Environmental Dynamics and Interactions with Innovation

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for the Degree of Doctor of Philosophy

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Declaration

I certify that the thesis I have presented for examination for the MPhil/PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others.

This thesis consists of approximately 33,000 words (excl. notes, references, figures, tables and appendices).

Statement of co-authored work

I confirm that Chapters 1 and 2 are my own work.

I confirm that Chapter 3 was jointly co-authored with Eugenie Dugoua and Sefi Roth. I contributed 70% to the work presented in this chapter.

I confirm that Chapter 4 was jointly co-authored with Eugenie Dugoua and Sefi Roth. I contributed 33.3% to the work presented in this chapter.

Abstract

Throughout history, environmental dynamics and risks have both necessitated and inspired innovation. In this thesis I explore the interaction between the environment and innovation in four standalone chapters. The first two chapters examine environmental dynamics in the context of climate change adaptation, while the latter two chapters explore how environmental factors can influence inventor productivity. Specifically, in Chapter 1, I examine how flooding affects the development of flood adaptation innovation. Using county-level data from the United States, I focus particularly on the local effect of flooding. Chapter 2 presents a departure from the empirical research methods and explores how climate uncertainty affects the decision-making of inventors for climate adaptation innovation using a real option valuation approach. In Chapters 3 and 4, I focus on exploring environmental factors as possible negative stimulants for innovation. Tracking inventors' patenting output over time, Chapter 3 empirically examines the influence of temperature variations on inventor productivity, while Chapter 4 explores the impact of air pollution. The findings of this thesis suggest that various environmental factors, particularly amid the growing threat of climate change, continue to shape the development of innovations today.

Acknowledgements

I begin by expressing my gratitude to my supervisors: Eugenie Dugoua, Marion Dumas and Sefi Roth. This PhD has largely been shaped by their guidance, support and mentorship. I am especially grateful to Eugenie Dugoua for the pivotal role she played throughout this journey. I thank them all for their constructive feedback and valuable advice over the years. I would also like to express thanks to Frank Venmans for his encouragement, humour and calming presence which provided steady support during challenging times. Similarly, I am deeply indebted to Leanne Cass for being a voice of reason, for patiently listening to my concerns and for sharing invaluable practical guidance. I am also very grateful for the support and friendship that I have experienced through my PhD colleagues, with special thanks to Sarah Elven who has been on this journey with me from the beginning.

I thank the London School of Economics and Grantham Research Institute for providing the unique academic environment for my studies. My deepest gratitude goes to the Grantham Research Institute for the financial support that has allowed me to pursue this PhD.

I dedicate this thesis to my family and friends. I thank them for their unconditional support, the welcome distractions they provided, and their ability to keep me grounded. Their steadfast encouragements have helped me navigate challenges and I cannot fully express how fortunate I feel to be surrounded by them.

Contents

List of Figures

List of Tables

Introduction

Nature is the essence of human existence. It provides the air we breathe, the food we eat, and other resources necessary to sustain life on Earth. However, as much as nature is vital to humanity, it also gives rise to threats including dangerous wildlife, extreme weather events and disease. For millennia, innovation has enabled us to overcome these risks and advance as a species. From the control of fire to ward off animal predators to the development of housing for shelter and vaccines to combat disease, innovation has continuously shaped our development. At the same time, technological progress has also inflicted damage on the environment, contributing to issues such as air pollution, ozone depletion and most significantly anthropogenic climate change. Yet, just as innovation has contributed to these issues, it has also been key in addressing them. Technological advancements cut car emissions by over 95% in the latter half of the 20th Century (Mondt 2000), while innovations following the Montreal Protocol reduced chlorofluorocarbons by 80% (Dugoua 2023). Recently, a surge in innovation for clean energy, electric transportation and emerging technologies like carbon capture and storage among others have significantly helped curb the growth of greenhouse gas emissions. Aside from environmental risks shaping the need for innovation, natural processes frequently serve as inspiration. For example, the invention of Velcro drew inspiration from burrs sticking to animal fur while birds' flight patterns influenced the design of airplane wings. Though the pursuit of knowledge is intrinsic to human nature, history suggests that the environment has and continues to have a significant influence on the dynamics of innovation.

This thesis lies at the intersection of innovation and the environment. I explore how environmental dynamics influence innovation, acting both as a driver and impediment. Specifically, I focus on the development of innovation and inventors as decision-making agents. In the first two chapters I examine innovation dynamics in the context of climate adaptation, while in the latter two chapters, I analyse the effect of environmental factors on inventor productivity.

I begin my study in Chapter 1, by examining to what extent local experiences of flooding influence the development of flood adaptation innovation. Flooding is the most frequent mass natural disaster today and climate change is expected to further amplify the magnitude and frequency of flood events over time. Using a novel dataset of flood adaptation patents from the United States between 2007 and 2020, I find that one additional flood episode in a county leads to an increase of 9.4% in flood-related patents filed by resident inventors the following year. I find that geographic proximity to the shock is important and provide some tentative evidence that flood insurance may moderate the effect. The results indicate that, to a certain degree, progress in flood-related innovation is driven by inventors' local experiences of flooding and points towards an incidental development of adaptation innovation rather than a coordinated effort.

In Chapter 2, I present a theoretical model that examines the role of climate uncertainty in the development of climate adaptation innovation. Specifically, I employ a real option valuation approach to analyse the effect of uncertainty on the decision-making of inventors. I find that the uncertainty surrounding climate outcomes and the possibility of rare and extreme climate disasters raise the investment threshold for inventors. The prospects of future breakthroughs in climate science further complicate the investment decisions, and, in some cases, contribute to additional delays. The analysis suggests that the highly stochastic and dynamic nature of the market for climate adaptation presents a unique environment for inventors and may, to some extent, explain the slow growth we have observed so far. Inventors' subjective expectations play a crucial role, and government policy requires careful consideration as the mere anticipation of future government action may, in some cases, further delay investment.

In Chapter 3, co-authored with colleagues, we analyse the effect of temperature on inventor productivity. Increasing evidence shows detrimental impacts of higher temperatures on the labour market. However, temperature fluctuations are likely to have varying impacts across the workforce due to differences in work environments, tasks, and adaptive capacity. In this paper, we explore the impacts of temperatures on inventor productivity as a group of high-skilled workers who not only contribute significantly to a country's wealth but also play a critical role in economic growth. Using inventor-level data from the United States from 2000 to 2020, we find that higher temperatures have a negative and significant impact on patenting output. Specifically, we find that one additional day above 20°C in the past three years, reduces the number of patent applications filed by the inventor by 0.12% today. Temperatures seem to impact labour productivity not only in the short-term but also in the longer-term cumulative output processes that define innovation. Our results further suggest that the results are driven by California and wide-spread air conditioning mitigates the effect, albeit not eliminating it.

Finally, in Chapter 4, co-authored with colleagues, we focus on the role of air pollution on inventor productivity. This chapter builds on a well-established literature documenting a wide range of health and productivity outcomes linked to air pollution. For identification, we employ an inventor fixed effects model and an instrumental variable (IV) approach that leverages the 2005 PM2.5 National Ambient Air Quality Standards (NAAQS) nonattainment designations as a plausible exogenous shock to pollution levels. Using both fixed-effects and IV approaches, we find that air pollution significantly hinders innovation. Specifically, our fixed-effects estimates indicate that one standard deviation increase in PM2.5 over the preceding three years reduces inventor productivity by 4.1%, while our IV estimates suggest that $1\mu g/m^3$ increase in PM2.5 decreases patent output by 9.8%. Given the important role of inventors for economic growth, this highlights an additional cost of air pollution that has yet to be accounted for in policy discussions.

While each chapter details its specific contributions, it is worth highlighting the two overarching contributions of this thesis here. The first primary contribution is to the literature on innovation for climate adaptation. While ever-increasing evidence of climate impacts has fuelled a surge in research on climate mitigation innovation, studies on climate adaptation innovation remain strikingly sparse. This is despite the opportunities that technological advancements offer to navigate the many challenges of adaptation, including social and economic ties, pre-existing built environments, and high costs, and the limited growth of these innovations that has been observed over time.

The second overarching contribution is to the literature on environmental influences on labour outcomes. Previous studies have largely overlooked inventors, assuming that their higher propensity to work indoors shields them from environmental factors. However, this assumption has not been tested, and our results indicate that this is not the case. Given that many individuals in high-income countries work indoors in high-skilled professions with long-term output processes, our findings highlight the vulnerability of workers whose profiles align closely with a significant part of the modern workforce.

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Chapter 1

Local Flood Exposure and Flood Adaptation Innovation

1.1 Introduction

While considerable strides have been made in addressing climate change, there is a consensus among scientists that human-induced climate change is already underway. Global surface temperatures from 2011 to 2020 were 1.09 degrees Celsius above pre-industrial levels (IPCC 2023a) and since 1993, global sea levels have increased by around 10 centimetres, averaging 3.4 millimetres per year (NOAA National Centers for Environmental Information 2022). In fact, some researchers have estimated that even if we stopped emitting carbon dioxide today it would take around 1,000 years to fully reverse the impact on climate change due to the longevity of carbon dioxide concentration in the atmosphere (Solomon et al. 2009).

Increased risk of flooding is one of the many consequences associated with climate change, directly through sea level rise and indirectly through water cycle disruptions. Increased global temperatures lead to a greater moisture capacity in the atmosphere, which in turn causes more frequent and intense storms and heavy rainfall, along with changes in the precipitation patterns (IPCC 2023a). Not only is the risk of flooding estimated to increase over time (IPCC 2023b), but it will build on what is already a global threat. Between 1990 and 2023, floods accounted for 22% of mass disasters, representing a higher proportion than any other type of natural disaster (EM-DAT 2023). 23% of the world population is already directly exposed to 1-in-100 year floods (Rentschler, Salhab, and Jafino 2022), and the financial costs are significant. In 2021 alone, flood disasters caused an estimated $82 bn in damages which is a conservative estimate since smaller flood events were excluded from these calculations (Bevere and Remondi 2022).

Effective adaptation to flooding is therefore both a necessity today and continues to grow in importance. However, the availability of adaptive strategies for flooding and other climate impacts is increasingly limited by pre-existing built environments, social constraints, economics ties and financial costs. Technological innovations offer an opportunity to address these challenges and, according to induced innovation theory, should see increased development as climate change impacts become more salient over time. However, in stark contrast to mitigation, the share of patents dedicated to climate adaptation technologies, including flooding, has not seen any significant increase from 1995 to 2015 (Dechezlepretre et al. 2020).

In this paper I examine, the role of weathers shocks in the development of climate adaptation innovation, focusing on flooding as an increasingly prominent and damaging threat. Specifically, I analyse to what extent local flooding influence the decision-making of resident inventors with respect to flood-related patenting. An innovation response may point to the importance of risk updating and/ or experience-based learning of inventors in climate adaptation innovation and may help partly account for the slow progress we have observed so far.

Empirically, I estimate the effect of flooding on flood adaptation innovation using a county-level fixed-effects model with data from the United States from 2007 to 2020. To overcome key data challenges, I develop a novel dataset of flood-related innovations that mitigates biases from automatic patent tagging systems. Furthermore, rather than relying on the commonly used EM-DAT database or remote sensing data, I use NOAA's Storm Events Database to capture smaller-scale flood events more comprehensively. The sub-national approach allows me to focus on the locality of flooding while omitting biases from differential patenting systems.

The results suggest that one additional flood episode in a county leads to a 9.4% increase in flood-related patent applications by resident inventors the following year. A large proportion of patents are applied for by individuals who only file for a flood-related patent once and receive no government funding. Geographic proximity to the shock seems important with flood episodes in neighbouring counties having a smaller yet positive effect on inventor activity, while episodes in the rest of the state and socially connected counties seem irrelevant. The results indicate that, to a certain degree, progress in flood-related innovation is driven by inventors' local experiences of flooding and points towards an incidental development of adaptation innovation rather than a coordinated effort.

I choose the United States for this analysis for three key reasons. Firstly, the United States has a high exposure to flooding. According to the U.S. Departmnet of Homeland Security (2024), 90%

of natural disasters in the United States include flooding. There is at least one flood event on 8 out of 10 days throughout the year (Tompkins and Watts 2022) and annual average flood losses are significant, estimated to be around $32.1 bn (Wing et al. 2022). Moreover, it is predicted that flood risk will rise by 26% in 2050, making it a dynamic and increasing threat for the United States (Wing et al. 2022). Secondly, the United States is a leader in technological innovation. It ranks second in the world in patenting activity and first in the economic value of patents which is estimated to be around $3 trillion (Toole, Miller, and Rada 2019). It also ranks first in the world high-value adaptation innovations (Dechezlepretre et al. 2020) and has a history of successful adaptation technologies, such as residential air conditioning to protect against heat (Barreca et al. 2016). Finally, the United States is unique in its universal availability of flood insurance, an important adaptive strategy that needs consideration in this context. Compared to the often fragmented markets in other countries, flood insurance in the United States is predominantly provided through the National Flood Insurance Program (NFIP), offering a comprehensive and reliable source of data.

The contributions of this study are fourfold. First and foremost, I contribute to the very sparse literature on the supply of innovation for climate adaptation. Though directly linked by the issue of climate change, the economic characteristics of mitigation and adaptation innovations differ. Whereas the benefits of mitigation innovations are a global public good, the benefits of adaptation innovations are often private or a mixture of public and private benefits. At the same time, adaptation innovations also differ from conventional innovations due to the unpredictable nature of their benefits which are tied to the considerable uncertainty of climate change impacts. Thus, the dynamics of climate adaptation innovations warrant an analysis in their own right. Though researchers have examined aspects of adaptation innovation such as efficiency of adaptation technology portfolios (Berrang-Ford et al. 2019) and barriers to technological adoption (Prince et al. 2013; Tambo and Abdoulaye 2012; Darkwa et al. 2016), very few have explored the dynamics of their development. In an early study Chhetri and Easterling (2010) find evidence that weather shocks are associated with increased innovations in rice-farming in Nepal in the early 2000s, but are limited to correlational results due to data short-comings. Miao and Popp (2014) builds on this and examine the effect of floods, droughts, and earthquakes on the developments of adaptation patents across countries. They find that floods have the most pronounced positive and long-term impact on adaptation innovation and attribute this to disaster-induced risk-updating which results in demand-pull innovation. However, the authors are unable to provide empirical evidence of the underlying mechanism due to the lack of the granularity in country-level analyses. More recently, in a study of the agricultural sector in the US, Miao (2020) finds that crop exposure to drought is associated with increases in crop innovation and that the prevalence of crop insurance mitigates this effect. By focusing on the local exposure of inventors, this paper contributes to the literature by analysing the importance of proximity to the shock in greater detail, presenting a conceptual framework that outlines mechanisms beyond demand-pull innovation, and providing an analysis specific to flooding as an increasingly damaging threat.

The second contribution of this paper it to the literature on protection motivation theory in environmental research. In the presence of a threat, protection motivation theory suggests that individual decision-making is based on threat appraisal and coping appraisal. The former consists of expectations regarding the magnitude and probability of a threat while the latter evaluates the efficacy of the available protective measures (Rogers 1975). In the context of climate adaptation, research has shown that exposure and subjective experiences of extreme weather events are positively correlated with climate risk-perception, i.e. threat appraisal (Marlon et al. 2019; Poudyal et al. 2021). In turn, increases in risk-perceptions have been found to positively correlate with adaptive behaviour (Valkengoed and Steg 2019), suggesting that protection motivation may be underlying the observed increases in adaptation demand in response to extreme weather events (McFadden, Smith, and Wallander 2022; Zaalberg et al. 2009; Grothmann and Reusswig 2006; Tasantab, Gajendran, and Maund 2022; Kreibich et al. 2005). In this paper, I extent the application of protection motivation theory to the inventor and the supply of climate adaptation rather than demand, presenting a conceptual framework that explores its potential role as a driver for the development of adaptation innovation in response to environmental shocks.

Thirdly, I contribute to the literature on the motivation of inventors. To understand what drives innovation, external factors such as organizational structures (Tushman and O'Reilly 1996), government policies, regulation and the uncertainty thereof (Porter and Van der Linde 1995; Noailly, Nowzohour, and Van Den Heuvel 2022), institutional setting (Nelson 1993) and market demand (Di Stefano, Gambardella, and Verona 2012) have all proven to play an important role. In addition, the motivation of the inventors themselves seems to influence the development of innovations. Inventors possess a deep amount of expertise and skills that often afford them considerable autonomy, even when working within larger organizations. In this context, the literature typically distinguishes between inventors' intrinsic and extrinsic motivation. While intrinsic motivation includes curiosity, passion and an inherent interest in solving difficult problems (Singh and Fleming 2010; Owan and Nagaoka 2011), extrinsic motivation relates to economic incentives, financial rewards, and professional recognition (Scherer and Harhoff 2000; Azoulay, Ding, and Stuart 2007; Dugoua and Gerarden 2023). I contribute to this literature by exploring environmental shocks as an additional determinant of inventors' motivation. I focus on the impact of flooding on inventors' decisions to develop flood adaptation solutions, thus the type of innovation produced in response to flooding rather than overall productivity effects.

Finally, this paper contributes by constructing a novel dataset on flood-related patents. Limited previous research has largely relied on the Cooperative Patent Classification Y02A – 'Technologies for Adaptation to Climate Change' to identify climate adaptation patents. Introduced in 2018, this classification also includes the subgroup Y02A 10/30 'Flood prevention; Flood or storm water management, e.g. using flood barriers'. However, because patents are indexed without a formal disclosure of the tagging mechanism, a simple word search reveals that many relevant patents remain undetected, yielding only 69 unique flood-related patents filed by inventors in the United States between 2007 and 2020. Furthermore, there seem to be clear instances of oversight and inaccurate tagging, such as the inclusion of patents unrelated to flood protection but associated with the term "overflow", resulting in misclassification of 20 patents related to toilet technologies. I develop a new classification approach based on a dictionary search, identifying 475 unique flood-related patents. I manually review and verify this more comprehensive universe of flood-related patents using the abstracts. Not only does this dataset underpin the analysis presented in this paper but it also offers valuable insights into the landscape of flood adaptation innovation and highlights the important shortcomings in the current use of the Y02A tagging. Moreover, it has the potential to be used in future analyses, contribute to the development of more advanced patent identification methods, or verify previous findings.

1.2 Conceptual Framework

I stipulate that inventors are decision-making agents in the supply of flood adaptation innovation. As such, they have a certain degree of agency in determining the level and direction of innovation. To some or full extent, they may decide if, when, and how much innovation to produce. Over time, inventors are exposed to varying degrees of flooding. Directly, this may include a flooded home or a closed road on their commute, or indirectly damages incurred by friends or family. This flood exposure may influence the inventors' decision-making with respect to flood adaptation innovation, either by shaping their expectations of future flooding leading to profit-motivated or protection-motivated innovation, or by inducing innovation through experience-based learning.

Under the first mechanism, flooding influences how inventors perceive the likelihood and severity of future flooding. Ex-ante inventors hold expectations regarding the magnitude of flooding they will be exposed to, directly or indirectly. This is built on an information set which among other factors include past occurrences of flooding. When a flood episode unfolds, its occurrence and impact either align with expectations or are unexpected. If they align, there are no updates to the information set and expectations of future flooding remain unchanged. However, if flooding occurs unexpectedly, inventors revise their information sets with this new information, leading to an adjustment of their expectations of future flooding which in turn may lead to profit-motivated or protection-motivated innovation for flood adaptation.

Under profit motivation, this increase in the expectation of future flooding may lead to higher anticipated demand for flood protection and flood adaptation innovation. Thus, flooding results in demand-pull and profit-motivated development of adaptation innovation. On the other hand, protection motivation theory suggests that inventors may be motivated by a desire to safeguard themselves against future flooding. In this case, inventors are driven by a personal desire for protection rather than economic incentives. Increased expectations of future flooding raise the threat appraisal and thus motivate inventors to engage in more flood adaptation innovation. This is conditional on a non-binding coping appraisal; that is, inventors are not constrained by their abilities and believe in the effectiveness of their adaptive solutions to mitigate future flooding.

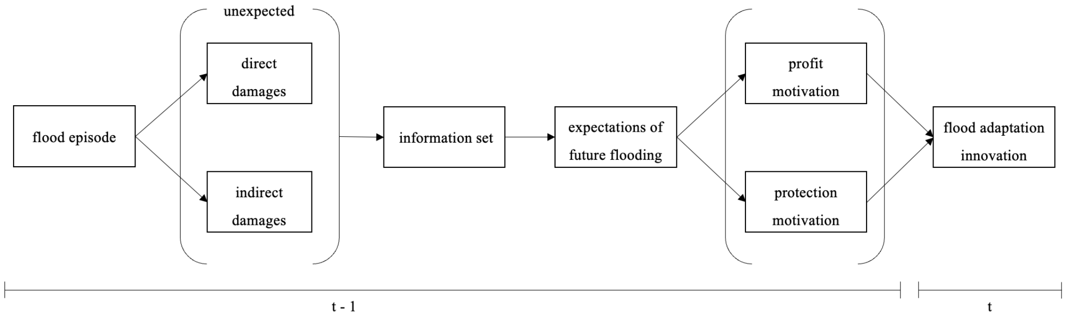


FIGURE 1.1: Illustration - expectation updating

Flood insurance in this context may have a moderating effect on this relationship. Flood insurance, which partially or fully compensates flood damages, may limit risk-updating of the inventor. Albeit that only financial damages can be insured, flood insurance may stimulate the magnitude of the increase in expectation after a flood episode leading to a weakening of profit- or protection-motivated innovation. It is also worth noting that flood insurance itself may have a causal effect on flood-related patenting. For example, flood insurance may increase awareness of flooding and thereby provide a more accurate information set about future flooding. Similarly, insurance premiums and requirements are based on flood maps along with flood elevation levels and flood adaptation innovation may be spurred by a desire to alter these.

Aside from updated expectation, the second mechanism that may underlie the relationship between flooding and flood adaptation innovation builds on the idea that repeated exposure to flooding may allow inventors to learn from their experiences. When an inventor experiences local

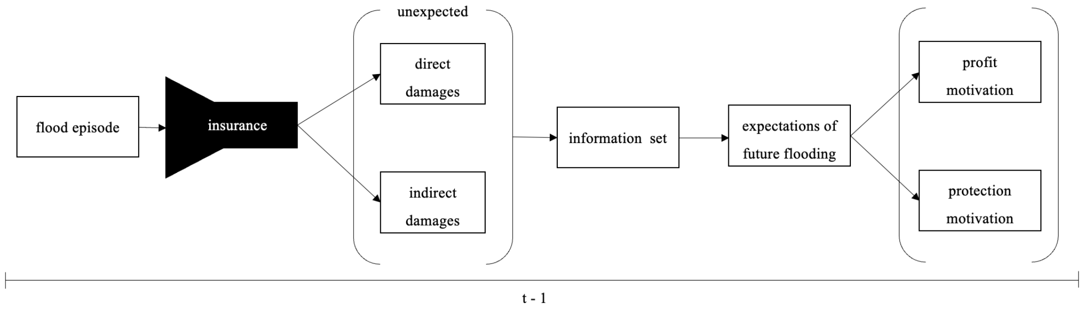


FIGURE 1.2: Illustration - insurance moderation

flooding, the variety of challenges associated with flooding and the effectiveness of protective solutions may become more salient. Similarly, local flooding may also highlight challenges specific to the local environment and the need for location-specific solutions. This iterative learning process may equip the inventors to develop more effective solutions, enabling better protection for themselves or others against future flooding and leading to increased development of flood adaptation innovation. Under this mechanism, the impact of flood adaptation innovation is driven by supply dynamics through inventors' experience-based learning.

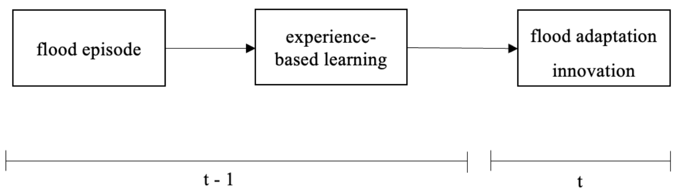


FIGURE 1.3: Illustration - experience-based learning

1.3 Data

1.3.1 Patents

To measure innovation in flood adaptation, I download data on patent applications from the U.S. Patent and Trademark Office (USPTO) via PatentsView from 2007 to 2020. The downloaded data files capture all applications submitted to the USPTO, including those for which patents were never granted, ensuring a comprehensive measure of formal innovative activity. Given the major shortcomings of the Y02A patent classification for flood adaptation patents, I employ my own dictionary search of patent abstracts and titles to identify patents related to flood prevention and mitigation[1]. The term ‘flood’ is used across a variety of disciplines which are often irrelevant in this context such as flooding of computer servers with requests or flooded reactions in chemistry. To address this issue, I focus solely on CPC section E – ’Fixed Constructions’, excluding class E21 (’Earth or Rock Drilling; Mining’) and E99 (’Subject Matter Not Otherwise Provided For In This Section’) to ensure relevance. As a result, I exclude patents rooted in more science-intensive domains, such as flood forecasting systems, from the main analysis. To check for robustness, I also download patent data related to flood forecasting systems using the imperfect Y02A classifications 10/40 (’Controlling or monitoring, e.g., of flood or hurricane; Forecasting, e.g., risk assessment or mapping’) and 90/10 (’Information and communication technologies [ICT] supporting adaptation to climate change, e.g., for weather forecasting or climate simulation’). I filter these patents using the same dictionary-based search criteria as before to identify those specifically related to flooding. However, due to the lack of clear guidance on the tagging system of Y02A patents as discussed previously, I cannot confidently assert that this dataset provides an unbiased measure of flood forecasting technologies. To ensure consistency, for the main analysis, I therefore focus on my restricted dataset of innovation for flood adaptation in fixed constructions. Nonetheless, I present the results of the main analysis including the forecasting technologies identified through the Y02A classification in the robustness check.

To identify inventors resident in the United States, I use the home address of the inventors listed on the patents. In some cases, new patent applications are filed as new claims are added. However, the patent applications in these cases still cover the same technical content, thus can be considered a singular innovation. I consolidate similar cases, retaining just one record for each unique abstract.

To construct the outcome variable, I aggregate flood-related patent applications by county using the home location of the inventor and identify the year of innovation as the first filing date

[1] See Appendix 1.A.1 for more details.

associated with the application. If a patent application lists multiple inventors, I attribute the patent application separately to each inventor. In addition to the absolute count of flood-related patent applications, I also calculate flood-related patent applications as a share of the total number of patent applications filed in CPC section ’E’.

In total, I identify 475 unique patent applications related to flood adaptation filed by 531 inventors resident in 223 counties in the contiguous United States from 2007 to 2020. The absolute number of patent applications for flood related patents seems to increase slightly over the period but there is notable variation from year to year (Figure 1.4). The number of flood-related patents as a share of other innovations in CPC section ’E’, seems to stay relatively flat over the period (Figure 1.5), aligning with the findings of overall adaptation innovation growth by Dechezlepretre et al. (2020).

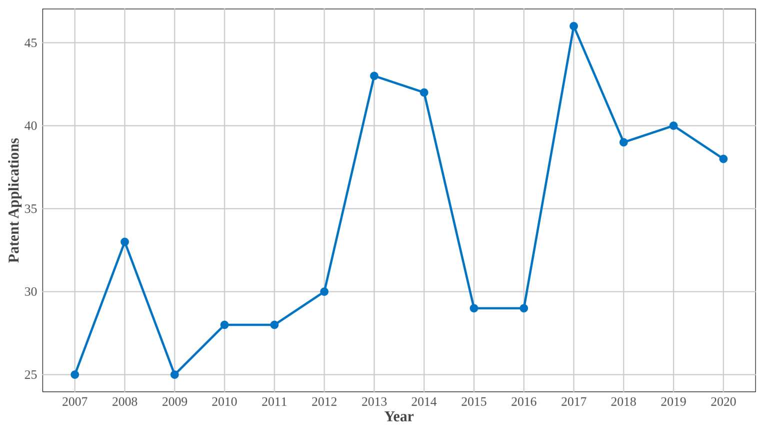


FIGURE 1.4: Flood-related patent applications per year

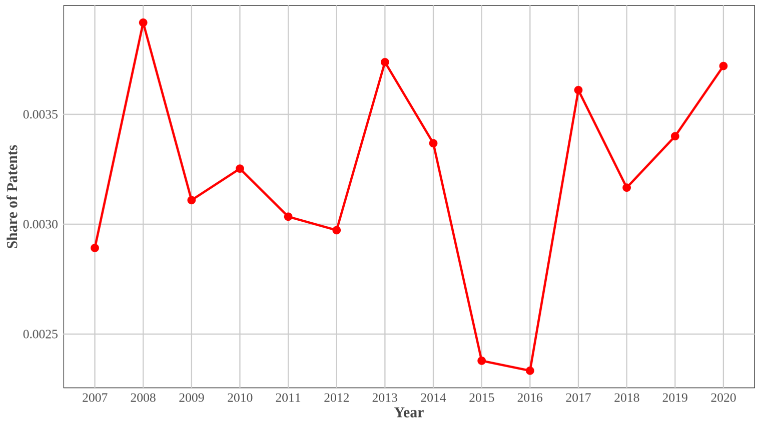


FIGURE 1.5: Share of flood-related patent applications per year

At closer inspection of the inventors, I find that 49% of inventors submitted their patent application independently, without listing an assignee[2]. This sharply contrasts with the average of 27% for CPC section 'E' during the same period and suggests that the decision making of individuals in flood patenting may play a larger role. Regarding the remaining inventors, 47% list a U.S. company as the assignee, while a minor segment, 4%, involve foreign companies. It is also worth noting that, aside from one application which listed the U.S. EPA, none of the patent applications list government interest which means that the innovation did not involve funding through government research grants or contracts. This poses an interesting question in itself and stands in contrast to the findings by Hötte and Jee (2022) who suggest that government funding for adaptation innovations is around 10% higher than average using the CPC Y02A classification.

23% of inventors filed only one patent in total over the whole period. Moreover, a large majority of inventors (75%) seem to be one-off inventors in flooding, filing for only one flood-related patent between 2007 and 2020. This is suggestive of an isolated catalytic event triggering innovation rather than a life-long commitment to patenting for flood adaptation.

[2] In this context, the assignee is a legal entity such as a firm, foundation or other partnership that holds the right to a patent rather than the inventor.

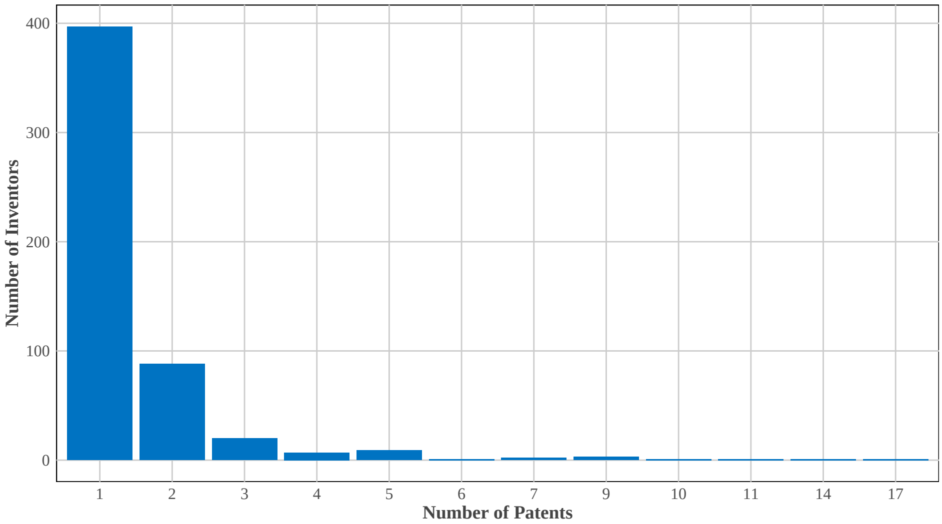


FIGURE 1.6: Number of inventors by number of patents

Finally, the mapping of inventors' home locations shows a strong association with proximity to water. Inventors are largely clustered in the coastal area of the North-East, Florida, Texas, California and Washington, while landlocked inventors are predominantly located near large rivers or other bodies of water such as Lake Michigan. Certainly, inventor locations also seem to be associated with larger cities which are often located near water but the proximity to water is noteworthy.

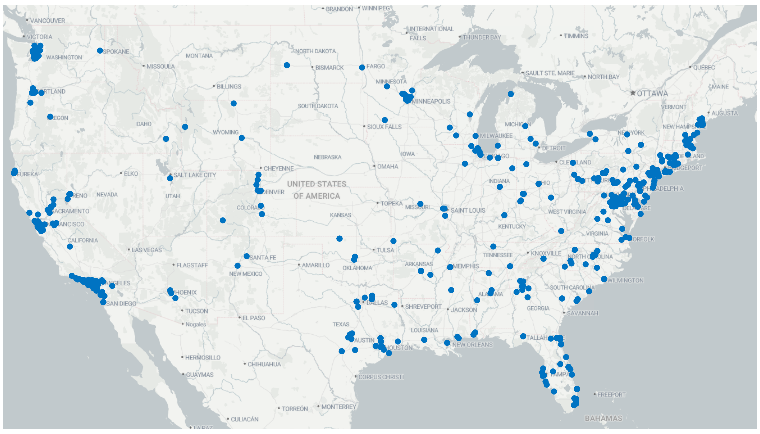


FIGURE 1.7: Inventor locations

In the case of patents with assignees, the location of the assignees closely relates to the location of the inventors (Figure 1.8), with assignees predominantly located in the same state as the inventor but not in the same county (Figure 1.A.2).

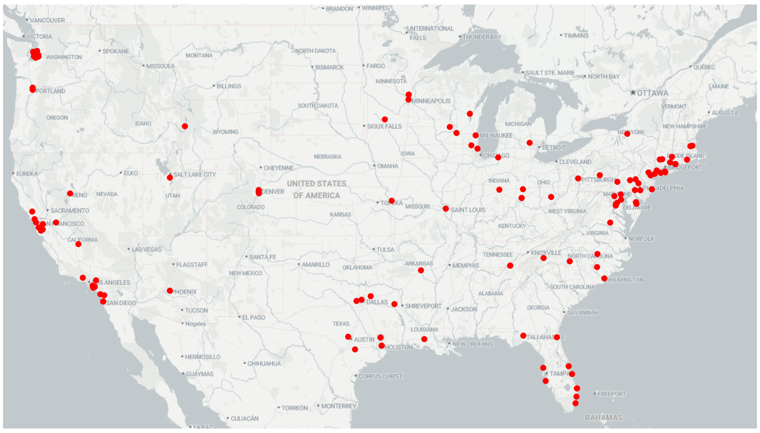


FIGURE 1.8: Assignee locations

1.3.2 Flooding

To measure exposure to flooding, I download data from the Storm Event Database, a comprehensive repository of weather and climate-related events in the United States maintained by NOAA National Centers for Environmental Information. Data is freely available from 1950 to 2023, and I download the Storm Event Details files for each year from 2007 until 2020. I disregard data pre-2007 to avoid data bias resulting from changes in the reporting systems in 2006. Sources for the database include among others: weather reports from the National Weather Service (NWS), law enforcement agencies, emergency management agencies and trained storm spotters. Due to the wide range of sources this database provides a more comprehensive record of flood events including smaller ones which remote sensing data is unable to detect due to cloud coverage and urban built environments. Each reported event is assigned an event and episode identification number. Multiple storm events, such as a flooded road, can be contained within a storm episode and I filter for episodes classified as “Coastal Flood”, “Flash Flood”, “Flood”, “Lakeshore Flood”, “Storm Surge/Tide”, “Heavy Rain”, “Hurricane (Typhoon)”, “Seiche”, “Tsunami” or “Tropical Depression”. The database also provides information on injury, fatality and damages for each event. However, property damages are not always official amounts but can also be estimates made by the reporting source, thus should be viewed with caution. For the main specifications I determine flood exposure by calculating number of flood episodes by county and year. If an episode spreads across different counties, I count it separately in each affected county.

From 2007 to 2020, 25,199 unique flood episodes were reported in the contiguous United States with 99% of counties (3079 out of 3109) affected. The average number of episodes per year was 1,798 with Figure 1.9 showing the inter-year variation over the period. Counties with flood-related patenting during the period experienced an average of 2.63 flood episodes per year compared to a lower average of 1.31 for counties without flood-related patenting. In the year before a county recorded a flood-related patent application filed by a resident inventor, the number of flood episodes in the county was higher with an average of 3.21, suggesting that flood-related patenting was preceded by increases in flood exposure. The total number of direct and indirect deaths over the whole period was 1,449 with Harris and Galveston County in Texas recording the most deaths, followed by Richmond County in New York. This correlates with impact areas of major Hurricanes Ike and Harvey in Texas in 2008 and 2017 and Hurricane Sandy in the coastal north east in 2012.

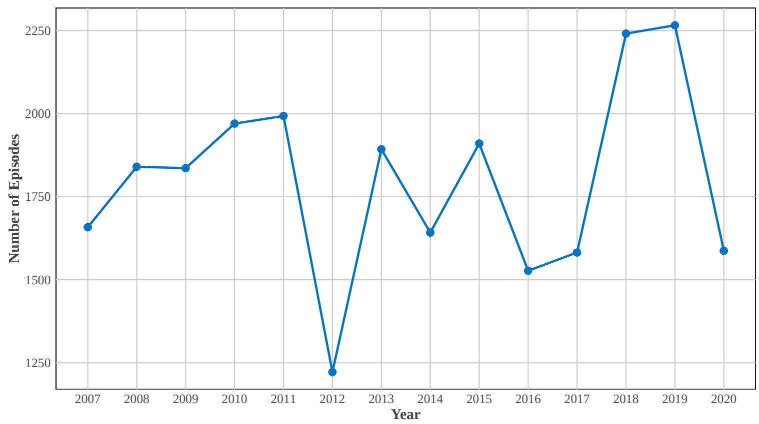


FIGURE 1.9: Flood episodes by year

In Figure 1.10, I plot the number of episodes by type. The overwhelmingly dominant type of episodes are flash floods and floods, making up 96% of all episodes. However, it is important to note that classification is nuanced and not always straightforward. Many episodes associated with larger weather phenomena such as hurricanes are more generally classified as floods, making further heterogeneity analysis of by type of flood exposure difficult.

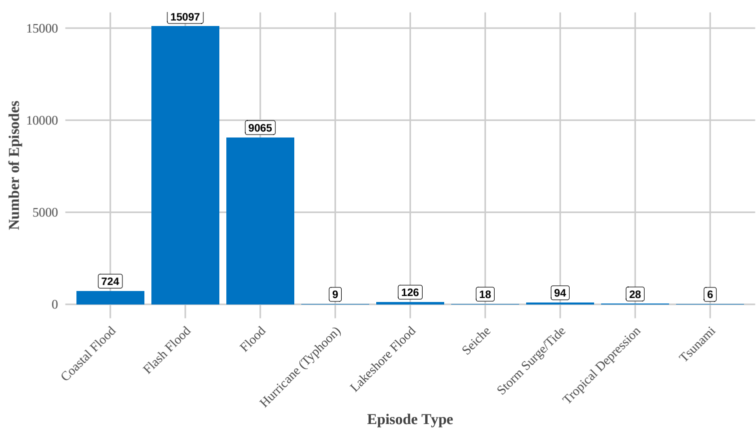


FIGURE 1.10: Flood episodes by type

Finally, I examine the spatial distribution of flood exposure. I merge annual county population estimates from the U.S. Census Bureau since it is not merely the occurrence of flooding that matters but its intersection with populated areas. A visualization of population-adjusted flood impact is shown in a bivariate map in Figure 1.11. The map shows the annual average number of flood episodes and annual average population from 2007 to 2020. Sizeable areas with high population and high flood exposure include the north east, Florida, Southern California and Arizona, and coincide noticeably with flood inventor locations. Flood inventor hubs around Seattle, Chicago and Houston equally show high correspondence of flood exposure and population. The counties with the highest coincidence of flood episodes and population are Cook County in Illinois, Los Angeles County and San Bernadino County in California, Miami-Dade County in Florida and Harris County in Texas.

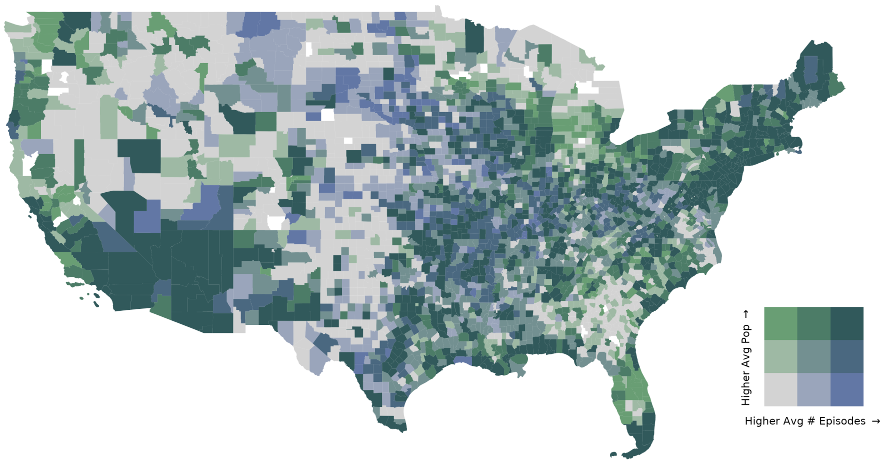


FIGURE 1.11: Average annual flood episodes and population 2007 - 2020

1.3.3 Flood Insurance

To account for the presence of flood insurance I download the ‘FIMA NFIP Redacted Policies – v2’ dataset which is freely available from the Federal Emergency Management Agency (FEMA). This dataset encompasses all flood insurance policy transactions under the National Flood Insurance Program (NFIP) which covers 96% of all flood insurance in the United States. Flood insurance policies provide coverage for buildings and contents rather than the individual per se and are limited to one dwelling per policy. In other words, a person who wishes to insure two homes will have to buy two separate policies. The redacted policy dataset lists every flood insurance policy purchased during the period, including comprehensive information about the insured buildings and contents, while omitting any information related to the buyer. Under the NFIP, any individual may purchase flood insurance as long as the dwelling to be insured is within the boundary of a participating community[3]. As of 2022, FEMA recognizes 24,774 communities of which 91% participate in the NFIP with the large majority joining in the 1970s and 1980s. To participate a community has to adopt a floodplain ordinance which meets the minimum NFIP floodplain management standards based on FEMAs flood risk mapping of the area. Until 2021, the cost of insurance, i.e. the premium, was determined by Flood Insurance Maps (FIRMs) which designated geographic areas into different zones depending on their flood risk. Flood insurance policies typically have a term length of one year after which policyholders may choose to terminate or renew their coverage. I use the ’policyEffectiveDate’ and the ’policyTerminationDate’ to determine the exact start and end date of insurance coverage for each policy. For the final insurance variable, I aggregate the number of active policies by county and year and divide them by the total estimated housing stock using annual data from the U.S. Census Bureau. The final insurance variable thus describes the proportion of homes covered by flood insurance in a given county and year.

The total number of active flood insurance policies rose from 2.7 million to 3.5 million between

[3] Communities in this context are political entities, such as cities, towns, townships, Indian tribes or authorized tribal organization which have the authority to adopt and enforce floodplain ordinances including rules and regulation regarding building standards and land use in flood risk zones.

2007 and 2020. This represents an increase in the proportion of homes covered by flood insurance from 2% to 2.6%, suggesting a modest upward trend but low flood insurance penetration overall. There is very limited inter-year variation but significant geographic variation which seems to correlate with exposure to hurricanes. For example, Louisiana which was majorly affected by Hurricane Katrina in 2005 has the highest flood insurance penetration with 15.7% followed by Florida, South Carolina and Texas.

1.3.4 Other

In addition to the data sources listed above, I access annual county population estimates from the U.S. Census Bureau and personal income estimates by county and year from the U.S. Bureau of Economic Analysis. Furthermore, I download data on FEMA's public assistance program, which provides financial support in response to major declared disasters and emergencies. These funds may be used for a variety of issues post flooding, such as debris removal or restoration of disaster-damaged facilities. The grants also encourage the allocation of funds for resilient infrastructure rebuilding. The data is categorized by project, grant date and disaster type. I filter for flood-related disasters and aggregate the data by county and year.

Additionally, I download the county adjacency file from the U.S. Census Bureau, which details each county's neighbouring counties, to calculate the number of flood episodes in neighbouring counties. Finally, I download the Facebook Social Connectedness Index through The Humanitarian Data Exchange which measures inter-county connectivity through the number of Facebook Friends. I use this to calculate the number of flood episodes in counties that have strong social ties to the county of interest.

1.3.5 Summary Statistics

To provide an overview of the key variables used in the analysis, Table 1.1 presents summary statistics for all counties in the contiguous United States, as well as separately for innovating counties, i.e. those with at least one flood-related patent application between 2007 and 2020, and non-innovating counties. Innovating counties represent a small subsample (223) out of all counties (3,109) and exhibit some notable differences. It is worth highlighting, that in 30 counties, neither flooding nor flood-related patenting is observed and these counties are therefore excluded from the sample.

The table shows that innovating counties have an average of 0.259 patent applications per year. These counties experience nearly twice as many flood episodes per year on average compared to non-innovating counties and also show greater variation in flood exposure as reflected in a higher standard deviation. This increased exposure to flooding is also associated with higher average levels of flood insurance coverage in innovating counties, suggesting some response to flood risk.

Demographically, innovating counties have significantly higher populations on average and higher income levels, consistent with the broader geography of innovation concentrated in urban areas and hubs of economic activity. In addition, innovating counties also receive more FEMA assistance on average which may reflect both larger populations and greater exposure to flooding.

	All Counties		Innovating Counties		Non-Innovating Counties	
Variable	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Flood Patents	0.019	0.224	0.259	0.795	0.000	0.000
# Episodes	1.391	2.111	2.560	3.068	1.300	1.988
Insurance Coverage	0.021	0.053	0.042	0.082	0.019	0.049
Population	102,251	326,063	605,319	955,806	62,971	148,341
Income	39,514	11,709	50,644	19,488	38,645	10,380
FEMA Assistance	893,975	32,800,730	5,928,815	109,526,005	500,849	14,879,601
Observations	40,027	40,027	2,899	2,899	37,128	37,128
# Counties	3,079	3,079	223	223	2,856	2,856

Notes: Population is in 10,000s, Income in $1000, Insurance Coverage is expressed as a ratio of # policies divided by housing stock, and FEMA Assistance in $10,000,000.

TABLE 1.1: Summary statistics

1.4 Empirical Strategy

Empirically, I examine the effect of flooding on flood adaptation innovation by employing a Poisson pseudo-maximum likelihood (PPML) estimator with fixed effects. The use of a Poisson model addresses the non-negative and skewed nature of flood adaptation patents as a count variable, accounts for heteroscedasticity and ensures consistent estimation even with many zero observations when no patents are recorded in a county-year. Furthermore, the PPML estimator allows for consistent estimation without requiring the dependent variable to follow a true Poisson distribution, relying instead on correct specification of the conditional mean. The main specification is described by the following equation:

$$\begin{aligned} Pat_{c,t} = \exp\Big(&\alpha + \beta_1 Flood_{c,t-1} + \beta_2 Ins_{c,t-1} + \beta_3 Flood_{c,t-1} \times Ins_{c,t-1} \\ &+ \beta_4 Pop_{c,t-1} + \beta_5 Flood_{c,t-1} \times Pop_{c,t-1} \\ &+ \beta_6 Inc_{c,t-1} + \beta_7 FEMA_{c,t-1} + \gamma_c + \delta_t + \nu_c \cdot t\Big) \end{aligned} \tag{1.1}$$

The county serves as the most suitable and feasible unit for the analysis. The practicality of an inventor-level analysis with inventor fixed effects is hindered by the high number of inventors who only contribute once and would require making assumptions about inventors' active periods. Furthermore, the county provides a consistent geographical unit for both the flooding data and the inventor's geolocation, which becomes less precise with greater granularity. Finally, measuring flood exposure at the county level allows me to account for both direct and indirect local impacts, recognising that an inventor's exposure to flooding extends beyond their home address. For example, flooding may cause restrictions in movement for work or leisure and inventors may also be influenced by flood-related disruptions of nearby friends and family.

The outcome variable $Pat_{c,t}$ describes the number of patent applications filed by inventors resident in county c in year t. By definition this measures formal innovation and excludes other forms of innovation, such as policy or managerial innovation, which are likely influenced by different factors, including political and legal dynamics.

The main variable of interest is $Flood_{c,t-1}$ and represents the number of flood episodes in county c in year $t-1$. Though the primary time-unit for analysis is one year, I also account for contemporaneous and delayed effects of flood exposure by introducing current and up to three-year lags in a distributed lag analysis.

To control for the correlation of flood insurance with flooding and its potentially causal effect on flood-related patenting I add the insurance variable $Ins_{c,t-1}$. I further interact this with flood exposure to account for possible mitigating impacts on the relationship between flooding and innovation. Since flood insurance is lagged, I consider the endogeneity risk due to reverse causality from flood adaptation innovation to flood insurance to be minimal.

I include county-level population and personal income estimates, $Pop_{c,t-1}$ and $Inc_{c,t-1}$, to account for possible biases in the reporting of flooding with increasing population or income levels. I further interact flood exposure with population size to capture varying effects of flooding across different market sizes.

It is worth noting that interpreting interaction terms in non-linear models is not always straightforward. Ai and Norton (2003) show that in such models estimated coefficients on interaction terms do not directly correspond to marginal interaction effects. Instead, the interaction effect must be computed at specific covariate values and standard errors derived via the delta method. However, in this paper, I estimate a PPML model in which the log of the expected patent count is specified as a linear function of the covariates. This log-linear specification allows coefficients to be interpreted as semi-elasticities, i.e. percentage changes in expected patent counts. The interaction terms then indicate how the percentage effect of flooding varies with insurance coverage and population size. This interpretation in terms of semi-elasticities avoids the limitations associated with level-based interaction terms discussed by Ai and Norton (2003) and allows for the direct use of coefficient estimates and their standard errors [4].

[4] See Appendix 1.A.2 for more details.

To account for changes in public spending after flooding, I calculate the value of all granted FEMA public assistance in county c in year $t-1$, $FEMA_{c,t-1}$. This not only correlates with flooding but may also influence the development of flood-adaptation innovation. For example, after a major storm, FEMA may fund the rebuilding of a hospital. Since the program promotes resilient reconstruction, firms involved in the reconstruction may be encouraged to invest in flood adaptation innovation. While the variable serves as an approximation of flood-induced investments, I stipulate that it captures significant changes in spending.

Finally, I add county-fixed effects, γ_c, to address any unobserved time-invariant characteristics of counties and year-fixed effects, δ_t, to address any unobserved overall time-trends. In addition to this, I also add county-specific time trends, $\nu_c \cdot t$ to allow for varying tendencies within counties. This aims to control for differences in county trends that may correlate with the flood variable and influence flood-related innovation. For example, county-specific trends in education may lead to better reporting of flood episodes while simultaneously fostering an environment that supports the development of innovation.

While county-level fixed effects help address endogeneity and omitted variable bias, they lead to the exclusion of counties that never file any flood-related patents during the period, as the lack of within-county variation prevents identification under the PPML estimator. Consequently, the estimated effect of flooding pertains to the 223 counties with at least one flood-related patent and should be interpreted as conditional on patenting occurring.

To address concerns that the estimated effects may not generalise to counties that experience flooding but never patent, I also employ a linear specification and a Mundlak approach using the full sample of counties. While these methods allow for the inclusion of all counties, both come with caveats, particularly regarding functional form assumptions and the treatment of unobserved heterogeneity, and are therefore presented as robustness checks. Given the non-negative, skewed, and count-based nature of the patent data, PPML's robustness to heteroscedasticity, and the greater ability of county fixed effects to account for unobserved heterogeneity, I retain the PPML estimator with county-level fixed effects as the main specification.

1.5 Results

1.5.1 Main

The results of the main specification are presented in Table 1.2. The analysis reveals a positive and significant effect of flooding on flood-related patenting. Specifically, I find that one additional flood episode in a county leads to a 9.4% increase in the number of unique flood-related patent applications filed by inventors resident in the county the following year. The experience of local flooding seems to motivate an adaptation innovation response. While the literature indicates that financial shocks negatively impact overall inventor productivity (Bernstein, Mcquade, and Townsend 2021), flooding as an environmental shock seems stimulate innovation to a certain extent. In line with the conceptual framework this may be driven by experience-based learning or risk-updating, leading to a profit- or protection-motivated innovation response. The relatively quick response to flooding further implies that these innovations are readily accessible opportunities or require limited experience-based learning. More generally, the results suggests that inventors' decisions to develop climate adaptation innovation may to a certain extent be influenced by their local experience of environmental shocks.

As proposed, the presence of flood insurance appears to weaken this relationship, indicated by the negative coefficient on the interaction term between flood insurance coverage and flooding. Although the coefficient is not statistically significant, the size of the standard error is insufficient to attribute this finding definitively to noise, and is more likely due to limited annual variation in flood insurance coverage across counties. The positive coefficient on the interaction term tentatively suggests that flood insurance to some extent limits inventors' updating of expectation after local flood episodes. This is further supported by the slightly larger coefficient associated with flooding when flood insurance is included in the model. However, these results are only indicative.

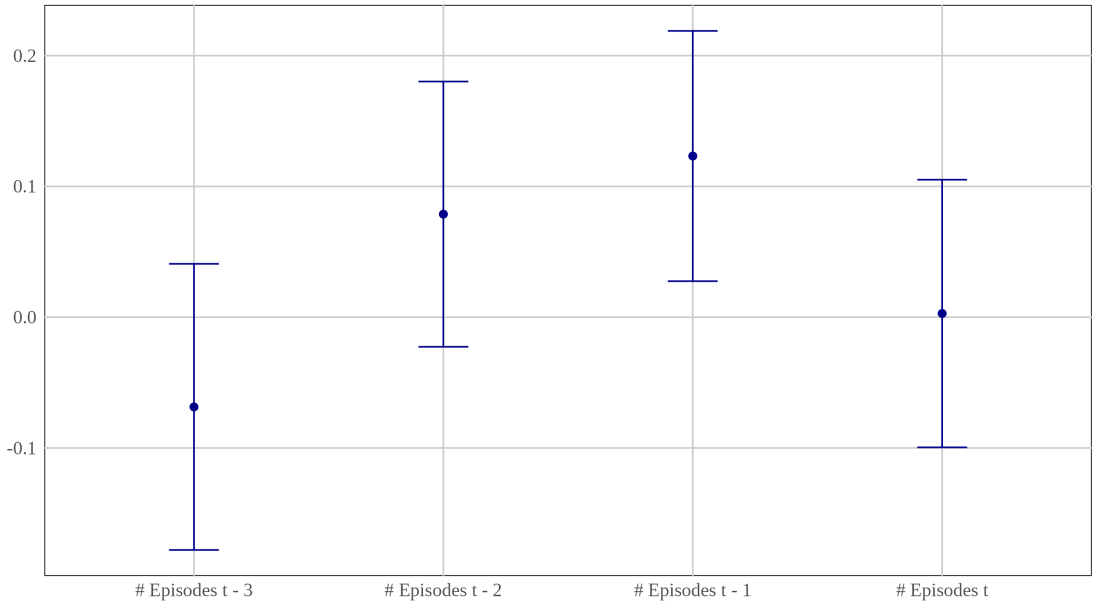
Meanwhile, I do not find evidence that population size influences the relationship between flooding and flood-related patenting. The exact coefficient of '# Episode t-1 x Population t-1' is 0.000046 with a standard error of 0.000097, indicating a statistically insignificant effect. There may be two possible explanations for this. Firstly, this may point to a lack of demand-pull for flood adaptation innovation in response to a shock. A homogeneous effect of flooding across different numbers of affected individuals and thus potential market size for future flood adaptation, may suggest that profit motivation is not a key driver of innovation in this context. Secondly, it is also possible that the demand increase generated by the local market in the county is simply too small to induce demand-pull innovation. In this case, the demand-pull channel may be active but the effect of local flooding on expectations of future demand may be too weak to drive a measurable effect.

	Flood Patents	
	(1)	(2)
# Episodes t-1	0.082***	0.090***
	(0.030)	(0.034)
Population t-1	-0.057	-0.080**
	(0.041)	(0.038)
Income t-1	-0.035	-0.037
	(0.039)	(0.039)
FEMA Assistance t-1	-0.002	-0.002
	(0.002)	(0.002)
# Episodes t-1 × Population t-1	0.000	0.000
	(0.000)	(0.000)
Insurance Coverage t-1		-0.136
		(0.087)
# Episodes t-1 × Insurance Coverage t-1		-0.004
		(0.003)
Year FEs	X	X
County FEs	X	X
County-Year Trends	X	X
Observations	2,899	2,899
Squared Correlation	0.33210	0.34243

Notes: This model is estimated using a Poisson pseudo-maximum likelihood estimator. Standard errors are in parenthesis and are clustered at the county level. The significance codes are: ***: 0.01, **: 0.05, *:0.1. Model (1) excludes flood insurance and Model (2) represents the results of the main specification. The outcome variable is flood patent applications at t and the main variable of interest is # Episodes t -1. Population t-1 is in 10,000s, Income t-1 in $1000, Insurance Coverage t-1 in %, and FEMA Assistance t-1 in $10,000,000.

TABLE 1.2: Main specification

To allow for delayed or immediate effects of flood exposure and address uncertainty regarding the time required to develop an innovation, I run a distributed lag model of the main specification with current and up to three-year lags of the explanatory variables. The coefficients of the various flood exposures are plotted in Figure 1.12. The coefficient on one-year lagged flood exposure is the only coefficient to achieve statistical significance and remains robust in size when including additional lags and current year flood exposure. The results suggests that inventors react within one-year of being exposed to flooding and seem to engage in innovation that does not require more extended development horizons such as innovative drug developments which have a mean development phase of 9 years (Brown et al. 2022). This aligns with the descriptive finding that a large share of flood-related patent applications are filed by individuals who only patent in this field once rather than showing a career commitments to flood adaptation innovation. The complete absence of patents supported by government grants and high share of inventors who file without assignees, thus may have limited resource to invest in long-term R&D projects, further emphasize this observation. For patents with assignees, it is also worth noting, that institutions such as research institutes and universities who tend to have a longer-term outlook on innovation development are only listed on three flood-related patents. Based on the results of the distributed lag model, I focus on one-year lagged flood exposure for the remainder of the analysis.



Notes: The plot depicts the 95% confidence intervals for flood episodes at t-3, t-2, t-1, and t. The outcome variable is flood patent applications at t. Coefficients are estimated using a Poisson pseudo-maximum likelihood estimator that incorporates the same control variables and their associated lags as in the main specification, along with county fixed effects, year fixed effects, and county-year trends. Standard errors are clustered at the county level.

FIGURE 1.12: Lag analysis

1.5.2 Locality of Flooding

Following the baseline analysis, I shift my focus to examine the importance of proximity to flooding in more detail, where proximity may be defined in geographic or social terms. In order to do so, I introduce flood episodes that occur outside the county but within the same state, in neighbouring counties and in socially connected counties. The results of this analysis are shown in Table 1.3. Across all three models, the effect of own-county flood episodes remains robust and relatively stable in magnitude. However, flood episodes in the rest of the state and in socially connected counties do not seem to affect own-county flood-related patenting. In other words, flood episodes that occur in the rest of the state or in other counties connected via strong social ties do not affect the decision-making of local inventors with respect to flood adaptation innovation. In contrast to this, flood episodes that occur in neighbouring counties seem to have some positive effect on the development of flood-related innovation, albeit to a significantly lesser extent than own-county flood episodes.

The results suggests that geographic proximity to flooding matters. For one, there may be informational frictions in flood reporting, such that information about more distant flooding and changes in demand for flood protection innovation may not always reach inventors effectively. Although possible, given the highly connected nature of the United States and the likely substantial information exchange between socially connected counties, this may not be sufficient to explain the results. Another explanation may be that personal experience of flooding is important in this context. Flood episodes that happen far away may not be as salient for the inventor and flood reporting via news, friends and family may not be sufficiently tangible to lead to updated expectation of future flooding. Geographic proximity to flooding may also be important in the context of flood adaptation innovation due to the possible need for hyper-local solutions. Innovations in flood protection products may simply not be applicable in different environments. In this context, flood episodes in neighbouring counties may still stimulate the development of flood innovation. Saliency of flood risk may be more pronounced as inventors' daily lives may span neighbouring county borders, local news reporting may reduce informational friction or neighbouring counties may have similar geographical landscapes such that local flood protections which may not have broad geographic application are still effective locally.

An alternative interpretation of these results relates to the prevalence of the underlying mechanisms. Assuming that all flooding, irrelevant of where it occurs, results in updating of expectation of future flooding, at least to some extent, the profit-motivated inventor should also respond to flood episodes outside the county. Whether the expected increase in demand for flood protection innovation originates from the local county, other counties or state markets should not impact the decision-making process of a rational inventor. Under this interpretation, the irrelevance of flooding in the rest of the state and socially connected counties suggests demand-pull is not driving the relationship with protection motivation or experience-based learning are the more likely underlying mechanism. The relevance of flood episodes in neighbouring counties may still be supported under this interpretation as inventors' activities may span neighbouring county borders such that flooding in neighbouring counties can still lead to experience-based learning and increased threat appraisals.

Overall, geographic proximity to flooding appears to be important in the response of inventors to flooding. This finding may align with increased saliency of personal experiences with flooding, informational frictions, local applicability of flood solutions or suggest the prevalence of protection motivation or experience-based learning as the underlying mechanism.

	Flood Patents		
	(1)	(2)	(3)
# Episodes t-1	0.076**	0.065*	0.081**
	(0.034)	(0.035)	(0.034)
# Episodes State t-1	0.003		
	(0.002)		
# Episodes Neighbouring Counties t-1		0.025*	
		(0.014)	
Social Connectivity Weighted # Episodes t-1			0.017
			(0.015)
Controls	Yes	Yes	Yes
Year FEs	X	X	X
County FEs	X	X	X
County-Year Trends	X	X	X
Observations	2,899	2,899	2,899
Squared Correlation	0.34281	0.34799	0.34560

Notes: This model is estimated using a Poisson pseudo-maximum likelihood estimator. Standard errors are in parenthesis and are clustered at the county level. The significance codes are: ***: 0.01, **: 0.05, *:0.1. Model (1) estimates the effect of adding flood episodes outside the county but within the same state. Model (2) estimates the effect of adding flood episodes in neighbouring counties. Model (3) estimates the effect of adding flood episodes in socially connected counties. The outcome variable is flood patent applications at t. Controls include Population t-1, Income t-1, Insurance Coverage t-1, FEMA Assistance t-1, Population t-1 x # Episodes t-1 and Insurance Coverage t-1 x # Episodes t-1.

TABLE 1.3: Locality of flooding

1.5.3 Robustness

Due to the inclusion of county-level fixed effects, the PPML estimates reflect the effect of flooding on flood-related patenting conditional on at least one flood-related patent per county from 2007 to 2020. To test the robustness of the findings across the full sample of counties in the contiguous United States, including those that never see any flood-related patent filings, I implement two alternative estimation strategies.

First, I estimate the fixed-effects model using a linear specification instead of the Poisson specification. The results, shown in column (1) of Table 1.4, suggest that one additional flood episode increases the number of flood-related patents filed in a county by 0.0017 the following year. Given the sample mean of 0.019 flood-related patents per year, this corresponds to a 9% increase, consistent with the main results.

However, linear estimation of patent data can be problematic as patents are non-negative, skewed count data and linear models may suffer from heteroscedasticity. Therefore, I also re-estimate the model using a Mundlak approach. To implement this, I replace county-level fixed effects with county-level means of the covariates to account for the time-invariant differences in county characteristics. While this does not fully eliminate all time-invariant unobserved heterogeneity as county fixed effects do, it accounts for potential correlations between the covariates and county characteristics under the assumption that such correlation is captured by the covariate means. The model is then estimated using the PPML estimator as before, but without county-level fixed effects, allowing identification across the full sample of counties. The estimated model is described by the following equation:

$$
\begin{aligned}
Pat_{c,t} = \exp\Big(&\beta_1 Flood_{c,t-1} + \beta_2 Ins_{c,t-1} + \beta_3 Flood_{c,t-1} \times Ins_{c,t-1} \\
&+ \beta_4 Pop_{c,t-1} + \beta_5 Flood_{c,t-1} \times Pop_{c,t-1} \\
&+ \beta_6 Inc_{c,t-1} + \beta_7 FEMA_{c,t-1} \\
&+ \theta_1 \overline{Flood}_c + \theta_2 \overline{Ins}_c + \theta_3 \overline{Pop}_c + \theta_4 \overline{Inc}_c + \theta_5 \overline{FEMA}_c \\
&+ \delta_t + \nu_c \cdot t\Big)
\end{aligned}
\tag{1.2}
$$

The result of this alternative specification is presented in column (2) of Table 1.4. The estimated coefficient on flooding remains statistically significant and is quantitatively consistent with the main findings.[5] In fact, the coefficient is estimated with greater precision likely due to the increase

[5] All main text estimations re-estimated using the Mundlak approach can be found in Appendix 1.A.4. The results

in number of observations. Including counties that experience flooding but never produce flood-related patents does not dilute the estimated effect of flooding on flood adaptation innovation. This is likely because these counties differ systematically in ways that are accounted for by the covariate means and make flood-related innovation unlikely in those counties, regardless of flood exposure. The results of the Mundlak estimation thus reinforce the main result and strengthens confidence in its robustness.

	Flood Patents	
	(1)	(2)
# Episodes t-1	0.002**	0.091***
	(0.001)	(0.027)
Insurance Coverage t-1	-0.005	-0.062*
	(0.003)	(0.036)
Population t-1	0.014	0.036***
	(0.012)	(0.012)
Income t-1	-0.001**	-0.027
	(0.000)	(0.023)
FEMA Assistance t-1	0.000	-0.001
	(0.001)	(0.002)
# Episodes t-1 × Population t-1	0.000*	0.000**
	(0.000)	(0.000)
# Episodes t-1 × Insurance Coverage t-1	0.000	-0.002
	(0.000)	(0.002)
Year FEs	X	X
County FEs	X	
County-Year Trends	X	X
County-Means		X
Observations	40,027	40,027
Squared Correlation	0.33950	0.31955

Notes: Model (1) represents the linear estimation and Model (2) represents the Mundlak approach. Standard errors are in parenthesis and are clustered at the county level. The significance codes are: ***: 0.01, **: 0.05, *:0.1. The outcome variable is flood patent applications at t and the main variable of interest is # Episodes t -1. Population t-1 is in 10,000s, Income t-1 in \$1000, Insurance Coverage t-1 in %, and FEMA Assistance t-1 in \$10,000,000.

TABLE 1.4: Linear and Mundlak estimations

To evaluate the robustness of the results further, I introduce a few additional specifications which are illustrated in Figure 1.13. First, I redefine the outcome variable as the share of flood-related patent applications relative to all applications filed in CPC section 'E'. The results tentatively show that one-year lagged flooding also has a positive effect on the share of flood adaptation

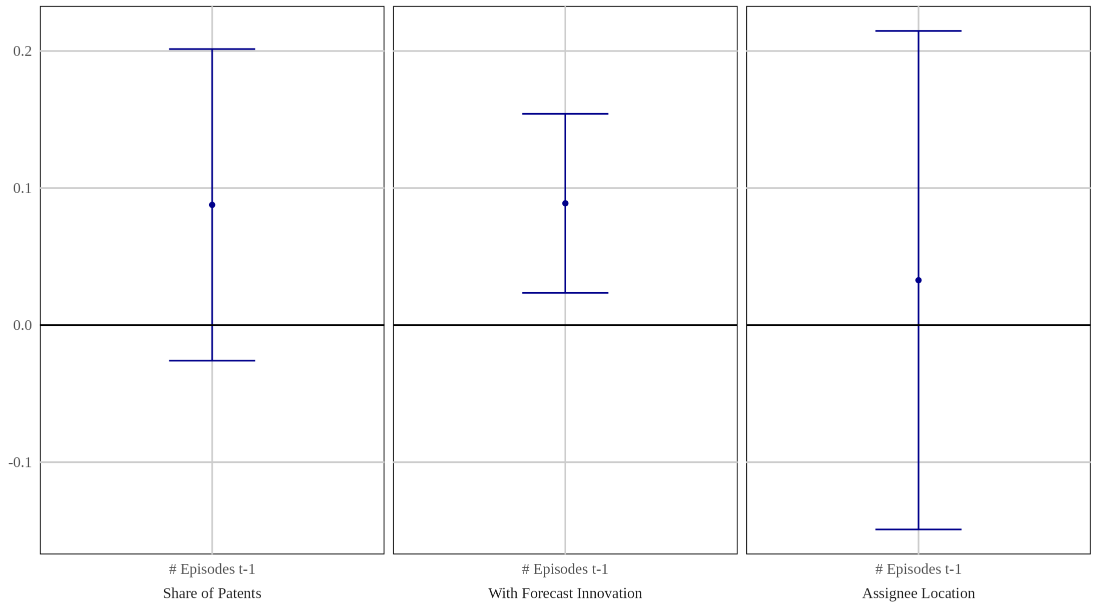
are consistent throughout.

patents in CPC section ‘E’ filed for in the county in the following year. Although the estimate is more noisy, the results indicate that the effect of flood exposure on flood-related patenting extends beyond a general increase in construction-related patenting. It suggests that the overall effect is not merely attributable to an overall increase in innovation for the purpose of rebuilding and repairing of flood damages but specific to future flood protection.

Next, I modify the outcome variable to include flood adaptation innovation beyond fixed constructions. For this purpose, I include the additional patents I identified using a mixed approach of Y02A tagging and the dictionary search as described in the data section. The results show that the effect of flooding on flood-related innovation, including flood forecasting, is positive and consistent. Not only does this support the robustness of the main results but it also suggests that the innovative response to local flood exposure may extend beyond innovation focused on physical flood adaptation and also includes more science-intensive innovation.

Additionally, I re-examine the results using the location of the assignee instead of the location of the inventor. Specifically, I calculate the number of flood episodes and flood-related patenting in the county based on the assignee’s address listed on the patent application, which typically represents the entity’s headquarters. The assignee’s county-location is different to the inventor’s county in all cases (Figure 1.A.2). The results suggests that flooding at the assignee’s location does not affect flood-related patenting in the same way. Since only 47% of flood patents list a US assignee this analysis is based on a smaller sample and therefore produces slightly noisier results. Nevertheless, the finding supports the robustness of our main results, suggesting that the effect of flooding is driven by exposures of the inventor rather than the assignee. Since the assignee’s address represents a business location and the inventor’s address is a home address, it may imply that experiences outside the workplace play a more significant role in the innovative response. Alternatively, it may also suggest that those affected by flooding at headquarters such as high-level management, have little involvement in the day-to-day decisions made by inventors.

Finally, given the relatively small sample size, I perform a permutation test where I randomly reassign flood episodes across counties and re-estimate the model 1,000 times using these randomised assignments. 5.8% of the estimations produce a p-value for the flood episodes coefficient that reaches above the significance threshold. This is consistent with the expected Type I error rate and further supports the robustness of the findings. The exact distribution of p-values from this test is detailed in Appendix 1.A.4.



Notes: The plots depict the 95% confidence intervals of the flood variable under different specifications. Plot 1 shows the coefficient for # Episodes t-1 when the outcome variable is share of flood patent applications at t. Plot 2 shows the coefficient for # Episodes t-1 when the outcome variable is flood patent applications including forecast innovation. Plot 3 shows the coefficient for # Episodes t-1 based on the assignee location. Coefficients are estimated using a Poisson pseudo-maximum likelihood estimator that incorporates the same control variables as in the main specification, along with county fixed effects, year fixed effects, and county-year trends. Standard errors are clustered at the county level.

FIGURE 1.13: Robustness

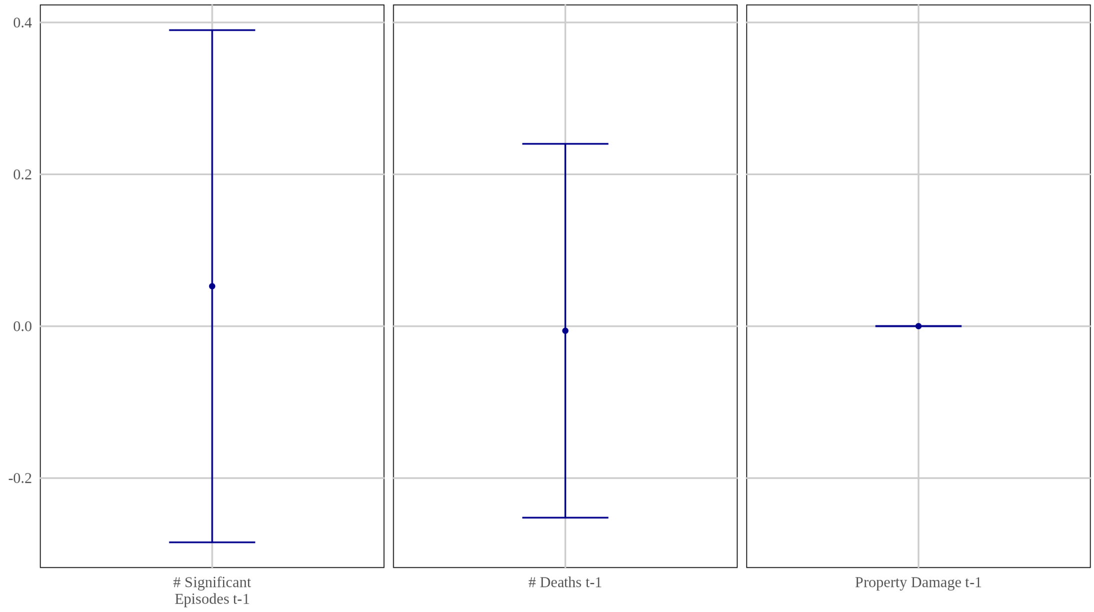
1.5.4 Heterogeneity

To detect heterogeneous effects in the relationship, I begin by re-examining the model under different types of flooding intensity. First, I filter for flood episodes that last at least 48 hours as such episodes are commonly the ones detected by satellite data or categorized as significant flood events. By definition, this measure excludes the majority of flood episodes defined as flash floods. The results in Figure 1.14 suggests that an increase in number of long-lasting flood episodes does not affect flood patenting in the county. Inventors do not seem to respond the same way when only accounting for flooding that persists for several days.

Secondly, I measure flood intensity by focusing on the impact on human health. I calculate the number of direct and indirect deaths due to flooding in a county and do not find an effect of one-year lagged flood related deaths on flood patenting the following year. Considering the relatively low mortality associated with flooding in the United States, this measure of flood exposure focuses only on severe incidents of flooding.

Both of these results indicate that inventors are more reactive to moderate and frequent episodes of flooding rather than extreme events. Possible explanations may include that inventors assume flood episodes associated with deaths or lasting for several days are far outliers with a lower chance of recurrence. Under a protection motivation mechanism, this could also indicate the presence of a binding coping appraisal, where inventors believe that their innovation would not be sufficient to protect against extreme flood episodes. Additionally, more severe flood episodes may cause significant damage that diverts inventors' focus away from research and development.

I further analyse flood intensity by calculating flood-induced property damages in the county. Though I do not find a meaningful effect, I believe that this result should be examined with caution. As discussed in the data section, damages in the data set are not always official amount but often estimates made by the reporting source which may be imprecise. In addition, property damages are likely to correlated with time-varying inter-county differences in housing stock values which I am unable to account for and therefore may lead to endogeneity concerns. Despite these issues, it is important to note that many property damages include damages to public infrastructure, which may not be transparent to inventors or irrelevant when considering own protection or experience-based learning as motivation.



Notes: The plots depict the 95% confidence intervals of the flood variable under varying definitions. Plot 1 shows the coefficient of the flood variable when flooding is measured by # significant episodes at t-1. Plot 2 shows the coefficient of the flood variable when flooding is measured by # deaths at t-1. Plot 3 shows the coefficient of the flood variable when flooding is measured by property damages at t-1. The outcome variable is flood patent applications at t. Coefficients are estimated using a Poisson pseudo-maximum likelihood estimator that incorporates the same control variables as in the main specification, along with county fixed effects, year fixed effects, and county-year trends. Standard errors are clustered at the county level.

FIGURE 1.14: Flood intensity

Next, I examine heterogeneity of the relationship by the type of inventor. Specifically, subset the sample for patent applications that list an assignee, i.e. patents that are not filed by individuals. The results suggests that the effect of local flood episodes for this subsample is significantly larger than the effect for the full sample. I find that one additional flood episodes in a county, leads to an increase of 21.4% in flood-related patents that are filed with an assignee (Table 1.5). This suggests that the observed increase in flood-patenting in response to a flood episode is likely driven by firm-affiliated inventors. When a flood episode occurs, they may be able respond by switching between different areas of innovation more quickly and leverage their existing infrastructure. However, given that 68% of inventors with assignee only file for a flood adaptation patent once, this does not necessarily mean they are dedicated to flood innovation. Rather, their ability to respond to local flood exposure may stem from their existing resources and institutional support. In contrast, the results also suggests that the large share of flood-related patent applications applied for by individuals may not necessarily be the result of local flood exposure, at least not in the short-run. It is worth noting that, under the specification with assignee-listed patents, the moderating effect of insurance is statistically significant. Specifically, the results suggest that a 1% increase in county-wide insurance coverage reduces the impact of flooding on innovation from 21.4% to 18.9%. While the decrease is modest, it reinforces the tentative findings of insurance moderation from the main specification.

In the final part of the analysis, I examine how the impact of flooding on innovation varies across patents of different quality. Given that patent quality is notoriously difficult to measure and often prone to errors, I use a simple indicator of whether the patent is granted as a proxy for quality to subset my data. This includes approximately 75% of patents. The coefficient on one-year flood exposure remains positive but is more noisy. Although this may in part be due to the reduced sample size, the results suggest that flooding has a more significant effect on the number of applications for patents that are not ultimately granted. This may indicate a lower quality of applications, but other factors should also be considered. Patent applications are complicated processes, often associated with high legal costs and requiring a strategic approach. Since the majority of inventors only file for a flood-related patents once, they may have less expertise in submitting effective applications in this area and may be unaware of conflicting patents. Nonetheless, the results speak to the economic value of flood-related patenting post-flooding, albeit that it is possible that inventors are also bringing their innovations to market through more informal channels.

	Flood Patents with Assignee	Granted Flood Patents
	(1)	(2)
# Episodes t-1	0.193***	0.047
	(0.049)	(0.038)
Population t-1	0.034	-0.066
	(0.058)	(0.041)
Income t-1	-0.069	-0.056
	(0.066)	(0.047)
Insurance Coverage t-1	-0.188	-0.115
	(0.142)	(0.121)
FEMA Assistance t-1	-0.007	-0.002
	(0.007)	(0.003)
# Episodes t-1 × Population t-1	0.000***	0.000
	(0.000)	(0.000)
# Episodes t-1 × Insurance Coverage t-1	-0.020***	-0.003
	(0.008)	(0.004)
County	X	X
Year	X	X
County-Year Trends	X	X
Observations	1,807	2,418
Squared Correlation	0.35912	0.34536

Notes: This model is estimated using a Poisson pseudo-maximum likelihood estimator. Standard errors are in parenthesis and are clustered at the county level. The significance codes are: ***: 0.01, **: 0.05, *:0.1. The outcome variable in Model (1) is flood patents with assignee at t. The outcome variable in Model (2) is flood patent applications that have been granted at t. The the main variable of interest is # Episodes t-1. Population t-1 is in 10,000s, Income t-1 in $1000, Insurance Coverage t-1 in %, and FEMA Assistance t-1 in $10,000,000

TABLE 1.5: Assignee and granted patents

1.6 Conclusion

Overall, the results of this study suggest that local flooding has a positive effect on the development of innovations for flood adaptation. Using a new classification of flood adaptation patents in the United States from 2007 to 2020, I find that one additional flood episode in a county leads to an increase of 9.4% in flood-related patents filed by resident inventors in the following year. The analysis suggests that this effect is the result of frequent, moderate flooding rather than extreme events and more pronounced for patents with assignee and for patents that are applied for but not ultimately granted. Furthermore, the response to flooding seems to occur promptly, with flood episodes lagged by more than one year showing little to no impact on current innovative activity, implying short-development horizons and/ or readily available opportunities for innovation in flood adaptation. This stands in contrast to the finding of Miao and Popp (2014) who suggest that the impact of flooding on flood-related patenting last up to 7 years after exposure, though national-level analyses may involve other complicating dynamics.

The observed effect of flood exposure may be explained by inventors' updated expectation of future flooding, leading to profit- or protection-motivated innovation, or experience-based learning. Though it is difficult to determine which mechanism is most prevalent, I find that geographic proximity to the shock is key. Flood episodes in the rest of the state and in counties in close social proximity do not influence the local development of flood adaptation innovation. However, flood episodes in neighbouring counties have some effect, albeit to a lesser extent than own-county flood episodes. This result may have different interpretations. For one, informational frictions or reduced prominence of distant flood episodes, may lead to break down of risk-updating, preventing demand-pull or protection-motivated innovation. Alternatively, flood innovation may be hyper-local with inventors only responding to local flooding because they are developing solutions for the local market where the environment is familiar. Furthermore, in the absence or limited presence of these challenges, the importance of geographic proximity may also point to a prevalence of protection-motivation or experience-based learning over demand-pull as the underlying mechanism.

Although I am unable to provide a causal analysis of the role of flood insurance in this context due the lack of exogenous variation, there seems to be some suggestive evidence of a moderating effect of flood insurance on the relationship between flood exposure and flood adaptation innovation. Considering the sizeable cost of the National Flood Insurance Program and the possible unintended consequences on flood adaptation innovation, this remains an important area of future research. Key to exploring this further will be to identify exogenous variation in flood insurance coverage which is challenging due to the often political dynamics in the management of the NFIP. Future researchers may explore the variation introduced by the introduction of NFIP's new pricing approach in 2023. "Risk Rating 2.0" has replaced the static Flood Insurance Rate Maps used to determine flood premia, providing a more accurate measure of flood risk and significant changes to the cost of insurance for policy holders. Though this new pricing approach is too recent to be exploited for the purpose of this paper, it provides a promising avenue for further analysis of the suggestive findings of this paper.

Naturally, this study is not without caveats. Firstly, due to lack of data availability I am unable to account for flood-induced changes in research and development spending. Though I approximate changes in public investment via FEMA's public assistance program and control for county levels and trends, there is room for future researchers to explore this interaction further. Additionally, I am unable to differentiate between different types of flood exposure beyond intensity due to imprecision in the reporting nor am I able to examine the effect of varying types of damages such as home damages, road closures, etc., due to the lack of granularity in the flood data and geolocation of inventors. Finally, I believe there is value in constructing a more comprehensive dataset of flood-related innovation beyond fixed construction or formal innovation.

Nonetheless, the findings of this paper present compelling evidence that the local experience of the inventor plays a role in the development of adaptation innovation. Flooding, as an environmental shock, can act as a catalyst for innovation activity. To a certain extent, inventors seem to react to flood episodes rather than proactively preparing for them, potentially missing opportunities to pre-emptively mitigate flood damage. The importance of local flood exposure, along with the significant presence of one-off inventors, points to a rather uncoordinated development in flood adaptation innovation and a possible explanation for the slow progress that we have observed so far. The development of flood adaptation innovations appears to be more incidental driven by subjective experience of inventors rather than strategically planned. Improving the dissemination of information about future flood risks or devising clear adaptation innovation policy and incentives may help accelerate efforts in light of the ever-increasing damages of flooding.

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1.A Appendix

1.A.1 Search Strategy

To identify flood-related patents, I filter for all patents within CPC Section ’E’ – ’Fixed Construction’ – excluding those classified under E21 (’Earth or Rock Drilling; Mining’) and E99 (’Subject Matter Not Otherwise Classified’). I retain the title and abstract of each patent and search for case-insensitive occurrences of: "flood", "storm surge" and "storm water". Rather than a whole-word match, I use a substring search which does not require word boundaries. This ensures that terms such as "flooding" and "storm surges" or alternative spelling such as "stormwater" instead of "storm water" are also detected. I further eliminate all patents that contain the world "toilet". The search yields 475 unique patent applications filed at the USPTO by US resident inventors from 2007 to 2020.

Example: US10364564B2

Filing Year: 2018

CPC Classifications: E02B5/02; E03F1/002; E02B3/02; E02B3/04; E03F1/00; E02B11/00

Assignee: Individual

Title: Super drainage system and method for flood control

Abstract: A super drainage system and a method for flood control comprise an open channel, a reinforced concrete conduit (RCC) inside the open channel. The RCC has a bottom slab supported on a riverbed, a bank-side wall for retaining bank soils, and a top slab elevated above a predetermined level. The RCC supports a road below the top of river banks for traffic traveling along the river banks during normal weather conditions. The traffic is either on the top slab or on the bottom slab. During extreme weather conditions, traffic is evacuated from the super drainage system and the entire space is available for water conveyance.

Link to CPC Classification E: Link

1.A.2 Note on Interaction Term

An interaction term measures the change in marginal effect of one variable with respect to changes in another and is defined by the cross-partial derivative: $\frac{\partial^2 E[y|x]}{\partial x_1 \partial x_2}$.

Consider first a linear model: $E[y|x] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2$.

The marginal effect of x_1 is: $\frac{\partial E[y|x]}{\partial x_1} = \beta_1 + \beta_3 x_2$ and the interaction effect is given by: $\frac{\partial^2 E[y|x]}{\partial x_1 \partial x_2} = \beta_3$

In this case, the coefficient β_3 on the interaction term directly represents the interaction effect, making interpretation straightforward.

Now consider a Poisson model: $E[y|x] = \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2)$.

The marginal effect of x_1 becomes: $\frac{\partial E[y|x]}{\partial x_1} = \exp(\cdot) \cdot (\beta_1 + \beta_3 x_2)$

Applying the product rule, the interaction effect is: $\frac{\partial^2 E[y|x]}{\partial x_1 \partial x_2} = \exp(\cdot)\,[\beta_3 + (\beta_1 + \beta_3 x_1)(\beta_2 + \beta_3 x_2)]$

As shown by Ai and Norton (2003), in non-linear models like this, the interaction effect depends on all covariates and their values. Hence, β_3 does not directly represent the interaction effect and must be evaluated at specific covariate values with standard errors via the delta method.

However, the PPML model uses a log-link specification: $\log E[y|x] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2$.

The marginal effect of x_1 on the log scale is: $\frac{\partial \log E[y|x]}{\partial x_1} = \beta_1 + \beta_3 x_2$ and the interaction effect is: $\frac{\partial^2 \log E[y|x]}{\partial x_1 \partial x_2} = \beta_3$

Thus, in the PPML estimation, interaction coefficients can be interpreted directly as changes in the log of expected outcomes. Since coefficients are interpreted as semi-elasticities, the interpretation of β_3 and the associated standard error remains valid and avoids the concerns raised by Ai and Norton (2003).

1.A.3 Additional Descriptive Figures

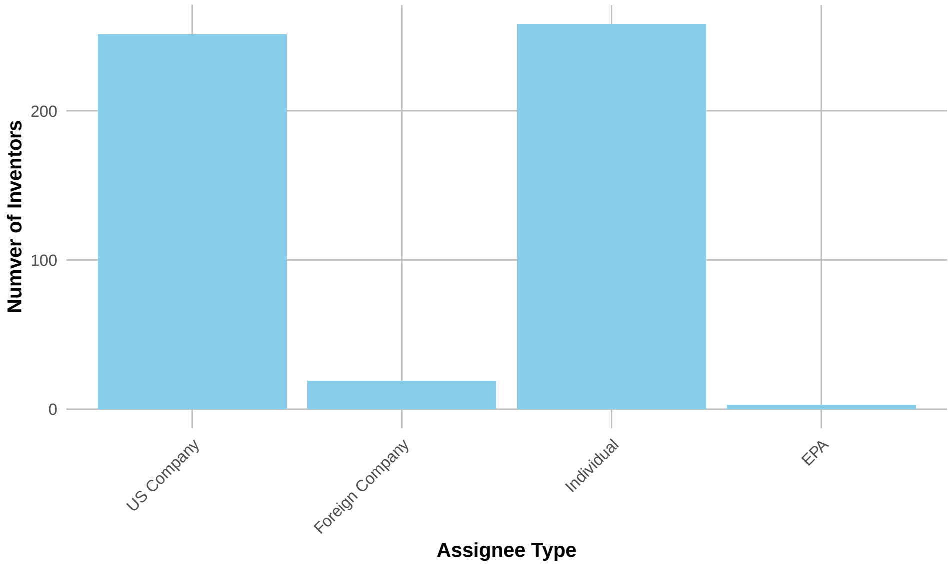


FIGURE 1.A.1: Assignee type listed on inventor applications

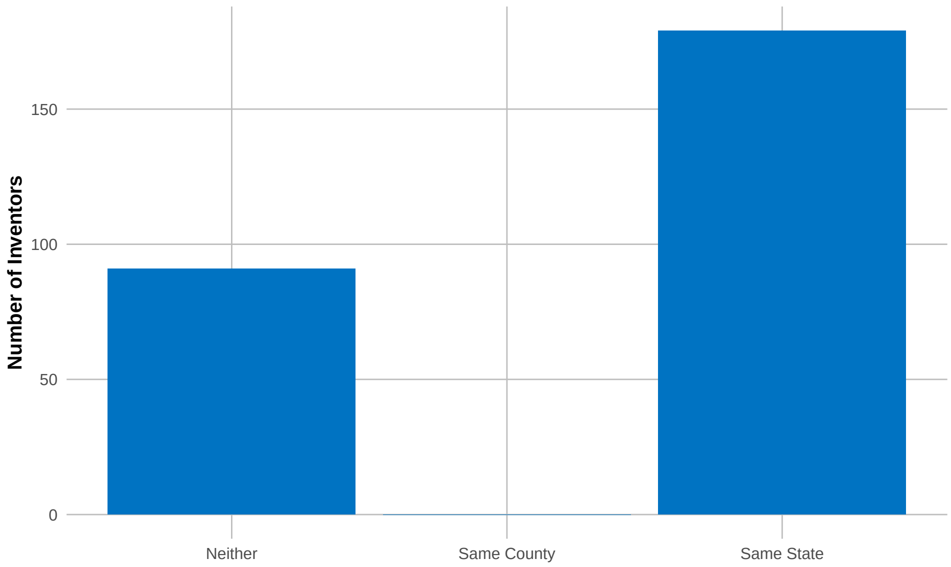


FIGURE 1.A.2: Inventor - assignee location

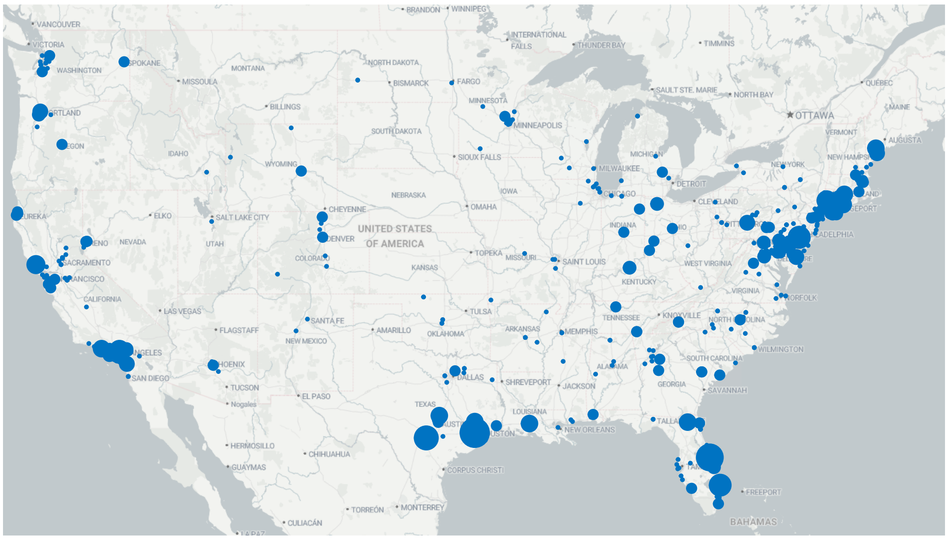


FIGURE 1.A.3: Inventor location scaled by number of patent applications

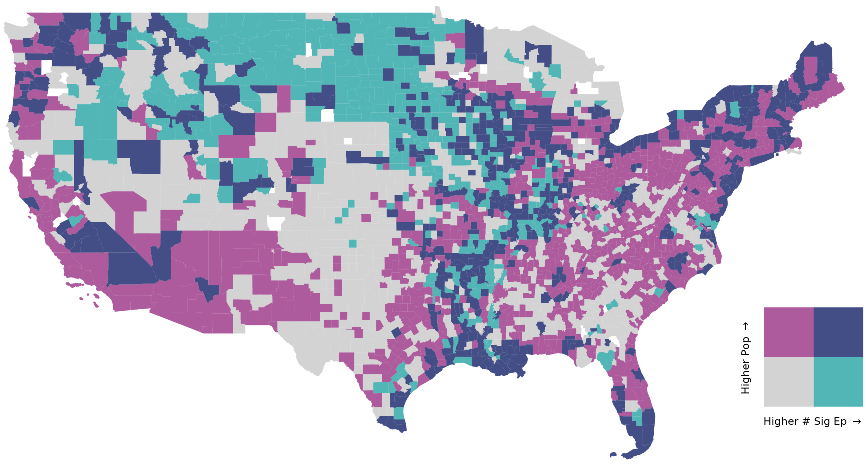
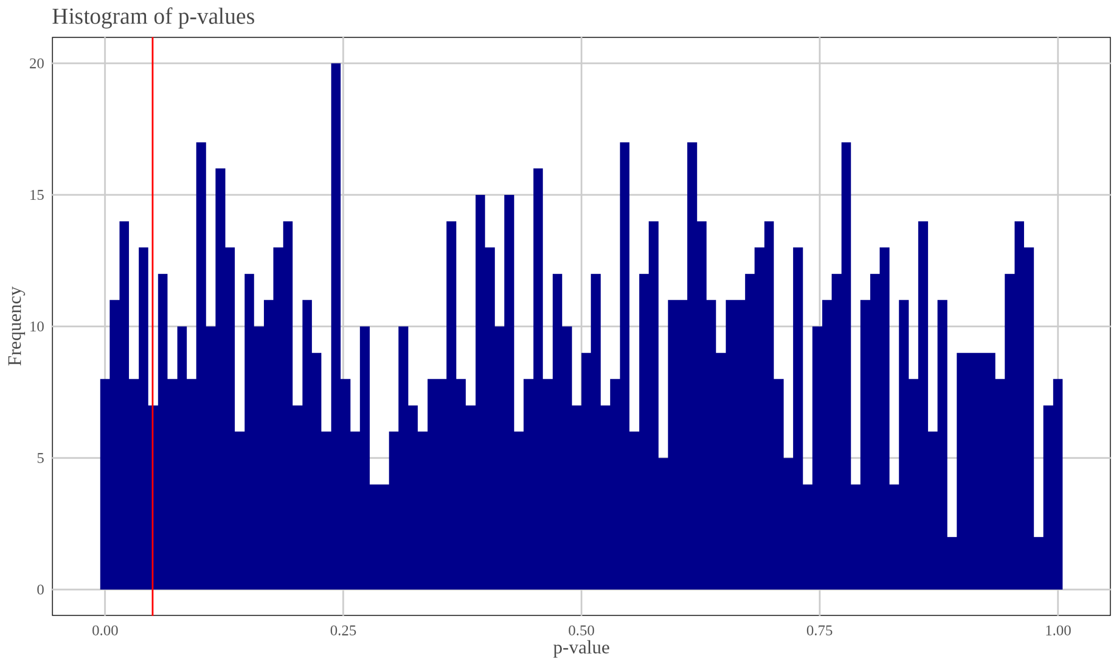


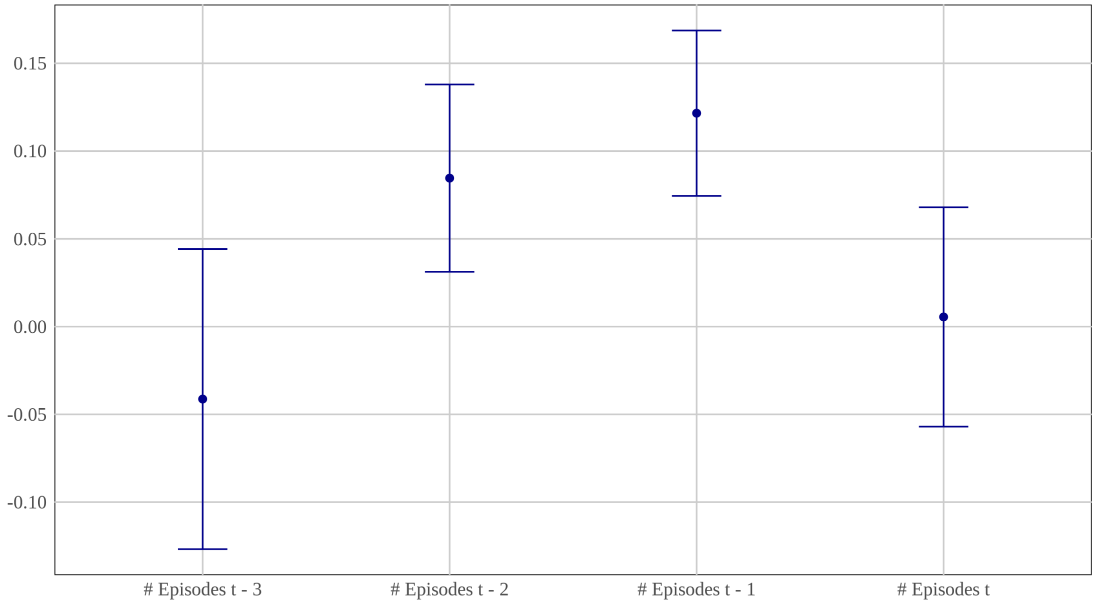
FIGURE 1.A.4: Average annual significant flood episodes and population 2007 - 2020

1.A.4 Additional Result Tables and Figures



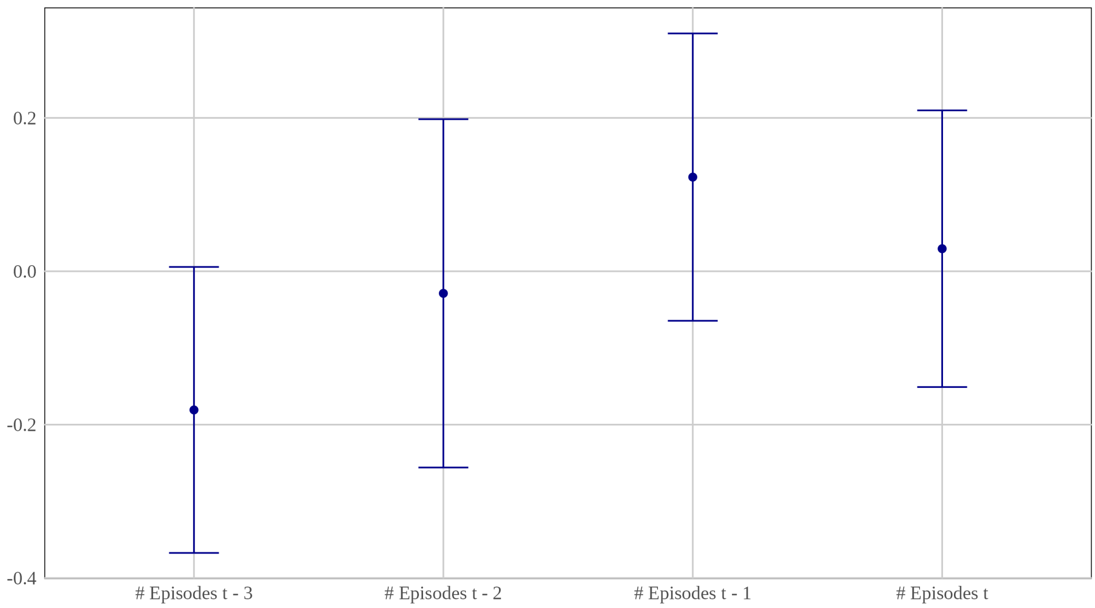
Notes: The plot displays the results of a permutation test conducted via Monte Carlo simulations over 1,000 iterations. The distribution shows the p-values of the flood variable when flood episodes are reassigned randomly across counties. The vertical red-line represents the 95% confidence threshold. The vertical red line marks the 95% significance threshold, with p-values falling below this line indicating statistical significance. The outcome variable is flood patent applications at t. Coefficients are estimated using a Poisson pseudo-maximum likelihood estimator that incorporates the same control variables and their associated lags as in the main specification, along with county fixed effects, year fixed effects, and county-year trends. Standard errors are clustered at the county level.

FIGURE 1.A.5: Distribution of p-values in randomisation test



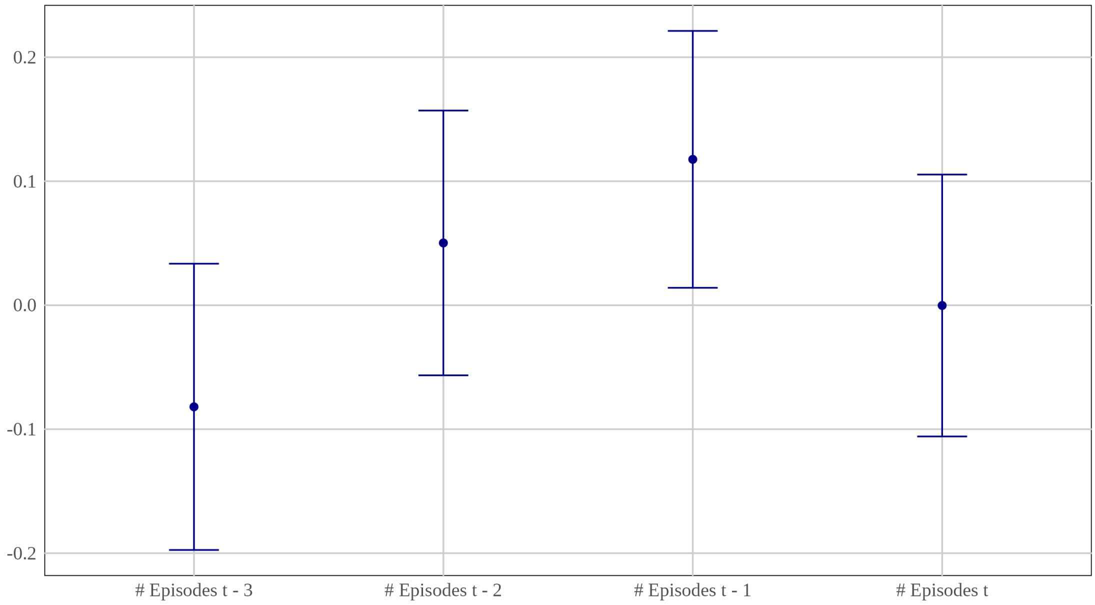
Notes: The plot depicts the 95% confidence intervals for flood episodes at t-3, t-2, t-1 and t. The outcome variable is flood patent applications at t. Coefficients are estimated using a Mundlak approach with a Poisson pseudo-maximum likelihood estimator that incorporates the same control variables and their associated lags as in the main specification, along with county-level means of the covariates, year fixed effects, and county-year trends. Standard errors are clustered at the county level.

FIGURE 1.A.6: Lag analysis - Mundlak approach



Notes: The plot depicts the 95% confidence intervals for flood episodes at t-3, t-2, t-1 and t. The outcome variable is the share of flood patent applications at t. Coefficients are estimated using a Poisson pseudo-maximum likelihood estimator that incorporates the same control variables and their associated lags as in the main specification, along with county fixed effects, year fixed effects, and county-year trends. Standard errors are clustered at the county level.

FIGURE 1.A.7: Lag analysis - share of flood patents



Notes: The plot depicts the 95% confidence intervals for flood episodes at t-3, t-2, t-1 and t. The outcome variable is flood patent applications (including forecast innovation) at t. Coefficients are estimated using a Poisson pseudo-maximum likelihood estimator that incorporates the same control variables and their associated lags as in the main specification, along with county fixed effects, year fixed effects, and county-year trends. Standard errors are clustered at the county level.

FIGURE 1.A.8: Lag analysis - including forecast innovation

	Flood Patents		
	(1)	(2)	(3)
# Episodes t-1	0.075***	0.074***	0.089***
	(0.027)	(0.028)	(0.027)
# Episodes State t-1	0.003		
	(0.002)		
# Episodes Neighbouring Counties t-1		0.015	
		(0.010)	
Social Connectivity Weighted # Episodes t-1			0.003
			(0.013)
Controls	Yes	Yes	Yes
Year FEs	X	X	X
County-Year Trends	X	X	X
County-Means	X	X	X
Observations	40,027	40,027	40,027
Squared Correlation	0.31771	0.32086	0.31971

Notes: This model is estimated using a Mundlak approach with a Poisson pseudo-maximum likelihood estimator. Standard errors are in parenthesis and are clustered at the county level. The significance codes are: ***: 0.01, **: 0.05, *:0.1. Model (1) estimates the effect of adding flood episodes outside the county but within the same state. Model (2) estimates the effect of adding flood episodes in neighbouring counties. Model (3) estimates the effect of adding flood episodes in socially connected counties. The outcome variable is share of flood patent applications at t. Controls include Population t-1, Income t-1, Insurance Coverage t-1, FEMA Assistance t-1, Population t-1 x # Episodes t-1 and Insurance Coverage t-1 x # Episodes t-1.

TABLE 1.A.1: Locality of flooding - Mundlak approach

	Share of Flood Patents		
	(1)	(2)	(3)
# Episodes t-1	0.050	0.073	0.091
	(0.063)	(0.066)	(0.064)
# Episodes State t-1	0.005		
	(0.005)		
# Episodes Neighbouring Counties t-1		0.031	
		(0.029)	
Social Connectivity Weighted # Episodes t-1			0.009
			(0.033)
Controls	Yes	Yes	Yes
Year FEs	X	X	X
County FEs	X	X	X
County-Year Trends	X	X	X
Observations	2,860	2,471	2,247
Squared Correlation	0.38794	0.40844	0.37513

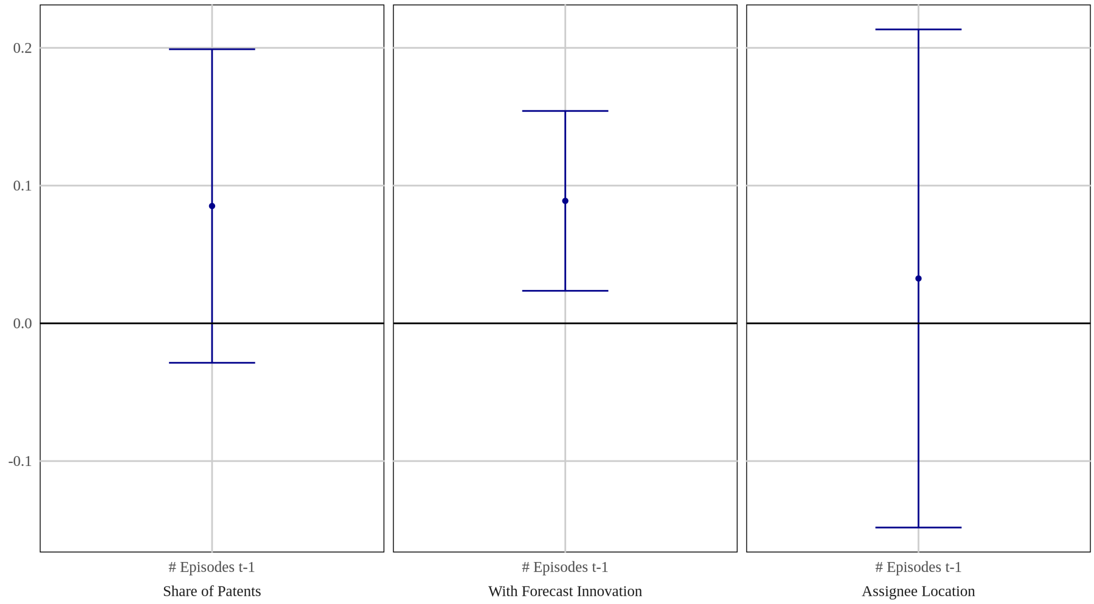
Notes: This model is estimated using a Poisson pseudo-maximum likelihood estimator. Standard errors are in parenthesis and are clustered at the county level. The significance codes are: ***: 0.01, **: 0.05, *:0.1. Model (1) estimates the effect of adding flood episodes outside the county but within the same state. Model (2) estimates the effect of adding flood episodes in neighbouring counties. Model (3) estimates the effect of adding flood episodes in socially connected counties. The outcome variable is share of flood patent applications at t. Controls include Population t-1, Income t-1, Insurance Coverage t-1, FEMA Assistance t-1, Population t-1 x # Episodes t-1 and Insurance Coverage t-1 x # Episodes t-1.

TABLE 1.A.2: Locality of flooding - share of flood patents

	Flood Patents		
	(1)	(2)	(3)
# Episodes t-1	0.091**	0.064*	0.096**
	(0.037)	(0.038)	(0.040)
# Episodes State t-1	0.001		
	(0.002)		
# Episodes Neighbouring Counties t-1		0.038***	
		(0.014)	
Social Connectivity Weighted # Episodes t-1			0.024*
			(0.014)
Controls	Yes	Yes	Yes
Year FEs	X	X	X
County FEs	X	X	X
County-Year Trends	X	X	X
Observations	2,628	2,293	2,113
Squared Correlation	0.34095	0.36870	0.37584

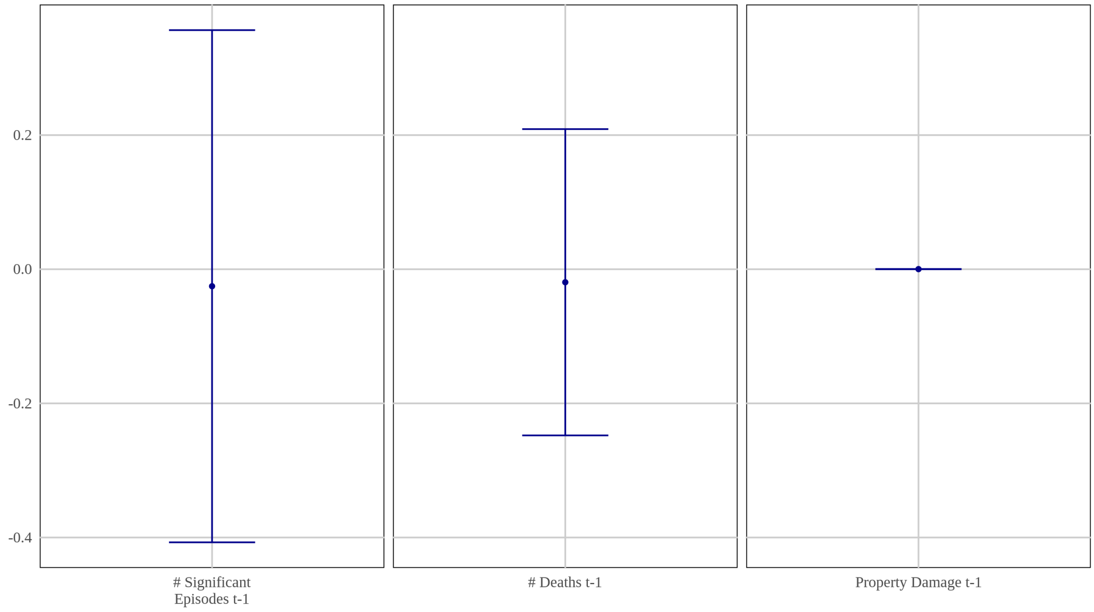
Notes: This model is estimated using a Poisson pseudo-maximum likelihood estimator. Standard errors are in parenthesis and are clustered at the county level. The significance codes are: ***: 0.01, **: 0.05, *:0.1. Model (1) estimates the effect of adding flood episodes outside the county but within the same state. Model (2) estimates the effect of adding flood episodes in neighbouring counties. Model (3) estimates the effect of adding flood episodes in socially connected counties. The outcome variable is flood patent applications (including forecast innovation) at t. Controls include Population t-1, Income t-1, Insurance Coverage t-1, FEMA Assistance t-1, Population t-1 x # Episodes t-1 and Insurance Coverage t-1 x # Episodes t-1.

TABLE 1.A.3: Locality of flooding- including forecast innovation



Notes: The plots depict the 95% confidence intervals of the flood variable under different specifications. Plot 1 shows the coefficient for # Episodes t-1 when the outcome variable is share of flood patent applications at t. Plot 2 shows the coefficient for # Episodes t-1 when the outcome variable is flood patent applications including forecast innovation. Plot 3 shows the coefficient for # Episodes t-1 based on the assignee location. Coefficients are estimated using a Poisson pseudo-maximum likelihood estimator that incorporates the same control variables and their associated lags as in the main specification, along with county fixed effects, year fixed effects, and county-year trends. Standard errors are clustered at the county level.

FIGURE 1.A.9: Robustness - Mundlak approach



Notes: The plots depict the 95% confidence intervals of the flood variable under varying definitions. Plot 1 shows the coefficient of the flood variable when flooding is measured by # significant episodes at t-1. Plot 2 shows the coefficient of the flood variable when flooding is measured by # deaths at t-1. Plot 3 shows the coefficient of the flood variable when flooding is measured by property damages at t-1. The outcome variable is flood patent applications at t. Coefficients are estimated using a Poisson pseudo-maximum likelihood estimator that incorporates the same control variables and their associated lags as in the main specification, along with county fixed effects, year fixed effects, and county-year trends. Standard errors are clustered at the county level.

FIGURE 1.A.10: Flood intensity - Mundlak approach

	Flood Patents with Assignee	Granted Flood Patents
	(1)	(2)
# Episodes t-1	0.180***	0.053
	(0.032)	(0.033)
Population t-1	0.062***	0.030***
	(0.023)	(0.011)
Income t-1	-0.032	-0.032
	(0.033)	(0.031)
Insurance Coverage t-1	-0.157	-0.073*
	(0.112)	(0.044)
FEMA Assistance t-1	-0.004	-0.001
	(0.004)	(0.002)
# Episodes t-1 × Population t-1	0.000***	0.000
	(0.000)	(0.000)
# Episodes t-1 × Insurance Coverage t-1	-0.019***	-0.003
	(0.007)	(0.004)
Year	X	X
County-Year Trends	X	X
County-Means	X	X
Observations	40,027	40,027
Squared Correlation	0.26191	0.32088

Notes: This model is estimated using a Mundlak approach with a Poisson pseudo-maximum likelihood estimator. Standard errors are in parenthesis and are clustered at the county level. The significance codes are: ***: 0.01, **: 0.05, *:0.1. The outcome variable in Model (1) is flood patents with assignee at t (including forecast innovation). The outcome variable in Model (2) is flood patent applications that have been granted at t (including forecast innovation). The main variable of interest is # Episodes t-1. Population t-1 is in 10,000s, Income t-1 in \$1000, Insurance Coverage t-1 in %, and FEMA Assistance t-1 in \$10,000,000.

TABLE 1.A.4: Assignee and granted patents - Mundlak approach

	Flood Patents with Assignee	Granted Flood Patents
	(1)	(2)
# Episodes t-1	0.183***	0.073*
	(0.052)	(0.043)
Population t-1	-0.006	-0.085*
	(0.076)	(0.049)
Income t-1	-0.010	-0.008
	(0.081)	(0.058)
Insurance Coverage t-1	-0.543	-0.071
	(0.365)	(0.200)
FEMA Assistance t-1	-0.005	-0.002
	(0.006)	(0.003)
# Episodes t-1 $\times$ Population t-1	0.000**	0.000
	(0.000)	(0.000)
# Episodes t-1 $\times$ Insurance Coverage t-1	-0.026**	-0.005
	(0.012)	(0.006)
County	X	X
Year	X	X
County-Year Trends	X	X
Observations	1,680	2,172
Squared Correlation	0.35571	0.33762

Notes: This model is estimated using a Poisson pseudo-maximum likelihood estimator. Standard errors are in parenthesis and are clustered at the county level. The significance codes are: ***: 0.01, **: 0.05, *:0.1. The outcome variable in Model (1) is flood patents with assignee at t (including forecast innovation). The outcome variable in Model (2) is flood patent applications that have been granted at t (including forecast innovation). The main variable of interest is # Episodes t-1. Population t-1 is in 10,000s, Income t-1 in $1000, Insurance Coverage t-1 in %, and FEMA Assistance t-1 in $10,000,000.

TABLE 1.A.5: Assignee and granted patents - including forecast innovation

Chapter 2

Climate Uncertainty: Real Option Theory in Climate Adaptation Innovation

2.1 Introduction

The existence of anthropogenic climate change is well-established today. In 2023 global CO_2 emissions reached a record high of 37.4 billion tonnes (IEA 2023), coinciding with global temperature reaching their highest levels since the start of global weather recordings in 1850 (NOAA National Centers for Environmental Information 2023). Since 1993, global sea levels have increased by around 10 centimetres, averaging 3.4 millimetres per year and the water loss of mountain glaciers since 1970 reached 26 metres in 2022 (NOAA National Centers for Environmental Information 2025). As certainty over the existence of climate change has grown, so have the efforts to mitigate it. An important component of this has been technological innovation such as advancements in renewable energies, energy efficiency, transportation, agriculture and emerging technologies such as carbon capture and storage. In fact, green patents have grown by 500 % from 2000 - 2019 (IPO UK 2024), far outperforming other technologies.

However, significant uncertainty remains over the extent of climate change with estimated temperature increases varying anywhere between 1.4°C to 4.4°C by the end of the century compared to pre-industrial levels (IPCC 2023). Even more uncertainty remains over the magnitude, geolocation and frequency of climate damages. Aside from the scientific uncertainty, there also remains significant socio-economic uncertainty introduced by unpredictability of government, firm and individual decision-making. Nonetheless, we have already seen some of the impacts of climate change. In 2022, the international disaster database, EM-DAT, recorded over 12,000 lives lost in climate disasters (Save the Children International 2023) and a recent study suggests that climate damages between 2000 and 2019 already resulted in annual financial losses of $143 billion (Newman and Noy 2023). Similar to mitigation, innovation in climate adaptation can play a pivotal role in addressing the novel challenges posed by climate change, given its unprecedented scale, distribution, scope and the often limited availability of adaptive strategies due to pre-existing built environments, social constraints, economic ties and financial costs. However, in contrast to mitigation, the share of adaptation patents remained constant from 1995 to 2015 (Dechezlepretre et al. 2020).

In this paper, I present a theoretical model to analyse how the persistent and significant uncertainty surrounding climate outcomes may be impacting inventors for climate adaptation and their decisions to invest. Using a real option valuation approach, I find that the continuous uncertainty over the market for adaptation and the anticipation of rare climate disasters can raise the investment threshold whereas uncertainty over future scientific discoveries may have a more ambiguous effect. Extending the lifetime of patents can mitigate the effect of the uncertainties, but all outcomes are largely dependent on inventors' subjective expectations. In terms of policy, climate treaties, pledges and mandates may lower uncertainty and decrease the investment threshold, but under certain circumstances, their anticipation alone can lead to further delays in investment. Competition incentives and innovation protections may also be viable policy options but need to be designed in consideration of each other. Though inventors in all sectors of the economy are exposed to uncertainty, I propose the complexities of uncertainty in climate adaptation warrant a more careful consideration, may contribute to the stagnant growth over time and point to a possible need for more distinct policy action.

My contribution to the literature is two-fold. Firstly, I contribute to the very limited literature on innovations for climate adaptation, which has thus far primarily focused on the demand side, with researchers exploring topics such as the diffusion of patents for climate change adaptation (Dechezlepretre et al. 2020), efficiency of adaptation portfolios (Berrang-Ford et al. 2019) and barriers to adoption (Tambo and Abdoulaye 2012; Darkwa et al. 2016; Prince et al. 2013). On the supply side there are few empirical studies which have focused on exploring adaptation innovation in response to climate disasters (Miao and Popp 2014; Miao 2020; Dechezlepretre et al. 2020). This paper furthers the study of supply-side dynamics in adaptation innovation by taking climate uncertainty into consideration and introducing a theoretical framework to study the decision-making of the inventors.

My second contribution is to the literature on real option theory through an extension of its application in the context of climate adaptation innovation. Originating in finance in the 1970s, real option theory has received increasing attention in various research areas following its translation to general investment decisions under uncertainty in the seminal works of McDonald and Siegel (1986) and Dixit and Pindyck (1994). In the innovation literature, real option theory has been applied to study a variety of topics, such as uncertainty over future cash flows (Bloom, Bond, and Van Reenen 2001), choice between different R&D projects (Childs and Triantis 1999), process uncertainty (Berk, Green, and Naik 2004), the timing of patent filings and abandonments (Jou 2018), and the impact of R&D uncertainty on market valuation of firms (Bloom and Van Reenen 2002; Oriani and Sobrero 2008). Similarly, real option theory has also found applications in environmental economics; for example in the study of natural resource management (Cortazar and Casassus 1998; Insley 2002; Laughton and Jacoby 1993; Saphores 2001) and decision-making for environmental policy (Wesseler and Zhao 2019). In the context of climate economics specifically, real option theory has predominantly been studied as a tool to empirically evaluate investments in mitigation and adaptation projects, focusing on examining the difference in evaluation approaches and often contrasting net present value calculations with a real option valuation approach (Abadie, Sainz de Murieta, and Galarraga 2017; Linquiti and Vonortas 2012; Woodward, Gouldby, Kapelan, et al. 2011; Heumesser et al. 2012). In this paper, I integrate these strands of literature to develop a theoretical model tailored to the unique dynamics and uncertainties of climate adaptation innovation. Despite the clear significance of uncertainty in this context and the widespread use of real options theory, to the best of my knowledge, it has not been applied here but offers a valuable framework for analysing the dynamics and observed trends in climate adaptation innovation.

The rest of the paper is structured as follows. I will begin by presenting some economic characteristics of climate adaptation innovation and a brief introduction to real option theory. I will then introduce the theoretical framework and analysis of the impact of climate uncertainty on inventors' decision-making in climate adaptation. This will be followed by a discussion of selected policy options and a conclusion.

2.2 Background

2.2.1 Climate Adaptation Innovation

Although both adaptation and mitigation innovations are linked to climate change, they differ in their economic characteristics. The benefits of climate mitigation innovations are a global public good. The benefits of reduced emissions and mitigated climate change are non-excludable and non-rival, resulting in little private incentives for investment and presenting a standard case for government intervention. Conversely, the benefits of climate adaptation can be either private or public. For example, innovations in flood-proofing for households provide private benefits, while innovations in dams and dikes offer public benefits enjoyed by many. Consequently, there exist private incentives for investment in climate adaptation to some extent and the need for government intervention beyond addressing knowledge externalities, common across all innovation, is less straightforward. Given this difference in economic incentives, the theoretical analysis of mitigation innovation cannot directly be applied to adaptation innovation. At the same time, the unique nature of climate change and its uncertainties present distinct market dynamics for climate adaptation innovation compared to other innovation.

In this paper, I will consider adaptation innovation as any scientific or technological developments that help limit or prevent the impacts of climate change. Among many others these may include innovations for drainage systems, cool roof designs, forecasting technologies or drought-resistant crops. The end users of adaptation innovations may be local or national governments, firms, or individuals. Given the wide range of climate change impacts, adaptation innovations span across various sectors and are influenced by diverse sector dynamics. Although this paper focuses on uncertainty as a common aspect of climate innovations across all sectors, there is room for future research to focus on specific sectors and account for their unique dynamics.

The limited evidence so far suggests that the market for adaptation is primary local, with no significant patent dispersion across borders (Dechezlepretre et al. 2020). However, it remains unclear whether this is because bespoke local solutions are required due to factors such as pre-built environments, compatibility across systems, local preferences, or because there are other barriers, such as informational or legal obstacles, that prevent the spread of innovations.

2.2.2 Real Option Theory

In classical economic theory, uncertain outcomes are traditionally modelled using a net present value approach. However, this approach assumes that all possible outcomes are known at the time of decision-making and there is no volatility in the outcomes over time. Net present valuation further assumes that the decision is a one-time opportunity and the investment must be made immediately or not at all. In contrast, real option valuation allows for stochastic development of outcomes over time and flexibility in the timing of investments, enabling inventors to trade off the value of investing today with the value of the option to invest in the future. There is no "now or never" assumption as there is in net present value calculation and the option to be able to invest in the future holds value in itself. For example, let us assume we have an investment opportunity that, depending on the market conditions in the next period and with equal probability, will yield 20 or 5 each period from then onwards. With an investment cost of 100 and discount rate of 10%, the net present value of the future cash flows is 25[1]. Since this is positive, the valuation suggests we should invest today. Now, let us look at the real option valuation of the investment opportunity. If we wait one period, we will know whether we are facing favourable or unfavourable market conditions. If the market conditions are favourable, we will invest and receive 20 each period onwards; if the market conditions are unfavourable, we will abandon the investment opportunity. The real option value is 45.45[2]. While the parameters remain the same, having the option to wait increases the value of the investment opportunity by 20.45.

In the context of climate adaptation innovation, I propose that a real option valuation framework is better suited. Due to the significant scientific and socio-economic uncertainty of climate damages,

[1] $-100+\sum_{t=1}^{\infty}(0.5\cdot 20+0.5\cdot 5)/(1.1)^t = 25$

[2] $0.5\cdot[-100/1.1+\sum_{t=2}^{\infty}20/(1.1)^t]+0.5\cdot 0 = 45.45$

the value of climate adaptation evolves stochastically, with no deterministic probabilities for all future outcomes over time. Though inventors learn the value of adaptation innovation every period uncertainty always remains. Inventors are not obliged to make a decision today but hold flexibility to delay their investment decision.

2.3 Theoretical Analysis

2.3.1 Baseline Model

The baseline framework I adopt relies on the established mathematical formulations of investment under uncertainty by Dixit and Pindyck (1994). While I preserve the core mathematical structure of the framework, I apply and reinterpret its parameters in the context of decision-making for climate adaptation innovation. I focus on the option of the inventor to defer their investment decision rather than operating options or options to switch between technologies. Though the baseline framework yields similar comparative static results to those in general cases of value uncertainty, I later extend this framework to account for the more unique uncertainties associated with the market for climate adaptation innovation.

I begin with a simple model of an inventor who has the option to engage in research for climate adaptation at an irreversibly fixed cost I. When the inventor engages in research, she produces a climate adaptation patent which generates royalties every period, resulting in a series of cash flows V_t. However, royalties from the innovation are not paid indefinitely. They may cease if a more advanced adaptation patent supersedes the original, the original patent expires, or it faces legal challenges. The lifetime of patent royalties following the development of the innovation, denoted by T, follows a Poisson process with probability $\theta \, dT$ that royalties drop to zero over the interval dT.

The source of uncertainty in this analysis lies in the value of the adaptation patent royalties rather than technological uncertainties such as feasibility and costs of developing the adaptation innovation. This means that arrival of information over time is driven by market developments rather than insights from the research and development process itself. Learning is external rather than internal. At the point of investment, the value of the royalties for the climate adaptation innovation is uncertain due to uncertainties in the market that arise due to a variety of factors, for example ambiguity over spatial distributions or intensity of climate damages. Royalties therefore exhibit some random movements $\sigma V dz$ over time, where σ is a constant describing the volatility parameter and dz is the increment of the continuous-time stochastic Wiener process, z_t. Predictability of future royalties decreases over time modelled by linearly increasing variance $dz = \varepsilon\sqrt{dt}$, where ε is a standard normal random variable. Furthermore, I assume that the value of the adaptation patent exhibits some positive trend over time driven by economic growth and an expanding market for climate adaptation innovation due to past and predicted consistent upward trends in climate damages. This is described by $\alpha V dt$ where α is a constant describing the drift parameter. I assume increments in adaptation patent royalties dV are independent and royalties are not normally but log-normally distributed. They may never be negative and are likely skewed to the right due to the existence of rare, high-value disruptive adaptation innovation that result in high royalties. For example, a new meteorological AI technology that radically improves predicability of hurricane paths, limiting extremely expensive damages may be an adaptation innovation with exceptional impact and high royalties. Finally, I assume the Markov property holds suggesting that all relevant information on future royalties, V_{t+1}, is contained in the current value of the royalties, V_t. The resultant continuous stochastic process is a standard geometric Brownian Motion with drift of the form:

$$dV = \alpha V dt + \sigma V dz \tag{2.1}$$

with the generic solution[3]:

[3] See Appendix 2.A.1.1

$$V_t = V_0 e^{(\alpha - \frac{1}{2}\sigma^2)t + \sigma z_t}$$

and (2.2)

$$E[V_t] = V_0 e^{\alpha t}$$

Every period the inventor receives information by learning the value of V_t based on the developments in the market for adaptation innovation but the value of future royalties remains uncertain.

The present value of the royalties assuming the random lifetime of the patent, T, is[4]:

$$E[\int_0^T V_t e^{-\rho t}\, dt] = V_0 \frac{e^{(\alpha-\rho)T} - 1}{\alpha - \rho} \tag{2.3}$$

where ρ is the discount rate and V_0 represents the value of the initial royalties of the adaptation patent.

The lifetime of the royalties is given by the standard exponential cumulative probability function:

$$1 - e^{-\theta T} \tag{2.4}$$

with the associated probability density function:

$$\theta e^{-\theta T} \tag{2.5}$$

When the inventor decides to invest, she receives a termination payoff equal to the present value of the royalties over the lifetime of the patent, net of the investment cost [5]:

[4] See Appendix 2.A.1.2
[5] See Appendix 2.A.1.3

$$\int_0^\infty \theta e^{-\theta T} V_0 \frac{e^{(\alpha-\rho)T}-1}{\alpha-\rho} dT - I = \frac{1}{\rho+\theta-\alpha} V_0 - I \tag{2.6}$$

For the integral to converge we require $\rho + \theta > \alpha$. If the growth trend of patent royalties exceeds the effective discount rate including both time discounting and the risk of patent expiry, the innovation value will not be bounded, and the inventor will always invest immediately. While unbounded innovation value may be possible, it represents a different scenario from the one I aim to capture in this model.

Every period the inventor decides whether to invest and innovate for climate adaptation or wait another period, i.e. hold or trigger the option. I assume that there is no fixed finite time horizon for this innovation opportunity so that the value of the option is common across all periods and denoted by the Bellman equation $F(V)$:

$$F(V) = max\{\frac{1}{\rho+\theta-\alpha} V - I, \frac{1}{1+\rho} E[F(V')|V]\} \tag{2.7}$$

where $\frac{1}{\rho+\theta-\alpha} V - I$ is the termination payoff, V' is the value of the royalties in the next period and $\frac{1}{1+\rho} E[F(V')|V]$ is the expected payoff if she continues to wait. The inventor may hold multiple of such innovation options for climate adaptation at any point in time, each associated with a unique value function and investment costs. For the purpose of this paper, I will assume that these innovation decisions are additive in nature and therefore consider a single representative decision.

To analyse the investment decision of the inventor under varying levels of uncertainty, I stipulate that there exists some value V^* for which $V < V^*$ the inventor continues to wait and for which $V > V^*$ she engages in research to develop her climate adaptation innovation. She does not receive any cash flows from having the option to engage in research except for earning interest on capital, which I assume to be equal to the discount rate. Therefore, in the continuation region where $V < V^*$ the Bellman equation can be re-written as[6]:

$$\rho F(V)dt = E[dF] \tag{2.8}$$

We can expand dF using Itô calculus, omitting terms that go faster to zero than dt and taking expectations[7]:

$$E[dF] = E[F'(V)dV + 0.5F''(V)(dV)^2] \tag{2.9}$$

The Bellman equation in the continuation region thus becomes the homogeneous second order differential equation:

$$F'(V)\alpha V + 0.5F''(V)\sigma^2 V^2 - \rho F(V) = 0 \tag{2.10}$$

Boundary Condition 1: When the value of the royalties is zero, the value of the option to develop a patent for climate adaptation that would create such royalties is zero:

$$F(0) = 0 \tag{2.11}$$

Boundary Condition 2: The value of the option at the point of the investment is equal to the termination payoff, i.e. the value of the climate adaptation patent minus the cost of investment. If the value of the investment opportunity was higher than the payoff the inventor should not invest and innovate but continue to wait:

[6] See Appendix 2.A.1.4
[7] See Appendix 2.A.1.5

$$F(V^*) = \frac{1}{\rho + \theta - \alpha} V^* - I \tag{2.12}$$

Boundary Condition 3: Finally, I assume "smooth pasting" such that the derivative of the payoff function is equal to the derivative of the value function at the optimal stopping value. If this is not the case, then there is a discontinuity and the stopping value is not optimal:

$$F'(V^*) = \frac{1}{\rho + \theta - \alpha} \tag{2.13}$$

Assuming a functional form $F(V) = AV^{\gamma}$ to solve the second order differential equation we arrive at[8]:

$$(\alpha - 0.5\sigma^2)\gamma + 0.5\sigma^2\gamma^2 - \rho = 0 \tag{2.14}$$

with roots:

$$\begin{aligned} \gamma_1 &= \frac{-(\alpha - 0.5\sigma^2) + \sqrt{(\alpha - 0.5\sigma^2)^2 + 2\sigma^2\rho}}{\sigma^2} > 1 \\ \gamma_2 &= \frac{-(\alpha - 0.5\sigma^2) - \sqrt{(\alpha - 0.5\sigma^2)^2 + 2\sigma^2\rho}}{\sigma^2} < 0 \end{aligned} \tag{2.15}$$

and the general solution of the second order differential equation:

$$F(V) = A_1V^{\gamma_1} + A_2V^{\gamma_2} \tag{2.16}$$

However, V^{γ_2} approaches ∞ when $V = 0$ which means the boundary condition $F(0) = 0$ implies $A_2 = 0$, resulting in $F(V) = A_1V^{\gamma_1}$. For simplicity of notation, in the remainder of the analysis, I will redefine $A_1 = A$ and $\gamma_1 = \gamma$. We can use remaining boundary conditions to solve for the

[8] See Appendix 2.A.1.6

investment threshold, V^{*}[9]:

$$\begin{aligned} V^{*} &= \frac{\gamma}{\gamma - 1} I(\rho + \theta - \alpha) \\ \frac{\delta V^{*}}{\delta \gamma} &> 0 \end{aligned} \tag{2.17}$$

Since $\frac{\delta \gamma_1}{\delta \sigma} > 0$ (Eq. 2.15), the higher the uncertainty of the future value of the adaptation patent royalties, i.e. higher volatility of its random movements, the higher the critical value of the initial royalties V^{*} for which it is optimal to trigger the option and invest. In other words, the threshold to invest and innovate for climate adaptation increases with increasing uncertainty over the value of its future royalties. There is higher value in waiting and observing the development of V_t until it reaches V^{*}. This is the common result of higher value uncertainty in real option valuation investment models.

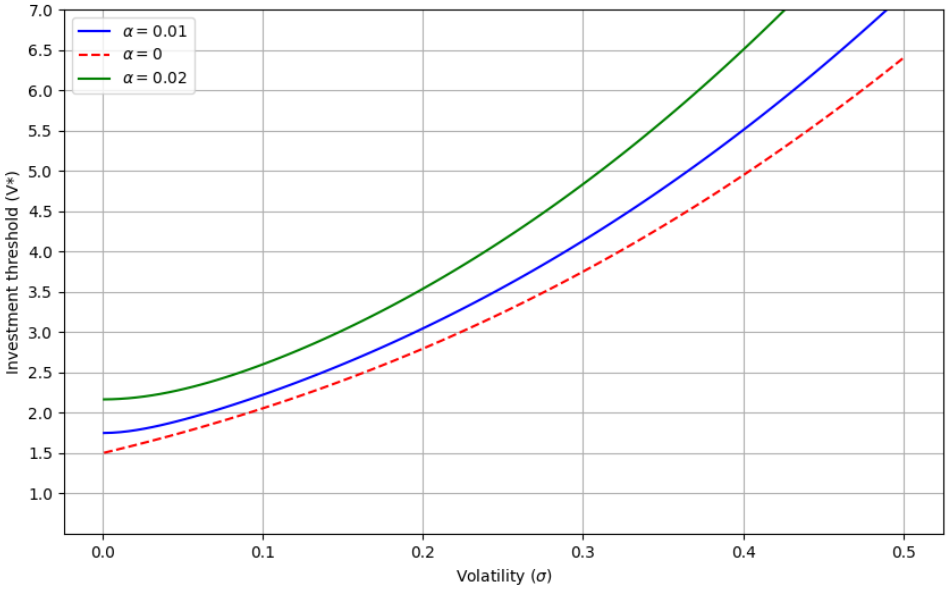
To illustrate these results, I have included some numerical examples of the investment threshold shown in Figure 2.1. The parameters are set as follows: the investment cost of the innovation at $I = 10$, the interest rate at $\rho = 0.05$ and the parameter describing the uncertainty over the lifetime of the climate adaptation patent royalties at $\theta = 0.1$. The red dotted line shows V^{*} in the absence of a growth trend in the value of climate adaptation innovation. In this case, when there is no volatility, the investment threshold is 1.5. The blue line shows the investment threshold with a drift rate of $\alpha = 0.01$. In both cases, higher volatility increases V^{*} exponentially. With $\alpha = 0.01$, under low uncertainty, for instance $\sigma = 0.01$, the value at which the adaptation becomes a worthwhile investment is 1.7586. However, as uncertainty increases, such as $\sigma = 0.2$, the investment threshold, V^{*}, rises to 3.0455 (Table 2.1). With greater uncertainty, the value of the initial royalties must be significantly higher for the inventor to invest and innovate in climate adaptation. Increased uncertainty in the market for climate adaptation innovation elevates the risk associated with investing today and raises the value of the option to delay the decision.

Simple in its form, the baseline model provides the theoretical foundation to analyse the effect

[9] See Appendix 2.A.1.7

of climate uncertainty in the development of adaptation innovation. The return to investments in research and development of all innovations involve various uncertainties, including market uncertainty, which result in the random movements, represented by σ in the model. For climate adaptation innovations, market uncertainty is particularly pronounced because their values are derived from their ability to protect from climate damages which are not only highly uncertain but also subject to interdependent and compounding uncertainties across multiple dimensions. For instance, although considerable strides have been made in climate sensitivity analysis and the impacts of greenhouse gas emissions on global temperature, predictions are not definite and are primarily presented as probability distributions rather than specific estimates which diverge significantly with increasing estimation horizons. Furthermore, even with accurate estimations of the impact of greenhouse gases on global temperatures, there remains much uncertainty regarding future emissions which are dependent on a variety of factors such as government mandates, firm and household decisions as well as technological advancement. Finally, even if these were known with certainty, there remains a tremendous amount of uncertainty regarding the implications and damages of higher temperatures including magnitude, spatial distributions and the mitigating or enhancing effect of socioeconomic developments. Inventors in climate adaptation are facing an underdeveloped, highly uncertain market, making the expected payoff of innovation also highly uncertain. The implications of this can be modelled through a high volatility parameter, σ, resulting in delayed investments in climate adaptation innovation and a high investment threshold, thus providing a theoretical explanation, at least in part, for the observed slow growth.

It is worth noting that in this model, the inventor faces a single decision: once the investment is made, they have no option but to complete the project. More generally, research and development may occur over several stages, and at each stage, the inventor may decide to abandon the project rather than continue investing. However, within this framework, an inventor who invests in stage one of the project will proceed to invest in the following stages until the innovation is complete. To illustrate this I present a two-stage model in the Appendix 2.A.2. The mathematical workings show that the investment threshold of the first stage will always exceed the one of the



Note: This figure plots the investment threshold for the climate adaptation innovation under different volatility parameters. The investment cost is fixed at $I = 10$ with interest rate at $\rho = 0.05$ and the uncertainty parameter for the lifetime of the patent royalties at $\theta = 0.01$. The different curves depict the impact of the volatility parameter on the investment threshold under varying trend rates, α.

FIGURE 2.1: Investment threshold with increasing volatility

second stage and the inventor will complete the innovation. For the remainder of the paper, I will therefore focus on the singular investment decision.

σ	γ	A	V*
0.0100	4.9043	40.8135	1.7586
0.0200	4.6590	40.3942	1.7826
0.0300	4.3457	40.1878	1.8184
0.0500	3.7284	41.1661	1.9131
0.0700	3.2323	43.9746	2.0272
0.1000	2.7016	50.8524	2.2228
0.1200	2.4480	56.9132	2.3669
0.1500	2.1645	68.0591	2.6023
0.1700	2.0205	76.8794	2.7719
0.2000	1.8508	92.3295	3.0455

Notes: This table shows the results for the investment threshold, V^*, and the parameters of the value function, γ and A, under varying levels of volatility, σ. The investment cost is fixed at $I = 10$, with interest rate at $\rho = 0.05$, the uncertainty parameter for the lifetime of the patent royalties at $\theta = 0.01$ and a positive drift in patent royalties at $\alpha = 0.01$.

TABLE 2.1: Investment threshold - baseline model

2.3.2 Climate Disasters

Following the results of the baseline model, I shift to consider additional uncertainty dynamics in climate adaptation and their respective implications for the inventor's decision-making.

A key component of the uncertainty associated with climate damages are climate disasters such as the Australian wildfires in 2020, the German floods in 2021 or the Southeast Asian floods in 2022. These are rare and extreme events with a small probability of occurrence but usually result in significant human and economic damages. This phenomenon is commonly modelled by fat-tails in climate damage distributions in the literature (Weitzman 2011). Following climate disasters, research has shown demand for climate adaptation increases (McFadden, Smith, and Wallander 2022; Zaalberg et al. 2009; Tasantab, Gajendran, and Maund 2022; Kreibich et al. 2005; Grothmann and Reusswig 2006). Reasons for this include protection motivation, updated expectations of future damages or policy changes. I propose that these are not just short-term reactions to the shock, but long-lasting shifts driven by climate disasters signalling the risk of future climate damages and importance of adaptation. For climate adaptation innovation, climate disasters can thus result in rare, sudden and significant positive jumps in the value of adaptation technologies as demand increases. The uncertainty over climate disasters differs from the random fluctuations discussed in the baseline model; they are rare and discrete, and therefore cannot be modelled by the continuous volatility parameter, σ. It should be noted that climate disasters could also result in negative jumps in the patent value if a disaster is so severe that it unveils the adaptation innovation as an inadequate protection. However, for the purpose of this discussion, I will focus on the more probable scenario of positive value impacts. In our model, we can add uncertainty of climate disasters by introducing Poisson jumps to the geometric Brownian motion:

$$dV = \alpha V dt + \sigma V dz + uV dq \tag{2.18}$$

where dq represents the increment of the Poisson process. For simplicity, I assume that jumps are discrete in size and increase the royalties of the adaptation patent by some percentage u such that the royalty after the occurrence of a climate disaster can be described by $(1+u)V$. Certainly, in reality, the scale of climate disasters and thereby the jump in royalties is not discrete and may vary. This could be modelled by a log-normal distribution of u. However, incorporating distributional jump sizes into the model requires a significantly more complex solution approach without offering additional insights within the scope of the paper. Due to the impact of climate disasters stretching beyond a short-term reaction, the jump in value is permanent. The arrival rate of climate disasters is described by λ such that the probability over a small interval of time is described by λdt. In other words, in each time period dt, the probability of a climate disaster occurring and leading to a jump in the value of the adaptation patent is λ.

The present value of the royalties at the point of investment now include the possibility of climate disasters[10]:

$$E[\int_0^T V_t e^{-\rho t}\, dt] = V_0 \frac{e^{(\alpha+\lambda u-\rho)T}-1}{\alpha+\lambda u-\rho} \tag{2.19}$$

The termination payoff, net of investment costs is[11] :

$$\int_0^\infty \theta\, e^{-\theta T}\, V_0 \frac{e^{(\alpha+\lambda u-\rho)T-1}}{\alpha-\rho}\, dT - I = \frac{1}{\rho+\theta-\alpha-\lambda u} V_0 - I \tag{2.20}$$

Using Itô calculus to expand dF, noting that we can ignore higher order derivatives of dq which approach zero faster as dt approaches zero, and taking expectation, the Bellman equation becomes[12]:

$$\begin{aligned} \rho F(V)dt &= E[dF] \\ &= \alpha V F'(V)dt + 0.5F''(V)\sigma^2 V^2 dt + \lambda[F((1+u)V) - F(V)]dt \end{aligned} \tag{2.21}$$

Following the same logic as the baseline model, the new boundary conditions are:

$$\begin{aligned} F(0) &= 0 \\ F(V^*) &= \frac{1}{\rho+\theta-\alpha-\lambda u} V^* - I \\ F'(V^*) &= \frac{1}{\rho+\theta-\alpha-\lambda u} \end{aligned} \tag{2.22}$$

Assuming the same functional form as before AV^γ, we can solve the Bellman equation to get the following quadratic equation:

[10] See Appendix 2.A.3.1 and 2.A.3.2
[11] See Appendix 2.A.3.1
[12] See Appendix 2.A.3.4

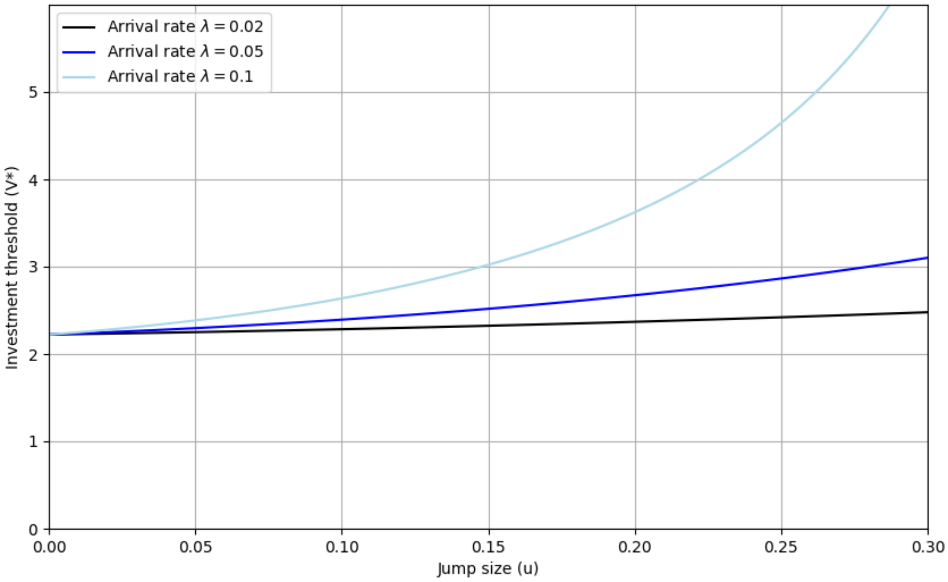
$$\begin{aligned} \gamma\alpha VAV^{\gamma-1}+0.5\sigma^2V^2\gamma(\gamma-1)AV^{\gamma-2}+\lambda A(1+u)^{\gamma}V^{\gamma}-\lambda AV^{\gamma}-\rho AV^{\gamma}=0 \\ (\alpha-0.5\sigma^2)\gamma+0.5\sigma^2\gamma^2-(\lambda+\rho)+\lambda(1+u)^{\gamma}=0 \end{aligned} \tag{2.23}$$

Finally, the new boundary conditions imply[13]:

$$V^*=\frac{\gamma}{\gamma-1}I\frac{1}{\rho+\theta-\alpha-\lambda u} \tag{2.24}$$

The quadratic equation is more complicated but can be solved numerically. I set the volatility parameter at $\sigma=0.1$ and maintain all other parameters from the reference model to ensure comparability between results. Similar to the reference model, I calculate the investment threshold, V^* but this time in the presence of climate disaster uncertainty modelled by the Poisson jumps. The numerical results under different arrival rates and jump sizes are presented in Figure 2.2. Accounting for climate disaster in the valuation of the adaptation patent ($\lambda>0$), increases the investment threshold and the value of the option to wait. This effect is exponentially increasing in the magnitude of the jump, u, and more significantly with the probability of the jump, λ. Some numerical results are presented in Table 2.2 for reference. This table also includes the equivalent volatility parameter of the reference model that would result in the same increase in the investment threshold. Assuming a 2% risk of a climate disaster occurring over the time interval dt and a magnitude of the impact on the value of adaptation patents of 10%, the investment threshold increases from 2.2228 to 2.2839. Increasing the size of the impact to 30% raises the investment threshold to 2.4782, equivalent to a volatility of $\sigma=13.45\%$. Increasing the likelihood of the climate disaster from 2% to 10%, the increase in the investment threshold with a jump size of 30 percent is equivalent to a volatility of $\sigma=47.35\%$.

[13] See Appendix 2.A.3.5



Note: This figure plots the investment threshold, V^*, for the climate adaptation innovation under the possibility of climate disasters with varying jump sizes, u, and arrival rates, λ. The investment cost is fixed at $I = 10$, with interest rate at $\rho = 0.05$, the uncertainty parameter for the lifetime of the patent royalties at $\theta = 0.01$, a positive drift at $\alpha = 0.01$ and volatility at 0.1.

FIGURE 2.2: Investment threshold with climate disasters

λ	u	γ	V*	Equivalent σ
0.0000	0.1000	2.7016	2.2228	0.1000
0.0000	0.2000	2.7016	2.2228	0.1000
0.0000	0.3000	2.7016	2.2228	0.1000
0.0200	0.1000	2.5267	2.2839	0.1087
0.0200	0.2000	2.3482	2.3687	0.1202
0.0200	0.3000	2.1773	2.4782	0.1345
0.0500	0.1000	2.2940	2.3933	0.1235
0.0500	0.2000	1.9471	2.6726	0.1584
0.0500	0.3000	1.6751	3.1016	0.2058
0.1000	0.1000	1.9725	2.6367	0.1542
0.1000	0.2000	1.4954	3.6224	0.2562
0.1000	0.3000	1.1962	6.7079	0.4735

Notes: This table shows the results for the investment threshold, V^*, the parameter of the value function γ and the volatility equivalent under varying arrival rates, λ, and sizes, u, of the climate disasters. The investment cost is fixed at $I = 10$, with interest rate at $\rho = 0.05$, the uncertainty parameter for the lifetime of the patent royalties at $\theta = 0.01$, a positive drift at $\alpha = 0.01$, and volatility at $\sigma = 0.1$.

TABLE 2.2: Investment threshold - climate disaster model

The results suggest that the possibility of climate disasters increases the inventor's opportunity costs of investing in climate adaptation innovation today. Although climate disasters increase the value of the royalties in the future, the arrival of the disaster is uncertain. This uncertainty over the timing of the disaster makes the inventor more willing to wait for future increases in value, earning interest on their capital in the meantime.

However, the results hinge on the assumptions about the lifetime of the patent. With a smaller probability of patent decay (smaller θ), the increases in value of the royalties from climate disaster-induced jumps become more significant as they are longer lasting. This counteracts the effect of uncertainty over arrival of the disaster, resulting in a less pronounced increase of the investment threshold. As the lifetime of the patent approaches infinity ($\theta \to 0$), climate disasters can even decrease the investment threshold. The inventor receiving royalties far into the future, benefits from the cumulative increase in value of the patent caused by climate disasters over time making immediate investment more attractive than in the absence of climate disasters. I illustrate the results of this in Table 2.3. In practice, it is worth noting that, even in the absence of legal challenges or newer innovations superseding the original, patents have a fixed maximum lifespan. This means that royalties will eventually cease and are not infinite, though it is also true that first mover advantages such as brand recognition under certain circumstances may effectively extend benefits beyond this.

Overall, the uncertainty of future climate disaster resulting in sudden positive jumps in the value of adaptation innovation can increase the investment threshold as inventors wait for the jump in value to materialise before investing. This effect increases with the size of the jump and the arrival rate of such disasters. However, the effect decreases with increased lifetime of the patent and may even have the opposite effect if royalties are paid indefinitely as the positive effect of increased value outweighs the added uncertainty over the arrival of the jumps.

θ	$V^*_{\lambda=0}$	$V^*_{\lambda=0.2}$	% Difference
0.0100	0.7938	0.8012	0.9245
0.0500	1.4289	1.4979	4.8250
0.1000	2.2228	2.3687	6.5663
0.0010	0.6510	0.6444	-1.0019

Notes: This table compares the impact of a climate disaster with arrival rate, $\lambda = 0.2$, on the investment threshold, V^*, under varying probabilities of patent decay, θ. The final column in the table describes the percentage difference in the investment threshold when climate disasters are introduced into the model. The investment cost is fixed at $I = 10$, with interest rate at $\rho = 0.05$, a positive drift at $\alpha = 0.01$, volatility at $\sigma = 0.1$, and jump size at 0.02.

TABLE 2.3: Climate disaster under varying theta

2.3.3 Scientific Discoveries

A significant part of the uncertainty associated with the future value of climate adaptation stems from the scientific uncertainty that persists in our understanding of climate change. Nevertheless, progress continues with the number of climate science related publications having increased exponentially since the 1970s, both in absolute and in relative terms (Klingelhöfer et al. 2020). As climate science progresses, so does our understanding of damages and the need for climate adaptation. However, uncertainty remains regarding what future scientific discoveries may reveal. In this part of the analysis, I will focus on the uncertainty surrounding future scientific discoveries and its effect on the inventor's decision-making for climate adaptation innovation.

To incorporate this in the model, I consider scientific discoveries as non-transitory and long-lasting changes that substantially alter the stochastic development of the value of adaptation innovation. As such they may influence the drift as well as the volatility parameter. This stands in contrast to climate disaster which lead to discrete jumps in the value of adaptation innovation but do not affect the parameters of change. It is important to note that these scientific discoveries do not include the smaller, continuous scientific insights, as their effects and uncertainties are already captured by the existing drift and volatility parameters. I stipulate further that scientific discoveries have no impact on the arrival rate or size of rare climate disasters. Scientific discoveries do not occur every period but are rare and discrete, following a Poisson process. The arrival rate is π such that the probability of a scientific discovery over a small interval dt is πdt.

The effect of the scientific discovery on the drift parameter is $(1+\omega)\alpha$ and the effect on the volatility parameter is $(1+\nu)\sigma$. Importantly, the change to the drift and volatility parameter are permanent and do not revert back:

$$d\alpha = \begin{cases} 0, & \text{with probability } 1-\pi, \\ \\ \omega, & \text{with probability } \pi. \end{cases} \tag{2.25}$$

$$d\sigma = \begin{cases} 0, & \text{with probability } 1-\pi, \\ \\ \nu, & \text{with probability } \pi. \end{cases} \tag{2.26}$$

Scientific discoveries may have zero, positive or negative effects on each of the parameters. For example, a positive effect on the drift parameter might stem from identifying a new greenhouse gas that accelerates climate change, thereby solidifying a need for adaptation. A negative effect could be the result of widespread implementation of stratospheric aerosol injections which could mitigate climate change and the need for adaptation. In terms of volatility, scientific discoveries that decrease uncertainty could include better geospatial forecasting of climate impacts or refinements in climate sensitivity analysis. However, negative impacts on volatility might arise from discoveries that reveal previously 'unknown unknowns', thus increasing the uncertainty around the future need for climate adaptation. Furthermore, a single scientific discovery may influence both parameters at the same time. For example, the discovery of deep ocean warming increased our expectations of climate warming and at the same time added a new dimension of climate uncertainty. For the purpose of this analysis, I will suggest that the inventor holds some expectation regarding the impact that scientific discoveries will have on the parameters of change for the value of adaptation innovation (ω and ν), and analyse the effect of this in a series of numerical examples. If the inventor expects the overall effect of discoveries on drift and volatility to be zero, their decision-making process will remain unaffected.

Under the arrival of scientific discoveries over time, the stochastic process of the value of the adaptation patent becomes:

$$dV = (\alpha + \omega ds)V dt + (\sigma + \nu ds)V dz \tag{2.27}$$

where ds is the increment of the Poisson process with arrival rate π, taking the value 1 if a scientific discovery occurs and 0 otherwise. For simplicity, I assume that over the small time interval dt, only one scientific discovery may occur, such that for small dt:

$$dV = (\alpha + \pi\omega)V dt + (\sigma + \pi\nu)V dz \tag{2.28}$$

The expected payoff for a patent with lifetime T is[14]:

$$E[\int_0^T V_t e^{-\rho t}\, dt] = V_0 \frac{e^{(\alpha+\pi\omega-\rho)T} - 1}{\alpha + \pi\omega - \rho} \tag{2.29}$$

with termination payoff[15]:

$$\int_0^\infty \theta\, e^{-\theta T}\, V_0 \frac{e^{(\alpha+\pi\omega-\rho)T} - 1}{\alpha + \pi\omega - \rho}\, dT - I = \frac{1}{\rho + \theta - \alpha - \pi\omega} V_0 - I \tag{2.30}$$

As before, the Bellman equation in the continuation region using Itô calculus is:

[14] See Appendix 2.A.3.6 and 2.A.4.1

[15] See Appendix 2.A.4.2

$$\begin{aligned} \rho F(V)dt = &\quad E[dF] \\ = &\quad E[F'(V)dV + 0.5F''(V)(dV)^2] \end{aligned} \tag{2.31}$$

Since ds only takes value 0 or 1 over the small time interval dt (i.e. at most one scientific discovery occurs during dt) and $(ds)^2 = ds$, higher-order exponentials of ds do not converge to zero. Further, we know that $E[\omega ds]$ over the small time interval dt is equal to $(1-\pi)*0+\pi\omega$ as discoveries are rare. We can therefore expand the previous equation to[16]:

$$F'(V)(\alpha+\omega\pi)Vdt + 0.5F''(V)(\sigma^2+2\sigma\nu\pi+\nu^2\pi)V^2dt - \rho F(V)dt = 0 \tag{2.32}$$

The new boundary conditions are:

$$\begin{aligned} F(0) &= 0 \\ F(V^*) &= \frac{1}{\rho+\theta-\alpha-\pi\omega}V^* - I \\ F'(V^*) &= \frac{1}{\rho+\theta-\alpha-\pi\omega} \end{aligned} \tag{2.33}$$

I assume the same functional form as before, $F(V) = AV^\gamma$:

$$\begin{aligned} \gamma AV^{\gamma-1}(\alpha+\omega\pi)V + 0.5\gamma(\gamma-1)AV^{\gamma-2}(\sigma^2+2\sigma\nu\pi+\nu^2\pi)V^2 - \rho AV^\gamma = 0 \\ \gamma(\alpha+\omega\pi) + 0.5\gamma(\gamma-1)(\sigma^2+2\sigma\nu\pi+\nu^2\pi) - \rho = 0 \end{aligned} \tag{2.34}$$

The resultant termination payoff with scientific discoveries is[17]:

$$V^* = \frac{\gamma}{\gamma-1}I\frac{1}{\rho+\theta-\alpha-\pi\omega} \tag{2.35}$$

[16] See Appendix 2.A.4.3
[17] See Appendix 2.A.4.4

We can solve this equation for γ, bearing in mind that we can disregard $\gamma < 0$ due to the boundary conditions (see Baseline Model). Utilizing the same parameter values for α, σ, ρ, θ and I as before, the numerical solutions for V^* under different expectations of scientific discoveries are shown in Table 2.4.

I assume scientific discoveries have an arrival rate of 2%, although naturally, similar to climate disasters, increasing the arrival rate will amplify the effects. When either π or both ω and ν are equal to zero we remain at the baseline threshold, $V^* = 2.2228$. $\pi = 0$ implies no scientific discoveries, whereas $\omega = 0$ and $\nu = 0$ imply that the inventor's expectations over the effect of scientific discoveries are neutral. For example, this may be because the inventor assigns equal likelihoods to positive and negative effects of discoveries or assumes a normal distribution for ω and ν.

Now, let us examine the results when the inventor holds specific expectations regarding the impact of future scientific discoveries. Consider an inventor who believes that scientific discoveries will reveal a greater need for climate adaptation, thus higher climate adaptation innovation royalties, $\omega > 0$. Holding the effect of the discovery on the volatility parameter at zero, an expectation of a 50% increase in the drift parameter will result in a 0.11 % increase in the investment threshold. Although the inventor expects the payoff from the adaptation innovation to increase eventually, there is uncertainty over the timing of this and they prefer to wait. While this may seem counter-intuitive at first, the key lies in the opportunity cost. Investing now is more costly as the option to invest later when the drift of adaptation value increases has become more rewarding. Contrary, an inventor who believes scientific discoveries will reveal a decrease in the need for adaptation innovation, ($\omega < 0$), will have a lower investment threshold. This inventor wants to capitalize on current growth rates before scientific discoveries reveal less need for adaptation.

With regards to volatility, inventors expecting scientific discoveries to resolve some of the uncertainty ($\nu < 0$), face a decreased investment threshold. For example, an expected 50% decrease in volatility due to scientific discoveries results in a 23.48% decrease in the investment threshold. Contrary an increase of 50% results in an increase of 38.90%. Changes in volatility have a more pronounced and asymmetric effect on the investment threshold as uncertainty affects the threshold exponentially, as seen in the baseline model. An inventor who expects reduced uncertainty in the value of adaptation innovation due to future scientific discoveries, is more confident in investing today, i.e. has a lower investment threshold and innovates earlier.

Furthermore, the effects on volatility and drift due to a scientific discovery are independent, with the overall impact on the investment threshold being the sum of their individual effects. However, for the same percentage change in the parameters, volatility changes have a greater influence on the investment decision.

Similar to climate disasters, these results hinge on the assumptions about the lifetime of the patent and the duration of royalty payments. The effect of scientific discoveries on the investment threshold via the volatility parameter remains consistent in an prolonged/ infinite royalty payment time horizon. Increased uncertainty always raises the investment threshold, irrespective of the time horizon. Though a longer time horizon mutes this effect, it has no benefits to counteract them.

On the other hand, changes in the drift parameter bring along changes to the expected termination payoff. The longer the time horizon, the more the effects of the scientific discoveries on the drift parameter will be accounted for. The benefits of the impact on the payoff will counteract the effect of uncertainty surrounding the arrival of the scientific discoveries. As the lifetime of the patent approaches infinity ($\theta \to 0$), depending on the size and arrival rate, scientific discoveries that affect the drift parameter can have a reverse effect on the investment threshold. In other words, the anticipation of scientific events that result in a significant positive change in the drift parameter would decrease the investment threshold as the increase in future expected royalties outweighs the uncertainty over the arrival of the discoveries.

Overall, the uncertainty over significant scientific discoveries adds yet another element of uncertainty for inventors in climate adaptation. Expectation of inventors regarding the magnitude and direction on the growth rate and volatility of adaptation innovation are crucial in determining the effect of discoveries on the investment thresholds. Anticipation that scientific discoveries may resolve future uncertainty will always lead to a decrease in the investment threshold. On the other hand, anticipation of scientific discoveries that point to more need for adaptation, thus increased drift in adaptation royalties, can under a limited patent lifetime actually raise the investment threshold as the opportunity cost of investing today increases.

ω	ν	V*	% diff
0.0025	0.0000	2.2240	0.0562
0.0050	0.0000	2.2253	0.1126
0.0075	0.0000	2.2265	0.1692
-0.0025	0.0000	2.2215	-0.0560
-0.0050	0.0000	2.2203	-0.1117
-0.0075	0.0000	2.2191	-0.1672
0.0000	0.0250	2.2267	0.1754
0.0000	0.0500	2.2314	0.3890
0.0000	0.0750	2.2370	0.6402
0.0000	-0.0250	2.2197	-0.1368
0.0000	-0.0500	2.2176	-0.2348
0.0000	-0.0750	2.2162	-0.2937
0.0000	0.0000	2.2228	0.0000
0.0050	0.0500	2.2339	0.5018
0.0050	-0.0500	2.2201	-0.1224
-0.0050	0.0500	2.2289	0.2770
-0.0050	-0.0500	2.2151	-0.3463

Notes: This table shows the results for the investment threshold, V^* under the possibility of scientific discoveries with varying magnitudes of the impact on the drift, ω and volatility, ν. The final column describes the percentage change of the investment threshold compared to the model without scientific discoveries. The investment cost is fixed at $I = 10$, with interest rate at $\rho = 0.05$, the uncertainty parameter for the lifetime of the patent royalties at $\theta = 0.01$, a positive drift at $\alpha = 0.01$, and volatility at $\sigma = 0.1$.

TABLE 2.4: Investment threshold - scientific discoveries

2.4 Policy Discussion

In this section, I analyse a limited selection of policy options to lower the investment threshold in climate adaptation innovation and incentivise earlier innovation.

2.4.1 Climate Treaties, Pledges and Government Mandates

The first international climate treaty was ratified in 1992 at the Earth Summit in Rio de Janeiro. Since then, a series of international treaties and national climate pledges have followed, with 107 countries having net zero targets as of June 2024 (United Nations Environment Programme 2024). Similarly, more recently, there has also been a notable increase in government commitments to climate adaptation, such as the increasing adoption of National Adaptation Plans.

For inventors in climate adaptation, government commitments to climate mitigation and adaptation can reduce some of the uncertainty over the future market size for adaptation innovation. This can reduce the volatility parameter, lowering the investment threshold and incentivise earlier investment. Moreover, if treaties and pledges include mandates that specifically require the procurement of adaptation products and support the development of adaptation technologies, this could also lead to a jump in the value of adaptation innovation and growth, accelerating the timeline to reach the investment threshold.

However, there are caveats to this. Firstly, the effectiveness of government action largely relies on its credibility. Treaties and pledges often lack enforcement mechanism and government changes can lead to sudden reversals of climate policy as seen with the United States exiting the Paris Agreement under Donald Trump. For climate treaties, pledges and government mandates to effectively reduce uncertainty, they must be credible and inspire confidence among inventors.

Secondly, while immediate government action could yield positive results, uncertainty about the timing and nature of future government climate policy could have the opposite effect. Similar to scientific discoveries, this can be modelled as the uncertain arrival of a regime shift that alters the drift and volatility parameter. If the majority of uncertainty stems from scientific uncertainty, inventors may anticipate minimal reductions in uncertainty from government action. At the same time, if inventors expect significant future government procurement that increases the drift parameter of adaptation value, the investment threshold may actually increase. In this case, the anticipation of future government action may lead to a rise of the opportunity cost of investing early. As before, the outcomes of this depend on the lifetime of royalties, the anticipated arrival rate of government action and the magnitude of changes to the parameters but is a caveat that needs to be considered.

2.4.2 Competition Incentives

Next, I will consider competition incentives as a policy to reduce the investment threshold in adaptation innovation. So far, in this model I have assumed that the inventor holds the option to invest in climate adaptation indefinitely. However, over time other inventor with similar ideas may innovate first and capture the market, thereby reducing the value of the option, $F(V)$, to zero. To incorporate this competition risk, we can introduce negative Poisson jumps with size $u = -1$. This is akin to the modifications of the baseline model with climate disasters, except that now the value of the option drops to zero when an event occurs. Therefore, we can immediately see that the presence of competition will decrease the investment threshold as the risk of another inventor capturing the market increases the opportunity cost of waiting. Though the effect of general uncertainty, climate disasters and scientific discoveries will remain, increasing competition could weaken these effects and reduce the investment threshold. Government policies to increase competition may include support for innovation clusters, competitions or research funding.

However, this needs to be carefully considered as increasing competition may also decrease the expected lifetime of royalty payments following the development of the innovation (higher θ). More competition increases the likelihood that other inventors will produce adaptation patents that supersede the original, thus leading to an earlier decline in patent royalties and a higher investment threshold.

2.4.3 Innovation Protections

This caveat leads to the final policy option I consider, namely innovation protections such as intellectual property rights. Longer protection of the innovation result in a longer stream of royalty payments (higher θ) and therefore a higher expected payoff. This will reduce the investment threshold and incentivise inventors to invest earlier. It will also decrease the negative effects of uncertainty of climate disasters and scientific discoveries. However, it will be important to develop protections that have limited effect on competition as this may otherwise increase the threshold of investment. Possible options may be increasing accessibility of patent application, expanding legal protection, patent duration and enforcement.

Overall, the policy options I have discussed here show different approaches to incentivise earlier innovation in climate adaptation. Many others exist, such as educational climate campaigns for inventors or funding for climate science to reduce the uncertainty of future adaptation needs. Considering the complex dynamics that depend heavenly on subjective expectations of inventors, this section demonstrates that policy in climate adaptation policy may not be straightforward and requires careful consideration.

2.5 Concluding Remarks

Climate impacts continue to involve a vast amount of uncertainty resulting from uncertainty in greenhouse gas emissions, climate sensitivity to those emissions, uncertainty over the type, magnitude and geographic location of climate damages and path dependencies from decisions made by governments, firms, and individuals. The possibility of rare catastrophic disasters and scientific breakthroughs further amplify this. The uncertainties in climate damages translate directly into uncertainties in the market for climate adaptation. In this paper, I have presented a real option valuation model to analyse the impact of these uncertainties on the decisions by inventors in climate adaptation.

The results show that the scale and complexities of uncertainty in climate adaptation can lead to a high investment threshold for inventors and the decision to delay investment. The significant interdependent and compounding uncertainties in the market for adaptation may outweigh market uncertainties experienced by inventors in other markets and can have an exponential effect on the investment threshold. Additionally, the anticipation of climate disasters, which may trigger sudden increases in demand for adaptation, can raise the opportunity cost of investing today. Although inventors may expect future climate disaster to increase the value of their adaptation, uncertainty over the timing of such events can outweigh the expected present value of future benefits. However, increased lifetime of patent royalties will mitigate this effect, and near infinite patent royalties coupled with significant positive jumps in value, may even decrease in the investment threshold. Effects of uncertainty over future scientific discoveries are nuanced. Whereas expectations of future uncertainty-reducing discoveries will lower the investment threshold, expectations that future research will unveil additional unknowns will raise the investment threshold. Paradoxically, inventors anticipating research that reveals higher future demand for adaptation may face an increased opportunity cost of investing today, as uncertainty over the timing of discoveries can outweigh the benefits of the increased present value from future royalties. While the volatility effects of scientific discoveries remain constant over a patent's lifetime, anticipated changed to the drift depend, as with climate disasters on the size of the impact and the lifetime of the patent. The effects of discoveries on volatility and drift are additive, with the overall impact depending on the relative magnitude of the effects.

In terms of policy, in this paper I briefly presented three policy options. Climate treaties, pledges and mandates have the potential to reduce the investment threshold for adaptation innovation by reducing the uncertainty over future market demand or increasing its value. For this, the credibility of governments and their commitments is key. However, in a seeming contradiction, the anticipation of future policy that inflates the value of adaptation innovation can delay inventors' investment decisions akin to climate disasters. In fact, the anticipation of government investment in adaptation after climate disaster can further raise the threshold and deter inventors from early investments. Secondly, policies to increase competition in the market for adaptation innovation may encourage early investment, as inventors who wait risk being outpaced by competitors. However, increased competition may also shorten the lifetime of patent royalties if newer patents begin to more quickly supersede the original. Finally, to address this, governments may introduce enhanced innovation protections such as accessibility in the patenting process and enforcements of patents but these must be designed carefully to avoid eroding competition. Though I only presented a selection of policy options, there remain many others that should be taken into consideration such as funding for climate impact research and education. Bearing the context in mind, some uncertainty will invariably continue to exist. Central to this issue are the views of the inventors and their expectations of future prospects, highlighting the need for information campaigns to minimise frictions between inventors and the scientific community.

The insights of this paper are of course not without caveats. Firstly, the results of the analysis hinge on the assumption that inventors hold ideas for viable adaptation products. If inventors perceive the impacts of climate change as insurmountable, they may not believe they can develop effective innovations thereby reducing the option value to zero. Furthermore, this paper only provides the theoretical argument of the impact of uncertainty. To corroborate and refine the results, surveying potential inventors would therefore be a valuable area for future research. Finally, I believe that there remains a significant need for future research in the study of the supply of adaptation innovation including the incorporation of considerations beyond uncertainty, such as choice models between different types of adaptation innovation and sector or climate impact specific analyses.

Overall, I propose that the scale and complexities of climate damages, in addition to the common uncertainty dynamics faced by inventors across all sectors, may lead to a higher investment threshold for inventors in climate adaptation and contribute to the slow growth we have observed so far. Although market demand may exist, the uncertainty over its future may hinder the development of innovative solutions. To foster innovation for adaptation, distinct policy action may therefore be required, as standard innovation incentives may not be sufficient to overcome the investment barriers.

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2.A Mathematical Appendix

2.A.1 Baseline Model

2.A.1.1 Solution to the Geometric Brownian Motion - Baseline

In this section I will provide the generic derivation of the solution to the geometric Brownian motion:

$$dV_t = \alpha V_t dt + \sigma V_t dz_t$$

Please note for simplicity, I omitted the time subscripts throughout the analysis but am re-introducing it here for clarity.

Let us assume a function $f(V_t) = ln(V_t)$ such that $X_t = lnV_t$. Applying Itô calculus:

$$\begin{aligned}
dX_t &= \frac{1}{V_t}dV_t + \frac{1}{2V_t^2}dV_t^2 \\
dX_t &= \frac{1}{V_t}(\alpha V_t dt + \sigma V_t dz_t) - \frac{1}{2V_t^2}\sigma^2 V_t^2 dt \\
dX_t &= (\alpha - \frac{1}{2}\sigma^2)dt + \sigma dz_t
\end{aligned}$$

Integrating from 0 to t:

$$\begin{aligned}
X_t &= X_0 + \int_0^t (\alpha - \frac{1}{2}\sigma^2)ds + \int_0^t \sigma dz_t \\
X_t &= X_0 + (\alpha - \frac{1}{2}\sigma^2)t \ + \sigma z_t
\end{aligned}$$

Exponentiating to return to V_t gives:

$$V_t = V_0 e^{(\alpha - \frac{1}{2}\sigma^2)t\ + \sigma z_t}$$

The expectation of V_t is given by:

$$E[V_t] = V_0\, e^{(\alpha - \frac{1}{2}\sigma^2)t} + E[e^{\sigma z_t}]$$

Since the Wiener process z_t is normally distributed with mean zero and variance t, the standard moment generating function for a normal distribution implies

$$E[e^{\sigma z_t}] = e^{\frac{1}{2}\sigma^2 t}$$

and therefore:

$$E[V_t] = V_0\, e^{(\alpha - \frac{1}{2}\sigma^2)t + \frac{1}{2}\sigma^2 t}$$
$$E[V_t] = V_0\, e^{\alpha t}$$

2.A.1.2 Present Value of Royalties - Baseline

Since royalties are non-negative, under Tonelli's theorem:

$$E[\int_0^T V_t e^{-\rho t}\, dt] - I = \int_0^T E[V_t e^{-\rho t}]\, dt - I$$

and thus:

$$
\begin{aligned}
&\int_0^T E[V_t e^{-\rho t}]\,dt - I \\
=&\int_0^T V_0 e^{\alpha t} e^{-\rho t}\,dt - I \\
=&V_0 \left[\frac{1}{\alpha-\rho} e^{(\alpha-\rho)t}\right]_0^T \\
=&V_0 \frac{e^{(\alpha-\rho)T}-1}{\alpha-\rho} - I
\end{aligned}
$$

2.A.1.3 Termination Payoff - Baseline

The present value of the royalties assuming the random lifetime of the patent, T, and a discount rate ρ is:

$$
\begin{aligned}
&= \int_0^\infty \theta\, e^{-\theta T}\, V_0 \frac{e^{(\alpha-\rho)T}-1}{\alpha-\rho}\, dT \\
&= \frac{V_0}{\alpha-\rho}\left[\int_0^\infty \theta\, e^{(\alpha-\rho-\theta)T}\, dT - \int_0^\infty \theta\, e^{-\theta T}\, dT\right] \\
&= \frac{V_0}{\alpha-\rho}\left[\frac{\theta}{\alpha-\rho-\theta} e^{(\alpha-\rho-\theta)T}\right]_0^\infty + \left[e^{-\theta T}\right]_0^\infty \\
&= \frac{V_0}{\alpha-\rho}\left[-\frac{\theta}{\alpha-\rho-\theta} - 1\right] \\
&= \frac{1}{\rho+\theta-\alpha} V_0
\end{aligned}
$$

2.A.1.4 Derivation of Bellman Equation - Baseline

In the continuation region the Bellman equation is:

$$
F(V) = \frac{1}{1+\rho} E[F(V')|V]
$$

In continuous time the discount factor over a short time interval dt is $e^{-\rho dt}$ which can be approximated via the Taylor expansion by:

$$\begin{aligned} e^{-\rho dt} &= 1 - \rho dt + \frac{(\rho dt)^2}{2} - \frac{(\rho dt)^3}{3} \dots \\ &\approx 1 - \rho dt \end{aligned}$$

Furthermore, the expectation of the value function over the small time interval dt:

$$E[F(V')|V] = F(V) + E[dF]$$

Substituting these back into the original equation gives:

$$\begin{aligned} F(V) &= (1 - \rho dt)(F(V) + E[dF]) \\ &= F(V) - \rho F(V) dt + E[dF] + \rho dt\, E[dF] \end{aligned}$$

where $\rho dt\, E[dF]$ is of order $(dt)^2$, thus goes to zero faster than dt, and can be dropped as dt becomes small, giving:

$$\rho F(V) dt = E[dF]$$

2.A.1.5 Expansion of the Bellman Equation - Baseline

$$\begin{aligned} dF &= F'(V)dV + 0.5F''(V)(dV)^2 \\ &= F'(V)(\alpha V dt + \sigma V dz) \\ &\quad + 0.5F''(V)[(\alpha^2 V^2 dt^2 + \alpha\sigma V^2 dt dz + \sigma^2 V^2 dz^2)] \\ &= F'(V)(\alpha V dt + \sigma V dz) \\ &\quad + 0.5F''(V)[(\alpha^2 V^2 dt^2 + \alpha\sigma V^2 dt dz + \sigma^2 V^2 dt)] \end{aligned}$$

Omitting terms that go to zero faster than dt and taking expectations:

$$E[dF] = F'(V)\alpha V dt + 0.5F''(V)\sigma^2 V^2 dt$$

The Bellman equation in the continuation region becomes the homogeneous second order differential equation:

$$\begin{aligned} &F'(V)\alpha V dt + 0.5F''(V)\sigma^2 V^2 dt - \rho F(V)dt = 0 \\ &F'(V)\alpha V + 0.5F''(V)\sigma^2 V^2 - \rho F(V) = 0 \end{aligned}$$

2.A.1.6 Solving second order differential equation - Baseline

Since:

$$\begin{aligned} F(V) &= AV^{\gamma} \\ F'(V) &= \gamma AV^{\gamma-1} \\ F''(V) &= \gamma(\gamma-1)AV^{\gamma-2} \end{aligned}$$

Substituting $F(V) = AV^{\gamma}$ into $F'(V)\alpha V + 0.5F''(V)\sigma^2 V^2 - \rho F(V) = 0$

$$\begin{aligned}
F'(V)\alpha V + 0.5F''(V)\sigma^2 V^2 - \rho F(V) &= 0 \\
\gamma AV^{\gamma-1}\alpha V + 0.5\sigma^2\gamma(\gamma-1)AV^{\gamma-2}V^2 - \rho AV^{\gamma} &= 0 \\
(\alpha - 0.5\sigma^2)\gamma + 0.5\sigma^2\gamma^2 - \rho &= 0
\end{aligned}$$

2.A.1.7 Solving for V^* - Baseline

The boundary conditions are:

$$\begin{aligned}
F(0) &= 0 \\
F(V^*) &= \frac{1}{\rho+\theta-\alpha}V^* - I \\
F'(V^*) &= \frac{1}{\rho+\theta-\alpha}
\end{aligned}$$

Using the solution $F(V) = AV^{\gamma}$

$$\begin{aligned}
\frac{1}{\rho+\theta-\alpha} &= \gamma AV^{*\gamma-1} \\
\frac{1}{\rho+\theta-\alpha}V^* &= \gamma AV^{*\gamma} \\
\frac{1}{\rho+\theta-\alpha}V^* - I &= AV^{*\gamma} \\
\frac{1}{\rho+\theta-\alpha}V^* &= \gamma\left(\frac{1}{\rho+\theta-\alpha}V^* - I\right) \\
V^*(1-\gamma) &= -(\rho+\theta-\alpha)\gamma I \\
V^* &= \frac{\gamma}{\gamma-1}I(\rho+\theta-\alpha) \\
\frac{\delta V^*}{\delta\gamma} &> 0
\end{aligned}$$

2.A.2 Multi-Stage Investment

I apply a simple proof of multi-stage investment from Dixit and Pindyck (1994) to my model. Assuming a two-stage process for developing the innovation, the first stage involves an investment cost I_1 and a value function $F_1(V)$. In the second stage, the investment cost is I_2, and the value function is $F_2(V)$. The inventor only receives patent royalties upon completion in stage two. Using the results from the baseline model, the value function in the second stage is:

$$F_2(V) = \begin{cases} A_2 V^{\gamma} & \text{if } V < V_2^*, \\ \frac{1}{\rho+\theta-\alpha} V^* - I_2 & \text{if } V > V_2^*, \end{cases}$$

The value function in period 1 is:

$$F_1(V) = max\{\frac{1}{\rho+\theta-\alpha} V - I_1, \frac{1}{1+\rho} E[F_2(V')|V]\}$$

with boundary conditions:

$$F_1(0) = 0$$

$$F_1(V_1^*) = F_2^*(V_1^*) - I_1$$

$$F_1'(V_1^*) = F_2'(V_1^*)$$

If $V < V_2^*$ the value function is $F_2(V) = A_1 V^{\gamma}$ and the second boundary condition implies $A_1 \neq A_2$ since:

$$F_1(V_1^*) = A_1 V_1^{*\gamma}$$

$$F_1(V_1^*) = A_2 V_1^{*\gamma} - I_1$$

However, the third boundary condition would imply $A_1 = A_2$ since:

$$\gamma A_1 V_1^{*\gamma-1} = \gamma A_2 V_1^{*\gamma-1}$$

Using backwards induction we therefore know that $V_2^* > V$ and $F_2(V) = \frac{1}{\rho+\theta-\alpha}V_2^* - I_2$, resulting in:

$$F_1(V_1^*) = \frac{1}{\rho+\theta-\alpha}V_2^* - I_2 - I_1$$

Finally, this implies that $V_1^* > V_2^*$, suggesting that if the inventor invests in the first stage of the research and development project, they will always complete the second stage and produce the innovation.

2.A.3 Climate Disasters

2.A.3.1 Solution to the Geometric Brownian Motion - Climate Disasters

The geometric Brownian motion with climate disasters is defined as:

$$dV_t = \alpha V_t dt + \sigma V_t dz_t + uV_t dq_t$$

Let us assume a function $f(V_t) = ln(V_t)$ such that $X_t = lnV_t$. Applying Itô calculus:

$$
\begin{aligned}
dX_t &= \frac{1}{V_t}dV_t + \frac{1}{2V_t^2}dV_t^2 + [ln((1+u)V_t) - ln(V_t) - \frac{1}{V_t}uV_t]dq_t \\
dX_t &= \frac{1}{V_t}(\alpha V_t dt + \sigma V_t dz_t + uV_t dq_t) - \frac{1}{2}\sigma^2 dt + [ln(1+u) - u]dq_t \\
dX_t &= (\alpha - \frac{1}{2}\sigma^2)dt + ln(1+u)dq_t + \sigma dz_t
\end{aligned}
$$

Integrating from 0 to t:

$$
\begin{aligned}
X_t &= X_0 + \int_0^t (\alpha - \frac{1}{2}\sigma^2)ds + \int_0^t \sigma dz_s + \int_0^t ln(1+u)dq_s \\
X_t &= X_0 + (\alpha - \frac{1}{2}\sigma^2)t \; + \sigma z_t + ln(1+u)N_t
\end{aligned}
$$

where N_t is the number of jumps up to time t.

Exponentiating to return to V_t gives:

$$
V_t = V_0 \, e^{(\alpha - \frac{1}{2}\sigma^2)t \; + \sigma z_t} \; ln(1+u)^{N_t}
$$

Since z_t and N_t are independent the expectation of V_t is given by:

$$
E[V_t] = V_0 E[e^{(\alpha - \frac{1}{2}\sigma^2)t \; + \sigma z_t}] E[ln(1+u)^{N_t}]
$$

The Wiener process z_t is normally distributed with mean zero and variance t so the standard moment generating function for a normal distribution implies:

$$
E[e^{\sigma z_t}] = e^{\frac{1}{2}\sigma^2 t}
$$

Furthermore, for the Poisson process N_t the standard probability generating function implies:

$$E[(1+u)^{N_t}] = e^{\lambda ut}$$

Therefore:

$$E[V_t] = V_0\, e^{(\alpha+\lambda u-\frac{1}{2}\sigma^2)t} + E[e^{\sigma z_t}]$$
$$E[V_t] = V_0\, e^{(\alpha-\frac{1}{2}\sigma^2)t+\frac{1}{2}\sigma^2 t}$$
$$E[V_t] = V_0\, e^{(\alpha+\lambda u)t}$$

2.A.3.2 Present Value of Royalties - Climate Disasters

Since royalties are non-negative, under Tonelli's theorem:

$$E[\int_0^T V_t e^{-\rho t}\, dt] - I = \int_0^T E[V_t e^{-\rho t}]\, dt - I$$

and thus:

$$\begin{aligned}
&\int_0^T E[V_t e^{-\rho t}]\, dt - I \\
&= \int_0^T V_0 e^{(\alpha+\lambda u)t} e^{-\rho t}\, dt - I \\
&= V_0 \left[\frac{1}{\alpha+\lambda u-\rho} e^{(\alpha+\lambda u-\rho)t}\right]_0^T \\
&= V_0 \frac{e^{(\alpha+\lambda u-\rho)T} - 1}{\alpha+\lambda u-\rho} - I
\end{aligned}$$

2.A.3.3 Termination Payoff - Climate Disasters

The present value of the royalties assuming the random lifetime of the patent, T, and a discount rate ρ is:

$$
\begin{aligned}
&= \int_0^{\infty} \theta\, e^{-\theta T}\, V_0\, \frac{e^{(\alpha+\lambda u-\rho)T}-1}{\alpha+\lambda u-\rho}\, dT \\
&= \frac{V_0}{\alpha+\lambda u-\rho}\left[\int_0^{\infty} \theta\, e^{(\alpha+\lambda u-\rho-\theta)T}\, dT - \int_0^{\infty} \theta\, e^{-\theta T}\, dT\right] \\
&= \frac{V_0}{\alpha+\lambda u-\rho}\left[\frac{\theta}{\alpha+\lambda u-\rho-\theta} e^{(\alpha+\lambda u-\rho-\theta)T}\right]_0^{\infty} + \left[e^{-\theta T}\right]_0^{\infty} \\
&= \frac{V_0}{\alpha+\lambda u-\rho}\left[-\frac{\theta}{\alpha+\lambda u-\rho-\theta}-1\right] \\
&= \frac{1}{\rho+\theta-\alpha-\lambda u} V_0
\end{aligned}
$$

2.A.3.4 Expansion of the Bellman Equation - Climate Disasters

The Bellman equation is expanded using Itô calculus similar to before but adjusted for the jumps from the climate disasters:

$$
\begin{aligned}
\rho F(V)dt &= E[dF] \\
&= E[F'(V)dV + 0.5F''(V)(dV)^2 + [F((1+u)V) - F(V)] - F'(V)uVdq] \\
&= E[F'(V)(\alpha V dt + \sigma V dz) + 0.5F''(V)(dV)^2 + [F((1+u)V) - F(V)]dq] \\
&= \alpha V F'(V)dt + 0.5F''(V)\sigma^2 V^2 dt + \lambda[F((1+u)V) - F(V)]dt
\end{aligned}
$$

2.A.3.5 Solving for V^* - Climate Disasters

The boundary conditions are:

$$F(0) = 0$$
$$F(V^*) = \frac{1}{\rho+\theta-\alpha-\lambda u}V^* - I$$
$$F'(V^*) = \frac{1}{\rho+\theta-\alpha-\lambda u}$$

Using the solution $F(V) = AV^\gamma$

$$\frac{1}{\rho+\theta-\alpha-\lambda u} = \gamma AV^{*\gamma-1}$$
$$\frac{1}{\rho+\theta-\alpha-\lambda u}V^* = \gamma AV^{*\gamma}$$
$$\frac{1}{\rho+\theta-\alpha-\lambda u}V^* - I = AV^{*\gamma}$$
$$\frac{1}{\rho+\theta-\alpha-\lambda u}V^* = \gamma\left(\frac{1}{\rho+\theta-\alpha-\lambda u}V^* - I\right)$$
$$V^*(1-\gamma) = -(\rho+\theta-\alpha-\lambda u)\gamma I$$
$$V^* = \frac{\gamma}{\gamma-1}I(\rho+\theta-\alpha-\lambda u)$$

2.A.3.6 Solution to the Geometric Brownian Motion - Scientific Discoveries

The geometric Brownian motion with scientific is defined as:

$$dV_t = (\alpha+\omega ds)V_t dt + (\sigma+\nu ds)V_t dz_t$$

For small dt, a scientific discovery occurs at most once with probability π:

$$dV_t = (\alpha+\pi\omega)V_t dt + (\sigma+\pi\nu)V_t dz_t$$

Let us assume a function $f(V_t) = ln(V_t)$ such that $X_t = lnV_t$. Applying Itô calculus:

$$dX_t = \frac{1}{V_t}dV_t + \frac{1}{2V_t^2}dV_t^2$$
$$dX_t = \frac{1}{V_t}[\alpha + \pi\omega)V_t dt + (\sigma + \pi\nu)V_t dz_t] - \frac{1}{2V_t^2}(\sigma + \pi\nu)^2 V_t^2 dt$$
$$dX_t = [\alpha + \pi\omega - \frac{1}{2}(\sigma + \pi\nu)^2]dt + (\sigma + \pi\nu)dz_t$$

Integrating from 0 to t:

$$X_t = X_0 + \int_0^t [\alpha + \pi\omega - \frac{1}{2}(\sigma + \pi\nu)^2]ds + \int_0^t (\sigma + \pi\nu)dz_t$$
$$X_t = X_0 + [\alpha + \pi\omega - \frac{1}{2}(\sigma + \pi\nu)^2]t \; + (\sigma + \pi\nu)z_t$$

Exponentiating to return to V_t gives:

$$V_t = V_0 e^{[\alpha + \pi\omega - \frac{1}{2}(\sigma + \pi\nu)^2]t \; + (\sigma + \pi\nu)z_t}$$

The expectation of V_t is given by:

$$E[V_t] = V_0 e^{[\alpha + \pi\omega - \frac{1}{2}(\sigma + \pi\nu)^2]t} + E[e^{(\sigma + \pi\nu)z_t}]$$

Since the Wiener process z_t is normally distributed with mean zero and variance t, the standard moment generating function for a normal distribution implies

$$E[e^{(\sigma + \pi\nu)]z_t}] = e^{\frac{1}{2}(\sigma + \pi\nu)^2 t}$$

and therefore:

$$E[V_t] = V_0\, e^{([\alpha+\pi\omega-\frac{1}{2}(\sigma+\pi\nu)^2]t+\frac{1}{2}(\sigma+\pi\nu)^2 t}$$
$$E[V_t] = V_0\, e^{(\alpha+\pi\omega)t}$$

2.A.4 Scientific Discovery

2.A.4.1 Present Value of Royalties - Scientific Discovery

Since royalties are non-negative, under Tonelli's theorem:

$$E[\int_0^T V_t e^{-\rho t}\, dt] - I = \int_0^T E[V_t e^{-\rho t}]\, dt - I$$

and thus:

$$\begin{aligned}
&\int_0^T E[V_t e^{-\rho t}]\, dt - I \\
=&\int_0^T V_0 e^{(\alpha+\pi\omega)t} e^{-\rho t}\, dt - I \\
=&V_0 \left[\frac{1}{\alpha+\pi\omega-\rho} e^{(\alpha+\pi\omega-\rho)t}\right]_0^T \\
=&V_0\, \frac{e^{(\alpha+\pi\omega-\rho)T}-1}{\alpha+\pi\omega-\rho} - I
\end{aligned}$$

2.A.4.2 Termination Payoff - Scientific Discovery

The present value of the royalties assuming the random lifetime of the patent, T, and a discount rate ρ is:

$$
\begin{aligned}
&= \int_0^\infty \theta\, e^{-\theta T}\, V_0\, \frac{e^{(\alpha+\pi\omega-\rho)T}-1}{\alpha+\pi\omega-\rho}\, dT \\
&= \frac{V_0}{\alpha+\pi\omega-\rho}\left[\int_0^\infty \theta\, e^{(\alpha+\pi\omega-\rho-\theta)T}\, dT - \int_0^\infty \theta\, e^{-\theta T}\, dT\right] \\
&= \frac{V_0}{\alpha+\pi\omega-\rho}\left[\frac{\theta}{\alpha+\pi\omega-\rho-\theta} e^{(\alpha+\pi\omega-\rho-\theta)T}\right]_0^\infty + \left[e^{-\theta T}\right]_0^\infty \\
&= \frac{V_0}{\alpha+\pi\omega-\rho}\left[-\frac{\theta}{\alpha+\pi\omega-\rho-\theta} - 1\right] \\
&= \frac{1}{\rho+\theta-\alpha-\pi\omega} V_0
\end{aligned}
$$

2.A.4.3 Expansion of Bellman Equation - Scientific Discoveries

We need to expand the Bellman equation:

$$\rho F(V)dt = E[F'(V)dV + 0.5F''(V)(dV)^2]$$

We will do this in two parts:

$$
\begin{aligned}
E[dV] =& E[(\alpha+\omega ds)Vdt] + E[(\sigma+\nu ds)Vdz] \\
=& (\alpha+\omega\pi)Vdt
\end{aligned}
$$

And

$$
\begin{aligned}
E[(dV)^2] =& E[(\alpha+\omega ds)^2V^2(dt)^2 + (\alpha+\omega ds)Vdt(\sigma+\nu ds)Vdz + (\sigma+\nu ds)^2V^2(dz)^2] \\
=& (\sigma+\nu ds)^2V^2dt \\
=& (\sigma^2+2\sigma\nu\pi+\nu^2\pi)V^2dt
\end{aligned}
$$

Substituting the results back into the Itô-expanded Bellman equation:

$$F'(V)(\alpha+\omega\pi)Vdt+0.5F''(V)(\sigma^2+2\sigma\nu\pi+\nu^2\pi)V^2dt-\rho F(V)dt=0$$

2.A.4.4 Solving for V^* - Scientific Discoveries

The boundary conditions are:

$$\begin{aligned}
F(0) &= 0 \\
F(V^*) &= \frac{1}{\rho+\theta-\alpha-\pi\omega}V^*-I \\
F'(V^*) &= \frac{1}{\rho+\theta-\alpha-\pi\omega}
\end{aligned}$$

Using the solution $F(V)=AV^{\gamma}$

$$\begin{aligned}
\frac{1}{\rho+\theta-\alpha-\pi\omega} &= \gamma AV^{*\gamma-1} \\
\frac{1}{\rho+\theta-\alpha-\pi\omega}V^* &= \gamma AV^{*\gamma} \\
\frac{1}{\rho+\theta-\alpha-\pi\omega}V^*-I &= AV^{*\gamma} \\
\frac{1}{\rho+\theta-\alpha-\pi\omega}V^* &= \gamma\left(\frac{1}{\rho+\theta-\alpha-\pi\omega}V^*-I\right) \\
V^*(1-\gamma) &= -(\rho+\theta-\alpha-\pi\omega)\gamma I \\
V^* &= \frac{\gamma}{\gamma-1}I(\rho+\theta-\alpha-\pi\omega)
\end{aligned}$$

Chapter 3

Temperature and Inventor Productivity

3.1 Introduction

According to NOAA's National Centers for Environmental Information, 2024 was the hottest year on record since measurements began (NOAA National Centers for Environmental Information 2025). In 1960, a person born in Miami experienced around 85 days of extreme heat on average, but today, they can expect an average of 133. Furthermore, projections suggest that by the time they reach 80 years of age, the yearly average will rise to around 143 days of extreme heat (Popovich et al. 2018). Aside from the human costs associated with rising temperatures, extensive research shows that higher annual temperatures negatively impact economic output (e.g. Dell, Jones, and Olken 2012; Linsenmeier 2023). As CO2 emissions continue to rise, understanding the underlying drivers of this has become increasingly important to develop effective adaptation strategies and policies, and mitigate damages.

A key component to this is understanding the effect of temperature on the labour market. The International Labour Organisation estimates that 70% of the global workforce is already at risk of extreme heat today, with more than 18,000 annual work-related deaths attributed to heat stress (Flouris et al. 2024). However, temperatures are unlikely to have a homogeneous effect across the whole workforce. Not only do physical work environments differ, but depending on the occupation, the individual may employ different skills, perform a wide variety of tasks, follow different timelines and have varying ability and agency in adapting to higher temperatures. The analysis of temperature and labour outcomes therefore requires careful consideration of the diversity of sectors and employment types.

In this paper, we focus on the effect of temperature on the productivity of inventors. Inventors form a unique group of high-skilled workers who not only contribute largely to the wealth of an economy but also play a critical role in driving economic growth (Romer 1990; Rosenberg 2006; Aghion et al. 1998). Even modest effects of temperature on inventor productivity can thus have substantial implications and hence warrant an analysis in its own right. Furthermore, since inventors, like much of the workforce in high-income countries, primarily work indoors, the analysis offers insights into temperature effects on labour beyond outdoor-intensive sectors.

However, the study of inventor productivity is not without challenges. The productivity of inventors depends substantially on individual attributes. Compared to many other sectors, personal factors such as motivation, expertise, and creative thinking are particularly influential. Though innovation requires original insights, these often emerge alongside considerable routine and methodical work. Thus, innovation encompasses both unique ideas and systematic, incremental efforts. To examine the effect of temperature, it can therefore be important to account for inventor-specific characteristics. At the same time, tracking inventors over time is challenging due to inconsistencies in patent applications, including name variations and changes, spelling mistakes and the inclusion or omission of middle names and titles, which can lead to identification issues. Additionally, the inventors' environment including city networks and innovation hubs therein can play an important role in determining productivity, thus their existence and trends are important control for.

To overcome these challenges, we employ an inventor-level fixed-effects model using the recent disambiguation efforts by the U.S. Patent and Trademark Office to track inventors' patent applications over time. In our Poisson pseudo-maximum likelihood estimation, we control for inventor characteristics and the wider innovation environment by introducing inventor and time fixed effects as well as city-specific time trends. The geographic focus of this paper is the United States as a key player in the innovation space (Dutta et al. 2022) with a diverse climate, access to detailed climate and patent data, and high adaptive capacity through measures such as air conditioning (U.S. Energy Information Administration 2022). Our analysis of inventors from 2000 to 2020 suggests that higher temperatures have a negative effect on inventor productivity. Specifically, we find that one additional day with daily maximum temperatures above 20°C compared to a day between 10°C to 15°C leads to a decrease in patenting activity by around 0.12%. This effect does not increase exponentially with higher temperatures. we further find evidence that higher air conditioning penetration in the county significantly mitigates this result. Though not the primary focus of this paper, the results also suggest that extremely low temperatures increase the patenting output of inventors, possibly indicating a substitution between leisure and labour.

Our main contribution is to the growing body of research on the effects of temperature in the labour market. In terms of labour supply, evidence from the American Time Use Survey suggests that working hours drop with rising temperatures, specifically for workers in outdoor settings who seem to substitute this with more indoor leisure time (Graff Zivin and Neidell 2014). Similarly, using payroll data, Behrer and Park (2017) find that payrolls decrease on hotter days for workers across outdoor industries, though the authors state that this may be attributed to either labour productivity or labour supply. In contrast to this, a study by Cai, Lu, and Wang (2018) finds no change in labour supply at increasing temperatures, potentially due to the rigidity or lack of flexibility of work schedules.

In terms of labour productivity, negative effects of temperatures have been observed in both indoor and outdoor settings when workers are not shielded by climate controls. For example, research from India shows that per-worker output in the manufacturing sector declines on hot days (Somanathan et al. 2021), with similar evidence found for workers in call centres in Finland, (Niemelä et al. 2002), automobile manufacturing plants in the US (Cachon, Gallino, and Olivares 2012) and construction workers in China (Zhang et al. 2023). For high-skilled workers, the evidence is more sparse, largely due to increased difficulty in measuring and evaluating individual labour productivity in higher-skilled professions. Nonetheless, studies have found declines in labour productivity in professional tennis players (Burke et al. 2023) and helicopter pilots (Froom et al. 1993), who appear to be more prone to errors at higher temperatures. A study of US immigration judges further reveals increased probabilities of unfavourable rulings on hot days, despite the climate-controlled settings of courthouses (Heyes and Saberian 2019).

A common thread among the existing studies is the emphasis on short-term temperature exposure and instantaneous labour output. However, high-skilled workers largely engage in more long-term, cumulative production processes where short-term fluctuations in temperatures may be less influential. For example, while increased temperature may lead to a drop in productivity one day, it can rebound the next, potentially resulting in a negligible or net-zero effect. Furthermore, high-skilled workers, including inventors, are also likely to have greater agency in their work schedules and work environments to adapt to varying temperatures.

This paper contributes by studying a distinct part of the workforce that is not only a critical component of the economy but also varies in their work patterns and adaptive capacity from previous studies. Our analysis focuses on prolonged temperature exposures and longer-term labour output processes. Since inventors' occupational profiles align more closely with a large share of high-skilled workers in high-income economies, the results provide new evidence of temperature effects for the wider labour market.

Our second contribution is to the literature on the effect of temperature on economic output and growth. Though there is a general consensus that higher annual temperatures negatively affect the level of economic output, the influence on growth remains highly debated. While researchers such as Dell, Jones, and Olken (2012), Burke, Hsiang, and Miguel (2015) and Nath, Ramey, and Klenow (2024) find evidence for negative effects of annual mean temperature on economic growth, other studies challenge this view. Some findings suggest that while temperature influences total factor productivity, it does not affect its growth rates, implying that temperature effects might be temporary (Casey, Fried, and Goode 2023). This paper contributes to the discussion of temperature and economic growth by examining the productivity of inventors, a group of workers who are a critical component of economic growth. As such, evidence of a negative effect may offer an additional perspective to this debate.

Our final contribution is to the more general literature on inventor productivity. Understanding the drivers of innovation has long been of interest due to its economic significance. While earlier research largely focused on market and firm dynamics, the productivity of inventors themselves has received increasing attention over time. Inventor productivity has been shown to improve with increasing job mobility (Trajtenberg, Shiff, and Melamed 2006; Hoisl 2007), firm size (Kim, Lee, and Marschke 2009; Mariani and Romanelli 2007) and knowledge resources (Nooteboom et al. 2007). Furthermore, research suggests that the institutional structure of universities and research centres can influence innovative output (Lissoni et al. 2008). Spatially, inventors tend to cluster geographically (Carlino et al. 2015), and those in larger clusters (Moretti 2021) or near academic research centres (Kantor and Whalley 2014) appear to be more productive. Similarly, individual characteristics can influence productivity, including age (Jones 2010), risk attitude and creative skills (Frosch et al. 2015), and childhood exposures (Bell et al. 2019) as well as intrinsic (Owan and Nagaoka 2011; Singh and Fleming 2010; Hess et al. 2008) and extrinsic motivation (Azoulay, Ding, and Stuart 2007; Dugoua and Gerarden 2023). Furthermore, factors beyond the inventors' control, such as abrupt changes in wealth (Bernstein, Mcquade, and Townsend 2021) and conflict exposure (Luo, Chen, and Lin 2024), may reduce their productivity.

Despite the extensive research on various determinants of inventor productivity and the significance of environmental factors in other economic contexts, research on environmental factors and inventor productivity remains sparse. One study by Chen et al. (2016) finds that inventors exposed to more sunlight produce higher-quality patents, but to the best of our knowledge, no existing studies examine the effects of temperature on inventor productivity. Given the significance of inventor productivity, we believe this contribution is therefore both novel and valuable in this context.

3.2 Background

The mechanisms underlying the relationship between temperature and labour productivity present a complex picture due to the various physiological and psychological impacts of higher temperatures.

Physiologically, evidence suggests that extreme heat increases hospital admissions, particularly among vulnerable groups such as children and the elderly (Gronlund et al. 2014; White 2017) and results in excess deaths (Carleton et al. 2022). Higher temperatures also seem to negatively affect a variety of bodily functions, including the cardiovascular system (Donaldson, Keatinge, and Saunders 2003), brain activity (Nielsen et al. 2001) and sleep patterns (Minor et al. 2022). Cognitive performance, which is particularly relevant to inventors, has also been shown to decline on high-temperature days, as evidenced by lower student test scores (Park et al. 2020). While medical research suggests that the human body can partially acclimate to heat over time (Lorenzo et al. 2010; Cheung and McLellan 1998; Sexton, Wang, and Mullins 2022), this adaptation seems to diminish in the absence of continuous high temperatures (Périard, Racinais, and Sawka 2015).

Psychologically, higher temperatures seem to have a negative impact on emotional well-being and mood. Evidence by Hsiang, Burke, and Miguel (2013) and Burke et al. (2009) indicates that people exhibit increased conflict propensity in hotter environments, while Ranson (2014) and Jacob, Lefgren, and Moretti (2005) find increased crime rates on hotter days. Furthermore, a study analysing data from X (formerly Twitter) finds that higher temperatures are associated with more negative sentiments in online communication (Baylis 2015).

An inventor exposed to heat may thus experience declines in labour productivity and labour supply for a variety of reasons. Directly, the inventor may suffer from poor health at increased temperatures, slower cognitive performance or disrupted sleep, resulting in lower performance or reduced working hours. Reduced concentration may also make the inventor more prone to errors. For instance, Park, Pankratz, and Behrer (2021) find that workplace accidents, such as falls from heights, increase with higher temperatures. Similarly, mood changes induced by heat may affect the inventor's ability to focus or engage creatively.

Beyond the direct effects, inventors may also be indirectly impacted by temperature fluctuations. For example, they may be at greater risk of becoming victims of crime or have increased care-giving responsibilities for dependents who are vulnerable to extreme temperatures. The relevance of temperature-induced disruption will likely depend on the nature of work, such as whether desk-based or manual, the work environment and the level of agency in adapting to disruptions.

Furthermore, temperature fluctuations may also induce labour-leisure substitution. Higher temperatures may not only raise the cost of labour but also increase the appeal of leisure.

Activities such as surfing or beach days may be unavailable on colder days but become accessible in warmer weather, increasing the opportunity cost of labour and possible reducing hours worked by the inventor. Conversely, colder days may lead inventors to substitute leisure for work. However, the opposite may also be true, depending on the individual inventor's preferences for warm- versus cold-weather leisure activities.

It is important to note that the effect of increased temperatures on inventor productivity is unclear ex-ante. Though previous evidence suggests that higher temperatures negatively impact labour productivity, a work pattern that closely aligns with the inventor has not been studied yet. Prolonged exposure to higher temperatures may have a different effect than short-term exposures, just as the effect on instantaneous output may be different to the effect on long-term, cumulative output processes. Furthermore, inventors may be able to take advantage of shifting work schedules or of the biological adaptability of the body to mitigate productivity influences over a longer time horizon. Whereas some mechanisms, such as heat-induced workplace accidents, may be relevant in manual labour settings, they may not be relevant for inventors in desk-based jobs. Inventors may work less due to disrupted sleep or increase their outdoor leisure time at higher temperatures, or they may increase their labour supply by preferring to stay indoors in climate-controlled environments. For example, a study on gaming behaviour revealed that while gaming performance declined at extreme high and low temperatures, gaming time increased as individuals spent more time indoors to escape temperature extremes (Bao and Fan 2020). Additionally, inventors are more likely to already be working in climate-controlled environments and have more flexibility in adapting to temperature variations, such as by working from home. Whether the effect of temperature on productivity persists due to exposure outside working hours is not straightforward. Based on this, we thus begin this study without clear expectations of where the results may lead.

3.3 Data

3.3.1 Patents

We retrieve data on patent applications filed at the U.S. Patent and Trademark Office (USPTO) from 2000 to 2020 through PatentsView. Data from PatentsView provides inventor disambiguation directly, assigning unique inventor IDs that enable us to consistently track individual inventors and their patent outputs over time. To incorporate additional details, including information on patent families, we merge the PatentsView data with PATSTAT, the global patent database maintained by the European Patent Office (EPO). This merge is performed directly using official patent application numbers. We filter for inventors based in the contiguous United States, as temperature data is unavailable for areas outside this region.

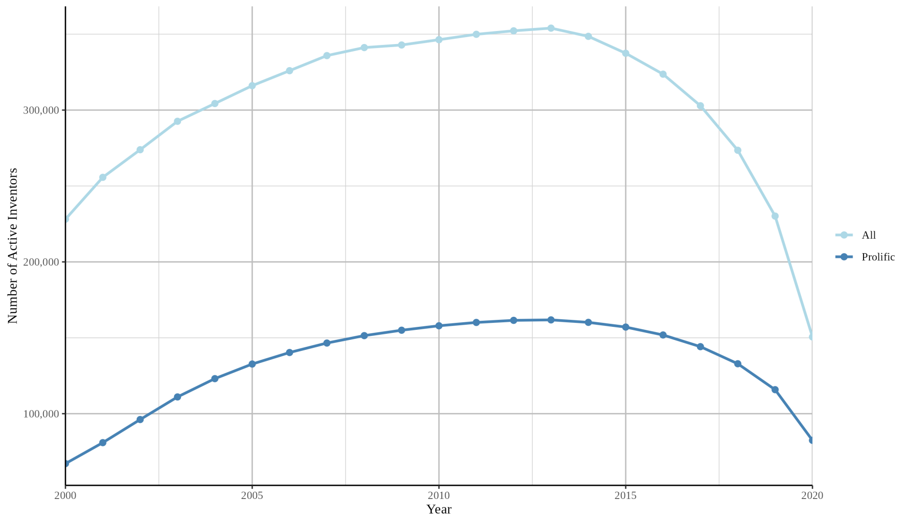
To determine the inventor's location, we use the city listed in their home address on the patent application. Although patent applications sometimes include more specific geographic details, such as street names, this data is not always available, making a more granular definition of inventor location challenging and the city the smallest consistent geographic unit. Some inventors change residences during the sampling period, listing different home addresses on different patent filings. However, since we only observe addresses during filing years, we cannot determine when these moves occur. Therefore, we drop any inventors who report multiple addresses, assuming that the remaining inventors have not moved during the sampling period, providing us with a continuous measure of inventor location. This conservative approach minimises the risks of misclassifying inventors' locations but also means that we are unable to capture relocation as an adaptive response to temperature changes.

To measure an inventor's annual patent output, we first group patent applications into patent families, which consist of sets of patents protecting the same invention. For each patent family, we identify the earliest filing date on which the inventor appears and attribute the patent to the inventor's output in that year. Using the global PATSTAT database, we determine the earliest and latest filing dates across all patent families for each inventor, defining their active patenting period. An inventor is considered active from their first observed filing date until their last. Within this period, years without patent filings are assigned a value of zero. Years outside this active range are classified as missing due to the absence of accurate information about the inventor's career timeline.

We restrict our main analysis sample to prolific inventors, defined as the top 25% of inventors who filed the most patents during the period (those with 13 or more). This selection simplifies the analysis computationally and focuses attention on inventors who significantly contribute to innovation, given that inventive activity is highly skewed towards a small number of highly productive individuals. However, we retain the full inventor sample for robustness checks.

We identify a total of 1,331,426 unique inventors resident in the United States in the period from 2000 to 2020. After filtering for inventors who only list one address through the period and prolific inventors, we retain 181,777 inventors resident in 7,237 cities. The number of patent applications varies widely, with a mean number of patent applications per year of 4.64 but a standard deviation of 14.22. The large standard deviation is primarily driven by inventor outliers, such as Tao Luo, who has filed several thousand patent applications over the years. Within individual inventors, the mean inter-year standard deviation is much smaller, at 4.18 patents.

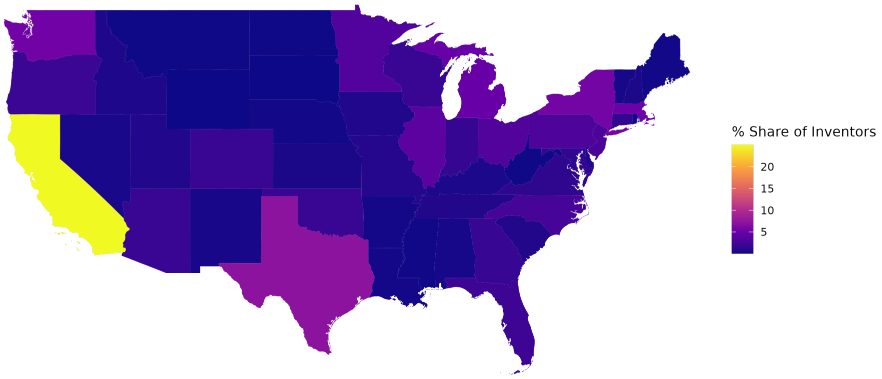
The number of inventors increased consistently until 2014 but then began to drop off with sharp declines after 2018 (Figure 3.1). This is likely due to the fact that our dataset only includes patent filings up to 2021, such that inventors who file patents infrequently may be classified as inactive even if they file additional patent applications after 2021. For example, an inventor who filed for a patent in 2008, 2014 and 2022 will be classified as active from 2008 to 2014 but inactive thereafter. Since prolific inventors file more frequently, the effect is less pronounced in this sample. Although this leads to an under-sampling of active inventors toward the end of the observation period, its uniform nature ensures that any misclassification of inventor activity is systematic rather than correlated with other explanatory factors and thus should not pose an endogeneity issue.



Notes: The graph depicts the number of active prolific inventors in the sample from 2000 to 2020. The graph excludes movers, i.e. inventors who list multiple addresses, since these are excluded from our sample. A graph showing all inventors, including movers, can be found in the Appendix and shows a similar pattern.

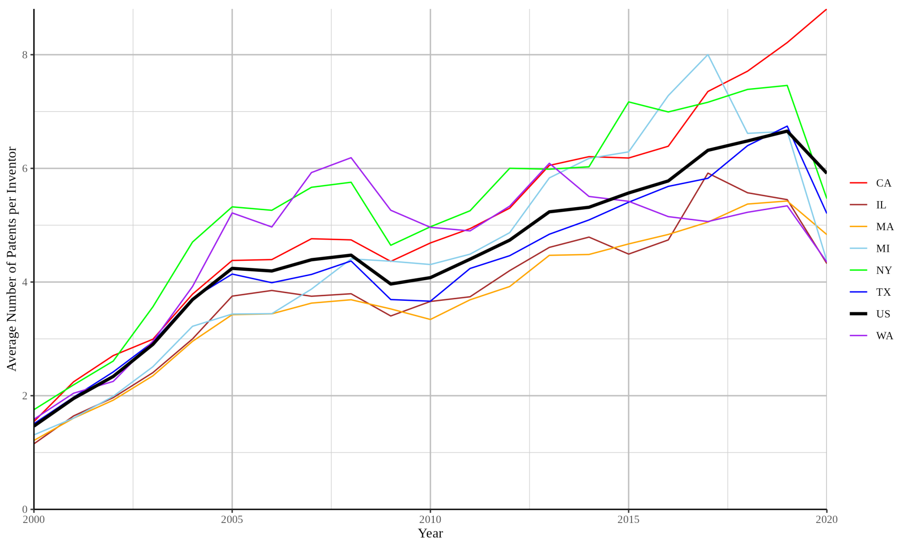
FIGURE 3.1: Number of inventors over time

The geographic distribution shows that the largest proportion of prolific inventors by a considerable margin reside in California (25%). This is followed by Texas, 7.1%, New York, 5.6%, and Washington 5.4% (Appendix Figure 3.A.2). The number of patents per inventor and year, both nationwide and in states with high patenting activity, increases over the period (Figure 3.3). However, data toward the end of the period should be interpreted with caution due to the potential undersampling of active inventors stemming from the aforementioned limitations in the construction of the panel. Examining California as a hub for innovation more closely, we find that a major share of patent activity is concentrated in the Bay Area, with notable contributions from San Diego, Los Angeles, and Irvine in the southern region (Figure 3.4). In particular, San Diego stands out with a sharp exponential increase in the average number of patents per inventor starting in 2006 (Figure 3.5), likely attributed to its emergence as a hub for biotech and human genome research during this period. This trend is not merely a result of a reduction in the number of inventors but is characterized by a marked rise in patent filings (Appendix Figure 3.A.4). Overall, the descriptive findings suggest significant variation in inter-year inventor patenting activity while also indicating differences across states and possible city-level trends.



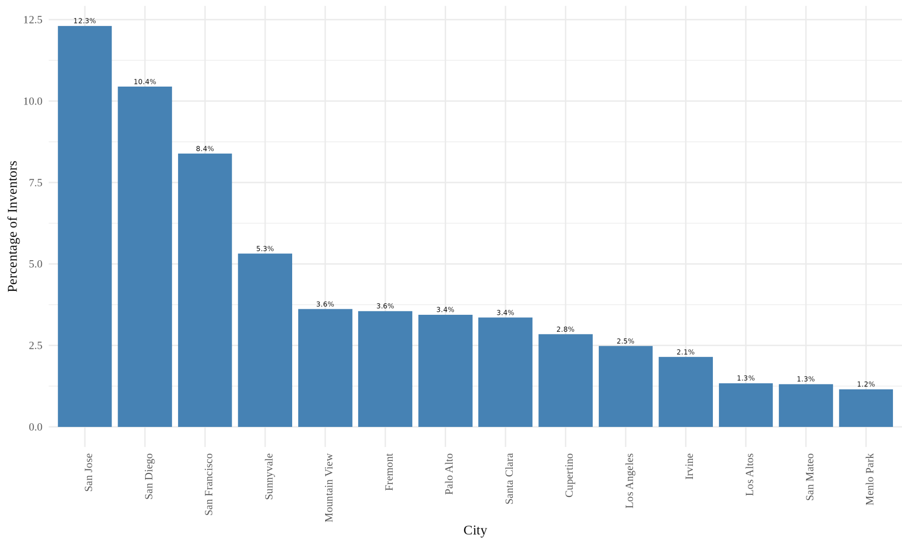
Notes: The map depicts the distribution of unique prolific inventors by state from 2000 to 2020. The distribution including non-prolific inventors by states can be found in the Appendix and shows a similar pattern. Both charts exclude movers, i.e., inventors who list multiple addresses, since these are excluded from our sample.

FIGURE 3.2: Patenting by state



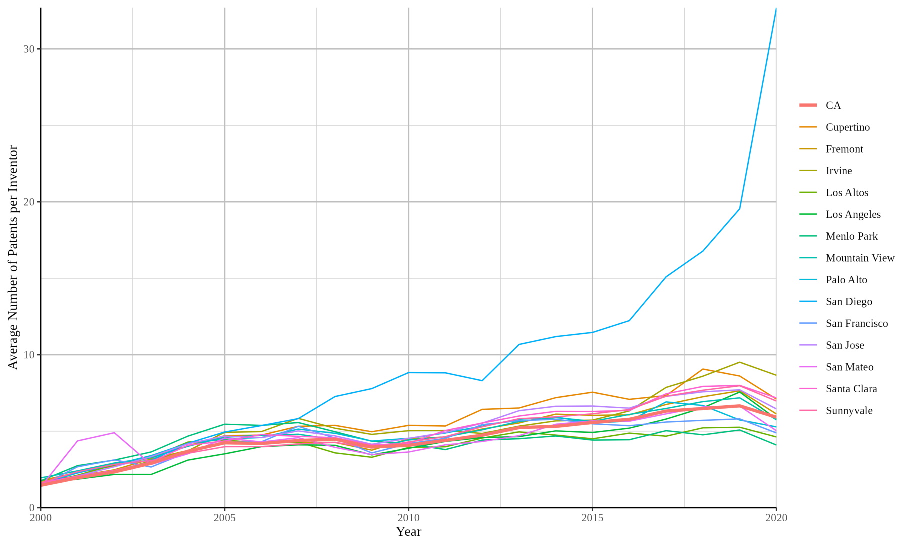
Notes: The graph depicts the average number of patent family applications per inventor from 2000 to 2020 for the subset of prolific inventors. This is calculated by dividing the total number of patent family applications filed by prolific inventors by the number of active prolific inventors. The graph including non-prolific inventors can be found in the Appendix and shows a similar pattern. Both charts exclude movers, i.e. inventors who list multiple addresses, since these are excluded from our sample.

FIGURE 3.3: Patenting trends in the US and high patenting States



Notes: The bar chart depicts the distribution of unique prolific inventors by city in California from 2000 to 2020. Prolific inventors are defined as those with 13 or more patent family applications during the period. The chart excludes cities with fewer than 1% of inventors. The distribution including non-prolific inventors by city can be found in the Appendix and shows a similar pattern. Both charts exclude movers, i.e., inventors who list multiple addresses since these are excluded from our sample.

FIGURE 3.4: Patenting by city - California



Notes: The graph depicts the average number of patent family applications per inventor from 2000 to 2020 for prolific inventors in cities in California with a high number of prolific inventors. This is calculated by dividing the total number of patent family applications filed by prolific inventors by the number of active prolific inventors. The graph including non-prolific inventors can be found in the Appendix and shows a similar pattern. Both charts exclude movers, i.e. inventors who list multiple addresses, since these are excluded from our sample.

FIGURE 3.5: Patenting trends in California and high patenting cities

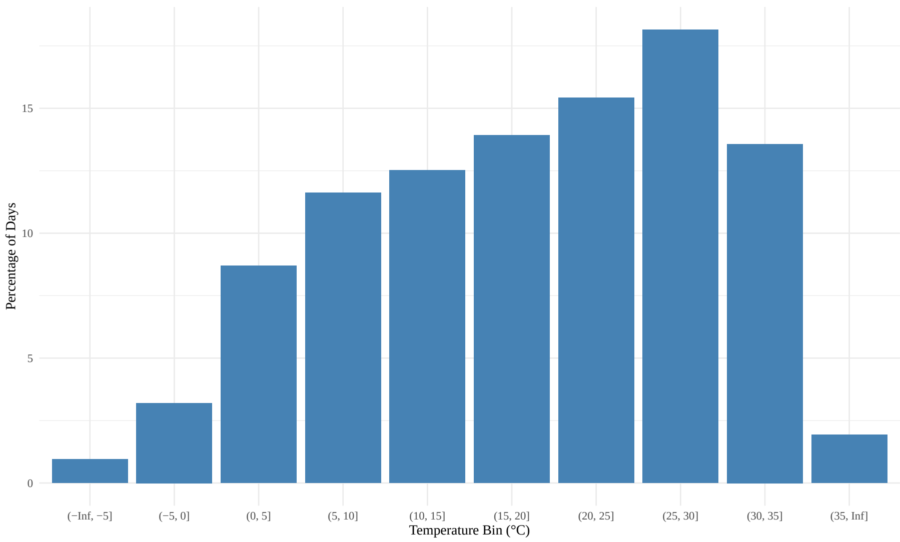
3.3.2 Temperature and Climate Controls

For our main explanatory variable, we download daily temperature data, measured in °C, for the contiguous United States from the PRISM Climate Group. The dataset is constructed using a regression-based spatial interpolation model that takes topographical influences into account and has a resolution of 4km x 4km. It is commonly used in temperature studies in the United States due to its high-resolution, peer reviewed methodology and use of extensive ground-based weather station observations. For our main specification we download daily maximum temperature data, although we also access daily mean and minimum temperature data for further analysis later on.

To construct our main explanatory variable, we group daily maximum temperature observations into 5°C temperature bins and, within each raster, compute the annual number of days falling in each temperature bin. Next, we download the Incorporated Place and Census Designated Place file from the U.S. Census Bureau to retrieve the geometric boundaries of cities. To aggregate raster temperature data at the city level, we perform a weighted spatial aggregation, assigning full weight to cells entirely within city boundaries and proportionally weighting those that are only partially encompassed. For example, suppose the annual number of days in the 25 to 30°C temperature bin for raster cells A, B, C, and D are 20, 35, 50, and 25, respectively. Further, assume that the city boundaries fully encompass raster A, cover 50% of raster B, 20% of raster C, and do not include raster D at all. The spatial aggregation computes the city-level count as follows: $\frac{20\times1+35\times0.5+50\times0.2}{1+0.5+0.2} = 28$. We perform this aggregation after classifying daily temperatures within each raster to ensure that we account for local variations, do not smooth over extremes and preserve the original distribution of temperature values. Once we have aggregated at the city level, we use a crosswalk to match the Place FIPS codes from the boundary file to the cities listed on the inventor applications. This requires some manual cleaning of city names to ensure consistent matching. The final temperature variable for the inventors consists of a series of count variables that delineate the annual number of days within each 5°C temperature bin, measured at the city location of the inventors' home addresses.

In addition to temperature, we download daily precipitation and dew point data from PRISM. These climatic controls account for the fact that higher moisture in the air increases stress on the body by reducing its ability to cool down, which may, in turn, impact inventor productivity. Similar to the temperature data, the PRISM precipitation and dew point data is available as raster data at 4km x 4km resolution. We perform the same weighted spatial aggregation to determine annual average precipitation, measured in millimetres, and annual average dew point, measured in °C, for each inventor city.

The average annual daily maximum temperature across all inventor cities was 19°C for both the full sample and the subset of prolific inventors. However, daily maximum temperatures naturally varied across locations and throughout the year. To illustrate the distribution of daily maximum temperatures, we plot the annual distribution for the year 2020 in Figure 3.6. Daily maximum temperatures exceeded 20°C on 49% of days, with 2% of days exceeding 35°C. Similar to the average annual daily maximum temperature, there is little difference in the distribution between the full sample and the subset of prolific inventors (Figure 3.A.7). We therefore focus on our main sample of prolific inventors for the remaining descriptive statistics.



Notes: The graph shows the percentage distribution of days within each temperature bin in inventor cities in 2020. Inventor cities are defined as cities with at least one resident prolific inventor. The temperature distribution for inventor cities including non-prolific inventor cities can be found in the Appendix. Both charts exclude movers, i.e. inventors who list multiple addresses since these are excluded from our sample.

FIGURE 3.6: Temperature distribution in 2020

On average, inventors experienced 9.84 days per year of daily maximum temperatures exceeding 35°C. The highest number of days above 35°C in any single year was recorded in Roma, Texas, where inventors were exposed to extreme heat over 35°C for nearly half of the year, 174 days. Mohave Valley in Arizona had the highest average annual number of days above 35°C, with 153.6 days per year. Arizona also recorded the hottest year among all states, with an average of 122.2 days exceeding 35°C across its inventor cities in 2020 and an annual average daily maximum temperature of 28.5°C. Although Arizona consistently saw the highest number of extremely hot days, Florida recorded the highest mean annual daily maximum temperature, suggesting that while Arizona experienced more extreme temperature fluctuations, Florida maintained a more consistently warm climate. Conversely, North Dakota was the coldest state, averaging the most days below -5°C annually at 52.6 and an average daily maximum temperature of 11.4°C across inventor cities. Badger, Minnesota, experienced the most extreme cold, with 93 days below -5°C in a single year.

The year-to-year variability of average annual daily maximum temperature differed across inventors. Inventors in Center, North Dakota, experienced the greatest inter-year variability at 1.34°C, while inventors in Wellington, Florida, experienced the least at 0.34°C. Freer, Texas, had the highest inter-year variation in the number of days above 35°C at 28.9 days. The inter-year standard deviation of inventors' average annual daily maximum temperature on average was 0.79°C. At the extreme end of the temperature distribution, the average inter-year variation in the number of days exceeding 35°C was 4.8 days, while for days below -5°C, it was 4.2 days. The results for all temperature bins are shown in Table 3.1. It is also worth noting that not all cities experienced the full range of temperatures. For example, Alabama never experienced days above 35°C, while Arcata, California, never recorded any days with daily maximum temperature below -5°C. Overall, our data shows significant variation in temperature across years and cities, accommodating a wide range of climates along with temperature variations within inventors.

Temperature Bin	Average Standard Deviation
(-Inf, -5]	4.20
(-5, 0]	5.29
(0, 5]	6.99
(5, 10]	7.70
(10, 15]	7.41
(15, 20]	8.69
(20, 25]	9.42
(25, 30]	10.49
(30, 35]	11.16
(35, Inf]	4.84

Notes: The table describes the average inter-year standard deviation of days per temperature bin for prolific inventors. For each prolific inventor, we calculate the standard deviation of days in every bin over the period from 2000 to 2020, then average these values across all prolific inventors.

TABLE 3.1: Inter-year standard deviations

3.3.3 Summary Statistics

Table 3.2 presents summary statistics for key variables across the full inventor sample, as well as the prolific and non-prolific subsamples. Due to the data limitations described above, the dataset excludes inventors who list more than one address over the period. The full sample includes over 6 million inventor-year observations across nearly one million unique inventors.

By construction, prolific inventors file significantly more patent family applications per year than prolific inventors. The share of granted applications is similar across groups, averaging 74% for prolific and 72% for non-prolific inventors, suggesting that prolific and non-prolific inventors are equally likely on average to be successful in their patent applications. When weighting patent families by the number of inventors listed on the application, the average output for prolific inventors falls to about 33% of the unweighted count, compared to 40% for non-prolific inventors. This indicates that non-prolific inventors are slightly more likely to file alone while prolific inventors seem to collaborate more frequently.

In terms of the temperature distribution, the average number of days in each temperature bin is broadly similar across inventor groups. Notably, exposure to extreme cold days (below -5°C) are less common than exposure to extremely hot days (above 35°C) for inventors. Dew point and precipitation levels are also nearly identical across groups.

Among all inventors, 42% file only once during the sample period. As expected, this share rises to 51% among non-prolific inventors.

	All Inventors		Prolific Inventors		Non-prolific Inventors	
Variable	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Simple Count	2.37	9.63	4.64	14.22	0.61	0.87
Simple Granted	1.74	6.74	3.43	9.92	0.44	0.73
Weighted	0.80	2.84	1.53	4.17	0.24	0.41
Weighted - Granted	0.60	2.12	1.14	3.11	0.17	0.35
# Days (Inf, -5]	5.76	10.24	5.74	10.27	5.77	10.22
# Days (-5, 0]	11.68	13.62	11.55	13.63	11.79	13.62
# Days (0, 5]	22.88	20.50	22.60	20.66	23.10	20.37
# Days (5, 10]	31.01	22.71	30.77	23.03	31.19	22.45
# Days (10, 15]	45.91	22.03	46.65	22.28	45.33	21.81
# Days (15, 20]	61.56	32.34	63.09	33.04	60.37	31.74
# Days (20, 25]	66.80	25.66	67.85	26.40	65.98	25.04
# Days (25, 30]	68.35	23.23	67.62	22.37	68.92	23.86
# Days (30, 35]	41.33	32.52	39.56	31.19	42.69	33.46
# Days (35, Inf)	9.99	21.94	9.84	21.70	10.11	22.13
Dew Point	6.95	3.96	6.92	3.77	6.97	4.11
Precipitation	2.51	1.16	2.48	1.16	2.54	1.16
Observations	6,385,797	6,385,797	2,790,051	2,790,051	3,595,746	3,595,746
# Inventors	994,669	994,669	181,780	181,780	812,889	812,889
One-Time Inventors	0.42	0.42	0	0	0.51	0.51

Notes: The table above describes annual averages of key variables.'Simple Count' describes patent family applications per year; 'Simple Granted' describes patent family applications per year that were granted; 'Weighted' describes patent family applications per year weighted by the number of inventors listed on the application; 'Weighted-Granted' describes patent family applications per year that were granted weighted by the number of inventors listed on the application; 'Dew Point' is measured in °C; 'Precipitation' is measured in millimetres and describes annual averages of daily rainfall not total yearly accumulation of rain; 'One-Time Inventors' is the ratio of one-time inventors divided by total number of inventors.

TABLE 3.2: Summary Statistics

3.4 Methodology

We estimate an inventor-level panel fixed effect model that tracks inventors' temperature exposures and patent application output from 2000 to 2020. Our main specification, estimated using a Poisson pseudo-maximum likelihood estimator (PPML), is defined by the following equation:

$$\begin{aligned} Patent_{i,c,t} = \exp\Bigg(\alpha + \sum_{b \neq 10-15}^{B} \beta_b \left(\sum_{k=1}^{3} Temp^{b}_{c,t-k} \right) \\ + \gamma_1 \left(\sum_{k=1}^{3} Ppt_{c,t-k} \right) + \gamma_2 \left(\sum_{k=1}^{3} Dew_{c,t-k} \right) + \delta_i + \sigma_t + \nu_c \cdot t \Bigg) \end{aligned} \tag{3.1}$$

The main outcome variable is $Patent_{i,c,t}$ and describes the number of patent families filed by inventor i residing in city c in year t. This variable captures all patent applications independent of whether they are ultimately granted. This approach mitigates biases arising from varying time horizons for patent approvals and quality judgments while providing a comprehensive measure of formal innovative activity. By focusing on the number of patent applications per inventor, this measure addresses the intensive margin of innovation rather than the extensive margin, which would consider the number of new inventors entering under varying temperature fluctuations.

The main variable of interest, $Temp^{b}_{c,t-k}$, is the number of days in the past three years, with temperatures in bin b in city c. With limited prior assumptions about the influence of temperature on innovation, our preferred functional form is a bin specification. This allows for non-linear effects as well as an easy interpretation of results. We measure temperature exposure based on the temperatures inventors were likely exposed to over the preceding three years. This lag choice aligns with survey evidence from Nagaoka and Walsh (2009), who find that inventors typically spend up to three years developing a new invention. Due to the lag structure of the analysis, we deem the risk of reverse causality to be minimal. Patenting activity today is unlikely to affect temperature variations in previous years.

To mitigate potential endogeneity concerns, we engage several empirical strategies. Since higher moisture in the air has been associated with increased stress on the body and reduced ability to cool down, we control for precipitation and humidity in the temperature exposure period. These variables may not only correlate with the temperature inventors perceive but may also independently influence productivity. Examples of this may include commute delays caused by flooding, inability to take breaks outdoors or general discomfort that inhibits creativity. We add inventor fixed effects to account for individual characteristics that may correlate with temperature and affect patenting output. For example, this may include pre-existing health conditions, which likely influence sensitivity to temperature but may also independently lead to variations in inventor productivity.

Furthermore, we include year fixed effects to address endogeneity concerns related to general trends in temperature and patenting. To further account for varying time trends within cities that may correlate with temperature exposure and innovation activity and to capture potential dynamics specific to innovation clusters, we add city-specific time trends. An example of such a trend may be infrastructure projects contributing to urban heat island effects but simultaneously attracting economic activity, thus both potentially influencing temperature and inventor productivity. Another example may be city-wide investments in health care that could enhance inventors' ability to cope with heat stress while also influencing productivity through broader health improvements. Given the large sample size and the divergent patenting trends across cities observed in the descriptive analysis, we include both linear and squared city time trends to allow for nonlinearity. Finally, we control for spatial correlation in the patenting activities of inventors by clustering standard errors at the city level. This addresses any arbitrary correlation in error terms among inventors within the same city over time, recognising the spatial nature of temperature variations and innovation clusters.

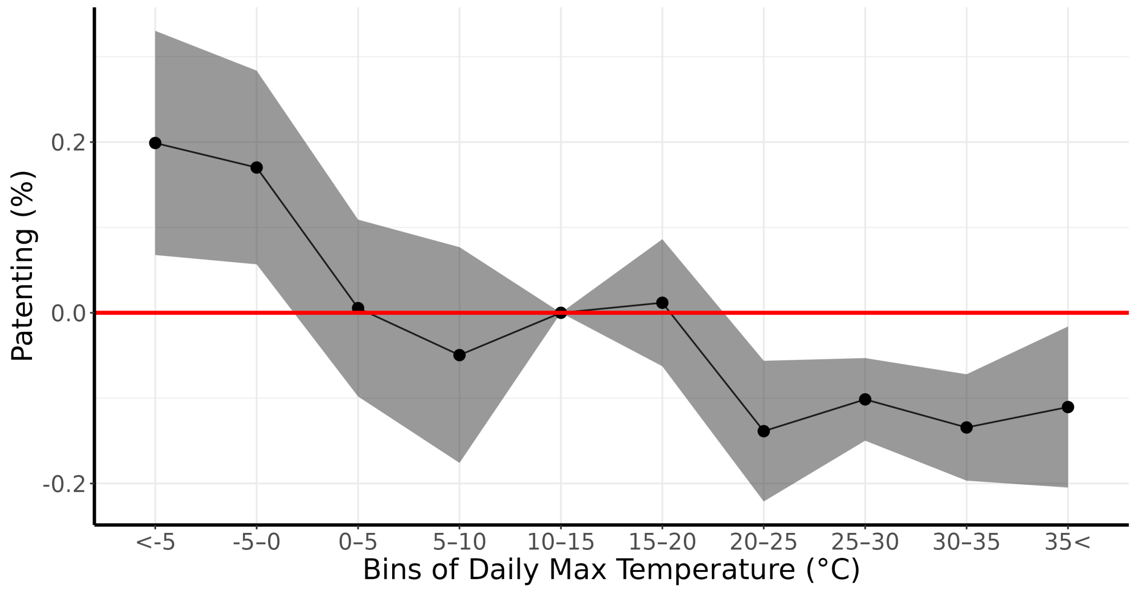
3.5 Results

3.5.1 Main

We present the outcome of the main specification, including all controls, fixed effects and time trends in Figure 3.7. The 10 to 15°C temperature bin serves as the reference category and is omitted from the regression. Consequently, the results are to be interpreted relative to this baseline, meaning the effect of an additional day in a given temperature bin is measured in comparison to a day in the 10 to 15°C temperature range. The estimated inventor temperature response function differs from the commonly observed inverted U-shape of previous temperature-labour studies. At the high end of the temperature distribution, the results suggest that one additional day of temperatures exceeding 20°C decreases the number of patent applications of the inventor by 0.12%. In other words, an inventor who experienced an additional day with a maximum temperature above 20°C in the last three years will file 0.12% fewer patent applications today, relative to experiencing a maximum daily temperature between 10 to 15°C. This effect is relatively stable in magnitude for all temperature bins above 20°C, indicating that once the threshold is crossed, the effect persists but does not intensify with further increases in temperatures. In contrast, at the low end of the temperature distribution, additional days with daily maximum temperatures below freezing, 0°C, seem to increase patenting activity. An inventor who experiences one additional day with maximum temperatures not exceeding -5°C will file 0.2% more patent applications.

The magnitude of the effects may seem small at first. For the average inventor, who has 4.64 patent filings per year, it would take an additional 180 days above 20°C over three years to result in the loss of a single patent filing. However, since patent filings are influenced by a wide range of factors, it is unsurprising that the effect of temperature alone, while significant, is not overwhelmingly large. On the contrary, an excessively large effect would more likely raise suspicions about the robustness of our empirical strategy. Furthermore, our estimate reflects an aggregate effect, likely masking significant heterogeneity among certain inventors, firms or sectors, some of whom may experience substantially larger impacts. For example, for a highly prolific inventor with an average of 83 patent filings per year, a 0.12% decrease in patenting means that just 10 additional days above 20°C would result in one less patent filing.

Though the shape of the temperature response function differs, the results indicate that inventors are not immune to variations in temperatures. Many possible mechanisms may underlie this relationship. While inventors are more likely to work indoors, not all workplaces may have



Notes: The temperature response function is estimated using a PPML estimator and includes inventor and year fixed effects, as well as linear and squared time trends and controls for humidity and precipitation. Standard errors are clustered at the city level. The grey shaded area represents the 95% confidence interval for the coefficient estimate. The outcome variable is expressed as the percentage change in patent family application filings, with 10 to 15°C as the reference category. This analysis is based on three-year cumulative lagged exposure.

FIGURE 3.7: Temperature response function - main

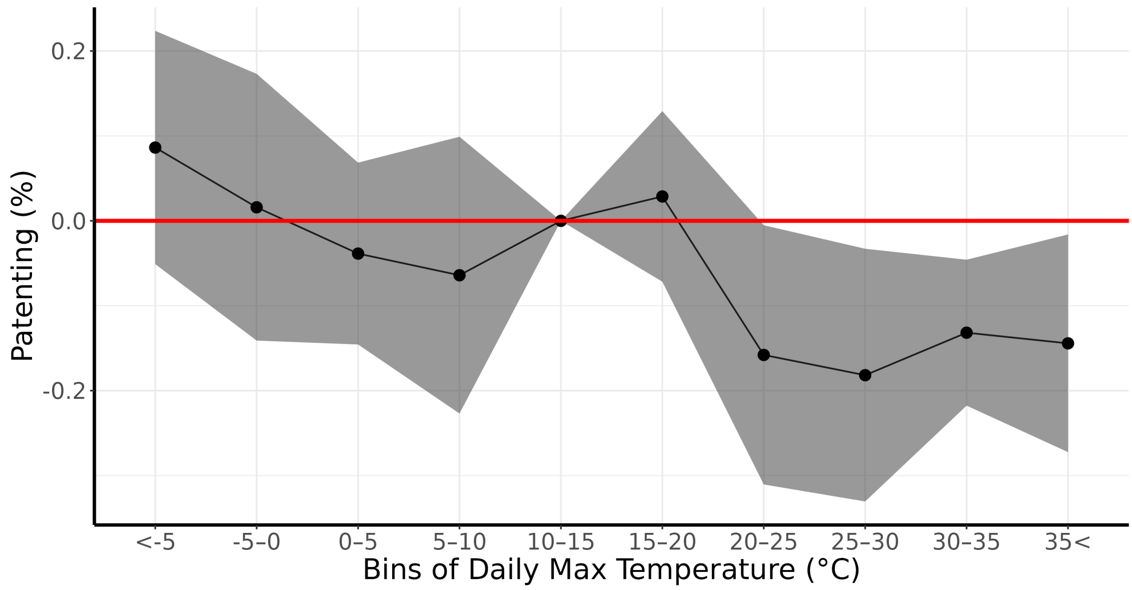
effective climate controls and temperature exposures outside the workplace may have delayed or spillover productivity effects during work hours. Similarly, inventors may work closely with individuals who are temperature-exposed such that the productivity effects of these workers may have knock-on effects on inventors' patenting output.

Furthermore, given that inventors are likely to have some agency in their work schedule, they may engage in leisure-labour substitution. In warmer periods, inventors may substitute work for outdoor leisure time leading to decreases in patent filings. Conversely, increased patenting at very low temperatures may reflect a substitution of leisure time for work. As daily maximum temperatures fall below 0°C, leisure activities may be increasingly limited, encouraging inventors to stay indoors and work instead.

Finally, the distinct shape of the response function, particularly the absence of an exponential increase at higher temperatures, may be supported by a lack of direct physiological stress among inventors. Individuals who perform manual work in outdoor industries are more likely to be subject to exponential declines in productivity as physiological stress intensifies with both increasingly high and low temperatures. Since inventors are more likely to engage in cognitive tasks and work indoors, it is plausible that temperatures may not have the same exponential effect.

Though identifying the underlying mechanism lies beyond the scope of this paper, our findings indicate that inventors are not immune to temperature variations, and higher temperatures may have a significant negative effect on innovative activity.

Further to analysing the 3-year cumulative temperature exposure, we also examine the effect of temperature variation nearer the filing date by estimating the model with only one-year lagged exposure. This provides insights into potential variation in effects during the final stages of innovation or shorter-term projects. As an innovation nears completion, inventors may, for instance, be more willing to compensate for temperature-induced productivity losses by increasing work hours. Alternatively, temperature effects on productivity may differ depending

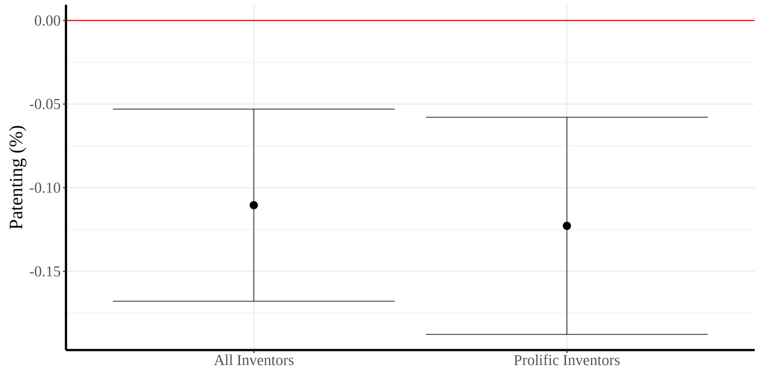


Notes: The temperature response function is estimated using a PPML estimator and includes inventor and year fixed effects, as well as linear and squared time trends and controls for humidity and precipitation. Standard errors are clustered at the city level. The grey shaded area represents the 95% confidence interval for the coefficient estimate. The outcome variable is expressed as the percentage change in patent family application filings, with 10 to 15°C as the reference category. This analysis is based on 1-year lagged exposure.

FIGURE 3.8: Temperature response function - 1-year lag

on the tasks involved at various development stages. For example, temperature-induced stress may be more or less harmful during the initial creative phases or strategic stages closer to patent filing. Furthermore, inventors working on shorter-term projects may experience temperature effects differently. Short-term projects may be more accessible, whereas long-term projects may be more complex and thus more significantly affected by temperature-induced cognitive impairments or disruptions.

The estimated temperature response function based on one-year lagged exposure is illustrated in Figure 3.8. While the negative effect at the high end of the temperature distribution persists, we no longer detect a positive effect at low temperatures. However, these estimates are noisier and less clearly defined and suggest that temperature variations closer to the patent filing may be less significant for inventor productivity.



Notes: The plot shows the results for the coefficient of the temperature bin covering days above 20°C for all inventors and the subsample of prolific inventors of the main specification. The model is estimated using a PPML estimator and includes inventor and year fixed effects, as well as linear and squared time trends and controls for humidity and precipitation. Standard errors are clustered at the city level, and the plot shows the 95% confidence interval for the coefficient estimate. The outcome variable is expressed as the percentage change in patent family application filings. This analysis is based on three-year cumulative exposure.

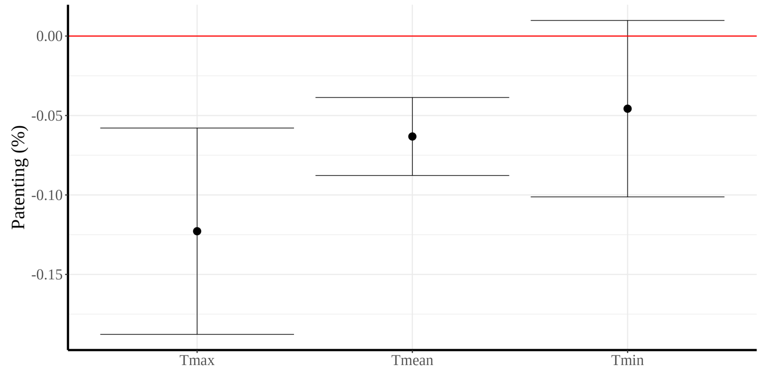
FIGURE 3.9: Robustness - all versus prolific inventors

3.5.2 Robustness

Given the focus of this paper and the slightly noisier results at lower temperatures, we concentrate on the high end of the temperature distribution for our robustness checks. For computational reasons, we collapse the temperature variable to a single bin describing the number of days with daily maximum temperatures above 20°C.

To begin, we extend our analysis to the sample that includes non-prolific inventors. The results show that the negative effect of temperatures above 20°C is consistent and robust when estimated using the full sample (Figure 3.9). Inventors independent of their output or work intensity seem to be equally affected by higher temperatures.

Next, we test the robustness of our temperature metric. Instead of using daily maximum temperatures, we calculate the number of days above 20°C based on the daily mean and daily minimum temperatures. Daily maximum and minimum temperatures capture extremes at different times of the day: maximum temperatures typically occur during the day when the



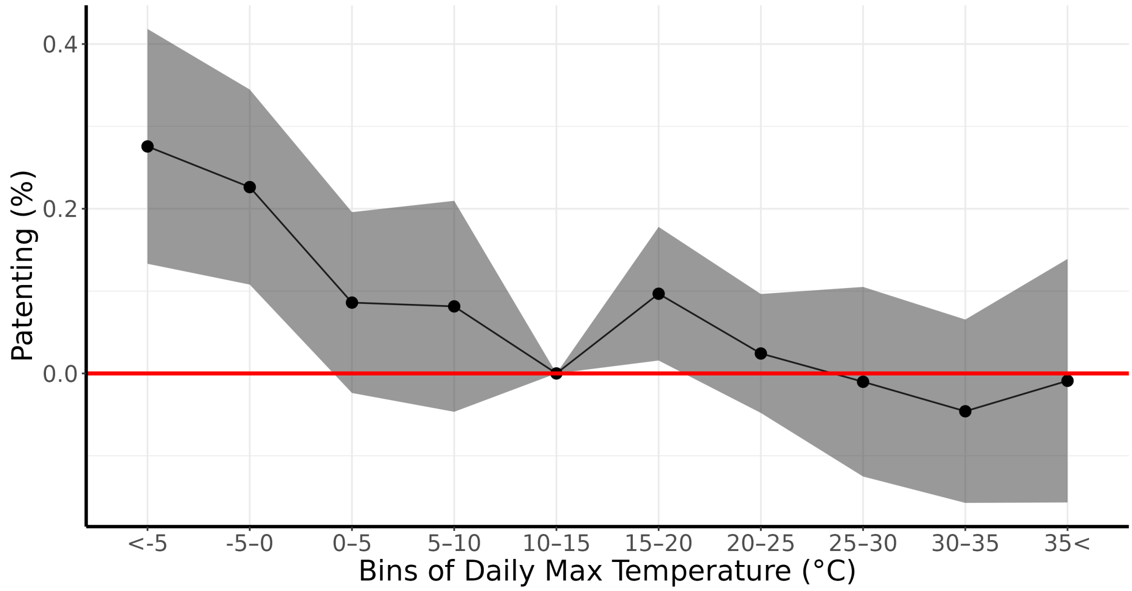
Notes: The plot shows the results for the coefficient of the temperature bin covering days above 20°C when this is calculated using daily maximum, daily mean or daily minimum temperatures. The model is estimated using a PPML estimator and includes inventor and year fixed effects, as well as linear and squared time trends and controls for humidity and precipitation. Standard errors are clustered at the city level, and the plot shows the 95% confidence interval for the coefficient estimate. The outcome variable is expressed as the percentage change in patent family application filings. This analysis is based on three-year cumulative exposure

FIGURE 3.10: Robustness - maximum, minimum, mean temperatures

inventor is likely to be at work, while minimum temperatures occur at night, likely when the inventor is asleep. More pronounced effects of daily maximum temperature would suggest that temperature primarily impacts productivity through daytime activities. In contrast, the strong effects of daily minimum temperature may suggest disrupted sleep as a driver for the negative effect on inventor productivity.

The results, shown in Figure 3.10, confirm that the effect of temperature is more pronounced when using daily maximum temperatures, suggesting that daytime heat is more relevant in influencing inventor productivity. Possible explanations include that inventors may be shielded at night by residential air conditioning or that variations in temperature are more important during work hours, with limited spillover effects from variations at night.

Finally, we assess the robustness of our results to geographic subsampling of our data. Specifically, we remove California as the largest contributor to innovation and home to around a quarter of the country's inventors. The results in Figure 3.11 suggest that the main results are largely



Notes: This graph shows the temperature response function without inventors resident in California. It is estimated using a PPML estimator and includes inventor and year fixed effects, as well as linear and squared time trends and controls for humidity and precipitation. Standard errors are clustered at the city level. The grey shaded area represents the 95% confidence interval for the coefficient estimate. The outcome variable is expressed as the percentage change in patent family application filings, with 10 to 15°C as the reference category. This analysis is based on three-year cumulative lagged exposure.

FIGURE 3.11: Temperature response function - no California

driven by California. In the estimation without California, higher temperatures do not seem to affect inventors' patent filings, whereas the positive effect of low temperatures persists. Given the significantly divergent patenting trends observed in San Diego, we also subset our sample to exclude San Diego while keeping the rest of California. In this case, the effect of temperatures above 20°C persists, indicating that San Diego is not solely responsible for the observed change in patterns (Appendix Figure 3.A.11). Though California is the fifth-largest economy in the world, and results specific to California hold value on their own, in the following section, we explore factors that may lead to heterogeneous effects.

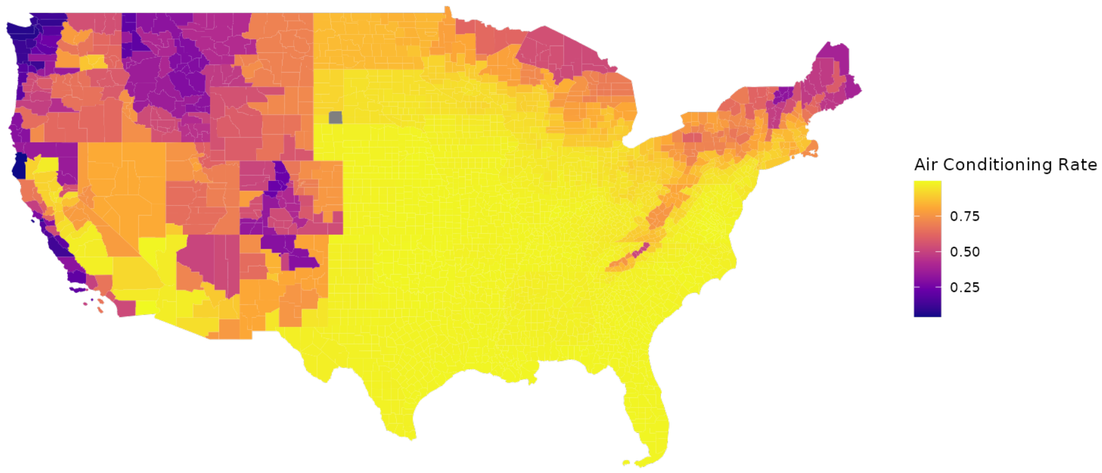
3.5.3 Heterogeneity

Air conditioning is the most obvious form of adaptation to higher temperatures and can shield inventors from temperature fluctuations. Thus, variations in the prevalence of air conditioning are likely to influence how inventors respond to these changes. Importantly, the presence of air conditioning may be relevant not only at the workplace but also in other environments that intersect with the life of the inventor, such as at home, in shops or on public transport. Disruptions due to temperature in these settings may carry over and affect productivity during work hours.

Since we are unable to track the inventor's exact movements and their access to air conditioning over time, we rely on an approximation of air conditioning exposure. Though detailed-time series air conditioning data is not readily available, we utilise a dataset constructed by Shrader, Bakkensen, and Lemoine (2023), which estimates annual household air conditioning rates by county from 2005 to 2017. Using individual-level restricted access data from the American Housing Survey alongside climate data, the authors employ a multi-step model selection process to estimate coefficients predicting household air conditioning take-up. They then apply these coefficients to standardized American Community Survey data to generate household predictions that are aggregated by county and year and subsequently smoothed over time. The final air conditioning variable is expressed as a penetration rate between 0 and 1, where 0 indicates no air conditioning and 1 universal coverage. Although this data does not capture air conditioning outside the household, it provides our best available approximation of overall air conditioning levels. We subset our sample to fit the availability of the data and create three-year rolling averages of air conditioning penetration by county.

The distribution of average household air conditioning penetration between 2005 and 2017 is shown in Figure 3.12. For the United States overall, the mean air conditioning penetration during this period is 84%. However, there is significant geographical variation, with notably lower air conditioning rates in the western and northeastern United States. In California, the mean household air conditioning rate is 66%, while in densely populated counties along the coast of California, it is even lower with an average of 34%.

To analyse how differences in air conditioning may lead to heterogenous effects of temperature on inventor productivity, we interact the temperature variable with county-level air conditioning penetration (Figure 3.13). Interpreting interaction terms in non-linear models can be complex



Notes: The map shows the air conditioning penetration rates by county from 2005 to 2017. Penetration rates are expressed from 0 to 1, where 0 indicates no air conditioning and 1 full air conditioning.

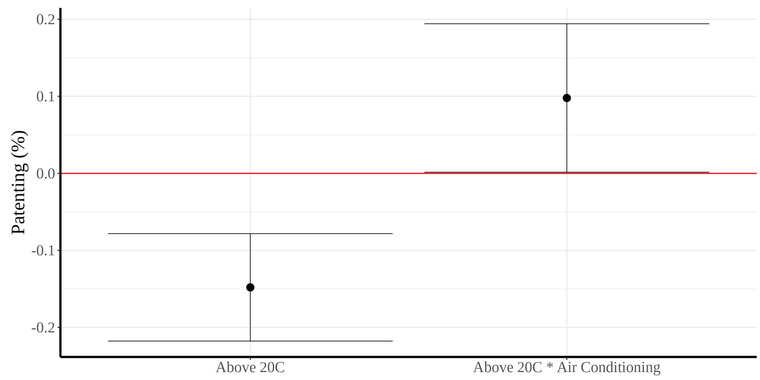
FIGURE 3.12: Air conditioning penetration

as coefficients generally do not correspond to marginal effects when the outcome is expressed in levels (Ai and Norton 2003). However, the PPML model used here specifies the log of expected patent family applications as a linear function of temperature, allowing coefficients to be interpreted as percentage changes[1]. In this context, interaction terms capture how the percentage effect of temperature varies with air conditioning penetration and can be directly interpreted from the estimated coefficients, avoiding the concerns raised by Ai and Norton (2003). Under full household air conditioning (AC = 1), the effect of temperature is the sum of the coefficient and the interaction term. It suggests that net of air conditioning, one additional day above 20C decreases an inventor's patent filings by 0.05%. While the negative effect of higher temperatures is significantly smaller with air conditioning, it persists and suggests that widespread air conditioning may not be sufficient to fully mitigate the impacts. However, it is important to remember that the air conditioning variable is an approximation, capturing household air conditioning penetration but not accounting for air conditioning in other environments, such as workplaces or commercial spaces. While this is our best available measure, the incomplete

[1] See Appendix 3.A.2 for more details.

mitigation effect may thus also result from limited air conditioning in other settings. Nonetheless, the evidence suggests that air conditioning can significantly reduce the negative impact of temperature on productivity.

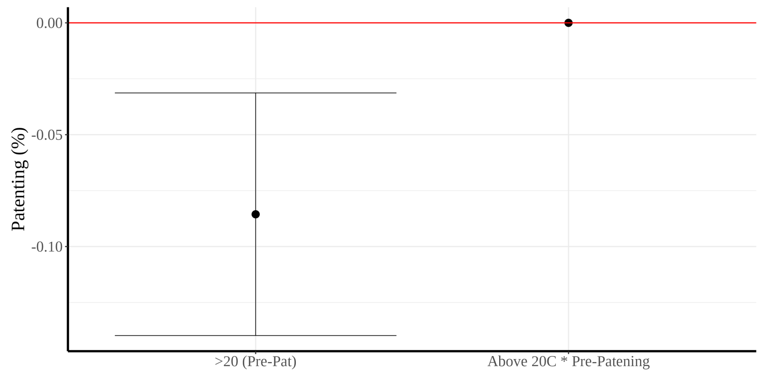
Not only does this finding make intuitive sense, but given the significantly lower air conditioning rates in California, it also offers a compelling explanation for the differential effect without California observed in the previous section. Furthermore, it is worth noting that the US, including California, already has significantly higher rates of air conditioning compared to Europe and many other regions globally. This suggests that the effects of higher temperatures on inventor productivity may be even more pronounced elsewhere.



Notes: The plot shows the results for the coefficient of the temperature bin covering days above 20°C, as well as the interaction of this coefficient with the air conditioning penetration variable. The model is estimated using a PPML estimator and includes inventor and year fixed effects, as well as linear and squared time trends and controls for humidity and precipitation. Standard errors are clustered at the city level, and the plot shows the 95% confidence interval for the coefficient estimate. The outcome variable is expressed as the percentage change in patent family application filings. This analysis is based on three-year cumulative exposure.

FIGURE 3.13: Heterogeneity - air conditioning

Beyond air conditioning, we also examine how differences in patenting intensity may lead to heterogeneous effects. As the number of inventors increases, their interconnectivity also grows. Minor decreases in temperature-induced productivity may compound and lead to spillover effects throughout the network. For example, in a highly connected network, if one inventor is suffering from temperature-induced health problems, it may delay the progress of inventors in the same network who rely on the innovative developments of the specific individual, thus leading to compounded decreases in patent filings. To test this, we produce a measure for patenting intensity in inventor cities by using the number of patent applications five years prior to our estimation period (1995 – 1999). Though the coefficient on our main temperature variable remains consistent, the coefficient on the interaction term of temperature with patenting intensity is zero, suggesting that patenting intensity does not influence the relationship between higher temperatures and inventor productivity.

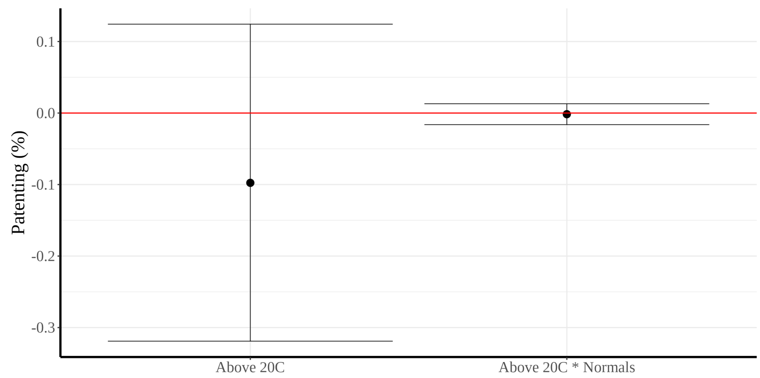


Notes: The plot shows the results for the coefficient of the temperature bin covering days above 20°C, as well as the interaction of this coefficient with the patenting intensity variable. The model is estimated using a PPML estimator and includes inventor and year fixed effects, as well as linear and squared time trends and controls for humidity and precipitation. Standard errors are clustered at the city level, and the plot shows the 95% confidence interval for the coefficient estimate. The outcome variable is expressed as the percentage change in patent family application filings. This analysis is based on three-year cumulative exposure.

FIGURE 3.14: Heterogeneity - patenting intensity

Finally, we explore whether climate may lead to heterogeneous effects of temperature on inventor productivity. On the one hand, in a warmer climate, socioeconomic infrastructure may be better adapted, and inventors may be more accustomed to higher temperatures, enabling them to cope better with additional hot days. On the other hand, additional heating days in a warmer climate may also reduce the essential reprieve that cooler days provide in mitigating the effects of prolonged heat exposure. For example, an inventor who has already experienced two weeks of high temperatures may experience greater heat stress from an additional hot day compared to someone who has had intermittent cooler days. Similarly, socioeconomic infrastructure such as hospitals may be stretched thin during prolonged heat exposure, making additional hot days more disruptive.

To approximate climate, we download 30-year annual temperature normals (1991 – 2020 from PRISM) and aggregate these to the inventor city-level using the same weighted spatial aggregation methods as before. The inclusion of temperature normals introduces some noise to the main temperature variable as some of the variation is inevitably absorbed by the normals. However, interacting the normals with our main temperature variable, we do not find evidence that climate influences the relationship between high temperatures and inventor productivity.



Notes: The plot shows the results for the coefficient of the temperature bin covering days above 20°C, as well as the interaction of this coefficient with the climate normals. The model is estimated using a PPML estimator and includes inventor and year fixed effects, as well as linear and squared time trends and controls for humidity and precipitation. Standard errors are clustered at the city level, and the plot shows the 95% confidence interval for the coefficient estimate. The outcome variable is expressed as the percentage change in patent family application filings. This analysis is based on three-year cumulative exposure.

FIGURE 3.15: Heterogeneity - climate

3.6 Conclusion

In this study, we have explored the effect of temperature variations on inventor productivity. Using data from the United States from 2000 to 2020, our inventor-level analysis suggests that one additional day above 20°C in the past three years compared to a day between 10 to 15°C leads to a 0.12% decrease in the patent applications filed by the inventor today. On the other hand, temperatures below 0°C seem to increase inventor patenting activity, possibly explained by labour-leisure substitution. The results suggest that temperatures can impact labour productivity not only in the short term but also in the longer-term cumulative processes of research and development.

Furthermore, our analysis indicates that the negative effect of higher temperatures is largely driven by California. Since the state is home to a quarter of the inventors in the United States and is considered to be the fifth-largest economy in the world, results pertaining to California hold value in themselves. Nonetheless, we have attempted to identify the specific factors underlying these results. We find evidence that while climate and patenting intensity do not influence the relationship between temperature and inventor productivity, air conditioning penetration does. Specifically, we find that higher rates of air conditioning decrease the negative effect of temperature on inventor productivity. Given significantly lower than average air conditioning rates in California compared to other parts of the United States, these findings align with the geographic heterogeneity of our results.

In addition, although we cannot test this directly, it is possible that lower patenting in California on warmer days partly reflects substitution away from work towards leisure. Inventors who choose to live in California may have stronger preferences for outdoor activities, making them more likely to shift time towards leisure when temperatures increase. The state's emphasis on outdoor living, extensive coastline and abundance of warm-weather recreational activities may reinforce this tendency. From a welfare perspective, this then raises the question of whether such responses warrant policy intervention, particularly if reduced productivity is offset by increased leisure utility.

Of course, this study is not without caveats. Firstly, we acknowledge that we are unable to capture changes in R&D investments that may correlate with temperature fluctuations and could impact inventor patent filings. Ideally, we would control for changes in R&D expenditure of the firm employing the inventor to separate this effect. However, this data is difficult to obtain, as it requires both firm-level data on R&D spending and matching inventors to firms over time. For public U.S. firms, R&D data may be obtained via Compustat, but attributing it to individual inventors would require detailed tracking of their career paths. While this is not straightforward, it remains an avenue for future research. Furthermore, we are limited by the geographic precision of inventors' home addresses as listed on the patent applications, and while cities provide a relatively granular unit, there may be additional temperature variations within the cities that we are unable to account for. Finally, we are also limited by the geographic precision of air conditioning data and are unable to determine where air conditioning might be most relevant, for example, whether at home or at work. Though we have outlined several possible mechanisms underlying the relationship between temperature and inventor productivity, there remains a need for future research to determine their relative importance.

Nonetheless, we believe that our study makes an important contribution to the literature. Understanding the impact of temperature on the labour market has become increasingly important in light of rising global temperatures. Inventors are a critical economic component of the workforce, yet the effects of environmental shocks on their productivity have largely been overlooked. Albeit that inventors are more likely to work indoors, our results challenge the notion that this renders inventors immune to the disruptions associated with variations in temperature. This finding also adds a new perspective to the debate on the level versus economic growth effects of rising temperatures, with productivity effects of inventors possibly contributing to the negative impacts on growth. However, these effects may also be offset by an expanding inventive workforce. Future policy discussions in this context should thus further consider human capital formation in a warming world. Importantly, our study suggests that air conditioning constitutes an effective adaptation strategy. However, for it to be truly protective, our findings also indicate that penetration rates need to be sufficiently high, and residential air conditioning alone may not be enough. Given that air conditioning rates are much lower in Europe and in many parts of the rest of the world compared to California, the impact of rising temperatures on inventor productivity may be even more severe in these regions and will require future study.

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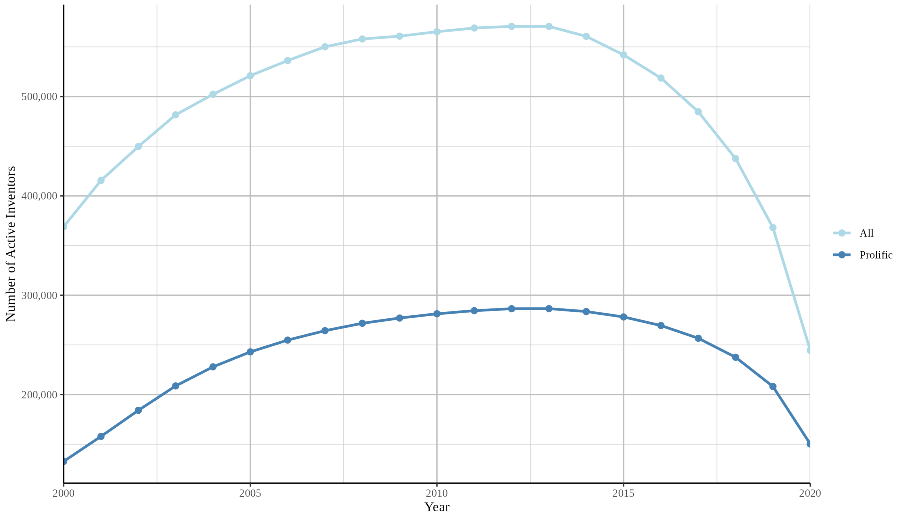
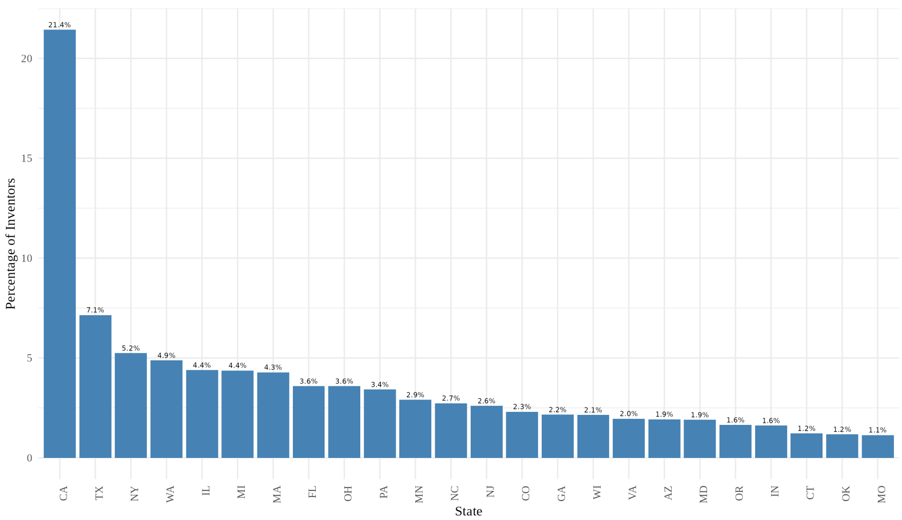
3.A Appendix

3.A.1 Additional Descriptive Figures



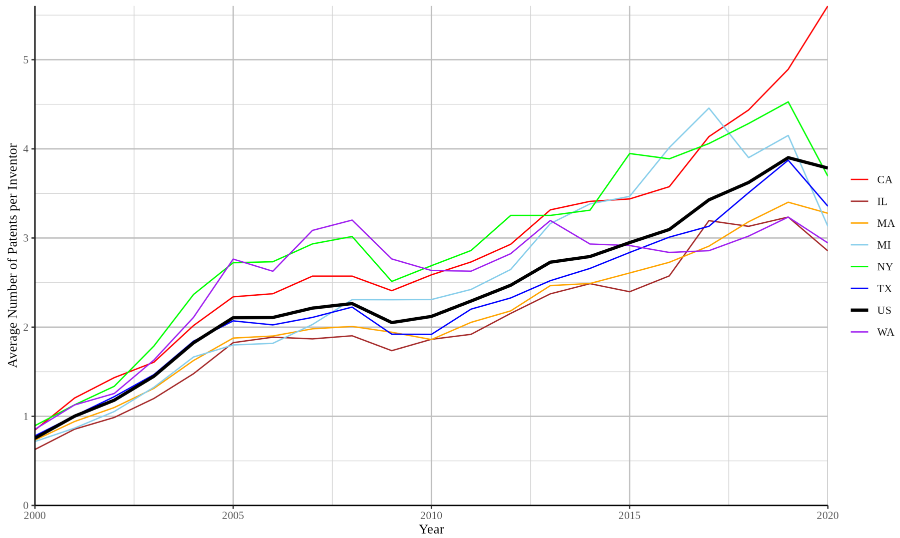
Notes: The graph depicts the number of all active inventors in the sample from 2000 to 2020. The graph includes movers, i.e. inventors who list multiple addresses.

FIGURE 3.A.1: Number of inventors over time - incl. movers



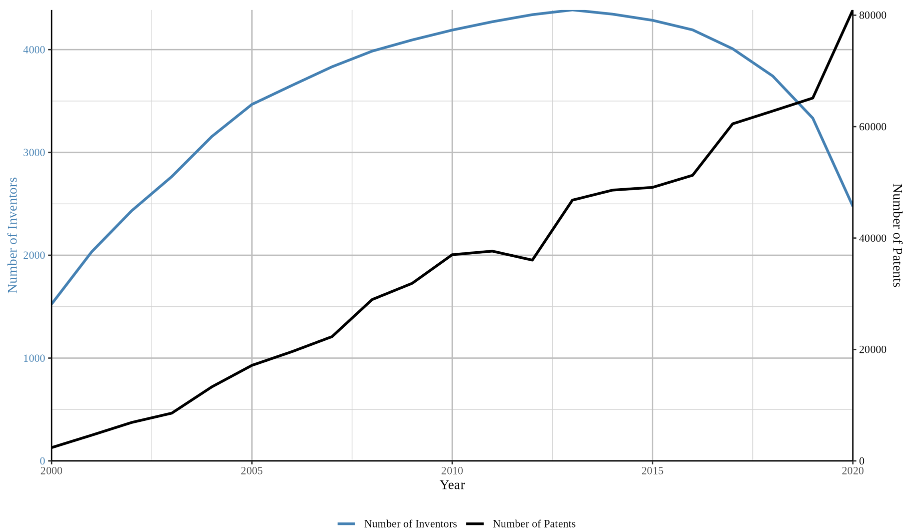
Notes: The bar chart depicts the distribution of unique inventors by state from 2000 to 2020. The chart excludes states with fewer than 1% of inventors. The chart excludes movers, i.e., inventors who list multiple addresses since these are excluded from our sample.

FIGURE 3.A.2: Patenting by state - incl. non-prolific



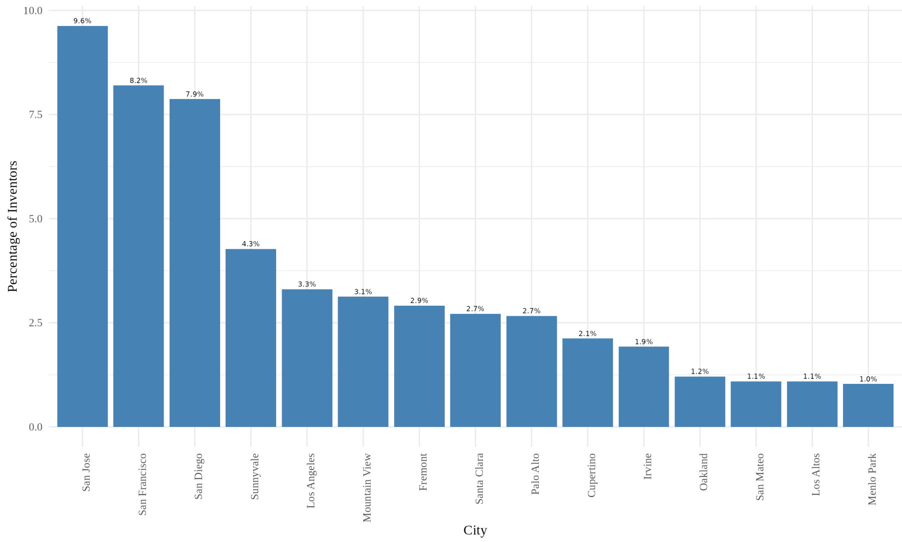
Notes: The graph depicts the average number of patent family applications per inventor from 2000 to 2020. This is calculated by dividing the total number of patent family applications by the number of active inventors. The chart excludes movers, i.e. inventors who list multiple addresses since these are excluded from our sample.

FIGURE 3.A.3: Patenting trends in the US and high patenting states - incl. non-prolific



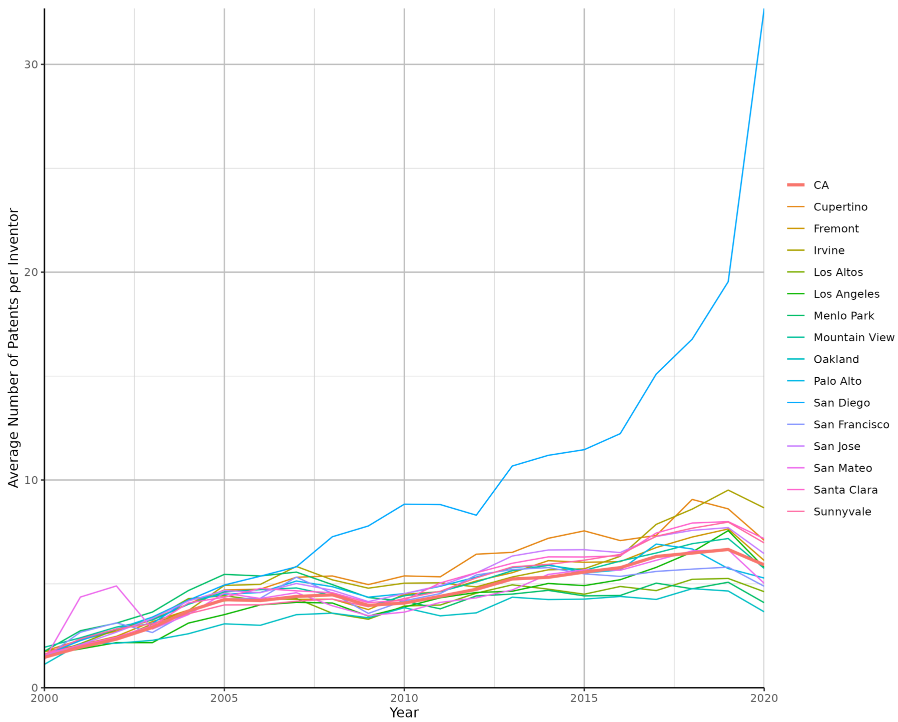
Notes: The graph depicts the number of prolific inventors and the number of patent family application filings in San Diego from 200 to 2020. The y-axis on the left provides the scale for the number of inventors, while the y-axis on the right provides the scale for the number of patent family application filings.

FIGURE 3.A.4: Inventors and patenting in San Diego



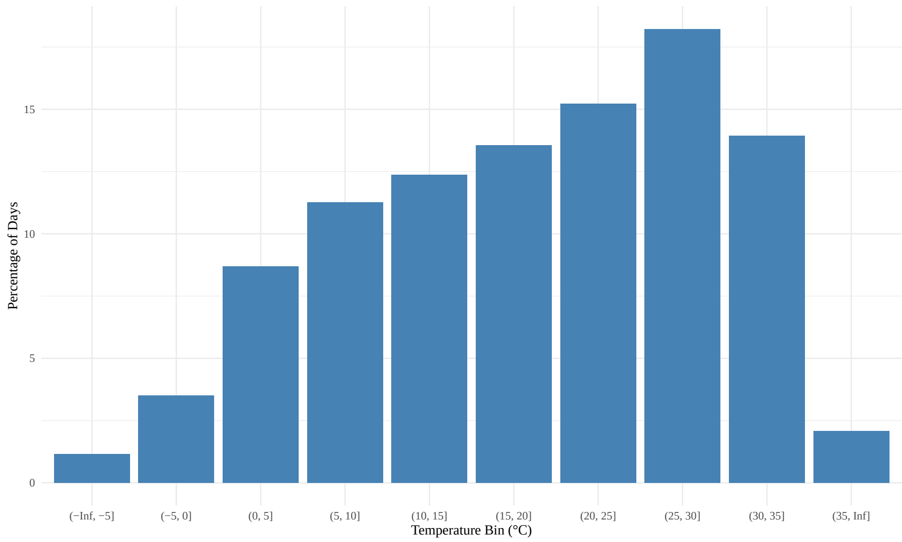
Notes: The bar chart depicts the distribution of unique inventors by city in California from 2000 to 2020. The chart excludes cities with fewer than 1% of inventors. The chart excludes movers, i.e., inventors who list multiple addresses, since these are excluded from our sample.

FIGURE 3.A.5: Patenting by city - California - incl. non-prolific



Notes: The graph depicts the average number of patent family applications per inventor from 2000 to 2020 in cities in California with a higher number of inventors. This is calculated by dividing the total number of patent family applications by the number of active inventors. The graph excludes movers, i.e. inventors who list multiple addresses, since these are excluded from our sample.

FIGURE 3.A.6: Patenting trends in California and cities - incl. non-prolific



Notes: The graph shows the percentage distribution of days within each temperature bin in inventor cities in 2020. Inventor cities are defined by the home address of inventors. The chart excludes movers, i.e. inventors who list multiple addresses since these are excluded from our sample

FIGURE 3.A.7: Temperature distributions in 2020 - incl. non-prolific

3.A.2 Note on Interaction Terms

[This note is equivalent to the explanation provided in Appendix 1.A.2 of Chapter 1, as the econometric structure and interpretation of interaction terms are identical across both chapters.]

An interaction term measures the change in marginal effect of one variable with respect to changes in another and is defined by the cross-partial derivative: $\frac{\partial^2 E[y|x]}{\partial x_1 \partial x_2}$.

Consider first a linear model: $E[y|x] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2$.

The marginal effect of x_1 is: $\frac{\partial E[y|x]}{\partial x_1} = \beta_1 + \beta_3 x_2$ and the interaction effect is given by: $\frac{\partial^2 E[y|x]}{\partial x_1 \partial x_2} = \beta_3$

In this case, the coefficient β_3 on the interaction term directly represents the interaction effect, making interpretation straightforward.

Now consider a Poisson model: $E[y|x] = \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2)$.

The marginal effect of x_1 becomes: $\frac{\partial E[y|x]}{\partial x_1} = \exp(\cdot) \cdot (\beta_1 + \beta_3 x_2)$

Applying the product rule, the interaction effect is: $\frac{\partial^2 E[y|x]}{\partial x_1 \partial x_2} = \exp(\cdot)\,[\beta_3 + (\beta_1 + \beta_3 x_1)(\beta_2 + \beta_3 x_2)]$

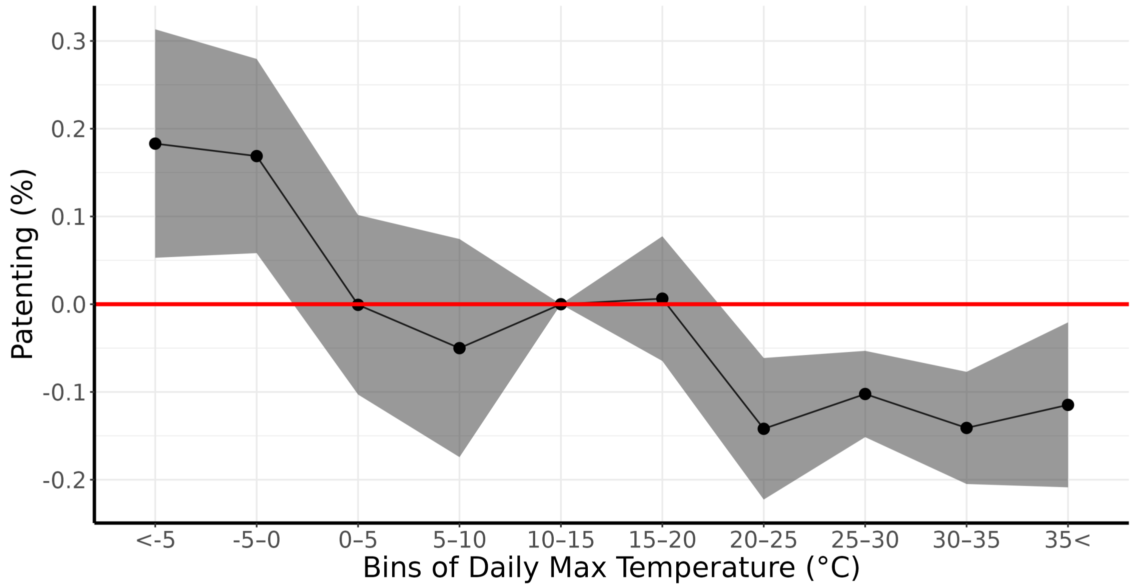
As shown by Ai and Norton (2003), in non-linear models like this, the interaction effect depends on all covariates and their values. Hence, β_3 does not directly represent the interaction effect and must be evaluated at specific covariate values with standard errors via the delta method.

However, the PPML model uses a log-link specification: $\log E[y|x] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2$.

The marginal effect of x_1 on the log scale is: $\frac{\partial \log E[y|x]}{\partial x_1} = \beta_1 + \beta_3 x_2$ and the interaction effect is: $\frac{\partial^2 \log E[y|x]}{\partial x_1 \partial x_2} = \beta_3$

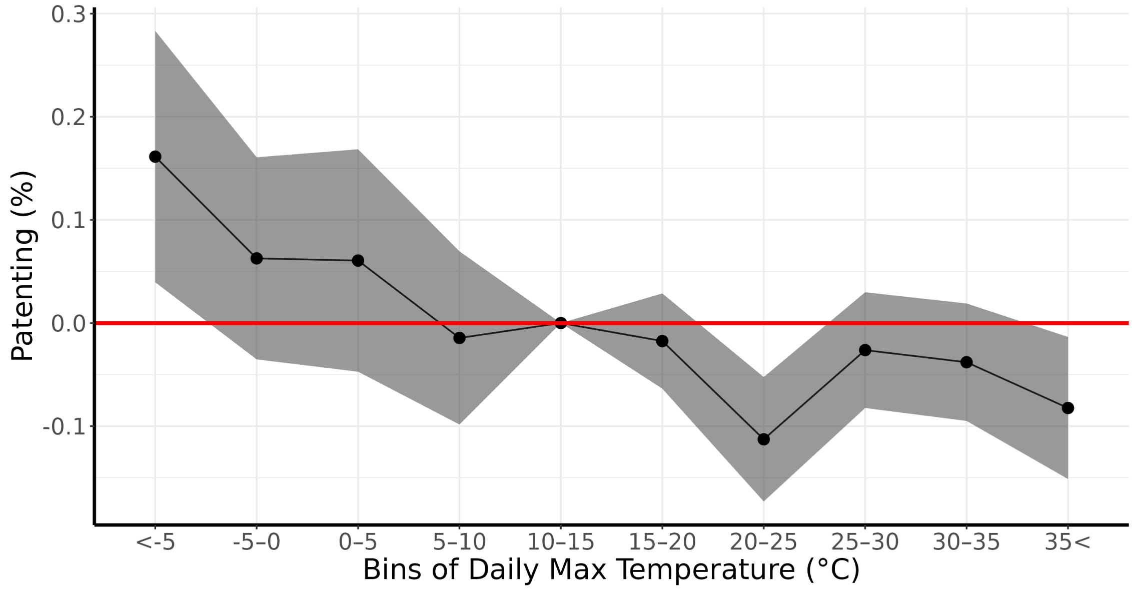
Thus, in the PPML estimation, interaction coefficients can be interpreted directly as changes in the log of expected outcomes. Since coefficients are interpreted as semi-elasticities, the interpretation of β_3 and the associated standard error remains valid and avoids the concerns raised by Ai and Norton (2003).

3.A.3 Additional Result Figures



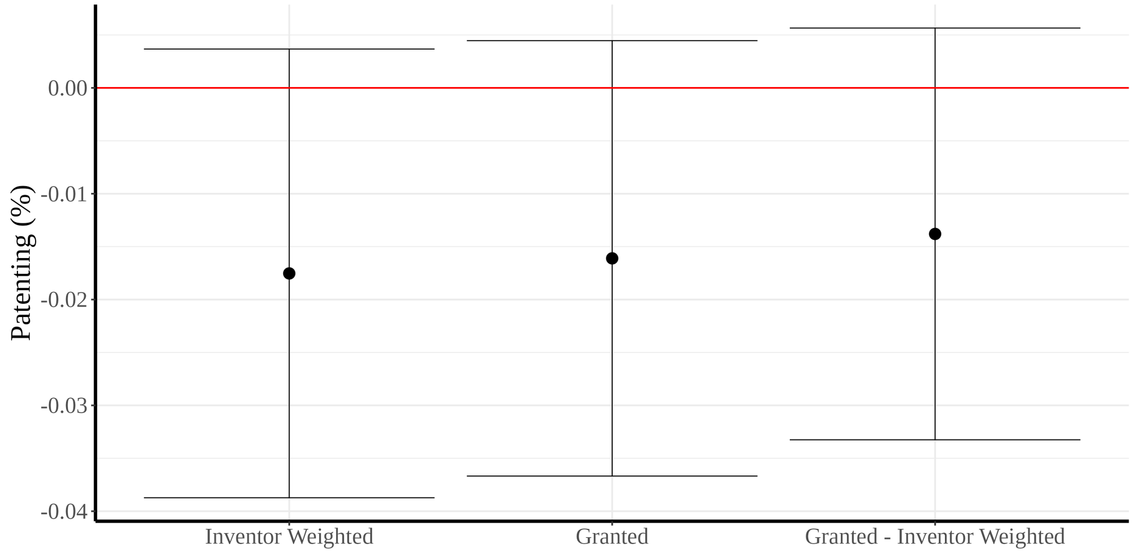
Notes: This graph shows the temperature response function of the main specification when tenure fixed effects are added. It is estimated using a PPML estimator and also includes inventor and year fixed effects, linear and squared time trends, as well as controls for humidity and precipitation. Standard errors are clustered at the city level. The grey shaded area represents the 95% confidence interval for the coefficient estimate. The outcome variable is expressed as the percentage change in patent family application filings, with 10 to 15°C as the reference category. This analysis is based on three-year cumulative lagged exposure.

FIGURE 3.A.8: Robustness - tenure fixed effects



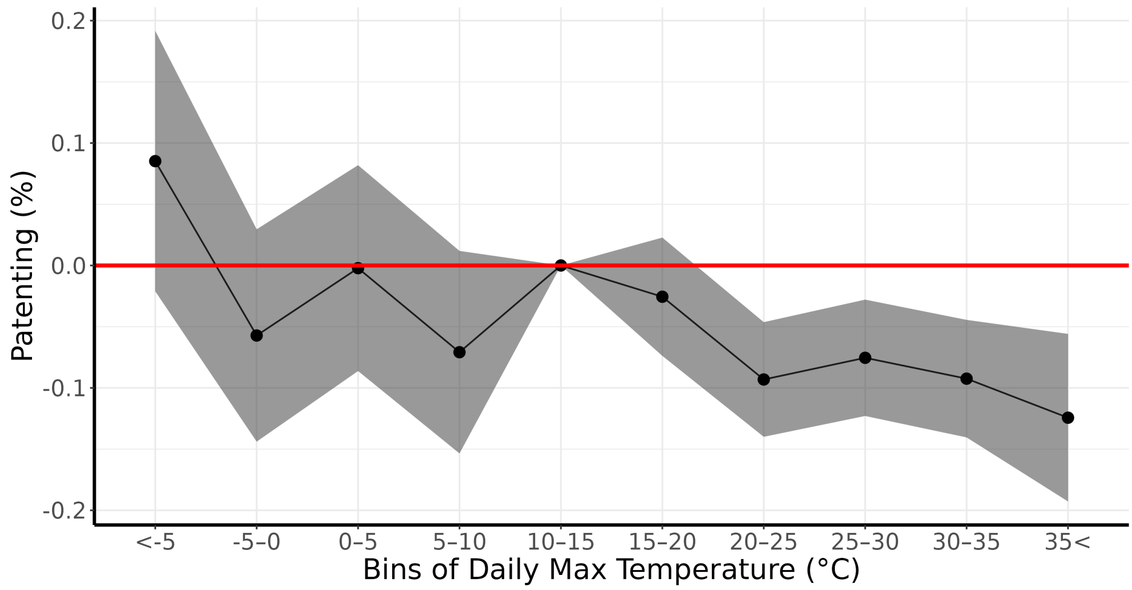
Notes: This graph shows the temperature response function of the main specification when pollution controls are added. It is estimated using a PPML estimator and also includes inventor and year fixed effects, linear and squared time trends, as well as controls for humidity and precipitation. Standard errors are clustered at the city level. The grey shaded area represents the 95% confidence interval for the coefficient estimate. The outcome variable is expressed as the percentage change in patent family application filings, with 10 to 15°C as the reference category. This analysis is based on three-year cumulative lagged exposure.

FIGURE 3.A.9: Robustness - pollution controls



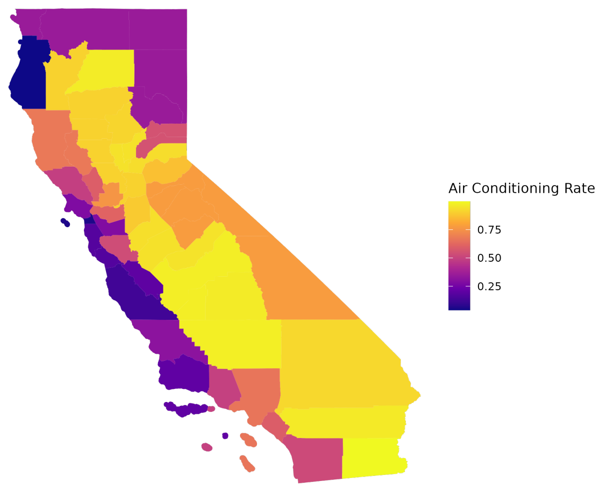
Notes: The plot shows the results for the coefficient of the temperature bin covering days above 20°C for different outcome variables. Model 1 shows the effect of temperature on patent families that are weighted by the number of inventors listed on the patent. Model 2 shows the effect of temperature on granted patent families. Model 3 shows the effect of temperature on granted patent families that are weighted by the number of inventors listed on the patent. The models are estimated using a PPML estimator and include inventor and year fixed effects, as well as linear and squared time trends and controls for humidity and precipitation. Standard errors are clustered at the city level, and the plot shows the 95% confidence interval for the coefficient estimate.

FIGURE 3.A.10: Robustness - weighted and granted patents



Notes: This graph shows the temperature response function without inventors resident in San Diego. It is estimated using a PPML estimator and includes inventor and year fixed effects, as well as linear and squared time trends and controls for humidity and precipitation. Standard errors are clustered at the city level. The grey shaded area represents the 95% confidence interval for the coefficient estimate. The outcome variable is expressed as the percentage change in patent family application filings, with 10 to 15°C as the reference category. This analysis is based on three-year cumulative lagged exposure.

FIGURE 3.A.11: Robustness - no San Diego



Notes: The map shows the air conditioning penetration rates by county from 2005 to 2017 in California. Penetration rates are expressed from 0 to 1, where 0 indicates no air conditioning and 1 full air conditioning.

FIGURE 3.A.12: Air conditioning rates - California

Chapter 4

Air Pollution and Inventor Productivity

4.1 Introduction

Air pollution has been increasingly recognized as a significant determinant of economic performance, affecting labour productivity (Borgschulte, Molitor, and Zou 2024; Neidell and Pestel 2023), health outcomes (Chay and Greenstone 2003; Neidell 2004; Currie 2011; Schlenker and Walker 2016; Deschênes, Greenstone, and Shapiro 2017; Zhang, Chen, and Zhang 2018; Deryugina et al. 2019; Barreca, Neidell, and Sanders 2021; Graff Zivin et al. 2023), cognitive performance (Ebenstein, Lavy, and Roth 2014; Zhang, Chen, and Zhang 2018; Carneiro, Cole, and Strobl 2021; Krebs and Luechinger 2024) and other dimensions of human well-being (Chay and Greenstone 2003; Currie et al. 2015; Sager 2019; Bondy, Roth, and Sager 2020). A growing body of literature in economics demonstrates that elevated pollution levels substantially reduce worker productivity specifically, predominantly focusing on low-skilled occupations and short-term exposure periods such as daily or weekly fluctuations (Graff Zivin and Neidell 2012; Chang et al. 2016; He, Liu, and Salvo 2019). A few studies have also documented negative effects of daily pollution exposure on high-skilled professionals in performance-based occupations, such as professional athletes and umpires (Archsmith, Heyes, and Saberian 2018; Lichter, Pestel, and Sommer 2017). However, despite these important contributions, little is known about the longer-term effects of pollution on productivity, especially among high-skilled workers whose contributions play a critical role in driving sustained economic growth.

This paper addresses this gap in knowledge by examining the impact of air pollution on inventor productivity over multi-year horizons, specifically measuring innovative output through patenting activities. Innovation has long been recognized as a cornerstone of long-term productivity growth, shaping the trajectory of economic development and societal welfare (Romer 1990; Aghion et al. 1998; Jones 1995). High-skilled professionals, particularly scientists and engineers, play a central role in this process, as their creativity and productivity underpin technological advances and sustained economic progress (Mokyr 2005; Hanlon 2022). Given the crucial role these inventors play in fostering innovation and economic growth, understanding how environmental factors such as air pollution influence their productivity provides valuable insights into the determinants of long-run economic performance.

Estimating the causal relationship between air pollution and innovation is challenging primarily due to the potential presence of correlated omitted variables and measurement error in pollution exposure. To overcome these empirical issues, we leverage detailed inventor-level panel data combined with city-level measures of Fine Particulate Matter (PM2.5) pollution. Our analysis employs two complementary identification strategies to ensure robust causal inference. First, we use a fixed-effects approach, exploiting rich inventor-level variation in pollution exposure over time, using inventor-specific fixed effects to capture time-invariant unobserved confounding factors. We augment this specification with year fixed effects to account for common trends in patenting across locations and include controls for local weather conditions that might jointly affect pollution and innovation. Second, we adopt an instrumental variable (IV) approach that exploits exogenous variation arising from changes in regulatory designation under the PM2.5 National Ambient Air Quality Standards (NAAQS), providing plausibly exogenous shocks to local air quality. Our IV strategy, therefore, addresses remaining concerns about time-varying omitted variables and potential measurement error in pollution exposure. Together, these complementary empirical strategies enable us to provide credible causal estimates of pollution's impact on innovation.

We find statistically and economically significant negative effects of PM2.5 pollution on innovation, showing that increased exposure leads to substantial declines in patenting productivity. Using a Poisson Pseudo-Maximum Likelihood estimator (PPML), we estimate that a one-standard-deviation increase in PM2.5 concentrations ($4.6\mu g/m^3$) in the previous year leads to a 2.6% reduction in patents per inventor. This result is consistent across multiple measures of patenting activity, including simple patent-family counts and fractional patenting measures that account for co-inventorship. To quantify the potential innovation losses, we conduct a counterfactual exercise: if all inventors had been exposed to air pollution levels capped at $5\mu g/m^3$, approximately 10,300 additional patents would have been filed in 2016 alone, translating into an estimated economic loss of at least \$10.3 billion (0.05% of GDP in 2016).

Extending our analysis over a longer time horizon, we incorporate three-year pollution exposure lags and estimate cumulative effects to capture the longer-term relationship between pollution and innovation. We find that the negative effect of pollution strengthens over time, with the largest decline in patenting occurring at a three-year lag. The cumulative estimates suggest that a one-standard-deviation increase in pollution leads to a 4.1% decline in patenting per inventor over a three-year period. These findings highlight that pollution does not only impose short-term productivity losses but also disrupts the longer-term innovation process, an effect that has been largely overlooked in the existing literature.

To further strengthen identification, we implement an IV approach that exploits regulatory changes in attainment status under the PM2.5 NAAQS, similar to the approach of Sager and Singer (2025). Our reduced-form analysis confirms that pollution-control policies significantly increased inventor productivity, with compliance leading to about a 10% increase in innovation over a three-year period. In our main control function estimates, we find that a $1\mu g/m^3$ increase in PM2.5 pollution leads to a 9.8% decline in patenting activity, a larger effect than that estimated in our fixed-effects models. Several factors may explain this discrepancy. First, the difference is consistent with attenuation bias in the fixed-effects estimates due to measurement error in pollution exposure, which would bias the coefficient toward zero. Second, our fixed-effects models may not fully account for time-varying confounders correlated with both pollution and innovation, while our IV approach plausibly mitigates these concerns. Third, our IV estimates identify a Local Average Treatment Effect (LATE). Nonetheless, the alignment between our reduced-form and control function estimates provides strong support for the robustness of our IV findings, as the reduced-form relies on less restrictive assumptions. Overall, our results provide compelling empirical evidence that air pollution significantly impairs high-skilled productivity, with persistent and economically meaningful effects on innovation. These findings highlight an important but often overlooked channel through which environmental quality influences economic growth and technological progress.

Our paper contributes to both the academic literature and ongoing policy debates in several key ways. First, we extend the literature on the economic costs of air pollution, particularly in the context of labour productivity, which has largely focused on low-skilled occupations and short-term exposure effects (Graff Zivin and Neidell 2012; Chang et al. 2016; He, Liu, and Salvo 2019). The empirical evidence on the relationship between pollution and innovation remains extremely limited, with only two recent studies examining this causal link to the best of our knowledge. Bracht and Verhoeven (2025) analyse the impact of air pollution on patenting activity at the NUTS3 level across European regions, identifying negative effects using regional-level variation. Similarly, Cui, Huang, and Wang (2023) investigate the impact of pollution on patent applications in China at the city level, finding that an annual increase of $1\mu g/m^3$ PM2.5 concentration leads to a 1.3% decline in patenting activity. Our study builds on and significantly extends these contributions by providing the first rigorous causal estimates for the United States and, crucially, by focusing on individual inventors rather than aggregated regional or city-level data. This granular approach allows us to directly examine the mechanism through which pollution affects innovation via the productivity of high-skilled innovators, a group central to technological advancement and long-run economic growth. Using detailed inventor-level panel data and implementing a quasi-experimental identification strategy, our findings offer novel insights into how environmental conditions shape knowledge production at the micro level, complementing and expanding the existing literature on the economic consequences of pollution.

Second, our analysis contributes to the broader literature examining the hidden or less visible costs of air pollution, which extends beyond traditional measures such as direct health outcomes (Aguilar-Gomez et al. 2022). By documenting sizable negative impacts on innovative activity, we provide new evidence that air pollution imposes substantial economic damages previously unaccounted for in standard policy analyses. Consequently, our findings suggest that the socially efficient level of air pollution is likely lower than previously estimated, and more stringent regulation may yield substantial economic returns.

Third, by employing a policy-driven IV strategy, exploiting exogenous variation arising from regulatory changes in attainment status under the U.S. NAAQS, we provide robust causal evidence of the significant economic benefits achievable through targeted pollution-reduction policies. This result has important implications for policymakers, reinforcing the potential economic returns to improved air quality beyond health considerations alone.

Finally, our study contributes directly to the literature on economic growth and innovation. While previous research has identified various determinants of innovation at the firm level, emphasizing market structures and incentives (Aghion et al. 2005; Bloom, Schankerman, and Van Reenen 2013), recent work increasingly recognizes the central role played by individual inventors and scientists in transforming knowledge into productive technologies (Acemoglu and Cao 2015; Bell et al. 2019). Our paper expands this line of research by identifying environmental factors, specifically air pollution, as a novel determinant influencing individual innovators' productivity. In doing so, we provide valuable insights into previously fairly overlooked channels through which environmental quality shapes the process of innovation and long-term economic growth.

4.2 Data

4.2.1 Inventor

To build the inventor-level patenting panel, we download data on patent applications filed at the U.S. Patent and Trademark Office (USPTO) from 1981 to 2016 via PatentsView. The disambiguated data files provide us with unique inventor IDs, allowing us to track inventors over time. We use the home address of the inventors listed on the application filings to filter for US-based inventors and supplement this data with information from PATSTAT, the global patent database maintained by the European Patent Office (EPO). This enables us to identify the full universe of patents filed by inventors over the period as well as patent families, collaboration networks and whether patent applications are granted. We assign each patent family a filing year based on the earliest patent application in which the inventor appears.

To measure productivity, we count the number of unique patent families by inventor and year. Since patenting activity is inherently irregular, with many inventors not filing patents annually, we construct our panel by including years with zero patents. Specifically, we input zeros for all years between an inventor's first and last observed patent application, allowing us to capture both active and less active periods in the inventor's career. We further approximate the individual inventor's experience by calculating the number of years since their first ever filing. In addition to the count of all patent families, we calculate a count of the patent families where at least one application was ultimately granted.

We construct a fractional patenting measure, also referred to as the weighted count, which adjusts patent counts based on co-authorship. If a patent lists N inventors, each is assigned a weight of $1/N$. For instance, an inventor on a patent with three co-inventors receives 0.25 of the patent count. This approach accounts for teamwork in innovation and helps assess whether collaboration mitigates the negative effects of air pollution on inventor productivity.

In our sample from 1981 to 2016, we identify 1,584,065 unique inventors. On average, inventors file 1.96 patent applications per year with a standard deviation of 7.73. When considering only granted patents, the mean number of patent families drops only slightly to 1.6 patents per year, while the mean for patent families, weighted by the number of inventors listed on the application, is 0.71. Just over a third of inventors file only one patent during the period (36.8%).

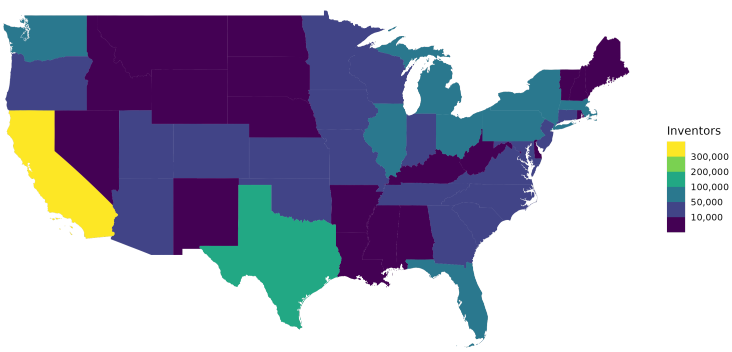


FIGURE 4.1: Total number of resident inventors by state 1981 to 2016

By a significant margin, California has the largest number of resident inventors (20.5%), followed by Texas (6.75%) and New York (6.22%). The full distribution of inventors across states is illustrated in the map in Figure 4.1. Inventors reside in 16,667 cities, which constitutes 53.4% of incorporated places in the contiguous United States recognised by the U.S. Census Bureau. The bar chart in Figure 4.2 shows the number of inventors in the 15 cities with the most inventor. A chart depicting the top 15 cities based on patenting count can be found in the Appendix 4.A.1. In both cases, cities in California largely lead the rankings. The widespread distribution of inventors across the United States allows for sufficient geographic variation for the purpose of this analysis.

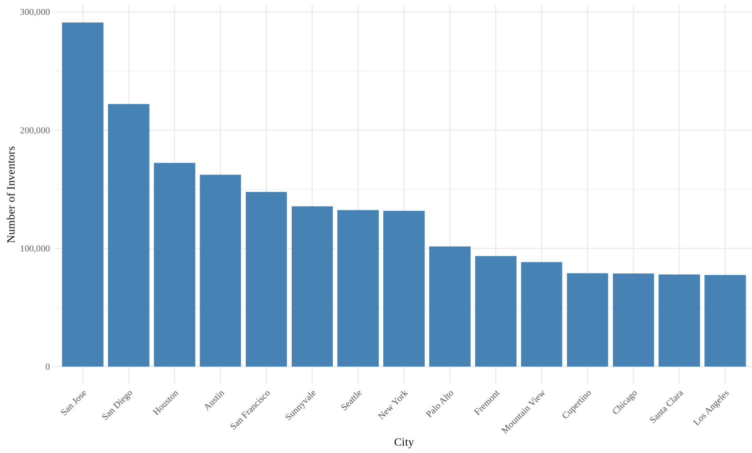


FIGURE 4.2: Top 15 cities with the largest number of resident inventors 1981 to 2016

4.2.2 Air Pollution

To determine the inventors' air pollution exposures, we access the dataset built by Meng et al. (2019). Using information from chemical transportation models, satellite remote sensing and ground-based monitoring, the raster data maps PM2.5 concentrations for the United States from 1981 to 2016 at a fine spatial resolution of 0.01 x 0.01 degrees (approximately 1km x 1km). We download city boundary shapefiles from the U.S. Census Bureau and aggregate PM2.5 concentrations by city and year. We use a weighted spatial aggregation method that assigns each raster cell a weight based on the proportion of the cell falling within the city boundary and matches the annual city air pollution values to the inventor panel using the city location of the inventors' home address. Due to discrepancies and human error in patent filings, the city serves as the smallest consistent geographic unit for the inventors' location. Although this approach does not capture exact exposure, it provides a reasonable approximation as most inventors will spend a significant portion of their time in the city of their home address. They are also likely to work relatively close to where they live, making city-level data the best available option. Nonetheless, it is important to note that city-level averages may mask within-city variation in pollution exposure. This measurement error would likely bias our estimates toward zero, making our results conservative. Since the data excludes Hawaii, US overseas territories and the majority of Alaska, we subset for inventors resident in the contiguous United States.

Furthermore, we address the possibility that inventors may move between cities during our sampling period. We track these moves through changes in reported addresses and carefully assign pollution exposure based on observed locations. Specifically, we observe inventors' locations at every patent filing but lack information between filings. Thus, to approximate pollution exposures between filings, we assign them the pollution levels of their previous location up until the midpoint between observed addresses. For example, if an inventor appears in San Francisco in 2000 and then in New York in 2010, we assign them San Francisco's air pollution levels until 2005 and New York's levels thereafter. While this approach ensures we maintain a consistent measure of exposure, we also create a sub-sample of non-movers for inventors who list the same address in their patent filings throughout the sampling period.

The final panel delineates an inventor's annual air pollution in their city of residence. We create up to three-year lags of exposure and z-standardise the pollution variable for easier interpretability.

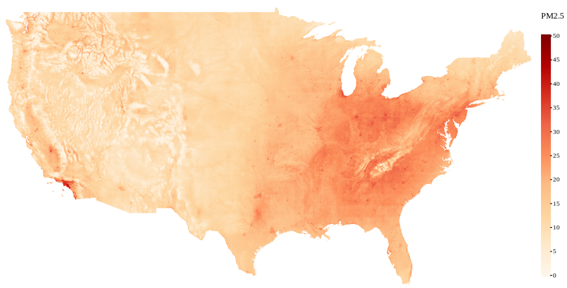
Across the sampling period and all inventor cities, the average annual PM2.5 concentration was 11.87. From 1981 to 2016, this average declined significantly, dropping from 21.73 in 1981 to 6.65 in 2016. The maximum annual PM2.5 concentration also decreased notably: in 1981, the highest recorded level for an inventor city was 41 in Santa Ana, California, whereas by 2016, the maximum had fallen to 13.81 and was experienced by inventors resident in Tustin, California.

Year	Mean PM2.5	Min PM2.5	Max PM2.5	Mean PM2.5 (Same Cities)
1981	21.73	2.45	41.01	22.06
2016	6.65	0.39	13.81	6.81

Notes: PM2.5 is measured in $\mu g/m^3$. Mean PM2.5 (Same Cities) refers to results in the subsample of cities that had resident inventors in both 1981 and 2016.

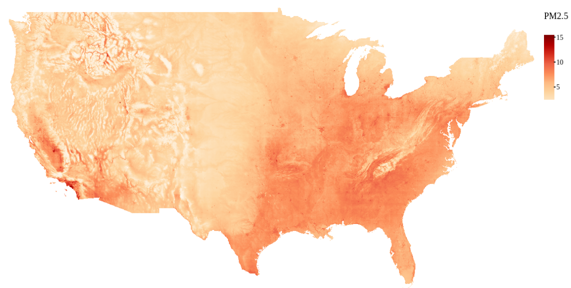
TABLE 4.1: Pollution statistics in 1981 and 2016

While California dominates the inventor landscape, it is also home to the most polluted cities, with all of the top 10 most polluted inventor cities in both 1981 and 2016 located in the state. The full geographic distribution of PM2.5 concentrations in 1981 and 2016 is illustrated in Figures 4.3 and 4.4. Despite the significant decline in PM2.5 levels, the geographic distribution of the most and least affected areas has remained relatively stable.



Notes: The map shows annual PM2.5 concentration measured in $\mu g/m^3$ in 1981. The resolution of the raster is 0.01 x 0.01 degrees.

FIGURE 4.3: Ambient air pollution in 1981



Notes: The map shows annual PM2.5 concentration measured in $\mu g/m^3$ in 2016. The resolution of the raster is 0.01 x 0.01 degrees.

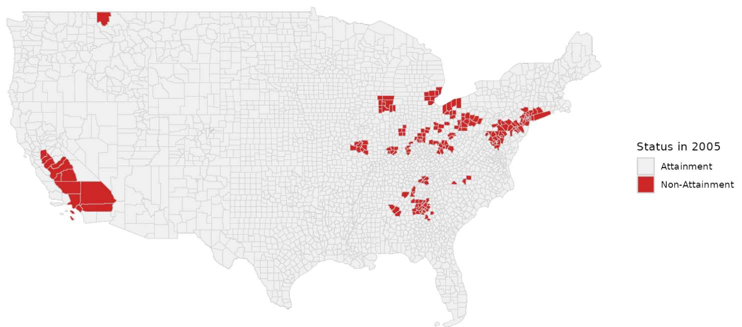
FIGURE 4.4: Ambient air pollution in 2016

4.2.3 Weather Controls and Nonattainment

To control for possible interactions of air pollution with climate, we download data on temperature and humidity from the PRISM Climate Group. Specifically, we access annual mean temperatures and annual dew points for the United States from 1981 to 2016. The raster data has a slightly larger resolution of approximately 4km x 4km. We aggregate the annual climate data to the city level using the U.S. Census Bureau city boundary shapefiles and the same weighted spatial aggregation method as before. Once aggregated at the city level, we match annual temperatures and dew points to the inventor panel, using z-standardisation for easier interpretability.

Furthermore, for our IV, we download the list of nonattainment counties for all criteria pollutants from the U.S. Environmental Protection Agency (EPA). The data file provides the annual status of counties in nonattainment for various NAAQS. We filter for counties in nonattainment of the PM2.5 (1997) NAAQS in 2005 and match this information to the inventor panel.

In total, 209 counties were deemed in nonattainment of the PM2.5 (1997) NAAQS in 2005. The geographic distribution of nonattainment counties is illustrated in Figure 4.5.



Notes: The map depicts the status of counties in 2005. 209 counties were designated in nonattainment of the 1997 PM2.5 NAAQS.

FIGURE 4.5: Nonattainment counties

A comprehensive set of descriptive statistics is provided in Table 4.2, detailing key variables across our full fixed-effects sample as well as our IV sample, which includes both movers and non-movers. As expected, the IV sample is naturally smaller, given that it is restricted to observations within three years before and after the regulatory change. The non-movers subsample is also smaller due to the additional restriction on relocation. Reassuringly, PM2.5 levels appear similar across samples, though they remain above the current regulated threshold of $9\mu g/m^3$, a level that was slightly higher throughout the study period. In terms of patenting activity, we observe slightly higher average patent counts in the IV sample, but values remain nearly identical when comparing movers and non-movers within the IV sample.

	Sample - Movers		Sample - Non-Movers		IV Sample - Movers		IV Sample - Non-Movers	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
PM2.5	11.87	4.63	11.69	4.62	11.08	2.71	11.04	2.73
Temperature	13.44	4.14	13.42	4.13	13.47	3.90	13.42	3.94
Dew point	5.81	3.97	5.78	3.96	5.89	3.80	5.85	3.83
Simple Count	1.96	7.73	1.76	6.79	2.74	8.23	2.47	7.46
Simple count granted	1.60	6.29	1.43	5.51	2.21	6.50	2.01	5.97
Weighted	0.71	2.51	0.63	2.19	0.99	2.83	0.88	2.57
Weighted - Granted	0.58	2.08	0.52	1.83	0.80	2.34	0.72	2.18
Observations	13,798,206		7,378,701		699,790		313,658	

Notes: The table depicts descriptive statistics for the full sample, IV sample and non-mover IV sample. 'Simple Count' measures the number of patent family applications filed, 'Simple Count Granted' measures the number of patent family applications that were filed and ultimately granted, 'Weighted' measures the number of patent family applications weighted by the number of co-inventors and 'Weighted-Granted' measures the number of patent family applications that were filed and ultimately granted weighted by the number of co-inventors. PM2.5 is measured in $\mu g/m^3$, Temperature is measured in °C, Dew Point is measured in °C.

TABLE 4.2: Descriptive statistics - full sample vs IV samples

4.3 Methods

Estimating the causal relationship between air pollution and inventor productivity presents several identification challenges. The primary concern is potential omitted-variable bias arising from factors correlated with both pollution levels and innovative output. For example, highly productive inventors might systematically choose to reside in locations with lower pollution, leading naïve regression estimates to overstate the true impact of pollution on productivity.

We address these concerns using two different identification strategies. First, we use a fixed-effects model, which includes inventor fixed effects. Our fixed-effects model leverages changes in pollution exposure for the same inventor over time, either due to changes in local pollution levels or because of relocation to a different city. The key advantage of this approach is that it controls for any fixed differences across inventors that might affect both their location choices and their productivity. We also include year fixed effects in our specification to account for any common trends in patenting activity across all locations, such as changes in patenting practices. We address further potential confounders by including weather conditions. The causal interpretation of our fixed-effects estimates relies on the assumption that changes in air pollution are uncorrelated with other time-varying factors that affect inventor productivity after controlling for inventor and year fixed effects and our set of time-varying controls.

More formally, our main fixed effect specification is estimated via a Poisson pseudo-maximum likelihood (PPML) estimator and described as follows:

$$Patents_{i,k,c,t} = \exp\left(\alpha + \beta Pollution_{i,c,t-1} + \gamma X_{i,c,t-1} + \delta_i + \delta_k + \delta_t\right) \tag{4.1}$$

$Patent_{i,k,c,t}$ is a proxy for the productivity of inventor i in year t, where inventor i resides in city c and possesses k years of patenting experience, termed as a "tenure" of k years. The primary variable used as a proxy for inventor's productivity is the number of patent applications (simple count) filed by inventor i in year t, although we also consider alternative productivity measures as described earlier.

$Pollution_{i,c,t-1}$ represents the concentration of PM2.5 exposure for inventor i (residing in city c) in the preceding year/s (e.g. year $t-1$) or other years and durations. In particular, our key explanatory variable is the PM2.5 level in the previous three years in the city where the inventor resides. We link inventors to city-level PM2.5 data from the three previous years to account for the time it typically takes to develop patentable innovations. This is particularly important as the creative process underlying innovation often extends over multiple years. This choice of lags is supported by survey evidence on inventor activities, who report that between 80% and 90% of patents involve three or fewer years of research leading up to an application (Nagaoka and Walsh 2009). This lag structure also helps mitigate potential reverse causality concerns, as current patenting activity cannot affect past pollution levels. To account for potential spatial correlation in innovation activities, we cluster standard errors at the city level, allowing for arbitrary correlation in the error terms across inventors within the same city and over time. This approach provides conservative inference that acknowledges the spatial nature of both pollution exposure and innovation clusters.

As mentioned above, we examine alternative specifications using different outcome variables. Firstly, since many inventors work on patents together with a team of other inventors, we calculate "fractional" equivalents of patent counts. Secondly, we investigate the influence of air pollution on patent quality by counting only patent applications that eventually were granted.

Despite its strengths, the fixed-effects approach has limitations. It cannot fully account for biases arising from unobserved time-varying factors correlated with both innovation and pollution, nor can it correct for measurement errors in our pollution measure, which may introduce attenuation bias. To address these issues, we implement an IV approach, leveraging exogenous variation from changes in regulatory designation under the PM2.5 NAAQS, following Sager and Singer (2025).

Unlike our fixed-effects approach, which utilises a full inventor-year panel, the IV analysis focuses on a balanced panel spanning three years before and three years after the 2005 policy change. For each inventor, we aggregate patent counts over these periods and compute the average number of patents in the pre- and post-policy periods. Thus, the time variable t in our specifications represents either the pre- or post-policy period rather than individual years.

We begin by estimating the following reduced-form equation using a PPML estimator:

$$Patents_{i,c,t} = \exp\left(\alpha_1 + \theta NA_{i,c,t} + \gamma_1 X_{i,c,t} + \delta_i + \delta_t\right) \tag{4.2}$$

Equation (4.2) directly estimates the impact of regulatory changes under the PM2.5 NAAQS on inventor productivity. Here, $Patents_{i,c,t}$ represents the average number of families filed by inventor i during either the pre-policy or post-policy period. For each inventor i resident in city c in period t, $NA_{i,c,t} = 1$ if city c is located within a county designated as being in "nonattainment" under the PM2.5 NAAQS in period t, and 0 otherwise. We include the same vector of temperature and humidity controls ($X_{i,c,t}$) as well as inventor (δ_i) and time fixed effects (δ_t). Tenure fixed effects are not included, as tenure in the two-period setup increases uniformly across all inventors with time and is thus collinear with the time fixed effects.

This reduced-form relationship is of substantial independent interest because it provides a direct measure of the policy's impact on innovation, a critical driver of economic growth. Additionally, this reduced-form estimation approach relies on fewer identifying assumptions, notably avoiding the need for the exclusion restriction required by IV approaches.

To further isolate the effect of pollution itself on innovation, we employ a control function approach. The standard two-stage least squares (2SLS) method is inappropriate in this context because it assumes a linear functional form in both stages. Instead, the control function approach corrects for endogeneity by including a residual-based adjustment term that captures the endogenous variation in pollution exposure and is compatible with the non-linear Poisson specification. The first-stage regression is estimated linearly and given by:

$$Pollution_{i,c,t} = \alpha_2 + \pi NA_{i,c,t} + \gamma_2 X_{i,c,t} + \delta_i + \delta_t + \mu_{i,c,t} \tag{4.3}$$

Equation (4.3) estimates the impact of regulatory designation changes on pollution exposure. Specifically, it exploits variation in PM2.5 levels induced by nonattainment status to construct a control function for pollution exposure. Here, $Pollution_{i,c,t}$ represents the pollution exposure level for inventor i in city c at time t, measured as the average PM2.5 concentration in the city of residence. We obtain the residuals, $\widehat{\mu_{i,c,t}}$, from this first-stage regression.

In the second stage, we estimate the causal effect of instrumented pollution exposure on patent productivity using a PPML estimator:

$$Patents_{i,c,t} = \exp\left(\alpha_3 + \beta Pollution_{i,c,t} + \rho \widehat{\mu_{i,c,t}} + \gamma_3 X_{i,c,t} + \delta_i + \delta_t\right) \tag{4.4}$$

Equation (4.4), rather than using predicted pollution values as in 2SLS, includes the residuals from the first stage as an additional regressor. These residuals act as a control function, capturing the endogenous variation in pollution that is correlated with the structural error term. The validity of our IV strategy relies on the exclusion restriction: changes in regulatory designation under the PM2.5 standards must affect inventor productivity only through their impact on pollution exposure.

By structuring our estimation approach in this manner, we provide a robust identification strategy to quantify the causal impact of air pollution on inventor productivity. Standard errors are clustered at the city level to account for spatial correlation over time.

4.4 Results

4.4.1 Fixed-Effects Results

Table 4.3 examines the relationship between air pollution and patenting productivity using a fixed-effects model estimated with PPML and with a one-year lag. Specifically, we estimate how pollution concentrations in the previous year affect inventor productivity, measured by four distinct indicators. The first two columns of Table 4.3 report results using simple patent-family counts: column (1) considers all patent families, while column (2) restricts attention to patent families with at least one granted patent. The rationale for the latter measure is that granted patents are typically indicative of higher-quality innovation. The last two columns of Table 4.3 present the results using our fractional counts where families are weighted inversely by the number of co-inventors. Column (3) reports results for all fractional patent-family counts, while column (4) focuses specifically on fractional counts of patent families with at least one granted patent.

We find robust and statistically significant negative impacts of PM2.5 concentrations on inventor patenting across all our outcome measures. Specifically, our estimates indicate that a one-standard-deviation ($4.6\mu g/m^3$) increase in PM2.5 pollution in the preceding year reduces the number of patents filed per inventor by approximately 2.57%. Given an average baseline productivity of 1.96 patents per inventor annually in our sample, this translates into about 0.05 fewer patents per inventor per year.

Importantly, this effect is economically meaningful at an aggregate level. To illustrate this, we conduct a counterfactual analysis using the elasticities estimated with fractional patent counts (thus avoiding double-counting patents across inventors): If all inventors in our sample had experienced PM2.5 levels capped at $5\mu g/m^3$, approximately 10,300 additional patents would have been filed in the year 2016 alone. To arrive at this figure, we first calculate the hypothetical reduction in PM2.5 concentrations for inventors initially exposed to pollution levels exceeding $5\mu g/m^3$. We then convert this pollution reduction into expected increases in patenting using our estimated elasticity. Finally, we sum the observed patents for each inventor with the predicted incremental patents attributable to the simulated pollution reduction.

Given that private returns per patent typically range from $100,000 to $20 million (Stevenson 2022), even a midpoint valuation of $1 million per patent implies an aggregate economic loss of approximately $10.3 billion. This represents about 0.05% of GDP in 2016, highlighting the substantial economic cost associated with air pollution-induced reductions in inventive productivity.

	(1) Simple Count	(2) Simple Count Granted	(3) Weighted	(4) Weighted - Granted
PM2.5 (Z score, t-1)	-0.026*	-0.031**	-0.025**	-0.029***
	(0.016)	(0.013)	(0.012)	(0.011)
Temp and Dew Controls	X	X	X	X
Year FEs	X	X	X	X
Inventor FEs	X	X	X	X
Tenure FEs	X	X	X	X
Observations	13,798,206	13,625,141	13,797,986	13,624,935

Notes: The models are estimated using a Poisson pseudo-maximum likelihood estimator. Standard errors are in parenthesis and are clustered at the city level. The significance codes are: ***: 0.01, **: 0.05, *:0.1. Model (1) estimates the effect on patent family applications, Model (2) estimates the effect on granted patent family application, Model (3) estimates the effect on patent family application weighted by the number of co-inventors and Model (4) estimates the effect on granted family applications weighted by the number of co-inventors. The models are estimated using the full sample of inventors.

TABLE 4.3: Fixed-effects results - full sample & standardised

Next, we examine the effects of pollution on inventor productivity over a longer time horizon. Specifically, we employ the same PPML fixed-effects models described previously but now incorporate three yearly lags, as well as the cumulative effects across these lags. This approach enables us to better capture the dynamics through which pollution exposure influences the innovation process. Table 4.4 presents the results. Notably, the adverse effect of pollution exposure is strongest at the three-year lag and diminishes monotonically toward the one-year lag, underscoring the persistent and dynamic impact of pollution on inventive productivity. The cumulative effects (over all three lags) are statistically significant and exhibit reassuring consistency in magnitude across all our outcome measures. Specifically, our cumulative estimates for fractional counts of patent families with at least one granted patent (reported in column (4)) show that a one-standard-deviation increase in PM2.5 pollution is associated with a reduction of approximately 4.1% in patents filed per inventor over a three-year period or 0.09 of a standard deviation.

Our findings align closely with previous economics research documenting productivity losses attributable to air pollution. For instance, Graff Zivin and Neidell (2012) document adverse effects of daily ozone pollution on agricultural worker productivity in California. There is also growing evidence that pollutants such as PM2.5 and CO adversely affect productivity across various other sectors, including manufacturing (Chang et al. 2016; He, Liu, and Salvo 2019), professional sports (Lichter, Pestel, and Sommer 2017; Archsmith, Heyes, and Saberian 2018), and multiple other industries (He, Liu, and Salvo 2019). However, most existing studies examine productivity effects primarily among low-skilled workers or high-skilled professionals in performance-based occupations only (professional athletes and umpires) and over relatively short time frames (mainly daily). Our study extends this literature by quantifying productivity effects over a longer horizon, specifically within the context of innovation and patenting activity. Notably, we demonstrate that negative productivity effects persist and remain economically meaningful among high-skilled workers engaged in innovation—one of the key drivers of economic growth.

	(1) Simple Count	(2) Simple Count Granted	(3) Weighted	(4) Weighted - Granted
PM2.5 (z-score, t-1)	-0.007	-0.011	-0.006	-0.010
	(0.012)	(0.010)	(0.010)	(0.009)
PM2.5 (z-score, t-2)	-0.017	-0.018**	-0.016**	-0.015***
	(0.010)	(0.009)	(0.007)	(0.006)
PM2.5 (z-score, t-3)	-0.018**	-0.019***	-0.020***	-0.019***
	(0.007)	(0.007)	(0.007)	(0.007)
PM2.5 (z-score, cum 3 lags)	-0.042***	-0.048***	-0.041***	-0.044***
	(0.017)	(0.015)	(0.014)	(0.013)
Temp and Dew Controls	X	X	X	X
Year FEs	X	X	X	X
Inventor FEs	X	X	X	X
Tenure FEs	X	X	X	X
Observations	13,798,206	13,625,141	13,797,986	13,624,935

Notes: The models are estimated using a Poisson pseudo-maximum likelihood estimator. Standard errors are in parenthesis and are clustered at the city level. The significance codes are: ***: 0.01, **: 0.05, *:0.1. Model (1) estimates the effect on patent family applications, Model (2) estimates the effect on granted patent family application, Model (3) estimates the effect on patent family application weighted by the number of co-inventors and Model (4) estimates the effect on granted family applications weighted by the number of co-inventors. The models are estimated using the full sample of inventors

TABLE 4.4: Fixed effects results - full sample & lags

As discussed previously, our fixed-effects approach leverages within-inventor variation to mitigate many confounding factors. Nevertheless, some important identification challenges remain. One key concern is that inventors may relocate over time, complicating exposure measurement and interpretation. To address this issue within our fixed-effects framework, we repeat our analysis focusing exclusively on inventors who remain in the same location throughout the study period ("non-movers"), following an approach commonly used in labour economics (e.g. Moretti 2004). These results are presented in Appendix Tables 4.A.1 and 4.A.2, corresponding directly to Tables 4.3 and 4.4 but restricted to the subsample of non-moving inventors. The estimated coefficients remain similar in magnitude to our main results, though they are less precisely estimated due to the substantially reduced sample size.

In a further robustness check, we extend the fixed-effects specification by adding city-specific linear time trends. This aims to control for unobserved city-level trends over time that may jointly influence both pollution and inventor productivity. However, this approach presents some practical challenges, and, for computational reasons, we must exclude tenure fixed effects.

In addition, we are limited to including linear trends, as higher-order specifications such as quadratic city-trends are too demanding given the available time-series variation of pollution within cities. Even so, the models using granted and weighted-granted patent counts fail to converge. For the simple and weighted patent counts, the estimated effects remain directionally consistent but are smaller in magnitude and no longer statistically significant (See Appendix Table 4.A.3). While this may raise concerns about robustness, city-specific trends may also overfit the data, inadvertently absorbing meaningful within-city variation and thus attenuating our estimates. Nonetheless, this robustness exercise indicates that accounting for within-city time varying factors may be important, providing further motivation for our complementary instrumental variable strategy.

4.4.2 Instrumental Variable Results

The fixed-effects results presented above provide strong evidence of the relationship between air pollution and inventor productivity. However, these models address only time-invariant confounding factors, leaving unresolved concerns about time-varying factors that may be correlated with both pollution exposure and innovation outcomes. Although we directly control for some of these variables (e.g., weather conditions), others remain unobserved or uncontrolled. Furthermore, fixed-effects models do not account for measurement error, which may be particularly significant when analysing pollution exposure.

To address these concerns, we complement our fixed-effects approach with an alternative identification strategy based on an IV framework. This IV approach allows us to mitigate both time-varying omitted-variable bias and measurement error. Specifically, our IV strategy exploits exogenous variation arising from the designation of attainment or nonattainment status under the PM2.5 National Ambient Air Quality Standards (NAAQS), similar to Sager and Singer (2025) and as described in our Methods section.

We begin our IV analysis by presenting results that directly estimate the reduced-form impact of pollution-control policies on inventor productivity. Table 4.5 reports the reduced-form effect of attainment status designation under the PM2.5 National Ambient Air Quality Standards (NAAQS) on innovation outcomes. This analysis provides two important advantages: first, it offers valuable evidence of the policy's direct impact on the productivity of inventors before we turn to the control function analysis, which estimates the causal effect of PM2.5 concentrations on inventor productivity. Second, the reduced-form analysis does not rely on the exclusion restriction assumption required by the subsequent analysis.

We find that the pollution-control policy had a significant positive impact on inventor productivity. Specifically, innovation increased substantially following policy implementation, with our estimates indicating that attaining compliance with the PM2.5 standards (approximately a reduction of $1\mu g/m^3$) is associated with an increase in inventor productivity of between 9.4 to 10.2% over a three-year period. This corresponds to an increase of about 0.27 patents per inventor on average. Additionally, the results obtained using the subsample of inventors who remain in the same location throughout the study period ("non-movers") are presented in Appendix Table 4.A.5. Although the estimates are smaller and less precise, they are qualitatively in line with the main findings.

	(1) Simple Count	(2) Simple Count Granted	(3) Coinventor-Weighted	(4) Coinventor-Weighted Granted
Nonattainment	0.097**	0.096**	0.092**	0.090*
	(0.042)	(0.047)	(0.042)	(0.048)
Temp and Dew Covariates	X	X	X	X
Year FEs	X	X	X	X
Inventor FEs	X	X	X	X
Observations	571,752	544,252	571,718	544,219

Notes: The regressions are estimated using a Poisson pseudo-maximum likelihood estimator. Standard errors are in parenthesis and are clustered at the city level. Temperature and Dew Point controls are included. The significance codes are: ***: 0.01, **: 0.05, *:0.1. 'Nonattainment' is the indicator for treatment status in period t: 0 not treated, 1 treated. Model (1) shows the reduced-form estimates for patent family applications, Model (2) shows the reduced-form estimates for granted patent family applications, Model (3) shows the reduced-form estimates for patent family applications weighted by the number of co-inventors and Model (4) shows the reduced-form estimates for granted family applications weighted by the number of co-inventors. The models are estimated using the full subsample of inventors. PM2.5 is not z-score standardised.

TABLE 4.5: Reduced-form estimates - full sample

Next, we turn to our IV analysis to estimate the causal effect of PM2.5 pollution on inventor productivity. Table 4.6 presents the results. First, the first-stage relationship between our instrument and pollution exposure is very strong (F-statistic of 100), validating the relevance condition[1]. Focusing now on the second-stage results, our IV estimates indicate that a one-unit increase in PM2.5, approximately equivalent to the magnitude of the policy-induced reduction in PM2.5 concentrations, leads to a 9.8% decrease in patenting activity[2]. These estimates are qualitatively consistent with our fixed-effects results, though larger in magnitude. The IV estimate implies that a one-unit ($1\mu g/m^3$) reduction in PM2.5 increases innovation by roughly 9.8%, while the fixed-effects estimates suggest that a one-standard deviation ($4.6\mu g/m^3$) increase in pollution is associated with a cumulative productivity decline of approximately 4.1% over a three-year period. Several factors may explain this difference. Firstly, the difference is consistent with attenuation bias in the fixed-effects estimates, potentially arising from measurement error in pollution exposure. Secondly, it may reflect the presence of omitted time-varying confounders that the fixed-effects model does not fully account for but which are effectively addressed by our IV strategy. Finally, the IV identifies a Local Average Treatment Effect (LATE) for inventors in the subset of cities affected by the policy and active in both periods, over a shorter and more recent time frame than the fixed-effects model. Extrapolating this effect to larger pollution changes or broader context may therefore require caution. Nonetheless, since the IV estimates address both measurement error and time-varying confounders, two serious concerns in the context of pollution, they provide an important complement to the fixed-effects results.

[1] See Appendix Table 4.A.4.

[2] As before, analogous IV results restricted to inventors who remain in the same location ("non-movers") are presented in Appendix Table 4.A.7.

	(1)	(2)	(3)	(4)
	Simple Count	Simple Count Granted	Coinventor-Weighted	Coinventor-Weighted Granted
PM2.5 (instrumented)	-0.103**	-0.101**	-0.097**	-0.095*
	(0.042)	(0.048)	(0.042)	(0.049)
Temp and Dew Covariates	X	X	X	X
Year FEs	X	X	X	X
Inventor FEs	X	X	X	X
Observations	571,752	544,252	571,718	544,219

Notes: The regressions are estimated using a Poisson pseudo-maximum likelihood estimator with first-stage residuals incorporated in a control-function approach. Standard errors are in parentheses and are clustered at the city level. Temperature and Dew Point controls are included. The significance codes are: ***: 0.01, **: 0.05, *:0.1. Model (1) shows the instrumented PM2.5 effect on patent family applications, Model (2) shows the instrumented PM2.5 effect on granted patent family application, Model (3) shows the instrumented PM2.5 effect on patent family application weighted by the number of co-inventors and Model (4) shows the instrumented PM2.5 effect on granted family applications weighted by the number of co-inventors. The models are estimated using the full sample of inventors. PM2.5 is not z-score standardised.

TABLE 4.6: IV results - full sample

Overall, our IV estimates reinforce both our fixed effects findings and the broader evidence linking air pollution to declines in productivity while also providing novel contributions to the literature. Specifically, our results demonstrate that the negative effects of pollution on productivity persist over significantly longer time horizons,measured in years rather than days, and extend beyond lower-skilled occupations to high-skilled professionals whose innovation activities are key drivers of long-term economic growth. These effects are economically meaningful, statistically robust across multiple outcome measures, and consistent across a range of empirical specifications, underscoring the substantial impact of pollution on technological progress.

4.5 Conclusion

This paper provides rigorous empirical evidence of the impact of air pollution on inventor productivity, highlighting substantial yet previously overlooked costs of pollution. Leveraging detailed inventor-level data combined with robust identification strategies, including inventor and year fixed effects and an instrumental-variable approach, we document economically significant negative effects of PM2.5 exposure on patenting activity over the years. The fixed-effects results suggest that a one-standard-deviation increase in PM2.5 concentrations reduces inventor productivity by roughly 2.6% annually, with cumulative effects increasing to around 4.1% over a three-year horizon. Complementing this, our instrumental variable approach addresses concerns that the fixed-effects model may not fully capture. In particular, the IV approach helps mitigate measurement error in pollution exposure and account for unobserved time-varying confounders by exploiting exogenous regulatory changes under the U.S. National Ambient Air Quality Standards (NAAQS). These estimates provide causal evidence that policy driven reductions in PM2.5 pollution lead to meaningful increases in innovation. Specifically, the results suggest that a $1\mu g/m^3$ increase in PM2.5 reduces patenting by approximately 9.8%. While these estimates differ in magnitude and scope from the fixed-effects results, they jointly reinforce the evidence that air pollution negatively affects inventor productivity.

Our results have significant implications for both the economic literature and public policy. By establishing that air pollution adversely affects the productivity of high-skilled inventors, a critical driver of technological advancement and sustained economic growth, our findings extend the literature on environmental economics beyond traditional analyses focused predominantly on health impacts or labour market outcomes that mainly explore short-term (daily) fluctuation in pollution exposure. Our results suggest that the true economic costs of pollution are likely underestimated in current regulatory analyses, indicating that more stringent air quality standards may yield substantial economic benefits through enhanced innovation and productivity.

Nevertheless, our study is subject to several important limitations that future research should address. First, while we provide credible causal evidence linking pollution exposure to reduced inventor productivity, the exact underlying mechanisms remain unclear. Multiple plausible explanations exist for this relationship, including health-related absenteeism, diminished cognitive performance, or reduced creativity induced by pollution exposure. A detailed investigation into these channels, potentially utilising richer data sources and experimentation, could significantly improve our understanding of how environmental conditions affect innovation. Second, our instrumental-variable estimates rely on the assumption that regulatory changes targeting PM2.5

exposure did not systematically affect other pollutants, an assumption that, if violated, could introduce bias into our estimates. While we consider this scenario unlikely, we cannot completely rule it out and acknowledge this potential limitation. However, the robustness of our reduced-form estimates (the effect of the policy on inventor productivity), which do not rely on the exclusion restriction, provides reassuring consistency, supporting our overall conclusions.

Overall, our findings underscore the importance of environmental quality not only as a matter of public health but also as a crucial determinant of innovation and economic growth. By highlighting these broader economic consequences, our study offers valuable insights for policymakers seeking to foster sustained technological progress and economic development through effective environmental regulation.

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4.A Appendix

4.A.1 Additional Descriptive Figures

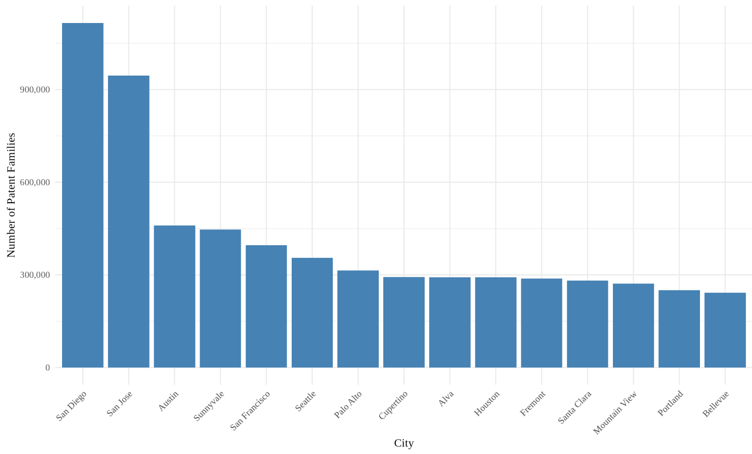

FIGURE 4.A.1: Total number of patents filed in cities 1981 to 2016 - top 15

4.A.2 Additional Result Tables

	(1) Simple Count	(2) Simple Count Granted	(3) Weighted	(4) Weighted - Granted
PM2.5 (Z score, t-1)	-0.021	-0.029	-0.027	-0.034
	(0.032)	(0.026)	(0.026)	(0.024)
Temp and Dew Controls	X	X	X	X
Year FEs	X	X	X	X
Inventor FEs	X	X	X	X
Tenure FEs	X	X	X	X
Observations	7,378,701	7,224,064	7,378,583	7,223,942

Notes: The models are estimated using a Poisson pseudo-maximum likelihood estimator. Standard errors are in parenthesis and are clustered at the city level. The significance codes are: ***: 0.01, **: 0.05, *:0.1. Model (1) estimates the effect on patent family applications, Model (2) estimates the effect on granted patent family application, Model (3) estimates the effect on patent family application weighted by the number of co-inventors and Model (4) estimates the effect on granted family applications weighted by the number of co-inventors. The models are estimated using the subsample of inventors who do not move.

TABLE 4.A.1: Fixed-effects results - non-movers

	(1) Simple Count	(2) Simple Count Granted	(3) Weighted	(4) Weighted - Granted
PM2.5 (z-score, t-1)	0.015	0.004	0.010	-0.002
	(0.029)	(0.023)	(0.024)	(0.021)
PM2.5 (z-score, t-2)	-0.020	-0.016	-0.018	-0.014
	(0.022)	(0.017)	(0.015)	(0.011)
PM2.5 (z-score, t-3)	-0.045**	-0.041**	-0.047**	-0.040**
	(0.023)	(0.021)	(0.020)	(0.018)
PM2.5 (z-score, cum 3 lags)	-0.050	-0.054	-0.055	-0.056*
	(0.043)	(0.035)	(0.035)	(0.030)
Temp and Dew Controls	X	X	X	X
Year FEs	X	X	X	X
Inventor FEs	X	X	X	X
Tenure FEs	X	X	X	X
Observations	7,378,701	7,224,064	7,378,583	7,223,942

Notes: The models are estimated using a Poisson pseudo-maximum likelihood estimator. Standard errors are in parenthesis and are clustered at the city level. The significance codes are: ***: 0.01, **: 0.05, *:0.1. Model (1) estimates the effect on patent family applications, Model (2) estimates the effect on granted patent family application, Model (3) estimates the effect on patent family application weighted by the number of co-inventors and Model (4) estimates the effect on granted family applications weighted by the number of co-inventors. The models are estimated using the subsample of inventors who do not move.

TABLE 4.A.2: Fixed-effects results - non-movers & lags

	Simple Count (1)	Simple Count Granted (2)	Weighted (3)	Weighted - Granted (4)
PM2.5 (z-score, t-1)	-0.012	-0.018	-0.014	-0.019
	(0.018)	(0.016)	(0.015)	(0.014)
Temp and Dew Controls	X	X	X	X
Year FEs	X	X	X	X
Inventor FEs	X	X	X	X
City-Year Trends	X	X	X	X
Convergence	TRUE	FALSE	TRUE	FALSE
Observations	13,798,206	13,625,141	13,797,986	13,624,935

Notes: The models are estimated using a Poisson pseudo-maximum likelihood estimator. Standard errors are in parenthesis and are clustered at the city level. The significance codes are: ***: 0.01, **: 0.05, *:0.1. Model (1) estimates the effect on patent family applications, Model (2) estimates the effect on granted patent family application, Model (3) estimates the effect on patent family application weighted by the number of co-inventors and Model (4) estimates the effect on granted family applications weighted by the number of co-inventors. The models are estimated using the full sample of inventors.

TABLE 4.A.3: Fixed-effects results - city trends

	(1)
	PM2.5
Nonattainment	-0.956***
	(0.096)
Temp and Dew Covariates	X
Year FEs	X
Inventor FEs	X
Observations	699,790

Notes: The regression is estimated linearly and shows the effect of nonattainment designation on PM2.5. The reported F-statistic is 100.09. Standard errors are in parenthesis and are clustered at the city level. Temperature and Dew Point controls are included. The significance codes are: ***: 0.01, **: 0.05, *:0.1. The model is estimated using the full sample of inventors. PM2.5 is not z-score standardised.

TABLE 4.A.4: IV first stage - movers

	(1)	(2)	(3)	(4)
	Simple Count	Simple Count Granted	Coinventor-Weighted	Coinventor-Weighted Granted
Nonattainment	0.025	0.013	0.020	0.005
	(0.063)	(0.072)	(0.061)	(0.070)
Temp and Dew Covariates	X	X	X	X
Year FEs	X	X	X	X
Inventor FEs	X	X	X	X
Observations	249,442	237,448	249,422	237,427

Notes: The regressions are estimated using a Poisson pseudo-maximum likelihood estimator. Standard errors are in parenthesis and are clustered at the city level. Temperature and Dew Point controls are included. The significance codes are: ***: 0.01, **: 0.05, *:0.1. 'Nonattainment' is the indicator for treatment status in period t: 0 not treated, 1 treated. Model (1) shows the reduced-form estimates for patent family applications, Model (2) shows the reduced-form estimates for granted patent family applications, Model (3) shows the reduced-form estimates for patent family applications weighted by the number of co-inventors and Model (4) shows the reduced-form estimates for granted family applications weighted by the number of co-inventors. The models are estimated using the subsample of inventors who do not move. PM2.5 is not z-score standardised.

TABLE 4.A.5: Reduced-form estimates - non-movers

	(1)
	PM2.5
Nonattainment	-0.963***
	(0.073)
Temp and Dew Covariates	X
Year FEs	X
Inventor FEs	X
Observations	313,658

Notes: The regression is estimated linearly and shows the effect of nonattainment designation on PM2.5. The reported F-statistic is 175.18. Standard errors are in parenthesis and are clustered at the city level. Temperature and Dew Point controls are included. The significance codes are: ***: 0.01, **: 0.05, *:0.1. The model is estimated using the subsample of inventors who do not move. PM2.5 is not z-score standardised.

TABLE 4.A.6: IV first stage - non-movers

	(1)	(2)	(3)	(4)
	Simple Count	Simple Count Granted	Coinventor-Weighted	Coinventor-Weighted Granted
PM2.5 (instrumented)	-0.029	-0.015	-0.021	-0.005
	(0.063)	(0.073)	(0.062)	(0.071)
Temp and Dew Covariates	X	X	X	X
Year FEs	X	X	X	X
Inventor FEs	X	X	X	X
Observations	249,442	237,448	249,422	237,427

Notes: The regressions are estimated using a Poisson pseudo-maximum likelihood estimator with first-stage residuals incorporated in a control-function approach. Standard errors are in parentheses and are clustered at the city level. Temperature and Dew Point controls are included. The significance codes are: ***: 0.01, **: 0.05, *:0.1. Model (1) shows the instrumented PM2.5 effect on patent family applications, Model (2) shows the instrumented PM2.5 effect on granted patent family application, Model (3) shows the instrumented PM2.5 effect on patent family application weighted by the number of co-inventors and Model (4) shows the instrumented PM2.5 effect on granted family applications weighted by the number of co-inventors. The models are estimated using the subsample of inventors who do not move. PM2.5 is not z-score standardised.

TABLE 4.A.7: IV results - non-movers

Concluding Remarks

Innovation and the pursuit of knowledge are an omnipresent cornerstone of society. In 2023, global research and development spending grew close to $3 trillion, with 1.8 million scientific articles published, $228 billion invested in venture capital, and 3.5 million patents filed (World Intellectual Property Organization 2024a, 2024b). Throughout history, environmental dynamics have both necessitated and inspired innovation. As the environment continues to evolve, new interactions with innovation emerge while others shift, making it a continually evolving field of study. In this thesis, I have examined different aspects of this interaction in four chapters.

In Chapter 1 I find evidence that local flooding positively influences the development of flood adaptation innovation. Geographic proximity of inventors to flooding seems particularly important, suggesting that flood-related innovation is often incidental rather than strategically planned. I believe future research would benefit from a more comprehensive, standardized, and transparent approach to identifying climate adaptation patents, one that extends beyond flood-related patents and addresses the shortcomings of the Y02A classification. Additionally, examining sector-specific dynamics and the types of adaptation patents produced in response to shocks could provide further valuable insights.

The theoretical analysis presented in Chapter 2 highlights that the unique uncertainties related to climate damages and the market for adaptation innovations can discourage inventors from investing, leading to delays in development. These uncertainties extend beyond the general market risks in other sectors and may affect policy outcomes. Given the critical role of inventor expectations in this context, future surveys on the nature of these expectations would likely enhance our understanding further.

Chapter 3 and 4, show that environmental factors can negatively impact inventor productivity. Specifically, we find that increased temperatures and air pollution over the past three years leads to decreases in the number of patents filed by inventors today. Future research may explore the prevalence of the underlying mechanisms driving these effects and examine differences across sectors, types of innovation and countries.

More broadly, I believe that while patents offer a consistent measure of formal innovation activity, developing additional metrics for informal innovation activity would likely be beneficial and lead to interesting new discoveries. Additionally, Chapters 1 and 2 underscore the need for further research to address the limited academic and policy attention currently devoted to climate adaptation innovation, despite growing evidence of climate impacts. Finally, I believe there is value in exploring the inspirational role of the environment in more detail, such as understanding how inventors may adapt to climate change by learning from the way nature mitigates threats.

Overall, ever-evolving environmental dynamics and risks, including climate change, continue to shape and redefine interactions with innovation. While much research remains, I hope this thesis has contributed new and valuable insights, highlighted key areas for further study and provided a foundation for future researchers to build upon.

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