Journal of Corporate Finance 73 (2022) 102170

Contents lists available at ScienceDirect

Journal of Corporate Finance

journal homepage: www.elsevier.com/locate/jcorpfin

Does air quality affect inventor productivity? Evidence from the NOx budget program

Yue Luo [a], Yangyang Chen [b,*], Ji-Chai Lin [c]

[a] School of Accounting, Nanjing University of Finance and Economics, China
[b] Department of Accountancy, City University of Hong Kong, Hong Kong SAR, China
[c] School of Accounting and Finance, The Hong Kong Polytechnic University, Hong Kong SAR, China

ARTICLE INFO

Editor: Dr X Tian

JEL classification:
G39
G40
O31

Keywords:
Air quality
Inventor productivity
Innovation strategy
Innovation quality

ABSTRACT

Using the NOx budget program (NBP) as a quasi-natural experiment, we study how air quality affects the productivity of patent inventors. Motivated by previous studies linking air quality to people's risk-taking tendencies and cognitive abilities, we find that after the implementation of the NBP, inventors located in NBP participating states produce more patents and the quality of their patents increases. These inventors engage more in exploratory innovation and less in exploitative innovation, and they shift their strategies toward risky, high-value innovation. Our findings suggest that risk-taking and cognitive ability are the channels through which improved air quality enhances inventor productivity.

1. Introduction

Air pollution presents a major global health concern. The World Health Organization (WHO) lists air pollution from both outdoor and indoor sources as the greatest environmental health risk globally. Medical studies document the numerous adverse effects of air pollution on physical health (e.g., Evans and Jacobs, 1981; Seaton et al., 1995; Brunekreef and Holgate, 2002; Mauzerall et al., 2005; Pope III and Dockery, 2006; Maher et al., 2016). According to the latest WHO data, 9 out of 10 people worldwide breathe highly polluted air, and air pollution kills around seven million people every year.[1]

In addition to its detrimental effects on physical health, air pollution is known to impair people's mental health. Increases in air pollution levels are associated with an intensification of negative moods, including annoyance, anxiety, depression, tension, stress, and low spirits (Jones and Bogat, 1978; Evans et al., 1988; Bullinger, 1989; Chattopadhyay et al., 1995). Negative moods can lead to pessimistic evaluations of future events, resulting in biased estimates of risk (Johnson and Tversky, 1983; Schwarz and Clore, 1983; Constans and Mathews, 1993; Mittal and Ross Jr, 1998). Consequently, people affected by high levels of air pollution become more risk-averse when making decisions.[2] In support of this argument, a number of studies document the negative effect of air pollution on stock returns and propose that increased investor risk aversion associated with air pollution-induced depression drives this effect (Levy

* Corresponding author at: 13-202, Lau Ming Wai Academic Building, City University of Hong Kong, Kowloon, Hong Kong.
E-mail addresses: yue.luo@connect.polyu.hk (Y. Luo), ychen722@cityu.edu.hk (Y. Chen), jclin@polyu.edu.hk (J.-C. Lin).

[1] https://www.who.int/health-topics/air-pollution#tab=tab_1.

[2] Medical studies show that higher levels of stress and tension induced by air pollution lead to higher levels of the stress hormone cortisol in the body. High levels of cortisol are linked to increased risk-averse behavior (Rosenblitt et al., 2001; Coates and Herbert, 2008; Mehta et al., 2015).

https://doi.org/10.1016/j.jcorpfin.2022.102170
Received 3 July 2021; Received in revised form 20 February 2022; Accepted 22 February 2022
Available online 8 March 2022

and Yagil, 2011; Heyes et al., 2016; Lepori, 2016; Li and Peng, 2016).

In addition, air pollution is known to impede people's cognitive abilities. As Clark and Sokoloff (1999) argue, given that the brain requires a large amount of oxygen, any reduction in oxygen quality can have a negative influence on cognition. Air pollution also impairs the nervous system, possibly leading to symptoms such as memory disturbance, fatigue, and blurred vision (Kampa and Castanas, 2008). Indeed, several studies find that children living in highly polluted areas perform poorly on examinations or cognitive function assessments (Suglia et al., 2008; Wang et al., 2009; Lavy et al., 2014). These studies provide empirical evidence attesting to air pollution's negative influence on cognitive performance.

Given the adverse effects of air pollution on people's mental health and cognitive abilities, we assess whether air quality affects the productivity of patent inventors. Innovation is both essential for the long-term success of corporations and is a key driving force in the development of the modern economy (Henderson and Cockburn, 1994). Inventors, as producers of innovations, are inevitably affected by their environment. Therefore, it is important to assess the environmental factors that can influence inventor productivity.

As innovation activities tend to be long-term in nature and have highly uncertain outcomes, promoting innovation requires risk-taking incentives, tolerance for early failure, and rewards for long-term success (Manso, 2011). Due to the high likelihood of failure, firms or individuals who are successful in innovation often have the desire to take risks in the innovation process. For example, numerous studies document that risk-taking is one of the key determinants of firms' innovation success (e.g., Hirshleifer et al., 2012; Chemmanur et al., 2014; Chen et al., 2014). As high levels of air pollution are associated with negative moods, which make people more risk-averse, inventors affected by heavy air pollution are likely to be more conservative in their decision-making. This characteristic may lead to sub-optimal risk-taking actions in the innovation process, and result in lower inventor productivity. In addition, innovation is an intellectual process that requires strong cognitive abilities. Air pollution may negatively affect inventors' cognitive abilities (Suglia et al., 2008; Wang et al., 2009; Lavy et al., 2014), thereby compromising investors' ability to integrate diverse cognitive elements, to make novel associations, or to undertake new initiatives (Amabile, 1996). As such, air pollution may impede inventors' productivity by impairing their cognitive function when making decisions.

We adopt the Nitrogen Oxide (NOx) Budget Program (NBP) as a quasi-natural experiment to examine whether a reduction in air pollution levels improves inventor productivity. The NBP is a cap-and-trade program designed to reduce NOx emissions in eastern U.S. states during the summer ozone season.[3] According to the U.S. Environmental Protection Agency (EPA), the NBP dramatically improves air quality in eastern U.S. states by reducing NOx emissions from power plants and industrial sources during the summer months. Because the implementation of the NBP is largely exogenous to local innovation activities, the program provides a setting in which endogeneity is unlikely to be a concern.

We collect patent data and inventor information from the Harvard Business School (HBS) patent inventor database (Li et al., 2014), which contains detailed information about the inventor(s) of each patent, including their names, cities of residence, and zip codes. We restrict our main analysis to inventors affiliated with U.S. publicly listed firms so that we can control for innovation inputs and the characteristics of the firms in which the inventors work. Nineteen states participated in the NBP during 2003 and 2004. We define inventors located in these states as treated inventors. All remaining inventors, excluding those living in states adjacent to NBP participating states, are defined as controlled inventors. We examine inventor productivity three years before and three years after the implementation of the NBP, and define 2000 to 2002 as the pre-treatment period and 2005 to 2007 as the post-treatment period.

We perform difference-in-differences (DiD) tests using U.S. inventor-level data around the time of the implementation of the NBP. The test results show that treated inventors produce significantly more patents than controlled inventors following the implementation of the NBP. The patents produced by treated inventors also generate more forward citations and have higher economic value. Specifically, relative to controlled inventors, treated inventors produce on average 2.8% more patents, and their patents receive 11.8% more forward citations and create 14.7% more economic value following the implementation of the NBP. Overall, these findings suggest that reducing air pollution enhances investors' innovation decisions and makes them more productive. Furthermore, our findings hold after various robustness checks. We also perform a placebo test that randomizes the states participating in the NBP. The results of the placebo test suggest that our findings are unlikely to be obtained by chance.

To investigate the underlying channels through which air pollution affects inventor productivity, we first test whether treated inventors change their innovation strategies to pursue high-risk, high-reward innovation after the implementation of the NBP. Specifically, we compare changes in their exploratory innovation (i.e., innovation in unfamiliar fields) versus exploitative innovation (i.e., innovation based on existing knowledge and expertise). The former involves more risk and is more challenging than the latter. We find that treated inventors engage in more exploratory innovation and less exploitative innovation after the implementation of the NBP, suggesting greater risk-taking by the treated inventors. Next, we examine whether increased innovation output by treated inventors is caused by improved cognitive function, a feature that could allow inventors to make beneficial decisions when engaging in R&D activities. We find that the average quality of each patent (e.g., average number of citations per patent and average economic value per patent) generated by treated inventors increases relative to the quality of patents generated by controlled inventors after NBP implementation. This evidence suggests that improved cognitive performance serves as a supplementary channel for the increased innovation levels when air pollution levels are reduced.

Finally, we investigate whether improved air quality associated with the NBP increases inventors' working hours and, as a result, their productivity. We fail to find evidence that air pollution reduces the working hours of local residents, suggesting that the effects of improved air quality on inventors' innovation output are not related to an increase in inventors' working hours. Our findings regarding

[3] NOx is a group of gases made up of nitrogen and oxygen, mainly nitric oxide (NO) and nitrogen dioxide (NO_2).

innovation strategies are also inconsistent with the working hours channel. Indeed, if the channel is effective, treated inventors should increase both their exploration and exploitation efforts, rather than increasing their exploration efforts while reducing their exploitation efforts. Taken together, these findings are consistent with the idea that reducing air pollution enhances inventors' risk-taking tendencies and improves their cognitive function in the innovation process, in turn making them more productive.

In our cross-sectional analyses, we show that the reduction in air pollution arising from the NBP has a greater effect on the productivity of less experienced inventors (i.e., inventors with shorter tenure or "non-superstar" inventors) than on the productivity of more experienced investors. This result is likely to be related to less experienced investors' low resilience levels with regard to the effects of air pollution. We also show that the NBP has a more pronounced effect on inventors living in areas with poorer air quality prior to the implementation of the program, where the improvement of air quality is likely to be greater. Furthermore, we conduct two additional analyses. We show that our main findings hold for all inventors, regardless of whether or not they work in publicly listed firms, implying that our findings are not limited to publicly listed firms. Our findings also hold in a large-scale panel regression in which air pollution is directly measured by the air quality index of the local area.

Our study contributes to the literature in three ways. First, we contribute to the literature on the effects of air pollution on inventor behavior. Several studies that examine the effects of air pollution on stock market participants (e.g., Levy and Yagil, 2011; Heyes et al., 2016; Lepori, 2016; Li and Peng, 2016) report a negative relationship between air pollution and stock market returns, and propose increased investor risk aversion associated with air pollution as the explanation. Other studies show that negative moods induced by air pollution affect analyst forecast bias (Dong et al., 2021) and investor trading behavior (Huang et al., 2020; Li et al., 2021). Our study adds to this line of research by demonstrating the ways in which air pollution affects patent inventors' productivity through its effects on their risk-taking and cognitive function. Given the importance of innovation to firm growth, our findings document a real effect of air pollution on the economy and provide a better understanding of the social and economic value of efforts to reduce air pollution.

Second, our study adds to the literature on the negative effects of air pollution on worker productivity. Studies focusing on labor-intensive work document that high levels of air pollution reduce the productivity of agricultural workers (Graff Zivin and Neidell, 2012), indoor pear packers (Chang et al., 2016), and call center workers (Chang et al., 2019). However, there is little research on whether air pollution affects the productivity of workers whose output depends on intellectual undertakings. Our study fills this gap in the literature by documenting that air pollution also affects the productivity of patent inventors, the most creative and valuable personnel in many firms.

Third, our study contributes to the growing literature that examines the determinants of innovation success.[4] The literature mainly focuses on the determinants of innovation success at the firm level. There is a lack of empirical work examining which factors influence innovation output from the perspective of inventors, who have direct control over the innovation process. Inventors, like other people, display various behavioral traits. Our study identifies air pollution as an important determinant of inventor productivity through its effects on inventor mood. These findings deepen our understanding of the key role of behavioral factors in shaping innovation success.

Gao et al. (2020) note that firms located in states that adopt smoke-free laws are more innovative than those located in states that do no adopt such laws. Our study differs from that of Gao et al. (2020) in terms of the underlying channels. Gao et al. (2020) suggest that smoke-free laws affect corporate innovation by improving inventors' health and working conditions and by attracting productive inventors. Our study argues that the reduction in air pollution associated with the implementation of the NBP stimulates local inventors' risk-taking tendencies and cognitive abilities, resulting in greater inventor productivity. We also test the inventor physical health and inventor relocation channels but do not find supporting evidence. Furthermore, while Gao et al. (2020) examine the effects of smoke-free laws on firm-level innovation output, we examine the effects of the NBP on inventor-level innovation output.

The remainder of the paper is organized as follows. Section 2 provides the background to the NBP. Section 3 describes the data, sample, and variables. Section 4 presents the baseline results and the results of the various robustness checks. Section 5 reports the results of the channel tests. Section 6 details the results of further analyses, and Section 7 concludes the paper.

2. Air pollution and the NBP

According to the EPA,[5] "ground-level ozone is created by chemical reactions between NOx and volatile organic compounds (VOC). This happens when pollutants emitted by cars, power plants, industrial boilers, refineries, chemical plants, and other sources chemically react in the presence of sunlight." While the chemical structure of ozone remains unchanged both miles above the earth and at ground level, ground-level ozone is considered harmful because it has negative effects on people and the environment. Specifically, breathing ozone can trigger a series of health problems, such as chest pain, coughing, and reduced lung function. Ground-level ozone is also harmful for sensitive vegetation and ecosystems. In addition to contributing to the formation of ground-level ozone, NOx is itself a major air pollutant associated with environmental problems, including the formation of acid rain, smog, and elevated fine particulate matter (PM2.5).

The NBP is a cap-and-trade program designed to reduce NOx emissions in eastern U.S. states during the summer ozone season (May 1 through September 30), the period of the year during which ground-level ozone concentrations are at their highest levels.[6] This

[4] See Ederer and Manso (2011), Kerr and Nanda (2015), and He and Tian (2018) for detailed reviews of the corporate innovation literature.

[5] https://www.epa.gov/ground-level-ozone-pollution/ground-level-ozone-basics.

[6] Beginning in 2009, the NBP was effectively replaced by the ozone season NOx program under the Clean Air Interstate Rule, which required further summertime NOx reductions in the power sector.

market-based program sets a regional cap on NOx emissions from power plants and other large combustion sources during the ozone season. To meet the cap, facilities in each participating state that emit NOx are required to reduce emissions significantly below baseline levels. States allocate allowances to these facilities (each allowance equals one ton of emissions), and the facilities then engage in emissions trading to achieve the most cost-efficient reductions possible. For example, companies can install emission control devices, switch to low NOx burners, or buy emission allowances on the open market. If emission levels are below the cap, sources can bank unused allowances and use or trade the banked allowances to cover emissions in a subsequent ozone season.

Eight northeastern states (Connecticut, Delaware, Maryland, Massachusetts, New Jersey, New York, Pennsylvania, and Rhode Island), and the District of Columbia joined the NBP on May 1, 2003. Eleven additional states (Alabama, Illinois, Indiana, Kentucky, Michigan, North Carolina, Ohio, South Carolina, Tennessee, Virginia, and West Virginia) joined the program on May 31, 2004. Fig. 1 shows the geographic implementation of the NBP in U.S. states.

The NBP has dramatically reduced NOx emissions from power plants and industrial sources during the summer months, contributing to significant air quality improvements in eastern U.S. states. According to the EPA (2009), ozone season NOx emissions from all NBP sources decreased monotonically and dramatically from 2003. In 2007, the NOx emissions from NBP sources were approximately 506,000 tons, about 60% below the level reported in 2000. Because most of the reductions in NOx emissions occurred after 2003, it is clear that the NBP has played an important role in improving air quality in eastern U.S. states. The EPA estimates that more than 78 million people living in these areas have experienced improved air quality. Furthermore, a case study conducted by the Maryland Department of the Environment (MDE) in conjunction with the University of Maryland, finds that NOx emissions reductions driven by the implementation of the NBP dramatically decrease observed ground-level ozone concentrations. The study further notes a significant improvement in air quality in Maryland since the implementation of the NBP. In another study, Deschênes et al. (2017) find that the NBP decreases pharmaceutical expenditure and mortality rates, suggesting that the reduction in air pollution in NBP participating states improves residents' health.

3. Data and sample

3.1. Sample construction

We collect patent data and inventor information from the HBS patent inventor database (Li et al., 2014). This database records every patent granted by the U.S. Patent and Trademark Office (USPTO) from 1976 to 2010. From the database, we obtain detailed information about the inventor(s) of each patent, including their names, cities of residence, and zip codes. Using a disambiguation algorithm method, the database assigns each inventor a unique identifier, which enables us to track their innovation records, along with their accurate residential location. To account for heterogeneity among inventors, we also control for innovation inputs and the characteristics of the firms for which the inventors work. As such, we restrict our main analysis to inventors affiliated with U.S. publicly listed firms. Patent inventors are matched with U.S. publicly listed firms based on patent data from Kogan et al. (2017), who provide the Center for Research in Security Prices (CRSP) firm identifier for each patent. We collect the financial data of these publicly listed firms from Compustat. We also use forward citation data and patent value data from Kogan et al. (2017) to measure the scientific and economic value of inventors' innovation output.

Because an inventor appears in the HBS patent inventor database only when they file a patent, our original sample consists of inventor-year observations in which inventors file at least one patent in a given year. We identify the first and last year in which an inventor files patents in the patent inventor dataset. We then assign a value of 0 to the inventor's innovation output variables for all years with no patent record. In this way, we create consecutive time series data for all inventors. As an inventor's residential information is available only when they file a patent, we assign the inventor's most recent residential information to the years for which the inventor does not have a patent record. We use the year in which the inventor applied for the patent, rather than the year in which the patent was granted, as the time indicator in our empirical analysis, because the application year is closer to the time when the new technology is invented.[7]

As innovation is a long-term process, it takes time for the NBP to produce a real effect on inventors' innovation output. We therefore examine the three years before and the three years after the implementation of the NBP in our empirical analysis. Specifically, we exclude 2003 and 2004 from the analysis as the years in which the NBP was introduced. We set 2000 to 2002 as the pre-treatment period and 2005 to 2007 as the post-treatment period. Following Deschênes et al. (2017), we exclude states that are adjacent to NBP states (Wisconsin, Iowa, Missouri, Georgia, Mississippi, Manie, New Hampshire, and Vermont) from our empirical analysis. Although they did not participate in the NBP, air quality in these states may have been indirectly affected by the program. We therefore classify inventors located in NBP participating states as the treatment group, and the remaining inventors, excluding those living in adjacent states, as the control group.[8] Our final sample spans the period from 2000 to 2007 (excluding 2003 and 2004) and includes 34,340 unique inventors from 1276 publicly listed firms.

[7] Hall et al. (2001) also note that the application year is a better indicator of the actual innovation date.

[8] If inventors have ever moved between NBP states and non-NBP states, we classify them as treated inventors if they lived in NBP states in 2003 or 2004.

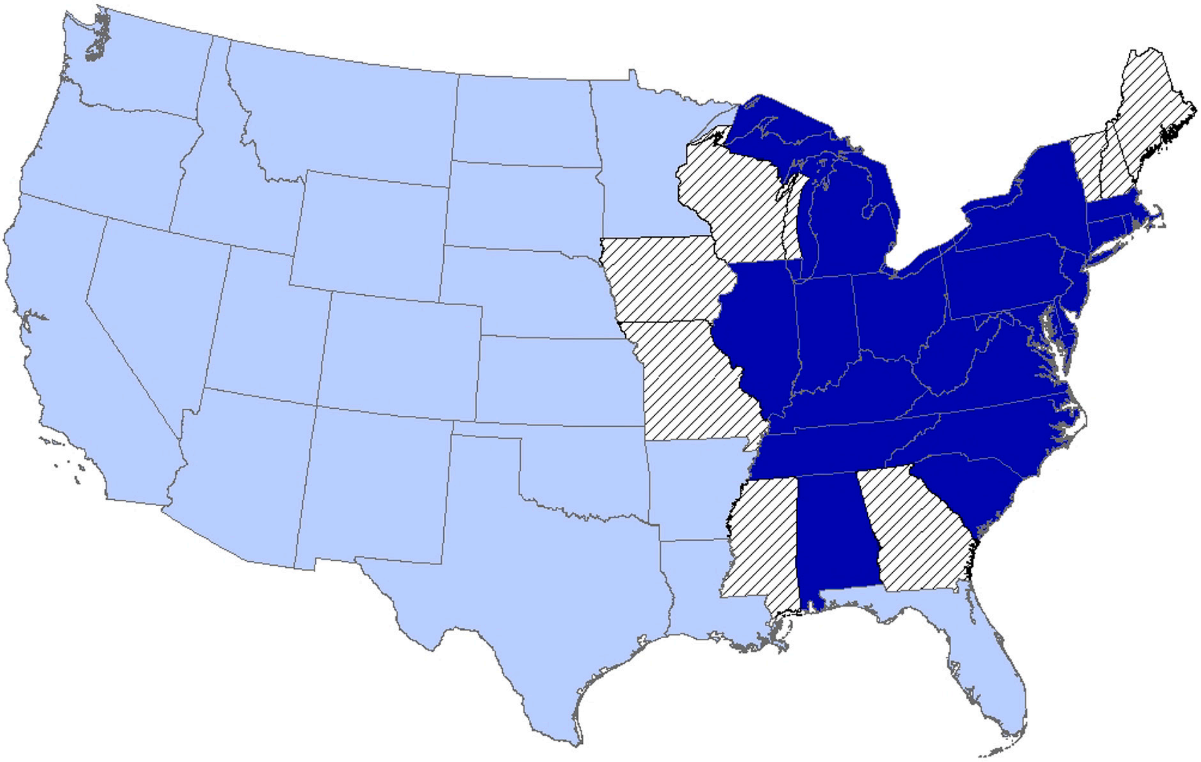

Fig. 1. Participation in NBP by State.
This figure presents the NBP participation status for U.S. states. Dark blue area indicates states that participated in the NBP during the 2003–2007 period; inventors located in these states are treated inventors. Light blue area indicates states that did not participate in the NBP; inventors located in these states are controlled inventors. Inventors in the shaded states are excluded from our empirical analysis. The figure comes from Deschênes et al. (2017). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.2. Variables

We use three measures of an inventor's innovation output. The three measures are based on newly filed patents by the inventor during the filing year that are eventually granted. The first measure, the number of patents, is calculated as the number of newly filed patents. The second measure is the number of citations, which is calculated as the sum of all forward citations received by these newly filed patents. Studies show that forward citations received by a patent reflect the patent's scientific value, and breakthrough patents are expected to receive more citations than less ground-breaking patents (Hall et al., 2001; Hall et al., 2005; Aghion et al., 2013). The third measure is total patent value, calculated as the sum of the economic value of all newly filed patents. According to Kogan et al. (2017), this measure is calculated as the increase in the market value of the firm (after adjusting for benchmark returns) within a three-day window following the patent grant announcement. As the three innovation output measures are highly skewed, we take the natural logarithm of 1 plus number of patents (*LnPat*), number of citations (*LnCit*), and total patent value (*LnPatVal*) separately, and use these log transformed measures in the analysis.

Our analysis is based on a sample of inventors affiliated with U.S. public firms, which enables us to control for a set of firm-level variables in our analysis. First, as large firms usually generate more patents and citations than small firms (Hall and Ziedonis, 2001), we include firm size (*Firm Size*), defined as the natural logarithm of total assets, in the control set. To control for firms' innovation inputs, we include R&D expenses (*R&D*), defined as R&D expenditure scaled by total assets. Following prior studies (e.g., Hirshleifer et al., 2012), we set *R&D* for observations with missing R&D information in Compustat to 0. We also control for firms' capital investment (*CapEx*), defined as capital expenditures scaled by total assets, return on assets (*ROA*), defined as earnings before interest and tax divided by total assets, cash holdings (*Cash*), defined as cash and short-term investments scaled by total assets, and leverage (*Leverage*), defined as the book value of debt scaled by total assets. To control for firms' growth opportunities, we include the book-to-market ratio (*BM*), defined as the book value of equity scaled by the market value of equity. Finally, we control for the effect of the life cycle of firms by including firm age (*Firm Age*), defined as the natural logarithm of 1 plus the number of years elapsed since the first year in which that firm appeared in the Compustat database. As information about inventor characteristics is limited, the only inventor-level variable we control for is inventor tenure (*Tenure*), defined as the natural logarithm of 1 plus the number of years between the year in which the inventor entered the patent database and the observation year. Detailed descriptions of all variables are provided in the appendix.

3.3. Descriptive statistics

Table 1 reports the descriptive statistics of the key variables in the empirical analysis. The table shows that the means of *LnPat* and *LnCit* are 0.66 and 1.08, corresponding to 0.93 patents and 1.94 forward citations, respectively. The mean of *LnPatVal* is 1.77, corresponding to US$4.87 million. With regard to the control variables, the mean of *Firm Size* is 9.41 and the mean of *R&D* is 0.07. The average values of *ROA*, *Leverage*, *CapEx*, *BM*, *Cash*, and *Firm Age* for the firms in our sample are 0.14, 0.19, 0.05, 0.29, 0.21, and 3.38, respectively. In addition, the mean of *Tenure* is 1.89, corresponding to 5.62 years, which suggests relatively long time series data for the average inventor.

4. Empirical results

4.1. Baseline analysis

We use a DiD approach as our main identification strategy to examine whether air pollution has a real effect on the treated inventors' innovation output. First, we perform a univariate analysis of the changes in innovation output around the time of the implementation of the NBP. We calculate the average values of each innovation output measure (i.e., *LnPat*, *LnCit*, and *LnPatVal*) for the treated and controlled inventors each year, and plot the average values in Fig. 2. In the pre-NBP period (i.e., 2000–2002), inventors in the control group have higher average innovation output levels than inventors in the treatment group, and the trends in the average values of the two groups are almost parallel.[9] In the post-NBP period (i.e., 2005–2007), the differences between the two groups decrease over time, and even reverse for *LnPatVal*. These findings are consistent with our hypothesis that treated inventors experience greater increases in innovation output relative to controlled inventors, after the implementation of the NBP.

Next, we perform a multivariant regression analysis using the following regression specification:

$$\begin{aligned}&Innovation_{i,t}=\beta_0+\beta_1 Treat\times Post_{i,t}+\beta_2 Firm\ Size_{i,t-1}+\beta_3 R\&D_{i,t-1}\\&+\beta_4 ROA_{i,t-1}+\beta_5 Leverage_{i,t-1}+\beta_6 CapEx_{i,t-1}+\beta_7 BM_{i,t-1}+\beta_8 Cash_{i,t-1}\\&+\beta_9 Firm\ Age_{i,t-1}+\beta_{10} Tenure_{i,t-1}+State+Inventor+Year+Industry+\varepsilon_{i,t}\end{aligned}\tag{1}$$

where subscripts *i* and *t* denote inventor *i* and year *t*, and ε is the error term. *State* denotes state fixed effects, *Inventor* denotes inventor fixed effects, *Year* denotes year fixed effects, and *Industry* denotes industry fixed effects. *Innovation* refers to the three innovation output variables (i.e., *LnPat*, *LnCit*, and *LnPatVal*). The treatment dummy (*Treat*) is a dummy variable equal to 1 if the inventor belongs to the treatment group (i.e., located in an NBP participating state), and 0 if the inventor belongs to the control group (i.e., all remaining inventors apart from those living in adjacent states). *Post* is a dummy variable equal to 1 for the post-NBP period (i.e., 2005–2007), and 0 for the pre-NBP period. (i.e., 2000–2002). The independent variable of interest is the interaction term *Treat*×*Post*, which captures the change in innovation output of the treated inventors, relative to the controlled inventors, around the time of the implementation of the NBP. We do not include *Treat* and *Post* as independent variables in the regression model because inventor and year fixed effects absorb the effects of *Treat* and *Post*, respectively. All independent variables except *Treat*×*Post* are lagged by one year relative to the dependent variable.[10] The regressions are performed using ordinary least squares, with standard errors clustered at the inventor level.[11]

Table 2 reports the regression results for the baseline analysis. Column (1) shows that the coefficient of *Treat*×*Post* is positive and statistically significant at the 1% level (coefficient = 0.028 with *t*-statistic = 4.00) for the *LnPat* regression, suggesting that treated inventors generate more patents after the implementation of the NBP, relative to controlled inventors. In columns (2) and (3), the coefficient of *Treat*×*Post* is also positive and significant for the *LnCit* regression (coefficient = 0.118 with *t*-statistic = 7.38) and for the *LnPatVal* regression (coefficient = 0.147 with *t*-statistic = 7.74), indicating that the implementation of the NBP not only improves the quantity but also the quality of the treated investors' patents. In terms of economic significance, treated inventors file 2.8% more patents, and their patents receive 11.8% more forward citations, and create 14.7% more economic value relative to controlled inventors after the implementation of the NBP.[12] Therefore, the effect of the NBP on inventor innovation is also economically significant.

Regarding the control variables, *Firm Size* and *Cash* are positively associated with all three inventor innovation output measures, suggesting that inventors affiliated with larger firms and firms with more cash holdings—which tend to possess more resources than other types of firms—are able to produce higher innovation output. *R&D* is negatively associated with the innovation output measures,

[9] The "V" shape for *LnPat* and *LnPatVal* around 2004 is likely to be caused by the R&D bust of 2001 and 2002. Brown et al. (2009) document a steady growth in R&D for publicly listed firms from 1980 to 2001. When this trend came to an end, R&D reduced rapidly in 2001 and 2002, which explains the sudden drop in inventors' innovation output in 2004. As 2003 and 2004 are the years in which the NBP was introduced, we exclude them from the analysis. As such, the "V" shape is unlikely to affect our results.

[10] Using a one-year lag is reasonable because it takes time for inventors to generate patents. The one year lag is widely used in empirical innovation studies (e.g., Balsmeier et al., 2017, and Bhattacharya et al., 2017).

[11] The results are similar when the standard errors are two-way clustered by inventor and year.

[12] The economic significance of our study is reasonable, in particular when compared with that documented in prior studies. For example, Chen et al. (2014) find that a one standard deviation increase in the Catholics-to-Protestant ratio, an indicator of local gambling preferences, is associated with a rise of approximately 8% of a firm's patent counts. Furthermore, Galasso and Simcoe (2011) note that the presence of an overconfident CEO is associated with a 25% to 35% increase in citation-weighted patent counts. Hirshleifer et al. (2012) report a 28% increase in patent counts for firms led by overconfident CEOs.

Table 1
Summary statistics.

	Obs.	Mean	Std.	25%	Median	75%
Treat×Post	149,704	0.19	0.39	0.00	0.00	0.00
LnPat	149,704	0.66	0.62	0.00	0.69	1.10
LnCit	149,704	1.08	1.38	0.00	0.00	1.95
LnPatVal	149,704	1.77	1.64	0.00	1.74	3.03
Firm Size	149,704	9.41	2.06	8.19	9.70	10.78
R&D	149,704	0.07	0.06	0.03	0.06	0.10
ROA	149,704	0.14	0.11	0.09	0.15	0.20
Leverage	149,704	0.19	0.16	0.04	0.18	0.29
CapEx	149,704	0.05	0.04	0.02	0.04	0.07
BM	149,704	0.29	0.22	0.14	0.24	0.36
Cash	149,704	0.21	0.20	0.06	0.14	0.30
Firm Age	149,704	3.38	0.75	2.83	3.89	3.95
Tenure	149,704	1.89	0.87	1.39	1.95	2.49

This table presents the summary statistics of the variables used in the analysis. Variable definitions are shown in the appendix.

likely because R&D expenditure is measured at the firm level, whereas we measure innovation output at the inventor level. It is possible that firms with high R&D expenditure have greater overall innovation output. However, this does not necessarily mean that productivity per inventor is higher, as it is possible that these firms hire a large number of inventors, which could result in lower productivity per inventor.[13] Furthermore, *BM* and *Firm Age* are negatively associated with innovation output, implying that inventors who work in growth firms and younger firms are more innovative than inventors who work in other types of firms. Regarding the inventor-level control, the coefficient of *Tenure* is significantly negative, suggesting that inventors with longer tenure become less innovative than those with shorter tenure.

Overall, the results of the baseline analysis suggest that the implementation of the NBP makes inventors located in NBP participating states more productive in terms of innovation than inventors located in non-NBP states. These results are consistent with our expectation that reducing air pollution improves inventors' mood, their risk-taking behavior, and cognitive function. Because risk-taking and cognitive ability are key determinants of firms' innovation success, inventors become more innovative after experiencing a reduction in air pollution levels.

4.2. Robustness tests

To check the validity of our results and exclude alternative explanations, we conduct a number of robustness tests. First, we conduct a pre-trend test and report the results in Panel A of Table 3. Specifically, we take 2000 and 2001 as the benchmark years and define *Year2002* as a dummy variable equal to 1 for 2002, and 0 otherwise. *Year2005*, *Year2006*, and *Year2007* are defined in the same way. We interact *Treat* with the four dummy variables separately, and replace *Treat×Post* with these interaction terms in Eq. (1). The results show that the coefficient of *Treat×Year2002* is either significantly negative or insignificant, suggesting that innovation is not significantly higher in the year prior to the implementation of the NBP. The coefficients of *Treat×Year2005*, *Treat×Year2006*, and *Treat×Year2007* are mostly positive and significant, suggesting that the effect of the NBP on inventors' innovation output only emerges after the implementation of the program. Furthermore, the coefficients of the interaction terms for later years are larger, indicating that it takes time for air quality improvements to exert a material influence on inventors' innovation output.

In the second set of tests, we examine whether our results are sensitive to an alternative sample. The results are reported in Panel B of Table 3. First, in the baseline analysis, we assign a value of 0 to the innovation output variables for all years with no patent record and between the first and last years in which the inventor filed a patent. To ensure that our results are not driven by this treatment, we only keep non-zero patent observations in the sample and re-estimate the baseline analysis on this sample. We obtain consistent findings, which are presented in row (1) of Panel B.

Second, our baseline DiD test is conducted on an unbalanced sample (i.e., an inventor can have missing data during the sample years). To ensure that our results are not driven by this imbalance, we re-estimate our DiD test using a balanced sample, in which we require inventors to have no missing data three years before and three years after the implementation of the NBP. The results are reported in row (2) of Panel B and are consistent with those based on the full (i.e., unbalanced) sample.

Third, instead of using the full sample, we use a propensity score matched sample in the robustness test to address the concern that our findings are driven by differences in characteristics between treated and controlled inventors. We use *Firm Size*, *Tenure*, and the firms' industries based on the Fama–French 48-industry classification to generate the propensity scores. To construct the matched sample, we use one-to-one nearest neighbor matching, which allows us to match each treated inventor with a controlled inventor with similar characteristics. We re-estimate the baseline regression model based on this matched sample. The results are presented in row (3) of Panel B. Once again, the results are consistent with those using the full sample.

[13] To further investigate this issue, we perform a firm-level regression based on our sample. Specifically, we calculate the firm-level number of patents, number of citations, and total patent value, and then respectively regress these measures on *R&D*, and other firm-level control variables. The results (untabulated) show that *R&D* is positively related to these innovation output measures at the firm level.

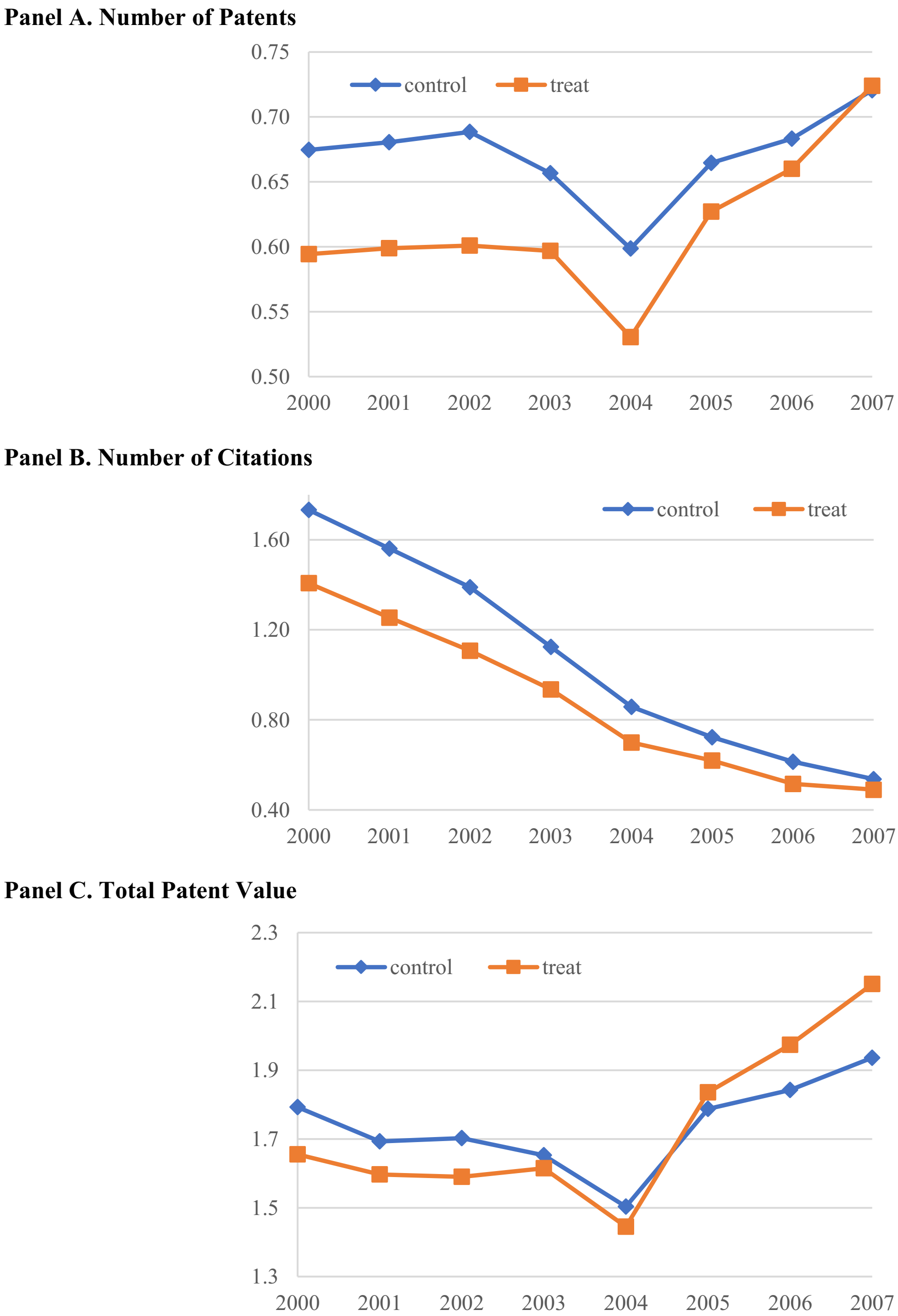

Fig. 2. Innovation output of treated and controlled inventors around the implementation of NBP.
This figure presents the trends in innovation output for the treated inventors and controlled inventors around the implementation of NBP.
Panel A. Number of patents.
Panel B. Number of citations.
Panel C. Total patent value.

Finally, we only include states that joined the program in 2003, as it is possible that inventors in other NBP participating states anticipated the implementation of the NBP and changed their innovation practices accordingly in advance. We re-estimate the baseline regression model based on the reduced sample. The results, reported in row (4) of Panel B, show that our findings hold with this sample.

In the third set of tests, we examine whether our results are sensitive to alternative regression specifications. The results are reported in Panel C of Table 3. First, in our baseline analysis, we exclude 2003 and 2004 because it is difficult to determine whether these

Table 2
NBP implementation and inventor innovation output.

	(1)	(2)	(3)
Variable	*LnPat*	*LnCit*	*LnPatVal*
Treat×Post	0.028***	0.118***	0.147***
	(0.007)	(0.016)	(0.019)
Firm Size	0.035***	0.024**	0.262***
	(0.004)	(0.010)	(0.011)
R&D	−0.373***	−1.252***	−0.724***
	(0.076)	(0.171)	(0.184)
ROA	−0.138***	−0.212***	0.069
	(0.030)	(0.070)	(0.078)
Leverage	−0.080***	−0.044	−0.045
	(0.025)	(0.056)	(0.062)
CapEx	0.268***	0.345	1.028***
	(0.096)	(0.218)	(0.237)
BM	−0.123***	−0.330***	−0.482***
	(0.012)	(0.027)	(0.028)
Cash	0.169***	0.212***	0.203***
	(0.023)	(0.052)	(0.058)
Firm Age	−0.130***	−0.260***	−0.437***
	(0.010)	(0.022)	(0.025)
Tenure	−0.189***	−0.513***	−0.710***
	(0.006)	(0.014)	(0.015)
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Obs.	149,704	149,704	149,704
Adj. R^2	0.309	0.346	0.301

Panel A presents the regression results of the baseline difference-in-differences test on a sample of inventors affiliated with public firms. The regressions are performed using ordinary least squares, with standard errors (reported in parentheses) clustered at the inventor level. All independent variables except *Treat×Post* are lagged by one year. Panel B shows the regression results of firm-level innovation output on firm-level controls. The regressions are performed using ordinary least squares, with standard errors (reported in parentheses) clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the appendix.

two years are in the pre- or post-NBP period. However, the NBP may have already partially affected inventors' innovation output during these two years. To account for this possibility, we include 2003 and 2004 in the analysis. We set *Post* to 0.5 for these two years and re-estimate the baseline test. The results are shown in row (1) of Panel C and are similar to those of the baseline regression.

Second, in the baseline test, if there are multiple applicants associated with a patent, we count the patent for each inventor. This approach may lead to biased innovation output measures. To address this concern, we split the patent between inventors for patents with multiple applicants (i.e., each inventor has a patent count of 1/N if there are N applicants). We recalculate the number of citations and the economic value using the same approach. We re-estimate the baseline regression model using the new measures of innovation output. The results are shown in row (2) of Panel C. Our findings still hold.

Finally, to mitigate the concern that our results are obtained from biased estimates due to the fact that the dependent variables in the baseline regression are serially correlated, we follow Bertrand et al. (2004) and collapse the innovation output variables by the implementation of the NBP. For each firm, we calculate the sum of the innovation output variables across all years for the pre- and post-NBP periods, respectively. We also calculate the average value of the control variables across all years in the two periods. We then collapse the sample of inventor-year observations into a sample of inventor-period observations. We re-estimate the baseline regression using this sample and report the results in row (3) of Panel C. Our findings still hold.

In the fourth set of tests, we investigate whether our findings are driven by economic changes induced by the implementation of the NBP. It is possible that the NBP influences inventor productivity through its effect on the local economy or the business operations and corporate policies of any affiliated firms, which in turn affects these firms' ability to finance innovation projects. In the baseline analysis, we focus on inventors affiliated with public firms so that we can control for a number of firm characteristics that may affect inventor productivity. We further address this issue using four tests and report the results in Panel D of Table 3.

First, studies (Palmer et al., 2001; Linn, 2010) show that because of the imposed restrictions on NOx emissions, the NBP primarily affects firms directly in the utility sector, especially those that operate power plants. As such, we exclude inventors who work in utility firms from the sample and re-estimate the baseline regression. The results are shown in row (1) of Panel D. All of our findings hold.

Second, the EPA (1999) and Platts Research and Consulting (2003) predict that the NBP could increase electricity prices, which

Table 3
Robustness tests.

Variable	(1)	(2)	(3)
	LnPat	*LnCit*	*LnPatVal*
Panel A. Pre-trend test			
Treat×Year2002	−0.023***	−0.019	−0.038*
	(0.008)	(0.020)	(0.022)
Treat×Year2005	−0.003	0.080***	0.054**
	(0.009)	(0.019)	(0.024)
Treat×Year2006	0.037***	0.138***	0.202***
	(0.011)	(0.023)	(0.029)
Treat×Year2007	0.069***	0.181***	0.304***
	(0.014)	(0.029)	(0.038)
Controls and FEs included			
Obs.	149,704	149,704	149,704
Adj. R^2	0.309	0.346	0.302
Panel B. Alternative samples			
(1) Exclude zero-patent observations			
Treat×Post	0.036***	0.177***	0.183***
	(0.007)	(0.018)	(0.015)
Controls and FEs included			
Obs.	96,298	96,298	96,298
Adj. R^2	0.322	0.537	0.630
(2) Balanced sample			
Treat×Post	0.055***	0.187***	0.182***
	(0.015)	(0.033)	(0.036)
Controls and Fes included			
Obs.	39,726	39,726	39,726
Adj. R^2	0.401	0.422	0.352
(3) Results from matched sample			
Treat×Post	0.077***	0.166***	0.267***
	(0.022)	(0.047)	(0.060)
Controls and FEs included			
Obs.	51,734	51,734	51,734
Adj. R^2	0.246	0.300	0.255
(4) Exclude states joining NBP after 2003			
Treat×Post	0.008	0.070***	0.072***
	(0.009)	(0.019)	(0.022)
Controls and FEs included			
Obs.	126,004	126,004	126,004
Adj. R^2	0.314	0.350	0.307
Panel C. Alternative research design			
(1) Sample includes 2003 and 2004			
Treat×Post	0.023***	0.121***	0.130***
	(0.007)	(0.015)	(0.017)
Controls and FEs included			
Obs.	249,671	249,671	249,671
Adj. R^2	0.334	0.351	0.313
(2) Split innovation output by the number of inventors			
Treat×Post	0.026***	0.157***	0.123***
	(0.005)	(0.012)	(0.014)
Controls and FEs included			
Obs.	149,704	149,704	149,704
Adj. R^2	0.369	0.370	0.329
(3) Collapse the sample by NBP implementation			
Treat×Post	0.087***	0.233***	0.266***
	(0.010)	(0.020)	(0.020)
Controls and FEs included			

(*continued on next page*)

Table 3 (*continued*)

Variable	(1)		(2)		(3)	
	LnPat		*LnCit*		*LnPatVal*	
Obs.	59,612		59,612		59,612	
Adj. R^2	0.355		0.436		0.442	
Panel D. Exclude alternative interpretations						
(1) Exclude inventors in the utility industry						
Treat×Post	0.028***		0.118***		0.146***	
	(0.007)		(0.016)		(0.019)	
Controls and FEs included						
Obs.	149,684		149,684		149,684	
Adj. R^2	0.309		0.346		0.301	
(2) Exclude inventors in the manufacturing industries						
Treat×Post	0.023***		0.103***		0.121***	
	(0.006)		(0.014)		(0.017)	
Controls and FEs included						
Obs.	127,710		127,710		127,710	
Adj. R2	0.308		0.346		0.303	
(3) Exclude inventors in the pollution-intensive industries						
Treat×Post	0.022***		0.092***		0.091***	
	(0.007)		(0.015)		(0.017)	
Controls and FEs included						
Obs.	115,143		115,143		115,143	
Adj. R2	0.317		0.349		0.306	
(4) Exclude inventors in medical industries						
Treat×Post	0.029***		0.116***		0.146***	
	(0.008)		(0.017)		(0.019)	
Controls and FEs included						
Obs.	134,298		134,298		134,298	
Adj. R^2	0.316		0.348		0.303	
(5) Control for state-level macroeconomics conditions						
Treat×Post	0.030***		0.114***		0.100***	
	(0.009)		(0.020)		(0.024)	
Controls and FEs included						
Obs.	149,704		149,704		149,704	
Adj. R^2	0.310		0.347		0.302	
(6) Exclude inventors that ever moved between NBP states and non-NBP states						
Treat×Post	0.029***		0.124***		0.153***	
	(0.008)		(0.016)		(0.019)	
Controls and FEs included						
Obs.	143,708		143,708		143,708	
Adj. R^2	0.307		0.346		0.301	
(7) Test on the spillover effect of moved inventors						
	(1)	(2)	(3)	(4)	(5)	(6)
	More	Fewer	More	Fewer	More	Fewer
Treat×Post	0.017***	0.053***	0.102***	0.145***	0.115***	0.241***
	(0.006)	(0.011)	(0.013)	(0.025)	(0.016)	(0.029)
Controls and FEs included						
Obs.	138,800	96,768	138,800	96,768	138,800	96,768
Adj. R^2	0.311	0.314	0.348	0.351	0.303	0.299
p-Value	0.199		0.405		0.126	
Panel E. Randomized NBP participating states						
Treat×Post	0.009		0.014		0.020	
	(0.008)		(0.017)		(0.020)	
Controls and FEs included						
Obs.	233,388		233,388		233,388	
Adj. R^2	0.304		0.326		0.303	

This table presents the results for robustness tests. The regressions are performed using ordinary least squares, with standard errors (reported in parentheses) clustered at the inventor level. All independent variables except *Treat*×*Post* are lagged by one year. All control variables and year, inventor, and industry fixed effects are included in the regressions but are not reported. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the appendix.

could in turn affect manufacturing firms' business operations. As such, we exclude inventors working in manufacturing firms from the sample and re-estimate the baseline regression. We present the results in row (2) of Panel D, and our findings still hold.

Third, the NBP may increase the cost of pollution, which naturally creates a demand for eco-friendly innovation for pollution-intensive firms in NBP participating states. To mitigate the concern that our findings are driven by eco-friendly patents, we re-estimate the baseline regression using a sample excluding inventors working in pollution-intensive industries.[14] We report the results in row (3) of Panel D, and our findings still hold.[15]

Fourth, the adoption of the NBP may have an effect on the innovation output of inventors in the healthcare, medical equipment, or pharmaceutical industries, as these inventors may have more incentives to develop medicines or pharmaceutical products that fight diseases caused by air pollution. To mitigate this concern, we exclude inventors from these industries and re-estimate the baseline model. The results are presented in row (4) of Panel D, and our findings still hold.

Fifth, we include a number of state-level macroeconomic variables to mitigate the concern that our findings are driven by changes in local economic conditions. These variables include state-level labor income, state-level GDP growth, the relative state-level unemployment rate, and aggregate sales of all firms headquartered in the state. We obtain state-level labor income and GDP growth data from the Bureau of Economic Analysis (BEA), state-level unemployment data from the Bureau of Labor Statistic (BLS), and aggregate state-level firm sales from Compustat. We take the natural logarithm of state-level labor income and aggregate state-level firm sales. State-level GDP growth is the annual growth rate of GDP in a state. The relative state-level unemployment rate is defined as the state-level unemployment rate in each year divided by the moving average of the state-level unemployment rate over the previous four years. The results are reported in row (5) of Panel D and show that our findings hold after controlling for local macroeconomic factors.

Finally, studies document that inventor movements could lead to knowledge spillovers across locations (e.g., Almeida and Kogut, 1999; Corredoira and Rosenkopf, 2010; Akcigit et al., 2016). It is possible that many inventors moved from non-NBP participating states to NBP participating states after the implementation of the NBP, leading to knowledge spillovers and, as a result, higher levels of productivity among inventors in NBP participating states. Nevertheless, among the 34,340 inventors in our sample, only 1284 inventors (3.74%) moved between NBP participating states and non-NBP participating states. Furthermore, among the 1284 inventors that moved, 732 moved from NBP participating states to non-NBP participating states, and 552 moved from non-NBP participating states to NBP participating states. As such, we do not observe greater inventor movements from non-NBP participating states to NBP participating states, casting doubt on the effects of this alternative channel.

To further mitigate this concern, we perform two tests. First, we exclude inventors that moved between NBP participating states and non-NBP participating states during our sample period and re-estimate our baseline regression. As shown in row (6) of Panel D, our findings hold for this subsample. Second, we divide NBP participating states into groups based on the number of inventors arriving after the implementation of the NBP. We then construct two subsamples. The first subsample includes all inventors in the control group and inventors living in NBP participating states with more inventors moving in. The second subsample includes all inventors in the control group and inventors living in NBP participating states with fewer inventors moving in. As the number of inventors in the first group of states is larger than in the second group of states, the first subsample is larger. We re-estimate Eq. (1) using the two subsamples separately and report the results in row (7) of Panel D. The results show that the coefficient of *Treat*×*Post* is positive and significant in all regressions, and the differences between the coefficients are all insignificant. Combining the findings from these two tests, we conclude that our findings are unlikely to be driven by the spillover effect.

Our final test is a placebo test aimed at mitigating the concern that our results could be obtained by chance. Because our analysis is based on a large sample of 149,704 inventor-year observations, it is possible that any variable could generate a statistically significant result. To address this issue, we randomly categorize 19 states as NBP participating states and define inventors located in these states as treated inventors. All remaining inventors are defined as controlled inventors. We then re-estimate the baseline regression model 100 times and report the means of the coefficients and the standard errors of the placebo test in Panel E of Table 3. The results show that the mean coefficient of *Treat*×*Post* is not statistically significant, indicating that our findings are not obtained by chance.

Overall, the results of the robustness checks suggest that our findings are not sensitive to alternative samples and regression specifications. In addition, our findings are not driven by the effects of the NBP on the local economy or the business operations and corporate policies of the relevant firms. The placebo test also suggests that our findings are not obtained by chance.

5. Channel tests

Our baseline analysis shows that the implementation of the NBP makes inventors in NBP participating states more innovative. In

[14] We follow List and Co (2000) and define pollution-intensive industries as those with the following two-digit SIC codes: 26 (Paper and Allied Products), 28 (Chemical and Allied Products), 29 (Petroleum and Coal Products), 32 (Stone, Clay, and Glass Products), 33 (Primary Metal Industries), 34 (Fabricated Metal Products), and 37 (Transportation Equipment).

[15] In an untabulated test, we divide our sample based on whether an inventor works in a pollution-intensive industry. Our results hold for both subsamples and there is no significant difference in the coefficient of *Treat*×*Post* between the two subsamples.

this section, we investigate the specific channels through which air pollution affects inventor productivity.

5.1. The effects of the NBP on inventor innovation strategies

The innovation process is unavoidably associated with risk, and there are significant variations in risk-taking across the various innovation strategies. Several studies note that inventors may explore new innovation or exploit and refine existing innovation (March, 1991; Benner and Tushman, 2002; Balsmeier et al., 2017). March (1991) argues that exploration is characterized by search, variation, risk-taking, experimentation, play, flexibility, discovery, and innovation, while exploitation is characterized by refinement, choice, production, efficiency, selection, implementation, and execution. In other words, an exploratory innovation strategy is associated with higher risk than an exploitative innovation strategy (March, 1991; Chava et al., 2013; Balsmeier et al., 2017). If air pollution affects inventor productivity primarily by reducing inventors' risk-taking incentives, we expect inventors to be more willing to enter new fields after local air quality improves. The enhancement in inventor productivity should therefore come primarily from exploratory innovation, rather than exploitative innovation.

To examine inventors' innovation strategies, we construct variables capturing inventors' propensity to pursue exploration versus exploitation strategies in innovation. First, we follow Benner and Tushman (2002) and calculate the number of exploratory and exploitative patents filed in a given year. A patent is defined as exploratory if more than 60% of its backward citations fall outside the inventor's existing knowledge base. A patent is defined as exploitative if more than 60% of its citations fall within the inventor's existing knowledge base. An inventor's existing knowledge base is defined as the combination of the inventor's patents and patents cited by the inventor's previous patents.

As an alternative measure of an inventor's exploration strategy, we follow Balsmeier et al. (2017) and define first patents as the number of newly filed patents during the year that belong to a technology class in which the inventor has never filed before. We also use self-citation as an alternative measure of the inventor's exploitation strategy. Following Chava et al. (2013) and Balsmeier et al. (2017), we define self-citation as the number of citations made by the inventor's newly filed patents that cite their previous patents. As exploratory patents and new patents fall outside an inventor's expertise, they reflect the inventor's efforts to pursue innovation in new fields (i.e., exploration strategy). In contrast, exploitative patents and self-citations are based on an inventor's expertise. As such, these patents capture the inventor's tendency to focus on existing fields (i.e., exploitation strategy). Therefore, we take the natural logarithm of 1 plus the number of explorative patents (*LnExplore*), the number of exploitative patents (*LnExploit*), the number of first patents (*LnFirstPat*), and the number of self-citations (*LnSelfcite*) separately.

Table 4
NBP implementation and inventor innovation strategy.

Variable	Exploration		Exploitation	
	(1)	(2)	(3)	(4)
	LnExplore	*LnFirstPat*	*LnExploit*	*LnSelfcite*
Treat×Post	0.020***	0.050***	−0.013***	−0.016**
	(0.005)	(0.007)	(0.005)	(0.007)
Firm Size	0.011***	0.022***	0.013***	0.003
	(0.003)	(0.004)	(0.003)	(0.004)
R&D	−0.251***	−0.311***	−0.208***	−0.229***
	(0.049)	(0.066)	(0.055)	(0.073)
ROA	−0.050**	−0.117***	−0.054**	−0.008
	(0.020)	(0.028)	(0.022)	(0.029)
Leverage	−0.066***	−0.130***	0.012	0.069***
	(0.016)	(0.022)	(0.017)	(0.024)
CapEx	0.126**	−0.002	0.270***	0.139
	(0.064)	(0.090)	(0.063)	(0.085)
BM	−0.077***	−0.132***	−0.020**	−0.031**
	(0.008)	(0.011)	(0.009)	(0.012)
Cash	0.028*	0.078***	0.109***	0.023
	(0.015)	(0.021)	(0.017)	(0.022)
Firm Age	−0.059***	−0.115***	−0.021***	−0.001
	(0.007)	(0.009)	(0.006)	(0.008)
Tenure	−0.381***	−0.298***	0.126***	0.122***
	(0.004)	(0.006)	(0.004)	(0.006)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Obs.	149,704	149,704	149,704	149,704
Adj. R^2	0.188	0.206	0.352	0.420

This table presents the regression results of the effect of NBP implementation on inventor innovation strategy. The regressions are performed using ordinary least squares, with standard errors (reported in parentheses) clustered at the inventor level. All independent variables except *Treat×Post* are lagged by one year. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the appendix.

We re-estimate the baseline regression model with these four variables as the dependent variable. The results are presented in Table 4. Columns (1) and (2) show that the coefficient of *Treat*×*Post* is positive and statistically significant when *LnExplore* and *LnFirstPat* are the dependent variables. These results indicate that inventors in NBP participating states increase their efforts to explore unfamiliar fields after the implementation of the NBP. In columns (3) and (4), where *LnExploit* and *LnSelfcite* are the dependent variables, the coefficient of *Treat*×*Post* is negative and statistically significant in both regressions, suggesting that inventors in NBP participating states reduce their innovation efforts in their areas of existing knowledge and expertise after the implementation of the NBP.

Overall, the results suggest that after the implementation of the NBP, inventors in NBP participating states are more likely to explore new and unfamiliar fields of research. Given that an exploratory innovation strategy involves more risk than an exploitative innovation strategy, the finding provides supporting evidence for the risk-taking channel. In other words, improving air quality in NBP participating states enhances inventors' mental state, thereby encouraging risk-taking behavior and resulting in greater inventor productivity.

5.2. *Effects of the NBP on patent quality*

Our baseline analysis suggests that inventors in NBP participating states produce more patents after the implementation of the NBP. These patents also generate more forward citations and have higher economic value than patents produced in non-NBP states. To examine whether the increase in innovation output by treated inventors is at least partly driven by improved cognitive function (which affects inventors' R&D decisions), we test whether patent quality among treated inventors improves after the implementation of the NBP. Higher patent quality indicates improved R&D capability and improved cognitive abilities of these investors.

To perform this test, we adopt two average patent quality measures. The average number of citations per patent (*LnAvgCit*) is defined as the natural logarithm of 1 plus the average number of forward citations received by an inventor's newly filed patents. Average economic value per patent (*LnAvgPatVal*) is defined as the natural logarithm of 1 plus the average economic value of an inventor's newly filed patents. We first calculate the two variables across all newly filed patents for each inventor. We also calculate the two variables across new exploratory patents and new exploitative patents separately.

We re-estimate the baseline regression model using the two average patent quality measures as dependent variables. The sample size of this test is much smaller than that of the baseline analysis, because observations with zero patents are excluded. The regression results are presented in Table 5. Columns (1) and (2) report the results of all newly filed patents. The coefficients of *Treat*×*Post* are

Table 5
NBP implementation and average patent quality.

Variable	All patents		Explorative patents		Exploitative patents	
	(1)	(2)	(3)	(4)	(5)	(6)
	LnAvgCit	*LnAvgPatVal*	*LnAvgCit*	*LnAvgPatVal*	*LnAvgCit*	*LnAvgPatVal*
Treat×*Post*	0.130***	0.135***	0.121***	0.140***	0.153***	0.133***
	(0.014)	(0.011)	(0.021)	(0.015)	(0.036)	(0.027)
Firm Size	−0.052***	0.215***	−0.057***	0.203***	−0.020	0.193***
	(0.009)	(0.009)	(0.014)	(0.013)	(0.023)	(0.021)
R&D	−0.447***	−0.191	−0.561**	−0.755***	−0.030	0.355
	(0.156)	(0.134)	(0.261)	(0.227)	(0.345)	(0.262)
ROA	−0.189***	0.439***	0.013	0.498***	−0.087	0.382***
	(0.062)	(0.051)	(0.098)	(0.076)	(0.136)	(0.108)
Leverage	0.120**	−0.140***	0.125	−0.097	−0.031	0.055
	(0.052)	(0.039)	(0.080)	(0.060)	(0.121)	(0.088)
CapEx	−0.136	0.389***	−0.308	0.628***	0.116	−0.241
	(0.192)	(0.148)	(0.283)	(0.213)	(0.458)	(0.315)
BM	−0.057**	−0.455***	−0.073*	−0.335***	0.082	−0.470***
	(0.026)	(0.020)	(0.039)	(0.028)	(0.060)	(0.044)
Cash	−0.057	−0.323***	−0.088	−0.252***	−0.113	−0.375***
	(0.046)	(0.041)	(0.074)	(0.065)	(0.104)	(0.086)
Firm Age	0.005	−0.170***	0.018	−0.203***	−0.045	−0.094*
	(0.020)	(0.021)	(0.028)	(0.029)	(0.056)	(0.048)
Tenure	0.012	−0.019**	0.002	−0.023*	−0.108**	−0.029
	(0.011)	(0.009)	(0.017)	(0.012)	(0.044)	(0.032)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	96,298	96,298	69,712	69,712	36,742	36,742
Adj. R^2	0.542	0.766	0.484	0.742	0.558	0.791

This table presents the regression results of the effect of NBP implementation on average patent quality, measured by the average citations and economic value per patent. The regressions are performed using ordinary least squares, with standard errors (reported in parentheses) clustered at the inventor level. All independent variables except *Treat*×*Post* are lagged by one year. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the appendix.

positive and statistically significant in both regressions, suggesting that the patents generated by inventors in NBP participating states have a higher average number of citations and higher economic value following the implementation of the NBP. As such, the improvement in air quality associated with the implementation of the NBP enhances not only the number but also the average quality of patents generated by inventors in NBP participating states. Both factors contribute to the increase in total patent citations and economic value.

Next, we examine exploratory and exploitative patents separately. Columns (3) to (6) show that the coefficients of *Treat*×*Post* are positive and statistically significant in all regressions, suggesting that the quality of exploratory and exploitative patents from investors in NBP participating states increases, despite the reduction in the number of exploitative patents. Collectively, the findings in this section suggest that improved cognitive performance serves as a supplementary channel through which reducing air pollution increases innovation.

5.3. Effects of the NBP on local working hours

Deschênes et al. (2017) document that the NBP improves air quality in participating states, which results in lower pharmaceutical expenditure and mortality rates in these areas. Because the NBP enhances local people's physical health, it is likely that it also improves inventors' productivity by making them healthier and therefore able to work longer hours, as they would need to take fewer sick days. Due to the unavailability of data on inventors' working hours, we are unable to directly test whether the NBP leads inventors in participating states to work longer hours. As an alternative, we examine how air quality influences the number of working hours for local residents.

We obtain data on local working hours from the American Time Use Survey (ATUS), which was conducted every year from 2003 to 2017 by the U.S. Census Bureau. The survey documents time use information for each respondent, including average working hours, sleeping hours, and time spent alone. We define *LnWorkingHours* as the natural logarithm of 1 plus the average weekly working hours of each respondent during the year. One shortcoming of the ATUS is its start date in 2003, making it impossible to perform a DiD test around the time of the implementation of the NBP. As an alternative, we perform a panel regression using two air quality measures, namely, annual air quality (*AnnualAQ*) and the proportion of unhealthy days (*Unhealthy*). *AnnualAQ* is calculated as the median of the daily Air Quality Index (AQI) for each county during the year. *Unhealthy* is the proportion of unhealthy days for each county during the year, where an unhealthy day is defined as a day when the AQI is higher than 100.[16] Higher values for the two measures indicate more severe air pollution. Because the ATUS data indicate the respondents' home states, rather than their home counties, we construct two state-level air quality measures, *StateAQ* and *StateUnhealthy*, which are the averages of *AnnualAQ* and *Unhealthy* for all counties in the state. We regress *LnWorkingHours* on the two state-level air quality measures and state, year, industry, and job category fixed effects. The regression results are presented in Table 6.

The coefficients of *StateAQ* and *StateUnhealthy* are not statistically significant, suggesting that air pollution does not significantly reduce the working hours of local residents. Therefore, we fail to find evidence that supports the working hours channel. Our findings in Section 5.1 are also inconsistent with the working hours channel, because if the working hours channel were to be effective, treated inventors would increase both their exploration and exploitation efforts, rather than increase their exploration efforts and reduce their exploitation efforts. It is therefore unlikely that our findings in the baseline analysis are driven by inventors in NBP participating states working longer hours following the implementation of the NBP.

6. Further analyses

6.1. The role of inventor experience

Graff Zivin and Neidell (2012) show that more experienced workers are more resilient to the effects of air pollution because they are better able to self-adjust. As such, we expect that only the productivity of more experienced inventors will be slightly influenced by air quality improvements associated with the NBP. We use two measures of inventor experience. The first measure is inventor tenure (*Tenure*), as inventors with longer tenure are likely to be more experienced. The second measure is the superstar inventor dummy (*Superstar*), defined following Akcigit et al. (2016) as a dummy variable equal to 1 if an inventor's total adjusted forward citations are among the top 10% in our sample, and 0 otherwise. Indeed, superstar inventors are likely to be more experienced than other inventors. We interact *Treat*×*Post* with *Tenure* and *Superstar* separately, and include the interaction terms in the baseline regression model. We do not include *Superstar* as an independent variable because it is time-invariant, and thus its effects are absorbed by inventor fixed effects.

The results are reported in Table 7. Columns (1) to (3) show that the coefficients of *Treat*×*Post*×*Tenure* are negative and statistically significant in all three regressions, suggesting that the productivity of a treated inventor is less influenced by the implementation of the NBP for inventors with longer tenure than for those with shorter tenure. When we use *Superstar* to indicate inventors' experience in columns (4) to (6), the coefficient of *Treat*×*Post*×*Superstar* is also significantly negative in all regressions, confirming that inventors with more experience are more resilient to air pollution than inventors with less experience. The results therefore imply that relative to more experienced investors, the reduction in air pollution achieved by the NBP has a greater effect on the productivity of less

[16] The EPA constructs an AQI for five major air pollutants, including ground-level ozone, particle pollution, carbon monoxide, sulfur dioxide, and nitrogen dioxide. AQI values at or below 100 are generally considered to be satisfactory. For more information about the AQI, please refer to https://www.airnow.gov/aqi/aqi-basics/.

Table 6
Air pollution and local working hours.

Variable	(1)	(2)
	LnWorkingHours	*LnWorkingHours*
StateAQ	0.000	
	(0.001)	
StateUnhealthy		0.006
		(0.101)
State FE	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
Job Category FE	Yes	Yes
Obs.	112,456	112,456
Adj. R^2	0.070	0.095

This table shows how air pollution affects the working hours of local residents. The regressions are performed using ordinary least squares. All independent variables are in the same year as dependent variables. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the appendix.

Table 7
The role of inventor experience.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	LnPat	*LnCit*	*LnPatVal*	*LnPat*	*LnCit*	*LnPatVal*
Treat×Post	0.087***	0.274***	0.347***	0.069***	0.234***	0.244***
	(0.009)	(0.021)	(0.024)	(0.007)	(0.016)	(0.019)
Treat×Post×Tenure	−0.107***	−0.280***	−0.362***			
	(0.013)	(0.027)	(0.033)			
Treat×Post×Superstar				−0.374***	−1.053***	−0.887***
				(0.024)	(0.049)	(0.050)
Firm Size	0.035***	0.023**	0.262***	0.036***	0.025***	0.264***
	(0.004)	(0.010)	(0.011)	(0.004)	(0.010)	(0.011)
R&D	−0.368***	−1.240***	−0.708***	−0.358***	−1.211***	−0.689***
	(0.076)	(0.171)	(0.184)	(0.076)	(0.171)	(0.184)
ROA	−0.141***	−0.219***	0.058	−0.140***	−0.216***	0.065
	(0.030)	(0.070)	(0.078)	(0.030)	(0.070)	(0.078)
Leverage	−0.082***	−0.048	−0.050	−0.070***	−0.016	−0.022
	(0.025)	(0.056)	(0.062)	(0.025)	(0.056)	(0.062)
CapEx	0.271***	0.352	1.037***	0.273***	0.357*	1.038***
	(0.096)	(0.218)	(0.236)	(0.096)	(0.217)	(0.236)
BM	−0.124***	−0.333***	−0.486***	−0.120***	−0.321***	−0.475***
	(0.012)	(0.027)	(0.028)	(0.012)	(0.027)	(0.028)
Cash	0.171***	0.217***	0.209***	0.171***	0.219***	0.209***
	(0.023)	(0.052)	(0.058)	(0.023)	(0.052)	(0.058)
Firm Age	−0.128***	−0.256***	−0.432***	−0.129***	−0.259***	−0.436***
	(0.010)	(0.022)	(0.025)	(0.010)	(0.022)	(0.025)
Tenure	−0.222***	−0.600***	−0.823***	−0.207***	−0.565***	−0.754***
	(0.007)	(0.016)	(0.018)	(0.006)	(0.014)	(0.015)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	149,704	149,704	149,704	149,704	149,704	149,704
Adj. R^2	0.310	0.347	0.302	0.313	0.353	0.305

This table shows how the effect of air pollution on inventor innovation output varies with inventor experience. The regressions are performed using ordinary least squares, with standard errors (reported in parentheses) clustered at the inventor level. All independent variables except *Treat×Post* are lagged by one year. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the appendix.

experienced inventors, as these investors are less resilient to air pollution.

6.2. The role of pre-NBP air pollution levels

We expect inventors living in counties with poorer air quality than other counties before the implementation of the NBP to experience a greater increase in productivity, as improvements in these counties' air quality should be greater than in counties with better air quality before the implementation of the NBP. We collect county-level air pollution data from the U.S. EPA.[17] We adopt two measures of air pollution, *AnnualAQ* and *Unhealthy*, as described in Section 5.3. Using the inventor location information from the HBS patent inventor database, we merge inventor data with air pollution data. We define pre-NBP air quality (*PreAQ*) as a dummy variable equal to 1 if an inventor lives in a county where the average *AnnualAQ* during the 2000–2002 period is above the sample median, and 0 otherwise. Similarly, we define pre-NBP *Unhealthy* (*PreUnhealthy*) as a dummy variable equal to 1 if an inventor lives in a county where the average *Unhealthy* during the 2000–2002 period is above the sample median, and 0 otherwise. Again, we interact *Treat*×*Post* with each of these air quality variables, and include the interaction terms in the baseline regression model. We do not include the two standalone dummy variables as independent variables because they are time-invariant and are therefore absorbed by inventor fixed effects.

The regression results are presented in Table 8. Columns (1) to (3) show that the coefficient of the interaction term between *Treat*×*Post* and *PreAQ* is positive and statistically significant in all regressions, indicating that inventors who live in counties with poorer air quality prior to the NBP react more strongly than those living in counties with better air quality to the implementation of the NBP. The results in columns (4) to (6) are similar and show that the coefficient of the interaction term between *Treat*×*Post* and *PreUnhealthy* is positive and statistically significant in all regressions. Overall, the findings are consistent with our expectation that inventors living in counties with poorer air quality before the implementation of the NBP show greater improvement in productivity than investors living in counties with better air quality.

6.3. All inventors

In the baseline analysis, we focus on inventors affiliated with publicly listed firms so that we can control for innovation inputs and the characteristics of the firms in which the inventors work. In this section, we extend the analysis to all inventors regardless of whether they are affiliated with publicly listed firms. As such, the sample in this test includes all U.S. inventors except those located in states that are adjacent to NBP participating states. We exclude *LnPatVal* from the analysis because this measure only applies to inventors affiliated with publicly listed firms. We control for *Tenure* and state, year, and inventor fixed effects in the regressions. The regression results are presented in Table 9.

The coefficient of *Treat*×*Post* is positive and statistically significant in both regressions. The results are consistent with our baseline analysis, which suggests that our findings hold for all inventors, not just those affiliated with publicly listed firms.

6.4. Direct measures of air pollution

In the final test, we directly examine the effect of local air pollution levels on inventor productivity using panel data. We adopt the same county-level air pollution measures as in Section 5.3, namely, *AnnualAQ* and *Unhealthy*. Because air pollution data are available from 1981 to 2008, the sample for this test is much larger than that used for the baseline analysis. We replace *Treat*×*Post* in the baseline regression with *AnnualAQ* and *Unhealthy* and then re-estimate the regression model. The results are reported in Table 10.

Columns (1) to (3) of Table 10 show that the coefficient of *AnnualAQ* is negative and statistically significant in all regressions, suggesting that relative to investors located in counties with low levels of air pollution, inventors located in counties with high levels of air pollution file fewer new patents, and these patents also receive fewer forward citations and generate lower economic value. Similarly, columns (4) to (6) show that the coefficient of *Unhealthy* is negative and significant in all regressions, confirming the negative effect of air pollution on inventor productivity. Collectively, the tests in this section provide additional evidence for the negative effect of air pollution on inventor productivity, further validating our findings in the NBP setting.

7. Conclusion

Motivated by studies showing that air pollution impairs people's mental health and cognitive abilities, we examine whether air pollution affects the productivity of patent inventors. We use the NBP, which has led to a significant reduction in NOx emissions in eastern U.S. states, as a quasi-natural experiment to investigate the effects of air pollution and perform a DiD analysis around the program's implementation.

We find that treated inventors produce significantly more patents, and their patents receive more forward citations and generate higher economic value than controlled inventors following the implementation of the NBP. In the channel tests, we find that inventors located in NBP participating states engage in more exploratory innovation and less exploitative innovation after the implementation of the NBP. We also find that after the implementation of the NBP, the quality of patents by inventors located in NBP participating states

[17] https://aqs.epa.gov/aqsweb/airdata/download_files.html#Annual.

Table 8
The role of pre-NBP air quality level.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	LnPat	*LnCit*	*LnPatVal*	*LnPat*	*LnCit*	*LnPatVal*
Treat×Post	0.012	0.060***	0.077***	0.013	0.056**	0.065***
	(0.009)	(0.020)	(0.023)	(0.010)	(0.022)	(0.024)
Treat×Post×PreAQ	0.045***	0.142***	0.212***			
	(0.012)	(0.025)	(0.031)			
Treat×Post×PreUnhealthy				0.032***	0.117***	0.188***
				(0.012)	(0.025)	(0.030)
Firm Size	0.034***	0.024**	0.259***	0.034***	0.023**	0.258***
	(0.004)	(0.010)	(0.011)	(0.004)	(0.010)	(0.011)
R&D	−0.382***	−1.235***	−0.776***	−0.381***	−1.231***	−0.770***
	(0.078)	(0.176)	(0.189)	(0.078)	(0.176)	(0.189)
ROA	−0.152***	−0.248***	0.001	−0.152***	−0.246***	0.004
	(0.031)	(0.072)	(0.081)	(0.031)	(0.072)	(0.081)
Leverage	−0.093***	−0.062	−0.097	−0.093***	−0.065	−0.104
	(0.026)	(0.058)	(0.065)	(0.026)	(0.058)	(0.065)
CapEx	0.296***	0.358	0.911***	0.299***	0.362	0.912***
	(0.101)	(0.229)	(0.247)	(0.101)	(0.229)	(0.247)
BM	−0.132***	−0.352***	−0.489***	−0.132***	−0.353***	−0.491***
	(0.013)	(0.029)	(0.029)	(0.013)	(0.029)	(0.029)
Cash	0.153***	0.202***	0.209***	0.153***	0.202***	0.209***
	(0.024)	(0.054)	(0.060)	(0.024)	(0.054)	(0.060)
Firm Age	−0.128***	−0.251***	−0.412***	−0.127***	−0.249***	−0.408***
	(0.010)	(0.023)	(0.026)	(0.010)	(0.023)	(0.025)
Tenure	−0.182***	−0.506***	−0.690***	−0.182***	−0.507***	−0.693***
	(0.006)	(0.014)	(0.015)	(0.006)	(0.014)	(0.016)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	136,444	136,444	136,444	136,444	136,444	136,444
Adj. R^2	0.312	0.349	0.303	0.312	0.349	0.303

This table shows how the effect of air pollution on inventor innovation output varies with the pre-NBP air quality level. The regressions are performed using ordinary least squares, with standard errors (reported in parentheses) clustered at the inventor level. All independent variables except *Treat×Post* are lagged by one year. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the appendix.

Table 9
Analysis on all the inventors.

Variable	(1)	(2)
	LnPat	*LnCit*
Treat×Post	0.033***	0.129***
	(0.004)	(0.010)
Tenure	−0.207***	−0.570***
	(0.003)	(0.008)
State FE	Yes	Yes
Year FE	Yes	Yes
Inventor FE	Yes	Yes
Obs.	381,903	381,903
Adj. R^2	0.297	0.325

This table presents the regression results of the difference-in-differences test on all the inventors (regardless of whether they are affiliated with public firms). The regressions are performed using ordinary least squares, with standard errors (reported in parentheses) clustered at the inventor level. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the appendix.

improves. Finally, we fail to find evidence that air pollution reduces the working hours of local residents. Taken together, these findings are consistent with our hypothesis that the reduction in air pollution achieved by the NBP improves the mental states and cognitive abilities of inventors, making them less risk-averse and more capable in the innovation process, resulting in higher levels of innovation output.

Our study contributes to the finance literature on the behavioral effects of air pollution by showing that the negative moods induced by air pollution not only affect stock market participants but also patent inventors, who play a key role in corporate innovation success.

Table 10
Local air quality and inventor innovation output.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	LnPat	*LnCit*	*LnPatVal*	*LnPat*	*LnCit*	*LnPatVal*
AQI	−0.013***	−0.044***	−0.042***			
	(0.004)	(0.011)	(0.011)			
Unhealthy				−0.027**	−0.125***	−0.132***
				(0.011)	(0.032)	(0.031)
Firm Size	0.030***	0.048***	0.204***	0.030***	0.048***	0.204***
	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)
R&D	0.064**	0.062	0.679***	0.064**	0.059	0.675***
	(0.030)	(0.084)	(0.076)	(0.030)	(0.084)	(0.076)
ROA	0.070***	0.291***	1.011***	0.071***	0.292***	1.011***
	(0.012)	(0.034)	(0.033)	(0.012)	(0.034)	(0.033)
Leverage	−0.030***	0.001	−0.070***	−0.030***	0.001	−0.070***
	(0.009)	(0.024)	(0.022)	(0.009)	(0.024)	(0.022)
CapEx	0.238***	0.615***	0.399***	0.238***	0.612***	0.395***
	(0.026)	(0.074)	(0.065)	(0.026)	(0.074)	(0.065)
BM	−0.024***	−0.048***	−0.129***	−0.025***	−0.049***	−0.130***
	(0.003)	(0.009)	(0.008)	(0.003)	(0.009)	(0.008)
Cash	0.104***	0.332***	0.368***	0.104***	0.333***	0.368***
	(0.010)	(0.028)	(0.026)	(0.010)	(0.028)	(0.026)
Firm Age	−0.106***	−0.305***	−0.266***	−0.106***	−0.305***	−0.266***
	(0.003)	(0.010)	(0.009)	(0.003)	(0.010)	(0.009)
Tenure	−0.256***	−0.939***	−0.824***	−0.256***	−0.939***	−0.824***
	(0.002)	(0.005)	(0.005)	(0.002)	(0.005)	(0.005)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,528,468	1,528,468	1,528,468	1,528,704	1,528,704	1,528,704
Adj. R^2	0.201	0.248	0.281	0.201	0.248	0.281

This table presents the regression results of the relation between local air quality and inventor innovation output. The regressions are performed using ordinary least squares, with standard errors (reported in parentheses) clustered at the inventor level. All independent variables are lagged by one year. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the appendix.

Our study also contributes to the economics literature in terms of the effects of air pollution on worker productivity. Unlike prior studies that focus on labor-intensive work, we explore the effect of air pollution on the productivity of inventors, whose output depends on intellectual undertakings. Finally, our study contributes to the growing literature exploring the determinants of innovation success by investigating an environmental factor that influences the innovation output of individual inventors. Our findings also have policy implications. Motivated by the positive externalities of the NBP, governments should play a more active role in improving air quality by imposing restrictions on emissions.

Declaration of Competing Interest

None.

Appendix A. Variable definitions

Variables	Description
Panel A. Key variables	
Treat	Dummy variable equal to one if the inventor lives in an NBP participating state and zero if the inventor lives in another state except for states that are adjacent to NBP participating states.
Post	Dummy variable equal to one for the 2005–2007 period and zero for the 2000–2002 period.
Panel B. Innovation variables	
LnPat	Natural logarithm of one plus the number of newly filed patents.
LnCit	Natural logarithm of one plus the number of forward citations received by newly filed patents.
LnPatVal	Natural logarithm of one plus the total economic value of newly filed patents.
LnExplore	Natural logarithm of one plus the number of newly filed patents for which more than 60% of backward citations are outside of the inventor's knowledge base.
LnExploit	Natural logarithm of one plus the number of newly filed patents for which more than 60% of citations are within the inventor's knowledge base.
LnFirstPat	Natural logarithm of one plus the number of newly filed patents that belong to technology classes in which the inventor has never filed before.
LnSelfcite	Natural logarithm of one plus the number of citations made by newly filed patents that cite this inventor's previously field patents.

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(*continued*)

Variables	Description
LnAvgCit	Natural logarithm of one plus the average number of forward citations received by the newly filed patents.
LnAvgPatVal	Natural logarithm of one plus the average economic value of newly filed patents.
Panel C. Control variables	
Firm Size	Natural logarithm of total assets.
CapEx	Capital expenditure scaled by total assets.
R&D	R&D expenditure scaled by total assets.
ROA	Operating income before interest and tax scaled by total assets.
Leverage	Book value of debt scaled by total assets.
BM	Book value of equity scaled by market value of equity.
Cash	Cash and short-term investments scaled by total assets.
Firm Age	Natural logarithm of one plus the number of years elapsed since the first year that firm appeared in the Compustat database.
Tenure	Natural logarithm of one plus the number of years between the year that the inventor enters the patent database and the observation year.
Panel D. Other variables	
Superstar	Dummy variable equal to one if the inventor has adjusted forward citations among the top 10% in our sample.
AnnualAQ	Median of the daily air quality index for a given year in a county.
Unhealthy	Proportion of the unhealthy days in a given year in a county, where the unhealthy day is defined as a day with air quality index larger than 100.
PreAQ	Dummy variable equal to one if the inventor lives in a county with average *AnnualAQ* during 2000 and 2002 higher than the sample median.
PreUnhealthy	Dummy variable equal to one if the inventor lives in a county with average *Unhealthy* during 2000 and 2002 higher than the sample median.
StateAQ	Average of the *AnnualAQ* of all counties in a state.
StateUnhealthy	Average of the *Unhealthy* of all counties in a state.
StateIncome	Natural logarithm of the state-level labor income.
StateGDPgrowth	Annual growth rate of GDP in a state.
StateUnemp	State-level unemployment rate in each year divided by the moving average of the state-level unemployment rate over the previous four years.
StateSale	Natural logarithm of the total sales of all firms headquartered in each state.
LnWorkingHours	Natural logarithm of one plus weekly working hours.

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