Knowledge Diversity and Innovation Resilience: Green Technological Change After Natural Disasters

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Abstract

Climate change leads to more destructive natural disasters, particularly hurricanes, which can significantly disrupt knowledge production. This paper studies the effects of Hurricane Katrina — one of the costliest and deadliest storms in U.S. history — on inventors' innovation outcomes, including green innovation which helps combat climate change. Using hazard and patent data for U.S. inventors in a difference-in-differences design, I find that Katrina reduced inventors' production of green patents, while non-green patents were unaffected. Specifically, affected inventors could have produced an additional 0.220 green patents following the storm, i.e., a potential 415 percent increase, had Katrina not occurred. The negative effects are driven by the greater distance in technological expertise (knowledge diversity) among collaborators in green innovation teams, making it harder to substitute for affected inventors and continue their technological tasks. These findings suggest that knowledge diversity can compromise the resilience of technological development when faced with disruptions to knowledge production.

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1 Introduction

Climate-related disasters have multiplied five-fold over the past 50 years, according to the World Meteorological Organization (2021). Scientific evidence suggests that climate change has led to the increased frequency and/or intensity of natural disasters.[1] Particularly, hurricanes are becoming stronger and more intense,[2] which can generate great economic and societal impacts. Figure 1 shows the increasing frequency of highly damaging storms, rising death tolls, and escalating monetary losses in the United States.[3] These hazard events can significantly disrupt various production activities, including the creation of new scientific and technological knowledge.

Technological progress and innovation are important for the combat against climate change and the transition to green growth which integrates environmental sustainability. Existing literature (e.g., Acemoglu et al. 2012; Aghion et al. 2016; Dugoua and Gerarden 2023) has largely focused on how the price mechanism can direct resources from non-green to green innovation to tackle climate and environmental challenges.[4] However, there is limited understanding of how climate change and related extreme weather events, such as hurricanes, affect the trajectory of green versus non-green innovation.

How do disruptions to knowledge production, such as natural disasters, shape the technological direction of individual inventors, specifically influencing green versus non-green innovation outcomes? Individual inventors play a pivotal role in the production of innovation, contributing their specialized knowledge and skills to create new technologies. Understanding how inventors' innovation outcomes are shaped by such disruptions can provide valuable insights into the role of individuals within collaborative projects and the broader organization of science and innovation processes, especially since team-based knowledge production is prevalent (Wuchty, Jones, and Uzzi 2007; Jones 2009; Jones 2021).

While natural disasters may raise inventors' environmental awareness and potentially

[1] See, for example, Intergovernmental Panel on Climate Change (IPCC) 2023.

[2] See, for instance, Emanuel 2005; Nordhaus 2006.

[3] According to NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2024), the distribution of damage from U.S. Billion-dollar disaster events from 1980 to 2024 is dominated by tropical cyclone losses. Tropical cyclones have caused the most damage ($1,418.2 billion, 2024 Consumer Price Index adjusted) and also have the highest average event cost ($22.5 billion per event, 2024 Consumer Price Index adjusted). Tropical cyclones are also responsible for the highest number of deaths (6,934).

[4] Green innovation generally refers to technologies that reduce environmental burdens and improve environmental performance (Rennings 2000; Popp, Newell, and Jaffe 2010; Popp 2019). In this paper, I specifically focus on technologies and applications for mitigating or adapting to climate change.

encourage green innovation, they also pose significant disruptions that could hinder the production of both green and non-green innovation. Previous research has focused on the disruptions to knowledge production caused by the deaths of scientists and inventors, and consistently found that such events negatively impact collaborators' overall innovation productivity and income (Azoulay, Graff Zivin, and Wang 2010; Oettl 2012; Jaravel, Petkova, and Bell 2018; Mohnen 2018). However, these studies have not accounted for the distribution of expertise within teams,[5] a key factor in determining the resilience of innovation outcomes in the face of disruptions.

The negative impact on innovation output may be more severe for green innovation, which inherently differs from its non-green counterpart. According to the World Bank,[6] green technology tends to be more complex and multifaceted than its non-green counterparts, spanning across all economic sectors. Academic research further supports this, showing that green innovation combine knowledge from a wider range of technological areas, compared to non-green counterparts.[7] Technological discoveries increasingly result from the aggregation of specialized knowledge through collaboration (Wuchty, Jones and Uzzi 2007), as individual knowledge is specialized due to "the burden of knowledge" (Jones 2009). Therefore, the knowledge diversity within a research team often reflects the range of collaborators' technological areas. As green innovation integrates knowledge from diverse technological fields, inventors within a green team tend to possess a wider variety of expertise and technological backgrounds than those in non-green teams.

This broader range of specialised fields within a green team often leads to a greater distance in terms of technological expertise among collaborators, i.e., greater technological distance.[8] Inventors in green teams fulfill distinct technological roles and tasks, reflecting their diverse technological backgrounds and skill sets. If a disruption event, like a natural disaster, strikes an individual inventor within a green team, it will be harder to substitute so as to continue the affected inventor's technological tasks. Therefore, the development of green technology may be more negatively affected than non-green innovation, where the technological expertise among team members tends to be more similar and substitutable.

In this paper, I use a difference-in-differences setup to investigate the effects of dis-

[5] Azoulay et al.(2010) considers the intellectual distance in terms of research topics between superstars and their collaborators but does not examine the distribution of expertise within teams.

[6] See, Pigato et al. 2020.

[7] See, De Marchi 2012; Barbieri et al. 2020; Orsatti et al. 2020; Fusillo 2023.

[8] Azoulay et al. (2010) distinguish co-authors of an academic superstar by the intellectual distance that defines how closely or distantly their research topics relate to those of the superstar.

ruptive events, specifically natural disasters, on inventors' green and non-green innovation production, within the context of the Hurricane Katrina. The 2005 storm, that killed 1833 people and resulted in $200 billion in damages, is the costliest and one of the deadliest storms in US history.[9] This study is based on a merged dataset of United States Patent and Trademark Office (USPTO) patent inventor data from PatentsView,[10] and the Spatial Hazard Events and Losses Database for the United States (SHELDUS). PatentsView provides disambiguated data on patent inventors' identities and geocoded information at the US county level of inventors' geographical locations listed on the patent applications. Additionally, it offers details on the technological classifications of patents produced by inventors. I use the Cooperative Patent Classification (CPC) System and the Y02 category to identify green patents. SHELDUS, a unique county-level database, provides information on the spatial distribution of counties with property damage from Katrina. I merge the inventor-level data and the hazard data through the county-level geographical information. Therefore, this merged data from PatentsView and SHELDUS allows me to identify inventors who likely lived and worked in counties (Akcigit, Baslandze and Stantcheva 2016; Moretti and Wilson 2017; Akcigit et al. 2022) affected by Katrina at the time of the storm (treatment group), and to track their patent production activities, including green patents. Using a one-to-one exact matching method, I construct a control group of patent inventors. These inventors did not list Katrina-affected counties as their addresses on patent applications filed before and around the time of the storm. However, they were otherwise identical to the treated inventors in terms of the year of their first patent filing, cumulative patent count, and cumulative green patent count prior to Katrina (Jaravel et al. 2018). The causal impact of Hurricane Katrina is identified in a difference-in-differences research design, comparing changes in patenting activities at inventor level before and after the storm between the treatment and control group.

I find that Hurricane Katrina hindered the growth of green patents, while non-green patents remained unaffected. Specifically, if Hurricane Katrina had not happened, a treated inventor could have produced 0.220 green patents more after 2005, implying a potential 415 percent increase compared to the pre-Katrina average of 0.053 green patents. This suggests that natural disasters could impede the green transition by adversely affect-

[9]The figures are sourced from NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2024). Costs are adjusted based on the 2024 Consumer Price Index

[10]PatentsView is a visualization, data dissemination, and analysis platform that focuses on patent data, supported by the Office of the Chief Economist at USPTO

ing inventors' production of green innovation, despite their potential to enhance environmental awareness and accelerate the development of green technology. Furthermore, the finding raises concerns about a vicious cycle, considering the potential increase in severe climate-related natural disasters and the importance of green innovation in combating climate change.

In the second part of the analysis, I investigate the mechanism behind this observed negative effect on green innovation and no effect on non-green innovation, relying on both patent team and individual inventor level analysis. Specifically, I test the hypothesis that there is a larger technological distance among inventors within a green team compared to a non-green team. Despite the limitation of using patent data to measure innovation, it allows me to measure technological distance within a patent team. Following Akcigit et al.(2022), I measure an inventor's technological expertise with the modal CPC subclass based on her patenting history before Katrina. Using the co-occurrence approach (Hidalgo et al. 2007; Azoulay et al. 2010), I construct a distance metric in technological expertise. Consistent with the hypothesis, I find that the average technological distance between a sample inventor and her collaborators is larger in a green patent team than in a non-green one. Additionally, the negative impacts of Katrina are more pronounced for patents produced by teams with greater technological distance, and for inventors with more technologically distant collaborators before Katrina. These findings imply that new technologies, such as green innovation, which rely on knowledge diversity for their development, may be more vulnerable to external shocks, such as natural disasters related to climate change.

This paper contributes to several strands of literature; the first of which is the growing literature on scientists and inventors that sheds light on the supply of innovation (e.g., Goolsbee 1998; Romer 2000; Bell et al. 2019). Previous research has primarily explored micro-level disruptions to knowledge production, such as the death of collaborators, consistently uncovering detrimental effects on individual inventors' productivity. For instance, Azoulay et al. (2010) find a lasting decline in the quality-adjusted publications of coauthors following the death of a superstar collaborator. Similarly, Oettl (2012) extends the definition of star collaborators to encompass productivity and helpfulness, and finds that the death of such individuals leads to a reduction in the output quality of surviving coauthors compared to the death of non-star collaborators. Furthermore, Jaravel et al. (2018) documents a significant long-term drop in co-inventors' earnings and citation-weighted

patents following an inventor's premature death. The predominant explanation in this body of work revolves around knowledge spillovers.

Departing from existing literature, this paper investigates the impact of a macro-level shock — specifically, Hurricane Katrina — and its differential effects on green versus non-green patent production by individual inventors. my findings reveal that Katrina significantly reduced inventors' green patent outputs, while non-green patents remained unaffected. This paper introduces a novel mechanism of knowledge substitutability, arguing that team members in green projects are less substitutable due to green innovation's dependence on broader knowledge diversity and a wider range of team members' specialized technological expertise. This highlights a unique aspect of how disruptions to knowledge production can differentially impact innovation, contingent on the knowledge domain and the inherent technological characteristics of the team involved.

Second, this paper also adds to the broad literature on the economic impacts of natural disasters.[11] It specifically addresses the subset of literature concerning the effects of natural disasters on innovation. Along this stream, most papers focus on general innovation or disaster-specific innovation at aggregate level.[12] For example, Miao and Popp (2013) study disaster-mitigating technologies in response to natural disasters using a panel of thirty countries over twenty-five years. Most related to this paper is Ballesteros (2022), which investigates the effects of Hurricane Katrina on county-level innovation. Different from Ballesteros (2022), this study delves into green and non-green innovation at the individual inventor level, identifying a detrimental effect on green innovation but no discernible impact on non-green innovation. Similar to this work, Zhao et al.(2022) finds that natural disasters are negatively associated with green innovation in energy sector at country level, but find no correlation with non-green energy innovation. Unlike Zhao et al. (2022), this research focuses on the causal impact of a specific natural disaster, Hurricane Katrina, on general green innovation at the individual inventor level.

While Ballesteros (2022) argues that natural disasters alter risk attitudes and thus influence innovation, Zhao et al. (2022) propose various macro channels through which natural disasters may impact innovation, including economic development level, trade and financial openness, interpersonal globalization, and government stability. This paper introduces a novel channel by arguing that team members in green projects are less substi-

[11] See review papers, e.g., Dell, Jones and Olken (2014), Botzen et al. (2019)

[12] One exception is the paper by Le et al.(2023) on natural disasters and corporate innovation.

tutable due to green innovation's dependence on broader knowledge diversity and a wider range of team members' specialized technological expertise. This distinctive dependency suggests that inventors' green innovation output was more negatively impacted by the disruption caused by Hurricane Katrina.

Third, this paper also contributes to the literature on labour responses to climate change and weather shocks. The existing research focuses on workers with high exposure to these environmental changes, particularly in the agricultural sector in developing countries, exploring how they respond through geographical migration or sectoral reallocation. For instance, Jayachandran (2006) finds that agricultural workers tend to migrate away from regions affected by negative productivity shocks due to rainfall fluctuations. Colmer (2021) shows that rising temperatures, which reduce agricultural productivity, prompt labor shifts from agriculture to manufacturing and services within the same district. While much of this literature highlights climate inequality, where lower-skilled, high-exposure workers bear the brunt of environmental shocks, my work demonstrates that highly-skilled labor, such as patent inventors, can also be significantly affected. Specifically, I find that an extreme weather event — Hurricane Katrina — reduced inventors' production of green patents, underscoring that climate-related disruptions can affect a wide range of skill levels and sectors.

The paper is structured as follows. Section 2 presents my argument how disruptions to knowledge production affect differently individual inventors' production of green versus non-green innovation. Section 3 provides background information on Hurricane Katrina, describes the data and research design. Section 4 presents the empirical results. In section 5, I establish that greater knowledge diversity and technological distance within a green innovation team is a possible explanatory channel. Section 6 concludes.

2 The Role of Knowledge Diversity in Shaping Individual Inventors' Green vs Non-Green Innovation Amidst Disruptions

2.1 Green Innovation with Greater Knowledge Diversity

Green, sustainable, environmental, environmentally friendly, or eco-innovation is regarded as an important means of reducing environmental burdens and improving environmental performance (Rennings 2000; Popp, Newell and Jaffe 2010; Popp 2019). The

development of such green technologies involves complex challenges, often requiring information and skills that are distant from the traditional knowledge base (De Marchi 2012). The inherent complexity of these technologies is evident in their multi-purpose and systemic nature (Ghisetti, Marzucchi and Montresor 2015). Green technologies are expected to satisfy various interconnected objectives, including improved production efficiency and product quality (Florida 1996; Oltra and Saint Jean 2005), while also adhering to stringent regulatory standards (Carrillo-Hermosilla, Del Río and Könnölä 2010). Furthermore, Mealy and Teytelboym (2022) find that green and renewable energy products typically exhibit higher Product Complexity Index values than the industry average. Overall, the development of green technologies is more intricate than that of non-green technologies, requiring more knowledge and information (Horbach et al., 2013).

The production of new ideas and technologies fundamentally relies on combining existing knowledge (Schumpeter 1934; Weitzman 1998). The breadth of this knowledge search, crucial for technological development, can enhance problem-solving capabilities when it extends beyond current knowledge structures (Winter, 1984; Kaplan and Vakili, 2015). This is especially relevant for green technologies, which are at the forefront of addressing complex environmental and economic challenges simultaneously. The diverse environmental needs — from energy savings and pollution reduction to CO2 capture and new materials — also benefit significantly from integrating a wide array of knowledge sources.

Empirical evidence indicates that the sources of knowledge for green technologies often span diverse technological fields that do not share significant commonalities, reflecting higher knowledge diversity during the knowledge search phase. For example, Fusillo (2023) uses patent data to show that green technologies exhibit a higher degree of diversity in knowledge sources, measured through co-citations of patent classes in the backward citations of focal patents, weighted by cognitive distance—an indicator of technological proximity between patent classes. Similarly, Barbieri et al. (2020) and Orsatti et al. (2020) find that green technologies draw from a broader knowledge base, as evidenced by the range of patent classes cited and the frequent use of broad collaborations. Moreover, the development of green technologies often involves the collaborative efforts across diverse actors, integrating various competencies and organizational structures. International collaborations, diversified teams, industry-university connections, and public research play crucial roles in advancing green technological development (Fusillo et al., 2020; Orsatti et

al., 2020; De Marchi, 2012; Quatraro and Scandura, 2019; Hötte et al., 2021).

The diversity of knowledge effectively recombined also defines the boundaries and scope of invention outcomes. Greater diversity of knowledge sources positively leads to greater knowledge diversity contained in the technological outcomes. Barbieri et al. (2020) analyse patents from 1980 to 2012 and find that green patents exhibit a broader scope, as evidenced by their assigned patent classes. Similarly, Fusillo (2023) identifies greater technological diversity in the knowledge output phase, measured through the co-classification of technology classes in patents, which reflects the amount of knowledge recombined and integrated into protected inventions. Higher diversity of knowledge sources also positively influences the impact of technological outcomes on subsequent inventions. Barbieri et al. (2020) and Dechezleprêtre et al. (2022) find that green innovations with greater knowledge diversity generate more knowledge spillovers and have a larger and more pervasive impact on subsequent technological development. Furthermore, the higher diversity of knowledge sources increase the potential applications and the widespread adoption of these technologies. According to the World Bank,[13] green technologies, that are fundamentally more complex and multifaceted than their non-green counterparts, have applications that that span all economic sectors.

2.2 Greater Technological Distance among Inventors within A Green Innovation Team

Inventors rely on their own knowledge stock to create new ideas and technologies. However, they are not born at the cutting edge of knowledge; instead, they must pursue considerable education and complete substantial training. If innovation builds the stock of knowledge, subsequent generations of innovators may face a greater educational and training load, known as the "knowledge burden" (Jones 2009). This increasing knowledge burden can lead to a trend where innovators choose to specialize in narrower fields, concentrating their expertise to manage the growing complexity of knowledge. Jones (2009) uses patent data to demonstrate a strong and consistent trend among solo inventors to remain within their specialized fields, indicating a move towards greater specialization.

There has been a significant shift towards team-based knowledge production across various fields, including the sciences, social sciences, patenting, and economics (de Solla

[13] See, Pigato et al. 2020

Price, 1963; Adams et al., 2005; Wuchty et al., 2007). Analysis of patent data from 1975 to 1999 reveals a rapid increase in team size, with the average rising from 1.73 in 1975 to 2.33 by the end of the period, representing a 35% increase (Jones, 2010). Similarly, in the field of economics, Jones (2019) documents that in 1950, the average number of authors per paper was 1.2. By 2010, it had reached 2.0, and by 2018, the average team size had grown to 2.7. The increase in team size in economics papers over the past decade surpasses the growth observed over the previous fifty years.

Green technologies, which often involve complex and multifaceted problems, typically draw upon a broader range of knowledge from diverse technological fields. Consequently, inventors working on green innovations are often more technologically diverse from each other compared to those working on non-green technologies. This increased technological distance within a green innovation team is a result of the need to integrate knowledge from various disciplines to address both complex environmental and economic challenges effectively. As green technologies require the integration of diverse expertise and knowledge from different fields, the team members may have specialized knowledge that is more distinct from each other, compared to teams working on less complex, non-green innovations. This diversity in knowledge sources can enhance the creative problem-solving capabilities of the team, fostering innovative solutions that span multiple fields. However, it also presents challenges in coordinating and integrating diverse perspective and introduces vulnerabilities to disruptions.

2.3 More Negative Impact of Disruptions on Inventors' Green Innovation Output

The existing literature consistently points to the negative effects on individual inventors from disruptions to knowledge production, with the death of collaborators being a significant disruptive event. Azoulay et al. (2010) document a 5%to 10% lasting decline in the quality-adjusted publications of coauthors following the death of a superstar collaborator. Oettl (2012) reports that the output quality of surviving coauthors falls between 14% and 16% when a star collaborator dies, as opposed to the death of a nonstar collaborator. Furthermore, Jaravel et al. (2018) demonstrate that an inventor's premature death leads to a substantial and enduring decrease in their co-inventors' earnings and citation-weighted patents, with losses of 4 percent in earnings and 15 percent in patent citations after eight years.

Scientific evidence suggests that climate change will lead to increasingly frequent and destructive natural disasters, which can significantly disrupt various production activities, including knowledge production. Such hazards can destroy inventors' homes and laboratories, both crucial for their productivity. Without stable housing, inventors cannot focus on utilizing their knowledge and skills to generate new ideas. Similarly, the absence of labs and equipment prevents them from conducting experiments essential for innovation. As a result, inventors may see a decline in their output of innovations following a disruptive natural disaster.

The negative effects of disruptive events, such as natural disasters, are likely to be more severe for green innovation outcomes, primarily due to the greater distance in technological expertise among team members involved in green projects. Green innovation often entails a wider array of knowledge (De Marchi 2012; Barbieri et al. 2020; Orsatti et al. 2020; Fusillo 2023). Resulted from this knowledge diversity, inventors within a green team often possess distinct technological expertise, making them less substitutable compared to those in non-green teams. If a disruptive event strikes an individual inventor in a green team, finding a substitute to continue the affected inventor's technological tasks becomes more challenging. Consequently, the development of green technology may suffer more significantly than non-green innovation.

Meanwhile, the overall innovation performance of firms may remain relatively unaffected by such natural disasters. Firms typically have the advantage of diversifying risk across their innovation portfolios, controlling large groups of inventors and maintaining operations in multiple locations, which helps buffer against the effects of localized disruptions.

2.4 Potential Positive Impact of Natural Disasters on Inventors' Production of Green Innovation

Nonetheless, natural disasters may raise inventors' environmental awareness, potentially fostering increased production of green innovation. Experiences shape beliefs and perceptions;[14] natural disasters, with their significant losses and damages, can alter subjective beliefs about the frequency and severity of future events, as well as perceptions regarding the impact of human activities on the natural environment. These altered be-

[14]See, for instance, Mullainathan 2002; Malmendier and Nagel 2016; Bordalo et al. 2023.

liefs and perceptions may, in turn, influence individual behaviours and decision-making processes (Bernile et al. 2017). Therefore, inventors who have lived through such disasters may be more motivated to develop green innovation, driven by increased environmental awareness.

Additionally, consumers affected by natural disasters may also become more environmentally conscious, showing greater concern for their consumption patterns and environmental footprints. This increased awareness often leads to greater demand for green products. In response, firms may develop green technologies and produce green products as a strategic measure to soften price competition (Aghion et al., 2022).

3 Background on Hurricane Katrina, Data and Research Design

In this section, I provide background information on Hurricane Katrina, describe the various datasets I use and outline the research design.

3.1 Background on Hurricane Katrina

Hurricane Katrina developed from a tropical depression southeast of the Bahamas.[15] It first made landfall on August 25th in southern Florida near the Miami area. After crossing southern Florida, Katrina intensified into a Category 5 hurricane on August 28th, located approximately 250 miles south-southeast of the Mississippi River's mouth, with peak winds of 175 miles per hour. By August 29th, when it reached the Louisiana coast, it was a strong Category 3 hurricane with winds exceeding 100 miles per hour, particularly impacting New Orleans. As Katrina moved north-northeast across Mississippi, it gradually weakened but remained at hurricane strength up to 100 miles inland near Laurel, Mississippi. The storm finally downgraded to a tropical depression near Clarksville, Tennessee, on August 30th.

Katrina is the costliest hurricane in U.S. history, incurring $200 billion in damages

[15]The basic facts about Hurricane Katrina cited throughout are from publications of the National Oceanic and Atmospheric Administration (Graumann et al. 2005; NOAA National Centers for Environmental Information 2005).

according to NOAA.[16] It is also the second deadliest since 1930, claiming 1,833 lives.[17] The storm caused extensive storm surge damage, with surges possibly exceeding 30 feet along the coasts of Louisiana, Mississippi, and Alabama. Additionally, it led to significant wind damage and the failure of parts of the New Orleans levee system. Inland effects included high winds and some flooding across Alabama, Mississippi, Florida, Tennessee, Kentucky, Indiana, Ohio, and Georgia. Appendix Figure A1 illustrates the geographical distribution of property damage from Katrina, primarily clustered in the Southern United States, with damage extending to northeast areas.[18]

3.2 Data Description

Inventors, Patents and Green Patents. — I obtain the disambiguated inventor data from PatentsView,[19] which identifies unique inventors in the USPTO data. This dataset provides comprehensive information on inventors, including their patent number identifiers and geographical locations listed on patent applications. The granular geographical information, encompassing details such as country, state, city, and latitude and longitude coordinates, is likely to reflect the actual location where an inventor lives and works (Akcigit et al. 2016; Moretti and Wilson 2017; Akcigit et al. 2022). To get information on each patent's characteristics, such as the application year and technological classes, I merge the inventor data with the patent data from PatentsView by patent number identifier.

I use a novel classification scheme within the Cooperative Patent Classification (CPC) system to identify green patents aimed at addressing climate change. Specifically, I rely on the Y02 class, which targets technologies and applications for mitigating or adapting to climate change. The Y02 class functions as an additional classification assigned by the patent office, complementing standard technology classifications. Notably, it spans multiple fields and captures innovations in both mitigation and adaptation technologies (Haščič and Migotto 2015). This classification is particularly useful for identifying ICT

[16] See, NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2024). Dollar amounts are adjusted based on the 2024 Consumer Price Index

[17] See publications of the National Oceanic and Atmospheric Administration (Blake et al. 2011; NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters 2024)

[18] For example, the remnants of Hurricane Katrina, combined with an approaching cold front, led to strong winds across Eastern Massachusetts. These damaging wind gusts resulted in fallen tree branches and wires in Hingham, and a tree was also knocked onto power lines in Haverhill (NOAA National Centers for Environmental Information 2005).

[19] https://patentsview.org/

and related energy efficiency technologies, which are often more challenging to categorize in terms of their climate change mitigation contributions. A patent is identified as a green patent, if it falls within the Y02 class; otherwise, it is classified as non-green.

I allocate a patent to a specific year according to its application year rather than its year of eventual grant, as this aligns closely with the actual creation of the innovation. An inventor is regarded as active in every year between their first patent and last patent. During the inventor's active period, if there is no patent application record for them in a particular year, I assign zero to their patent number for that year.

Counties Affected by Hurricane Katrina. — The Spatial Hazard Events and Losses Database for the United States (SHELDUS) offers comprehensive data on county locations and property losses linked to natural hazard events that have impacted the country. I utilize relevant SHELDUS data to identify counties affected by Katrina and visualize their geographic distribution in Figure 2. The majority of the damage is concentrated in the Southern US, with the impact reaching northeastern areas due to strong winds, heavy rain, flooding, and other weather events associated with Katrina.

3.3 Treatment and Control Group Construction

I use two criteria to identify the treatment group, i.e., inventors who were likely to reside in the area affected by Hurricane Katrina. First, they filed at least one patent in 2004, or in 2005 before 25 August – the date of Katrina's first landfall – with one of the Southern US counties,[20] which suffered property damage from Katrina, listed as the inventor's address in the patent application. The majority of counties affected by Katrina were concentrated in the Southern US region (Figure 2). Second, their first patent is before the year 2005 when Katrina occurred.

Next, I construct a control group. I first apply two analogous criteria to decide the pool of potential control inventors. First, they filed at least one patent in 2004, or in 2005 before 25 August with one of the Southern US counties listed as the inventor's address in the patent application. However, none of the inventor locations listed on those patent applications filed during 2004 or in 2005 before August 25, are situated in the Southern US counties affected by Katrina. Second, their first patent predates the year

[20] As defined by the U.S. Census Bureau (https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf), the Southern US includes the following states: Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, and West Virginia.

2005 when Katrina occurred. To find the control inventors who appeared similar to the treatment group before Katrina, I use a one-to-one exact matching method based on three observables: year of first patent filing, cumulative patent count by 2005, and cumulative green patent count by 2005 (Jaravel et al. 2018).

Additionally, I focus solely on inventors whose first patent is in 1983 and afterwards, as the data for Louisiana are unreliable before 1983 (Akcigit et al. 2022). Therefore, there are 4773 pairs of treated and control patent inventors. Patent inventors are included in the sample between the years they first apply for a patent and the year of their patent application. To avoid the confounding effects of the COVID-19 pandemic, my sample period ends in 2019. Further robustness exercises will be conducted: 1. Including years 2000, 2001, 2002, 2003; 2. Removing the restriction of the Southern US. Panels A and B in Figure 3 show the geographical distribution of treated and control inventors at the county level, respectively. The treatment group is located in counties affected by Hurricane Katrina, while the control group is in counties spread throughout the southern U.S.

3.4 Estimation Strategy

In order to study the effect of Hurricane Katrina on inventors' innovation activities, I run a difference-in-difference regression:

$$Y_{ist} = \beta_0 + \beta_1 Treatment_i \times Post_t + tenure_{it} + \gamma_i + \sigma_s + \tau_t + \epsilon_{ist} \tag{1}$$

Where i indexes inventors, c denotes the counties of inventor i, and t is the year of patent applications. Y_{it} represents the two innovation outcomes: (i) green patents, (ii) non-green patents. To capture intensive- and extensive-margin responses to Hurricane Katrina, I construct three variables for each innovation outcome, all measured over a three-year window between and including years t and t+2 (Akcigit et al. 2022): (i) patent counts ; (ii) having any patent or not; (iii) the natural logarithm of patent counts. When the dependent variable is patent counts, I use a Poisson estimator. Year is defined as year of patent application, as this is the date closest to the actual creation of the innovation (Akcigit, Baslandze and Stantcheva 2016; Moretti and Wilson 2017; Akcigit et al. 2022).

$Treatment$ is an indicator variable for treated inventors; $Post_t$ denotes an indicator variable that equals 1 starting in the year 2005 when Hurricane Katrina happened. I

measure an inventor's tenure as the number of years that have passed since the inventor's first successful patent application, and include tenure fixed effects $tenure_{it}$ to account for variation in the speed of invention across the life cycle of an inventor. Additionally, I control for inventor, state and year fixed effects, denoted by γ_i, σ_s, and τ_t , respectively. Throughout the analysis, I use two-way clustered standard errors at the state and year level to allow for both serial and spatial correlation.

4 Results

4.1 Descriptive Statistics

Table 1 presents summary statistics for the variables of interest in the main sample used in the analysis. Full sample is defined as inventors who filed at least one patent in 2004 or 2005 with the address of US listed on the patent application, and filed their first patent after in 1983 and afterwards.[21] Statistics on green and non-green patent counts are computed based on the entire panel for the full sample of inventors, and based on years before Katrina for treated and control inventors. Cumulative patent counts, cumulative green patent counts, and the number of years since the first patent application are computed in the year 2005 when Katrina happened for treatment and control group, and across all years for the full sample. By construction, the means and distributions of cumulative patent counts, cumulative green patent counts, and the number of years since the first patent application for the control group exactly match those of the treatment group. The means and distributions of green and non-green patent counts over three years are also very similar in these two groups, although this match algorithm did not match exactly on these variables.

Panels A and B in Figure 4 illustrate the trajectory of annual mean patents, divided into green and non-green categories, for both treated and control inventors around the year 2005 when Hurricane Katrina occurred. They confirm nonparametrically that inventors in both the treatment and control groups followed similar patent trends before 2005, which bolsters the validity of the research design. Before Katrina, treatment and control inventors exhibited similar levels of production in both green and non-green patents. However, following Katrina, control inventors began to produce more green patents than treated inventors (Panel A), while no significant divergence was observed in the production of

[21] The data for Louisiana are unreliable before 1983 (Akcigit et al. 2022)

non-green patents by inventors (Panel B).

4.2 Main Results

Table 2 presents the core results. Overall, I find that Hurricane Katrina negatively impacted the production of green patents by inventors, while it had no effect on non-green patents. Specifically, following 2005, treated inventors could have, on average, produced 0.220 more green patents in the subsequent three years if Hurricane Katrina had not occurred (column 1 in Panel A). This implies a 415 percent increase in green patent production in the absence of Katrina, compared with a mean of 0.053 green patents before Katrina. Similarly treated inventors could have been more likely to file a green patent (column 2 in Panel A), and conditional on filing any green patent, they could have produced more green patents (column 3 in Panel A). Panel B shows that Katrina did not affect the production of non-green patents by inventors, as the point estimates are neither economically nor statistically significant.

I further explore the dynamics of the observed effects uncovered in Table 2, and employ a second specification. This includes interactions between $Treatment_i$ and a series of year indicator variables spanning from 1999 to 2010, and 2004 is the excluded category. I also extend this interaction to include indicators for periods before 1998 and after 2011 to fully capture the pre- and post-event effects. This specification is estimated with patent counts as the dependent variable and a Poisson regression. This specification is as follows:

$$\begin{aligned} Y_{ist} =& \beta_0 + \beta_{1998} 1_{[t<=1998]} \times Treatment_i + \sum_{m=1999}^{2010} \beta_m 1_{[t=m]} \times Treatment_i + \\ & \beta_{2011} 1_{[t>=2011]} \times Treatment_i + tenure_{it} + \gamma_i + \sigma_s + \tau_t + \epsilon_{ist} \end{aligned} \tag{2}$$

Figure 5 reports the point estimates and 95 percent confidence interval for the coefficients β_m, β_{1998} and β_{2011}, obtained from specification (2). Consistent with Table 2, Figure 5 shows a negative effect on green patents but no effect on non-green patents, although the negative effect on green patents appears to be temporary. There is no pre-trending for any of the outcome variables, which lends credibility to the research design. Annual coefficients for green innovation (Panel A in Figure 5) exhibits a notable decline in 2006, followed by a further decrease to their lowest point in 2008. Especially, during the years 2006 to 2010, these point estimates are significantly below zero. However, starting from 2011, these annual points began to rebound and approach zero. In contrast, annual coefficients for non-green patents (Panel B in Figure 5) exhibits no significant decline after

2005. Most annual coefficients for non-green patents are not significantly different from zero, regardless of the period before or after Katrina.

5 Do Green Patents and Non-Green Patents Differ in Technological Distance?

In this section, I seek to understand why Katrina had different effects on green and non-green patents. Specifically, I examine the hypothesis of different technological distance between green and non-green patents. I first construct the measurement of technological distance between inventors. Then, I show that technological distance between a sample inventor and collaborators within a patent team is greater for green patents compared to non-green ones. Moreover, I examine whether the negative impacts of Katrina are more pronounced for patents produced by teams with greater technological distance, and for inventors with more technologically distant collaborators before Katrina.

5.1 Measurement of Technological Distance

To examine whether technological distance is larger within a green patent team than within a non-green one, I first construct the measurement of technological distance between inventors. Following Akcigit et al.(2022), an inventor's technological expertise is defined as the modal class listed on patents filed before Katrina with her as an inventor. I look at 4-digit CPC subclass level, which is equivalent to USPTO three digit level in Akcigit et al. (2022), and focus on classes that are invention information.[22]

After identifying an inventor's technological expertise, I construct the measurement of technological distance between two inventors. The technological distance d_{ij} between inventors i with modal class a and inventor j with modal class b is defined as:

$$d_{ij} = 1 - \phi_{a,b}$$

Where $\phi_{a,b}$ is the technological proximity between modal class a and b. Following Hidalgo

[22]There are two types of information regarding technological classifications, i.e., invention information and additional information. Invention information is technical information in the total disclosure of a patent document that represents an addition to the state of the art. Additional information is non-trivial technical information which does not in itself represent an addition to the state of the art but might constitute useful information for the searcher.

et al.(2007) and Azoulay et al.(2010), I adopt the co-occurrence approach to calculate the technological proximity. If two patent classifications are related because they cover similar knowledge and technical subject matter, they are likely to be assigned to one patent simultaneously, whereas dissimilar patent classifications are less likely to be assigned to one patent. This outcomes-based measure does not rely on ex-ante assumptions on which factors potentially affect technological proximity between two patent classifications. Formally, the technological proximity between patent classification a and b is the minimum of the pairwise conditional probabilities of a patent being classified under one given it is classified under the other:

$$\phi_{a,b} = \min\{P(a \in C_p | b \in C_p), P(b \in C_p | a \in C_p)\}$$

Where C_p is the set of patent classifications that are assigned to patent p.

5.2 Difference in Technological Distance between Green and Non-Green Patent Teams

Figure 6 presents the distribution of average technological distance within a patent team for green and non-green patents produced by sample inventors before Katrina. The average technological distance within a patent team is calculated as the mean of all technological distances between a focal inventor, i.e., a sample inventor, and her collaborators. The distribution for green patent teams (green bars) is more skewed to the right, indicating a wider technological distance. In contrast, the distribution for non-green patent teams (red bars) is more concentrated on the left, indicating a narrower technological distance. This pattern persists both after Katrina and over the full time period, with green patents consistently showing a wider technological distance.

To empirically test the difference in technological distance between green and non-green invention teams my sample inventors belong to, I estimate the following simple model (Barbieri et al. 2020; Fusillo et al. 2023):

$$dist_p = \alpha + \eta green_p + \theta X_p + state_p + tech_p + year_p + \epsilon_p \tag{3}$$

where $dist_p$ is the average technological distance between a sample inventor and collaborators within the research team that produces the patent p. $green_p$ is my focal

explanatory variable, and it is a dummy variable taking value 1 if the patent p is classified as green and 0 otherwise. X_p is a set of controls, including the number of distinct inventors and assignees in the patent p, and the average geographical distance between a sample inventor and collaborators within the research team produce patent p. To account for potential geographical heterogeneity and time-varying effects, I include a set of state dummies based on sample inventors' locations listed on patents, and a set of time dummies corresponding to patent application year. To rule out heterogeneity in technology area, I include technology class dummies at the 3-digit CPC level. Standard errors are clustered at the state-3-digit-CPC level.

Table 3 presents the main results of my empirical analysis. Columns 1-3 correspond to different sample periods: 1) the full sample period, 2) the period before Katrina, and 3) the period after Katrina. The coefficients on the green dummy are all significantly positive, ranging from 0.0439 to 0.0585. Focusing on column 2, the distance between a sample inventor and collaborators within a green team is, on average, 0.0585 larger than that within a non-green team. This difference accounts for 26.35% of the mean average distance (0.222) before Katrina and 21.67% of the corresponding standard deviation (0.270). These results corroborate my hypothesis, indicating that, on average, the technological distance within a green patent team is larger than within a non-green team. Robustness checks conducted with the full sample of patents show similar results, further supporting the finding that inventors within a green patent team are more technologically distant from each other than those within a non-green patent team.

5.3 Differential Effects on Patents of Small vs. Large Technological Distance

Patents produced by inventors within teams characterized by greater technological distance are likely to experience a more severe negative impact due to the disaster, if differences in technological distance within patent teams determine the differential effects of Hurricane Katrina on inventors' green and non-green patent outcomes. To test this hypothesis empirically, I categorize patents into groups with small and large technological distances. This classification is based on the distribution of average technological distances before Katrina, using the median value of 0 as the threshold. Patents with an average technological distance above 0 are categorized as having a large technological distance, whereas those with a distance of 0 are considered to have a small technological distance.

I then conduct a separate regression analysis for each group, re-estimating the coefficient of interest, β_1, using specification (1) and the Poisson estimation method. The dependent variables for these analyses are the number of patents with small technological distance and the number of patents with large technological distance, respectively. I analyse three categories of patents — overall, green, and non-green. The results, presented in Table 4 and Figure 7, consistently show that patents with large technological distances suffered significant negative impacts from Hurricane Katrina across overall, green, and non-green innovation.[23] In contrast, the results for patents with small technological distances show positive but insignificant coefficients across all types of innovation. Additionally, tests confirm that the impacts on patents with small versus large technological distances are statistically different.

5.4 Heterogeneity by Technological Distance with Collaborators before Katrina

If the difference in technological distance within a patent team contributes to the differential effect of Katrina on inventors' green and non-green patent outcomes, I would expect that inventors who worked with more technologically distant collaborators before Katrina would experience a more negative impact on their total patent outcomes. To empirically test this, I estimate the following model:

$$Y_{ist} = \beta_0 + \sum_{m=1}^{3} \beta_m X_{im} \times Treatment_i \times Post_t + \sum_{m=1}^{2} \beta_m X_{im} \times Post_t + tenure_{it} + \gamma_i + \sigma_s + \tau_t + \epsilon_{ist} \tag{4}$$

Where X_{im} is a dummy variable indicating whether the average technological distance between inventor i and collaborators before Katrina falls between the $(m-1)th$ and the mth percentile. Table 5 presents the regression results, and Figure 8 displays the point estimates and 95 percent confidence interval for the coefficients β_m. The analysis reveals that the point estimates for the first and second tertiles hover around zero, while those for the third tertile are significantly below zero, across all innovation types — whether overall, green, or non-green patents. Furthermore, tests confirm that the point estimates for β_m are significantly different between the first and third tertiles for all innovation types. For

[23] The effect on non-green patents is marginally significant, with a p-value of 0.11.

green innovation, a significant difference also exists between the first and second tertiles. These findings suggest that inventors who collaborated with more technologically distant partners before Hurricane Katrina experienced a greater negative impact on their patent output following the disaster.

6 Conclusion and Discussion

Climate change will lead to more destructive natural disasters including hurricanes, which can cause significant disruptions in the creation of knowledge and technology. Meanwhile green innovation, which draws on knowledge from a broader scope of the knowledge space, offers a solution to combat climate change. In this paper, I study the effect of disruptions, such as natural disasters, on inventors' innovation production, including green and non-green ones, within the context of the Hurricane Katrina, one of costliest and deadliest storms in US history. Using hazard data and patent data for US inventors in a difference-in-differences setup, I find that Hurricane Katrina reduced inventors' production of green patents, while non-green patents remained unaffected.

Specifically, had Hurricane Katrina not occurred, a treated inventor could have produced an additional 0.220 green patents after 2005, representing a 415 percent increase. This suggests that natural disasters could impede the green transition by negatively impacting inventors' green innovation production, despite the potential for such events to increase environmental consciousness and accelerate the development of green technology. Moreover, this finding spark worries about a vicious cycle, given the potential rise in severe climate-induced natural disasters and the critical role of green innovation in addressing climate change.

It is important to understand the mechanism behind the observed negative effect on green innovation and no effect on non-green innovation. One possible explanation lie in the difference between green and non-green innovation regarding the distance in technological expertise among inventors within a research team. Green technology tends to be more complex and multifaceted than its non-green counterparts, spanning across all economic sectors (Pigato et al. 2020). Additionally, it draws from a broader range of knowledge stock (De Marchi 2012; Barbieri et al. 2020; Orsatti et al. 2020; Fusillo 2023). Thus, the development of green technology may require collaboration among inventors with more diverse expertise and technological backgrounds, each fulfilling distinct roles and tasks.

Within a green innovation team, there could be more significant technological distance among inventors. If a disruption event, like a natural disaster, strikes an individual inventor within a green team, it will be harder to substitute so as to continue the affected inventor's technological tasks. Therefore, the development of green technology may be more negatively affected than non-green innovation

Consistent with this conjecture, I find that average technological distance between a sample inventor and collaborators within a green patent team is larger than that in a non-green one. The negative impacts of Katrina are more pronounced for patents produced by teams with greater technological distance, and for inventors with more technologically distant collaborators before Katrina. This suggests that greater knowledge diversity in inventors' expertise within a research team make the technological development more fragile and vulnerable, in the face of disruptions to knowledge production, such as natural disasters related to climate change.

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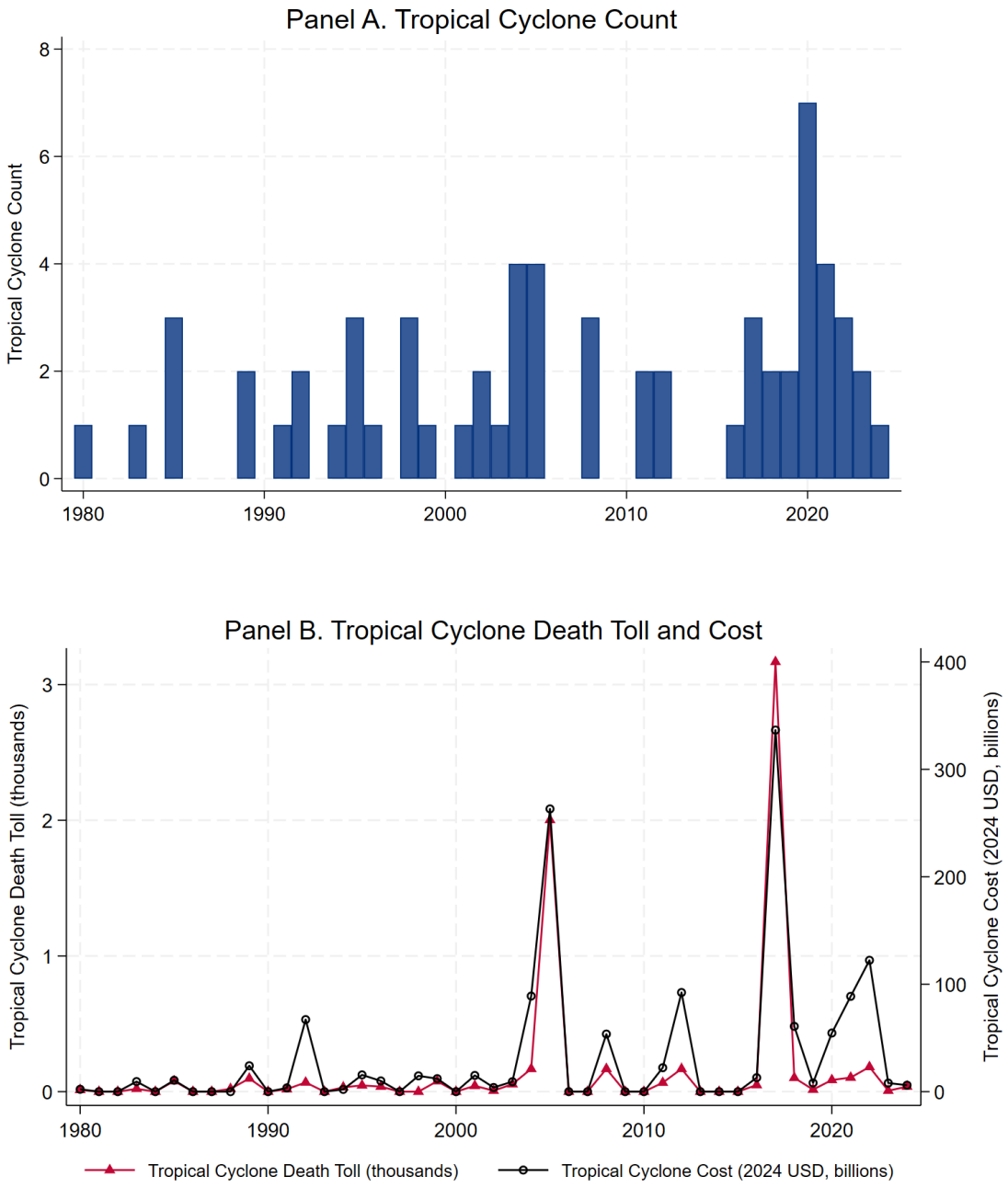
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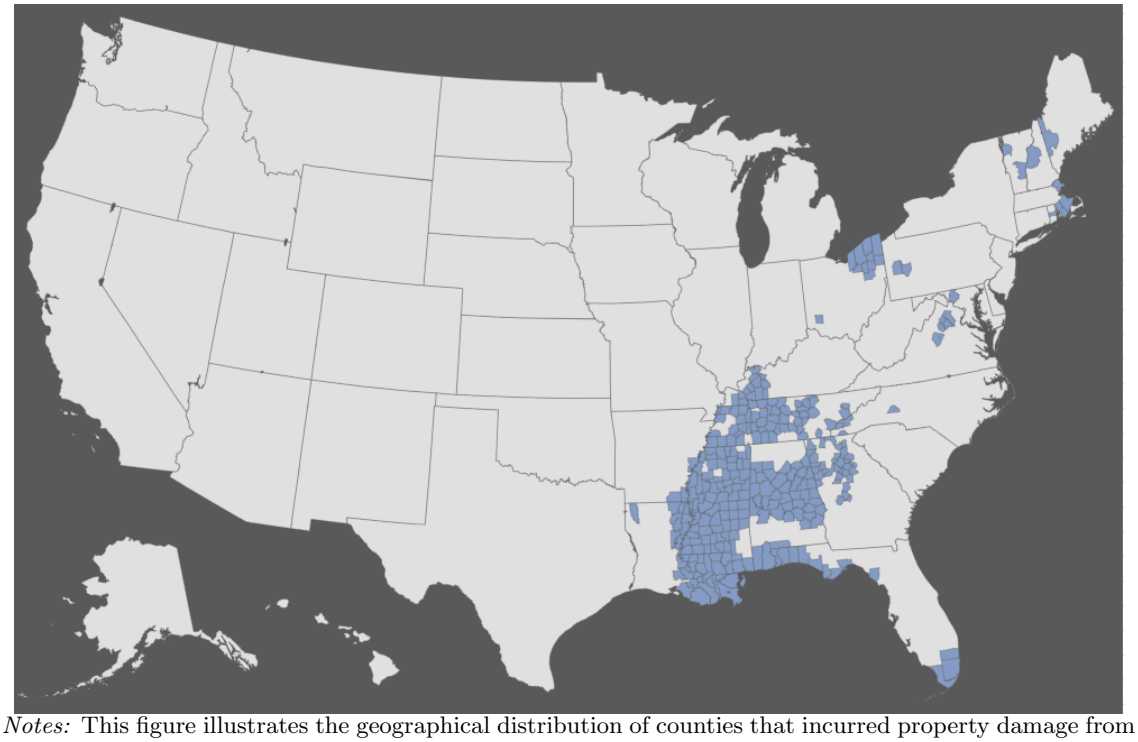
Figures

FIGURE 1: UNITED STATES BILLION-DOLLAR TROPICAL CYCLONE EVENTS 1980-2024



Notes: Panels A and B of this figure show the trends in the number, death count, and cost of billion-dollar tropical cyclones affecting the United States. The data is sourced from the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NCEI) — Billion-Dollar Weather and Climate Disasters (https://www.ncei.noaa.gov/access/billions/). This dataset includes only weather and climate disasters with losses exceeding one billion dollars, adjusted for the 2024 Consumer Price Index.

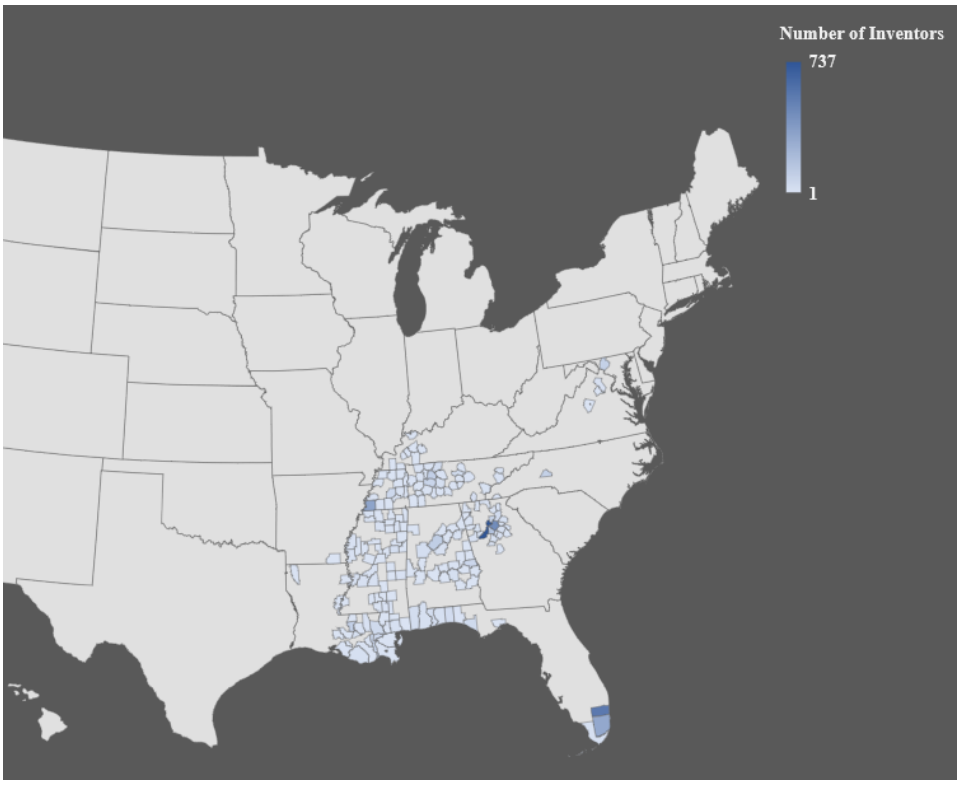
Figure 2: Geographical Distribution of Counties Affected by Katrina



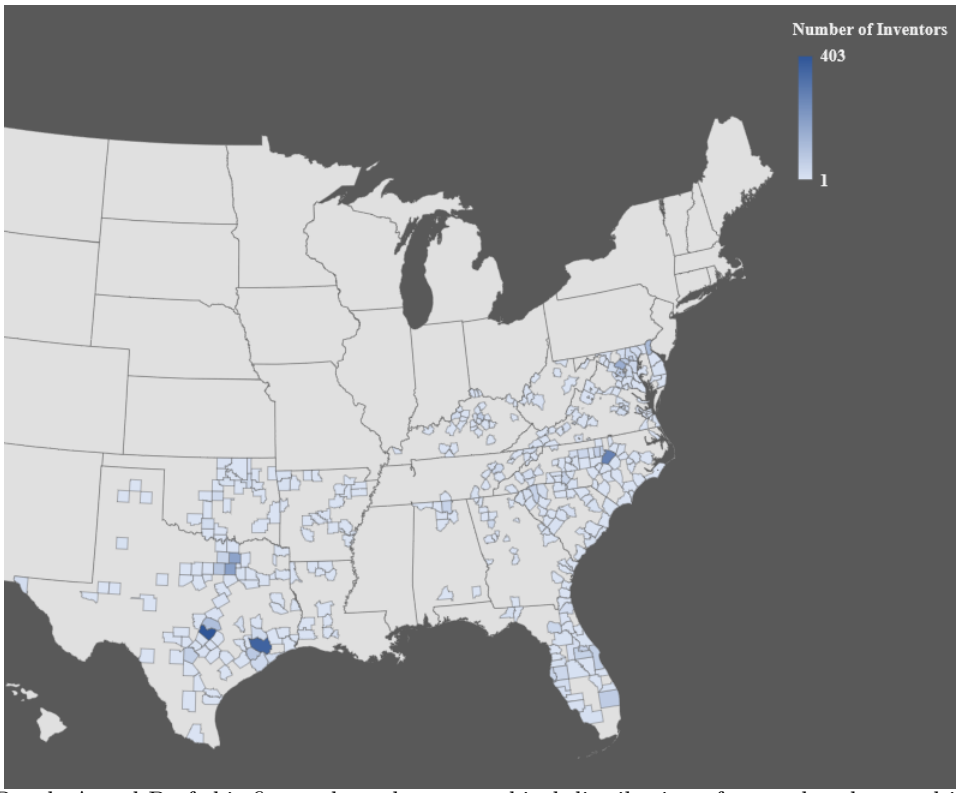
Notes: This figure illustrates the geographical distribution of counties that incurred property damage from Hurricane Katrina, with affected counties highlighted in blue. The majority of the damage is concentrated in the Southern United States, with impacts extending to northeastern regions due to Katrina-related weather events such as strong winds, heavy rain, and flooding. The data is sourced from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), with further details provided in Section 3.2.

Figure 3: Geographical Distribution of Treatment and Control Groups

Panel A. Treatment Group

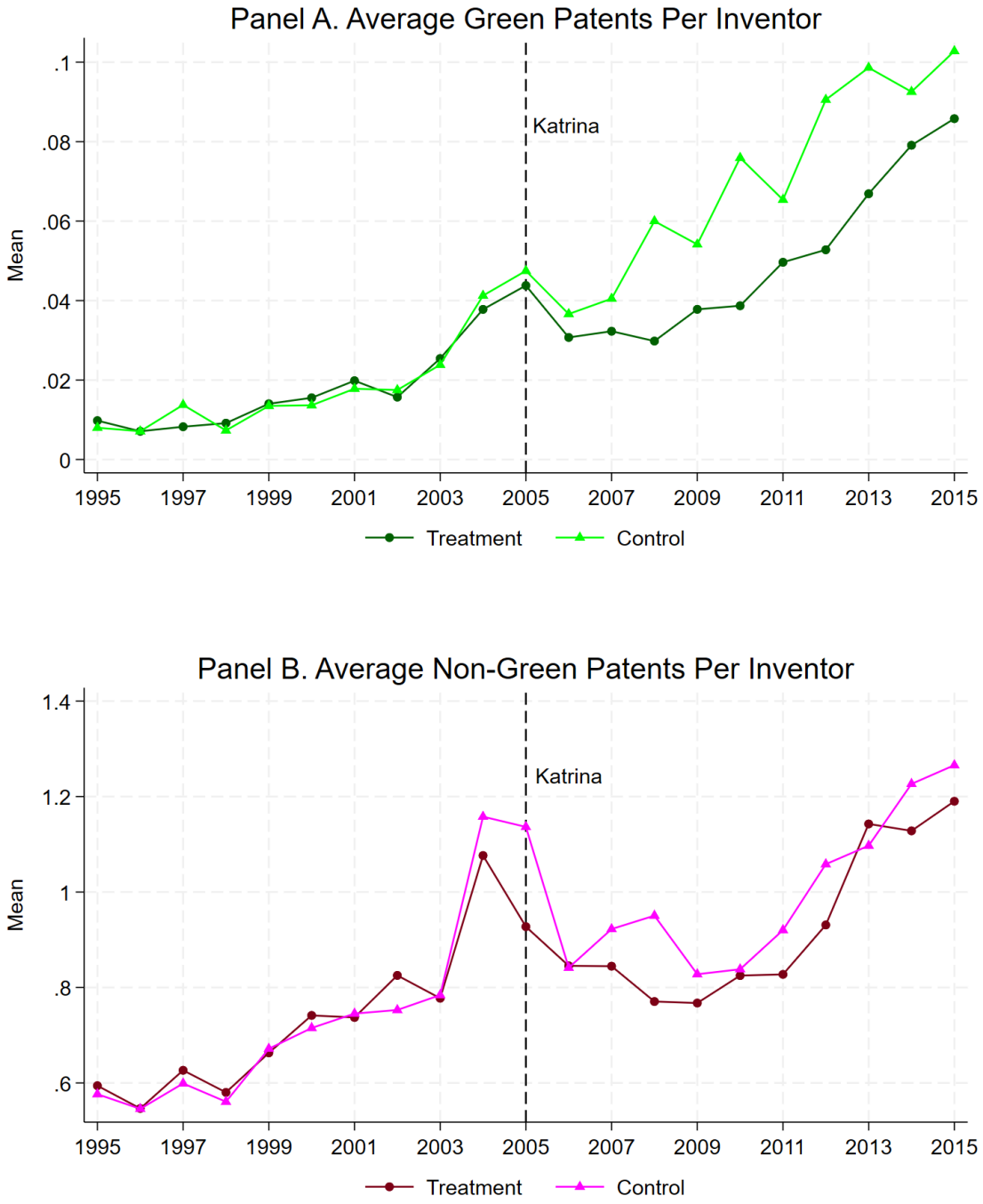


Panel B. Control Group



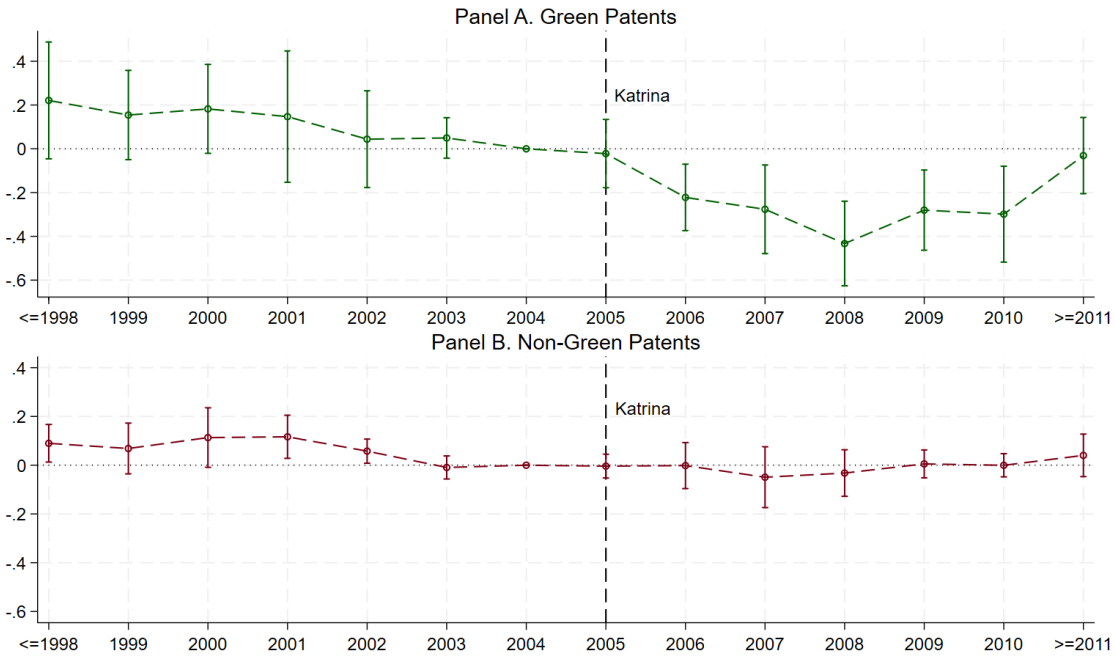
Notes: Panels A and B of this figure show the geographical distribution of treated and control inventors at the county level, respectively. Section 3.3 provides the definitions of the treatment and control groups.

FIGURE 4: PATH OF INVENTORS' PATENT OUTCOMES AROUND HURRICANE KATRINA



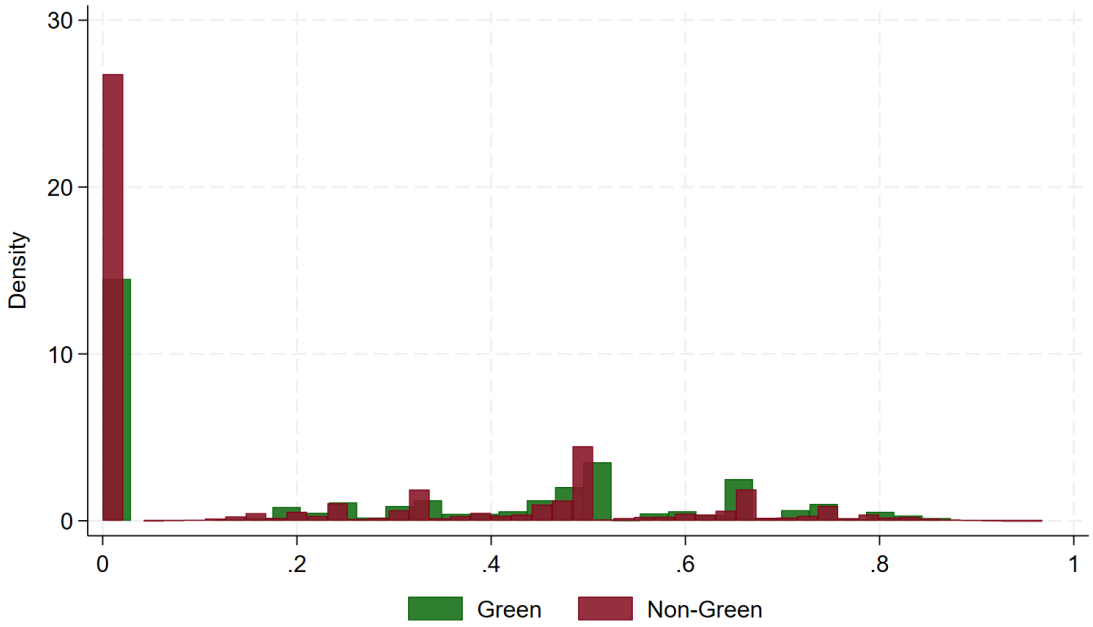
Notes: Panels A and B of this figure display the trends in mean green and non-green patents for treated and control inventors around 2005, the year Hurricane Katrina occurred. The sample inventors were selected based on their patent applications during 2004-2005, which accounts for an observed spike in patent activity during these years. Section 3.3 provides the definitions of the treatment and control groups.

FIGURE 5. DYNAMIC EFFECTS OF KATRINA ON INVENTORS' PATENT PRODUCTION



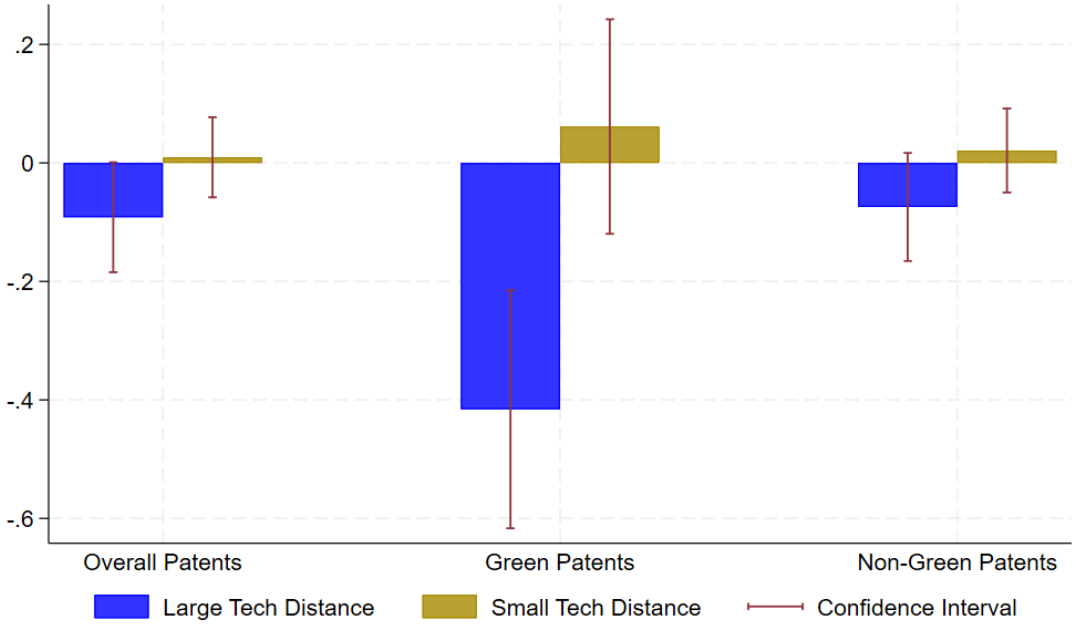
Notes: Panels A and B of this figure show the estimated coefficients β_m, β_{1998} and β_{2011} from Poisson specification (2) for two outcome variables – green and non-green patent counts, which aggregate over three years: between period t and t + 2. This specification includes inventor, tenure, state and year fixed effects. Tenure is measured as as the number of years that have passed since the inventor's first successful patent application. Inventors are included in the sample between the years they first apply for a patent and the year of their final patent application. Standard errors are clustered at the state and year level.

Figure 6. Distribution of Average Technological Distance within a Patent Team



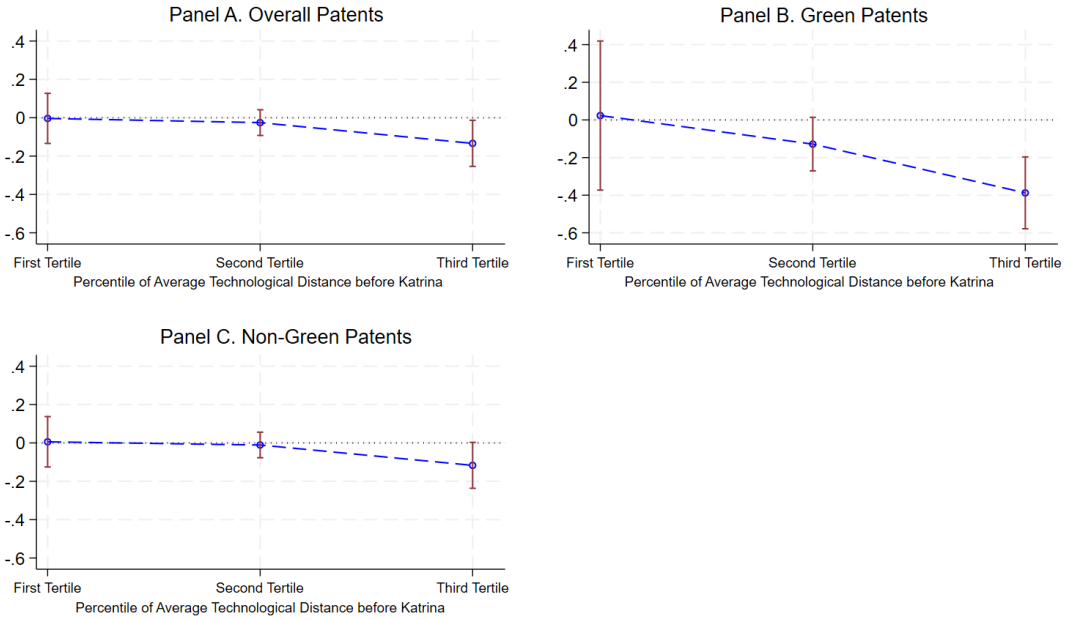
Notes: This figure shows the distribution of average technological distance within a patent team for green and non-green patents produced by sample inventors before Katrina. Section 5.1 details the methodology for measuring technological distance between two inventors. The average technological distance within a patent team is calculated as the mean of all technological distances between a focal inventor, i.e., a sample inventor, and her collaborators.

Figure 7. Differential Effects on Patents of Small vs. Large Technological Distance



Notes: This figure plots the point estimates for the coefficient β_1 from specification (1) for two dependent variables: the number of patents with small technological distance and the number of patents with large technological distance. The median value of average technological distance for each patent before Katrina is 0. Patents with an average technological distance above 0 are categorized as having a large technological distance, whereas those with a distance of 0 are considered to have a small technological distance. Section 5.1 provides a detailed explanation of the methodology used to measure technological distance between two inventors. The analysis is conducted across three categories of patents: overall, green, and non-green, using the Poisson estimation method. Standard errors are clustered at the state and year levels. For more details on the specification, refer to Section 3.4.

FIGURE 8. HETEROGENEITY BY TECHNOLOGICAL DISTANCE WITH COLLABORATORS BEFORE KATRINA



Notes: Panels A to C of this figure plot the estimated coefficients β_m from specification (4) for three categories of patents: overall, green, and non-green, respectively. The estimation is performed using the Poisson method. The tertiles are computed based on the average technological distance between sample inventors and their collaborators before Katrina. Section 5.1 provides a detailed explanation of the methodology used to measure technological distance between two inventors. Standard errors are clustered at the state and year levels. For more details on the specification, refer to Section 5.4.

Tables

Table 1. Summary Statistics on Inventors

Variable	Sample	Mean	SD
Green patent counts	Full sample	0.073	0.489
	Treatment	0.019	0.145
	Control	0.019	0.148
Non-green patent counts	Full sample	2.024	3.041
	Treatment	0.743	1.179
	Control	0.743	1.177
Cumulative patents	Full sample	9.212	18.472
	Treatment	4.614	5.676
	Control	4.614	5.676
Cumulative green patents	Full sample	0.520	2.644
	Treatment	0.113	0.441
	Control	0.113	0.441
Number of years since first patent application	Full sample	10.214	8.206
	Treatment	5.056	5.689
	Control	5.056	5.689
No. inventors	Full sample	224,891	
	Treatment	4773	
	Control	4773	

Notes: This table presents summary statistics for the full sample, as well as for treatment and control groups of inventors. Statistics include green and non-green patent counts, calculated for the entire panel from 1983 to 2019 for the full sample, and for the pre-Katrina years for treated and control inventors. Cumulative patent counts, cumulative green patent counts, and the number of years since the first patent application are computed specifically in 2005 — the year Hurricane Katrina occurred — for both treatment and control groups, and across all years for the full sample. For detailed information on data sources and sample construction, refer to Sections 3.2 and 3.3.

Table 2. Effects of Katrina on Inventors' Patent Production

Dependent variable	(1) Patent counts over three years	(2) Has any patents over three years	(3) Log (patent counts over three years)
Panel A: Green patents			
Treatment × Post	-0.220***	-0.0129**	-0.116**
	(0.0646)	(0.00595)	(0.0429)
Observations	102,621	102,621	6,749
Year fixed effects	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
Inventor fixed effects	Yes	Yes	Yes
Tenure fixed effects	Yes	Yes	Yes
Estimation method	Poisson	OLS	OLS
Mean of dep. var before Katrina	0.053	0.041	0.166
Panel B: Non-green patents			
Treatment × Post	-0.0419	-0.00980	-0.00317
	(0.0349)	(0.0119)	(0.0310)
Observations	102,621	102,621	75,126
Year fixed effects	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
Inventor fixed effects	Yes	Yes	Yes
Tenure fixed effects	Yes	Yes	Yes
Estimation method	Poisson	OLS	OLS
Mean of dep. var before Katrina	2.084	0.726	0.744

Notes: Panel A and B report the estimated coefficients β_1 from specification (1) for green patents and non-green patents, respectively. Each dependent variable is aggregated over a three-year period, from year t to t + 2. The dependent variables are: column (1) patent counts, column (2) an indicator for whether the inventor has a patent, column (3) the natural logarithm of patent counts. The variable *tenure* is measured as the number of years that have passed since the inventor's first successful patent application. Standard errors clustered at the state and year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3. Difference in Technological Distance between Green and Non-Green Patents

VARIABLES	(1) Full Period	(2) Before Katrina	(3) After Katrina
Green	0.0510***	0.0585***	0.0439***
	(0.0104)	(0.0126)	(0.0117)
Observations	109,450	42,972	66,477
R-squared	0.218	0.155	0.217
Year fixed effects	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
CPC 3-digit fixed effects	Yes	Yes	Yes
Mean of dep. var	0.293	0.222	0.339
Standard deviation of dep. var	0.294	0.270	0.300

Notes: This table reports the estimated coefficients η from specification (3), where the dependent variable is the average technological distance between a sample inventor and their collaborators within a patent team. Section 5.1 provides a detailed explanation of the methodology used to measure technological distance between two inventors. Columns 1-3 correspond to different sample periods: 1) the full sample period, 2) the period before Katrina, and 3) the period after Katrina. The model controls for several factors, including the number of distinct inventors and assignees associated with each patent, as well as the average geographical distance between a sample inventor and their collaborators within the patent team. To account for potential geographical heterogeneity and time-varying effects, I include state dummies based on the locations of the sample inventors as listed on patents, along with time dummies corresponding to the patent application year. Additionally, to account for variations across different technology areas, I incorporate technology class dummies at the 3-digit CPC level. Standard errors clustered at the state-3-digit-CPC level are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4. Differential Effects on Patents of Small vs. Large Technological Distance

	Overall patents		Green patents		Non-Green patents	
	Large	Small	Large	Small	Large	Small
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × Post	-0.0917*	0.00947	-0.416***	0.0614	-0.0744	0.0210
	(0.0473)	(0.0345)	(0.103)	(0.0924)	(0.0466)	(0.0362)
Observations	102,621	102,621	102,621	102,621	102,621	102,621
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Inventor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Tenure fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the point estimates for the coefficient β_1 from specification (1) for two dependent variables: the number of patents with small technological distance and the number of patents with large technological distance. The median value of average technological distance for each patent before Katrina is 0. Patents with an average technological distance above 0 are categorized as having a large technological distance, whereas those with a distance of 0 are considered to have a small technological distance. The analysis is conducted across three categories of patents: overall, green, and non-green, using the Poisson estimation method. The model includes fixed effects for tenure, inventor, year, and state. The variable *tenure* is defined as the number of years since the inventor's first successful patent application. Standard errors clustered at the state and year levels are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

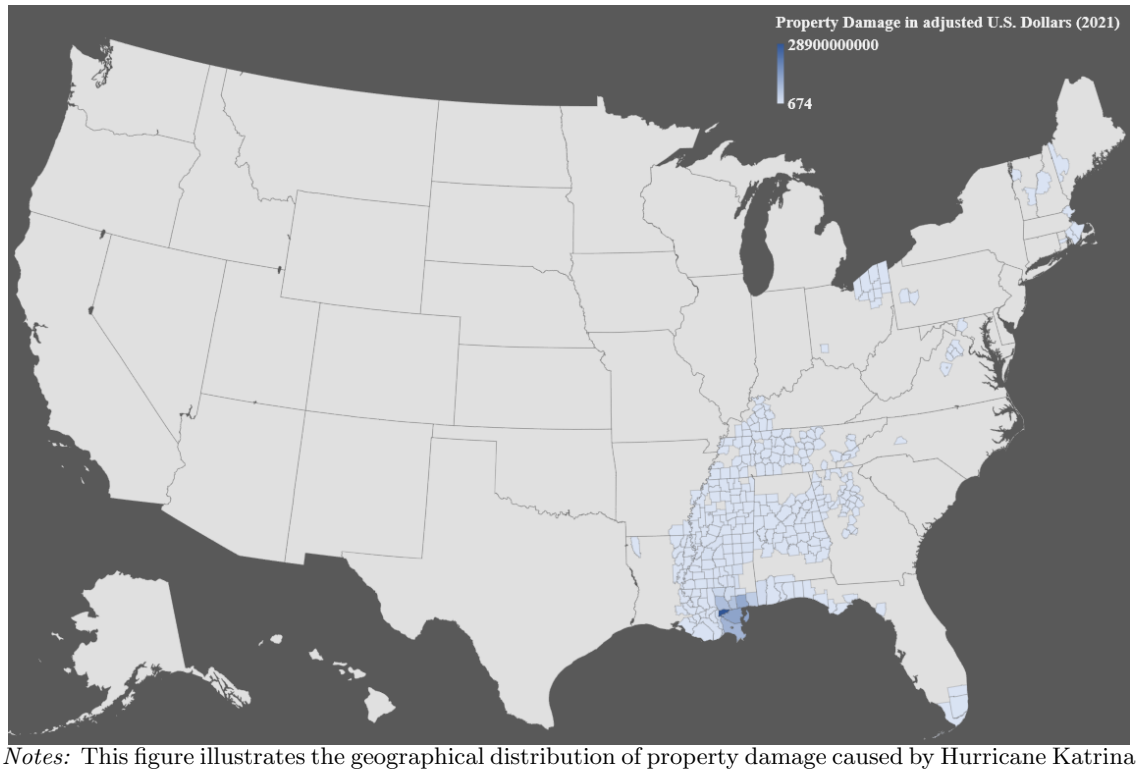
Table 5. Heterogeneity by Technological Distance with Collaborators before Katrina

VARIABLES	(1) Overall patents	(2) Green patents	(3) Non-Green patents
First tertile × Treatment × Post	-0.00350	0.0233	0.00579
	(0.0666)	(0.202)	(0.0670)
Second tertile × Treatment × Post	-0.0254	-0.129*	-0.0108
	(0.0341)	(0.0726)	(0.0340)
Third tertile × Treatment × Post	-0.134**	-0.388***	-0.117*
	(0.0614)	(0.0974)	(0.0611)
Observations	102,621	102,621	102,621
Year fixed effects	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
Inventor fixed effects	Yes	Yes	Yes
Tenure fixed effects	Yes	Yes	Yes

Notes: This table reports the estimated coefficients β_m from specification (4) for three categories of patents: overall, green, and non-green, respectively. The tertiles are computed based on the average technological distance between sample inventors and their collaborators before Katrina. Section 5.1 provides a detailed explanation of the methodology used to measure technological distance between two inventors. The estimation is performed using the Poisson method. The model includes fixed effects for tenure, inventor, year, and state. The variable *tenure* is defined as the number of years since the inventor's first successful patent application. Standard errors clustered at the state and year levels are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix

Figure A1. Geographical Distribution of Property Damage by Katrina



Notes: This figure illustrates the geographical distribution of property damage caused by Hurricane Katrina at the county level, with damage amounts adjusted to 2021 dollars. The shading intensifies from light to dark blue to indicate increasing levels of damage, with the darkest blue representing the most severe impact. New Orleans, Louisiana, is marked as the epicenter of the damage. The data is sourced from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), with further details provided in Section 3.2.