.970***	-2.872***			
	(-4.77)	(-3.27)	(-3.07)			
$Air\ pollution_{Feb-Oct}$				-6.289***	-3.748***	-3.581**
				(-4.81)	(-2.69)	(-2.52)
GDP growth			-0.026			1.178
			(-0.02)			(0.91)
GDP per capita			1.288			0.268
			(0.98)			(0.17)
Constant	-2.746***	-2.485***	-0.492	-2.679***	-0.347	-0.590
	(-6.59)	(-3.47)	(-0.59)	(-6.40)	(-0.43)	(-0.71)
Controls	No	Yes	Yes	No	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	16,638	16,638	16,638	16,638	16,638	16,638
Pseudo R-squared	0.044	0.087	0.087	0.044	0.086	0.086

Table 13. Further robustness checks

This table reports the results of robustness checks on the baseline results. In panel A, we use the expense value of the M&A deals to replace the M&A dummy as the proxy for M&A. In panel B, we use PM 2.5 which is the logarithm value of the average yearly level of PM 2.5 in each acquirer's city and the natural logarithm of yearly average Air Quality Index (AQI), as the proxy for air pollution. In panel C, we use the sample period from 2013 to 2020 which includes the main independent variable AQI. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Alternative M&A metrics			
Variables	M&A expense value	M&A expense value	M&A expense value
	(1)	(2)	(3)
AQI (Air pollution)	-12.794***	-9.387***	-4.249***
	(-6.06)	(-4.11)	(-3.87)
GDP growth			0.287
			(0.13)
GDP per capita			2.139
			(1.49)
Constant	0.888**	1.505	1.077
	(1.99)	(1.26)	(0.86)
Controls	No	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
N	22,327	22,327	22,327
Adj R-squared	0.044	0.071	0.071

Panel B: Alternative air pollution metrics			
Variables	M&A	M&A	M&A
	(1)	(2)	(3)
PM 2.5 （Air pollution）	-0.690***	-0.503***	-0.489***
	(-5.28)	(-3.70)	(-3.55)
GDP growth			0.331
			(0.21)
GDP per capita			1.472
			(1.15)
Constant	-1.682***	0.062	-0.109
	(-6.45)	(0.09)	(-0.15)
Controls	No	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
N	18,046	18,046	18,046
Pseudo R-squared	0.043	0.084	0.085

Continue

Panel C: Alternative air pollution measurement			
Variables	M&A	M&A	M&A
	(1)	(2)	(3)
Log AQI	-0.487***	-0.347***	-0.345***
	(-5.95)	(-4.17)	(-4.07)
GDP growth			-0.039
			(-0.03)
GDP per capita			0.980
			(0.77)
Constant	-1.993***	-1.172	-1.332
	(-4.43)	(-1.44)	(-1.58)
Controls	No	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
N	22,327	22,327	22,327
Adj R-squared	0.098	0.095	0.095

Panel D: Alternative sample period (2013-2020)			
Variables	M&A	M&A	M&A
	(1)	(2)	(3)
AQI （Air pollution）	-5.900***	-4.201***	-4.057***
	(-5.64)	(-3.81)	(-3.61)
GDP growth			0.179
			(0.11)
GDP per capita			1.474
			(1.16)
Constant	-1.584***	0.113	-0.051
	(-5.97)	(0.15)	(-0.07)
Controls	No	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
N	18,046	18,046	18,046
Pseudo R-squared	0.044	0.084	0.085

Appendix A. Variables definition

This table presents definitions of all the variables.

	Variables	Definition
Dependent variable	M&A	Dummy variable that equals 1 if firm *i* makes at least one acquisition announcement in year t, and 0 otherwise.
Explanatory variable	Air pollution	Yearly average Air Quality Index (AQI) divide 1000 of the city where firm *i*'s headquarters located.
	AAQI	Yearly average Air Quality Index (AQI) divide 1000 of each acquirer's city.
	TAQI	Yearly average Air Quality Index (AQI) divide 1000 of each target's city.
Control variables	Size	Natural logarithm of total assets.
	Lev	The ratio of total debt to total assets.
	ROA	Returns on assets, calculated as net income over total assets.
	Growth	The growth rate of income.
	BM	The ratio of the book value of assets to the market value of assets.
	CH/at	The ratio of net cash holding to the total assets.
	Capex/at	The funds used by a company to acquire, upgrade, and maintain physical assets such as property, plants, buildings, technology, or equipment divided by total assets.
	INST	Total shares held by institutional investors divided by outstanding share capital.
	Top 5	The sum of the shareholding ratio of the top 5 major shareholders.
	ListAge	The natural log of current year minus listed year and plus one, ln (current year-listed year+1).
	BoardSize	Take the natural log of the number of board members.
	IndepR	The proportion of independent directors.
	Dual	The dummy variable equals 1 if chairman of the board and CEO are the same individual, and 0 if otherwise.
	SOE	The dummy variable equals 1 if the firm is SOE, and 0 if otherwise.
	Deal ratio	The ratio of deal value to total assets.
	Polluter	Dummy variable that equals 1 if firm *i* belongs to the polluting industries, and 0 otherwise. Categorizations of these industries follow the CSRC Listed Company Industry Classification Guidelines (2012).
	Cash dummy	The dummy variable that equals 1 if an M&A deal is fully funded by cash, and 0 otherwise.
	Stock dummy	The dummy variable that equals 1 if an M&A deal is fully funded by stock, and 0 otherwise.
	Diversifying dummy	The dummy variable equals 1 if the deal is a diversified M&A, and 0 otherwise.
	Intellectual Property dummy	The dummy variable that equals 1 if an M&A deal is related to the intellectual property transaction, and 0 otherwise.
	CF	The ratio of net operating cash flow to the total assets.
	SA	Financial constraint, the larger the value of SA index is, the higher the degree of financing constraint is.
	Environmental investment	Firm's environmental investment each year.
	Thermal_Inversion_Dummy	The dummy variable equals one means there exists the thermal inversions in the city in a given year, and 0 otherwise

Notes: All control variables are about acquirer's characteristics.

Appendix B. Distribution of M&As by year and industry

This table reports the annual and 2-digit code industry distribution of M&A subsample for the period 2010–2020.

Panel A: M&A Subsample Distribution by Year.

Year	Frequency	Percent
2010	27	0.76%
2011	100	2.82%
2012	199	5.62%
2013	178	5.03%
2014	452	12.76%
2015	653	18.44%
2016	553	15.62%
2017	467	13.19%
2018	382	10.79%
2019	329	9.29%
2020	201	5.68%
Total	3,541	100.00%

Panel B: M&A Distribution by Industries.

2-digit code industry	Industry Description	Frequency	Percent
C39	Computer, Communications, and other electronic equipment manufacturing	374	10.56%
I	Information transmission, software, and information technology service	330	9.32%
C26	Chemical material and products manufacturing	257	7.26%
C35	Special equipment manufacturing	220	6.21%
C27	Medicine manufacturing	193	5.45%
F	Wholesale and retail	168	4.74%
C34	Common machines manufacturing	152	4.29%
K	Real estate	109	3.08%
C36	Automobile manufacturing	94	2.65%
C30	Non-metal mineral products	88	2.49%
C38	Electric equipment and parts manufacturing	88	2.49%
E	Construction	86	2.43%
C18	Textile clothing, apparel manufacturing	81	2.29%
C33	Metal products industry	75	2.12%
C40	Instrument manufacturing	73	2.06%
G	Transportation	62	1.75%
C29	Rubber and plastic products manufacturing	61	1.72%
R	Culture, sports, and entertainment	60	1.69%
B	Mining	56	1.58%
D	Utilities	55	1.55%
	Industries with <1.5% representation		
	Total	3,541	100.00%

Appendix C. Distribution of air pollution by year and province

This table provides the summary statistics for air quality index from 2010 to 2020 in each province in China.

Province	Mean	Median	Min	Max	STD
Gansu	0.091	0.094	0.053	0.117	0.013
Jilin	0.078	0.071	0.018	0.146	0.021
Shanxi	0.092	0.097	0.051	0.162	0.019
Fujian	0.056	0.055	0.043	0.084	0.007
Hubei	0.095	0.088	0.065	0.225	0.033
Yunnan	0.057	0.055	0.041	0.112	0.010
Liaoning	0.080	0.078	0.056	0.150	0.014
Guangxi	0.066	0.059	0.047	0.199	0.024
Heilongjiang	0.085	0.076	0.042	0.197	0.033
Anhui	0.087	0.085	0.042	0.222	0.029
Henan	0.109	0.112	0.070	0.174	0.022
Chongqing	0.080	0.075	0.067	0.130	0.016
Jiangsu	0.089	0.085	0.062	0.196	0.026
Jiangxi	0.071	0.069	0.048	0.135	0.016
Guizhou	0.062	0.061	0.039	0.178	0.019
Shanxi	0.092	0.097	0.051	0.162	0.019
Tianjin	0.099	0.098	0.073	0.156	0.021
Shandong	0.095	0.086	0.040	0.243	0.031
Zhejiang	0.080	0.072	0.001	0.198	0.026
Hebei	0.116	0.113	0.054	0.246	0.038
Shanghai	0.080	0.074	0.058	0.158	0.023
Sichuan	0.088	0.080	0.038	0.240	0.027
Hainan	0.044	0.042	0.021	0.103	0.013
Nei Mongol	0.081	0.080	0.033	0.139	0.017
Guangdong	0.061	0.057	0.041	0.132	0.015
Hunan	0.083	0.082	0.051	0.177	0.025
Qinghai	0.083	0.085	0.069	0.104	0.009
Xinjiang	0.101	0.099	0.048	0.251	0.021
Beijing Shi	0.097	0.094	0.079	0.125	0.016
Ningxia	0.083	0.081	0.063	0.108	0.011
Tibet	0.056	0.053	0.038	0.078	0.011

Appendix D. Correlation Matrix

This table reports the correlation coefficients between key variables. Definitions of variables are in Appendix 1. The superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variables		1	2	3	4	5	6	7	8	9
1	M&A	1.000								
2	Air pollution	-0.007***	1.000							
3	Size	-0.051**	0.028***	1.000						
4	Lev	-0.021***	0.024***	0.485***	1.000					
5	ROA	-0.021***	-0.014***	-0.019***	-0.358***	1.000				
6	Growth	0.080***	0.006	0.034***	0.048***	0.189***	1.000			
7	BM	-0.117***	0.004	0.582***	0.340***	-0.154***	-0.047***	1.000		
8	CH/at	-0.021***	-0.065***	0.074***	-0.119***	0.119***	0.028	-0.022***	1.000	
9	Capex/at	-0.074***	-0.119***	-0.034***	-0.075***	0.135***	0.041***	-0.008	0.067***	1.000
10	INST	-0.038***	0.040***	0.468***	0.243***	0.040***	0.008	0.068***	-0.031***	-0.025***
11	Top 5	-0.041***	-0.005	0.156***	-0.088***	0.216***	0.015***	0.148***	0.078***	0.123***
12	ListAge	0.004	0.030***	0.389***	0.408***	-0.238***	0.004	0.129***	-0.017***	-0.239***
13	BoardSize	-0.065***	0.041***	0.279***	0.165***	0.005	-0.012	0.172***	-0.004***	0.035***
14	IndepR	0.014***	-0.029***	0.000	-0.008	-0.020***	-0.002	-0.023***	-0.004	-0.008
15	Dual	0.040***	-0.061***	-0.187***	-0.162***	0.058***	0.008	-0.123***	0.052	0.067***
16	SOE	-0.123***	0.077***	0.371***	0.317***	-0.100***	-0.053***	0.249***	-0.048***	-0.082***
17	Polluter	-0.017***	0.023***	0.050***	-0.018***	0.017***	-0.016***	0.039***	-0.023***	0.098***

(Continuous)

Variables		10	11	12	13	14	15	16	17
1	M&A								
2	Air pollution								
3	Size								
4	Lev								
5	ROA								
6	Growth								
7	BM								
8	CH/at								
9	Capex/at								
10	INST	1.000							
11	Top 5	0.284***	1.000						
12	ListAge	0.415***	-0.351***	1.000					
13	BoardSize	0.210***	0.009	0.138***	1.000				
14	IndepR	-0.041***	0.047***	-0.024***	-0.535***	1.000			
15	Dual	-0.207***	0.027***	-0.261***	-0.181***	0.101***	1.000		
16	SOE	0.412***	0.033***	0.438***	0.267***	-0.048***	-0.313***	1.000	
17	Polluter	0.042***	0.012	0.063***	0.087***	-0.050***	-0.023***	0.032***	1.000

Appendix E. Baseline regression between SOEs and Non-SOEs

This table reports the results of baseline regressions. It shows the impact of air quality on the M&A deals' decisions. Definitions of variables are presented in Appendix Table 1. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	SOE	Non-SOE	SOE	Non-SOE
	(1)	(2)	(3)	(4)
Air pollution	-8.002***	-3.001**	-6.876***	-3.302***
	(-3.21)	(-2.48)	(-2.79)	(-2.66)
Size	0.014	0.043	0.014	0.043
	(0.22)	(1.23)	(0.22)	(1.25)
Lev	-0.028	0.451***	-0.014	0.453***
	(-0.09)	(2.93)	(-0.05)	(2.95)
ROA	0.250	-1.269	0.244	-1.263
	(0.28)	(-1.52)	(0.27)	(-1.52)
Growth	0.321***	0.390***	0.321***	0.389***
	(3.83)	(7.76)	(3.80)	(7.74)
BM	-0.538*	-0.901***	-0.530*	-0.909***
	(-1.82)	(-4.89)	(-1.79)	(-4.93)
CH/at	1.516**	0.052	1.499**	0.052
	(2.17)	(0.19)	(2.15)	(0.19)
Capex/at	-1.547	-1.959***	-1.648	-1.942***
	(-1.23)	(-3.19)	(-1.30)	(-3.16)
INST	-1.771	0.120	-1.889*	0.095
	(-0.92)	(0.14)	(-0.98)	(0.11)
Top 5	-0.513	0.327	-0.504	0.330
	(-1.15)	(1.52)	(-1.13)	(0.75)
ListAge	-0.148	0.261***	-0.134	0.260***
	(-1.50)	(6.18)	(-1.35)	(6.16)
BoardSize	-0.739***	-0.483***	-0.734***	-0.482***
	(-2.62)	(-2.97)	(-2.60)	(-2.97)
IndepR	-1.553	-0.619	-1.530	-0.618
	(-1.55)	(-1.04)	(-1.53)	(-1.04)
Dual	0.194	0.039	0.196	0.039
	(1.28)	(0.76)	(1.29)	(0.75)
Polluter	0.064	-0.096	0.064	-0.098
	(0.50)	(-1.48)	(0.50)	(-1.52)
GDP growth			9.610***	-2.271
			(2.59)	(-1.28)
GDP per capita			-6.015*	1.718

Continue

			(-1.91)	(1.18)
Constant	-1.703	-4.039***	-2.610	-3.898***
	(-0.93)	(-3.82)	(-1.40)	(-3.62)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	7,876	14,451	7,876	14,451
Pseudo R-squared	0.049	0.094	0.051	0.094

Appendix F. Air pollution and shareholder value

This table reports results of the remaining acquirer CAR cross-sectional regressions. The dependent variable is CAAR [-5, 0], CAAR [-3, 0], CAAR [0, 1], CAAR [0, 3], CAAR [0, 5], CAAR [-1, 1], CAAR [-3, 3], CAAR [-5, 5] separately. AAQI (TAQI) is the yearly average Air Quality Index (AQI) divide 1000 of each acquirer's (target's) city. Other variables are defined in Appendix A. The *t*-statistics are reported in parentheses. The symbol *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variables	CAAR [-5, 0]	CAAR [-3, 0]	CAAR [0, 3]	CAAR [0, 5]	CAAR [-1, 1]	CAAR [-3, 3]	CAAR [-5, 5]
	(1)	(2)	(4)	(5)	(6)	(7)	(8)
AAQI	-0.000	-0.010	0.004	-0.001	-0.029	0.001	0.000
	(-0.02)	(-0.55)	(0.13)	(-0.04)	(-0.91)	(0.06)	(0.03)
TAQI	0.006	0.023	-0.023	-0.025	0.014	0.001	-0.010
	(0.44)	(1.32)	(-0.67)	(-0.89)	(0.44)	(0.05)	(-0.62)
Deal ratio	0.000	0.000*	-0.000	0.000	-0.000	0.000	0.000
	(1.48)	(1.68)	(-0.74)	(0.09)	(-1.07)	(0.54)	(1.10)
Diversifying dummy	0.001	0.002**	0.003	0.003	0.004**	0.002	0.001
	(1.55)	(2.02)	(1.55)	(1.59)	(2.04)	(1.46)	(1.41)
Cross-city dummy	0.001**	0.002*	0.002	0.002	0.002	0.001	0.001
	(2.06)	(1.96)	(0.91)	(1.13)	(1.29)	(0.93)	(1.30)
Intellectual Property dummy	0.009	0.017*	0.050***	0.033**	0.031*	0.033***	0.019**
	(1.33)	(1.85)	(2.75)	(2.24)	(1.85)	(3.01)	(2.30)
Constant	0.038***	0.055***	0.071***	0.058***	0.100***	0.046***	0.035***
	(4.04)	(4.21)	(2.74)	(2.74)	(4.26)	(2.96)	(2.95)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,273	3,273	3,273	3,273	3,273	3,273	3,273
Adj R-squared	0.065	0.071	0.107	0.106	0.094	0.109	0.110

6. References

Adhvaryu, A., Kala, N., & Nyshadham, A. (2014). Management and shocks to worker productivity: evidence from air pollution exposure in an Indian garment factory. *Unpublished working paper, University of Michigan*.

Ahuja, G., & Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic management journal, 22*(3), 197-220.

Alshwer, A. A., Sibilkov, V., & Zaiats, N. S. (2011). Financial constraints and the method of payment in mergers and acquisitions. *Available at SSRN 1364455*.

Andrade, G., & Stafford, E. (2004). Investigating the economic role of mergers. *Journal of Corporate Finance, 10*(1), 1-36.

Anthony, M. (2017). Effects of merger and acquisition on financial performance: case study of commercial banks. *International Journal of Business Management & Finance, 1*(6), 93-105.

Arceo, E., Hanna, R., & Oliva, P. (2016). Does the effect of pollution on infant mortality differ between developing and developed countries? Evidence from Mexico City. *The Economic Journal, 126*(591), 257-280.

Bai, J. J., Chu, Y., Shen, C., & Wan, C. (2021). Managing Climate Change Risks: Sea Level Rise and Mergers and Acquisitions. *Yongqiang and Shen, Chen and Wan, Chi, Managing Climate Change Risks: Sea Level Rise and Mergers and Acquisitions (May 11, 2021)*.

Bakian, A. V., Huber, R. S., Coon, H., Gray, D., Wilson, P., McMahon, W. M., & Renshaw, P. F. (2015). Acute air pollution exposure and risk of suicide completion. *American journal of epidemiology, 181*(5), 295-303.

Bao, R., & Liu, T. (2022). How does government attention matter in air pollution control? Evidence from government annual reports. *Resources, conservation and recycling, 185*, 106435.

Bauguess, S., & Stegemoller, M. (2008). Protective governance choices and the value of acquisition activity. *Journal of Corporate Finance, 14*(5), 550-566.

Berman, E., & Bui, L. T. (2001). Environmental regulation and productivity: evidence from oil refineries. *Review of Economics and Statistics, 83*(3), 498-510.

Bonaime, A., Gulen, H., & Ion, M. (2018). Does policy uncertainty affect mergers and acquisitions? *Journal of Financial Economics, 129*(3), 531-558.

Bond, S., & Van Reenen, J. (2007). Microeconometric models of investment and employment. *Handbook of econometrics, 6*, 4417-4498.

Brockman, P., Rui, O. M., & Zou, H. (2013). Institutions and the performance of politically connected M&As. *Journal of international business studies, 44*(8), 833-852.

Carpenter, R. E., & Guariglia, A. (2008). Cash flow, investment, and investment opportunities: New tests using UK panel data. *Journal of Banking & Finance, 32*(9), 1894-1906.

Chang, T. Y., Graff Zivin, J., Gross, T., & Neidell, M. (2016). Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy, 8*(3), 141-169.

Chay, K. Y., & Greenstone, M. (2005). Does air quality matter? Evidence from the housing

market. *Journal of Political Economy, 113*(2), 376-424.
Chen, S., Oliva, P., & Zhang, P. (2022). The effect of air pollution on migration: evidence from China. *Journal of Development Economics, 156*, 102833.
Chen, Y., Ebenstein, A., Greenstone, M., & Li, H. (2013). Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. *Proceedings of the National Academy of Sciences, 110*(32), 12936-12941.
de Bodt, E., Cousin, J.-G., & Officer, M. S. (2022). Financial constraints, ownership dilution, and the method of payment in M&A transactions. *Journal of Corporate Finance, 75*, 102250.
DePamphilis, D. (2019). *Mergers, acquisitions, and other restructuring activities: An integrated approach to process, tools, cases, and solutions*: Academic Press.
Dong, M., Hirshleifer, D., Richardson, S., & Teoh, S. H. (2006). Does investor misvaluation drive the takeover market? *The journal of Finance, 61*(2), 725-762.
Dong, R., Fisman, R., Wang, Y., & Xu, N. (2021). Air pollution, affect, and forecasting bias: Evidence from Chinese financial analysts. *Journal of Financial Economics, 139*(3), 971-984. doi:10.1016/j.jfineco.2019.12.004
Ebenstein, A., Fan, M., Greenstone, M., He, G., Yin, P., & Zhou, M. (2015). Growth, pollution, and life expectancy: China from 1991-2012. *American economic review, 105*(5), 226-231.
Ebenstein, A., Fan, M., Greenstone, M., He, G., & Zhou, M. (2017). New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy. *Proceedings of the National Academy of Sciences, 114*(39), 10384-10389.
Ekelund Jr, R. B., Ford, G. S., & Thornton, M. (2001). The measurement of merger delay in regulated and restructuring industries. *Applied Economics Letters, 8*(8), 535-537.
Erel, I., Liao, R. C., & Weisbach, M. S. (2012). Determinants of cross-border mergers and acquisitions. *The journal of Finance, 67*(3), 1045-1082.
Faccio, M., & Masulis, R. W. (2005). The choice of payment method in European mergers and acquisitions. *The journal of Finance, 60*(3), 1345-1388.
Feldman, E. R., & Hernandez, E. (2021). Synergy in mergers and acquisitions: Typology, lifecycles, and value. *Academy of Management Review*(ja).
Fracassi, C. (2017). Corporate finance policies and social networks. *Management Science, 63*(8), 2420-2438.
Fuller, C. S., & Pusateri, N. R. (2018). A holistic approach to merger models with an emphasis on heterogeneity. *The Quarterly Review of Economics and Finance, 69*, 260-273.
Gan, T., Li, Y., & Jiang, Y. (2022). The impact of air pollution on venture capital: evidence from China. *Environmental Science and Pollution Research*, 1-17.
Goel, A. M., & Thakor, A. V. (2010). Do envious CEOs cause merger waves? *The Review of Financial Studies, 23*(2), 487-517.
Gokkaya, S., Liu, X., & Stulz, R. M. (2021). *Do firms with specialized M&A staff make better acquisitions?* Retrieved from
Graff Zivin, J., & Neidell, M. (2013). Environment, health, and human capital. *Journal of Economic Literature, 51*(3), 689-730.
Greenstone, M. (2002). The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 clean air act amendments and the census of

manufactures. *Journal of Political Economy, 110*(6), 1175-1219.
Guariglia, A., & Yang, J. (2016). A balancing act: managing financial constraints and agency costs to minimize investment inefficiency in the Chinese market. *Journal of Corporate Finance, 36*, 111-130.
Hadlock, C. J., & Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *The Review of Financial Studies, 23*(5), 1909-1940.
Han, L., Cheng, X., Chan, K. C., & Gao, S. (2022). Does air pollution affect seasoned equity offering pricing? Evidence from investor bids. *Journal of Financial Markets, 59*, 100657.
Hart, S. L. (1995). A natural-resource-based view of the firm. *Academy of Management Review, 20*(4), 986-1014.
He, G., & Lin, T. (2022). Does air pollution impair investment efficiency? *Economics Letters, 215*, 110490.
Hossain, M. S. (2021). Merger & Acquisitions (M&As) as an important strategic vehicle in business: Thematic areas, research avenues & possible suggestions. *Journal of Economics and Business, 116*, 106004.
Hu, N., Xue, X., & Liu, L. (2022). The impact of air pollution on financial reporting quality: evidence from China. *Accounting & Finance, 62*(3), 3609-3644.
Hu, Z., & Chang, J.-C. (2022). Does air pollution affect dividend policy. *Finance Research Letters, 49*, 103183.
Huang, J., & Kisgen, D. J. (2013). Gender and corporate finance: Are male executives overconfident relative to female executives? *Journal of Financial Economics, 108*(3), 822-839.
Huang, S., Ding, Y., & Failler, P. (2022). Does the Government's Environmental Attention Affect Ambient Pollution? Empirical Research on Chinese Cities. *Sustainability, 14*(6), 3242.
Jiang, D., Li, W., Shen, Y., & Yu, S. (2022). Does air pollution affect earnings management? Evidence from China. *Pacific-Basin Finance Journal, 72*, 101737.
Jovanovic, B., & Rousseau, P. L. (2008). Mergers as reallocation. *The Review of Economics and Statistics, 90*(4), 765-776.
Jung, J., Herbohn, K., & Clarkson, P. (2018). Carbon risk, carbon risk awareness and the cost of debt financing. *Journal of business ethics, 150*(4), 1151-1171.
Kozlenkova, I. V., Samaha, S. A., & Palmatier, R. W. (2014). Resource-based theory in marketing. *Journal of the academy of marketing science, 42*(1), 1-21.
Lazarus, R. S., & Cohen, J. B. (1977). Environmental stress. In *Human behavior and environment* (pp. 89-127): Springer.
Lepori, G. M. (2016). Air pollution and stock returns: Evidence from a natural experiment. *Journal of Empirical Finance, 35*, 25-42.
Levine, O. (2017). Acquiring growth. *Journal of Financial Economics, 126*(2), 300-319.
Levy, T., & Yagil, J. (2011). Air pollution and stock returns in the US. *Journal of Economic Psychology, 32*(3), 374-383.
Li, B., Liu, X., Liu, Y., & Liu, M. (2020). Green M&A, Business Model Innovation and Sustainability of Heavy Polluters: Evidence from the China's Environmental Protection Storm'. *Available at SSRN 3597310*.
Li, B., Xu, L., McIver, R., Wu, Q., & Pan, A. (2020). Green M&A, legitimacy and risk-taking: evidence from China's heavy polluters. *Accounting and Finance, 60*(1), 97-127.

doi:10.1111/acfi.12597
Li, C., Li, H., & Zhao, Z. (2022). Geographic proximity and M&As: Evidence from China. *Emerging Markets Review*, 100892.
Li, J. J., Massa, M., Zhang, H., & Zhang, J. (2021). Air pollution, behavioral bias, and the disposition effect in China. *Journal of Financial Economics, 142*(2), 641-673.
Lin, Y., Huang, R., & Yao, X. (2021). Air pollution and environmental information disclosure: An empirical study based on heavy polluting industries. *Journal of Cleaner Production, 278*, 124313.
Liu, B., Wu, J., & Chan, K. C. (2021). Does air pollution change a firm's business strategy for employing capital and labor? *Business Strategy and the Environment, 30*(8), 3671-3685.
Liu, S., Yang, D., Liu, N., & Liu, X. (2019). The effects of air pollution on firms' internal control quality: Evidence from China. *Sustainability, 11*(18), 5068.
Luypaert, M., & De Maeseneire, W. (2015). Antecedents of time to completion in mergers and acquisitions. *Applied Economics Letters, 22*(4), 299-304.
Maksimovic, V., & Phillips, G. (2001). The market for corporate assets: Who engages in mergers and asset sales and are there efficiency gains? *The journal of Finance, 56*(6), 2019-2065.
Martynova, M., & Renneboog, L. (2008). A century of corporate takeovers: What have we learned and where do we stand? *Journal of Banking & Finance, 32*(10), 2148-2177.
Meyer, J., Gremler, D. D., & Hogreve, J. (2014). Do service guarantees guarantee greater market value? *Journal of Service Research, 17*(2), 150-163.
Nguyen, N. H., Phan, H. V., & Simpson, T. (2020). Political corruption and mergers and acquisitions. *Journal of Corporate Finance, 65*, 101765.
Peteraf, M. A. (1993). The cornerstones of competitive advantage: a resource-based view. *Strategic management journal, 14*(3), 179-191.
Phan, H. V. (2014). Inside debt and mergers and acquisitions. *Journal of Financial and Quantitative analysis, 49*(5-6), 1365-1401.
Rahayu, Y. S., & Wardana, G. K. (2021). The Effect of financial performance and dividend policy on cumulative abnormal return. *El Dinar: Jurnal Keuangan dan Perbankan Syariah, 9*(1), 62-76.
Ray, K. G. (2022). *Mergers and acquisitions: Strategy, valuation and integration*: PHI Learning Pvt. Ltd.
Rhodes-Kropf, M., & Viswanathan, S. (2004). Market valuation and merger waves. *The journal of Finance, 59*(6), 2685-2718.
Sahu, S. K., & Agarwal, N. (2017). Inter-firm differences in mergers and acquisitions: a study of the pharmaceutical sector in India. *Journal of Economic Studies*.
Salvi, A., Petruzzella, F., & Giakoumelou, A. (2018). Green M&A deals and bidders' value creation: the role of sustainability in post-acquisition performance. *International Business Research, 11*(7), 96-105.
Sankar, B., & Leepsa, N. (2018). Payment methods in mergers and acquisitions: A theoretical framework. *International Journal of Accounting and Financial Reporting, International Journal of Accounting and Financial Reporting, ISSN*, 2162-3082.
Shleifer, A., & Vishny, R. W. (2003). Stock market driven acquisitions. *Journal of Financial Economics, 70*(3), 295-311.

Solikhah, B., & Maulina, U. (2021). Factors influencing environment disclosure quality and the moderating role of corporate governance. *Cogent Business & Management, 8*(1), 1876543.

Tan, J., Chan, K. C., & Chen, Y. (2022). The impact of air pollution on the cost of debt financing: Evidence from the bond market. *Business Strategy and the Environment, 31*(1), 464-482.

Tan, J., Tan, Z., & Chan, K. C. (2021). Does air pollution affect a firm's cash holdings? *Pacific-Basin Finance Journal, 67*, 101549.

Tan, J., Zhang, X., Zhang, P., & Chan, K. C. (2021). Does air pollution matter in a supplier's trade credit strategy? Evidence from an emerging market. *Borsa Istanbul Review, 21*, S70-S79.

Tan, Z., & Yan, L. (2021). Does air pollution impede corporate innovation? *International Review of Economics & Finance, 76*, 937-951. doi:10.1016/j.iref.2021.07.015

Teerikangas, S., & Very, P. (2006). The culture–performance relationship in M&A: From yes/no to how. *British journal of management, 17*(S1), S31-S48.

Thompson, E. K., & Kim, C. (2020). Post-M&A performance and failure: Implications of time until deal completion. *Sustainability, 12*(7), 2999.

Uysal, V. B., Kedia, S., & Panchapagesan, V. (2008). Geography and acquirer returns. *Journal of Financial Intermediation, 17*(2), 256-275.

Walker, W. R. (2013). The transitional costs of sectoral reallocation: Evidence from the clean air act and the workforce. *The Quarterly Journal of Economics, 128*(4), 1787-1835.

Wang, L., Dai, Y., & Kong, D. (2021). Air pollution and employee treatment. *Journal of Corporate Finance, 70*. doi:10.1016/j.jcorpfin.2021.102067

Wang, L., Xing, F., Yu, Y., & Dai, Y. (2021). Does severe air pollution affect firm innovation: evidence from China. *Applied Economics Letters, 28*(7), 551-558.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic management journal, 5*(2), 171-180.

White, M. J., & Hunter, L. M. (2009). Public perception of environmental issues in a developing setting: Environmental concern in coastal Ghana. *Social Science Quarterly, 90*(4), 960-982.

Wu, J., Liu, B., Chang, S., & Chan, K. C. (2022). Effects of air pollution on accounting conservatism. *International Review of Financial Analysis*, 102380.

Wu, Q. (2011). *Information conduit or agency cost: Top management and director interlock between target and acquirer.* Paper presented at the Midwest Finance Association 2012 Annual Meetings Paper.

Xu, E. Q. (2017). Cross-border merger waves. *Journal of Corporate Finance, 46*, 207-231.

Yang, H., Zhang, Q., Zhao, X., & Wang, Z. (2022). Does political corruption affect mergers and acquisitions decisions? Evidence from China. *International Review of Economics & Finance, 78*, 248-266.

Yim, S. (2013). The acquisitiveness of youth: CEO age and acquisition behavior. *Journal of Financial Economics, 108*(1), 250-273.

Zhang, E. Q. (2022). Why are distressed firms acquisitive? *Journal of Corporate Finance, 72*, 102126.

Zhang, S., Zhang, M.-a., Qiao, Y., Li, X., & Li, S. (2022). Does improvement of environmental information transparency boost firms' green innovation? Evidence from the air quality monitoring and disclosure program in China. *Journal of Cleaner Production, 357*, 131921.

Zhang, X., Tan, J., & Chan, K. C. (2021). Air pollution and initial public offering underpricing. *Applied Economics, 53*(39), 4582-4595.

Zhao, X., & Jia, M. (2022). Sincerity or hypocrisy: can green M&A achieve corporate environmental governance? *Environmental Science and Pollution Research*, 1-13.

Zheng, S., Cao, C.-X., & Singh, R. P. (2014). Comparison of ground based indices (API and AQI) with satellite based aerosol products. *Science of the total environment, 488*, 398-412.

Zheng, S., Cao, J., Kahn, M. E., & Sun, C. (2014). Real estate valuation and cross-boundary air pollution externalities: evidence from Chinese cities. *The Journal of Real Estate Finance and Economics, 48*(3), 398-414.

Zollo, M., & Singh, H. (2004). Deliberate learning in corporate acquisitions: post-acquisition strategies and integration capability in US bank mergers. *Strategic management journal, 25*(13), 1233-1256.