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Air pollution and stock returns: The cash flow risk channel

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ABSTRACT

This paper provides a novel explanation regarding the phenomenon that high local air pollution forecasts a low risk premium at the firm-level. Using Chinese stock market data, we show that there is a negative correlation between air pollution and stock return. Further empirical analysis reveals that pollution affects the stock market by changing the covariance between cash flows and the aggregate profitability shock. This result can be illustrated by a neoclassical q-theory model with air pollution as a factor affecting production.

1. Introduction

Along with the growing amount of social science research on air pollution, researchers are paying increasing attention to its impacts on financial markets. Empirical studies suggest that air pollution hurts stock market. Researchers have examined the corresponding effect through distorted investor behavior (Lu, 2020). On the one hand, existing literature has established the relationships between air pollution and investors' moods and between moods and stock returns (Levy and Yagil, 2011; Heyes et al., 2016; Li and Peng, 2016; Wu et al., 2018). On the other hand, Li et al. (2021) find that air pollution can affect stock markets by influencing investors' mental health and cognition. However, air pollution also affects labor productivity and human capital accumulation (Graff Zivin and Neidell, 2012; Ebenstein et al., 2016; Chang et al., 2016), which indicates that air pollution is likely to influence stock markets through factors related to firms' profitability. Nevertheless, research that examines this possibility is lacking.

This study investigates whether air pollution affects the stock market by influencing firms' profitability. We rely on Chinese stock market data to explore this question because it provides an advantageous setting to identify the adverse socioeconomic effects of air pollution. First, ambient air pollution is generally more severe in developing countries than in developed countries. For instance, in 2018, 66.3% of the 338 Chinese cities did not meet the national standard for ambient air quality.[2] Second, better working environments and occupational protection measures may prevent air pollution from reducing labor productivity in developed countries. Third, the industrial structure in China is different from those in developed countries. Labor intensive industries in China may suffer more from pollution than capital intensive industries in the US. Fourth, China is a large economy in which high GDP

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[2] These numbers are from the 2018 Bulletin of China's Ecology and Environment.

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and severe air pollution coexist. Therefore, Chinese stock markets provide a useful setting to examine our theoretical hypothesis. Regarding the air pollution variables, the central government of China launched a real-time pollution monitoring and disclosure program in 2013, which ensures high quality station-level air pollution data that are subject to little manipulation with a large geographical coverage. Thus, we rely on air pollution data at the monitoring station level from 2013 to 2018 for the empirical analysis. Specifically, we explore the effects of two air pollution variables in the empirical analysis: the air quality index (AQI), which is a composite air quality index calculated from the concentrations of six criteria atmospheric pollutants, and $PM_{2.5}$, which is the most serious and notorious air pollutant in China in recent years.

We examine the relationship between air pollution and stock returns by portfolio sorting and Fama-MacBeth regressions. First, we sort stocks into five portfolios based on air pollution indices of the city where each firm is located and construct a zero-cost portfolio going long the bottom 20% of firms ranked by air pollution indices while shorting the top 20%. These portfolios are rebalanced every year and portfolio returns are calculated every month, which are adjusted by the risk-free rate or pricing factors. We find that pollution-linked returns can forecast firm returns effectively. The portfolios of the firms located in more (less) polluted areas earn lower (higher) subsequent returns, and the zero-cost portfolio delivers significantly positive alpha when the pricing factors are controlled. The negative relationship between pollution and alpha exists regardless of the pollution indicator used ($AQI/PM_{2.5}$). We then conduct Fama–MacBeth regressions by running monthly stock returns on local air pollution indices and firm characteristics. We find that pollution ($AQI/PM_{2.5}$) exhibits strong predictive power for firm returns in the next month in cross-section across various specifications that control different characteristics. Instead of using city-level pollution variables, we also calculate the local aggregate pollution using the pollution indices of the nearest air pollution monitoring station of the firm – the portfolio sorting and Fama-MacBeth estimation results are highly robust.

The effects of air pollution on stock returns may be biased because of measurement errors in the pollution variables, omitted variables in the cross-sectional regressions, and reverse causality. An increasing number of studies that estimate the socioeconomic impacts of air pollution have used thermal inversion as an instrumental variable (IV) for air pollution (Arceo et al., 2016; Fu et al., 2021). Thus, we first regress air pollution ($AQI/PM_{2.5}$) on thermal inversion, weather characteristics, BM, Beta, Size, city fixed effects (FE) and year-by-month FE, and compute an exogenous proportion of air pollution ($AQI\_IV/PM_{2.5}\_IV$) that only comes from the plausibly exogenous variation of thermal inversion. We then estimate the relationship between stock returns and the exogenous self-constructed pollution variables ($AQI\_IV/PM_{2.5}\_IV$). The results of the Fama-MacBeth regressions indicate that stock returns are negatively correlated with air pollution. Using air pollution from the nearest monitoring station instead of city-level pollution indices also yields highly consistent results.

Regarding the mechanisms of how air pollution decreases stock returns, mounting research has explored the channels through which pollution influences the psychological status of individuals, thereby resulting in behavioral bias of investors. However, in a neoclassical q-theory model with air pollution as a factor affecting production, higher pollution leads to a lower covariance between cash flows and the aggregate productivity shock, which in turn leads to a lower risk premium. We refer to this mechanism as the cash flow risk channel. To test this channel, we conduct further empirical analyses in two steps.

First, we estimate the effect of air pollution on the conditional covariance of cash flows and aggregate productivity growth. We use the real growth rate of operating profit, firm cash flow to asset and equity cash flow to asset as the proxies for the firm's cash flow and regress the cash flow measures on the interaction between air pollution indices and aggregate productivity growth. We find that the estimated coefficients on the interaction term are all significantly negative, which means air pollution decreases the conditional covariance of cash flows with the aggregate profitability shock.

Further, we rule out the possibility that distorting investor behaviors is the only channel through which air pollution influences stock returns. This step includes two analyses. First, we conduct double sorting on pollution and firm characteristics to investigate the conditional effects of air pollution across firm characteristics. Using a similar portfolio sorting approach, Baker and Wurgler (2006) find significant conditional effects of investor behavior. However, our double sorting results do not reveal significant conditional effects of pollution. None of the conditional differences across the deciles of firm characteristics reveal an obvious trend, although the unconditional effects of firm characteristics are consistent with the literature. We therefore infer that the sentiment channel may not be the mechanism through which pollution affects stock returns or at least not the only mechanism.

Second, most institutional and individual investors in China are located in large cities. If the investor behavior channel is the only mechanism through which pollution affects stock returns, we should find no effects of air pollution on stock returns in the sample that only includes firms in small cities. Thus, we remove the observations of large cities in China and test if the pollution effect on stock returns remains. We construct two samples to rerun the Fama–MacBeth regressions. One excludes the observations in Shanghai, Beijing, Shenzhen and Guangzhou, and the other excludes the observations in the 16 largest cities in China with a population greater than eight million according to the sixth national census. Using the two samples that exclude large cities, the Fama–MacBeth regressions still reveal significantly negative impacts of air pollution on stock returns. Therefore, air pollution indeed affects stock returns through other mechanisms than investor behaviors.

The remainder of the paper is organized as follows. Section 2 discusses related literature. Section 3 describes the data. Section 4 introduces the portfolio sorting and Fama-MacBeth estimation results. Section 5 discusses the method of addressing the endogeneity problem and presents the estimation results. Section 6 presents the empirical results from examining the mechanisms of the effect of air pollution on stock returns. Section 7 concludes. A theoretical model that illustrates the cash flow risk channel is included in the appendix.

2. Related literature

This study contributes to the literature on the effects of air pollution on stock market performance. Levy and Yagil (2011) and Heyes et al. (2016) find that air pollution in areas where stock exchanges are located can decrease stock returns. Lepori (2016) argue that the correlation between air pollution and equity returns is mediated by trading floor technology. Li and Peng (2016) document that the negative effect of air pollution on stock returns exists in an order-driven trading system. Wu et al. (2018) find a negative correlation between air pollution and stock returns of locally headquartered firms. Meanwhile, Li et al. (2021) find that air pollution affects stock markets by influencing mental health and cognition of investors. Huang et al. (2020) find that investors make worse trades when air pollution is severe. Existing studies attribute the negative correlation between air pollution and stock returns to distorted investor behavior induced by pollution. In other words, air pollution can negatively influence people's mood or intensify cognitive bias, which leads to increased risk aversion or the disposition effects of investors. However, this study establishes a theoretical link between pollution and equity pricing through the channel of firms' cash flow risk, and confirms the theoretical implication empirically.

This paper also adds to the literature that estimates the impacts of air pollution on labor productivity or firms' profitability. Some studies find that daily air pollution has instantaneous negative effects on labor productivity in physically demanding occupations and jobs in the service sector. Graff Zivin and Neidell (2012) find significant negative impacts of ozone pollution on the labor productivity of agricultural harvest workers in the United States. Chang et al. (2016) observe that $PM_{2.5}$ significantly decreases the labor productivity of pear-packing workers in the United States. Adhvaryu et al. (2022) find significant negative effects of fine particulate matter on the productivity of assembly line workers in a ready-made garment firm in India. Chang et al. (2019) find significant negative impacts of air pollution index (API) on the labor productivity of call center workers in China. Some studies estimate the long-term effects of particulate matters on labor productivity in the manufacturing sector (Fu et al., 2021; Hansen-Lewis, 2018). While existing studies focus on the impacts on labor productivity measures, the cash flow risk channel found in this paper provides evidence that air pollution negatively influences firm profitability using stock market data.

Additionally, this study is related to the broad literature that estimates the socioeconomic costs of air pollution and benefits of environmental regulation that improves air quality. Existing literature mostly focus on the pollution impacts on health or productivity outcomes probably because of data availability. For example, Chen et al. (2013) estimate the reduction in life expectancy at birth due to long-term exposure to total suspended particulates following a winter heating policy that increased coal combustion in northern China relative to southern China. This study illustrates that air pollution significantly decreases equity prices, which renders economic costs to firms. Thus, this research corroborates the importance of environmental regulation, which is not merely a tax on producers but can benefit share holders. Policies that induce firms to adopt cleaner production technology may thus eventually lead to lower ambient air pollution and reduce the negative effects of air pollution on stock returns.

Another possible influencing mechanism of the impact of air pollution on firm value is that air pollution may cause talented people to migrate out and result in the loss of human capital, which in turn decreases firm value. On the one hand, existing literature finds that air pollution increases migration intention and outmigration of high-skilled workers. Qin and Zhu (2018) find that air pollution increases emigration sentiment using Baidu search index. Using census data, Chen et al. (2022) find that air pollution increases net outmigration in the long term, which is driven by well-educated people at the beginning of their professional careers. Lai et al. (2021) find that higher PM2.5 concentration drives college graduates away from their college city. Xue et al. (2021) find that people experiencing high air pollution exhibit an intention to look for jobs in less polluted areas and that the level of skilled executives and employees drops significantly when the firm experiences higher pollution levels. On the other hand, existing literature also finds that human capital influences firm value. Vomberg et al. (2015) finds that human capital and brand equity create relatively more value in a service setting. Crook et al. (2011) find that human capital relates strongly to firm performance from a meta-analysis of 66 studies. Overall, examining this influencing mechanism is beyond the scope of this study and we leave it for future studies.

3. Data

In this section, we describe the data used for the empirical analysis. We first introduce the air quality data in China. The central government of China launched a real-time pollution monitoring and disclosure program in 2013. This program includes the installation of more than 1,600 U.S. EPA-grade monitoring stations that are equipped with automated, real-time monitoring devices that track concentrations of six criteria air pollutants ($PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3, CO), which are immediately reported to city-, province- and central-level governments (Greenstone et al., 2021). By the end of 2014, this network of air quality monitoring stations has spread to the whole country, which ensures high quality air pollution data that are subject to little manipulation with a large geographical coverage.

We choose not to use air quality data prior to 2013 for three reasons. First, city level air quality data based on records from monitoring stations prior to 2013 is only available for 113 prefecture-level cities in China. Second, previous research has found evidence that city level air quality data before 2013 suffers from manipulation in many Chinese cities (Ghanem and Zhang, 2014). Third, China's Ministry of Ecology and Environment (referred to as MEE thereafter) changed the computing formula of AQI in 2013. The AQI measure after 2013 incorporates concentrations of $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3, CO, whereas concentrations of $PM_{2.5}$, O_3, and CO were not reported by the MEE before 2013 and the AQI measure before 2013 only includes concentrations of PM_{10}, SO_2,

NO_2. In addition, the weight of the concentration of NO_2 has also changed before and after 2013.[3] The update of the formula of AQI suggests that the composite air pollution measure is incomparable before and after 2013. Therefore, we rely on monitoring-station level air quality data in China from 2013 for this analysis.

We collect the hourly AQI value at the monitoring station level from 2013 to 2018 from the MEE in China. $PM_{2.5}$ is the primary air pollutant in China in recent years. For instance, according to the 2016 Bulletin of China's Environment, $PM_{2.5}$ accounts for 57.5% of days with an AQI higher than 100. Therefore, we also collect the station-level hourly concentration of $PM_{2.5}$. We then average the hourly AQI and $PM_{2.5}$ levels to the station-daily level. In this step, we only keep daily AQI and $PM_{2.5}$ observations that are constructed from at least 18 h to avoid the influences of intermittent monitoring records within a day. In addition, since the air quality monitoring stations are distributed sparsely across space and many counties do not have any station, we construct the daily average air pollution concentrations at the city level by averaging across the values of all the stations in each prefecture-level city for AQI and $PM_{2.5}$, respectively. We then construct monthly AQI and $PM_{2.5}$ by averaging the daily values for each month.

We collect stock trading data as well as financial and geographic information at the firm level from 2013 to 2018 from the China Stock Market and Accounting Research (CSMAR) database. Our sample includes all A-share stocks from the mainboard market of the Shanghai and Shenzhen Stock Exchanges as well as the board of the Growth Enterprise Market. We use the one-year deposit rate as the risk-free rate.

We impose several filters in the data cleaning process. First, we exclude stocks that became public within the past six months. Second, we exclude stocks (i) with less than 120 days of trading records in the past 12 months and (ii) having less than 15 days of trading records in the most recent month. This filter helps prevent the results from being influenced by stock returns following long trading suspensions. Third, we exclude stocks of the financial industry. Finally, to reduce the impact of micro-cap stocks, we eliminate the bottom 10% of stocks ranked by market capitalization at the end of the last month. When we sort the stocks based on information from the financial statements, and the sorting variable at the end of a given month is derived from the firm's financial report with the most recent public release date before the end of that month.

We match the stock trading and financial information at the firm level with the air pollution variables by city, year, and month.[4] Table 1 presents the descriptive statistics. In total, there are 98,532 firm-month observations (20,179 firm-quarter observations) from 260 cities. When examining the influencing mechanisms of pollution effects on stock returns, we use total factor productivity (TFP) to construct a measure of aggregate productivity growth. TFP is taken from the Penn World Table 9.0, which is available at an annual frequency before 2018. As TFP is available annually before 2018, there are 6,426 firm-year observations.

Table 2 shows the pairwise correlations of key characteristics. The Pearson (Spearman) correlations are above (below) the diagonal. The pollution variables show much larger correlations with price momentum (MOM) than the other traditional stock return predictors. In the empirical analysis, we show that the return predictability of the pollution variables holds after controlling for price momentum and other firm characteristics.

4. Relationship between air pollution and stock returns

This section presents our first set of empirical findings of the correlation between excess returns and air pollution.

4.1. Portfolio sort

To investigate the relationship between excess returns and local air pollution stock, we form five portfolios sorted by AQI following the methodology of Fama and French (1993). At the beginning of year n, we sort the stocks into five portfolios based on the average air pollution indices of the city where firms are located in year n−1. Given that air pollution differs by seasons, yearly average pollution is a reasonable indicator of the severity of air pollution in an area and thereby a reasonable sorting indicator. Once the portfolios are formed, their value-weighted and equal-weighted returns are computed from January to December in year n and these portfolios are then rebalanced at the beginning of year n+1. Further, we construct a zero-cost portfolio going long the bottom 20% of firms ranked by city-level average air pollution indices while shorting the top 20% (low-high). The returns are adjusted by the risk-free rate or pricing factors.

Panel A of Table 3 reports the result of portfolio sort based on AQI. It provides strong evidence that pollution stock has implications for stock returns. In other words, pollution-linked returns can forecast firm returns. Overall, we find that the portfolios of firms located in more (less) polluted areas earn lower (higher) subsequent returns. Specifically, we find that the value-weighted returns of the hedge pollution strategy (low-high), yields average monthly returns of 89 basis points, or roughly 11% per year. The corresponding equal-weighted returns from the zero-cost portfolio (low-high) are 46 basis points per month, or approximately 6% per year. In the next four columns, we control for other known return determinants. The same hedge strategy delivers monthly abnormal returns of 0.86% (0.42%) in the value- (equal-) weighted portfolios adjusted by Fama and French (1993) three-factor model. If we augment this model by adding the stock's own price momentum (Carhart, 1997), the low-high portfolio delivers 0.85% (0.44%) per month for the value- (equal-) weighted portfolios. Finally, we adjust returns using Fama and French (2015) five-factor model, and also conduct a test using the five-factor model plus the momentum factor. We find that the strategy's alpha only decreases slightly

[3] The measure was actually known as the Air Pollution Index (API) before the change in 2013 and termed as Air Quality Index (AQI) afterward. See Ghanem and Zhang (2014) and https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/jcffbz/201203/W020120410332725219541.pdf for more information.

[4] As a robustness check, we also match firm characteristics with air pollution data of the nearest station within 50 km from the firm and redo the empirical analyses. Results are in column (7) of Table 6 and are highly consistent with our main results.

Table 1
Descriptive statistics.

VARIABLES	N	Mean	sd	Min	p25	p50	p75	Max
Ret (%)	98,532	0.59	13.05	−60.95	−6.60	−0.45	6.52	166.30
BM	98,532	0.47	0.34	0.00	0.23	0.38	0.60	2.75
Size	98,532	13.79	22.02	1.25	4.44	7.37	13.98	288.00
Beta	98,532	1.17	1.08	−5.54	0.61	1.14	1.70	11.19
ROE	98,532	0.02	0.03	−0.42	0.01	0.02	0.03	0.62
IA	98,532	0.31	1.16	−0.43	0.04	0.12	0.26	41.61
EP	98,532	0.03	0.03	0.00	0.01	0.02	0.04	0.25
TUR	98,532	1.02	0.61	0.12	0.59	0.87	1.30	5.43
MOM	98,532	0.14	0.52	−0.71	−0.20	0.02	0.33	6.11
TI	98,532	9.76	7.70	0.00	3.00	9.00	16.00	31.00
AQI	98,532	78.39	34.69	16.10	53.87	70.89	93.47	370.70
$PM_{2.5}$	98,532	51.72	28.72	4.48	31.60	45.49	63.30	316.20
AQI_IV	98,532	78.49	23.53	36.95	60.41	75.55	91.32	181.60
$PM_{2.5}\_IV$	98,532	51.78	20.56	6.23	36.26	48.52	63.36	138.80
$QAQI\_IV$	20,179	78.73	20.47	32.31	63.64	76.42	92.45	143.20
$QPM_{2.5}\_IV$	20,179	51.95	18.07	13.75	38.11	49.90	65.18	108.30
Retq (%)	20,179	1.10	8.14	−64.67	−3.80	0.00	5.41	91.33
ROA (%)	20,179	1.17	2.60	−39.22	0.33	1.00	1.96	21.27
ΔOP	6,426	0.00	1.00	−11.67	−0.06	0.01	0.07	15.42
Rcash1	6,426	0.00	1.00	−4.19	−0.47	0.13	0.57	4.48
Rcash2	6,426	0.00	1.00	−5.84	−0.23	0.25	0.51	2.50
$YPM_{2.5}\_IV$	6,426	58.01	10.48	25.85	51.18	57.44	62.79	118.20
$YAQI\_IV$	6,426	85.11	11.67	49.86	77.50	84.68	90.52	152.30

This table reports the summary statistics of the key variables in our empirical analysis. Our sample includes all A-share stocks from the mainboard market of the Shanghai and Shenzhen Stock Exchanges as well as the board of the Growth Enterprise Market. Financial firms, stocks that have become public within the past six months, the bottom 10% of stocks ranked by market capitalization, and stocks involving long trading suspensions are excluded. All the firms' variables except for stock returns are winsorized at the 0.5% and 99.5% levels. See Table 11 for the definitions of the variables. The sample consists of 98,532 (20,179/6,426) firm-month (quarter-month/year-month) observations from 260 cities from January 2013 to September 2018.

Table 2
Pairwise correlations.

	AQI	AQI_IV	$PM_{2.5}$	$PM_{2.5}\_IV$	Size	BM	Beta	MOM	ROE	IA	EP	TUR
AQI		0.74	0.98	0.74	0.00	0.10	−0.02	0.09	−0.02	0.02	0.07	0.06
AQI_IV	0.74		0.75	0.99	−0.03	0.11	−0.03	0.14	−0.02	0.01	0.08	0.09
$PM_{2.5}$	0.98	0.77		0.77	0.01	0.09	−0.02	0.10	−0.02	0.02	0.07	0.06
$PM_{2.5}\_IV$	0.74	0.99	0.78		−0.02	0.10	−0.04	0.14	−0.02	0.01	0.08	0.08
Size	0.00	−0.04	0.00	−0.03		0.12	−0.05	0.14	0.20	0.05	0.29	0.02
BM	0.09	0.10	0.08	0.08	−0.09		−0.04	−0.08	−0.06	−0.05	0.52	0.11
Beta	−0.02	−0.04	−0.02	−0.04	−0.04	−0.07		0.03	−0.02	0.00	−0.05	0.03
MOM	0.16	0.24	0.18	0.24	0.18	−0.11	0.02		0.09	−0.02	0.05	0.20
ROE	−0.05	−0.04	−0.04	−0.04	0.30	−0.11	−0.05	0.13		0.04	0.28	0.01
IA	−0.03	−0.02	−0.03	−0.02	0.17	−0.17	0.02	−0.02	0.17		0.01	−0.01
EP	0.05	0.07	0.05	0.07	0.20	0.44	−0.07	0.08	0.41	0.05		0.08
TUR	0.07	0.09	0.07	0.09	0.01	0.08	0.00	0.25	0.03	0.00	0.10	

This table reports the pairwise correlations of the key characteristics used in the empirical analysis. The Pearson (Spearman) correlations are above (below) the diagonal. The sample includes all A-share stocks from the mainboard market of the Shanghai and Shenzhen Stock Exchanges as well as the board of the Growth Enterprise Market. Financial firms, stocks that have become public within the past six months, the bottom 10% of stocks ranked by market capitalization, and stocks involving long trading suspensions are excluded. All the firms' variables except for stock returns are winsorized at the 0.5% and 99.5% levels. See Table 11 for the definitions of the variables. The sample consists of 98,532 firm-month observations from 260 cities spanning January 2013 to September 2018.

after controlling for these factors, with the five-factor and six-factor alphas of 0.76% (0.41%) and 0.76% (0.45%), respectively, for the value- (equal-) weighted portfolios. These results indicate that the pollution factor has significant risk premium and that excess returns are negatively correlated with air pollution stock.

In Panel B of Table 3, we further show the sorting results of the pollution-linked portfolios based on the monthly concentration of $PM_{2.5}$. Consistent with the results of portfolio sorting based on AQI, the hedge strategy earns significantly positive returns and delivers significantly positive abnormal returns after controlling for common risk factors.

4.2. Cross-sectional analysis

To further examine the relationship between air pollution and average stock returns, we conduct Fama–MacBeth regressions of monthly stock returns on city-level air pollution indices and other characteristics. Specifically, the dependent variable is monthly excess return of each stock in month t and the independent variable of interest is air pollution in month t−1. Other control variables include lagged size (Size), book-to-market ratio (BM), market beta (Beta), price momentum (MOM), return on equity (ROE), asset

Table 3
Abnormal returns for pollution-linked portfolios.

Panel A: AQI					
Decile	Excess returns(%)	3-Factor alpha(%)	4-Factor alpha(%)	5-Factor alpha(%)	6-Factor alpha(%)
1 (low)	2.20	1.32	1.33	1.20	1.20
	(2.22)	(8.12)	(8.07)	(7.16)	(7.07)
2	1.95	1.11	1.10	1.17	1.17
	(2.2)	(6.9)	(6.81)	(6.84)	(6.73)
3	1.85	0.96	0.93	0.96	0.92
	(1.91)	(6.1)	(6.11)	(6.04)	(5.84)
4	2.03	1.18	1.13	1.19	1.08
	(2.08)	(4.37)	(4.35)	(4.11)	(3.91)
5 (high)	1.32	0.47	0.48	0.44	0.44
	(1.63)	(3.03)	(3.13)	(2.88)	(2.87)
low-high	0.89	0.86	0.85	0.76	0.76
(Value-weighted)	(2.00)	(3.74)	(3.67)	(3.29)	(3.23)
low-high	0.46	0.42	0.44	0.41	0.45
(Equal-weighted)	(1.86)	(2.99)	(3.16)	(2.73)	(2.97)

Panel B: $PM_{2.5}$					
Decile	Excess returns (%)	3-Factor alpha (%)	4-Factor alpha (%)	5-Factor alpha (%)	6-Factor alpha (%)
1 (low)	2.13	1.24	1.23	1.16	1.16
	(2.16)	(7.65)	(7.55)	(6.91)	(6.78)
2	2.01	1.2	1.2	1.27	1.28
	(2.3)	(7.29)	(7.23)	(7.27)	(7.22)
3	1.8	0.9	0.88	0.86	0.84
	(1.85)	(5.45)	(5.38)	(4.98)	(4.79)
4	1.91	1.03	0.98	0.96	0.85
	(2.00)	(3.88)	(3.83)	(3.39)	(3.16)
5 (high)	1.56	0.76	0.76	0.73	0.69
	(1.83)	(4.13)	(4.06)	(3.8)	(3.6)
low-high	0.57	0.47	0.48	0.43	0.47
(Value-weighted)	(1.27)	(1.99)	(1.99)	(1.79)	(1.92)
low-high	0.47	0.43	0.44	0.46	0.48
(Equal-weighted)	(2.09)	(3.28)	(3.35)	(3.25)	(3.39)

This table reports the abnormal returns for the pollution-linked portfolios adjusted by the risk-free rate or known pricing factors. The stocks are sorted into five portfolios based on the pollution level of the city in which the firm is located in year n-1, which is the average of the monthly pollution in year n-1, and are rebalanced at the beginning of year n+1. The zero-cost portfolio (low-high) holds the bottom 20% of firms ranked by pollution and sells short the top 20%. Once the portfolios are formed, their value-weighted returns and equal-weighted returns are computed from January to December in year n. Excess return is the excess return of the specific portfolio by subtracting the risk-free rate. Alpha is the intercept from the regression of monthly excess returns on factor returns. Panel A shows the results for AQI and Panel B shows the results for $PM_{2.5}$. Column (1) reports excess returns. Columns (2)–(5) report the alphas for Fama–French three-factor model, the four-factor model including Fama–French three-factor and Carhart (1997) momentum factor, Fama–French five-factor model and the six-factor model (Fama–French five-factor and momentum factor) respectively. The sample consists of 98,532 firm-month observations spanning January 2013 to September 2018. T-statistics are reported in parentheses.

growth (IA), PE ratio (EP) and turnover rate (TUR), following the literature. Definitions of the key variables are in Table 11. The value of each explanatory variable is extracted from the last available observation in month t with non-missing value.

Panel A of Table 4 reports the results of the Fama–MacBeth regressions. Columns (1) to (6) display the regression results when controlling for different firm characteristics. Consistent with the time-series factor-based tests in Table 3, AQI exhibits a strong predictive power for next month's firm return in all specifications. The coefficients on AQI are all significantly negative and comparatively stable whichever characteristics are controlled. For instance, column (3) shows that the coefficient on AQI is −0.006 with a t -statistic of −2.66 when controlling for the four-factor characteristics (Carhart, 1997). This coefficient on AQI suggests that a one-standard-deviation increase in AQI (34.69) decreases stock returns by $34.69 \times 0.006 = 20.8\%$. The coefficients on the control variables are also consistent with those in the literature: size (Size), asset growth (IA), PE ratio (EP) and turnover rate (TUR) are significantly negatively correlated with future returns, while book-to-market (BM), return on equity (ROE), market beta (Beta) and price momentum (MOM) are positively correlated with future returns. As a robustness check, we use the AQI from the nearest station within 50 kilometers of each firm instead of using the city-level AQI. We present the results controlling for four-factor characteristics in column (7). Overall, these results reveal significant risk premiums and strong predictive power for air pollution. The stocks of firms located in more polluted areas earn lower returns than those of firms in less polluted areas. Moreover, the pollution effect is not driven by correlations with the other determinants of expected returns.

Similarly, we conduct Fama–MacBeth regressions of monthly stock returns on $PM_{2.5}$ instead of AQI. Panel B of Table 4 reports these results. Consistent with the results on AQI, $PM_{2.5}$ is also a strong predictor of next month's firm return in all specifications. The coefficients on $PM_{2.5}$ have higher significance levels than those on AQI. These results are consistent with the fact that $PM_{2.5}$ is

Table 4
Cross-sectional regressions.

Panel A: AQI							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable*100	Ret	Ret	Ret	Ret	Ret	Ret	Ret
AQI	−0.005*	−0.006**	−0.006***	−0.005**	−0.006**	−0.006**	−0.005**
	(−1.68)	(−2.52)	(−2.66)	(−2.36)	(−2.48)	(−2.41)	(−2.56)
Size		−0.016	−0.018	−0.020	−0.020	−0.019	−0.020
		(−1.25)	(−1.38)	(−1.62)	(−1.64)	(−1.64)	(−1.49)
BM		0.625	0.522	0.724	0.619	0.641	0.557
		(1.01)	(0.86)	(1.16)	(1.00)	(1.07)	(0.92)
Beta		0.575*	0.588*	0.598*	0.612*	0.659*	0.588*
		(1.83)	(1.82)	(1.84)	(1.83)	(1.94)	(1.85)
MOM			0.498		0.232	0.306	0.532
			(1.33)		(0.71)	(0.93)	(1.43)
ROE				12.829***	12.135**	12.437***	
				(2.66)	(2.54)	(2.67)	
IA				−0.131**	−0.137**	−0.119*	
				(−2.23)	(−2.24)	(−1.90)	
EP						−0.651	
						(−0.24)	
TUR						−1.187***	
						(−6.72)	
Constant	1.286	0.395	0.453	0.106	0.148	1.432	0.342
	(1.06)	(0.31)	(0.37)	(0.08)	(0.11)	(1.02)	(0.28)
Observations	98,532	98,532	98,532	98,532	98,532	98,532	95,142
R-squared	0.002	0.059	0.070	0.070	0.080	0.093	0.070

Panel B: $PM_{2.5}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable*100	Ret	Ret	Ret	Ret	Ret	Ret	Ret
$PM_{2.5}$	−0.006**	−0.007***	−0.007***	−0.006**	−0.007***	−0.007***	−0.005**
	(−2.03)	(−2.79)	(−3.02)	(−2.57)	(−2.80)	(−2.67)	(−2.56)
Size		−0.017	−0.018	−0.020	−0.020	−0.019	−0.020
		(−1.25)	(−1.38)	(−1.62)	(−1.64)	(−1.64)	(−1.49)
BM		0.620	0.517	0.720	0.615	0.638	0.557
		(1.00)	(0.85)	(1.15)	(0.99)	(1.06)	(0.92)
Beta		0.574*	0.587*	0.596*	0.610*	0.657*	0.588*
		(1.83)	(1.82)	(1.83)	(1.83)	(1.94)	(1.85)
MOM			0.502		0.236	0.311	0.532
			(1.34)		(0.72)	(0.94)	(1.43)
ROE				12.850***	12.153**	12.462***	
				(2.67)	(2.54)	(2.67)	
IA				−0.131**	−0.137**	−0.119*	
				(−2.23)	(−2.24)	(−1.91)	
EP						−0.637	
						(−0.24)	
TUR						−1.182***	
						(−6.73)	
Constant	1.153	0.269	0.317	−0.021	0.016	1.288	0.342
	(1.00)	(0.22)	(0.27)	(−0.02)	(0.01)	(0.95)	(0.28)
Observations	98,532	98,532	98,532	98,532	98,532	98,532	95,142
R-squared	0.002	0.059	0.070	0.070	0.080	0.092	0.070

This table reports the results of the Fama–MacBeth regressions of monthly excess returns on the pollution indicator ($AQI/PM_{2.5}$) and other characteristics. The dependent variable is the monthly excess return of each stock in month t and the independent variable of interest is pollution stock in month t-1. Other control variables include size (Size), book-to-market ratio (BM), market beta (Beta), momentum (MOM), return on equity (ROE), asset growth (IA), PE ratio (EP), and turnover rate (TUR) following the literature. See Table 11 for the definitions of the variables. The value of each explanatory variable is extracted from the last available observation with a non-missing value for each month t. Panel A shows the results for AQI, while Panel B shows the results for $PM_{2.5}$. Cross-sectional regressions are run every calendar month, and the time-series standard errors are Newey–West adjusted (up to 12 lags) for heteroskedasticity and autocorrelation. The table reports the average loadings for each cross-sectional regression and the corresponding Newey–West adjusted t-statistics (in parentheses). The sample consists of 98,532 firm-month observations spanning January 2013 to September 2018. Column (7) reports the results for the air pollution data from the nearest station of each firm. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

Table 5
Abnormal returns for the pollution-linked portfolios based on the IV of the pollution indicator.

Panel A: AQI					
Decile	Excess returns (%)	3-Factoralpha (%)	4-Factoralpha (%)	5-Factoralpha (%)	6-Factoralpha (%)
1 (low)	2.04	1.11	1.07	1.13	1.07
	(2.14)	(5.58)	(5.66)	(5.62)	(5.43)
2	2.13	1.33	1.35	1.31	1.35
	(2.30)	(9.54)	(9.84)	(8.79)	(9.07)
3	1.97	1.08	1.05	1.11	1.06
	(2.05)	(6.64)	(6.65)	(6.38)	(6.21)
4	1.83	0.91	0.88	0.92	0.85
	(1.90)	(4.24)	(4.2)	(3.99)	(3.77)
5 (high)	1.30	0.49	0.49	0.41	0.39
	(1.64)	(3.02)	(3.01)	(2.58)	(2.43)
low-high	0.74	0.63	0.58	0.71	0.68
(Value-weighted)	(1.76)	(2.43)	(2.33)	(2.98)	(2.81)
low-high	0.28	0.28	0.28	0.29	0.29
(Equal-weighted)	(1.86)	(2.14)	(2.12)	(2.08)	(2.05)
Panel B: $PM_{2.5}$					
Decile	Excess returns (%)	3-Factoralpha (%)	4-Factoralpha (%)	5-Factoralpha (%)	6-Factoralpha (%)
1 (low)	2.01	1.09	1.05	1.09	1.04
	(2.13)	(5.79)	(5.84)	(5.72)	(5.53)
2	2.25	1.42	1.43	1.43	1.45
	(2.32)	(8.85)	(8.91)	(8.38)	(8.38)
3	1.77	0.86	0.84	0.93	0.9
	(1.93)	(5.84)	(5.77)	(5.98)	(5.78)
4	1.91	1.04	1	1.03	0.94
	(2.04)	(4.56)	(4.54)	(4.24)	(4.03)
5 (high)	1.23	0.41	0.42	0.3	0.29
	(1.47)	(2.29)	(2.31)	(1.58)	(1.54)
low-high	0.78	0.68	0.64	0.79	0.74
(Value-weighted)	(2.12)	(2.66)	(2.57)	(3.1)	(2.9)
low-high	0.28	0.28	0.28	0.29	0.3
(Equal-weighted)	(1.94)	(2.05)	(2.06)	(2.02)	(2.04)

This table reports the results of portfolio sort based on AQI_IV ($PM_{2.5}\_IV$), the estimate of AQI ($PM_{2.5}$) from the monthly IV TI. It reports the abnormal returns for the pollution-linked portfolios adjusted by the risk-free rate or known pricing factors. The stocks are sorted into five portfolios based on the AQI_IV ($PM_{2.5}\_IV$) of the firms in year n-1, which is the average of the monthly AQI_IV($PM_{2.5}\_IV$) in year n-1, and are rebalanced at the beginning of year n+1. The zero-cost portfolio (low-high) holds the bottom 20% of firms ranked by the pollution and sells short the top 20%. Once the portfolios are formed, their value-weighted returns and equal-weighted returns are computed from January to December in year n. The excess return is the excess return of the specific portfolio by subtracting the risk-free rate. Alpha is the intercept from the regression of monthly excess returns on factor returns. Panel A shows the results for AQI_IV, while Panel B shows the results for $PM_{2.5}\_IV$. Column (1) reports excess returns. Columns (2)–(5) report the alphas for Fama–French three-factor model, four-factor model including Fama–French three-factor and Carhart's (1997) momentum factor, Fama–French five-factor model, and six-factor model (Fama–French five-factor and momentum factor) respectively. The sample consists of 98,532 firm-month observations spanning January 2013 to September 2018. T-statistics are reported in parentheses.

the primary air pollutant for Chinese cities from 2013 to 2018. The cross-sectional regression coefficients on $PM_{2.5}$ are negative and statistically significant at the 1% level in all specifications. Additionally, we use the concentration of $PM_{2.5}$ of the nearest station within 50 kilometers from each firm instead of the city-level $PM_{2.5}$ as a robustness check. Column (7) shows this set of results controlling for the four-factor characteristics. The coefficients on $PM_{2.5}$ of the nearest station are all significantly negative. Again, we find the negative correlation between excess returns and air pollution on the cross-section of stock returns.

5. Endogeneity problem and instrumental variable approach

5.1. Instrumental variable and the construction of the predicted air quality index

In Fama-MacBeth regressions, the estimated effects of air pollution on stock returns may be biased because of measurement errors in the pollution variable (Arceo et al., 2016). Measurement errors arise because pollution monitoring sites are sporadically distributed across the city, leading to the failure to identify an accurate air pollution level. Moreover, omitted variables in the cross-sectional regressions and reverse causality may also render biases in the Fama-MacBeth regressions. For example, policy uncertainty can be another channel for air pollution to affect risk premium and there may exist city-level variations of policy uncertainty that affect both pollution and firms' profitability. Thus, we investigate whether the negative correlation between excess returns and pollution stock found in Section 4 still holds using an exogenous component of AQI or $PM_{2.5}$ constructed from an instrumental variable (IV) approach.

Existing economics research on socioeconomic effects of air pollution often exploits thermal inversion as an IV for air pollution (Arceo et al., 2016; Fu et al., 2021). Thermal inversion is a meteorological phenomenon in which the temperature at

Table 6
Cross-sectional regressions on AQI_IV.

Panel A: AQI							
Dep. Variable*100	(1) Ret	(2) Ret	(3) Ret	(4) Ret	(5) Ret	(6) Ret	(7) Ret
AQI_IV	−0.025**	−0.025**	−0.026**	−0.023**	−0.023**	−0.023**	−0.035**
	(−2.13)	(−2.58)	(−2.63)	(−2.39)	(−2.46)	(−2.37)	(−2.60)
Size		−0.016	−0.018	−0.019	−0.020	−0.019	−0.018
		(−1.24)	(−1.38)	(−1.61)	(−1.63)	(−1.64)	(−1.39)
BM		0.637	0.533	0.735	0.629	0.649	0.524
		(1.03)	(0.88)	(1.17)	(1.01)	(1.09)	(0.86)
Beta		0.569*	0.582*	0.592*	0.606*	0.653*	0.585*
		(1.81)	(1.80)	(1.81)	(1.81)	(1.92)	(1.81)
MOM			0.506		0.241	0.316	0.514
			(1.34)		(0.73)	(0.95)	(1.38)
ROE				12.834***	12.138**	12.395***	
				(2.68)	(2.55)	(2.67)	
IA				−0.129**	−0.135**	−0.118*	
				(−2.20)	(−2.22)	(−1.89)	
EP						−0.556	
						(−0.21)	
TUR						−1.185***	
						(−6.73)	
Constant	3.014*	2.033	2.107	1.601	1.672	2.875	3.063
	(1.75)	(1.34)	(1.37)	(1.01)	(1.04)	(1.66)	(1.55)
Observations	98,532	98,532	98,532	98,532	98,532	98,532	95,142
R-squared	0.003	0.059	0.070	0.070	0.080	0.093	0.070
Panel B: $PM_{2.5}$							
Dep. Variable*100	(1) Ret	(2) Ret	(3) Ret	(4) Ret	(5) Ret	(6) Ret	(7) Ret
$PM_{2.5}\_IV$	−0.024***	−0.022***	−0.022***	−0.021**	−0.021**	−0.020**	−0.036***
	(−2.71)	(−2.68)	(−2.70)	(−2.52)	(−2.57)	(−2.50)	(−3.30)
Size		−0.016	−0.018	−0.019	−0.020	−0.019	−0.018
		(−1.25)	(−1.38)	(−1.62)	(−1.63)	(−1.64)	(−1.41)
BM		0.626	0.521	0.725	0.619	0.638	0.530
		(1.01)	(0.86)	(1.16)	(1.00)	(1.07)	(0.87)
Beta		0.567*	0.580*	0.590*	0.604*	0.652*	0.583*
		(1.80)	(1.79)	(1.81)	(1.80)	(1.92)	(1.80)
MOM			0.507	12.886***	0.242	0.318	0.521
			(1.35)	(2.69)	(0.74)	(0.96)	(1.39)
ROE				−0.132**	12.188**	12.440***	
				(−2.26)	(2.57)	(2.69)	
IA					−0.138**	−0.121*	
					(−2.27)	(−1.94)	
EP						−0.537	
						(−0.20)	
TUR						−1.183***	
						(−6.72)	
Constant	2.146	1.102	1.132	0.767	0.792	2.027	1.939
	(1.59)	(0.85)	(0.89)	(0.56)	(0.58)	(1.38)	(1.27)
Observations	98,532	98,532	98,532	98,532	98,532	98,532	95,142
R-squared	0.002	0.059	0.070	0.070	0.080	0.092	0.070

This table reports the results of the Fama–MacBeth regressions of monthly excess returns on AQI_IV ($PM_{2.5}\_IV$), the estimate of AQI ($PM_{2.5}$) from the monthly IV TI, and the other characteristics. The dependent variable is the monthly excess return of each stock in month t and the independent variable of interest is AQI_IV ($PM_{2.5}\_IV$) in month t-1. The other control variables include size (Size), the BM, market beta (Beta), momentum (MOM), return on equity (ROE), asset growth (IA), the PE ratio (EP), the and turnover rate (TUR) following the literature. See Table 11 for the definitions of the variables and all the explanatory variables are based on the last non-missing available observation for each month t. Panel A shows the results for AQI_IV, while Panel B shows the results for $PM_{2.5}\_IV$. Cross-sectional regressions are run every calendar month, and the time-series standard errors are Newey–West adjusted (up to 12 lags) for heteroskedasticity and autocorrelation. The table reports the average loadings for each cross-sectional regression and the corresponding Newey–West adjusted t-statistics (in parentheses). The sample consists of 98,532 firm-month observations spanning January 2013 to September 2018. Column (7) reports the results for the air pollution data from the nearest station of each firm. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

the surface falls below that above the surface. When thermal inversion happens, air pollutants, especially particulate matters, are easily trapped in the ground. Specifically, we first regress AQI and $PM_{2.5}$ on thermal inversion, weather characteristics, BM, Beta, Size, city fixed effects (FE), year-by-month FE, respectively. We then compute the predicted AQI (AQI_IV) and $PM_{2.5}$ ($PM_{2.5}\_IV$) using the coefficients on thermal inversion, which partials out the influences of weather controls, firm characteristics, city and time FE on air pollution. AQI_IV ($PM_{2.5}\_IV$) represents the component of AQI ($PM_{2.5}$) that only comes from the variation in our

Table 7
Controlling the fitted conditional expected return.

Dep. Variable*100	(1) Ret	(2) Ret	(3) Ret	(4) Ret	(5) Ret	(6) Ret
AQI_IV	−0.013*	−0.014*	−0.017**	−0.016**	−0.016**	−0.014*
	(−1.87)	(−1.76)	(−2.30)	(−2.27)	(−2.21)	(−1.69)
Fitted return	0.859***	0.840***	0.877***	0.872***	0.871***	0.902***
	(5.08)	(6.03)	(6.33)	(6.26)	(6.26)	(6.19)
Size		−0.008	−0.006	−0.007	−0.007	−0.009
		(−1.13)	(−0.74)	(−1.10)	(−1.10)	(−1.21)
BM		1.132*	0.743	0.859	0.853	0.653
		(1.84)	(1.16)	(1.32)	(1.32)	(0.91)
Beta		0.566*	0.593*	0.606*	0.609*	0.682**
		(1.89)	(1.97)	(1.99)	(1.99)	(2.14)
MOM			−1.361***	−1.605***	−1.602***	−1.501***
			(−3.47)	(−4.60)	(−4.59)	(−4.26)
ROE				11.215**	11.253**	10.554*
				(2.26)	(2.29)	(1.92)
IA					−0.075	−0.037
					(−1.40)	(−0.59)
EP						3.007*
						(1.82)
TUR						−2.201***
						(−6.10)
Constant	0.901	−0.226	0.195	−0.174	−0.178	1.878
	(0.72)	(−0.23)	(0.18)	(−0.15)	(−0.16)	(1.28)
Observations	83,181	83,181	83,181	83,181	83,181	83,181
R-squared	0.148	0.195	0.205	0.213	0.214	0.233

This table reports the results of the Fama–MacBeth regressions of monthly excess returns on AQI_IV, the fitted conditional expected return, and the other characteristics. The dependent variable is the monthly excess return and the independent variable of interest is lagged AQI_IV. The fitted expected return is from a time-series regression of the returns on lagged systematic instrumental variables, using data to time t. The minimum length of regression window is 12 months. The systematic instrumental variables used to form the fitted expected return include dividend yield of CSI300 Index, difference between 1-year and 5-year T-bill returns, difference between 1-year and 10-year T-bill returns, spread between AAA and AA yields of Chinese enterprise Bonds, difference between AAA Chinese enterprise Bonds and T-bill returns. The other control variables include size, the BM, market beta, momentum, return on equity, asset growth, the PE ratio, the and turnover rate. All the explanatory variables are based on the last non-missing available observation for each month t. Cross-sectional regressions are run every calendar month, and the time-series standard errors are Newey–West adjusted (up to 12 lags) for heteroskedasticity and autocorrelation. The table reports the average loadings for each cross-sectional regression and the corresponding Newey–West adjusted t-statistics (in parentheses). Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

Table 8
Air pollution and the conditional cash flow productivity beta.

Variables	(1) Rcash1	(2) Rcash1	(3) Rcash2	(4) Rcash2	(5) ΔOP	(6) ΔOP
ΔTFP	0.178*	0.048**	0.207	0.231***	0.323	0.245***
	(1.80)	(2.03)	(1.06)	(4.95)	(1.07)	(3.55)
$YAQI\_IV \times \Delta TFP$	−0.050**	−0.042*	−0.188***	−0.187***	−0.267***	−0.262***
	(−2.05)	(−1.76)	(−3.89)	(−3.96)	(−3.75)	(−3.79)
$ME \times \Delta TFP$	−0.122		0.024		−0.074	
	(−1.35)		(0.13)		(−0.27)	
$SG \times \Delta TFP$	0.006		0.021**		0.006	
	(1.32)		(2.25)		(0.40)	
Constant	0.000	−0.000	−0.001	−0.001	−0.000	−0.000
	(0.03)	(−0.03)	(−0.11)	(−0.08)	(−0.00)	(−0.00)
Observations	6,426	6,426	6,426	6,426	6,426	6,426
R-squared	0.002	0.001	0.014	0.012	0.003	0.003

Air pollution and the conditional cash flow productivity beta. This table reports the results of the link between air pollution and the conditional covariance of cash flows with aggregate productivity growth (ΔTFP). The table reports the results from the following regression: $CF_{i,t} = a+(b+cYAQI\_IV_{i,t-1}+dZ_{i,t-1})\times\Delta TFP_{i,t}+\epsilon_{i,t}$, where $CF_{i,t}$ is measured as the real growth rate of operating profit (ΔOP), firm cash flow to assets (Rcash1), and equity cash flow to assets (Rcash2). The vector $Z_{i,t-1}$ is a set of additional firms' control variables including sales growth (GS) and market capitalization (ME). All the variables are normalized to have mean zero and unit standard deviation. The regression is run annually and the firm fixed effect is controlled. The sample consists of 6,426 firm-year observations spanning 2013 to 2017. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

Table 9
Double sorting: Excess returns by firm characteristics and AQI_IV.

	Pollution	Decile											Comparisons		
		≤ 0	1	2	3	4	5	6	7	8	9	10	10-1	10-5	5-1
ME	Low		1.02	1.17	0.87	0.90	0.65	0.53	0.42	0.09	0.08	0.16	−0.86	−0.48	−0.38
	High		0.90	0.92	0.58	0.41	0.24	0.31	0.26	0.09	0.44	0.03	−0.88	−0.21	−0.67
	Diff		0.12	0.24	0.29	0.49	0.41	0.22	0.16	0.00	−0.35	0.14	0.02	−0.27	0.29
Age	Low		0.47	1.20	0.96	0.85	0.91	0.24	0.16	0.57	0.55	0.61	0.14	−0.30	0.44
	High		0.64	0.60	0.60	0.63	0.21	0.51	0.50	0.34	0.28	0.22	−0.42	0.01	−0.43
	Diff		−0.17	0.60	0.36	0.22	0.70	−0.27	−0.35	0.22	0.26	0.39	0.56	−0.31	0.87
Sigma	Low		0.95	0.84	0.65	1.08	1.01	0.63	0.78	0.54	0.48	0.40	−0.55	−0.62	0.07
	High		1.20	0.99	0.66	0.50	0.50	0.54	0.23	0.11	0.45	0.01	−1.19	−0.49	−0.70
	Diff		−0.25	−0.14	−0.01	0.58	0.51	0.09	0.55	0.44	0.03	0.38	0.64	−0.13	0.77
ROE	Low	0.14	0.55	0.51	0.51	0.56	0.81	0.76	0.80	0.76	1.01	0.82	0.26	0.00	0.26
	High	0.09	0.01	0.36	0.47	0.19	−0.01	0.83	0.53	0.81	0.68	0.85	0.85	0.87	−0.02
	Diff	0.05	0.55	0.15	0.04	0.38	0.83	−0.07	0.26	−0.04	0.34	−0.04	−0.59	−0.87	0.28
DBE	Low	0.38	0.98	0.82	0.86	0.77	1.02	0.93	0.76	0.52	0.55	0.18	−0.79	−0.84	0.04
	High	0.20	0.55	0.36	0.61	0.62	0.58	0.30	0.37	0.60	0.42	0.56	0.01	−0.02	0.03
	Diff	0.18	0.43	0.46	0.25	0.15	0.44	0.64	0.39	−0.08	0.13	−0.38	−0.81	−0.82	0.01
BM	Low		−0.23	0.21	0.64	0.79	0.56	0.80	0.72	0.92	0.90	0.86	1.09	0.30	0.79
	High		−0.12	0.24	0.38	0.15	0.40	0.41	0.50	0.52	0.66	0.81	0.92	0.40	0.52
	Diff		−0.11	−0.03	0.26	0.65	0.16	0.39	0.22	0.40	0.25	0.05	0.16	−0.10	0.27
EFA	Low		0.79	0.79	1.15	0.84	0.85	0.80	0.40	0.75	0.58	0.62	−0.18	−0.24	0.06
	High		0.20	0.73	0.71	0.59	0.67	0.45	0.83	0.44	0.31	0.13	−0.07	−0.53	0.46
	Diff		0.59	0.06	0.44	0.26	0.19	0.36	−0.43	0.32	0.27	0.48	−0.11	0.29	−0.40
GS	Low		0.42	0.58	0.86	0.80	1.03	0.69	0.91	0.74	0.75	0.74	0.32	−0.29	0.61
	High		0.38	0.70	0.47	0.67	0.44	0.75	0.51	0.46	0.40	0.31	−0.07	−0.12	0.05
	Diff		0.03	−0.12	0.38	0.13	0.59	−0.05	0.40	0.28	0.35	0.42	0.39	−0.17	0.56

This table reports the results of portfolio sort based on AQI_IV and firm characteristics including market capitalization(ME), age, total risk (Sigma), return on equity (ROE), dividend-to-book ratio (DBE), book-to-market ratio (BM), external finance over assets (EFA), and sales growth (GS). It reports monthly excess returns for those portfolios. The stocks are first divided into two groups based on AQI_IV. The bottom 50% of firms ranked by AQI_IV form the low pollution group and the top 50% form the high pollution group. Then, the high and low pollution groups are divided into 10 groups according to firm characteristics. The conditional difference between the low and high pollution groups across the deciles of each firm characteristic is also computed and the portfolios are rebalanced every month.

exogenous IV and should be uncorrelated with measurement errors in the original pollution variable and city FE and time-varying unobservables in the Fama-MacBeth regressions. Thus, using AQI_IV ($PM_{2.5}\_IV$) addresses the endogeneity issue of AQI ($PM_{2.5}$). Table 1 in the online appendix presents the results from regressing AQI and $PM_{2.5}$ on the IV, respectively. Thermal inversion significantly increase AQI and $PM_{2.5}$, reassuring the validity of our IV.

To compute the variables that represent the intensity of thermal inversion, we collect data on instantaneous temperature at different altitudes from the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2), which is a NASA atmospheric reanalysis for the satellite era using the Goddard Earth Observing System Model, Version 5 (GEOS-5) with its Atmospheric Data Assimilation System (ADAS), version 5.12.4. MERRA-2 provides temperature records at a spatial resolution of $0.5^\circ \times 0.625^\circ$ every six hours.

For each grid (latitude/longitude combination) in each six-hour period, we first keep the temperature at the lowest two layers with non-missing temperature records. Thermal inversion is calculated as the temperature of the second layer minus the temperature of the first layer if the former is no less than the latter, and 0 otherwise. We then calculate the daily intensity of thermal inversion in each grid by averaging across the four six-hour periods on each day.

Weather characteristics may be correlated with air pollution and have direct influences on firm productivity and thus stock returns (Fu et al., 2021). Thus, we collect rich weather variables from the China Meteorological Data Sharing Service System (CMDSSS), which includes daily average temperature, sunshine duration, relative humidity, wind speed, precipitation, and air pressure at 699 weather stations in China. We then calculate the daily weather variables at the city level using the inverse distance weighting method. For each city, we draw a circle of 150 km from the city's centroid and calculate the weighted average daily weather variables using all stations within this circle. We use the inverse of the distance between the city's centroid and each station as the weights. We then construct the monthly weather variables by averaging the daily values in each month, which are merged with the stock variables by city, year, and month.

5.2. Results from the instrumental variable approach

We conduct portfolio sorting and Fama–MacBeth regressions using AQI_IV and $PM_{2.5}\_IV$ as in Section 4. Table 5 reports the sorting returns. Panel A shows the results for AQI_IV, while Panel B shows the results for $PM_{2.5}\_IV$. Consistent with the results that rely on AQI, AQI_IV also shows strong predictive power of stock returns. We find that the portfolios of firms located in more (less) polluted areas earn lower (higher) subsequent returns. Specifically, monthly value-weighted returns of 74 basis points of the hedge strategy (low-high) decline slightly than those when AQI is used. The corresponding equal-weighted returns from the

Table 10
Cross-sectional regressions on AQI_IV with data from large cities removed.

Panel A: omit Beijing, Shanghai, Shenzhen, and Guangzhou						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable*100	Ret	Ret	Ret	Ret	Ret	Ret
AQI_IV	−0.031***	−0.032***	−0.032***	−0.031***	−0.031***	−0.030***
	(−2.90)	(−3.83)	(−3.74)	(−3.81)	(−3.78)	(−3.52)
Size		−0.018	−0.022	−0.025*	−0.027*	−0.025*
		(−1.12)	(−1.36)	(−1.72)	(−1.80)	(−1.75)
BM		0.458	0.317	0.608	0.477	0.612
		(0.66)	(0.46)	(0.86)	(0.67)	(0.84)
Beta		0.567*	0.570*	0.586*	0.594*	0.641**
		(1.96)	(1.90)	(1.96)	(1.91)	(2.00)
MOM			0.524		0.197	0.269
			(1.36)		(0.63)	(0.83)
ROE				16.340***	15.662***	16.520***
				(3.33)	(3.23)	(3.56)
IA				−0.119	−0.127*	−0.114
				(−1.65)	(−1.76)	(−1.61)
EP						−1.918
						(−0.75)
TUR						−1.275***
						(−6.08)
Constant	3.477*	2.599	2.794	2.229	2.406	3.700*
	(1.98)	(1.48)	(1.55)	(1.24)	(1.30)	(1.84)
Observations	65,716	65,716	65,716	65,716	65,716	65,716
R-squared	0.002	0.056	0.066	0.069	0.078	0.091
Panel B: omit the sixteen largest cities in China						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable*100	Ret	Ret	Ret	Ret	Ret	Ret
AQI_IV	−0.035**	−0.034***	−0.034***	−0.036***	−0.035***	−0.035***
	(−2.44)	(−3.14)	(−3.13)	(−3.34)	(−3.27)	(−3.20)
Size		−0.017	−0.021	−0.025*	−0.026*	−0.025*
		(−1.06)	(−1.27)	(−1.68)	(−1.72)	(−1.75)
BM		0.499	0.351	0.676	0.545	0.629
		(0.76)	(0.53)	(1.00)	(0.79)	(0.90)
Beta		0.562*	0.558	0.583*	0.584	0.626*
		(1.70)	(1.64)	(1.71)	(1.66)	(1.75)
MOM			0.521		0.180	0.229
			(1.43)		(0.63)	(0.78)
ROE				17.189***	16.229***	16.300***
				(3.21)	(3.01)	(3.11)
IA				−0.199**	−0.207**	−0.182*
				(−2.05)	(−2.11)	(−1.94)
EP						1.249
						(0.50)
TUR						−1.406***
						(−6.97)
Constant	3.840*	2.821	2.987	2.614	2.720	4.206*
	(1.87)	(1.37)	(1.44)	(1.24)	(1.27)	(1.85)
Observations	47,600	47,600	47,600	47,600	47,600	47,600
R-squared	0.004	0.057	0.068	0.072	0.081	0.096

This table reports the results for the Fama–MacBeth regressions of monthly excess returns on AQI_IV and other characteristics with data from large cities removed. Two samples are constructed. Sample A consists of all firms in cities other than Shanghai, Beijing, Shenzhen, and Guangzhou, while sample B consists of all firms in cities other than the 16 largest cities in China. The dependent variable is the monthly excess return of each stock in month t and the independent variable of interest is AQI_IV in month t-1. Other control variables include size (Size), book-to-market ratio (BM), market beta (Beta), momentum (MOM), return on equity (ROE), asset growth (IA), PE ratio (EP) and turnover rate (TUR) following the literature. Cross-sectional regressions are run every calendar month, and the time-series standard errors are Newey–West adjusted (up to 12 lags) for heteroskedasticity and autocorrelation. The table reports the average loadings for each cross-sectional regression and the corresponding Newey–West adjusted t-statistics (in parentheses). Panel A reports the results of sample A, which consists of 65,716 firm-month observations and Panel B reports the results of sample B, which consists of 47,600 firm-month observations spanning January 2013 to September 2018. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

Table 11
Definitions of the key variables.

Variable	Definition
Ret	Excess return, stock monthly raw return subtracted by the risk-free yield.
Retq	Quarterly excess return, quarterly average of Ret .
AQI	Monthly AQI, monthly average air quality index of the city where a specific firm is located in.
$PM_{2.5}$	Monthly $PM_{2.5}$, monthly average concentration of $PM_{2.5}$ of the city where a specific firm is located in.
AQI_IV	The estimate of the monthly AQI based on the instrumental variable (thermal inversion).
$PM_{2.5}\_IV$	The estimate of the monthly $PM_{2.5}$ based on the instrumental variable (thermal inversion).
$QAQI\_IV$	Quarterly average of AQI_IV.
$QPM_{2.5}\_IV$	Quarterly average of $PM_{2.5}\_IV$.
$YAQI\_IV$	Yearly average of AQI_IV.
$YPM_{2.5}\_IV$	Yearly average of $PM_{2.5}\_IV$.
TI	Monthly thermal inversion variable, the number of days when the daily thermal inversion is greater than 0 in a month.
Size	Firm size, the total market equity, (CSMAR Monthly Stock Price & Returns item "Msmvttl" times 1000) , billion.
BM	Book-to-market ratio, the book value divided by total market equity, where book value is measured as total shareholder equity (CSMAR balance sheet item "A003112000") minus the book value of preferred stocks (CSMAR balance sheet item "A003112101").
Beta	Market beta, the slope of regressing excess returns on the current as well as the lead and lag of the market return. Dimson (1979)
MOM	Momentum, cumulative return over month t-12 to t-2.
ROE	Return on equity, income before extraordinary items divided by book value, where income before extraordinary items is operating profit (CSMAR income sheet item "B001300000") minus tax expense (CSMAR income sheet item "B002100000").
IA	Asset growth, the annual change of total assets (CSMAR balance sheet item "A001000000") divided by total asset of last year.
EP	Earnings-to-price ratio, income before extraordinary items divided by market equity (CSMAR Monthly Stock Price & Returns item "Msmvttl" times 1000), where income before extraordinary items equals to operating profit (CSMAR income sheet item "B001300000") minus tax expense (CSMAR income sheet item "B002100000").
TUR	Turnover ratio, the ratio of average daily turnover over the past 20 days to average daily turnover over the past 250 days, where daily turnover equals to daily trading volume (CSMAR Daily Stock Price & Returns item "Dnshrtrd") divided by split-adjusted total shares outstanding (CSMAR Daily Stock Price & Returns item "Dsmvtll" times 1000 divided by "Clsprc").
ROA	Return on asset, quarterly net income (CSMAR income sheet item "B002000000") divided by book value of total asset.

low-high portfolio are 28 basis points per month. In columns (2)-(5), we control for the other known return determinants. The same low-high strategy delivers monthly abnormal returns of 0.63% (0.28%) in the value-weighted (equal-weighted) portfolios in Fama and French's (1993) three-factor model. If we augment this model by adding the stock's own price momentum (Carhart, 1997), the low-high portfolio delivers 0.58% (0.28%) per month for the value-weighted (equal-weighted) portfolios. Finally, we adjust returns using Fama and French's (2015) five-factor model and conduct a test using the five-factor model plus the momentum factor. We find that the strategy's alpha is robust across the controls of other factors, with the five-factor and six-factor alphas at 0.71% (0.29%) and 0.68% (0.29%), respectively for the value-weighted (equal-weighted) portfolios. In general, the portfolio sorting test on AQI_IV shows that excess returns are indeed negatively correlated with pollution stock. The results for $PM_{2.5}\_IV$ are consistent with those for AQI_IV as shown in Panel B of Table 5.

Table 6 reports the Fama–MacBeth regression results. Panel A exhibits the results for AQI_IV, while Panel B exhibits the results for $PM_{2.5}\_IV$. Similar to AQI, AQI_IV shows strong predictive power for firm returns in the next month in all specifications. The coefficients on AQI_IV are all significantly negative at the 5% level and comparatively stable across specifications that control for different characteristics. Compared with the coefficients on AQI, the coefficients on AQI_IV are much larger, suggesting the necessity of correcting the endogeneity and attenuation biases using the IV approach. The coefficient on AQI_IV is −0.026 when characteristics in the four-factor model are controlled (column [3]) and −0.023 when eight characteristics are controlled (column [6]). Using column (3), a one-standard-deviation increase in AQI_IV (23.53) decreases stock returns by $23.53 \times 0.026 = 61.2\%$. The coefficients on the control variables are also consistent with those in the previous literature: size, asset growth, PE ratio and turnover rate are significantly negatively correlated with future returns, while book-to-market ratio, return on equity, market beta, and price momentum are positively correlated with future returns. The coefficients on the constructed air pollution variable still indicate that stock returns are negatively correlated with pollution stock in each cross-section. The results for $PM_{2.5}\_IV$ are also consistent with those for AQI_IV. As robustness checks, we use the AQI_IV and $PM_{2.5}\_IV$ constructed from air pollution of the nearest station within 50 km of each firm instead of the city-level pollution variables. Column (7) of Table 6 presents these results when controlling the four-factor characteristics. The coefficients on AQI_IV and $PM_{2.5}\_IV$ of the nearest station are all significantly negative and have even larger magnitudes.[5]

[5] Notice that the number of observations is slightly smaller because the nearest station may be more than 50 km away from a firm.

5.3. Controlling the fitted conditional expected return

Previous studies identify predetermined variables with some power to explain the time series of stock and bond returns. Ferson and Harvey (1999) shows that loadings on the same variables also provide significant cross-sectional explanatory power for stock portfolio returns. So it raises a caution flag for researchers who would use the popular factors in an attempt to control for systematic patterns in risk and expected return. We conduct Fama–MacBeth regressions with the systematic return spreads controlled to justify the negative relation between air pollution and stock returns.

According to Ferson and Harvey (1999), we conduct the cross-sectional regression controlling the fitted conditional expected return. The fitted expected return is from a time-series regression of the returns on lagged systematic instrumental variables, using data to time t. The minimum length of regression window is 12 months. The systematic instrumental variables used to form the fitted expected return include dividend yield of CSI300 Index, difference between 1-year and 5-year T-bill returns, difference between 1-year and 10-year T-bill returns, spread between AAA and AA yields of Chinese enterprise Bonds, difference between AAA Chinese enterprise Bonds and T-bill returns.

Table 7 reports the Fama–MacBeth regression results. The coefficients on AQI_IV are all significantly negative at the 5% level and comparatively stable across specifications that control for different characteristics. The results suggest the negative relation between air pollution and stock returns does exist even if the systematic return spreads controlled.

6. Mechanisms

We find that stock returns are negatively correlated with pollution stock and confirm the causal effect of air pollution. One strand of the literature suggests that air pollution affects people's psychological status, resulting in bias in investor behaviors and thereby influencing stock returns. Aggregate pollution stock in the city in which firms are located is likely to significantly decrease stock returns given home bias in stock pricing and investor behavior channel of the pollution effect on stock returns. However, there appears to be an alternative explanation for this negative impact. Air quality may decrease labor productivity, thereby reducing firms' productivity and stock returns. For instance, higher aggregate pollution stock increases lost work days (Hanna and Oliva, 2015), decreases worker productivity for physically demanding tasks (Graff Zivin and Neidell, 2012; Chang et al., 2016) and indoor white-collar work (Chang et al., 2019), and lowers cognitive performance (Ebenstein et al., 2016). Thus, we introduce pollution stock into the neoclassical q-theory model of a production economy and establish the theoretical link between air pollution and stock returns through the cash flow risk channel (in appendix). Our model predicts a negative relationship between aggregate pollution stock and the firm's risk premium if pollution stock decreases the covariance between cash flows and aggregate productivity shocks, which is referred to as the cash flow risk channel. In this section, we perform tests to explore the cash flow risk channel in two steps. In the first step, we directly test the cash flow risk channel. Further, we rule out the possibility that air pollution affects stock returns only by influencing investor behaviors.

6.1. The cash flow risk channel

In this section, we directly explore the cash flow risk channel. We investigate if the firm's conditional covariance of cash flows with the aggregate profitability shock decreases with air pollution.

Following the approach in Ferson and Harvey (1999) and Belo and Yu (2013), we examine the effect of air pollution on the conditional covariance of cash flows with aggregate productivity growth (ΔTFP) by running the following regression:

$$CF_{i,t} = a + (b + cYAQI\_IV_{i,t-1} + dZ_{i,t-1}) \times \Delta TFP_t + \epsilon_{i,t}$$

Here, $CF_{i,t}$ is the firm's cash flow, which is measured in three ways: the real growth rate of operating profit (ΔOP), firm cash flow to assets (Rcash1),[6] and equity cash flow to assets (Rcash2).[7] $YAQI\_IV$ is the annual average of local pollution stock, which is yearly average of monthly AQI_IV. The vector $Z_{i,t-1}$ is a set of additional firm-level control variables including sales growth (SG) and market capitalization (ME). The firm fixed effect is controlled. As aggregate productivity growth (ΔTFP) is always computed annually, we run the regression from 2013 to 2017 at an annual frequency.

Table 8 reports the regression results. The odd and even columns report the results with and without the control variables, respectively. $YAQI\_IV$ significantly decreases the effect of ΔTFP on cash flow across all three cash flow indicators, which suggests that pollution stock decreases the conditional covariance of cash flows with the aggregate productivity shock. The t-statistic of the coefficient on $YAQI\_IV$ is 2.05 for firm cash flow to assets (Rcash1), 3.89 for equity cash flow to assets (Rcash2), and 3.75 for the real growth rate of operating profit (ΔOP). We also perform a similar test using $PM_{2.5}$ and find similar results (see Table 4 in the online appendix). Our results suggest that the negative link between air pollution and excess returns operates, at least partially, through the cash flow risk channel.

[6] Firm cash flow to assets equals net profits plus interest expenses, minus annual changes in total assets, plus annual changes in monetary funds, minus annual changes in total liabilities and minus the difference in cash received from equity investment and cash paid for distributing dividends and profits or paying interest, scaled by one-year-lagged total assets.

[7] Equity cash flow to assets equals net profits plus interest expenses, minus annual changes in total assets, plus annual changes in monetary funds, minus annual changes in total liabilities and minus the difference in cash received from equity investment and cash paid for distributing dividends and profits or paying interest, scaled by total assets.

6.2. Portfolio sorts on firm characteristics and air pollution

Baker and Wurgler (2006) find conditional effects for investor behavior across firm characteristics. When investor sentiment is low, subsequent returns are relatively high for small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks. When sentiment is high, on the contrary, these categories of stocks earn relatively low subsequent returns. This comparison indicates significant conditional differences between the high and low sentiment groups across deciles of each firm characteristic. If sentiment is the only factor through which air pollution can affect stock returns, we should observe similar conditional effects of air pollution on stock prices across firm characteristics. Based on a portfolio sorting approach similar to that of Baker and Wurgler (2006), we investigate whether air pollution also has heterogeneous effects on stock returns across those firm characteristics and whether the investor behavior channel is the only mechanism through which air pollution influences stock returns. We first divide the observations into two groups based on AQI_IV ($PM_{2.5}\_IV$). The bottom 50% of firms ranked by AQI_IV ($PM_{2.5}\_IV$) form the low pollution group and the top 50% form the high pollution group. We then divide the observations into 10 groups based on each firm characteristic for the high and low pollution groups, respectively. The selected characteristics are the same as those in Baker and Wurgler (2006), including market capitalization (ME), age, total risk (Sigma), return on equity (ROE), dividend-to-book ratio (DBE), book-to-market ratio (BM), external finance over assets (EFA), and sales growth (SG). We calculate monthly equal-weighted average returns for each group and rebalance the groups at the beginning of each month. We also identify the conditional difference between the low and high pollution groups across the deciles of each firm characteristic.

Table 9 reports the average return for each group and conditional differences based on AQI_IV. Fig. 1 shows the results in Table 9 graphically. Based on a similar portfolio sorting approach, these results do not show any significant conditional effects found by Baker and Wurgler (2006). None of the conditional differences across the deciles of those firm characteristics show an obvious trend although most of the unconditional effects of the characteristics are consistent with those in the literature. For example, the first rows of Table 9 show that regardless of the pollution level, smaller firms have higher returns than larger firms. The conditional difference across the deciles of ME does not show any obvious trend in Fig. 1, while that in Baker and Wurgler (2006) increases with ME. Pollution does not have a relatively sensitive effect on stock returns for smaller firms as sentiment does in Baker and Wurgler (2006). Similarly, pollution does not display significant conditional effects across any other firm characteristic. Table 2 and Figure 2 in the online appendix report the results based on $PM_{2.5}\_IV$, which are consistent with those for AQI_IV. As pollution does not display conditional effects as sentiment does in Baker and Wurgler (2006), we can infer that the investor behavior is not the only channel through which air pollution influences stock markets.

6.3. Fama–MacBeth regressions: Removing data on large cities

Since financial institutions tend to be located together in large cities, the shares of both stock exchanges in China are mostly traded by institutional and individual investors in such large cities, especially Shanghai, Beijing, Shenzhen, and Guangzhou. Therefore, air pollution in large cities is the main driver of the negative effect on stock returns through the investor behavior channel. As a comparison, pollution outside large cities is unlikely to affect the sentiment and behavior of most investors. To further examine whether the investor behavior channel is the only mechanism, we test if the pollution impact on stock returns remains after omitting the large cities. If the investor behavior channel is the only mechanism, the pollution impact would not exist in the smaller sample. Otherwise, it is possible that air pollution affects stock returns via other mechanisms besides influencing investor behaviors.

We rerun the Fama–MacBeth regressions using two subsamples. Sample A consists of all firms in cities other than Shanghai, Beijing, Shenzhen, and Guangzhou, while Sample B consists of all firms in cities other than the 16 largest cities in China.[8] Then, we conduct Fama–MacBeth regressions of monthly stock returns on pollution ($AQI\_IV \backslash PM_{2.5}\_IV$) and the other characteristics similar to Section 5.2. Specifically, the dependent variable is the monthly excess return of each stock in month t and the main independent variable of interest is IV-estimated pollution in month t−1 ($AQI\_IV \backslash PM_{2.5}\_IV$). The other control variables include size (Size), book-to-market ratio (BM), market beta (Beta), price momentum (MOM), return on equity (ROE), asset growth (IA), PE ratio (EP), and turnover rate (TUR).

Panels A and B of Table 10 report the Fama–MacBeth regression results for samples A and B, respectively. Different columns represent regressions that control for different firm characteristics. Consistent with the regressions for the full sample, AQI_IV shows strong predictive power for firm returns in the next month for both samples. In sample A, which consists of all firms in cities other than the four largest Chinese cities, the coefficients on AQI_IV are negative and even more significant than those for the full sample. In sample B, which consists of all firms outside the 16 largest cities, the coefficients on AQI_IV are negative and larger than those for the full sample and sample A. The coefficients are stable across different specifications. Column (4) of Panel B shows that the coefficient on AQI_IV is −0.036 after controlling for the five-factor characteristics. We also run the Fama–MacBeth regression results for $PM_{2.5}\_IV$, which are consistent with those for AQI_IV (Table 3 in the online appendix). These Fama–MacBeth regression results using the subsamples suggest that the negative pollution effects on stock returns still exist after the data from large cities are removed. Therefore, pollution indeed affects stock returns through other mechanisms than influencing investor behaviors.[9]

8 These 16 largest cities are Beijing, Shanghai, Tianjin, Shenzhen, Chongqing, Harbin, Qingdao, Hangzhou, Shenyang, Nanjing, Shijiazhuang, Zhengzhou, Xi'an, Wuhan, Chengdu, and Guangzhou.

9 An ideal way to exclude the influence from investor behaviors is to use air pollution measures that are collected only from industrial areas. However, we cannot distinguish air pollution measures in residential areas from that in industrial areas for two reasons. First, there is not a clear division of the functional

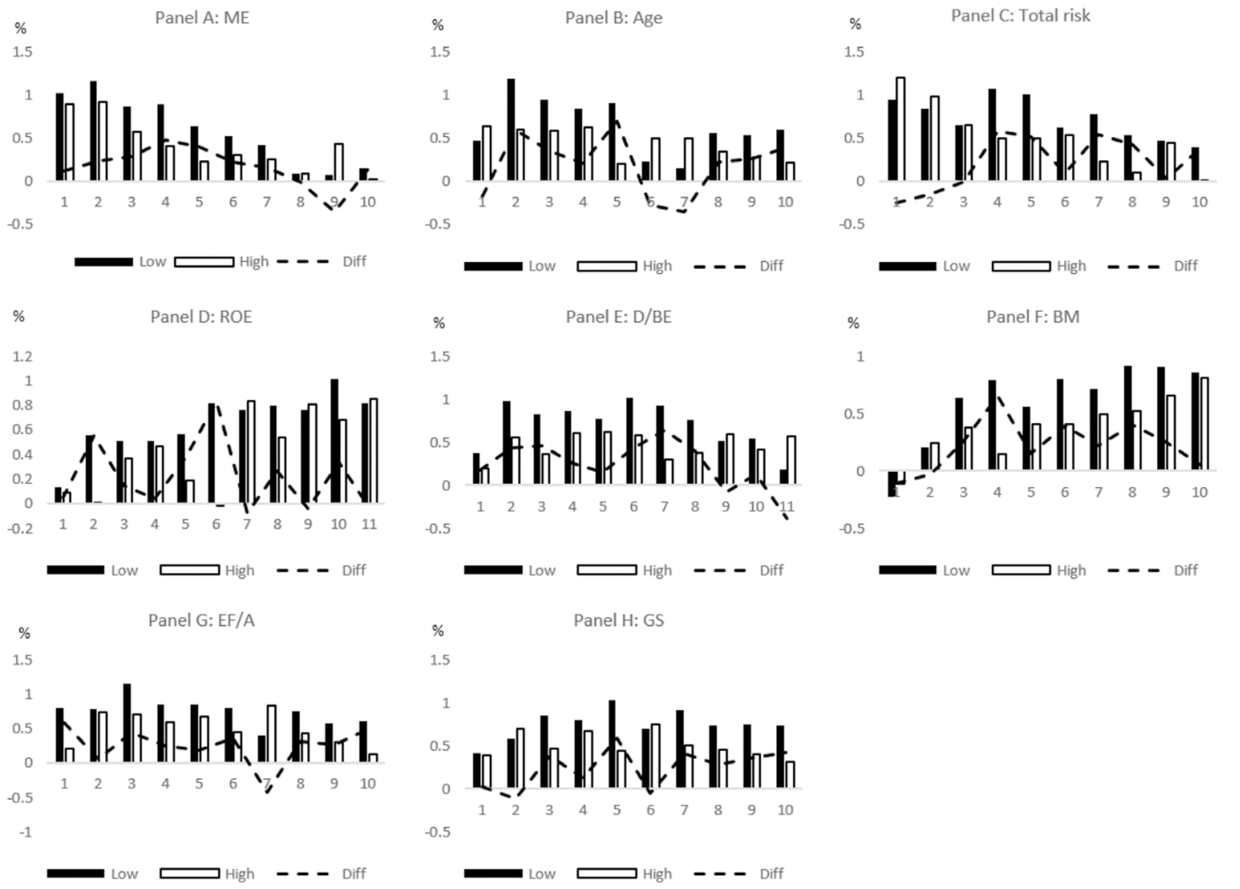

Fig. 1. Double sorting: Excess returns by firm characteristics and AQI_IV.
This figure reports the results of portfolio sort based on AQI_IV and firm characteristics including size (ME), age, total risk (Sigma), return on equity (ROE), dividend-to-book ratio (DBE), book-to-market ratio (BM), external finance over assets (EFA), and sales growth (GS). It reports monthly excess returns for those portfolios. The stocks are first divided into two groups based on AQI_IV. The bottom 50% of firms ranked by AQI_IV form the low pollution group and the top 50% form the high pollution group. Then, the high and low pollution groups are divided into 10 groups according to firm characteristics. The conditional difference between the low and high pollution groups across the deciles of each firm characteristic is also computed and the portfolios are rebalanced every month.

7. Conclusion

In this study, we explore whether the negative impact of air pollution on stock returns works through channels other than influencing investor behaviors. We rely on Chinese stock market data, because China is a large developing country in which air pollution is a severe problem. In addition, its relatively weak environmental protection in workplaces and wide scale labor-intensive industries may amplify the negative impact of air pollution on labor productivity and firms' profitability. We address the endogeneity problem using an IV approach. Our empirical analysis confirms the causal impact of air pollution on stock returns at the firm level.

We further examine the existence of the cash flow risk channel in two steps. First, we show that pollution stock does reduce the correlation between cash flow and the aggregate productivity shock. Furthermore, we rule out the possibility that the pollution impact on investor behaviors is the only channel through which air pollution may affect the stock market. Thus, we conclude that, besides influencing investor behaviors, air pollution affects stock returns through the cash flow risk channel.

Our results suggest a novel explanation of the causal effect of air pollution on stock markets and therefore offer implications on the importance of environmental protection in developing countries. Air pollution not only lowers trading efficiency by distorting investor behaviors but also reduces firms' profitability. Accordingly, the problem of air pollution could lead to much broader consequences than conventionally recognized. Our study therefore calls for further research and more attention from policymakers

area of different air pollution monitoring sites within a city. Monitoring stations within a city are often located at populated places and close to each other. Second, air pollution may lower labor productivity of the workers in firms that are located in commercial areas, which are often close to residential areas in Chinese cities. This implies air pollution in residential areas may also decrease firms' stock returns.

to lower air pollution. Notice that this study focuses on only one channel that is related to firm fundamental regarding the effects of air pollution on stock returns. Given an increasing demand for cleaner environments in China, firms in highly polluted areas could be subject to more stringent environmental regulation, which may feed back into stock returns in a different way. We leave other possible mechanisms of the air pollution effects on stock returns for future studies.

CRediT authorship contribution statement

Rong Li: Writing – review & editing, Writing – original draft, Methodology, Investigation, Funding acquisition, Conceptualization. **Luxi Liu:** Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation. **Yun Qiu:** Writing – review & editing, Investigation, Funding acquisition, Data curation. **Xiaohui Tian:** Writing – review & editing, Resources, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.pacfin.2024.102379.

References

Adhvaryu, A., Kala, N., Nyshadham, A., 2022. Management and shocks to worker productivity. J. Polit. Econ. 130 (1), 1–47.

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. Econ. J. 126 (591), 257–280.

Baker, M.P., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Finance 61 (4), 1645–1680.

Belo, F., Yu, J., 2013. Government investment and the stock market. J. Monetary Econ. 60 (3), 325–339.

Carhart, M.M., 1997. On persistence in mutual fund performance. J. Finance 52.

Chang, T., Graff Zivin, J., Gross, T., Neidell, M., 2016. Particulate pollution and the productivity of pear packers. Am. Econ. J.: Econ. Policy 8 (3), 141–169.

Chang, T.Y., Graff Zivin, J., Gross, T., Neidell, M., 2019. The effect of pollution on worker productivity: Evidence from call center workers in China. Am. Econ. J.: Appl. Econ. 11 (1), 151–172.

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. Proc. Natl. Acad. Sci. 110 (32), 12936–12941.

Chen, S., Oliva, P., Zhang, P., 2022. The effect of air pollution on migration: Evidence from China. J. Dev. Econ. 156, 102833.

Crook, T.R., Todd, S.Y., Combs, J.G., Woehr, D.J., Ketchen, Jr., D.J., 2011. Does human capital matter? A meta-analysis of the relationship between human capital and firm performance. J. Appl. Psychol. 96 (3), 443.

Ebenstein, A., Lavy, V., Roth, S., 2016. The long-run economic consequences of high-stakes examinations: Evidence from transitory variation in pollution. Am. Econ. J.: Appl. Econ. 8 (4), 36–65.

Ferson, W.E., Harvey, C.R., 1999. Conditioning variables and the cross-section of stock returns. J. Finance 54 (4), 1325–1360.

Fu, S., Viard, V.B., Zhang, P., 2021. Air pollution and manufacturing firm productivity: Nationwide estimates for China. Econ. J. 131 (640), 3241–3273.

Ghanem, D., Zhang, J., 2014. 'Effortless perfection:'Do Chinese cities manipulate air pollution data? J. Environ. Econ. Manag. 68 (2), 203–225.

Graff Zivin, J., Neidell, M., 2012. The impact of pollution on worker productivity. Amer. Econ. Rev. 102 (7), 3652–3673.

Greenstone, M., He, G., Li, S., Zou, E.Y., 2021. China's war on pollution: Evidence from the first 5 years. Rev. Environ. Econ. Policy 15 (2), 281–299.

Hanna, R., Oliva, P., 2015. The effect of pollution on labor supply: Evidence from a natural experiment in Mexico city. J. Public Econ. 122, 68–79.

Hansen-Lewis, J., 2018. Does air pollution lower productivity? Evidence from manufacturing in India. In: PAA 2018 Annual Meeting. PAA.

Heyes, A., Neidell, M., Saberian, S., 2016. The effect of air pollution on investor behavior: Evidence from the S&P 500. NBER Working Papers.

Huang, J., Xu, N., Yu, H., 2020. Pollution and performance: Do investors make worse trades on Hazy days? Manage. Sci..

Lai, W., Song, H., Wang, C., Wang, H., 2021. Air pollution and brain drain: Evidence from college graduates in China. China Econ. Rev. 68, 101624.

Lepori, G.M., 2016. Air pollution and stock returns: Evidence from a natural experiment. J. Empir. Financ. 35, 25–42.

Levy, T., Yagil, J., 2011. Air pollution and stock returns in the US. J. Econ. Psychol. 32 (3), 374–383.

Li, J., Massa, M., Zhang, H., Zhang, J., 2021. Air pollution, behavioral bias, and the disposition effect in China. J. Financ. Econ. 142 (2), 641–673.

Li, Q., Peng, C.H., 2016. The stock market effect of air pollution: Evidence from China. Appl. Econ. 48 (36), 3442–3461.

Lu, J.G., 2020. Air pollution: A systematic review of its psychological, economic, and social effects. Curr. Opin. Psychol. 32, 52–65.

Qin, Y., Zhu, H., 2018. Run away? Air pollution and emigration interests in China. J. Popul. Econ. 31 (1), 235–266.

Vomberg, A., Homburg, C., Bornemann, T., 2015. Talented people and strong brands: The contribution of human capital and brand equity to firm value. Strategic Manag. J. 36 (13), 2122–2131.

Wu, Q., Hao, Y., Lu, J., 2018. Air pollution, stock returns, and trading activities in China. Pacific-basin Finance J. 51, 342–365.

Xue, S., Zhang, B., Zhao, X., 2021. Brain drain: The impact of air pollution on firm performance. J. Environ. Econ. Manag. 110, 102546.