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The impact of air quality on innovation activities in China☆

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A B S T R A C T

Severe air quality hurts human capital and threatens innovative outcomes. Using unique data containing 12.8 million patent applications in China, this paper examines the causal effect of particulate matter with a diameter of 2.5 μm or less ($PM_{2.5}$) on patent innovation. We estimate a two-stage least square model with thermal inversion as an instrumental variable. Our findings show that a one μg/m^3 increase in the annual average $PM_{2.5}$ concentration leads to a 1.3% decrease in the number of patents. Annual fluctuations in $PM_{2.5}$ concentration levels across cities caused the total number of patents to decrease by 1.1% during the 2006–2010 period. From 2011 to 2015, the improvement in air quality increased the number by about 2.0%. It demonstrates another innovation co-benefit of improving air quality due to the tightened regulation.

1. Introduction

Air pollution harms human health across the globe. The burgeoning literature in environmental economics and health economics sheds light on the adverse effects of air pollution on physical and mental health, sleep time, human capital, academic performance, and cognitive abilities (see, for example, Stafford, 2015; Ebenstein et al., 2016; Archsmith et al., 2018; Zhang et al., 2018; Heyes and Zhu, 2019; Graff Zivin et al., 2020; He et al., 2019; Balakrishnan and Tsaneva, 2021). On the other hand, psychological and cognitive studies suggest that creative thoughts arise from inspirational moments, known as "eureka moments," when a person is physically and mentally relaxed (Subramaniam et al., 2009; Kounios and Beeman, 2014). Creating an innovation needs a new perspective, creativity, and other cognitive abilities. Worries, anxiety, depression, and cognitive impairment could reduce the likelihood of generating inspiration for new ideas. Existing studies provide unambiguous evidence suggesting that exposure to pollution raises the odds of anxiety and depression (Jacquemin et al., 2007; Power et al., 2015; Kim et al., 2016; Trushna et al., 2021). Little is known about the potential consequence of poor air quality on innovation activities, in which human capital plays a critical role (Squicciarini and Voigtländer, 2015; Cinnirella and Streb, 2017).

This paper seeks to examine the causal impact of $PM_{2.5}$ (i.e., particulate matter with a diameter of 2.5 μm or less) concentrations on patent innovation. While other air pollutants may also affect innovation activities, $PM_{2.5}$ is the leading indicator widely used by the

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health sciences literature to quantify exposure to air pollution.[1] It is also the fifth-ranking risk factor for global mortality (Cohen et al., 2017). Our study focuses on China for two reasons. First, similar to many developing countries, China is at the crossing road of economic transition into a sustainable development model. The rapid economic growth in the past four decades is at the tremendous cost of environmental degradation. Despite some recent improvements in air quality, pollution levels in China have been persistently more severe than those in most jurisdictions across the globe. In 2020, according to the 2020 World Air Quality Report,[2] 98% of the 388 cities in China failed to achieve the World Health Organization's annual $PM_{2.5}$ target of less than 10 μg/m^3, and 40% of them even did not meet China's national grade II annual target of less than 35 μg/m^3. Second, China experiences explosive growth in patent innovation. In 2019, the country became the world leader in international patent applications with more than 1.4 million applications. Despite the patent surge, the quality has received widespread attention and criticism.

Our identification strategy leverages the variations in air quality and innovation outcomes across cities and years. To mitigate the pressing concern of data manipulation on government-reported air quality (Ghanem and Zhang, 2014), we leverage the satellite-based $PM_{2.5}$ concentrations provided by van Donkelaar et al. (2016). To further address the potential endogeneity concern for $PM_{2.5}$, we follow previous studies (see, for example, Arceo et al., 2016) and adopt thermal inversion as an instrumental variable (IV).

Our findings demonstrate unambiguous evidence in support of the adverse effect of air pollution on patent innovation. A one μg/m^3 increase in the annual average $PM_{2.5}$ concentration leads to a 1.3% decrease in the number of patent applications. Evaluating this effect at the mean $PM_{2.5}$ concentration level in the sample (44.96 μg/m^3) yields an elasticity of −0.58. To examine the stability of our baseline conclusions, we carry out a series of robustness checks, including alternative $PM_{2.5}$ measures, alternative IV, different exposure windows to air pollution, model specifications, and some others. Overall, our baseline estimate survived. We further investigate the potential channels through which pollution may affect innovation. Our results indicate that air pollution hinders patenting innovation mainly through R&D workers' productivity, but not the migration of workers during the period. The estimates help us understand the magnitude of the impacts of air pollution. A back-of-the-envelope calculation suggests that annual fluctuations in $PM_{2.5}$ concentrations across cities caused the total number of patents to decrease by 1.1% during the 2006–2010 period. From 2011 to 2015, an improvement in air quality increased the number by about 2.0%. Our findings demonstrate another significant co-benefit of an improvement in air quality due to tremendous efforts in tightening air regulations.

This paper makes three contributions to related literature. First, we compile a unique and detailed patent database in China, allowing us to make a comprehensive assessment of the potential impacts of air pollution on innovation performance. The dataset presents some distinctive features. It reports a universe of 12.8 million patent applications granted by the State Intellectual Property Office (SIPO) of China during the study period of 1998–2016. Such tremendous patenting activities capture the big picture of the innovation phenomenon in a leading patent application country across the globe. Another notable feature is the wide range of dimensions covered by this novel dataset. It covers two types of patents (i.e., invention and utility model), all entities of the assignee (i.e., firm, university, person, and others), assignee name, and assignee address.

Second, this paper contributes to the growing empirical literature about the impacts of air pollution on human capital and labor productivity. Using a series of cross-section or panel data from a wide range of jurisdictions across the globe, the existing literature sheds light on the adverse effects of air pollution on physical and mental health (Ebenstein et al., 2016), sleep time (Heyes and Zhu, 2019), cognitive abilities (Zhang et al., 2018), and human capital (Graff Zivin et al., 2020). Moreover, air pollution leads to a substantial loss in labor productivity in China (Chang et al., 2019; Fu et al., 2021) and the United States (Graff Zivin and Neidell, 2012). Similar negative impacts are well-documented among highly skilled and quality-focused employees (Archsmith et al., 2018). Another recent work by Tan and Yan (2021) finds that air pollution reduces corporate innovation in China by increasing a firm's financial constraints while decreasing human capital. Their work focuses on publicly listed firms from 2014 to 2018. Our paper substantially extends this line of literature in the following ways. Leveraging a universe of patent applications during the fast-growing period of 1998–2016, we comprehensively assess the causal impact of air pollution on innovation. We explore how air pollution affects the intensive and extensive margin of innovation. Using the patent data with other city-level variables, we reveal the channel through which pollution affects patenting innovation by lowering R&D workers' productivity (the intensive margin) rather than migrating workers (the extensive margin). Lastly, we take advantage of the comprehensive data and use the back-of-the-envelope calculation to infer the magnitudes of the impacts of annual fluctuations in $PM_{2.5}$ concentration levels in China.

Third, this paper also contributes to the strand of the empirical literature on the driving forces of innovation. Existing studies quantify the impacts of market forces and government policies on the decision of innovation. A central issue in the discussions is the supply of human capital and its effects on innovation (Squicciarini and Voigtländer, 2015; Cinnirella and Streb, 2017). Specifically, recent studies on China empirically document that leading factors such as foreign direct investment (Hu and Jefferson, 2009), trade liberalization (Liu and Ma, 2020), tax incentives (Chen et al., 2021), infrastructure (Hanley et al., 2021), climate policy (Cui et al., 2018), and human capital (Sun et al., 2020) contribute to the surge of patent innovation. This paper departs this line of literature by documenting evidence of an unexplored yet crucial obstacle to innovation. Notorious air quality discourages innovation activities. The improved air quality due to recent regulatory efforts in China gives rise to an unintended consequence of the rising innovation outcomes.

The remaining paper proceeds as follows. Section 2 presents the background of air pollution and innovation activities in China. Section 3 introduces the identification strategy. Section 4 describes data sources, variable construction, and descriptive statistics.

[1] Another popular indicator is tropospheric ozone.

[2] The 2020 World Air Quality Report is available via the link: https://www.iqair.com/world-most-polluted-cities/world-air-quality-report-2020-en.pdf.

Section 5 presents the main empirical results, robustness checks, and implications of the baseline estimates. The last section concludes.

2. Background

Air pollution. Air pollution levels in China have been persistently staying high for a long time, causing huge welfare losses to both individuals and society. In January 2013, severe $PM_{2.5}$ pollution across the country received much attention domestically and internationally. The event affected over 600 million people in the country. Notorious air pollution poses significant challenges. According to an earlier study by The World Bank (2007), economic and health loss accounts for 1.16% of China's GDP. Although stringent environmental or climate policies caused air quality to improve in recent years, pollution levels in China have been persistently higher than those in most jurisdictions across the globe. The levels significantly exceed the WHO guideline level (i.e., the annual average concentration level of 10 μg/m^3). Fig. 1 illustrates the annual average $PM_{2.5}$ concentration levels across cities in 1998 and 2016. The darker the area, the higher the concentration level is. One could observe the substantial spatial disparities in the $PM_{2.5}$ level. In 2016, air quality in most cities has been drastically improved but the spatial disparities persist.

Innovation. In 1980, China founded its patent office, the State Intellectual Property Office (SIPO), and adopted a patent system akin to those used in Europe and Japan.[3] China grants three types of patents: invention patents, utility model patents, and design patents. The invention patents represent practical, inventive, and new technical innovations, while the utility model patents, or the so-called minor patents in China, are associated with technical solutions to the shape or structure of an object. The design patent refers to the ornamental design of an article of manufacture. The patent approval process differs substantially across patent types. The invention patent is required to go through the most meticulous application procedure including application acceptance, preliminary review, publication, substantive review for novelty and inventiveness, and the final grant. However, the utility model and design patents skip the process of publication and substantive review and are only subject to formality examinations. Therefore, invention patents represent the most important innovations in China's patent system due to the longer examination period and lower approval odds (Wei et al., 2017). As a comparison, utility model patents are often treated as incremental innovations (Liu and Ma, 2020). Both types follow the standardized International Patent Classification codes for defining technological fields. The design patent does not adopt this coding system, making it incomparable with similar patents in other countries. Thus, our analysis only accounts for both invention and utility model patents.

During the 1995–2014 period, China experienced explosive growth in patent innovation with an annual rate of 19% (Wei et al., 2017). Patent innovations are spatially concentrated in China, as in many other countries (Carlino and Kerr, 2015; Andrews and Alexander, 2021). Fig. 2 illustrates the spatial variations in the number of patent applications across cities in 1998 and 2016. The darker the area, the more patent applications are. We observe a substantial variation in patent counts across cities. Patent applications are concentrated in the Yangtze Delta region (i.e., Shanghai, Jiangsu, Zhejiang, and Anhui), the Pearl River Delta region (i.e., Guangdong), Sichuan Province, and Beijing. Such spatial disparities remain in 2016, the end of our sample period.

The ever-increasing patent growth is accompanied by the rising number of R&D personnel such as scientists and engineers. From 2000 to 2020, the full-time R&D personnel in China increased from 922,000 to 5,235,000 with an average annual growth of 9.07% (National Bureau of Statistics, 2021). The physical and mental status of R&D personnel is crucial to the quantity and quality of patents.

3. Empirical model

Taking advantage of the regional and temporal variations in air quality and innovation outcomes, this paper seeks to identify the causal impacts of air pollution on city-level innovation outcomes. Our empirical strategy anchors on a fixed-effect model. For each city c in year t,

$$Innovation_{ct} = \alpha Pollution_{ct} + f(W_{ct}) + \theta_c + \gamma_t + \delta_c T_t + \varepsilon_{ct} \tag{1}$$

In this specification, the outcome variable $Innovation_{ct}$ denotes the innovation outcomes. We assume that air quality in the current year, $Pollution_{ct}$, affects innovation activity. Innovation takes time. In the robustness checks, we account for the different exposure windows to test the contemporaneous and lagged effects. The vector W_{ct} includes a rich set of weather variables. In addition, we add city-level fixed effect θ_c to control for unobservable time-invariant city attributes. The year fixed effect γ_t absorbs temporal shocks that are common to all cities. Moreover, we include the city-specific linear trend $\delta_c T_t$ to control for city-specific time-varying confounding factors that affect innovation outcomes. The last one, ε_{ct}, is an unobservable error term.

The primary identification challenge in estimating the causal effect of pollution on innovation arises from the omitted-variable bias. For example, air pollution is potentially correlated with city-specific, time-varying socioeconomic confounders (e.g., human capital), which are also key determinants of innovation outcomes. Thus, an ordinary linear square regression for the coefficient of interests α in Eq. (1) would not yield an unbiased estimate. To overcome this bias, our identification strategy uses thermal inversions to instrument for air pollution. The first-stage regression is,

$$Pollution_{ct} = \beta TI_{ct} + f(W_{ct}) + \theta_c + \gamma_t + \delta_c T_t + u_{ct} \tag{2}$$

where TI_{ct} denotes the number of thermal inversions. Since weather may independently affect innovation, we control for the variables,

[3] Since August 28th of 2019, SIPO of China has been renamed to China National Intellectual Property Administration (CNIPA).

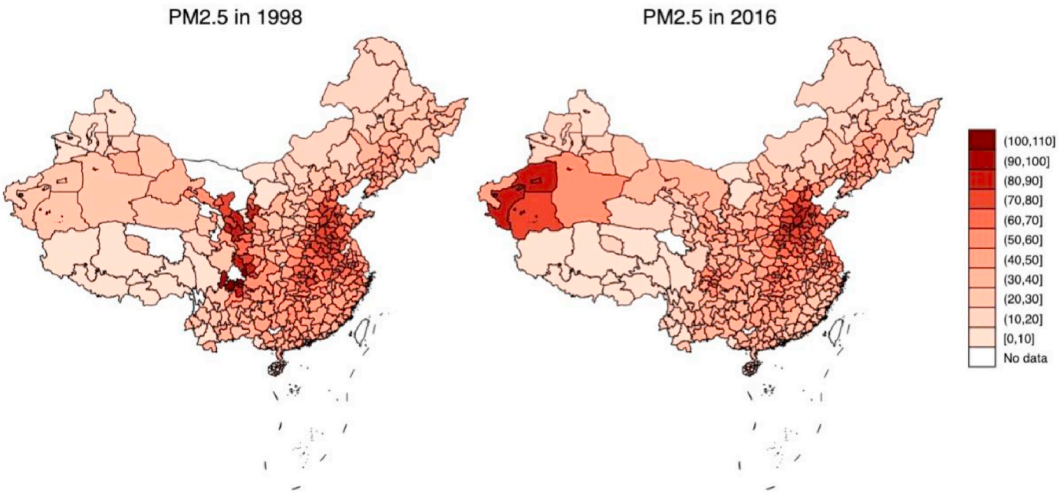

Fig. 1. Average $PM_{2.5}$ in 1998 and 2016. Unit: μg/m^3.

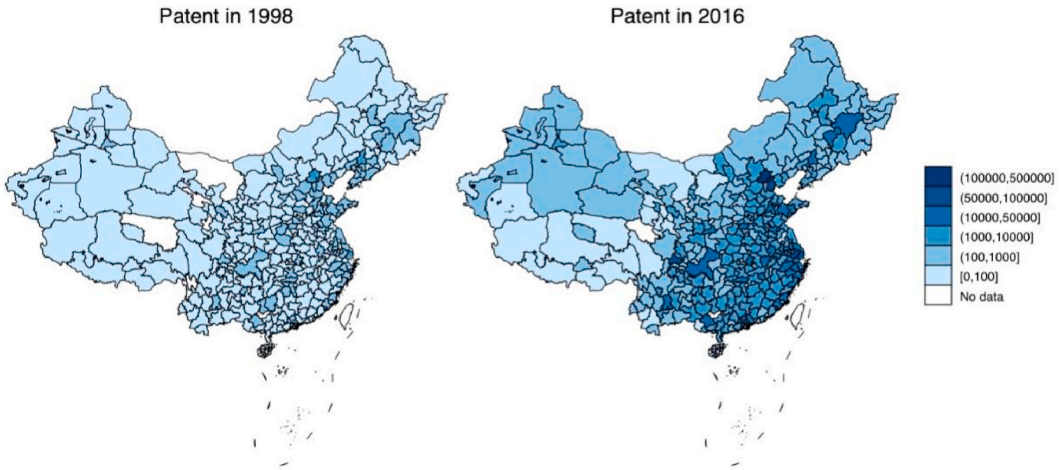

Fig. 2. Patent Numbers in 1998 and 2016. Unit: number.

$f(W_{ct})$, in the baseline 2SLS model consisting of Eqs. (2) and (1) to ensure that the instrument meets the exclusion restriction criteria.

The formation of thermal inversions is a complex meteorological phenomenon. When the temperature in the upper atmospheric layer is higher than that of the lower layer, thermal inversions occur. In that case, air pollution is trapped near the ground (Arceo et al., 2016). Thermal inversions are typically independent of economic activities, as we demonstrate the case for Chinese cities shortly. This variable has been widely used as a valid IV for air quality in developed and developing countries (Jans et al., 2018; Sager, 2019; Deschênes et al., 2020; Balakrishnan and Tsaneva, 2021; Fu et al., 2021). Following this convention, we count the number of thermal inversions across cities and years and use it as an instrument for $Pollution_{ct}$. To test the validity of this IV, we examine whether thermal inversions are orthogonal to social-economic activities at the city level, including GDP per capita, population, GDP share of the industrial sector, employment share of the industrial sector, employment share of the tertiary sector, fiscal expenditure, and fiscal expenditure on science & technology.

Different pollutants are correlated, posing a possible threat to identifying the causal effect of $PM_{2.5}$. In line with recent studies quantifying the impacts of air pollution (e.g., Fu et al., 2021), we focus on $PM_{2.5}$ but no other air pollutants. We argue that the IV estimation helps alleviate this concern to some extent because thermal inversions mainly affect $PM_{2.5}$ but not all pollutants.[4] However, some other pollutants (e.g., carbon monoxide) are indeed affected by thermal inversions (Arceo et al., 2016). Thus, the interpretation of our estimate shall be cautious. It is perhaps more desirable to interpret it as the effect of air pollution, but not that of $PM_{2.5}$ solely.

[4] We thank one anonymous reviewer for pointing out this co-pollutant concern.

4. Data

4.1. Data sources

We assemble data from four main sources. The SIPO of China reports patent applications. The satellite-based data supply the city-level pollution and thermal inversions. Weather stations record weather variables. *China City Statistical Yearbook* provides socioeconomic characteristics at the city level.

Our primary data is a universe of 12.8 million patent applications during the study period. The detailed patent applications are retrieved from the SIPO of China. The unique patent data report detailed information, including patent type (i.e., invention vs. utility model), assignee, address of assignee, application date, application number, grant date, grant number, inventor, patent agency, and many others. Unlike patent offices in other jurisdictions (e.g., the US Patent and Trademark Office, or the European Patent Office), the SIPO of China did not assign a unique identification code (ID) for patent assignees or inventors. Some assignees are persons rather than companies. Unfortunately, it is unlikely to trace out all assignees or inventors across years without unique IDs. Our analysis aggregates patent applications at the city level based on the city of assignees, which is retrieved from its address information.[5]

Other major data are city-level pollution, thermal inversions, and weather variables. The dataset for measuring city-level $PM_{2.5}$ concentration is obtained from van Donkelaar et al. (2016).[6] The rationale for using the data is listed as follows. First, official monitor-based measures are not available for the years before 2012. Second, satellite-based measures are not subject to manipulation by local governments (Ghanem and Zhang, 2014; Greenstone et al., 2022). As an alternative measure, we also adopt another method utilizing the satellite-based Aerosol Optical Depth retrieval techniques (Buchard et al., 2016). Thermal inversions are constructed by relying on the Modern-Era Retrospective Analysis for Research and Applications version 2 maintained by the National Aeronautics and Space Administration (NASA). Weather variables are constructed by using daily data from more than 820 weather stations in China. The data are maintained by the China Meteorological Data Sharing Service Center.

Lastly, various editions of the *China City Statistical Yearbook* provide socioeconomic characteristics during the study period. The variables include population, gross domestic product per capita, and others. The *Yearbooks* also provide data on employees in the scientific research and polytechnic services sector. We note that there are changes in city boundaries. For example, Chaohu city in Anhui province was split into three parts in 2011. Each was merged with the cities of Hefei, Wuhu, and Maanshan, respectively. For the following analyses, we delete these cities from the sample. An alternative is to merge these four cities into a big one with constant geographic boundaries over the sample years. The estimated coefficient does not alter the main conclusion.

4.2. Variable construction

Innovation outcome. Whereas not all innovations are patentable, the growing literature has been using patents as a consistent proxy for innovation outcomes in developed and developing countries (Hall et al., 2005; Hu and Jefferson, 2009; Liu and Ma, 2020). Following this convention, we measure innovation based on patent applications at the city level. We use the application year rather than the grant year to represent when innovation activities take place and adopt the city of the patent assignee to capture where innovations occur. We further account for the quantity and quality of city-level innovation outcomes. The former is the logarithm patent counts. To further examine innovation quality, we exploit the variation in patent types. Existing literature studying Chinese patents suggests that invention patents represent valuable and more critical innovation relative to utility patents (Wei et al., 2017). The former is related to technical innovations that are inventive and new, while the latter is associated with technical solutions to the shape or structure of an object. Following this convention, we separate the city-level innovation quantity by patent type.

PM2.5. The city-level satellite-based PM2.5 concentrations are constructed by using the datasets provided by van Donkelaar et al. (2016). Their datasets are gridded at the $0.01^\circ \times 0.01^\circ$ resolution. We aggregate the data and obtain the city-level data using the information on city boundaries. As a robustness check, we supplement our measurement by using the calculated PM2.5 concentrations in line with an alternative method proposed by Buchard et al. (2016).

Thermal inversions. NASA reports air temperature for each 50*60-km grid for different atmospheric layers every 6 h. We aggregate all data from the grid to the city. If the temperature in the second atmospheric layer is higher than that of the first layer, a thermal inversion exists. For every 6 h, we determine whether it occurs. Then, we aggregate the number of inversions to the year.

Weather. The city-level weather covariates include temperature bins,[7] relative humidity, sunshine duration, wind speed, and cumulative precipitation. The weather variables are constructed from daily station-level data. We obtain the city-level data by taking a weighted average of the data from weather stations that are located within a 200 km radius of each city's centroid (Deschênes and Greenstone, 2011). The weights are the inverse of the distance between the station and the centroid of the city. By doing so, we give less

[5] The address of inventor is not provided in the data.

[6] The data are available online at https://sites.wustl.edu/acag/datasets/surface-pm2-5/.

[7] The station-level data contain information on maximum and minimum temperature. Follow previous studies (e.g., Deschênes and Greenstone, 2011), we focus on daily mean temperature which is the average of the maximum and minimum. We then construct ten temperature bins for each city in each year. Each bin is 5 °C wide. The first temperature bin is for those days with mean temperature below −10 °C. The tenth bin is for those days with mean temperature higher than 30 °C. We count the number of days for each of the ten bins. For leap years, we drop weather information for February 29 to ensure that the sum of the number of days in the temperature bins is equal to 365 for any year. For the regressions, the number of days in nine of the ten bins enter the model. To avoid perfect multicollinearity, the reference bin (i.e., (10 °C,15 °C]) is omitted from the equations.

weight to stations that are more distant from the city.

Socio-economic characteristics. We obtain socioeconomic variables at the city level from various editions of the *China City Statistical Yearbook*. Population captures the city's size. Gross domestic product per capita indicates a city's economic development. We also include some other variables indicating the structure of the city's economic structure. These socioeconomic variables are used to examine the validity assumption of thermal inversions as an IV.

Finally, Table 1 provides descriptive summary statistics of selected key variables. It shows that cities vary significantly in the outcome variables, pollution level, and other characteristics.

5. Results

In this section, we begin with the baseline IV results on the effect of $PM_{2.5}$ on patent innovation. We then present a series of robustness checks, followed by mechanism analysis. Lastly, we simulate the magnitudes of the effect of a change in air quality on innovation outcomes.

5.1. Baseline results

Patent count. We first investigate how air pollution affects innovation outcomes. Table 2 presents the corresponding estimated coefficients for total patent counts and patent counts by type. Standard errors, clustered at the city level, are shown in the parenthesis. In all columns, we use the number of thermal inversions as an instrument for $PM_{2.5}$.

The first two columns focus on the patent count. Column (1) controls for city-fixed effects and year-fixed effects. The estimate is negative and statistically significant at the 1% level. When we further add city-specific linear trends in Column (2), the estimate remains negative and statistically significant at the 5% level. These findings suggest that cities with higher levels of $PM_{2.5}$ concentration produce fewer patents. Quantitatively, the magnitude of the estimate in Column (2) is substantially smaller than that in Column (1), indicating that the city-specific linear trend explains much of the changes in patent counts at the city level. The preferred specification in Column (2) finds that a one $\mu g/m^3$ increase in the annual average $PM_{2.5}$ concentration leads to a 1.3% decrease in the number of patents. Evaluating this effect at the mean $PM_{2.5}$ concentration level in the sample (44.96 $\mu g/m^3$) yields an elasticity of -0.58.

Existing studies show that changes in patenting and patent stock are positively correlated with changes in firms' total factor productivity (TFP) (see, e.g., Balasubramanian and Sivadasan, 2011). In an empirical study using Chinese firm-level data during the 1998–2007 period, Fang et al. (2020) find that a 10% increase in patent stock is correlated with a 0.26% increase in TFP annually. This finding helps understand the productivity impact of $PM_{2.5}$ through the innovation channel, but one needs to quantify the effect on patent stock if one desires to get an estimate. To give an example, we use our baseline result regarding the effect of $PM_{2.5}$ on patents (i.e., a 1 $\mu g/m^3$ increase in $PM_{2.5}$ causes patents to decrease by 1.3%) and information on the patent stock in 2014 and patents applied in 2015.[8] A back-of-the-envelope calculation indicates that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ is correlated with about a 0.1% decrease in TFP annually. One shall interpret this finding cautiously since the relationship between patent stock and productivity is purely a correlation but not causality.

With the preferred model specification, the last two columns report how the innovation effects of air pollution differ by patent type. We document that both estimates are negative, suggesting that air pollution causes the numbers to decrease regardless of patent type. The estimate is statistically significant at the 10% level for invention patents but insignificant for utility model ones. In terms of magnitude and significance, the negative effect of air pollution is more pronounced on valuable innovation captured by invention patents rather than utility model ones. Echoing the main finding in Column (2), air pollution has an adverse effect on the quality of innovation proxied by invention patents.

One may worry about the validity of thermal inversions as IVs. First, at the bottom of Table 2, we report the KP F-statistics. In all columns, the statistics values are sufficiently large to reject the null hypothesis of a weak instrument. We then examine how the IV correlates with air pollution. In the Appendix, Table A1 reports the estimated first-stage coefficients. The findings show that one additional thermal inversion (0.33% of the mean) in the year increases $PM_{2.5}$ concentrations in the same period by 0.055 $\mu g/m^3$ (0.12% of the mean). Lastly, we also conduct a rich set of checks to further validate the exogeneity assumption of thermal inversions as the IV. In the Appendix, Figures A1-A7 plot seven different city-level economic variables against the number of thermal inversions. These plots demonstrate that thermal inversions are not correlated with economic activities in the cities, suggesting that our instrument indeed meets the exclusion restriction criteria.

Comparison. We compare our estimates with recent empirical studies that examine the effect of $PM_{2.5}$ on related economic outcomes, especially those on labor productivity in China. As reviewed by Aguilar-Gomez et al. (2022), productivity estimates vary considerably. To facilitate the comparison across studies, we focus on elasticity. Table 3 summarizes the findings varying across sectors and productivity measures. It shows that the estimated elasticity values vary significantly. Our estimate (i.e., -0.58) is close to the upper bound of the estimated effect (i.e., -0.44) in Fu et al. (2021), which address how $PM_{2.5}$ affects value added per worker in the manufacturing sector in China. Our estimate is larger than estimates from the other studies summarized in the table.

Several factors are likely to explain the difference in the estimated elasticities. First, most existing studies focus on a small number of firms in limited regions (see, e.g., Chang et al., 2019; He et al., 2019), while our work aims to estimate the economy-wide impact of

[8] We assume the depreciation rate is 5%. Patent stock at the end of 2014 is about 7.2 million. The number of patents applied in 2015 is 1.8 million.

Table 1
Summary statistics.

Variables	N	Mean	Std	Min	Max	Period
Patent count	6380	5.143	2.114	0	11.825	1998–2016
Invention patent count	6187	4.033	2.163	0	11.338	1998–2016
Utility model patent count	6335	4.766	2.034	0	10.872	1998–2016
$PM_{2.5}$	6380	44.964	19.737	4.668	164.072	1998–2016
Thermal inversions	6380	302.473	122.522	8.762	618.477	1998–2016
R&D employees	4976	8.164	1.177	4.605	13.444	1999–2016
GDP per capita	4216	3.306	0.742	−2.100	6.172	2002–2016
Population	4216	8.152	0.686	5.114	12.518	2002–2016
Population density	4216	−1.195	0.934	−5.309	2.818	2002–2016
Fiscal expenditure	1955	15.979	0.982	13.758	19.829	2010–2016
Expenditure on S&T	1955	14.157	0.968	11.735	17.971	2010–2016
% Industrial GDP	4926	47.601	10.699	19.160	83.610	1999–2016
% Industrial Employment	4926	41.986	14.955	3.400	80.580	1999–2016
% Tertiary employment	4926	50.579	14.848	6.280	85.200	1999–2016

Notes: 1. All variables measured in the log except for $PM_{2.5}$, thermal inversions, and the shares. Monetary values measured in constant 2016 RMB *yuan* (Chinese currency). 2. $PM_{2.5}$ is measured in μg/m^3. 3. GDP per capita in thousand RMB yuan. Dividing GDP by GDP per capita gives us the number of permanent residents (i.e., the population measure). The population is measured in thousands of persons. Data on GDP per capita are not available until 2002. Thus, we can't infer the population for years earlier than 2002. Although data on the population of *Hukou* are available for those years, it is not appropriate to use it because there is a huge gap between the *Hukou* population and the number of permanent residents, especially in large major cities. The two expenditure variables are also in thousand RMB *yuan*. 4. Data sources: See the text.

Table 2
Effects of air pollution on innovation: Patent count.

VARS	Total Patent		Type	
			Invention	Utility
	(1)	(2)	(3)	(4)
$PM_{2.5}$	−0.076***	−0.013**	−0.013*	−0.009
	(0.017)	(0.005)	(0.007)	(0.006)
KP *F*-statistic	41.3	138.5	136.8	140.0
Observations	6380	6380	6185	6335
Weather variables	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
City-specific trend	N	Y	Y	Y

Notes: Dependent variables: Patent, Invention Patent, and Utility Model Patent are the logarithm number of all patents, invention patents, and utility model patents, respectively. Standard errors in parentheses are clustered at the city level. Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 3
Comparison with recent studies on the productivity effects of pollution in China.

Study	Sector	Productivity measure	Elasticity
Fu et al. (2021)	manufacturing	value added per worker	−0.440
Kahn and Pei (2020)	public service	cases handled per unit of time	−0.182
Chang et al. (2019)	service	worker's daily output	−0.023
He et al. (2019)	textile	average output per worker	−0.035 ~ −0.30

Notes: This table summarizes findings from several recently published studies on the productivity effects of pollution in China.

$PM_{2.5}$ in a large country. Previous studies also find relatively large economy-wide impacts. For instance, Dechezleprêtre et al. (2019) find that a one μg/m^3 increase in $PM_{2.5}$ reduces real GDP by 0.8% in the European Union. Using a dataset covering all large Chinese firms, Fu et al. (2021)'s findings suggest that a one μg/m^3 increase in the annual average concentration of $PM_{2.5}$ causes a 0.82% drop in labor productivity. Second, whereas recent studies focus on daily or monthly effects, our work investigates annual cumulative effects. We also note that the effects of air pollution on high-skill labor are relatively large in some other countries. For instance, Künn et al. (2023) examine the effects of indoor air quality on the quality of strategic decision-making. They find that a 10 μg/m^3 increase in the concentration of $PM_{2.5}$ increases a chess player's probability of making an erroneous move by 26.3%. In the robustness check section, we have conducted a rich set of robustness to test whether the choice of data samples, variable definitions, and estimation methods would bias our estimates about the impact on innovation outcomes. The findings are consistent with the baseline results.

Innovation outcomes per capita. Another interest of this paper is to explore the effects of pollution on innovation intensity, proxied by innovation outcomes per capita. Table 4 shows the results from re-estimating the baseline model. Panel A uses the *Hukou* population to calculate innovation intensities. The estimates are consistently negative and statistically significant at conventional levels, suggesting

Table 4
Effects of air pollution on innovation: Patents per capita.

VARS	Patent	Invention Patent	Utility Model Patent
	(1)	(2)	(3)
	Panel A. Based on *Hukou* population (1998–2016)		
$PM_{2.5}$	−0.019**	−0.016*	−0.014*
	(0.008)	(0.009)	(0.008)
KP *F*-statistic	90.4	87.9	90.5
Observations	4962	4939	4956
	Panel B. Based on the number of permanent residents (2002–2016)		
$PM_{2.5}$	−0.025**	−0.026*	−0.018
	(0.011)	(0.013)	(0.012)
KP *F*-statistic	41.9	40.0	42.0
Observations	4203	4188	4199
Weather variables	Y	Y	Y
City FE	Y	Y	Y
Year FE	Y	Y	Y
City-specific trend	Y	Y	Y

Notes: Dependent variables: Patent, Invention Patent, and Utility Model Patent are the logarithm number of all patents per resident, invention patents per resident, and utility model patents per resident, respectively. See the text for the difference between the *Hukou* population and permanent residents. We use the number of thermal inversions as an instrument for $PM_{2.5}$. Standard errors in parentheses are clustered at the city level. Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

that air pollution substantially leads to declining patents per capita. Because data on the number of permanent residents in each city were not available until 2002,[9] Panel B is obtained by applying the regression model to a slightly smaller sample. It shows that the magnitudes are larger in recent years. Overall, we find consistent and robust evidence suggesting that air pollution leads to declining innovations per capita, especially invention patents per capita.

5.2. *Robustness checks*

To test the stability of the baseline estimates, we perform a series of robustness checks, including the exclusion of outliers, alternative measures on IV, $PM_{2.5}$, and innovation, possible spatial attribution of innovation, as well as different exposure windows to air pollution. Fig. 3 summarizes the estimated coefficients for the effects of $PM_{2.5}$ on patent counts. Moreover, Table 5 and Table A2 in the Appendix present additional tests on alternative model specifications.

Outliers. In row 1 of Fig. 3, we exclude 1% of the observations with extreme values of patent number each year. Applying the regression model to this smaller sample without the outliers, we obtain a similar estimate to the baseline finding.

Alternative measures. In the baseline regression, our data on $PM_{2.5}$ concentration come from a widely cited study that calculates the concentration using information from satellite-, simulation- and monitor-based sources (van Donkelaar et al., 2016). An alternative measure can be obtained by using another method developed by Buchard et al. (2016) that utilizes satellite-based Aerosol Optical Depth retrieval techniques. Row 2 of Fig. 3 accounts for this proxy. Besides, our baseline instrument variable is the number of thermal inversions that are defined by the temperature difference between the first (110 m) and second layers (320 m). In row 3, we use an alternative definition for thermal inversions by checking if there are differences between the first and third layers (540 m). Patents may have multiple assignees across cities, making the imprecise exposure measurement to air pollution. In row 4, we limit the patents applied by a single applicant.

Spatial misattribution. To interpret the baseline estimates as an unbiased measure of the impact of pollution on innovation, an important assumption that there exists no spatial misattribution of innovation activities shall hold.[10] That is, a patent filed in one city captures an innovation activity that was made in the city, but not in another one. We believe that such a spatial misattribution accounts for a very small share of the patents filed in China since applicants have little incentive or need to travel across regions to submit their patent applications. Although the assumption of no spatial misattribution could not be directly tested, we have endeavored to assess its plausibility. Headquarters of large firms tend to be in large cities like Beijing or Shanghai. If innovations made by the subsidiaries located in other cities file patents through its parent company, our estimate is possibly biased. To address this concern, row 5 regresses a data sample that excludes the four provincial-level municipalities (i.e., Beijing, Chongqing, Shanghai, and Tianjin). Row 6 further excludes the capital cities of each province. In both rows, we find similar results as the baseline one.

Unmatched cities of assignees and inventors of Chinese patents in the USPTO. The SIPO of China does not provide cities of inventors. To crosscheck whether the cities of assignees overlap with those of inventors, we have retrieved mainland Chinese patent applications in the USPTO during the 1976–2019 period. We begin with a total of 90,129 patent applications associated with 13,684 unique assignees

[9] The *China City Statistical Yearbooks* report data on the population of *Hukou* (i.e., household registration). Due to the significant volume of internal migration, a substantial discrepancy exists between the *Hukou* population and the number of residents, particularly in large and major cities.

[10] We thank a reviewer for pointing out this assumption.

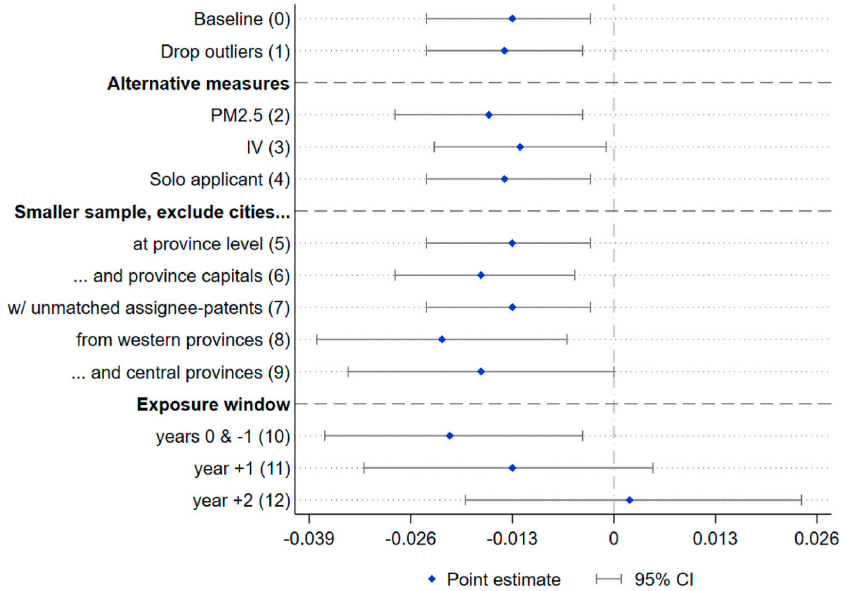

Fig. 3. Robustness Checks and Falsification Tests.
Notes: The dependent variable is the logarithm of the patent count. Based upon the baseline IV model, we regress patent count on air pollution while controlling for a set of weather variables, city-fixed effects, year-fixed effects, and city-specific trends.

Table 5
Alternative model specifications.

VARS	log-log	High-polluted days only		Count-data model
	(1)	(2)	(3)	(4)
log ($PM_{2.5}$)	−0.506**			
	(0.202)			
# days with $PM_{2.5} \geq$ 75 μg/m^3		−0.004*		
		(0.002)		
# days with $PM_{2.5} \geq$ 50 μg/m^3			−0.002*	
			(0.001)	
$PM_{2.5}$				−0.025***
				(0.003)
KP *F*-statistic	123.2	115.3	186.7	–
Observations	6380	5727	5727	6380
Weather variables	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
City-specific trend	Y	Y	Y	
Province-specific trend				Y

Notes: 1. This table summarizes results from using alternative specifications of the baseline model. For the first three columns, the outcome variable is the logarithm of the number of all patents. 2. Column (1) uses log($PM_{2.5}$) to measure pollution. 3. Column (2) uses the number of days with a mean $PM_{2.5}$ concentration higher than 75 μg/m^3. Column (3) uses the number of days with a mean $PM_{2.5}$ concentration higher than 50 μg/m^3. We calculate the daily concentration of $PM_{2.5}$ using the ChinaHighPM2.5 dataset (Wei et al., 2021). As the data are not available until 2000, the number of observations is smaller than the baseline regression. 4. Column (4) estimates a fixed-effects Poisson model that uses the number of patents as the outcome variable. Following Lin and Wooldridge (2019), we use a two-step procedure here. In the first stage, run the OLS estimation of Eq. (2) and get the residuals. In the second step, insert the estimated residuals into Eq. (1) and run Poisson regression. To avoid computational burdensome, the count-data model considers province-specific trends, instead of city-specific trends. 5. For columns (1)–(3), standard errors in parentheses are clustered at the city level. Column (4) reports bootstrapped standard error in parentheses. Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

and 69,214 unique inventors, all located in mainland China. We further dropped 4,153 patent applications due to missing city names of assignees (i.e., city column labeled with "None"). We then clean city names by converting all strings into uppercase letters, removing special characters and duplicate spaces, and retrieving city from the city-province combinations (such as, "Suzhou, Jiangsu", where "Suzhou" is a city of "Jiangsu" province). For each remaining patent application, finally, we start to crosscheck the city of the assignee with the city of the inventor. There are around 77% of patent applications with matched city names between assignees and inventors. For those un-matched patents (around 19,996 applications), 42.2% of them are located in Shenzhen, the next top-10 cities include Beijing (4.2%), Wuhan (4%), Hefei (3.8%), Dongguan (2.8%), Chengdu (2.4%), Hangzhou (1.7%), Suzhou (1.6%), Guangzhou (1.5%), Ningbo (1.4%), and Shanghai (1.4%). We add another robustness check by removing the above list of cities from the sample.[11] In row 7 of Fig. 3, the estimated coefficient remains negative and statistically significant at the 5% level, with a smaller magnitude. This robustness relieves the concern about different inventor/assignee city locations.

Data samples excluding central and western provinces. The majority of patents in China are in the eastern provinces. In the baseline regressions, we consider all provinces. By doing so, we somehow compare cities from eastern provinces with those cities from the western provinces, despite being fundamentally different places. How do the regression results change if the western cities are omitted?[12] Row 8 in the figure finds that the estimated coefficient is again negative and statistically significant. As shown in the next row, it is qualitatively the same if we further remove cities from the central provinces.

Exposure window. We measure air pollution by the contemporaneously annual average $PM_{2.5}$ concentration in the baseline model. The innovation process may take a longer time. We vary the exposure window by choosing two years (i.e., the current and previous years) and then calculate the average annual concentration. Row 10 presents the main estimation results from the new exposure window. The negative and statistically significant estimate remains.

Falsification tests. We perform several falsification tests by varying the exposure windows of air pollution. The last two rows of Fig. 3 consider one-year and two-year forward pollution concentrations. These exercises serve as falsification tests since future air pollution is unrelated to innovation activities in the current period. As expected, the estimated coefficients are not statistically significant at any conventional levels, reassuring our baseline conclusions.

Alternative model specifications. We have conducted a variety of model specifications to address specific concerns. First, we use the logarithm of the annual average concentration of $PM_{2.5}$ to measure pollution. The coefficient for this term could be interpreted as elasticity. Column (1) of Table 5 summarizes findings from the regression analysis with this specification. Qualitatively, the results are the same as the baseline results. Quantitatively, the estimated elasticity (i.e., -0.51) is slightly smaller than the baseline estimate (i.e., -0.58). Second, one may also worry that pollution may impede innovation activities only when its concentration is higher than a certain level. To address this concern, we collect daily concentration.[13] We then count the number of polluted days based on a mean concentration of 75 $\mu g/m^3$ (or 50 $\mu g/m^3$) and above. Columns (2) and (3) show the corresponding results regarding the number of polluted days. Both columns document consistently negative and statistically significant estimates at the 10% level, suggesting that the number of patents falls as the number of polluted days rises. Lastly, we resort to a count data model by directly using patent count, not in its logarithm, as the outcome variable for a fixed-effects Poisson model. As shown in column (4) of Table 5, we again find the consistently negative impact of $PM_{2.5}$ on the patent count.

Additional fixed effects. Although our baseline model includes city-specific, linear time trends, it does not consider sharp or non-monotonic changes in possible omitted determinants of pollution and innovation. For instance, internet expansion and connection facilitate better communications among researchers. To account for it, we add city-by-period fixed effects to the baseline model and run several regressions. In each regression, we choose a particular year and classify the years in the sample period from 1998 to 2016 into two subperiods. As summarized in Table A2 in the Appendix, our baseline results are robust to the inclusion of the city-by-period fixed effects.

Weighting the regressions by population. The baseline estimate assumes an unweighted regression. Since cities differ by population size, we further consider a regression weighted by city population (in Hukou registration). In the Appendix, Table A3 reports the corresponding results. Column (1) shows the weighted estimate, while column (2) displays the baseline unweighted result. These two estimated coefficients are roughly the same, reassuring our choice of the unweighted version for the baseline regressions that leverages a larger data sample.

Overall, the rich set of robustness checks confirms the baseline conclusion that the negative impact of pollution on innovation in Chinese cities is economically and statistically significant.

5.3. Mechanism

Identifying the mechanism of how air pollution affects innovation quantity and quality is a challenging task. One potential channel is the health damage to inventors. Air pollution could harm physical health conditions (Ebenstein et al., 2016; He et al., 2019), mental health (Zhang et al., 2017), and cognitive abilities (Ebenstein et al., 2016; Underwood, 2017; Zhang et al., 2018). It could also lead to anxiety and depression (Jacquemin et al., 2007; Power et al., 2015; Kim et al., 2016), lowering the likelihood of generating inspiration for new ideas. Another possible channel is worker productivity (Graff Zivin and Neidell, 2012; Chang et al., 2019; Fu et al., 2021), especially for those high-skilled workers and quality-focused employees (Archsmith et al., 2018). Admittedly, pollution may also trigger avoidance behavior and defensive expenditure by individuals and firms, leading to possible decreases in resources for innovation activities. To probe into these channels, one needs detailed information about the health outcomes or behavior of the patent assignees. Unfortunately, we have no such information for the assignees in our sample. Nevertheless, we try to collect relevant data and do further analysis to test for the channels indirectly.

[11] We thank a reviewer for making the comment and suggestion. Alternatively, we calculate the ratio of un-matched patents to total patents for each city. The top 10 list of cities substantially overlaps with the above list accounted for in the robustness check.

[12] We thank a reviewer for making the comment and suggestion.

[13] We calculate the daily concentration of $PM_{2.5}$ using the ChinaHigh$PM_{2.5}$ dataset (Wei et al., 2021). The dataset was generated using artificial intelligence, which considered the spatiotemporal heterogeneity of air pollution by integrating big data from various sources. For each city, we determine the $PM_{2.5}$ concentration by calculating the mean value of the raster cells within its boundary.

Pollution could affect patenting innovation by changing R&D workers' productivity (the intensive margin) (Chang et al., 2019; He et al., 2019) as well as causing the migration of workers (the extensive margin) (Qin and Zhu, 2018). Whereas both channels are possible, we argue that our estimates mainly capture the intensive margin since the baseline estimated effects in Table 2 arise from comparing short-term year-by-year activities. However, migration takes time, usually much longer than one year. Identifying this migration decision in response to air pollution requires collecting additional relevant data on the movement of R&D workers. Unfortunately, a direct measure of the number of migrating researchers is not available. To circumvent this data caveat, we obtain city-level data on employees in the scientific research and polytechnic services sector serving as an indirect measure of the number of R&D labor in the cities. Columns (1) and (2) of Table 6 report the regression results. While the estimated coefficients are negative, they are statistically insignificant. These findings suggest that the $PM_{2.5}$ concentration level does not affect the location decisions of R&D workers in our analysis. Inventors and R&D workers differ in capabilities and productivity. Though we do not find that pollution significantly causes employees to move out of highly polluted cities, it does not rule out the possibility that those more capable and high-productivity individuals respond to pollution by moving. We have no detailed information to evaluate this concern. However, we believe that the bias is not likely large because our estimate captures annual effects.

In columns (3)–(4) of Table 6, we further provide direct estimates for the intensive margin. Column (3) regresses the number of patents per R&D labor on air pollution using thermal inversions as an IV based on the baseline model. Column (4) uses the logarithm of the number of patents per R&D labor as the outcome variable. Both columns demonstrate the consistent negative estimated coefficients, statistically significant at the 1% level. These results indicate that labor productivity is lower in cities with higher $PM_{2.5}$ concentration levels. The results that focus on productivity are consistent with Bhaskarabhatla et al. (2021) who examine whether inventors or firms are the engines of innovation. Their results show that inventors' human capital is 5–10 times more important than firm capabilities for explaining the variance in inventor output.

5.4. *The magnitude of effects*

The baseline estimates help us understand the magnitudes of the impacts of annual fluctuations in $PM_{2.5}$ concentrations over the years on innovation activities across the cities. For each year, we predict a city's number of patents by assuming that the city's $PM_{2.5}$ concentration is at the same level as that in the previous year. If the $PM_{2.5}$ concentration stays unchanged between years $t-1$ and year t, which is $Pollution_{ct-1}$, the logarithm of the number of patents in city c and year t would be:

$$\widetilde{Innovation}_{ct} = \alpha Pollution_{ct-1} + f(W_{ct}) + \theta_c + \gamma_t + \delta_c T_t + \varepsilon_{ct} \tag{3}$$

Comparing Eqs. (1) and (3), we can calculate the change in the logarithm of the number of patents induced by the changes in $PM_{2.5}$ concentration between the two years:

$$Innovation_{ct} - \widetilde{Innovation}_{ct} = \alpha(Pollution_{ct} - Pollution_{ct-1}) \tag{4}$$

Thus, the (percentage) change in the number of patents is given by the natural exponent of the above difference. For each city, we sum the changes over five years for the periods of 2006–2010 and 2011–2015, respectively. To get a sense of the impacts of air pollution in relative terms, we calculate the ratio between the sum of the induced changes and the sum of the actual number of patents over five years. For instance, the share for the period 2001–2005 is equal to

$$\frac{\sum_c \sum_{t=2001}^{2005} [\exp(Innovation_{ct}) - \exp(\widetilde{Innovation}_{ct})]}{\sum_c \sum_{t=2001}^{2005} \exp(Innovation_{ct})} \times 100\%. \tag{5}$$

Fig. 4 illustrates the changes in $PM_{2.5}$ concentrations, while Fig. 5 plots the simulation results about the impacts on patent numbers. At the national level, the rising $PM_{2.5}$ concentrations caused the number of patents to decrease by 1.1% from 2006 to 2010. In recent years, especially after 2013, China made great efforts to improve air quality and saw positive signs in many cities (Zhang et al., 2019).

Table 6
Effects of Air Pollution on Innovation: Extensive vs Intensive Margins.

VARS	Extensive Margin		Intensive Margin	
	R&D labor	R&D labor (ln)	Patent count per labor	Patent count per labor (ln)
	(1)	(2)	(3)	(4)
$PM_{2.5}$	−197.831	−0.010	−0.011***	−0.006***
	(224.153)	(0.006)	(0.003)	(0.002)
KP *F*-statistic	88.3	88.3	88.3	88.3
Observations	4976	4976	4976	4976
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
City-specific trend	Y	Y	Y	Y

Notes: Dependent variables: R&D Labor and R&D Labor (ln) are the number of R&D employees and the logarithm number of R&D employees, respectively. Patent count per labor denotes the number of patents per R&D employee. We use the number of thermal inversions as an instrumental variable for $PM_{2.5}$. Standard errors in parentheses are clustered at the city level. Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

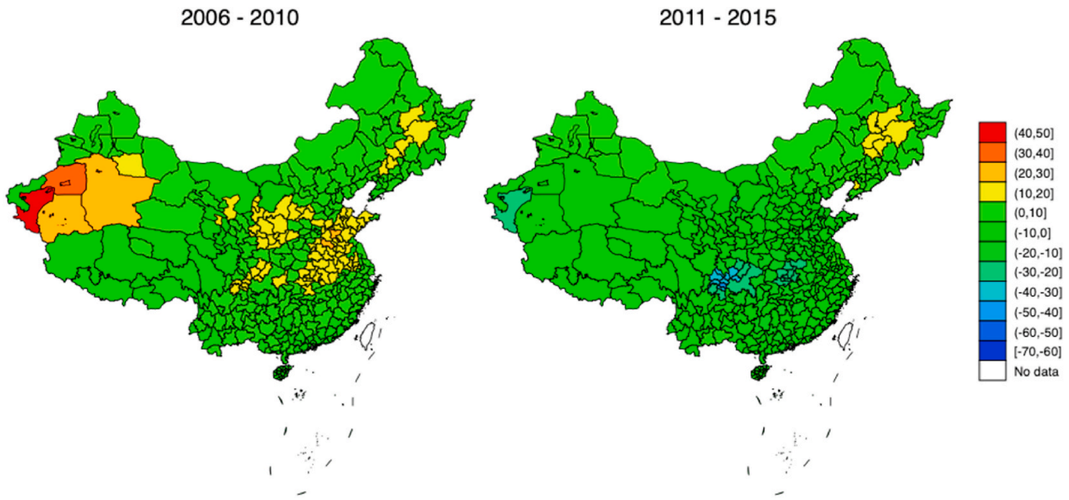

Fig. 4. $PM_{2.5}$ Changes in the 2006–2010 and 2011–2015 Periods. Unit: $\mu g/m^3$.

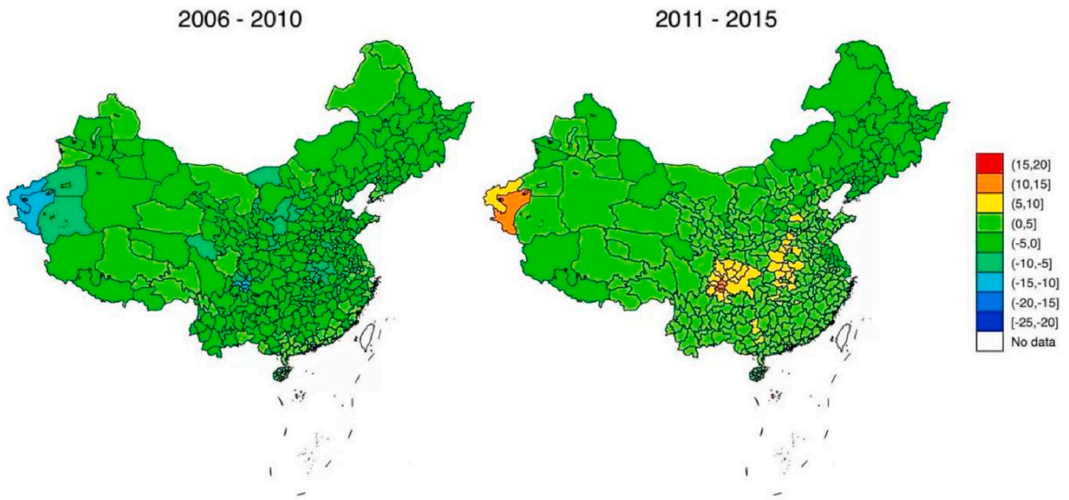

Fig. 5. Simulated Changes in Patent Numbers in the 2006–2010 and 2011–2015 Periods. Unit: percentage changes.

The improvement brought the benefits of more active innovation activities. Our calculations show that, from 2011 to 2015, the changes in $PM_{2.5}$ concentrations helped increase patent count by about 2.0%. Looking forward, as pollution levels in major cities (and innovation clusters) are still much higher than the WHO guideline standards and even China's national standards, we expect that China will gain much in innovations if the country achieves its goal of reducing $PM_{2.5}$ concentrations.

6. Discussions

As a driver of economic growth, innovation is essential for development. This paper documents the importance of better air quality in stimulating innovation. We assemble a unique city-level patent dataset aggregated from around 12.8 million patent applications during 1998–2016 in China. Our estimates demonstrate unambiguous findings that $PM_{2.5}$ hinders innovation. A one $\mu g/m^3$ increase in the annual average $PM_{2.5}$ concentration would decrease patent count by 1.3%. These findings have profound implications for academics and policymakers when discussing innovation and environmental policies.

First, this paper reveals that air pollution would lead to a substantial loss in innovation activities. China has implemented innovation policies, such as tax incentives and subsidies, to drive technological change. The design and implementation of these innovation policies have not involved any environmental regulators yet and failed to account for the potential innovation outcomes. Our findings suggest that innovation policies could be leaning towards areas disproportionately affected by environmental quality. Another note one should be aware of is that a city's annual average $PM_{2.5}$ concentration could also be affected by air pollution spillovers from neighboring cities. Given that local environmental regulations are imposed on polluting sources, it is important to coordinate these policies among cities.

Second, our results also have implications for environmental policies. Environmental regulation may cause a loss in employment, capital accumulation, and industrial output (Fu et al., 2021; Greenstone, 2002). It is one of the reasons why some developing countries are hesitant to tighten environmental regulations. Our results imply that an improvement in air quality arising from the tightened policy has co-benefits on innovation. $PM_{2.5}$ can be emitted directly from a diesel engine or form from chemical reactions of precursor gases (e.g., sulfur dioxide, nitrogen oxides, VOC, and ammonia). Therefore, the regulations limiting the emissions of those gases would eventually contribute to innovation. Due to the crucial role of innovation in long-term economic growth (Acemoglu et al., 2018), our calculation further suggests that pollution may also have long-term adverse impacts on economic growth.

Finally, a few caveats deserve consideration. Unfortunately, we are unable to directly test for the specific channels through which air pollution affects innovation activities. For future work, it may be interesting to search for more evidence and use innovative methods to analyze information regarding the health conditions of individual R&D workers when such information becomes available. That would greatly help us understand why pollution has such a significant effect on innovation activities.

Declaration of competing interest

The authors declare no known conflicts of interest related to this researh article.

Appendix

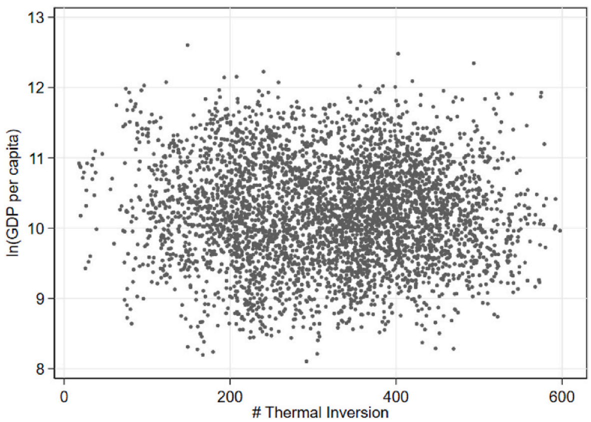

Fig. A1. The Number of Thermal Inversions and Income

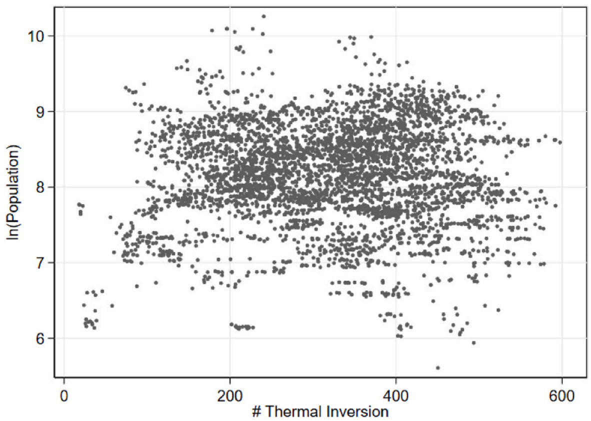

Fig. A2. The Number of Thermal Inversions and Population

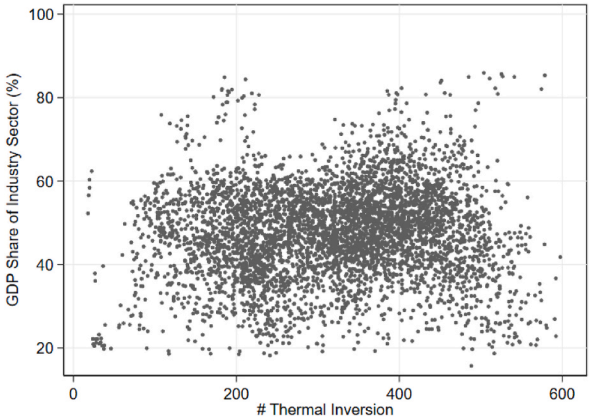

Fig. A3. The Number of Thermal Inversions and Industry Share of GDP

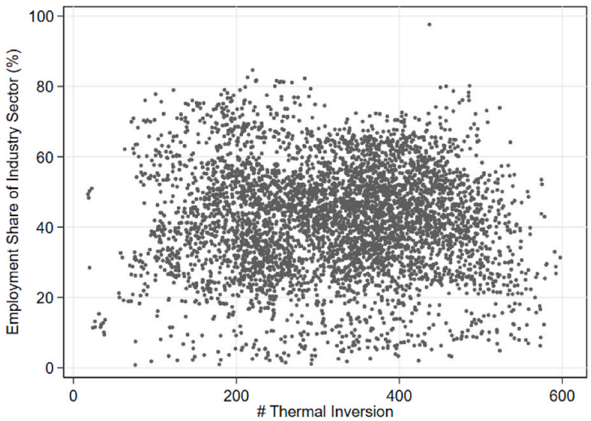

Fig. A4. The Number of Thermal Inversions and Industry Share of Employment

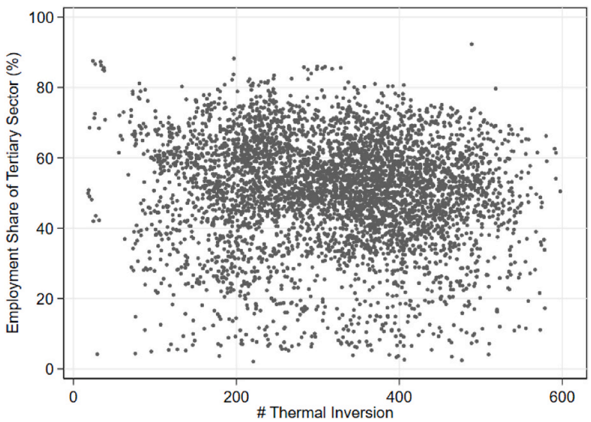

Fig. A5. The Number of Thermal Inversions and Tertiary Share of Employment

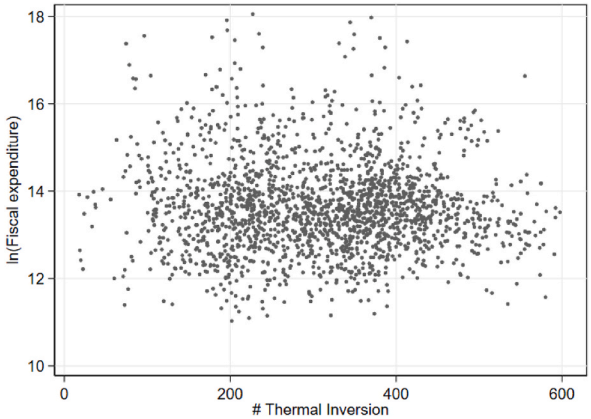

Fig. A6. The Number of Thermal Inversions and Fiscal Expenditure

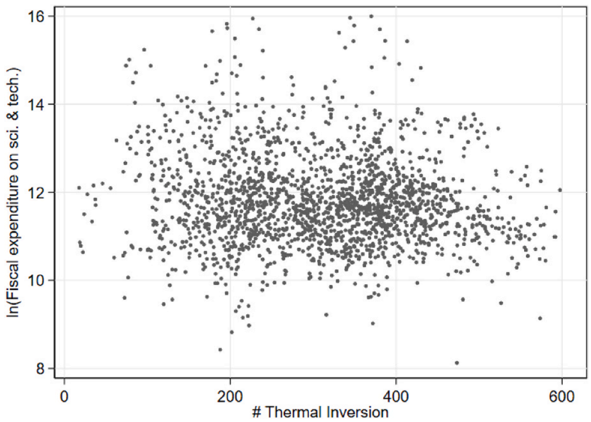

Fig. A7. The Number of Thermal Inversions and Fiscal Expenditure on S&T

Table A1
First-stage Results

VARS	$PM_{2.5}$			
	(1)	(2)	(3)	(4)
Thermal inversions	0.034***	0.055***	0.053***	0.054***
	(0.005)	(0.005)	(0.005)	(0.005)
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
City-specific trend	N	Y	Y	Y
Observations	6380	6380	6185	6335

Notes: These four columns correspond to those in Table 2, respectively. Standard errors in the parentheses are clustered at the city level. Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A2
Adding City-by-Period Fixed Effects into the Baseline Model

VARS	Patent					
	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$	−0.015**	−0.016**	−0.011**	−0.014**	−0.010*	−0.012**
	(0.007)	(0.007)	(0.005)	(0.006)	(0.005)	(0.005)
KP *F*-statistic	105.3	66.2	131.4	135.3	144.5	149.5
Observations	6373	6374	6370	6375	6375	6378
Year FE	Y	Y	Y	Y	Y	Y
City-specific trend	Y	Y	Y	Y	Y	Y
City by subperiod FE	Y	Y	Y	Y	Y	Y
Splitting year	2001	2003	2005	2007	2009	2011

Notes: The regressions include city by subperiod FEs. Thus, there is no need to control city FEs separately. The splitting year is the year we use to split the years in the sample period into two subperiods. For instance, in the first column, all years before 2001 are treated as subperiod 1. The remaining ones are in subperiod 2. Standard errors in parentheses are clustered at the city level. Significance: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A3
Effects of Air Pollution on Innovation: Weighted and Unweighted Regressions

VARS	Weighted	Unweighted	Weighted	Unweighted
	(1)	(2)	(1)	(2)
$PM_{2.5}$	−0.0158**	−0.0154***	−0.0182*	−0.0182*
	(0.0059)	(0.0059)	(0.0097)	(0.0099)
KP *F*-statistic	90.5	90.4	42.1	41.9
Observations	4962	4962	4203	4203
Weather variables	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
City-specific trend	Y	Y	Y	Y
Weights	Population (*Hukou*)	–	Population (*Permanent Residents*)	–

Notes: Dependent variable: The logarithm number of all patents. Standard errors in parentheses are clustered at the city level. Significance: ***p < 0.01, **p < 0.05, *p < 0.1.

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