HOW EXTERNAL FACTORS INFLUENCE INVENTOR PRODUCTIVITY?

LUO YUE

PhD

The Hong Kong Polytechnic University

2020

The Hong Kong Polytechnic University

School of Accounting and Finance

How External Factors Influence Inventor Productivity?

LUO YUE

A thesis submitted in partial fulfilment of
the requirements for the degree of
Doctor of Philosophy

March 2020

CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

_________________________ (Signed)

______LUO YUE_________ (Name of student)

ABSTRACT

This thesis examines how external factors influence the productivity of inventors, the most creative and precious personnel in many firms. The first factor I examine is terrorist attacks. Using fatal terrorist attacks as man-made disasters that shock the society, I examine their effects on inventor productivity. I find that after experiencing high-fatality attacks, local inventors tend to become more risk-averse and have lower productivity in the subsequent years, while those who witnessed terrorist attacks with low fatality tend to behave more risk-taking and produce more innovation outputs afterwards. I also find that inventors affected by high-fatality attacks are more likely to move to places without any significant terrorist attack history, but there is no such effect for low-fatality attacks. My findings are consistent with the notion that what does not kill you make you more risk-taking, and suggest that shocks to the society can be important external factors to reshape inventors' risk-taking behaviour and affect their innovation.

The second factor I examine is air pollution. Using the NOx budget trading program (NBP) as a quasi-natural experiment, I examine whether reduction in air pollution enhances inventor risk-taking, which makes them more innovative. I find that inventors located in the NBP participating states produce more patents after the NBP. These patents also receive more forward citations and have higher economic value. The effect of the NBP is larger for less experienced inventors, or inventors living in high-pollution areas. Further, inventors located in the NBP participating states engage more in experimental innovation and less in specialization innovation after the NBP, which confirms the risk-taking channel.

In sum, my thesis shows that external factors, such as terrorist attacks and air pollution, can have significant effects on inventor productivity. I also identify that risk-taking is an important channel of such effects. My thesis highlights the vulnerability of inventors to external factors, and stresses the importance of the external factors in shaping the risk-taking behaviour of inventors in the innovation process.

Keywords: Terrorist attacks; Air pollution; Inventor productivity; Risk-taking.

Working Paper Available Online

Chapter 2 and Chapter 3of this thesis is available online. The detailed reference is as follows:

Luo, Y., Chen, Y., and Lin, J. C., 2019. Shocks and Inventor Productivity: Evidence from Terrorist Attacks. Unpublished working paper, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3321554

Luo, Y., Chen, Y., and Lin, J. C., 2019. Does Reducing Air Pollution Make Inventors More Innovative? Evidence from the NOx Budget Program. Unpublished working paper, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3547087

ACKNOWLEDGEMENT

Firstly, I would like to thank my chief supervisor, Professor Lin Ji-Chai, and my co-supervisor, Professor Chen Yangyang, for their continuous guidance, supports and help during my Ph.D. study period. They patiently teach me how to develop research ideas, how to think critically, and how to work efficiently. I cannot finish this thesis without their selfless help. Their passion for research sets examples for me and encourages me to work harder.

Next, I am grateful to my Board of Examiner Chair, Prof. Xu Xinpeng, and two external examiners, Dr. Huang Qianqian and Dr. Xu Yan, for their insightful comments and suggestions to my thesis. Many thanks to the faculty members and the doctoral student peers at AF PolyU for their caring and help during my Ph.D. journey. I would also like to thank my beloved friends, Dr. Feng Xiaoli, Dr. Hou Fangfang, Mr. Han Ziyang, Ms. Xie Jiawen, and Ms. Zhou Xiaolin, for their company and comport in the past years.

Last but not least, I also want to express my gratitude to my family, especially my parents, who give me a lot of love, understanding and supports in my life.

TABLE OF CONTENS

LIST OF FIGURES AND TABLES

Chapter 1 Introduction

Innovation is crucial for the long-term success of firms and is a key driving force of the development of the modern economy (Henderson and Cockburn, 1994). Since inventors are key figures in producing innovation outputs, it is important to understand factors that impact their productivity. As human beings, inventors are inevitably affected by the surrounding environment. In this study, I examine how inventors, the most creative and precious personnel in many firms, are affected by external factors, e.g. terrorist attacks and air pollution. More specifically, I examine whether these external factors induce changes to local inventors' productivity and innovation choices and the channels through which this occurs.

In Chapter 2, I examine how terrorist attacks influence the productivity of local inventors. Bernile et al. (2017) find that CEOs with early-life exposure to natural disasters with moderate or low numbers of fatalities are more willing to take risks in corporate management, while those who have early-life exposure to natural disasters with large numbers of fatalities lead the firms more conservatively. Their argument is that after experiencing disasters without tremendously negative effects, CEOs tend to become less sensitive to the adverse impacts of risk, while CEOs tend to have a more cautious and conservative attitude towards risk if they witness the tremendously damaging consequences of disasters.

As man-made disasters, terrorism is becoming one of the biggest threats to humanity,[1] and the horror and destruction are embodied in the September 11 attacks, known as 9/11, in which 2,996 people died and there was tremendous damage to infrastructure and property in the U.S.[2] As Scobell (2004) points out, after the attacks, many countries across the world enacted legislation to combat terrorism. Since then, despite the huge effort directed at fighting against terrorism, terrorist attacks seem to be occurring more frequently in recent years. Internationally, there was an increase in terrorism-related incidents from 1,813 in 2000 to 16,860 in 2014, and fatalities rose sharply from 4,402 in 2000 to 43,566 in 2014.[3] The emotional shock brought about by terrorist attacks is evident. For example, in a 2005 U.S. Gallup Poll, terrorist attacks are rated the highest ranked fear by a national sample of teenagers aged 13 to 17. Because terrorist attacks intensely affect people's emotions, I argue that they also affect inventors' emotions, which may further affect inventors' attitudes towards risk and thus their innovation outputs. The question is: Do terrorist attacks affects inventors' risk tolerance? If yes, is it a monotonic relation?

[1] In a 2004 UN report, Mr. Kofi Annan, Secretary General of United Nations, defines terrorism as any action "intended to cause death or serious bodily harm to civilians or non-combatants with the purpose of intimidating a population or compelling a government or an international organization to do or abstain from doing any act."

[2] The Organization for Economic Cooperation and Development (OECD) estimates that the direct economic cost of the 9/11 terror attacks was US$27.2 billion (Brück and Wickström, 2004). With regard to the psychological damage caused by terrorism, Galea et al. (2002) assess the prevalence and correlates of post-traumatic stress disorder (PTSD) and depression among residents of Manhattan after the 9/11 attacks, and report that many PTSD and/or depression cases were related to the attacks. Using a national survey, Schuster et al. (2001) report that respondents throughout the country exhibited symptoms of stress after 9/11, suggesting that even people who were not present at the attacks experienced stress reactions.

[3] The source of the statistics is the Global Terrorism Database (GTD). The website is: https://www.start.umd.edu/gtd/

This question is important because risk-taking is an essential determinant of inventors' engagement in R&D, which already carries considerable risk and has uncertain outcomes. Manso (2011) posits that promoting innovation requires strong risk-taking incentives, enough tolerance of early failures, and rewards for long-term success. Numerous studies confirm that risk-taking is one of the key success factors in innovation (e.g., Hirshleifer et al., 2012; Chemmanur et al., 2014; Chen et al., 2014). If inventors become more risk-averse after terrorist attacks, they may continue to engage in low risk R&D, and reduce or avoid R&D activities with high risk. Conversely, if inventors become greater risk-takers after terrorist attacks, they may pursue riskier R&D projects with potentially higher rewards.

When terrorists strike, they usually want to cause as many casualties and as much damage as possible to spread the horror and terror throughout the society. Hence, high-fatality terrorist attacks, such as 9/11, leaved people who experienced it with serious and long-term psychological shadow. I suppose people who experienced such extremely fatal attacks are more likely to be fearful and overestimate the negative outcomes of risk, and thus become more risk-averse. However, in some cases, the extent of the damage and casualties are limited by circumstances or by law enforcement officials. For example, the Centennial Olympic Park bombing in Atlanta, Georgia, on July 27, 1996, only killed only one person, largely because a security guard discovered the bomb before it detonated, and cleared most of the spectators out of the park. That attack was contained and under control. It can be considered a low-fatality attack. Because these low-fatality attacks do not cause very negative consequences in the end, such experience may lead the witnesses ignore the possible tremendously negative consequences. As a result, they tend to become more confident and underestimate negative outcomes of risk, and thus are more willing to take risks.

With this reasoning and the importance of risk-taking in the innovation process, I hypothesize that high-fatality terrorist attacks cause local inventors (i.e., inventors who live near the attacked venue) to become more risk-averse, which results in a decline in their future innovation. In contrast, low-fatality attacks prompt local inventors to become greater risk-takers, which leads to an increase in their future innovation.

To test my hypotheses, I examine 19 fatal terrorist attacks in the U.S. occurring between 1994 and 2007.[4] To be included in the sample, a terrorist attack must be in the Global Terrorism Database (GTD) and The *Washington Post* (WP) Deadliest US Shooting list,[5] cause at least one death, and be covered by the major media outlets. For inventors, I obtain inventor information from the Harvard Business School (HBS) patent inventor database, and define a local or affected inventor as one who lives within a 100-mile radius of a

---

[4] I focus on the terrorist attacks occurring since the 1990s because terrorism has developed rapidly over the past quarter-century. According to Chalk (1999), terrorist attacks since the 1990s differ from those that happened before in two aspects. First, terrorist attacks have happened more frequently since the 1990s, with multiple actors leading to such situations, ranging from individual persons to fully organized groups. Second, with the development of modern weapons, terrorist attacks since the 1990s have become more effective and fatal. A single attack can lead to mass destruction and serious casualties.

[5] See http://www.washingtonpost.com/wp-srv/special/nation/deadliest-us-shootings/ for more information.

terrorist attack during the attack year. I use three measures of inventor productivity: the number of newly granted patents, the number of forward citations received by these patents, and the total economic value created by these patents.

Using the difference-in-difference approach, I find evidence consistent with my hypothesis. Specifically, the results of the baseline regression suggest that if an inventor is located near the area of a low-fatality (high-fatality) terrorist attack, he/she will file more (fewer) patents in the three years after the attack than before, and his/her patents will also receive more (fewer) citations and create more (less) economic value, compared to inventors who are not located in the attack areas. The findings suggest that affected inventors experience an increase (decrease) in productivity after living through a low-fatality (high-fatality) terrorist attack. In terms of economic significance, the number of patents, the number of citations, and the total economic value of the patents produced by local inventors affected by low-fatality attacks increase by 1.1%, 3.7%, and 3.0%, respectively. In contrast, after high-fatality attacks, the number of patents, the number of citations, and the total economic value of the patents produced by affected inventors decrease by 2.1%, 5.1%, and 5.2%, respectively. These numbers suggest that the effects of fatal terrorist attacks on inventor productivity are also economically significant. To validate my findings and exclude alternative interpretations, I conduct several robustness tests, including examining alternative definitions of high-fatality and low-fatality attacks, longer test windows, alternative samples and specifications, and additional control variables. The findings remain valid across all of the robustness tests.

To test whether risk-taking is the main channel through which terrorist attacks impact inventor productivity, I conduct two sets of analyses. First, social identity theory (Tajfel, 1981; Abrams and Hogg, 1988) posits that individuals have a tendency to conform to the dominant values and behavioural norms of the groups they are associated with. For my setting, this theory implies that after witnessing a fatal terrorist attack that results in low fatality, local inventors living in more risk-taking environments, will increase their own risk-taking more because social risk-taking magnifies the tendency of underweighting extreme negative outcomes of risk induced by the low-fatality attack. In contrast, after witnessing a high-fatality terrorist attack, local inventors living in more risk-taking environments will reduce their risk-taking less because social risk-taking mitigates the increased sensitivity to risk induced by the high-fatality attack. As a result, I expect that the innovation output of local inventors living in more risk-taking environments will increase more following low-fatality attacks and decrease less following high-fatality terrorist attacks.

Consistent with my expectation, I find that the positive (negative) effect of low-fatality (high-fatality) terrorist attacks on inventor productivity is stronger (weaker) for local inventors living in regions with more male residents because males generally take more risks than females (Powell and Ansic, 1997; Byrnes et al., 1999; Hartog et al., 2002; Eckel and Grossman, 2008). The positive (negative) effect is also stronger (weaker) for local inventors living in regions with high murder rates because people tend to behave more aggressively and take more risks if they are frequently exposed to violence (Fantuzzo and Mohr, 1999; Holt et al., 2008). In addition, the positive (negative) effect is weaker (stronger) for local inventors living in highly religious regions because people in such regions tend to exhibit more risk aversion in their decision making (Diaz, 2000; Miller, 2000; Steinman and Zimmerman, 2004; Hilary and Hui, 2009; Boone et al., 2012).

Second, prior studies suggest that after attacks inventors may exploit and refine existing innovation, or explore new innovation (March, 1991; Benner and Tushman, 2002; Balsmeier et al., 2017). Compared to exploitative innovation, explorative innovation requires more risk-taking and thus its success relies more on the inventor's willingness to take risk. If the positive (negative) effect of low-fatality (high-fatality) terrorist attacks on innovation is mainly through the risk-taking channel, the effects should be stronger for explorative innovation than exploitative innovation. Indeed, I find that local inventors affected by low-fatality (high-fatality) terrorist attacks increase (reduce) their explorative innovation, measured by the number of explorative patents and average patent originality. The effects on the exploitative innovation of local inventors (measured by the number of exploitative patents and average patent generality) are much weaker. Taken together, the findings from the two sets of tests are consistent with the notion that increased (reduced) risk taking induced by low-fatality (high-fatality) terrorist attacks strengthens local inventors' willingness (reluctance) to undertake riskier R&D projects.

In addition, I find that distance matters. That is, the positive (negative) effect of low-fatality (high-fatality) terrorist attacks on inventor productivity decays as the distance from the inventor's location to the attacked area increases. The results show that terrorist attacks are more salient for inventors located closer to the attacks, causing them to experience stronger psychological shock.

I also examine whether terrorist attacks affect inventors' relocation decisions. It is likely that the psychological distress caused by the shock of a high-fatality terrorist attack would not only reduce inventor productivity but would also prompt inventors to move to other places. My results show that inventors are indeed more likely to move to other cities, particularly those without any significant terrorist attack history, after the occurrence of a high-fatality terrorist attack in their local area. However, low-fatality attacks do not produce this effect.

In Chapter 3, I investigate whether reducing air pollution has an effect on inventor productivity. Air pollution has become one of the major health problems faced by people all over the world. The World Health Organization (WHO) lists the air pollution from both outdoor and indoor sources as the single largest environmental risk to health globally. Medical studies document numerous adverse effects of air pollution on physical health of local residents (e.g., Evans and Jacobs, 1981; Seaton et al., 1995; Brunekreef and Holgate, 2002; Mauzerall et al., 2005; Pope and Dockery, 2006; Maher et al., 2016). According to the latest WHO data, nine out of ten people worldwide breathe air containing high levels of pollutants, and air pollution kills around seven million people every year.

Besides physical health, air pollution is also shown to impair people's mental health. Psychology studies find that increases in air pollution are associated with higher levels of negative moods, such as annoyance, anxiety, depression, tension, stress, and low spirits (Bullinger, 1989; Chattopadhyay et al., 1995; Evans et al., 1988; Jones, 1978). These negative moods make people having pessimistic evaluations of future events, resulting in the biased-up risk estimates (Schwarz and Clore, 1983; Johnson and Tversky, 1983; Constans and Matthews, 1993; Mittal and Ross, 1998). Consequently, people affected by air pollution become more risk-averse when making decisions. [6] In supportive of this argument, there are a number of studies that document a negative effect of air pollution on stock returns and argue that increased investor risk aversion associated with air pollution-induced depression drives such effect (Levy and Yagil, 2011; Lepori, 2016; Li and Peng, 2016; Heyes et al., 2016).

Given the adverse impact of air pollution on people's physical and mental health, I examine a simple but important question in this study: Does air pollution affect the productivity of patent inventors? Innovation is crucial

---

[6] Medical studies show that higher levels of stress and tension induced by air pollution lead to a higher bodily level of cortisol, a stress hormone, and that cortisol is related with increased risk-aversion behavior (Rosenblitt et al., 2001; Coates and Herbert, 2008; Mehta et al., 2015).

for the long-term success of firms and is a key driving force of the development of the modern economy (Henderson and Cockburn, 1994). Inventors are key figures in producing innovation outputs. As human beings, they are inevitably affected by the surrounding environment. Therefore, it is important to understand behavioural factors that could impact inventor productivity.

As I mentioned, innovation activities tend to carry lots of risks and have highly uncertain outcomes, and risk-taking is an extremely important factor for the success of innovation. Since air pollution results in negative moods which makes people more risk-averse, inventors affected by air pollution are likely to be more risk averse in decision making. This may lead to sub-optimal risk-taking levels in the innovation process and hence lower inventor productivity.

I adopt the Nitrogen Oxide (NOx) budget trading program (NBP) as a quasi-natural experiment to examine whether reduction in air pollution 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.[7] According to U.S. Environmental Protection Agency (EPA), the NBP dramatically improves the 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, it provides a setting in which endogeneity is less of a concern.

[7] NOx is a group of gases made up of nitrogen and oxygen, mainly referring to nitric oxide (NO) and nitrogen dioxide (NO2). As one of the main air pollutants, NOx contributes to a series of environmental problems, such as the formation of acid rain, smog, and elevated PM2.5 and most importantly, ozone concentrations.

The patent data along with the inventor information also comes from the Harvard Business School (HBS) patent inventor database (Li et al., 2014). I restrict my main analysis to inventors affiliated with U.S. publicly listed firms so that I can control for innovation inputs and characteristics of the firms where the inventors work in the analysis. There are 19 states in the U.S. that participated in the NBP during 2003 and 2004. I define the inventors located in these states as treated inventors. All remaining inventors, excluding those living in the adjacent states of the NBP participating states, are defined as controlled or non-treated inventors. I examine 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.

I perform a difference-in-difference test using the U.S. inventor-level data around the implementation of the NBP. The results show that treated inventors (i.e., inventors living in the NBP participating states) produce significantly more patents than controlled inventors (i.e., inventors living in the other states except those in the adjacent states of the NBP participating states) 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 on average produce 2.8% more patents, and their patents receive 11.8% more forward citations and create 14.7% higher economic value following the implementation of the NBP. Overall, the findings suggest that reducing air pollution makes inventors more productive. My findings hold in various robustness checks. I also perform a placebo test that randomizes the NBP participating states. The results suggest that my findings are unlikely to be obtained by chance.

In cross-sectional analyses, I show that the reduction in air pollution by the NBP has a larger effect on the productivity of less experienced inventors (i.e., inventors with shorter tenure or non-superstar inventors). This is likely because these inventors are less resilient to air pollution due to the lack of experience. I also show that the NBP has a larger effect on inventors living in in counties with poorer air quality before its implementation, because the improvement of air quality is likely greater in these counties.

To investigate whether risk-taking is the specific channel through which air pollution affects inventor productivity, I first test whether treated inventors change their innovation strategies to purse high-risk-and-high-reward innovation after the implementation of the NBP. Specifically, I compare changes in their experimentation innovation (i.e., innovation in unfamiliar fields) versus specialization innovation (i.e., innovations based on existing knowledge and expertise). The former involves more risks and is more challenging than the latter. I find that treated inventors engage more in experimentation innovation and less specialization innovation after the implementation of NBP, suggesting greater risk-taking by treated inventors in innovation. Next, I investigate whether improved air quality associated with the NBP increases inventor working hours and hence their productivity. I fail to find evidence that air pollution reduces the working hours of local residents, which is inconsistent with the working hour channel. My findings about innovation strategies are also inconsistent with this channel because if it works, treated inventors should increase both experimentation and specialization efforts, rather than increasing experimentation effort, while reducing specialization effort. Taken together, these findings are consistent with the notion that reducing air pollution improves inventors' mood and hence their risk-taking behaviour in the innovation process, which in turn makes inventors more productive.

Last, I conduct a number of additional analyses. The results show that improved air quality associated with the NBP also enhances the average quality of patents generated by treated inventors. Further, I show that my main findings hold for all inventors, regardless of whether they work in publicly listed firms or not. My 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.

My study contributes to the finance and economic literature in several aspects. First, I extend the findings of Bernile et al. (2017) by showing that not only natural disasters, man-made disasters, like terrorist attacks, can have a nonmonotonic impact on the individuals' risk choices. In addition, unlike Bernile et al. (2017) focusing on early-life exposure to disasters, I examine the change of inventor productivity immediately after they experience terrorist attacks, which makes my results more straightforward and convincing.

Second, I extend recent studies on the impact of terrorist attacks on economic activities. Ahern (2018) analyzes the 2004 Madrid train bombing and the 2005 London metro attacks, the two largest terrorist attacks in European history, and finds that terrorist attacks negatively influence both individual psychology and macroeconomic outcomes. Antoniou et al. (2016a) find that financial analysts located near terrorist attacks issue more pessimistic earnings forecasts afterwards. They also show that firms located near terrorist events tend to carry out more conservative corporate policies–they increase their cash holdings and reduce their R&D expenditures and long-term leverage around such events. Further, Wang and Young (2019) find that increased terrorism levels in the U.S. reduce the aggregate investor risk preference. Dai et al. (2020) document higher compensation for the CEOs of firms located near terrorist attacks. My study adds to this strand of the literature by showing that although high-fatality terrorist attacks have a negative effect on inventor productivity, low-fatality attacks, surprisingly, have a positive effect on innovation. Thus, my findings reveal an indirect channel through which terrorist attacks affect local innovation and economic growth. More importantly, I show that high-fatality attacks and low-fatality attacks have opposite effects on inventors' risk-taking, in line with Bernile et al. (2017), who assert that CEOs with early-life exposure to natural disasters producing large numbers of fatalities are more risk-averse, whereas those with early life exposure to natural disasters with moderate or low numbers of fatalities are more willing to take risks.

Third, my study contributes to the finance literature about the behavioural impacts of air pollution. Existing studies in this regard mainly focus on the effects of air pollution on stock market participants. For example, a number of studies document a negative relation between air pollution and stock market returns and resort to increased investor risk aversion associated with air pollution as the explanation (e.g., Leve and Yagil, 2011; Lepori, 2016; Li and Peng, 2016; Heyes et al., 2016). There are also studies showing that air pollution-induced negative mood affects analyst forecast bias (Dong et al., 2019) and investor trading behaviour (Li et al., 2019; Huang et al., 2019). My study shows that in addition to stock market participants, air pollution also impacts the productivity of patent inventors through reshaping their risk attitudes. Given the importance of innovation in firm growth, our findings document a real effect of air pollution on the economy and help people better estimate the social and economic value of efforts that attempt to reduce air pollution.

Fourth, my study adds to the economics literature on the negative impact of air pollution on worker productivity. Prior studies document that high levels of air pollution reduces 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). Nevertheless, these studies mainly focus on labor-intensive worker. There is little research that investigates whether air pollution also affects the productivity of workers that rely more on intelligence. My study fills this gap in existing research by documenting that air pollution also affects the productivity of patent inventors, the most creative and precious personnel in many firms.

Last, my study contributes to the growing literature in both finance and economics that examines the determinants of innovation success.[8] The existing literature mainly focuses on the determinants of innovation at the firm level. There is a lack of empirical work on which factors influence innovation outputs from the perspective of inventors, who have direct control over the innovation process. As human beings, inventors are subject to various behavioural traits. My study identifies terrorist attacks and air quality as two important external factors that have effects on inventor productivity. The findings enhance our understanding of the roles external factors play in shaping corporate innovation success.

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

Chapter 2 Terrorist Attacks and Inventor Productivity

In this Chapter, I examine the effects of terrorist attacks on innovation output of affected inventors. Section 2.1 describes the data and sample. Section 2.2 shows the results of my baseline tests and robustness checks. Section 2.3 presents the results of channel tests and Section 2.4 reports the results of additional analyses. Section 2.5 concludes this chapter.

2.1. Data

2.1.1. Sample

The data used in this study come from several sources. I obtain data on terrorist attacks from the Global Terrorism Database (GTD). The GTD database offers information on the date, location (including latitude and longitude), number of causalities, and the type of terrorist attacks occurring internationally since 1970. Because the patent inventor data is for the U.S., I exclude terrorist attacks happening outside of the U.S. I follow Antoniou et al. (2016a, 2016b) and further restrict my sample to terrorist attacks that caused at least one casualty and were covered by major media outlets, including The Los Angeles Daily News, The New York Daily News, The New York Post, The New York Times, The Wall Street Journal (U.S. edition), The Washington Post, and USA Today. These events are more likely to raise the attention of local people, including local inventors. Information on the news coverage of these major media outlets is retrieved from Factiva. I only use terrorist attacks with fatalities that were covered by major media outlets because not all terrorist attacks are salient. I contend only relatively high-fatality attacks attract people's attention and hence are likely to affect inventors' risk preferences. Table 2.1 lists the 18 terrorist attacks used in my study, which are geographically dispersed among various regions of the U.S.

I obtain the patent data along with inventor information from the Harvard Business School (HBS) patent inventor database (Li et al., 2014), which covers every patent granted by the U.S. Patent and Trademark Office (USPTO) from 1976 to 2010. The database provides information on the inventor(s) of each patent, including the names, city of residence, zip code, latitude and longitude. Each individual inventor is assigned a unique identifier based on a disambiguation algorithm method. Thus, I am able to track the innovation information of each inventor, along with his/her accurate residential location. To control for innovation inputs and the characteristics of the firms where the inventors work, I restrict my analysis to inventors affiliated with U.S. public firms. I match the inventors to these firms based on the patent information of Kogan et al. (2017), which provides the CRSP firm identifier for each patent. Firm financial information is obtained from Compustat. To measure the scientific and economic importance of the patents, I use the forward citation data and patent value data of Kogan et al. (2017).

As the HBS patent inventor database only records inventor information when the inventor files a patent, my initial sample consists of inventor-year observations in which the underlying inventor files at least one patent during the year. To create time-series data for inventors, I follow Chen et al. (2019) and identify the first year and the last year an inventor appears in the patent inventor database (i.e., the first year and the last year the inventor files patents). I then assign a value of zero to the inventor's innovation output variables for the years in between when there are no patent records. As I can only observe inventor location when an inventor files a patent, I use this to update and assign the inventor location information for subsequent years in which there are no patent records until I observe another patent filed by the inventor.[9]

In my empirical analysis, I use the application year rather than the grant year of the patents because the former is closer to the time when the new technology appears.[10] Given that there are usually two to three years of time lag between the application year and the grant year (Hall et al., 2001), I exclude the last two years from the analysis (i.e., 2009 and 2010). My final sample includes 132,290 unique inventors from 2,792 publicly listed firms spanning the period from 1994 to 2007. The sample allows me to track the innovation record of each inventor, along with his/her location information and the financial information of the firm where he/she works.

2.1.2 Variables

2.1.2.1. Exposure to Terrorist Attacks

[9] I conduct robustness checks using different ways to assign location information for years with no patent records (see Panel A of Table 5). All of the results hold, which suggests that my findings are not driven by the particular way I assign inventor locations.
[10] Hall et al. (2001) note that the application year is a better indicator of the actual innovation date.

Following Antoniou et al. (2016a), I define an inventor as an affected inventor if he/she lives within a 100-mile radius of a terrorist attack during the attack year. I calculate the geographic distance between each inventor and terrorist attack using the latitude and longitude of both the inventor's residential address and the place where the terrorist attack occurs.[11] I define high-fatality attacks as attacks resulting in more than one casualty, and low-fatality attacks as attacks resulting in only one casualty.[12] The number of casualties is one of the most important characteristics of terrorist attacks, because those with larger numbers of casualties are usually more traumatic and thus generate stronger negative emotions among individuals. I define high-fatality attack (*High*) as a dummy variable equal to one if the inventor is located within 100 miles of a high-fatality terrorist attack, and zero otherwise. Similarly, I define low-fatality attack (*Low*) as a dummy variable equal to one if the inventor is located within 100 miles of a low-fatality terrorist attack, and zero otherwise.

Table 2.1 presents the fatalities for each terrorist attack. It also shows the total number of inventors for the year when the terrorist attack occurs, the number of inventors affected by the terrorist attack, and the proportion of affected inventors. The table shows that the proportion of inventors affected by the terrorist attacks ranges from 0.2% to 15.5%, suggesting that some of the terrorist attacks affect a large proportion of inventors and that there are large

[11] The distance is calculated using the Vincenty (1975) equation.

[12] In one of the robustness checks, I use three casualties as the cut-off to define high-fatality attacks. In another robustness check, I also use the media coverage of terrorist attacks to differentiate high-fatality attacks from low-fatality attacks. My results hold in both tests.

variations in the terrorist attacks that affect inventors. One thing to note is that both the total number of inventors and the number of affected inventors drop significantly for the terrorist attacks occurring in 2006 and 2007 (i.e., Seattle Jewish Federation and Virginia Tech). The decline is likely to be due to truncation bias. Even if I remove the last two years of patent data (i.e., 2009 and 2010) from my sample, some patent applications take more than two years to finalize. As a result, the number of patents and hence the total number of affected patent inventors drop when approaching the end of the sample. In one of the robustness checks, I exclude the last two terrorist attacks from the analysis and obtain consistent results.

[Insert Table 2.1]

2.1.2.2. Innovation Variables

I consider three measures of inventor innovation output. The first measure is the number of patents, calculated as the number of an inventor's newly filed patents that are eventually granted. The second measure is the number of citations, calculated as the sum of forward citations for all of the inventor's newly filed patents. Prior studies show that forward citations of a patent reflect the patent's scientific value. Breakthrough patents are expected to receive more citations than other 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 of the inventor's newly filed patents. Following Kogan et al. (2017), the patent value measure is calculated as the increase in the market value of the firm (after adjusting for benchmark returns) in a three-day window following the patent grant announcement. As the three innovation output measures are highly skewed, I take the natural logarithm of one plus the number of patents (*LnPat*), number of citations (*LnCit*), and total patent value (*LnPatVal*), respectively, and use these log transformed measures in the analysis.

To examine the inventors' innovation strategies, I construct variables capturing their propensity for exploration versus exploitation strategies in innovation. First, I follow Benner and Tushman (2002) and calculate the number of exploratory and exploitative patents filed during the year, respectively. A patent is defined as exploratory if more than 60% of its backward citations are outside the inventor's existing knowledge base. A patent is defined as exploitative if more than 60% of its citations are within the inventor's existing knowledge base. An inventor's existing knowledge base is defined as the combination of the inventor's patents and the patents that have been cited in the inventor's previous patents. As exploratory patents are outside the inventor's expertise, they reflect the inventor's pursuit of innovation in new fields (i.e., exploration strategy). In contrast, exploitative patents are based on the inventor's expertise. Thus, they capture the inventor's tendency to specialize in existing fields (i.e., exploitation strategy). Similarly, I take the natural logarithm of one plus the number of exploratory patents (*LnExplore*), and exploitative patents (*LnExploit*), respectively.

In addition, I follow Trajtenberg et al. (1997) and employ the patent originality and generality measures. Originality of each patent is calculated as the one minus the Herfindahl-Hirschman index of citations to other patents over patent classes, while generality is calculated as one minus the Herfindahl-Hirschman index of citations received from other patents over patent classes. Higher originality suggests that the patent cites a broader range of patent classes, indicating more efforts in exploration innovation strategy. In contrast, higher generality means the patent is cited by a broader range of patent class, implying more efforts in exploitative innovation strategy. To get the inventor-level measures, I calculate the average across all the patents for each inventor over the future three years.

2.1.2.3. Control Variables

My analysis is based on a sample of inventors affiliated with U.S. public firms. Because corporate policies may impact inventor productivity, I control for a set of firm-level variables in the analysis. This includes firm size (*FirmSize*), defined as the natural logarithm of total assets, because large firms usually generate more patents and citations (Hall and Ziedonis, 2001). To control for firm innovation input, I include R&D expenses (*R&D*), defined as R&D expenditures scaled by total assets. Following Hirshleifer et al. (2012), I set the R&D expenses of observations with missing R&D information in Compustat to zero. I control for firm capital investments (*CapEx*), defined as capital expenditures scaled by total assets; return on assets (*ROA*), defined as earnings before interest and tax divided by total assets; and leverage ratio (*Leverage*), defined as the book value of debt scaled by total assets. To control for firm growth opportunities, I include book to market ratio (*Book-to-market*), defined as the book value of equity scaled by the market value of equity. I also control for firm cash holdings (*Cash*), defined as cash and short-term investments scaled by total assets. Last, I control for the effect of firm life cycle by including firm age (*Firm Age*), defined as the natural logarithm of the number of years elapsed from the first year the firm appeared in the Compustat database.

As information on inventor characteristics is limited, inventor tenure (*Inventor Tenure*) is the only inventor-level variable I control. This is defined as the natural logarithm of one plus the number of years between the year the inventor enters the patent database and the observation year. Detailed descriptions of all the variables in the analysis are shown in the Appendix. 2.A.

2.1.3. Descriptive Statistics

Table 2.2 reports the summary statistics of the variables used in this study. The table shows that the mean values of the high-fatality attack dummy and the low-fatality attack dummy are 0.02 and 0.04, respectively. This suggests that 2% of inventor-years are affected by high-fatality attacks and 4% of inventor-years are affected by low-fatality attacks.

In terms of the innovation output variables, the mean values of *LnPat* and *LnCit* are 0.99 and 1.89, respectively, corresponding to 1.69 patents and 5.62 forward citations. Regarding the patent value measure, the mean value of *LnPatVal* is 2.62, corresponding to US$12.74 million. The mean values of *LnExploit* and *LnExplore* are 0.36 and 0.70, respectively.

With regard to the control variables, on average, the size of the firms affiliated with the inventors in my sample is 9.14, corresponding to US$9,320.77 million, and their R&D expense is 7% of total assets. The average return on assets, leverage ratio, capital investments, book to market ratio, cash holdings, and age of these firms are 0.14, 0.21, 0.06, 0.33, 0.16, and 3.43, respectively. In addition, the mean value of inventor tenure is 1.67, corresponding to 4.31 years. This suggests that there is relatively long time-series data for each inventor.

[Insert Table 2.2]

2.2. Empirical Results

2.2.1. Baseline Analysis

In this section, I perform regression analysis on whether experiencing terrorist attacks affects the productivity of inventors located near the attacked areas. The baseline regression specification is as follows.

$$
\begin{aligned}
Innovation_{i,t\ to\ t+2} &= \beta_0 + \beta_1 High_{i,t-1} + \beta_2 Low_{i,t-1} + \beta_3 Firm\ Size_{i,t-1} \\
&+ \beta_4 R\&D_{i,t-1} + \beta_5 ROA_{i,t-1} + \beta_6 Leverage_{i,t-1} + \beta_7 CapEx_{i,t-1} + \beta_8 BM_{i,t-1} \\
&+ \beta_9 Cash_{i,t-1} + \beta_{10} Firm\ Age_{i,t-1} + \beta_{11} Tenure_{i,t-1} \\
&+ \beta_{12} Past\ Performance_{i,t-1} \\
&+ Inventor + Year + Industry + \varepsilon_{i,t} \qquad (1)
\end{aligned}
$$

where subscript *i* and *t* denote inventor *i* and year *t*; and ε is the error term. The dependent variable *Innovation* in Eq. (1) consists of the three innovation output variables (i.e., *LnPat*, *LnCit*, and *LnPatVal*) in the following three years. *Inventor*, *Year*, and *Industry* denote inventor, year, and industry fixed effects, respectively. The variable of interest, the high-fatality (low-fatality) terrorist attack dummy, is a dummy variable equal to one if the inventor is located within 100 miles of a high-fatality (low-fatality) terrorist attack during the year and zero otherwise. The regressions are performed by ordinary least squares (OLS), with standard errors clustered at the inventor level.

[Insert Table 2.3]

The regression results are presented in Table 2.3. Column (1) shows that the coefficient of the high-fatality attack dummy is negative and significant at the 1% level. This suggests that inventors located near high-fatality attacks produce fewer new patents in the three years following the attacks. In contrast, the significantly positive coefficient of the low-fatality attack dummy indicates that inventors affected by low-fatality attacks file more patents following such attacks. Columns (2) and (3) show the results for the number of citations and the total patent value, respectively. Again, the coefficient of the high-fatality attack dummy is significantly negative whereas the coefficient of the low-fatality attack dummy is significantly positive in both regressions. This suggests that terrorist attacks also affect the scientific and economic value of the patents produced by the affected inventors. Therefore, high-fatality (low-fatality) terrorist attacks not only negatively (positively) affect the quantity of innovation, but also the quality of the innovation produced by the affected inventors.

The negative effects of high-fatality attacks on inventor productivity are also economically significant. On average, the affected inventors file 2.1% fewer patents, their patents receive 5.1% fewer forward citations, and they create 5.2% less economic value in the three years following an attack. In contrast, in the three years following low-fatality attacks, the affected inventors file 1.1% more patents, their patents receive 3.7% more citations and they create 3.0% more economic value. Overall, the findings are consistent with my hypothesis, that high-fatality attacks lead inventors to become more risk-averse and less innovative, whereas low-fatality attacks lead inventors to become more risk-tolerant and more productive.

In terms of control variables, firm size is positively associated with all three inventor innovation output measures, suggesting that large firms are able to produce more innovation output. Return on assets, capital investments, and cash holdings are also positively associated with innovation output, showing that more profitable firms, firms that invest more, and firms with large cash holdings, are more innovative. The significantly negative coefficients of firm age and book to market ratio indicate that young firms and growth firms are more innovative. Further, the coefficients of R&D expenses are significantly negative. This is likely to be due to the inclusion of inventor fixed effects, which may subsume some of the effects of R&D expenses. The reason could also be that the innovation output variables in my tests are at the inventor-level, whereas R&D expenses are measured at the firm-level, resulting in their limited explanatory power. Regarding inventor-level controls, inventor tenure is negatively associated with innovation output.

2.2.2. Robustness Tests

To further verify my findings and exclude alternative explanations, I conduct a number of robustness checks. Some people may be concerned that my findings do not hold if I use a longer sample period or remove some of the filters on terrorist attacks. To address this concern, I construct an alternative sample starting from 1976, and I use all of the terrorist attacks that cause at least one fatality, regardless of whether the attack is covered by the major media. I re-estimate the baseline regression model for this alternative sample and report the results in Panel A of Table 2.4. The coefficient of the high-fatality attack dummy remains negative and significant except for column (3), whereas the coefficient of the low-fatality attack dummy remains positive and significant across all three columns.

Second, I use three fatalities rather than one fatality as the cut-off. The attacks causing more than three fatalities are defined as high-fatality attacks, and the remainder are defined as low-fatality attacks. I re-estimate the regression model using the new definitions and show the results in Panel B of Table 2.4. The coefficient of the high-fatality attack dummy remains significantly negative, whereas the coefficient of the low-fatality attack dummy remains significantly positive.

Third, following previous studies (e.g., Antoniou et al., 2016a), I use news coverage as the alternative measure of the severity of terrorist attacks. I classify terrorist attacks as high-influence attacks if they were reported more than the sample median times by the major U.S. media outlets mentioned previously. The remainder of the terrorist attacks are defined as low-influence attacks. I obtain the number of news articles on terrorist attacks from Factiva. Then, I re-estimate the baseline model with definitions of the high-influence and low-influence attack dummies and present the results in Panel C of Table 2.4. The coefficient of the high-influence attack dummy remains significantly negative, and the coefficient of the low-influence attack dummy remains significantly positive in all three columns.

Fourth, I replace the future three years of innovation output with the future five years of innovation output as the dependent variables. Then, I re-estimate the baseline regression model and report the results in Panel D of Table 2.4. The coefficient of the high-fatality (low-fatality) attack dummy remains negative (positive) and statistically significant in all of the regressions.

Fifth, for one patent applied by N inventors, I count the patent as one for each inventor. To avoid the measurement error, in this robustness test, I count the patent as 1/N for each inventor. The number of citations received, and the economic value generated by this patent is also calculated as the original value divided by N for each patent. I updated the number of patents, the number of citations, and the total economic value of the patents produced by each inventor in each year using this new calculation approach, and then re-estimate the baseline regression. The results are shown in Panel E of Table 2.4. The coefficient of the high-fatality attack dummy remains significantly negative, whereas the coefficient of the low-fatality attack dummy remains significantly positive.

Sixth, in my baseline analysis, I assign the inventor's location information to the subsequent years when there is no patent record, because I can only observe the inventor's location in a given year if he/she files at least one patent during that year. A potential problem is that the inventors may move to new locations during the zero patent years, which may result in inaccurate location information and potential bias in my estimations. I take four steps to mitigate this concern. First, I only keep non-zero patent observations so that I do not need to make any assumption on inventor location. Second, I exclude inventors that ever change their location during my sample period. Third, instead of using the previous location of inventors that ever move, I assign a new location (i.e., the location shown in the next patent filling) to zero-patent observations. Finally, instead of assigning the previous location to all subsequent zero-patent observations for inventors that ever move, I assign the previous location to the first half and new location to the second half of the zero-patent periods. The results of the robustness checks are presented in Panels F-I of Table 2.4. In almost all of these tests, the coefficient of the high-fatality (low-fatality) attack dummy is negative (positive) and statistically significant, suggesting that my findings are not driven by the way I assign location information to zero-patent observations.

[Insert Table 2.4]

Seventh, one could argue that my findings are driven by the negative shock of terrorist attacks on the local economy, which in turn affects firms' ability to finance innovative projects. In the baseline regressions, I already control for firms' innovation input, R&D spending, and several variables related to firms' financial condition. To further mitigate the concern, I include a number of state-level macroeconomic variables in the robustness check, including state-level income, relative state unemployment rate, and the aggregate sales of all firms headquartered in the state. I obtain the state-level labor income data from the Bureau of Economic Analysis (BEA), the state-level unemployment data from the Bureau of Labor Statistic (BLS), and the aggregate state-level firm sales from Compustat. I take the natural logarithm of the state-level labor income and aggregate state-level firm sales. The relative state 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 Panel J of Table 2.4. They show that the coefficients of the high-fatality (low-fatality) attack dummy remain negative (positive) and statistically significant. This suggests that my baseline findings are not driven by the negative effect of terrorist attacks on the local economy.[13]

Eighth, Antoniou et al. (2016b) find that managers affected by terrorist attacks tend to switch to more conservative corporate policies. For example,

[13] I conduct an additional test to examine whether terrorist attacks have significant influence on these macro-economic indicators. The results suggest that terrorist attacks do not significantly damage state-level macro-economic conditions.

affected managers temporarily reduce R&D expenditures and long-term leverage, and increase cash holdings after terrorist attacks. Conservative corporate policies, in turn, may affect inventor productivity by reducing firm investments and risk-taking in innovation. As stated above, I already control for firm innovation input and several firm characteristics that are related to corporate policies. Nevertheless, there may still be some unobservable factors induced by conservative corporate policies that have a negative influence on inventor productivity. In the robustness check, I exclude inventors located in the same city as their firms' headquarters, so that terrorist attacks affecting the inventors are less likely to also impact their firms' policies. I present the results in Panel K of Table 2.4. The coefficients of the high-fatality (low-fatality) attack dummy remain significantly negative (positive), and the magnitudes are also similar to those in the baseline regression model in Table 2.3. Thus, I conclude that my findings are not driven by the influence of terrorist attacks on corporate policies.

Ninth, terrorist attacks could have differential impact across industries. To ensure that the results are not driven by firms operating in industries that are more affected by terrorist attacks, such as aircraft and defense industries, I conduct analysis by removing the firms operating in these two industries and then re-estimate the baseline regression. The results are shown in Panel L of Table 2.4. The coefficients of the high-fatality (low-fatality) attack dummy remain negative (positive) and statistically significant, suggesting that my main findings remain robust.

Tenth, instead of using the full sample, I use a propensity score matched sample to further address the concern that my findings are driven by differences in the characteristics of affected and non-affected inventors. I calculate the propensity score based on firm size, inventor tenure, and the Fama-French 48 industries. To construct the matched sample, I use the nearest one to one matching, which allows me to match each affected inventor with an unaffected inventor sharing similar characteristics. I re-estimate the baseline regression model based on this matched sample. The results are presented in Panel M of Table 2.4. The coefficients of the high-fatality (low-fatality) attack dummy remain negative (positive) and the magnitudes are even larger than those in the full sample.

Eleventh, given that my analysis is based on a sample of 736,699 inventor-year observations, it is possible that any variable could generate a statistically significant result. I conduct two placebo tests to examine this possibility. First, I randomize the date and location of terrorist attacks and re-estimate the baseline regression model for 100 times. Second, among the 18 18 terrorist attacks, I randomly assign 8 attacks as high-fatality attacks and the remaining 10 attacks as low-fatality attacks, and then re-estimate the baseline regression model for 100 times. I report the mean of the coefficients and the standard errors of these placebo tests in Panel N and Panel O of Table 2.4, respectively. The results show that for both placebo tests, the mean coefficients of the high-fatality attack dummy and the low-fatality attack dummy are statistically insignificant, indicating that my findings are not simply obtained by chance.

Last, in the baseline regression, I exclude years 2009 and 2010 from the analysis due to the time lag between the patent application year and the grant year. To further alleviate the concern over truncation bias, I re-estimate the baseline model on a sample that ends in 2006 (i.e., excluding years 2007-2010). The results, shown in Panel P of Table 2.4, suggest that my findings are not sensitive to truncation bias.

2.3. Testing the Channel of the Effects

I posit that high-fatality attacks cause inventors to become more risk-averse and less innovative, whereas low-fatality attacks lead inventors to become more risk-tolerant and innovative. The findings in the baseline analysis are consistent with my hypothesis. To examine whether risk-taking is the channel through which terrorist attacks affect inventor productivity, I perform two analyses. In the first analysis, I examine whether inventors located in regions with different levels of risk tolerance vary in their responses to terrorist attacks. In the second analysis, I investigate whether terrorist attacks affect inventors' innovation strategies.

2.3.1. Local Attitudes Toward Risk

Inventors have different personal characteristics and live in areas with varying cultural environments. The shocks of terrorist attacks on inventors' psychological states may vary depending on the inventors' attributes. If risk-taking is the channel through which terrorist attacks impact inventor productivity, I would expect risk-averse inventors to reduce their risk-taking activities more after high-fatality attacks because risk aversion could magnify their sensitivity to risks induced by high-fatality attacks. In this case, their innovation output would decrease more than it would for less risk-averse inventors. In contrast, after low-fatality attacks, risk-averse inventors should increase their risk-taking activities, but to a lesser extent, because their risk-aversion mitigates their willingness to take extra risks. Consequently, their innovation output would increase, but less, following low-fatality attacks.

I am unable to directly observe inventors' personal characteristics due to the limited inventor information in the HBS patent inventor database. Nevertheless, I have information on the inventors' locations, allowing me to infer their local social norms. Social norm theory suggests that individuals tend to conform to their peer groups so that social norms impact the behaviour of the local population (Kohlberg, 1984). Based on this, I test whether inventors' reactions to high-fatality attacks and low-fatality attacks are affected by local risk aversion.

Previous studies suggest that religious individuals have more conservative moral standards (Terpstra et al., 1993; Barnett et al., 1996; McGuire et al., 2012; Callen and Fang, 2015). They also exhibit greater anxiety and fear of uncertainty (Rokeach, 1968; Ahmad, 1973), which results in greater risk aversion in their decision making (Diaz, 2000; Miller, 2000; Steinman and

Zimmerman, 2004; Hilary and Hui, 2009; Boone et al., 2012). In addition to religiosity, gender is also related to individual reactions to emotional shock. Studies document that females are more sensational and anxious in the face of uncertain situations (Grossman and Wood, 1993; Kring and Gordon, 1998; Bradley et al., 2001; Stevens and Hamann, 2012), which results in their greater risk aversion in making decisions (Powell and Ansic, 1997; Byrnes et al., 1999; Hartog et al., 2002; Eckel and Grossman, 2008). Further, psychology studies show that exposure to violent environments may lead people to become more aggressive, and thus more risk-loving (e.g. Fantuzzo and Mohr, 1999; Holt et al., 2008). As a result, I expect inventors living in areas with higher levels of religiosity, larger proportions of female residents, and lower murder rates to experience a larger decline in productivity after encountering high-fatality attacks, and a smaller increase in productivity after experiencing low-fatality attacks.

Using the inventor location information in the HBS patent inventor database, I determine the county and state in which each inventor lives. I then merge the inventor data with the religiosity data from the American Religion Data Archive (ARDA), the male-female data from the U.S. Census Bureau, and the murder rate data from the FBI's uniform crime reporting (UCR) program. The religiosity ratio (*Religiosity*) is defined as a dummy variable equal to one if the inventor lives in a county where the ratio of religious people is higher than the sample median. The male-female ratio (*Male-female*) is a dummy variable equal to one if the inventor lives in a county where the male-female ratio is higher than the sample median. Murder rate (*Murder*) is a dummy variable equal to one if the inventor lives in a state where the murder rate is higher than the sample median.[14] I interact the high-fatality and low-fatality attack dummies with the three variables, respectively, and include the interaction terms in the baseline regression model. The regression results are presented in Table 2.5.

[Insert Table 2.5]

Columns (1)-(3) of Table 2.5 show that the coefficient of *High*Religiosity* is negative and significant in all three regressions, suggesting that the productivity of inventors living in regions with higher levels of religiosity declines more after high-fatality attacks. The coefficient of *Low*Religiosity* is negative and significant in columns (1)-(3), providing evidence that inventors living in regions with higher levels of religiosity have a lower increase in productivity after low-fatality terrorist attacks. Columns (4)-(6) show that the coefficients of both interaction terms (*High*Male-Female* and *Low*Male-Female*) are significantly positive in all of the regressions, indicating that inventors living in regions with higher proportions of female residents, react more negatively to high-fatality attacks and less positively to low-fatality attacks. Last, columns (7)-(9) show that the coefficients of both interaction terms (*High*Murder* and *Low* Murder*) are positive and significant in all the regressions as well, which is consistent with

[14] I use the state-level murder rate instead of the county-level murder rate due to the unavailability of accurate county-level data.

the argument that inventors living in regions where violence is low are more affected by high-fatality attacks and less affected by low-fatality attacks. Overall, the findings displayed in Table 2.5 are consistent with my expectation that high-fatality attacks have stronger impacts and low-fatality attacks have weaker impacts on local inventors' productivity when inventors are subject to more risk-averse social norms. The findings also suggest that risk-taking is the channel through which terrorist attacks affect inventor productivity.

2.3.2. Innovation Strategies

I document in the baseline analysis that inventors affected by high-fatality (low-fatality) terrorist attacks have lower (higher) productivity due to increased (reduced) risk aversion in the innovation process after such attacks. In this section, I perform tests on inventors' innovation strategies to further investigate whether risk-taking is the primary channel through which terrorist attacks affect inventor productivity.

The innovation process is unavoidably associated with risk and there are significant variations in risk-taking among different innovation strategies. Usually, an exploration innovation strategy (i.e., a strategy that pursues inventions in unfamiliar fields) is associated with greater risk than an exploitation innovation strategy (i.e., a strategy that innovates based on the inventor's existing knowledge and expertise). March (1991) argues that exploitation is characterized by refinement, choice, production, efficiency, selection, implementation, and execution, whereas exploration is captured by search, variation, risk-taking, experimentation, flexibility, and discovery. If high-fatality (low-fatality) terrorist attacks affect inventor productivity primarily by reducing (increasing) inventor risk-taking incentives, I would expect inventors to be more reluctant (willing) to enter into new fields after experiencing high-fatality (low-fatality) terrorist attacks. Thus, the effects of terrorist attacks should be stronger for exploratory innovation than exploitative innovation.

As described in Section 2.1.2, I use the number of explorative patents (*LnExplore*) and average patent originality (*Originality*)to measure inventors' explorative innovation strategies, and the number of exploitative patents (*LnExploit*) and average patent generality (*Generality*) to measure inventors' exploitative innovation strategies. I re-estimate the baseline regression model with the two variables as the dependent variable, respectively. The results are presented in Table 2.6.

[Insert Table 2.6]

Column (1) and (2) of Table 2.6 shows that the coefficients of the high-fatality (low-fatality) terrorist attack dummy are negative (positive) and statistically significant when the number of explorative patents and average patent originality are the dependent variable. The results indicate that inventors reduce (increase) their explorations of unfamiliar fields after experiencing high-fatality (low-fatality) terrorist attacks. In column (3), where the number of exploitative patents is the dependent variable, the coefficient of the high-fatality attack dummy is less significant and the magnitudes are also much smaller, whereas the coefficient of the low-fatality attack dummy becomes insignificant. In column (4), where the average patent generality is the dependent variable, the coefficients of both high-fatality attack dummy and low-fatality dummy are insignificant. This suggests that inventors make less change to innovation efforts using their existing knowledge and expertise after experiencing terrorist attacks. Overall, the findings demonstrate that terrorist attacks influence inventors' productivity primarily by changing their incentives to explore new and unfamiliar fields of research. This is consistent with the risk-taking channel in which inventors become more (less) risk-averse after being affected by high-fatality (low-fatality) terrorist attacks.

2.4. Additional Analysis

In this section, I conduct a number of additional analyses to further investigate the effect of terrorist attacks on inventor productivity. First, I examine whether the effect of terrorist attacks on inventor productivity diminishes when the geographical distance between the inventor and the attacks are larger. Then, I explore whether inventors are more likely to move to another location after the occurrence of a terrorist attack in their local area.

2.4.1. Test of Geographical Distance

In this test, I investigate whether the effect of terrorist attacks on inventor productivity becomes weaker when the attacks are more geographically distant from the inventors. As terrorist attacks occurring in more remote areas are usually less salient to individuals (Antoniou et al., 2016a; Antoniou et al., 2016b), I expect the emotional shocks associated with terrorist attacks to diminish when the distance between the inventor and the attack is larger. To perform the test, I include in my baseline regression model the variables *High(0 to 100miles)*, *High(100 to 150miles)* and *High(150 to 200miles)*, which are dummy variables equal to one if an inventor is located less than 100 miles, 100-150miles, and 150-200 miles from an high-fatality terrorist attack, respectively. Similarly, I include *Low(0 to 100miles)*, *Low(100 to 150miles)* and *Low(150 to 200miles)*, and then re-estimate the baseline regression model.

[Insert Table 2.7]

The results shown in Table 2.7 indicate that the negative (positive) effect of high-fatality (low-fatality) attacks is mainly limited to inventors living within 100 miles of the terrorist attacks. This finding confirms that the effect of terrorist attacks on inventor productivity is greater when the attacks are more salient and generate stronger psychological shocks to inventors.

2.4.2. Inventor Relocation

Prior studies show that high skilled workers such as inventors are quite mobile in general (Miguelez and Fink, 2013; Akcigit et al., 2016). Therefore, it is likely that the emotional shocks associated with terrorist attacks not only reduce inventor productivity, but also induce inventors to move to other places. In the second additional test, I examine whether inventors have a higher propensity to move to another city after experiencing terrorist attacks.

As I can only observe an inventor's location when he/she files a patent, I restrict the sample for this test to those with at least two years of consecutive patent records. Thus, this test is performed on a relatively small sample. I construct the inventor move dummy (*Inventor Move*) as a dummy variable equal to one if the inventor moves to another city (i.e., the inventor is located in a different city than the previous year), and zero otherwise. Further, I investigate the direction of the inventors' moves. If inventors move because of the emotional shocks associated with terrorist attacks, they are more likely to move to more peaceful cities (i.e., cities having no previous experience with significant terrorist attacks), rather than to cities with a significant history of terrorist attacks. To perform the test, I construct two dummy variables. The move to attack dummy (*Move to Attack*) is a dummy variable equal to one if the inventor moves to a city with a significant terrorist attack history,[15] and zero otherwise. The move to peace dummy (*Move to Peace*) is a dummy variable equal to one if the inventor moves to a city without a significant terrorist attack history, and zero otherwise.

[Insert Table 2.8]

I perform a Logit regression, with the dependent variable being the three dummy variables, respectively. I include all of the control variables in Equation (1), in addition to the state-level income, relative state unemployment rate and state-level total sales. I further include year, state, and industry fixed

[15] I define a city as having a significant terrorist attack history if at least one terrorist attack with a casualty happens there.

effects. The regression results are presented in Table 2.8. Column (1) shows that the coefficient of the high-fatality attack dummy is positive and statistically significant, but the coefficient of the low-fatality attack dummy is insignificant, suggesting that inventors are more likely to move to new places only after experiencing high-fatality attacks. With regard to the direction of inventor moves, columns (2) and (3) show that the coefficient of the high-fatality attack dummy is insignificant when the move to attack dummy is the dependent variable, and positive and significant when the move to peace dummy is the dependent variable. This suggests that inventors are only more likely to move to cities with a peaceful environment after experiencing high-fatality attacks. Further, the results show that the low-fatality attacks have no such effect on inventors' moving decisions.[16]

Overall, the results suggest that high-fatality attacks not only reduce the productivity of local inventors, but also give rise to inventor departures to more peaceful places. Given the importance of human capital in the innovation process, the findings of this section document another channel through which terrorist attacks affect local innovation and then local economic growth.

[16] I re-estimate the inventor relocation regression by excluding the relocations that are likely to be caused by inventors moving to the city where the firms' headquarters is located. My findings in Table 2.8 remain robust.

2.5. Conclusion

This study shows that low-fatality (high-fatality) terrorist attacks have a positive (negative) influence on the innovation performance of the inventors who are located nearby.

Based on the findings of Bernile et al. (2017), I conjecture that attack-induced change in individuals' attitudes towards risk is the transmission mechanism for this effect, i.e., high-fatality attacks increase witnesses' concerns of risk, leading affected inventors to become more risk-averse and less innovative, but low-fatality attacks make witnesses less sensitive to risk, causing affected inventors to take more risks and hence become more innovative.

Analysing U.S. inventor-level data, I provide compelling empirical evidence to support my hypothesis. Specifically, I find that after experiencing a low-fatality (high-fatality) terrorist attack, inventors tend to produce significantly more (fewer) patents during the three years after the attack than before, and that their patents receive more (fewer) forward citations and generate more (less) economic value. To augment my main findings, I conduct a battery of robustness tests to ensure that my results are not induced by the misallocation of the inventors' residential location, and to exclude other possible explanations.

Next, I perform two sets of analyses to examine whether risk-taking is the channel for the effect of terrorist attacks. I show that the positive (negative) effect of low-fatality (high-fatality) attacks is more (less) pronounced for inventors living in regions with a more risk-taking culture (e.g., regions with a greater proportion of male residents, a relatively high murder rate, or a lower level of religiosity). I also find that after experiencing low-fatality (high-fatality) terrorist attacks, inventors significantly increase (reduce) their exploratory activities, whereas the change in their exploitive activities is much less significant. The findings are consistent with the risk-taking channel. In additional tests, I find that terrorist attacks that are geographically closer to inventors have a stronger effect on inventor productivity. I further show that inventors are more likely to move to places without any significant history of terrorist attacks after experiencing high-fatality attacks.

Overall, this study shows the nonmonotonic effects of terrorist attacks on innovation because high-fatality attacks cause people to make risk-averse choices, while low-fatality attacks engender risk-seeking choices. My findings highlight the vulnerability of inventors, revealing the need for disaster management so that firms can care for their inventors if and when a high-fatality terrorist attack occurs. Although terrorist attacks create destruction in society, this study also reveals that low-fatality attacks appear to make inventors "stronger" and more innovative.

Chapter 3 Air Pollution and Inventor Productivity

In this chapter, I investigate whether reducing air pollution has an effect on inventor productivity. The rest of this chapter organized as follows. Section 3.1 introduces NOx budget trading program (NBP), which is used as a quasi-experiment in this study. Section 3.2 describes the data, sample, and variables. Section 3.3 shows the main empirical results. Section 3.4 presents the results of cross-sectional analyses. Section 3.5 reports the results of channel tests and Section 3.6 presents the results of additional analyses. Section 3.7 concludes this chapter.

3.1. Air pollution and NOx budget trading program

According to EPA, "ground-level ozone is created by chemical reactions between oxides of nitrogen (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 ozone has the same chemical structure whether it occurs miles above the earth or at ground-level, ground-level ozone is considered "bad" because it has negative impacts on people and 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 to the sensitive vegetation and ecosystems. In addition to contributing to the formation of ground-level ozone, NOx itself is one of the main air pollutants.

NOx contributes to a series of environmental problems, such as the formation of acid rain, smog, and elevated 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 (i.e., May 1 through September 30), when ground-level ozone concentrations are highest. Specifically, this 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, sources are required to reduce emissions significantly below baseline levels in each participating state. States allocate allowances (each allowance equals one ton of emissions) to sources and sources then use emissions trading to achieve the most cost-efficient reductions possible. For example, they can install emissions control equipment, switch to low NOx burners, or buy emission allowances through the open market. If emissions are below the cap levels, sources can "bank" unused allowances and use or trade the banked allowances to cover emissions in a subsequent ozone season.

Eight north-eastern states (Connecticut, Delaware, Maryland, Massachusetts, New Jersey, New York, Pennsylvania, and Rhode Island) and District of Columbia started to implement the NBP on May 1, 2003. Then, eleven states (Alabama, Illinois, Indiana, Kentucky, Michigan, North Carolina, Ohio, South Carolina, Tennessee, Virginia and West Virginia) joined this program on May 31, 2004. Figure 3.1 shows the implementation of the NBP among the U.S. states.

[Insert Figure 3.1]

According to EPA, the NBP dramatically reduced NOx emissions from power plants and industrial sources during the summer months, contributing significantly to improvements in ozone air quality in eastern U.S. states.[17] For example, a case study conducted by the Maryland Department of the Environment (MDE), cooperated with the University of Maryland, finds that NOx emissions reductions driven by the implementation of the NBP dramatically decreased the observed ground-level ozone concentrations and, as a result, the air quality in Maryland has enhanced remarkably since the implementation of the NBP. Also, EPA designated 126 areas as nonattainment for the 8-hour ozone standard in April 2004, of which 104 are in the east. Although there are still 35 nonattainment areas in the east in 2007, the concentrations have fallen by 7% on average for these areas.

As shown in Figure 3.2, ozone season NOx emissions from all NBP sources decreased monotonically and dramatically since 2003. In 2007, the NOx emissions from NBP sources are only about 506,000 tones, around 60% below that in 2000, and 74% below that in 1990. Because most of the reductions in NOx emissions occurred after 2003, it is obvious that the NBP plays an important role in improving air quality in eastern U.S. states. EPA estimates that more than 78 million American citizens living in these areas are experiencing improved air quality. In a recent study, Deschênes et al. (2017) find that the NBP decreases the pharmaceutical expenditures and mortality

[17] 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 from the power sector.

rates, suggesting that the NBP indeed reduces air pollutions of participating states, which, in turn, improves local people' health conditions.

[Insert Figure 3.2]

3.2 Data and Sample

3.2.1. Sample Construction

I collect the patent data along with the inventor information from the Harvard Business School (HBS) patent inventor database (Li et al., 2014). This database records every patent granted by the U.S. Patent and Trademark Office (USPTO) during the period from 1976 to 2010. From the database, I obtain detailed information of the inventor(s) of each patent, including their names and cities of residence and zip codes. Using a disambiguation algorithm approach, the database allocates each individual inventor a unique identifier, which enables me to track the innovation record of each inventor, along with his/her accurate residential information. To account for the heterogeneity among inventors, I need to control for innovation inputs and characteristics of the firms where the inventors work. Thus, I restrict my main analysis to inventors affiliated with U.S. publicly listed firms. Patent inventors are matched to U.S. publicly listed firms based on the patent data of Kogan et al. (2017), which provides the CRSP firm identifier for each patent. I collect the financial data of these publicly listed firms from Compustat. I also employ the forward citations data and patent value data from Kogan et al. (2017) to measure the scientific and economic values of inventors' innovation output.

Because the inventor appears in the HBS patent inventor database only when he/she files a patent, my original sample consists of inventor-year observations in which the underlying inventor files at least one patent during the year. I identify the first and last year an inventor files patents in the patent inventor dataset. Then, I assign a value of zero to the inventor's innovation output variables for the years in between and without any patent record. In this way, I create a consecutive time-series data for all the inventors. Since an inventor's residential information is available only when he/she files a patent, I assign the inventor's most recent residential information to the years when the inventor does not have any patent record. I use the application year of the patents instead of the grant year as the time indicator in my empirical analysis, because the application year is closer to the time when the new technology is invented.[18]

Since innovation is a long-term process, it takes time for the NBP to generate a real effect on inventors' innovation output. Therefore, I examine three years before and three years after the implementation of the NBP in the empirical analysis. Specifically, I exclude 2003 and 2004 from the analysis because these two years are the implementation years of the NBP. I set 2000 to 2002 as the pre-treatment period and 2005 to 2007 as the post-treatment period. Following Deschênes et al. (2017), I exclude states that are adjacent to the NBP states in my empirical analysis, including Wisconsin, Iowa, Missouri, Gerorgia, Mississippi, Manie, New Hampshire, and Vermont. Even though

[18] Hall, Jaffe, and Trajtenberg (2001) note that the application year is a better indicator of the actual innovation date.

these states did not participate in the NBP, the air quality in these states may also be affected by the program. As a result, I classify the inventors located in the NBP participating states as the treatment group, and the remaining inventors excluding those living in excluded adjacent states as the control group.[19] My final sample spans the period 2000 to 2007 (excluding 2003 and 2004) and includes 34,340 unique inventors from 1,276 publicly listed firms.

3.2.2. Variables

I employ three measures for an inventors' innovation output. The first measure, the number of patents, is calculated as the number of newly filed patents by the inventor during the year that are eventually granted**.** The second measure is the number of citations, which is calculated as the sum of the forward citations received by all the newly filed patents by the inventor during the year. Prior studies show that forward citations received by a patent reflect the patent's scientific value, where breakthrough patents are expected to receive more citations as compared to 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 the newly filed patents by the inventor during the year. Following Kogan et al. (2017), the patent value measure is calculated as the increase in the market value of the firm (after adjusting for benchmark returns) in a three-day window following the patent grant announcements. Since the three innovation output measures are highly skewed, I take the natural logarithm of one plus number of patents (*LnPat*),

[19] If the inventor has ever moved between the NBP states and the non-NBP states, I classify he/she as a treated inventor if he/she lived in a NBP state in 2003 or 2004.

number of citations (*LnCit*), and total patent value (*LnPatVal*), respectively, and use these log transformed measures in the analysis.

To examine inventor's innovation strategies, I construct variables capturing inventors' propensity to pursue experimentation versus specialization strategies in innovation. First, I follow Benner and Tushman (2002) and calculate the number of exploratory and exploitative patents filed during the year, respectively. A patent is defined as an exploratory patent if more than 60% of its backward citations are outside of the inventor's existing knowledge base. A patent is defined as an exploitative patent if more than 60% of its citations are within the inventor's existing knowledge base. An inventor's existing knowledge base is defined as the combination of the inventor's patents and the patents that have been cited by the inventor's previous patents. As an alternative measure of the inventor's experimentation strategy, I follow Balsmeier et al. (2017) and define first patents as the number of newly filed patents during the year that belong to the technology class that the inventor has never filed before. I also employ self-citations as an alternative measure of the inventor's specialization strategy. Following Chava et al. (2013) and Balsmeier et al. (2017), I define self-citations as the number of citations made by the inventor's newly filed patents that cite his/her previous patents. Since exploratory patents and first patents are outside of the inventor's expertise, they reflect inventors' efforts to pursue innovation in new fields (i.e., experimentation strategy). In contrast, exploitative patents and self-citations are based on the inventor's expertise. Thus, they capture inventors' tendency to be specialized in existing fields (i.e., specialization strategy). Similarly, I take the natural logarithm of one plus number of explorative patents (*LnExplore*), number of exploitative patents (*LnExploit*), number of first patents (*LnFirstPat*), and number of self-citations (*LnSelfcite*), respectively.

My analysis is based on a sample of inventors affiliated with U.S. public firms, which enables me to control for a set of firm-level variables in the analysis. First, since large firms usually generate more patents and citations (Hall and Ziedonis, 2001), I include firm size (*Firm Size*), defined as the natural logarithm of total assets, in the control set. To control for firm innovation input, I include R&D expenses (*R&D*), defined as R&D expenditures scaled by total assets. Following prior studies (e.g., Hirshleifer et al., 2012), I set R&D expenses of observations with missing R&D information in Compustat to zero. I also control for the firm's capital investments (*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 ratio (*Leverage*), defined as book value of debt scaled by total assets. To control for firm growth opportunities, I include book-to-market ratio (*Book-to-market*), defined as book value of equity scaled by market value of equity. Last, I control for the effect of firm life cycle by including firm age (*Firm Age*), defined as natural logarithm of the number of years elapsed since the first year that the firm appeared in the Compustat database. Since information about inventor characteristics is limited, inventor tenure (*Tenure*) is the only inventor-level variable I control for, which is defined as the natural logarithm of one plus the number of years between the year that the inventor enters the patent database and the observation year. Detailed descriptions of all the variables in the analysis are shown in the Appendix.

3.2.3. Descriptive statistics

Table 3.1 reports the descriptive statistics of the key variables in the empirical analysis. I present the descriptive statistics of the inventors in the treatment and the control groups separately. The treatment group (64,417 inventor-years) has a smaller number of observations than the control group (85,287 inventor-years). For treated inventors, the mean values of *LnPat* and *LnCit* are 0.63 and 0.95, which correspond to 0.87 patents and 1.59 forward citations, respectively. While for controlled inventors, the mean values of *LnPat* and *LnCit* are 0.69 and 1.18, which correspond to 0.99 patents and 2.25 forward citations, respectively. Regarding the patent value measure, the mean value of *LnPatVal* is 1.76 for treated inventors and 1.78 for controlled inventors, corresponding to $4.81 million and $4.93 million, respectively. Furthermore, the mean values of *LnExploit*, *LnExplore*, *LnSelfcit*, and *LnFirstPat* are 0.20, 0.42, 0.22, and 0.27, respectively, for the treated inventors. For the controlled inventors, the corresponding values are 0.24, 0.45, 0.30 and 0.25, respectively.

With regard to the control variables, on average, *Firm Size* for the treatment group is 9.81 and *R&D* is 0.06. As for the control group, *Firm Size* is 9.10 and *R&D* is 0.09. The average *ROA*, *Leverage*, *CapEx*, *Book-to-Market*, *Cash*, and *Firm Age* for the firms in the treatment group are 0.13, 0.27, 0.05, 0.30, 0.14, and 3.59, respectively. For the firms in the controlled group, the mean values of the corresponding variables are 0.15, 0.14, 0.05, 0.29, 0.27 and 3.22, respectively. In addition, the mean value of inventor tenure is 2.00 and 1.81 for the treated and the controlled inventors, corresponding to 6.39 years and 5.11 years, respectively, suggesting a relatively long time-series data for the average inventor in both the treated and the controlled group.

[Insert Table 3.1]

3.3. Empirical Results

3.3.1. Baseline Analysis

I employ the difference-in-difference (DiD) estimation approach as my main identification strategy to examine whether air pollution has a real effect on treated inventors' innovation output. First, I perform a univariate analysis of the changes in innovation output around the implementation of the NBP. I calculate the average values of each innovation output (i.e., *LnPat*, *LnCit*, and *LnPatVal*) measure for treated inventors and controlled inventors in each year, respectively, and plot the average values in Figure 3.3. The graphs show that in the pre-NBP period (i.e., 2000-2002), inventors in the control group have higher average innovation output than inventors in the treatment group and the average values of the two groups are almost parallel. In the post-NBP period (i.e., 2005-2007), the differences between the two groups are smaller and smaller over time, and even reversed for the total patent value measure. The findings are consistent with my hypothesis that treated inventors have greater increase in innovation output relative to controlled inventors after the implementation of the NBP.

[Insert Figure 3.3]

Next, I perform a multivariant regression analysis with the regression specification as follows:

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

(2)

where subscript *i* and *t* denotes 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* is the three innovation output variables (i.e., *LnPat*, *LnCit*, and *LnPatVal*). The treatment dummy (*Treat*) is a dummy variable equal to one if the inventor belongs to the treatment group (i.e., inventors located in the NBP participating states), and zero if the inventor belongs to the control group (i.e., remaining inventors excluding those living in adjacent states). The post dummy (*Post*) is a dummy variable equal to one for the post-NBP period (i.e., 2005-2007), and zero for the pre-NBP period. (i.e., 2000-2002). The independent variable of interest is *Treat*Post*, which is the product of two dummy variables, *Treat* and *Post*. The interaction term *Treat*Post* captures the changes in innovation output of the treated inventors, relative to the controlled inventors, around the implementation of the NBP. I do not include the *Treat* and *Post* as independent variables in the regression model because the inventor fixed effects and year fixed effects absorb the effects of *Treat* and *Post*, respectively. All independent variables except for *Treat*Post* are lagged one year relative to the dependent variable.[20] The regressions are performed by ordinary least squares, with standard errors clustered at the inventor level.[21]

[Insert Table 3.2]

Table 3.2 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*-statistics 4.00) in the *LnPat* regression, suggesting that treated inventors generate more patents after the implementation of the NBP as compared to controlled inventors. In columns (2) and (3), the coefficient of *Treat*Post* is positive and significant as well in the *LnCit* regression (coefficient 0.118 with *t*-statistics 7.38) and *LnPatVal* regression (coefficient 0.147 with *t*-statistics 7.74), indicating that the implementation of the NBP not only improves the quantity but also the quality of patents produced by treated inventors. 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% higher economic value relative to controlled inventors after the implementation of NBP. Therefore, the effect of the NBP on inventor innovation is also economically sound.

[20] Using one year's lag is reasonable because it takes time for the inventors to generate patents. Besides, one year's lag is widely used in empirical innovation studies (e.g. Balsmeier et al., 2017, and Bhattacharya et al., 2017).

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

In terms of 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 have more resources – are able to produce more innovation output. Furthermore, *Book-to-Market* and *Firm Age* are negatively associated with innovation output, implying that inventors, who work in growth firms and younger firms, are more innovative. Regarding inventor-level control, the coefficient of *Tenure* is significantly negatively, suggesting that inventors with longer tenure become less innovative.

Overall, the results in the baseline analysis suggest that the implementation of the NBP makes inventors located in the NBP participating states more productive in innovation. This is consistent with my expectation that reducing air pollution improves inventors' mood and hence their risk-taking behaviour. Because risk-taking is a key determinant of firm innovation success, inventors become more innovative after experiencing a reduction in air pollution.

3.3.2. Robustness Tests

To check the validity of my results and exclude alternative explanations, I conduct a number of robustness tests. In the first set of tests, I examine whether my results are sensitive to alternative sample. In the baseline analysis, I assign a value of zero to the innovation output variables for the years without any patent record and between the first year and that last year that the inventor files a patent. To assure that my results are not driven by this treatment, I only keep non-zero patent observations in the sample and re-estimate the baseline analysis on this sample. I present the results in Panel A of Table 3.3 and obtain consistent findings.

Next, some inventors in my sample have ever moved between the NBP states and the non-NBP states during my sample period, which makes their treatment status more ambiguous. To address the concern that my findings are affected by such inventors, I drop these inventors from the sample and then re-estimate my baseline regression. I report the results in Panel B of Table 3.3 and my findings hold.

Further, my baseline difference-in-difference test is conducted upon an unbalanced sample (i.e., an inventor can have missing data within sample years). To make sure that my results are not driven by such unbalance, I re-estimate my difference-in-difference test on a balanced sample, where I require inventors must have non-missing data three years before and three years after the implementation of the NBP. The results are reported in Panel C of Table 3.3 and are consistent with those based on the full (i.e., unbalanced) sample.

Instead of using the full sample, I also use a propensity score matched sample in the robustness test to address the concern that my findings are driven by differences in characteristics among treated and controlled inventors. I use firm size, inventor tenure and Fama-French 48 industries to generate the propensity score. To construct the matched sample, I use nearest one-to-one matching, which allows me to match each affected inventor with an unaffected inventor sharing similar characteristics. I re-estimate the baseline regression model based on this matched sample. The results are presented in Panel D of Table 3.3. Once again, the results are consistent with the full sample.

Last, I only focus on those states joining the program in 2003 as it is possible that inventors in other states may anticipate the implementation of NBP so exogeneity could be weakened. To address this concern, I exclude the states joining the program in 2004 from the sample and then re-estimate the baseline regression. I present the results in Panel E of Table 3.3 and my main findings remain robust.

In the second set of tests, I examine whether my results are sensitive to alternative regression specifications. In my baseline analysis, I exclude year 2003 and 2004 because the post status for these two years are ambiguous. However, it is possible that the NBP have already partially affected inventors' innovation output during these two years. To take this into account, I include 2003 and 2004 in the analysis. I set *Post* equal to 0.5 for these two years and re-estimate the baseline test. The results are shown in Panel F of Table 3.3 which are similar to those in the baseline regression.

Second, for one patent applied by multiple inventors, the patent count is recorded as one for each inventor. People may complain that this approach will lead to biased up innovation output measures at inventor level, and thus inaccurate regression estimates. To address this concern, in this robustness test, I count the patent as 1/N for each inventor, where N is the number of inventors for each patent. I also re-calculate the number of citations received, and the economic value generated for each patent using this new approach, and then update the inventor-level measures. Then, I use these updated innovation output measures as dependent variables and re-estimate the baseline regression. The results are shown in Panel G of Table 2.4. My findings still hold.

Further, to mitigate the concern that my results are obtained from biased estimates due to that the dependent variables in the baseline regression are positively serially correlated, I follow Bertrand et al. (2004) and collapse the innovation output variables by NBP implementation. For each firm, I calculate the sum of the innovation output variables across all years in the pre-NBP period and post-NBP period, respectively. I also calculate the average value of control variables across all years in the two periods as well. Then, I collapse the sample of inventor-year observations into a sample of inventor-period observations. I re-estimate the baseline regression on this sample and report the results in Panel H of Table 3.3. My findings hold.

[Insert Table 3.3]

In the third set of tests, I investigate whether my findings are driven by economic changes induced by the implementation of the NBP. It is possible that the NBP impacts inventor productivity through affecting the local economy or the business operations and corporate policies of the affiliated firms, which in turn affects firms' ability to finance innovation projects. In the baseline analysis, I focus on inventors affiliated with public firms so that I can control for a number of firm characteristics that might affect inventor productivity. I further address this issue using the following five tests.

First, to ensure that the results are not driven by firm policies, I directly examine the relation between the adoption of NBP and corporate risk taking, such as R&D, and policies that may affect inventor performance, i.e., corporate social responsibility. The regression is performed at firm-level. All controls except inventor tenure, firm fixed effects and year fixed are included. The regression results are displayed in Panel I of Table 3.3. I find that the adoption of NBP does not have a significant influence on firms' R&D or corporate social responsibility, indicating that my findings are less likely to be driven the effects of the implementation of NBP on firm policies.

Prior studies (Palmer et al., 2001; Linn, 2010) show that because of the imposed restrictions on NOx emissions, the NBP most directly affects firms in the utility industry, especially power plants. Thus, I exclude inventors that work in utility firms from the sample, and then re-estimate the baseline regression. The results are shown in Panel J of Table 3.3. All my findings hold.

Next, EPA (1999) and Platts Research and Consulting (2003) predicted that the NBP may increase electricity prices which may affect manufacturing firms' business operations. Thus, I exclude inventors working in manufacturing firms from the sample, and then re-estimate the baseline regression. I present the results in Panel K of Table 3.3 and my findings still hold.

In addition, the adoption of NBP may have adverse impact on the innovation output of inventors from healthcare, medical equipment or pharmaceutical products industries, as they may have been trying to develop medicines or pharmaceutical products against diseases related to air pollution before the NBP, but may discontinue afterwards. To ensure my estimates in baseline regression are not biased by this possibility, I exclude inventors from these industries and then re-estimate the baseline model. The results are presented in Panel L of Table 3.3 and my findings hold.

Further, I include a number of state-level macroeconomic variables to mitigate the concern that my findings are driven by changes in local economic conditions. These variables include state-level income, state GDP growth, relative state unemployment rate, and aggregate sales of all firms headquartered in the state. I obtain the state-level labor income and GDP growth data from Bureau of Economic Analysis (BEA), state-level unemployment data from Bureau of Labor Statistic (BLS), and aggregate state-level firm sales from Compustat. I take natural logarithm of the state-level labor income and aggregate state-level firm sales. The relative state 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 Panel M of Table 3.3, which show that my finding hold after controlling for local macroeconomic factors.

In the last test, I conduct a placebo test to mitigate the concern that my results are obtained by chance. Because my analysis is based on a sample of 149,704 inventor-year observations, it is possible that any variable can generate a statistically significant result in such a large sample. To address the issue, I randomly assign 19 states as the NBP participating states and define the inventors located in these states as treated inventors. All the remaining inventors are defined as controlled inventors. Then, I re-estimate the baseline regression model for 100 times and report the mean of the coefficients and the standard errors of the placebo test in Panel N of Table 3.3. The results show that the mean coefficient of *Treat*Post* is statistically insignificant, indicating that my findings are not simply obtained by chance.

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

3.4. Cross-Sectional Analysis

3.4.1. The Role of Inventor Experience

As suggested by Graff Zivin and Neidell (2012), more experienced workers are more resilient to the effects of air pollution because they are better able to self-adjust. As a result, their productivity should be influenced less by improvements in air quality associated with the NBP. I use two measures of inventor experience. The first one is inventor tenure (*Tenure*), because inventors with longer tenure are likely to be more experienced. The second one is the superstar inventor dummy (*Superstar*), defined following Akcigit et al. (2016) as a dummy variable if the inventor’s total adjusted forward citations are among the top 10% in my sample, and zero otherwise. Superstar inventors are more likely to be experienced as compared with the other inventors. I interact *Treat*Post* with these two variables, respectively, and include the interaction terms in the baseline regression model. I do not include the superstar inventor dummy as an independent variable because it is time-invariant and hence is absorbed by inventor fixed effects. The results are reported in Table 3.4.

[Insert Table 3.4]

Columns (1)-(3) of Table 3.4 show that the coefficients of the interaction term between *Treat*Post* and *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 if the inventor has a longer tenure. When I use *Superstar* to indicate the inventors' experience in column (4)-(6), the coefficient of the interaction term *Treat*Post*Tenure* is also significantly negative in all the regressions, confirming that inventors with more experience are more resilient to air pollution. Thus, the results imply that the reduction in air pollution by the NBP has a larger effect on the productivity of less experienced inventors as they are less resilient to air pollution.

3.4.2. Pre-NBP Air Pollution Level

I conjecture that inventors living in counties with poorer air quality before the implementation of the NBP should experience a greater increase in productivity, because the improvement of air quality is greater in these counties. Thus, the NBP should have a larger effect on inventors living in counties with poorer air quality prior to the NBP.

I collect the county-level air pollution data from the U.S. EPA.[22] I adopt two measures of air pollution. Annual air quality (*AnnualAQ*) is calculated as the median of the daily Air Quality Index (AQI) for each county during the year. Proportion of unhealthy days (*Unhealthy*) is the proportion of unhealthy days for each county during the year, where an unhealthy day is defined as a day with the AQI larger than 100. Higher value of the two measures indicate more severe air pollution. Using the inventor location information in the HBS patent inventor database, I merge the inventor data with the air pollution data. I define the pre-NBP air quality (*PreAQ*) as a dummy variable equal to one if the inventor lives in a county with the average *AnnualAQ* during 2000 to 2002 higher than the sample median, and zero otherwise. Similarly, I define pre-NBP unhealthy (*PreUnhealthy*) as a dummy variable equal to one if the inventor lives in a county with the average *Unhealthy* during 2000 to 2002 higher than the sample median, and zero otherwise. Again, I interact *Treat*Post* with each of these two air quality variables, and include the interaction terms in the baseline regression model, respectively. I do not include the two standalone dummy variables as independent variables because they are time-invariant and are thus absorbed by the inventor fixed effects. The regression results are presented in Table 3.5.

[Insert Table 3.5]

Columns (1)-(3) of Table 3.5 show that the coefficient of the interaction terms between *Treat*Post* and *PreAQ* is positive and statistically significant

---

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

in all regressions, indicating that inventors who live in counties with worse air quality prior to the NBP react more strongly to the implementation of the NBP. The results in columns (4)-(6) are similar which show that the coefficient of the interaction terms between *Treat*Post* and *PreUnhealthy* is positive and statistically significant in all regressions as well. Overall, the findings are consistent with my expectations that inventors living in counties with poorer air quality before the implementation of the NBP should have a greater improvement in their productivity.

3.5. Channel Tests

I document in the baseline analysis that the implementation of the NBP makes inventors in the NBP participating states more innovative. In this section, I further investigate whether risk-taking is the primary channel through which air pollution impacts inventor productivity.

3.5.1. The Effects of NBP on Inventor Innovation Strategies

The innovation process is unavoidably associated with risk and there are significant variations in risk-taking among different innovation strategies. March (1991) argues that experimentation is captured by search, variation, risk-taking, flexibility, and discovery, while specialization is characterized by refinement, choice, production, efficiency, selection, implementation and execution. Several studies have noted that inventors may explore brand-new innovation, or exploit and refine existing innovation (March, 1991; Benner and Tushman, 2002; Balsmeier et al., 2017). Usually, experimentation innovation strategy is associated with greater risk than specialization innovation strategy (March, 1991; Chava et al., 2013; Balsmeier et al., 2017). If air pollution affects inventor productivity primarily through reducing inventor risk-taking incentives, I would expect inventors to be more willing to enter into new fields after local air quality improves, and thus the enhancement in inventor productivity should come primarily from experimentation innovation rather than specialization innovation.

As described in Section 3.2., I employ the number of explorative patents (*LnExplore*) and the number of first patents (*LnFirstPat*) as the measures of inventors' experimentation innovation strategy, and the number of exploitative patents (*LnExploit*) and the number of self-citations (*LnSelfcite*) as the measures of inventors' specialization innovation strategy. I re-estimate the baseline regression model with the four variables as the dependent variable, respectively. The results are presented in Table 3.6.

[Insert Table 3.6]

Columns (1) and (2) of Table 3.6 show that the coefficient of *Treat*Post* is positive and statistically significant when *LnExplore* and *LnFirstPat* are the dependent variables. The results indicate that inventors in the NBP participating states increase their efforts in exploring 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 the

NBP participating states reduce innovation efforts in their existing knowledge and expertise after the implementation of the NBP.

Overall, the results suggest that after the implementation of the NBP, inventors in the NBP participating states delegate more efforts to exploring new and unfamiliar fields of research. Because experimentation innovation strategy involves more risks, the findings provide supporting evidence to the risk-taking channel. That is, improving air quality of the NBP participating states enhances the emotional states of inventors located in these states. This induces more risk-taking by these inventors, which results in greater inventor productivity.

3.5.2. The Effects of NBP on Local Working Hours

Deschenes et al. (2017) document that NBP improves the air quality of participating states, which results in lower pharmaceutical expenditures and mortality rates. Because NBP enhances local people's physical health, it is likely that it improves inventor productivity by making inventors healthier and hence having longer working hours. Due to the unavailability of data on inventor working hours, I am unable to directly test whether NBP makes inventors in participating states work longer. As an alternative, I examine how air quality influences the number of working hours by local residents.

I obtain the data on local working hours from the American Time Use Survey (ATUS), which is conducted every year from 2003 to 2017 by the U.S. Census Bureau. ATUS documents the time use information of each respondent, such as average working hours, sleeping hours, and time spent alone. I define

LnWorkingHours as the natural logarithm of one plus the average weekly working hour of each respondent during the year. One shortcoming of the ATUS data is that the data starts in 2003, which makes it unable to perform a difference-in-difference test around the implementation of NBP. As an alternative, I perform a panel regression using the two air quality measures defined in Section 5.2, namely, annual air quality (*AnnualAQ*) and proportion of unhealthy days (*Unhealthy*). Because the ATUS data only indicate the living state, rather than the living county, of the respondents, I construct two state-level air quality measures, *StateAQ* and *StateUnhealthy*, which are the averages of *AnnualAQ* and *Unhealthy* of all counties in the state, respectively. I regress *LnWorkingHours* against the two state-level air quality measures, as well as state, year, industry, and job category fixed effects. The regression results are report on Table 3.7.

[Insert Table 3.7]

The table shows that the coefficients of *StateAQ* and *StateUnhealthy* are both statistically insignificant, suggesting that the air pollution does not significantly reduce the working hours of local residents. Therefore, I fail to find evidence that supports the working hour channel. My findings in Section 6.1 are also inconsistent with the working hour channel because if the channel works, treated inventors should increase both experimentation and specialization efforts, rather than increasing experimentation efforts while reducing specialization efforts. Therefore, it is unlikely that my findings in the baseline analysis is driven by increased working hours by inventors in NBP participating states following the implementation of NBP.

3.6. Additional Analyses

3.6.1. Average Patent Quality

The evidence from my baseline analysis suggests that inventors in NBP participating states produce more patents after the implementation of NBP. These patents also generate more forward citations and have higher economic value. To perform the test, I adopt two average patent quality measures. Average citations per patent (*LnAvgCit*) is defined as the natural logarithm of one plus the average number of forward citations received by the inventor's newly filed patents. Average economic value per patent (*LnAvgPatVal*) is defined as the natural logarithm of one plus the average economic values of the inventor's newly filed patents. I re-estimate the baseline regression model using the two average patent quality measures. The sample size of this test is much smaller than the baseline test in the baseline analysis, because observations with zero patents are excluded by construction. The regression results are presented in Table 3.8.

[Insert Table 3.8]

The table shows that the coefficients of *Treat*Post* are positive and statistically significant in both regressions, suggesting that the patents generate by inventors in the NBP participating states have higher average citations and economic values following the implementation of NBP. Therefore, improvements air quality associated with the implementation of NBP enhances not only the number, but also the average quality of patents generated by inventors in NBP participating states, both of which contribute to the increase in total patent citations and economic values.

3.6.2. All Inventors

In the baseline analysis, I only focus on inventors affiliated with publicly listed firms so that I can control for innovation inputs and characteristics of the firms where the inventors work. In this section, I extend the analysis to all inventors regardless of whether they are affiliated with publicly listed firms or not. Hence, the sample in this test includes all U.S. inventors except for those located in the states that are adjacent to the NBP participating states. I exclude the patent value measure (i.e., *LnPatVal*) in this analysis because it only applies to the inventors affiliated with publicly listed firms. I control for inventor tenure, as well as state, year, and inventor fixed effects in the regressions. The regression results are presented in Table 3.9.

[Insert Table 3.9]

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

3.6.3. Direct Measures of Air Pollution

In the last test, I directly examine the effect of local air pollution levels on inventor productivity using a panel data. I adopt the same county-level air pollution measures as in Section 5.2, namely, annual air quality (*AnnualAQ*) and proportion of unhealthy days (*Unhealthy*). Because of the air pollution data is available from 1981 to 2008, the sample in this test is much larger than that in the baseline analysis. I replace *Treat*Post* in the baseline regression with these two air pollution measures and then re-estimate the regression model. The regression results are reported in Table 3.10.

[Insert Table 3.10]

Columns (1)-(3) of Table 3.10 show that the coefficient of *AnnualAQ* is negative and statistically significant in all regressions, suggesting that inventors located in counties with greater air pollution in general file fewer new patents, and these patents also receive fewer forward citations and generate lower economic value. Similarly, columns (4)-(6) show that the coefficient of *Unhealthy* is negative and significant in all the regressions as well, confirming the negative effect of air pollution on inventor productivity. Collectively, the test in this section provides additional evidence on the negative effect of air pollution on inventor productivity, which further validate my finding from the NBP setting.

3.7. Conclusion

Motivated by studies showing that air pollution impairs people's mental health and makes them pessimistic and risk averse, I examine whether air pollution affects productivity of patent inventors. I employ the NBP, which significantly reduced the NOx emissions in the eastern states in the U.S., as a quasi-natural experiment to air pollution and perform a difference-in-difference analysis around its implementation. I find that treated inventors (i.e., inventors living in the NBP participating states) produce significantly more patents and their patents receive more forward citations and generate higher economic value than controlled inventors (i.e., inventors living in the other states except those in the adjacent states of the NBP participating states) following the implementation of the NBP. The effect is stronger for less experienced investors or inventors living in counties with higher pre-NBP air pollution levels. Further, I show that inventors located in the NBP participating states create more experimentation innovation and less specialization innovation after the implementation of the NBP. I also fail to find evidence that air pollution reduces the working hours of local residents. Taken together, the findings are consistent with the story that reduction in air pollution by the NBP improves the mental states of inventors. This makes them less risk-averse in the innovation process and hence more innovative.

My study contribute to finance literature about the behavioural impacts of air pollution by showing that air pollution-induced mood not only affect stock market participant also patent inventors, who play a key role in corporate innovation success. My study also contributes to the economics literature about the impact of air pollution on worker productivity. Different from prior studies that mainly focus on labor-intensive workers, I explore the effect of air pollution on the productivity of inventors, who rely more on intelligence. Last, my study is related to the growing literature that explores the determinants of innovation success. I contribute to this literature by investigating behavioural factors that influence the innovation outputs of individual inventors. My findings also have policy implications in that motivated by the positive externalities of the NBP, the government should play a more active role in controlling air quality through imposing regulations on the emission of air pollutants.

Chapter 4 Conclusion

This study shows that both terrorist attacks and air pollution have an influence on inventor productivity, and the channel is risk-taking. I find that after experiencing high-fatality attacks, local inventors tend to become more risk-averse and have lower productivity in the subsequent years, while those who witnessed terrorist attacks with low fatality tend to behave more risk-taking and produce more innovation outputs afterwards, consistent with Bernile et al. (2017). I also find that reducing air pollution improves inventor productivity through making inventors become more risk-tolerant. I contribute to the literature by identifying terrorist attacks and air quality as two important external factors that have effects on inventor productivity.

My findings highlight the vulnerability of inventors to external factors, such as terrorist attacks and air pollution, which may adversely affect innovation through increased risk aversion among local inventors. The results on terrorist attacks and inventor productivity reveals the need for disaster management so that firms can care for their inventors if and when a high-fatality terrorist attack occurs. By showing the negative effects of air pollution on inventor productivity, my study also suggests that government can play an important role in helping inventors to generate high-value innovation and foster economic growth by adopting regulations to reduce air pollution.

Appendices

Appendix. 2.A Variable Definition

Variables	Description
Panel A. Terrorist attack variable	
High	Dummy variable equals to one if the inventor was affected by a high-fatality attack, and zero otherwise.
Low	Dummy variable equals to one if the inventor was affected by a low-fatality attack, and zero otherwise.
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 their 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 their citations are within of the inventor's knowledge base.
Originality	Originality of each patent is calculated as the one minus the Herfindahl-Hirschman index of citations to other patents over patent classes. To get the inventor-level measures, I calculate the average across all the patents for each inventor over the future three years.
Generality	Generality is calculated as one minus the Herfindahl-Hirschman index of citations received from other patents over patent classes. To get the inventor-level measures, I calculate the average across all the patents for each inventor over the future three years.
Panel C. Control variables	
Firm Size	Natural logarithm of total assets.
CapEx	Capital expenditure scaled by total assets.
R&D	R&D expenditures scaled by total assets.
ROA	Operating income before depreciation 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 the number of years elapsed since the first year that firm appeared in the Compustat database.
Tenure	Natural logarithm of the one plus number of years between the year that the inventor enters the patent database and the observation year.
Panel D. Other variables	
Religiosity	Dummy variable equals to one if the inventor lives in a county with the religious people ratio higher than the sample median.
Male-Female	Dummy variable equals to one if the inventor lives in a county with the male-female ratio higher than the sample median.
Murder	Dummy variable equals to one if the inventor lives in a state with the murder rate higher than the sample median.
Inventor Move	Dummy variable equals to one if the inventor moves to another city (i.e., did not locate at the same city as he/she did in the previous year).
Move to Attack	Dummy variable equals to one if the inventor move to a city with terrorist attack history.
Move to Peace	Dummy variable equals to one if the inventor move to a city without

	terrorist attack history.
StateIncome	Natural logarithm of the state-level labor income.
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.

Appendix. 3.A Variable Definition

Variables	Description
Panel A. Key variables	
Treat	Dummy variable equals to one if the inventor lives in NBP participating states, and zero if the inventor lives in the other states except for states that are adjacent to NBP participating states.
Post	Dummy variable equals to one for the period 2000-2002, and zero for the period 2005-2007.
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 their 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 their citations are within the inventor's knowledge base.
LnFirstPat	Natural logarithm of one plus the number of newly filed patents that belong to the technology class that 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.
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 expenditures scaled by total assets.
ROA	Operating income before depreciation 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 equals to one if the inventor has adjusted forward citations among top 10% in our sample.
AnnualAQ	Median of the daily AQI 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 AQI larger than 100.

PreAQ	Dummy variable equals to one if the inventor lives in a county with average *AnnualAQ* during 2000 and 2002 higher than the sample median.
PreUnhealthy	Dummy variable equals 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
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 the weekly working hours

Table 2.1. List of Terrorist Attacks

This table lists the 18 terrorist attacks used in this paper, which took place in the U.S., caused at least one casualty, and were covered by major media outlets. Affected inventors are inventors located within 100 miles to a terrorist attack.

No.	Events	Date	Location	Fatalities	Total Number of Inventors	Number of Affected Inventors	Proportion of Affected Inventors
1	Brooklyn Bridge	1-Mar-94	New York City, NY	1	49,681	7,643	0.154
2	Unabomber - Thomas Mosser	10-Dec-94	North Caldwell, NJ	1	49,681	7,708	0.155
3	Planned Parenthood Clinic	30-Dec-94	Brookline, MA	1	49,681	3,048	0.061
4	Alfred P. Murrah Federal Building Booming	19-Apr-95	Oklahoma City	168	55,987	271	0.005
5	Unabomber - Gilbert Murray	24-Apr-95	Sacramento, CA	1	55,987	6,005	0.107
6	Olympic Park Bombing	27-Jul-96	Atlanta, GA	1	57,258	586	0.010
7	Empire State Building	23-Feb-97	New York City, NY	1	60,789	8,460	0.139
8	Abortion Clinic Bombing	29-Jan-98	Birmingham, AL	1	61,579	154	0.003
9	U.S. Capitol	24-Jul-98	Washington, DC	2	61,579	1,766	0.029
10	Barnett Slepian Murder	23-Oct-98	Amherst, NY	1	61,579	2,819	0.046
11	Columbine High School	20-Apr-99	Littleton, CO	15	62,282	1,349	0.022
12	Korean Methodist Church	4-Jul-99	Bloomington, IN	2	62,282	858	0.014
13	9/11 Attacks: World Trade Center	11-Sep-01	New York City, NY	1383	63,925	7,472	0.117
14	9/11 Attacks: Hijacked Plane Crashed	11-Sep-01	Alexandria, VA	44	63,925	1,332	0.021
15	9/11 Attacks: Hijacked Plane Crashed	11-Sep-01	Somerset County, PA	189	63,925	365	0.006
16	Bank of America	5-Jan-02	Tampa, FL	1	63,980	138	0.002
17	LA International Airport	4-Jul-02	Los Angeles, CA	3	63,980	3,353	0.052
18	Seattle Jewish Federation	28-Jul-06	Seattle, WA	1	27,288	597	0.022

Table 2.2. Summary Statistics

This table shows the summary statistics of the variables used in the analysis. Variable definitions are shown in the Appendix. 2.A.

	Mean	Std.	25%	Median	75%
High	0.02	0.15	0.00	0.00	0.00
Low	0.04	0.20	0.00	0.00	0.00
LnPat	0.99	0.71	0.69	0.69	1.39
LnCit	1.89	1.66	0.00	1.79	3.14
LnPatVal	2.62	1.76	1.30	2.69	3.88
LnExploit	0.36	0.56	0.00	0.00	0.69
LnExplore	0.70	0.65	0.00	0.69	1.10
Originality	0.49	0.22	0.35	0.51	0.66
Generality	0.35	0.25	0.13	0.37	0.55
Firm Size	9.14	2.13	7.94	9.56	10.53
R&D	0.07	0.07	0.03	0.06	0.10
ROA	0.14	0.12	0.10	0.15	0.20
Leverage	0.21	0.15	0.09	0.20	0.30
CapEx	0.06	0.04	0.03	0.05	0.08
BM	0.33	0.22	0.18	0.27	0.42
Cash	0.16	0.18	0.03	0.09	0.21
Firm Age	3.43	0.71	3.00	3.83	3.93
Tenure	1.67	0.93	1.10	1.79	2.40

Table 2.3. Terrorist Attack and Inventor Innovation Output

This table presents the regression results of the effect of terrorist attack on inventor innovation output. The regressions are performed by ordinary least squares, with standard errors (reported in parentheses) clustered at the inventor level. ***, **, * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the Appendix. 2.A.

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	-0.021***	-0.051***	-0.052***
	(0.004)	(0.009)	(0.010)
Low	0.011***	0.037***	0.030***
	(0.003)	(0.008)	(0.008)
Firm Size	0.023***	0.029***	0.130***
	(0.002)	(0.005)	(0.005)
R&D	-0.286***	-0.571***	-0.260***
	(0.034)	(0.078)	(0.078)
ROA	0.041***	0.141***	0.802***
	(0.016)	(0.036)	(0.037)
Leverage	-0.100***	-0.022	0.130***
	(0.014)	(0.031)	(0.031)
CapEx	0.556***	1.114***	1.026***
	(0.041)	(0.096)	(0.094)
BM	-0.098***	-0.128***	-0.158***
	(0.006)	(0.014)	(0.013)
Cash	0.089***	0.210***	0.253***
	(0.013)	(0.029)	(0.030)
Firm Age	-0.163***	-0.363***	-0.337***
	(0.005)	(0.011)	(0.011)
Tenure	-0.052***	-0.107***	-0.113***
	(0.003)	(0.008)	(0.008)
Year FE	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Obs.	736,699	736,699	736,699
Adj. R^2	0.527	0.548	0.537

Table 2.4. Robustness Tests

This table presents the results for robustness tests. The regressions are performed by ordinary least squares, with standard errors (reported in parentheses) clustered at the inventor level. All the control variables and year, inventor, and industry fixed effects are included in the regressions but are not reported. ***, **, * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the Appendix. 2.A.

Panel A. Use alternative sample

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	-0.010***	-0.023***	-0.010
	(0.003)	(0.007)	(0.007)
Low	0.011***	0.025***	0.012**
	(0.002)	(0.006)	(0.005)
Controls and FEs included			
Obs.	1,403,451	1,403,451	1,403,451
Adj. R2	0.484	0.442	0.522

Panel B. Define high-fatality and low-fatality attacks using 3 fatalities as cut-off

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	-0.026***	-0.063***	-0.074***
	(0.005)	(0.012)	(0.013)
Low	0.007**	0.024***	0.021***
	(0.003)	(0.007)	(0.007)
Controls and FEs included			
Obs.	736,699	736,699	736,699
Adj. R2	0.527	0.548	0.537

Panel C. Define high-fatality and low-fatality attacks using news coverage

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	-0.019***	-0.044***	-0.044***
	(0.004)	(0.009)	(0.010)
Low	0.009***	0.032***	0.025***
	(0.003)	(0.008)	(0.008)
Controls and FEs included			
Obs.	736,699	736,699	736,699
Adj. R^2	0.527	0.548	0.537

Panel D. Use future five years' innovation output as dependent variables

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	-0.022***	-0.042***	-0.047***
	(0.004)	(0.008)	(0.008)
Low	0.011***	0.029***	0.029***
	(0.003)	(0.007)	(0.007)
Controls and FEs included			
Obs.	736,699	736,699	736,699
Adj. R^2	0.636	0.674	0.672

Panel E. Divide patent count, citations or economic value by the number of inventors

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	-0.017***	-0.039***	-0.047***
	(0.003)	(0.007)	(0.008)
Low	0.005**	0.025***	0.023***
	(0.002)	(0.006)	(0.007)
Controls and FEs included			
Obs.	736,699	736,699	736,699
Adj. R2	0.568	0.570	0.564

Panel F. Exclude zero-patent observations

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	-0.024***	-0.053***	-0.061***
	(0.007)	(0.015)	(0.015)
Low	0.008	0.021	0.005
	(0.006)	(0.013)	(0.014)
Controls and FEs included			
Obs.	352,453	352,453	352,453
Adj. R^2	0.486	0.518	0.516

Panel G. Exclude inventors that ever moved

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	-0.023***	-0.044***	-0.059***
	(0.005)	(0.011)	(0.012)
Low	0.008**	0.022**	0.012
	-0.023***	-0.044***	-0.059***
Controls and FEs included			
Obs.	472,600	472,600	472,600
Adj. R^2	0.529	0.567	0.557

Panel H. Assign new locations to zero-patent observations for inventors that ever moved

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	-0.020***	-0.048***	-0.052***
	(0.004)	(0.009)	(0.010)
Low	0.015***	0.044***	0.037***
	(0.003)	(0.008)	(0.008)
Controls and FEs included			
Obs.	735,000	735,000	735,000
Adj. R^2	0.528	0.548	0.538

Panel I. Assign new locations to half of zero-patent observations for inventors that ever moved

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	-0.020***	-0.048***	-0.052***
	(0.004)	(0.009)	(0.010)
Low	0.012***	0.035***	0.029***
	(0.003)	(0.008)	(0.008)
Controls and FEs included			
Obs.	735,508	735,508	735,508
Adj. R2	0.528	0.548	0.538

Panel J. Control for state-level macroeconomics conditions

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	-0.015***	-0.033***	-0.024**
	(0.004)	(0.009)	(0.010)
Low	0.007**	0.025***	0.012
	(0.003)	(0.008)	(0.008)
Controls and FEs included			
Obs.	726,130	726,130	726,130
Adj. R^2	0.529	0.550	0.540

Panel K. Exclude inventors located at the same city with their firms' headquarters

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	-0.019***	-0.045***	-0.048***
	(0.004)	(0.009)	(0.010)
Low	0.016***	0.047***	0.042***
	(0.003)	(0.008)	(0.008)
Controls and FEs included			
Obs.	659,094	659,094	659,094
Adj. R^2	0.525	0.546	0.538

Panel L. Exclude inventors in aircraft and defense industries

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	-0.022***	-0.051***	-0.055***
	(0.004)	(0.009)	(0.010)
Low	0.010***	0.036***	0.031***
	(0.003)	(0.008)	(0.008)
Controls and FEs included			
Obs.	711,273	711,273	711,273
Adj. R2	0.529	0.550	0.542

Panel M. Results from matched sample

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	-0.041***	-0.086***	-0.076***
	(0.010)	(0.023)	(0.026)
Low	0.013*	0.040**	0.022
	(0.008)	(0.019)	(0.021)
Controls and FEs included			
Obs.	56,381	56,381	56,381
Adj. R^2	0.515	0.501	0.499

Panel N. Randomized terrorist attack year and location

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	0.001	0.002	0.010
	(0.005)	(0.010)	(0.011)
Low	0.002	0.005	0.009
	(0.004)	(0.010)	(0.011)
Controls and FEs included			
Obs.	736,699	736,699	736,699
Adj. R^2	0.527	0.548	0.537

Panel O. Randomized high-fatality attacks and low-fatality attacks

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	0.001	0.012	0.007
	(0.004)	(0.009)	(0.010)
Low	-0.003	-0.007	-0.010
	(0.004)	(0.010)	(0.010)
Controls and FEs included			
Obs.	736,699	736,699	736,699
Adj. R^2	0.527	0.548	0.537

Panel P. Sample ends in 2006

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High	-0.020***	-0.046***	-0.048***
	(0.004)	(0.009)	(0.010)
Low	0.012***	0.037***	0.032***
	(0.003)	(0.008)	(0.008)
Controls and FEs included			
Obs.	694,181	694,181	694,181
Adj. R^2	0.549	0.548	0.544

Table 2.5. Cross-Sectional Tests by Local Demographic Characteristics

This table shows how the effect of terrorist attack on inventor innovation output varies with local demographic characteristics. The regressions are performed by ordinary least squares, with standard errors (reported in parentheses) clustered at the inventor level. All the control variables and year, inventor, and industry fixed effects are included in the regressions but are not reported. ***, **, * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the Appendix. 2.A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	*LnPat*	*LnCit*	*LnPatVal*	*LnPat*	*LnCit*	*LnPatVal*	*LnPat*	*LnCit*	*LnPatVal*
High	0.005	-0.001	0.008	-0.045***	-0.109***	-0.099***	-0.030***	-0.066***	-0.084***
	(0.007)	(0.014)	(0.016)	(0.006)	(0.012)	(0.014)	(0.005)	(0.011)	(0.013)
Low	0.020***	0.076***	0.068***	0.003	0.010	-0.011	0.004	0.006	-0.025**
	(0.006)	(0.015)	(0.016)	(0.004)	(0.010)	(0.010)	(0.004)	(0.010)	(0.010)
*High*Religiosity*	-0.042***	-0.083***	-0.098***						
	(0.009)	(0.019)	(0.021)						
*Low*Religiosity*	-0.013*	-0.060***	-0.056***						
	(0.007)	(0.018)	(0.019)						
Religiosity	-0.033***	-0.089***	-0.122***						
	(0.006)	(0.013)	(0.014)						
*High*Male-Female*				0.054***	0.125***	0.097***			
				(0.008)	(0.018)	(0.020)			
*Low*Male-Female*				0.021***	0.072***	0.117***			
				(0.007)	(0.017)	(0.018)			
Male-Female				-0.001	-0.024*	-0.096***			
				(0.006)	(0.013)	(0.013)			
*High*Murder*							0.023***	0.040**	0.085***
							(0.008)	(0.018)	(0.021)
*Low*Murder*							0.017**	0.076***	0.136***
							(0.007)	(0.017)	(0.018)
Murder							-0.008**	-0.011	-0.012
							(0.003)	(0.007)	(0.008)
Firm Size	0.023***	0.030***	0.131***	0.023***	0.030***	0.131***	0.023***	0.029***	0.131***
	(0.002)	(0.005)	(0.005)	(0.002)	(0.005)	(0.005)	(0.002)	(0.005)	(0.005)
R&D	-0.302***	-0.610***	-0.318***	-0.298***	-0.595***	-0.288***	-0.286***	-0.568***	-0.260***
	(0.035)	(0.080)	(0.080)	(0.035)	(0.080)	(0.080)	(0.034)	(0.078)	(0.078)
ROA	0.036**	0.125***	0.772***	0.038**	0.130***	0.778***	0.041***	0.140***	0.802***
	(0.016)	(0.037)	(0.037)	(0.016)	(0.037)	(0.037)	(0.016)	(0.036)	(0.037)

Leverage	-0.108***	-0.043	0.113***	-0.108***	-0.043	0.107***	-0.100***	-0.024	0.129***
	(0.014)	(0.032)	(0.032)	(0.014)	(0.032)	(0.032)	(0.014)	(0.031)	(0.031)
CapEx	0.559***	1.108***	0.991***	0.560***	1.114***	1.002***	0.555***	1.112***	1.020***
	(0.043)	(0.099)	(0.096)	(0.043)	(0.099)	(0.096)	(0.042)	(0.096)	(0.094)
BM	-0.098***	-0.130***	-0.156***	-0.097***	-0.129***	-0.155***	-0.098***	-0.130***	-0.160***
	(0.006)	(0.014)	(0.013)	(0.006)	(0.014)	(0.013)	(0.006)	(0.014)	(0.013)
Cash	0.079***	0.197***	0.245***	0.081***	0.201***	0.251***	0.090***	0.209***	0.252***
	(0.013)	(0.030)	(0.031)	(0.013)	(0.030)	(0.031)	(0.013)	(0.029)	(0.030)
Firm Age	-0.162***	-0.362***	-0.328***	-0.162***	-0.363***	-0.330***	-0.164***	-0.364***	-0.337***
	(0.005)	(0.012)	(0.012)	(0.005)	(0.012)	(0.012)	(0.005)	(0.011)	(0.011)
Tenure	-0.051***	-0.103***	-0.109***	-0.051***	-0.104***	-0.110***	-0.052***	-0.106***	-0.112***
	(0.004)	(0.008)	(0.008)	(0.004)	(0.008)	(0.008)	(0.003)	(0.008)	(0.008)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	705,270	705,270	705,270	705,268	705,268	705,268	736,426	736,426	736,426
Adj. R^2	0.529	0.549	0.540	0.529	0.549	0.539	0.528	0.548	0.537

Table 2.6. Terrorist Attack and Inventor Innovation Strategy

This table presents the regression results of the effect of terrorist attack on inventor innovation strategy. The regressions are performed by ordinary least squares, with standard errors (reported in parentheses) clustered at the inventor level. ***, **, * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the Appendix. 2.A.

	Exploration		Exploitation	
	(1)	(2)	(3)	(4)
Variable	*LnExplore*	*Originality*	*LnExploit*	*Generality*
High	-0.018***	-0.004**	-0.007**	-0.002
	(0.004)	(0.002)	(0.003)	(0.002)
Low	0.010***	0.005***	-0.002	-0.002
	(0.003)	(0.001)	(0.002)	(0.002)
Firm Size	0.014***	0.001	0.013***	-0.003***
	(0.002)	(0.001)	(0.002)	(0.001)
R&D	-0.249***	-0.024*	-0.186***	-0.012
	(0.031)	(0.012)	(0.027)	(0.015)
ROA	0.101***	-0.007	-0.069***	-0.002
	(0.015)	(0.006)	(0.013)	(0.007)
Leverage	-0.055***	-0.015***	-0.097***	0.023***
	(0.013)	(0.005)	(0.010)	(0.006)
CapEx	0.414***	0.015	0.288***	0.029*
	(0.040)	(0.015)	(0.031)	(0.017)
BM	-0.096***	0.005**	-0.041***	0.013***
	(0.006)	(0.002)	(0.004)	(0.003)
Cash	0.018	0.005	0.095***	-0.004
	(0.012)	(0.005)	(0.010)	(0.005)
Firm Age	-0.127***	-0.003*	-0.072***	-0.004*
	(0.005)	(0.002)	(0.004)	(0.002)
Tenure	-0.062***	-0.001	0.005*	0.001
	(0.003)	(0.001)	(0.003)	(0.001)
Year FE	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Obs.	736,699	338,662	736,699	282,564
Adj. R2	0.450	0.617	0.581	0.640

Table 2.7. Test on Geographical Distance

This table presents the regression results of the test on geographical distance between the affected inventors and terrorist attacks. The regressions are performed by ordinary least squares, with standard errors (reported in parentheses) clustered at the inventor level. ***, **, * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the Appendix. 2.A.

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
High(0 to 100miles)	-0.021***	-0.051***	-0.050***
	(0.004)	(0.009)	(0.010)
High(100 to 150miles)	-0.002	0.001	0.005
	(0.006)	(0.014)	(0.017)
High(150 to 200miles)	-0.005	0.007	0.024*
	(0.005)	(0.012)	(0.014)
Low(0 to 100miles)	0.012***	0.038***	0.032***
	(0.003)	(0.008)	(0.008)
Low(100 to 150miles)	0.013**	0.007	0.021
	(0.006)	(0.014)	(0.016)
Low(150 to 200miles)	0.011*	0.003	0.010
	(0.006)	(0.015)	(0.015)
Firm Size	0.023***	0.029***	0.130***
	(0.002)	(0.005)	(0.005)
R&D	-0.286***	-0.572***	-0.261***
	(0.034)	(0.078)	(0.078)
ROA	0.042***	0.141***	0.801***
	(0.016)	(0.036)	(0.037)
Leverage	-0.100***	-0.022	0.131***
	(0.014)	(0.031)	(0.031)
CapEx	0.557***	1.113***	1.023***
	(0.041)	(0.096)	(0.094)
BM	-0.097***	-0.128***	-0.159***
	(0.006)	(0.014)	(0.013)
Cash	0.089***	0.210***	0.253***
	(0.013)	(0.029)	(0.030)
Firm Age	-0.163***	-0.363***	-0.337***
	(0.005)	(0.011)	(0.011)
Tenure	-0.052***	-0.107***	-0.113***
	(0.003)	(0.008)	(0.008)
Year FE	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Obs.	736,699	736,699	736,699
Adj. R^2	0.527	0.548	0.537

Table 2.8. Terrorist Attack and Innovator Relocation

This table presents the regression results of the effect of terrorist attack on the probability and direction of inventor move. The regressions are performed by logit model. Standard errors are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the Appendix. 2.A.

Variable	(1) *Inventor Move*	(2) *Move to Attack*	(3) *Move to Peace*
High	0.112**	0.337	0.104**
	(0.046)	(0.224)	(0.047)
Low	0.029	0.043	0.035
	(0.038)	(0.213)	(0.038)
Firm Size	0.060***	0.096***	0.057***
	(0.006)	(0.031)	(0.006)
R&D	0.538***	-0.180	0.569***
	(0.158)	(0.732)	(0.160)
ROA	-0.109	-0.958**	-0.062
	(0.082)	(0.375)	(0.084)
Leverage	-0.362***	-1.026***	-0.323***
	(0.066)	(0.312)	(0.067)
CapEx	0.706***	-1.057	0.803***
	(0.223)	(1.080)	(0.227)
BM	0.033	-0.134	0.041
	(0.039)	(0.184)	(0.040)
Cash	0.401***	0.056	0.413***
	(0.057)	(0.255)	(0.059)
Firm Age	-0.098***	0.031	-0.101***
	(0.015)	(0.069)	(0.015)
Tenure	0.009	-0.004	0.010
	(0.007)	(0.031)	(0.007)
StateIncome	-0.005	-0.032	-0.005
	(0.024)	(0.110)	(0.025)
StateUnemp	-0.256***	-0.111	-0.264***
	(0.072)	(0.331)	(0.074)
StateSale	0.017	-0.011	0.020
	(0.023)	(0.096)	(0.024)
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Obs.	209,491	169,035	209,482
Pseudo R^2	0.013	0.010	0.013

Table 3.1. Summary Statistics

This table shows the summary statistics of the variables used in the analysis. Variable definitions are shown in the Appendix. 3.A.

	Treated Inventors (64,417 inventor-years)					Controlled Inventors (85,287 inventor-years)				
	Mean	Std.	25%	Median	75%	Mean	Std.	25%	Median	75%
LnPat	0.63	0.60	0.00	0.69	1.10	0.69	0.63	0.00	0.69	1.10
LnCit	0.95	1.28	0.00	0.00	1.79	1.18	1.44	0.00	0.69	2.20
LnPatVal	1.76	1.69	0.00	1.64	3.09	1.78	1.61	0.00	1.81	3.00
LnExploit	0.20	0.41	0.00	0.00	0.00	0.24	0.45	0.00	0.00	0.69
LnExplore	0.42	0.52	0.00	0.00	0.69	0.45	0.55	0.00	0.00	0.69
LnSelfcite	0.27	0.60	0.00	0.00	0.00	0.30	0.65	0.00	0.00	0.00
LnFirstPat	0.22	0.37	0.00	0.00	0.69	0.25	0.39	0.00	0.00	0.69
Firm Size	9.81	2.11	8.72	10.19	11.39	9.10	1.98	7.83	9.56	10.69
R&D	0.06	0.06	0.02	0.05	0.08	0.09	0.06	0.05	0.08	0.11
ROA	0.13	0.10	0.09	0.14	0.18	0.15	0.12	0.10	0.16	0.22
Leverage	0.27	0.17	0.16	0.24	0.35	0.14	0.14	0.01	0.10	0.22
CapEx	0.05	0.03	0.03	0.04	0.06	0.05	0.04	0.02	0.04	0.07
BM	0.30	0.23	0.14	0.25	0.37	0.29	0.21	0.15	0.24	0.36
Cash	0.14	0.16	0.04	0.08	0.17	0.27	0.20	0.10	0.21	0.40
Firm Age	3.59	0.70	3.58	3.93	4.01	3.22	0.75	2.77	3.37	3.93
Tenure	2.00	0.88	1.61	2.08	2.64	1.81	0.86	1.39	1.95	2.40

Table 3.2. NBP Implementation and Inventor Innovation Output

This table presents the regression results of the baseline difference-in-difference test on a sample of inventors affiliated with public firms. The regressions are performed by 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. ***, **, * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the Appendix. 3.A.

Variable	(1) *LnPat*	(2) *LnCit*	(3) *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

Table 3.3. Robustness Tests

This table presents the results for robustness tests. The regressions are performed by 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 the control variables and year, inventor, and industry fixed effects are included in the regressions but are not reported. ***, **, * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the Appendix. 3.A.

Panel A. Exclude zero-patent observations

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
*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

Panel B. Exclude inventors that ever moved between NBP states and non-NBP states

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
*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

Panel C. Results from balanced sample

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
*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

Panel D. Results from matched sample

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
*Treat*Post*	0.082***	0.183***	0.275***
	(0.022)	(0.047)	(0.060)
Controls and FEs included			
Obs.	51,734	51,734	51,734
Adj. R^2	0.248	0.306	0.255

Panel E. Exclude states joining NBP in 2004

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
*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 F. Sample includes 2003 and 2004

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
*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

Panel G. Divide patent count, citations or economic value by the number of inventors

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
*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

Panel H. Collapse the sample by NBP implementation

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
*Treat*Post*	0.087***	0.233***	0.266***
	(0.010)	(0.020)	(0.020)
Controls and FEs included			
Obs.	59,612	59,612	59,612
Adj. R^2	0.355	0.436	0.442

Panel I. NBP and corporate policies

Variable	(1) *R&D*	(2) *CSR*
*Treat*Post*	-0.002	-0.002
	(0.002)	(0.014)
Controls and FEs included		
Obs.	13,888	12,364
Adj. R^2	0.605	0.843

Panel J. Exclude inventors in utility industry

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
*Treat*Post*	0.028***	0.119***	0.146***
	(0.007)	(0.016)	(0.019)
Controls and FEs included			
Obs.	149,694	149,694	149,694
Adj. R^2	0.309	0.346	0.301

Panel K. Exclude inventors in manufacturing industries

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
Treat*Post	0.070***	0.204***	0.255***
	(0.009)	(0.020)	(0.023)
Controls and FEs included			
Obs.	103,565	103,565	103,565
Adj. R2	0.315	0.360	0.297

Panel L. Exclude inventors in medical industries

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
*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

Panel M. Control for state-level macroeconomics conditions

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
*Treat*Post*	0.037***	0.120***	0.167***
	(0.008)	(0.017)	(0.019)
Controls and FEs included			
Obs.	148,158	148,158	148,158
Adj. R^2	0.310	0.347	0.303

Panel N. Randomized NBP participating states

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*
*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

Table 3.4. Inventor Experience

This table shows how the effect of air pollution on inventor innovation output varies with inventor experience. The regressions are performed by ordinary least squares, with standard errors (reported in parentheses) clustered at the inventor level. ***, **, * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the Appendix. 3.A.

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*	(4) *LnPat*	(5) *LnCit*	(6) *LnPatVal*
*Treat*Post*	0.087***	0.274***	0.347***	0.084***	0.280***	0.283***
	(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*				-0.333***	-0.951***	-0.806***
				(0.019)	(0.039)	(0.041)
Firm Size	0.035***	0.023**	0.262***	0.035***	0.025**	0.263***
	(0.004)	(0.010)	(0.011)	(0.004)	(0.010)	(0.011)
R&D	-0.368***	-1.240***	-0.708***	-0.358***	-1.210***	-0.688***
	(0.076)	(0.171)	(0.184)	(0.076)	(0.171)	(0.183)
ROA	-0.141***	-0.219***	0.058	-0.142***	-0.222***	0.059
	(0.030)	(0.070)	(0.078)	(0.030)	(0.069)	(0.078)
Leverage	-0.082***	-0.048	-0.050	-0.072***	-0.021	-0.025
	(0.025)	(0.056)	(0.062)	(0.025)	(0.055)	(0.062)
CapEx	0.271***	0.352	1.037***	0.261***	0.326	1.011***
	(0.096)	(0.218)	(0.236)	(0.096)	(0.217)	(0.236)
BM	-0.124***	-0.333***	-0.486***	-0.118***	-0.316***	-0.471***
	(0.012)	(0.027)	(0.028)	(0.012)	(0.027)	(0.028)
Cash	0.171***	0.217***	0.209***	0.171***	0.216***	0.207***
	(0.023)	(0.052)	(0.058)	(0.023)	(0.051)	(0.058)
Firm Age	-0.128***	-0.256***	-0.432***	-0.129***	-0.257***	-0.434***
	(0.010)	(0.022)	(0.025)	(0.010)	(0.022)	(0.025)
Tenure	-0.222***	-0.600***	-0.823***	-0.211***	-0.577***	-0.764***
	(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	0.314	0.355	0.305

Table 3.5. Original Air Quality Level

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 by 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. ***, **, * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the Appendix. 3.A.

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*	(4) *LnPat*	(5) *LnCit*	(6) *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

Table 3.6. NBP Implementation and Inventor Innovation Strategy

This table presents the regression results of the effect of NBP implementation on inventor innovation strategy. The regressions are performed by 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. ***, **, * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the Appendix. 3.A.

	Exploration		Exploitation	
	(1)	(2)	(3)	(4)
Variable	*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

Table 3.7. Air Pollution and Working Hours

This table shows how air pollution affects the working hours of local residents. The regressions are performed by ordinary least squares. All independent variables are in the same year of dependent variables. ***, **, * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the Appendix. 3.A.

Variable	(1) *LnWorkingHours*	(2) *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

Table 3.8. NBP Implementation and Quality of Innovation

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 by 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. ***, **, * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the Appendix. 3.A.

	(1)	(2)
Variable	*LnAvgCit*	*LnAvgPatVal*
*Treat*Post*	0.130***	0.135***
	(0.014)	(0.011)
Firm Size	-0.052***	0.215***
	(0.009)	(0.009)
R&D	-0.447***	-0.191
	(0.156)	(0.134)
ROA	-0.189***	0.439***
	(0.062)	(0.051)
Leverage	0.120**	-0.140***
	(0.052)	(0.039)
CapEx	-0.136	0.389***
	(0.192)	(0.148)
BM	-0.057**	-0.455***
	(0.026)	(0.020)
Cash	-0.057	-0.323***
	(0.046)	(0.041)
Firm Age	0.005	-0.170***
	(0.020)	(0.021)
Tenure	0.012	-0.019**
	(0.011)	(0.009)
State FE	Yes	Yes
Year FE	Yes	Yes
Inventor FE	Yes	Yes
Industry FE	Yes	Yes
Obs.	96,298	96,298
Adj. R2	0.542	0.766

Table 3.9. Analysis on All the Inventors

This table presents the regression results of the difference-in-difference test on all the inventors (regardless of whether they are affiliated with public firms or not). The regressions are performed by ordinary least squares, with standard errors (reported in parentheses) clustered at the inventor level. ***, **, * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the Appendix. 3.A.

	(1)	(2)
Variable	*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

Table 3.10. Local Air Quality and Inventor Innovation Output

This table presents the regression results of the relation between local air quality and inventor innovation output. The regressions are performed by ordinary least squares, with standard errors (reported in parentheses) clustered at the inventor level. All independent variables are lagged by one year. ***, **, * indicate significance at the 1%, 5%, and 10% significance levels, respectively. Variable definitions are shown in the Appendix. 3.A.

Variable	(1) *LnPat*	(2) *LnCit*	(3) *LnPatVal*	(4) *LnPat*	(5) *LnCit*	(6) *LnPatVal*
AnnualAQ	-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

Figure 3.1. Participation in NBP by State

This figure presents the NBP participation status for U.S. states. Dark blue states were NBP participating states during the period 2003 to 2007, and the inventors in these states are treated inventors. Light blue states did not participate in the NBP, and the inventors in these states are controlled inventors. Inventors in the shaded states are excluded from my empirical analysis. This figure comes from Deschênes et al. (2017).

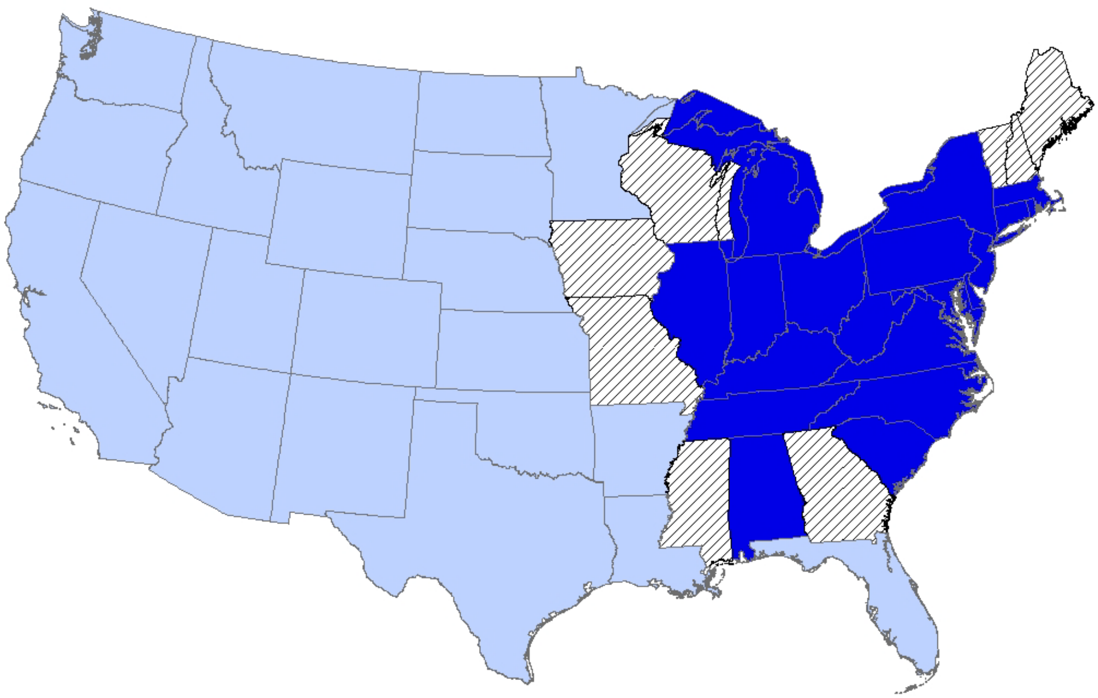


Figure 3.2. Ozone Season NOx Emissions from All NBP Sources

This figure presents the change of ozone season emissions in NBP participating states during the period 1990 to 2007. This figure comes from EPA (2007).

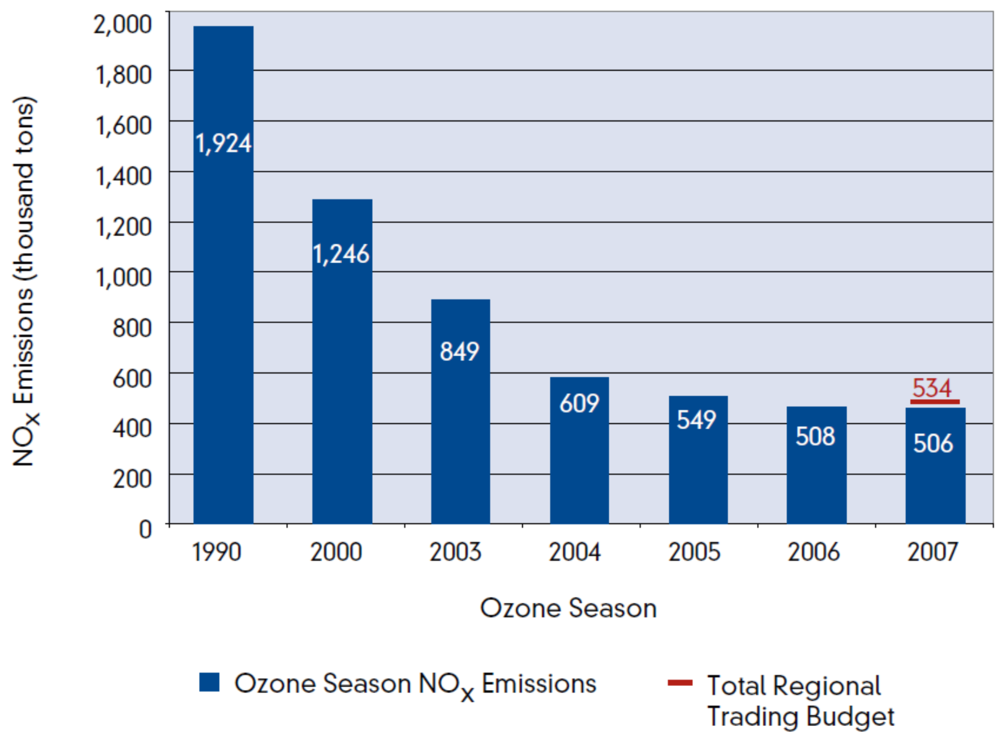
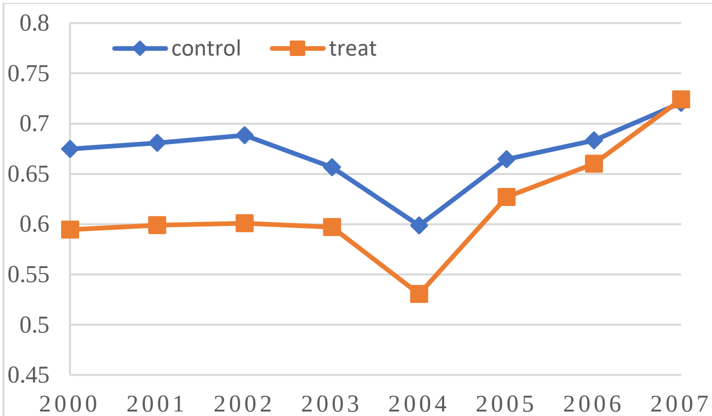


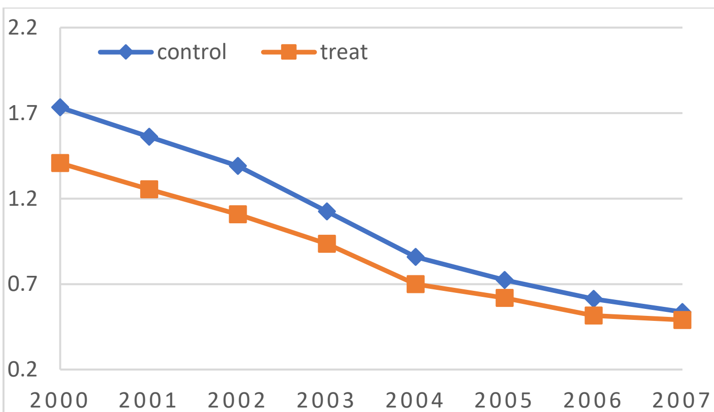
Figure 3.3. Parallel Trend of Innovation output around the implementation of NBP

This figure presents the trends in innovation output for the treatment and control group firms around the implementation of NBP.

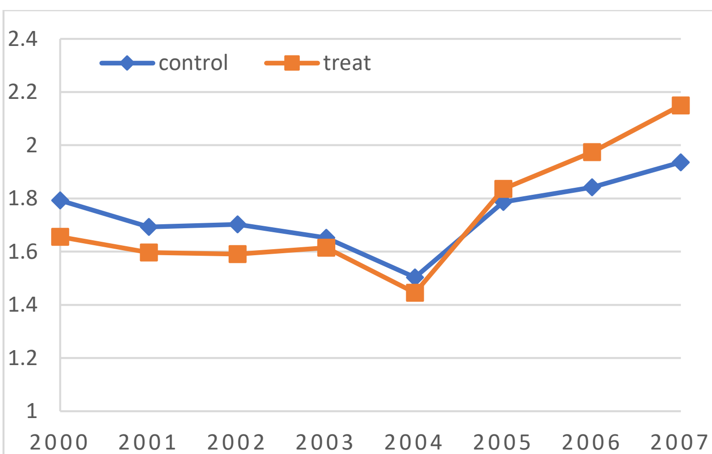
Panel A. Number of Patents



Panel B. Number of Citations



Panel C. Total Patent Value



References

Abrams, D., and Hogg, M. A., 1988. Comments on the motivational status of self-esteem in social identity and intergroup discrimination. *European journal of social psychology*, 18(4), 317-334.

Aghion, P., Van Reenen, J., and Zingales, L., 2013. Innovation and institutional ownership. *American Economic Review*, 103(1), 277-304.

Ahern, K. R., 2018. The importance of psychology in economic activity: Evidence from terrorist attacks, No. w24331. *National Bureau of Economic Research*.

Ahmad, M. H., 1973. Religiosity as a function of rigidity and anxiety. *Indian Journal of Experimental Psychology*.

Akcigit, U., Baslandze, S., and Stantcheva, S., 2016. Taxation and the international mobility of inventors. *American Economic Review*, 106(10), 2930-81.

Antoniou, C., Kumar, A., and Maligkris, A., 2016a. Terrorist Attacks, Analyst Sentiment, and Earnings Forecasts. Unpublished working paper.

Antoniou, C., Kumar, A., and Maligkris, A., 2016b. Terrorist Attacks, Sentiment, and Corporate Policies. Unpublished working paper.

Balsmeier, B., Fleming, L., and Manso, G., 2017. Independent boards and innovation. *Journal of Financial Economics*, 123(3), 536-557.

Barnett, T., Bass, K., and Brown, G., 1996. Religiosity, ethical ideology, and intentions to report a peer's wrongdoing. *Journal of Business Ethics*, 15(11), 1161-1174.

Benner, M. J., and Tushman, M., 2002. Process management and technological innovation: A longitudinal study of the photography and paint industries. *Administrative science quarterly*, 47(4), 676-707.

Bernile, G., Bhagwat, V., and Rau, P. R., 2017. What Doesn't Kill You Will Only Make You More Risk‐Loving: Early‐Life Disasters and CEO Behavior. *The Journal of Finance*, 72(1), 167-206.

Bertrand, M., Duflo, E., and Mullainathan, S., 2004. How much should I trust differences-in-differences estimates?. *The Quarterly journal of economics*, 119(1), 249-275.

Bhattacharya, U., Hsu, P.-H., Tian, X., and Xu, Y., 2017. What Affects Innovation More: Policy or Policy Uncertainty? *Journal of Financial and Quantitative Analysis*, 52(5), 1869-1901.

Boone, J. P., Khurana, I. K., and Raman, K., 2012. Religiosity and tax avoidance. *The Journal of the American Taxation Association*, 35(1), 53-84.

Bradley, M. M., Codispoti, M., Sabatinelli, D., and Lang, P. J., 2001. Emotion and motivation II: sex differences in picture processing. *Emotion*, 1(3), 300.

Brück, T., and Wickström, B.-A., 2004. The economic consequences of terror: guest editors' introduction. *European Journal of Political Economy*, 20(2), 293-300.

Brunekreef, B., and Holgate, S. T., 2002. *Air pollution and health*. The lancet, 360(9341), 1233-1242.

Bullinger, M., 1989. Psychological effects of air pollution on healthy residents—a time-series approach. *Journal of Environmental Psychology*, 9(2), 103-118.

Byrnes, J. P., Miller, D. C., and Schafer, W. D., 1999. Gender differences in risk taking: : a meta-analysis. *Psychological bulletin*, 125(3), 367.

Callen, J. L., and Fang, X., 2015. Religion and stock price crash risk. *Journal of Financial and Quantitative Analysis,* 50(1-2), 169-195.

Chalk, P., 1999. The evolving dynamic of terrorism in the 1990s. *Australian Journal of International Affairs*, 53(2), 151-167.

Chang, T. Y., Graff Zivin, J., Gross, T., and Neidell, M.,2019. The effect of pollution on worker productivity: evidence from call center workers in China. *American Economic Journal: Applied Economics*, 11(1), 151-72.

Chang, T., Graff Zivin, J., Gross, T., and Neidell, M., 2016. Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy*, 8(3), 141-69.

Chattopadhyay, P. K., Som, B., and Mukhopadhyay, P., 1995. Air pollution and health hazards in human subjects: Physiological and self-report indices. *Journal of environmental Psychology*, 15(4), 327-331.

Chava, S., Oettl, A., Subramanian, A., and Subramanian, K. V., 2013. Banking deregulation and innovation. *Journal of Financial Economics*, 109(3), 759-774.

Chemmanur, T. J., Loutskina, E., and Tian, X., 2014. Corporate venture capital, value creation, and innovation. *The Review of Financial Studies*, 27(8), 2434-2473.

Chen, Y., Hsu, P.-H., Podolski, E. J., Veeraraghavan, M., 2019. The Extra-Organizational Determinants of Innovation: Sunshine Exposure and Inventor Performance. Unpublished working paper.

Chen, Y., Podolski, E. J., Rhee, S. G., and Veeraraghavan, M., 2014. Local gambling preferences and corporate innovative success. *Journal of Financial and Quantitative Analysis*, 49(1), 77-106.

Coates, J. M., and Herbert, J., 2008. Endogenous steroids and financial risk taking on a London trading floor. *Proceedings of the national academy of sciences*, 105(16), 6167-6172.

Constans, J. I., and Mathews, A. M., 1993. Mood and the subjective risk of future events. *Cognition and Emotion*, 7(6), 545-560.

Dai, Y., Rau, P. R., Stouraitis, A., and Tan, W., 2020. An illd wind? Terrorist attacks and CEO compensation. *Journal of Financial Economics*, 135(2), 379-398.

Deschênes, O., Greenstone, M., and Shapiro, J. S., 2017. Defensive investments and the demand for air quality: Evidence from the NOx budget program. *American Economic Review*, 107(10), 2958-89.

Diaz, J. D., 2000. Religion and gambling in sin-city: A statistical analysis of the relationship between religion and gambling patterns in Las Vegas residents. *The Social Science Journal*, 37(3), 453-458.

Dong, R., Fisman, R., Wang, Y., and Xu, N., 2019. Air pollution, affect, and forecasting bias: Evidence from Chinese financial analysts. *Journal of Financial Economics*, forthcoming.

Eckel, C. C., and Grossman, P. J., 2008. Men, women and risk aversion: Experimental evidence. *Handbook of experimental economics results*, 1, 1061-1073.

Ederer, F., and Manso, G., 2011. Inventives for innovation: Bankruptcy, corporate governance, and compensation systems. *Handbook of Law, Innovation, and Growth*, 90-111.

EPA, 1999. Regulatory impact analysis for the final section 126 petition rule, Technical report, U.S. Environmental Protection Agency.

EPA, 2009. Nox budget trading program: 2008 highlights, Technical report, U.S. Environmental Protection Agency.

Evans, G. W., and Jacobs, S. V., 1981. Air pollution and human behavior. *Journal of Social Issues,* 37(1), 95-125.

Evans, G. W., Colome, S. D., and Shearer, D. F., 1988. Psychological reactions to air pollution. *Environmental Research*, 45(1), 1-15.

Fantuzzo, J. W., and Mohr, W. K., 1999. Prevalence and effects of child exposure to domestic violence. *The future of children*, 21-32.

Galea, S., Ahern, J., Resnick, H., Kilpatrick, D., Bucuvalas, M., Gold, J., and Vlahov, D., 2002. Psychological sequelae of the September 11 terrorist attacks in New York City. *New England Journal of Medicine*, 346(13), 982-987.

Graff Zivin, J., and Neidell, M., 2012. The impact of pollution on worker productivity. *American Economic Review*, 102(7), 3652-73.

Grossman, M., and Wood, W., 1993. Sex differences in intensity of emotional experience: a social role interpretation. *Journal of personality and social psychology*, 65(5), 1010.

Hall, B. H., and Ziedonis, R. H., 2001. The patent paradox revisited: an empirical study of patenting in the US semiconductor industry, 1979-1995. *RAND journal of economics*, 32, 101-128.

Hall, B. H., Jaffe, A. B., and Trajtenberg, M.,2001. The NBER patent citation data file: Lessons, insights and methodological tools, No. w8498. National Bureau of Economic Research.

Hall, B. H., Jaffe, A., and Trajtenberg, M., 2005. Market value and patent citations. *RAND journal of economics*, 36, 16-38.

Hartog, J., Ferrer-i-Carbonell, A., and Jonker, N., 2002. Linking measured risk aversion to individual characteristics. *Kyklos*, 55(1), 3-26.

He, J., and Tian, X., 2018. Finance and corporate innovation: A survey. *Asia‐Pacific Journal of Financial Studies*, 47(2), 165-212.

Henderson, R., and Cockburn, I., 1994. Measuring competence? Exploring firm effects in pharmaceutical research. *Strategic management journal*, 15(S1), 63-84.

Heyes, A., Neidell, M., and Saberian, S., 2016. The effect of air pollution on investor behavior: Evidence from the SandP 500, No. w22753. National Bureau of Economic Research.

Hilary, G., and Hui, K. W., 2009. Does religion matter in corporate decision making in America? *Journal of Financial Economics*, 93(3), 455-473.

Hirshleifer, D., Low, A., and Teoh, S. H., 2012. Are overconfident CEOs better innovators? *The Journal of Finance*, 67(4), 1457-1498.

Holt, S., Buckley, H., and Whelan, S., 2008. The impact of exposure to domestic violence on children and young people: A review of the literature. *Child abuse and neglect*, 32(8), 797-810.

Huang, J., Xu, N., and Yu, H., 2019. Pollution and performance: Do investors make worse trades on Hazy days? *Management Science*, forthcoming.

Johnson, E. J., and Tversky, A., 1983. Affect, generalization, and the perception of risk. *Journal of personality and social psychology*, 45(1), 20.

Jones, J. W., and Bogat, G. A., 1978. Air pollution and human aggression. *Psychological Reports*, 43(3), 721-722.

Kerr, W., and Nanda, R., 2015. Financing innovation. *Annual Review of Financial Economics*, 7, 445-462.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N., 2017. Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2), 665-712.

Kohlberg, L., 1984. Essays on moral development: Vol. 2. The psychology of moral development: Moral stages, their nature and validity.

Kring, A. M., and Gordon, A. H., 1998. Sex differences in emotion: expression, experience, and physiology. *Journal of personality and social psychology*, 74(3), 686.

Lepori, G. M., 2016. Air pollution and stock returns: Evidence from a natural experiment. *Journal of Empirical Finance*, 35, 25-42.

Levy, T., and Yagil, J., 2011. Air pollution and stock returns in the US. *Journal of Economic Psychology*, 32(3), 374-383.

Li, G.-C., Lai, R., D'Amour, A., Doolin, D. M., Sun, Y., Torvik, V. I., . . . Fleming, L., 2014. Disambiguation and co-authorship networks of the US patent inventor database, 1975–2010. *Research Policy*, 43(6), 941-955.

Li, J. J., Massa, M., Zhang, H., and Zhang, J., 2019. Air pollution, behavioral bias, and the disposition effect in China. *Journal of Financial Economics*, forthcoming.

Li, Q., and Peng, C. H., 2016. The stock market effect of air pollution: evidence from China. *Applied Economics*, 48(36), 3442-3461.

Linn, J., 2010. The effect of cap-and-trade programs on firms' profits: Evidence from the Nitrogen Oxides Budget Trading Program. *Journal of Environmental Economics and management*, 59(1), 1-14.

Maher, B. A., Ahmed, I. A., Karloukovski, V., MacLaren, D. A., Foulds, P. G., Allsop, D., ... and Calderon-Garciduenas, L., 2016. Magnetite pollution nanoparticles in the human brain. *Proceedings of the National Academy of Sciences*, 113(39), 10797-10801.

Manso, G., 2011. Motivating innovation. *The Journal of Finance*, 66(5), 1823-1860.

March, J. G., 1991. Exploration and exploitation in organizational learning. *Organization science*, 2(1), 71-87.

Mauzerall, D. L., Sultan, B., Kim, N., and Bradford, D. F., 2005. NOx emissions from large point sources: variability in ozone production, resulting health damages and economic costs. *Atmospheric Environment*, 39(16), 2851-2866.

McGuire, S., Newton, N., Omer, T., and Sharp, N., 2012. Does Local Religiosity Impact Corporate Social Responsibility? Unpublished working paper.

Mehta, P. H., Welker, K. M., Zilioli, S., and Carré, J. M., 2015. Testosterone and cortisol jointly modulate risk-taking. *Psychoneuroendocrinology*, 56, 88-99.

Miguelez, E., and Fink, C., 2013. Measuring the international mobility of inventors: A new database. World Intellectual Property Organization-Economics and Statistics Division.

Miller, A. S., 2000. Going to hell in Asia: The relationship between risk and religion in a cross cultural setting. *Review of Religious Research*, 5-18.

Mittal, V., and Ross Jr, W. T., 1998. The impact of positive and negative affect and issue framing on issue interpretation and risk taking. *Organizational behavior and human decision processes*, 76(3), 298-324.

Palmer, K. L., Burtraw, D., Bharvirkar, R., and Paul, A.,2001. Restructuring and the cost of reducing NOx emissions in electricity generation, , Resources for the Future Discussion Paper 01-10REV.

Platts Research and Consulting. 2003. “The NOx Challenge”.

Pope III, C. A., and Dockery, D. W., 2006. Health effects of fine particulate air pollution: lines that connect. *Journal of the air and waste management association*, 56(6), 709-742.

Powell, M., and Ansic, D., 1997. Gender differences in risk behaviour in financial decision-making: An experimental analysis. *Journal of economic psychology*, 18(6), 605-628.

Rokeach, M., 1968. Beliefs, attitudes and values: A theory of organization and change. San Francisco: Jossey-Bass.

Rosenblitt, J. C., Soler, H., Johnson, S. E., and Quadagno, D. M., 2001. Sensation seeking and hormones in men and women: exploring the link. *Hormones and behavior*, 40(3), 396-402.

Schuster, M. A., Stein, B. D., Jaycox, L. H., Collins, R. L., Marshall, G. N., Elliott, M. N., . . . Berry, S. H., 2001. A national survey of stress reactions after the September 11, 2001, terrorist attacks. *New England Journal of Medicine*, 345(20), 1507-1512.

Schwarz, N., and Clore, G. L., 1983. Mood, misattribution, and judgments of well-being: informative and directive functions of affective states. *Journal of personality and social psychology*, 45(3), 513.

Scobell, A., 2004. Terrorism in the Asia-Pacific: Threat and Response. Edited by ROHAN GUNARATNA. Singapore: Eastern Universities Press, 2003. xx, 259 pp. $39.00. *The Journal of Asian Studies*, 63(4), 1078-1079.

Seaton, A., Godden, D., MacNee, W., and Donaldson, K., 1995. Particulate air pollution and acute health effects. *The lancet*, 345(8943), 176-178.

Steinman, K. J., and Zimmerman, M. A., 2004. Religious activity and risk behavior among African American adolescents: Concurrent and developmental effects. *American journal of community psychology*, 33(3-4), 151-161.

Stevens, J. S., and Hamann, S., 2012. Sex differences in brain activation to emotional stimuli: a meta-analysis of neuroimaging studies. *Neuropsychologia*, 50(7), 1578-1593.

Tajfel, H., 1981. Human groups and social categories: Studies in social psychology. CUP Archive.

Terpstra, D. E., Rozell, E. J., and Robinson, R. K., 1993. The influence of personality and demographic variables on ethical decisions related to insider trading. *The Journal of Psychology*, 127(4), 375-389.

Trajtenberg, M., Henderson, R., and Jaffe, A., 1997. University versus corporate patents: A window on the basicness of invention. *Economics of Innovation and new technology*, *5*(1), 19-50.

Vincenty, T., 1975. Direct and inverse solutions of geodesics on the ellipsoid with application of nested equations. *Survey review*, 23(176), 88-93.

Wang, A. Y., and Young, M., 2019. Terrorist attacks and investor risk preference: Evidence from mutual fund flows. *Journal of Financial Economics*, Forthcoming.