Green Technological Change After Natural Disasters: Evidence from Hurricane Katrina

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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 — the costliest and one of the 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 climate change can disrupt human efforts aimed at addressing it, particularly through natural disasters and that knowledge diversity can compromise the resilience of technological development when faced with disruptions.

Key words: Inventors, Green Innovation, Knowledge Diversity, Natural Disasters, Climate Change

JEL Classifications: J24, M54, O31, O34, Q54, Q55

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"In nature, nothing exists alone."

— Rachel Carson, 1962. *Silent Spring*

1 Introduction

How does nature shape human development? Can increasingly intense natural disasters affect human innovation activities? How do these disruptive events hinder or inspire inventors as they develop new technologies, particularly those essential for addressing climate and environmental challenges?

Scientific evidence suggests that climate change has led to the increased intensity of natural disasters.[1] Hurricanes, in particular, are becoming stronger and more destructive,[2] which can significantly disrupt the creation of new technological or scientific knowledge. Innovation is important for productivity growth, and green innovation is especially crucial for the combat against climate change and transition to sustainable economy.[3] Existing theoretical frameworks (e.g., Acemoglu et al. 2012) usually treat environmental quality as exogenous to both green and non-green innovation supply, i.e., no feedback channel from environmental degradation and disasters to technological development. A considerable body of research also focuses on how the price mechanism can direct resources from non-green to green innovation to tackle climate and environmental challenges (e.g., Acemoglu et al. 2012; Aghion et al. 2016; Dugoua and Gerarden 2023). However, there is limited understanding of how climate change and extreme weather events, such as hurricanes, affect green and non-green innovation, specifically whether they are impacted in similar or different ways.

Individual inventors play a pivotal role in the production of innovation, contributing their specialized knowledge and skills to create new technologies, such as green innovation. While natural disasters may raise inventors' environmental awareness and potentially encourage green technological development, 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'

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

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

[3] 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.

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,[4] 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,[5] 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.[6] 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.[7] 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 disruptive 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.[8] This study is based on a merged dataset of United States Patent

[4] 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.

[5] See, Pigato et al. 2020.

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

[7] 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.

[8] The figures are sourced from NOAA National Centers for Environmental Information (NCEI) U.S.

and Trademark Office (USPTO) patent inventor data from PatentsView,[9] 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. The Y02 class is a classification scheme for technologies and applications that help mitigate or adapt to climate change. 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. The results are robust to: 1. Controlling geographical distance of sample inventors with co-inventors; 2. Using the alternative definition of green patents, based on the OECD ENV-TECH classification (Haščič and Migotto 2015); 3. Not restricting control inventors to the South US; 4. Excluding solo-inventor patents. The findings suggests that natural disasters could impede the green transition by adversely affecting inventors' production

Billion-Dollar Weather and Climate Disasters (2024). Costs are adjusted based on the 2024 Consumer Price Index

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

of green innovation, despite their potential to enhance environmental awareness and accelerate the development of green technology. Furthermore, this 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. Moreover, 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. Additionally, I find that the differential effects of Hurricane Katrina on inventors' green and non-green patent output are not driven by firms, by estimating with additional assignee or assignee-year fixed effects.[10] 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 literature on economic impacts of natural disasters. An extensive literature has examined the impact of extreme weather events and disasters on a range of outcomes, including aggregate economic activity at the country level (Dell et al. 2012; Acevedo et al. 2020), local economies (Kocornik-Mina et al. 2020; Elliott et al. 2015), and firm-level performance (Somanathan et al. 2021; Keiller and Van Reenen 2024). More specifically, my work is situated among a number of papers that analyse the impacts of natural disasters, on innovation. Most related to this paper is Ballesteros (2022), which explores the impact

[10] A patent assignee is an entity or individual that receives the rights to a patent or application. The majority of assignees are firms.

of Hurricane Katrina on county-level innovation, focusing on changes in risk attitudes. In contrast, this paper examines the effect on green and non-green innovation at the individual inventor level, uncovering a negative effect on green innovation but no significant impact on non-green innovation. This study also introduces a novel mechanism based on differences between the two types of innovation.

My study on the role of natural disasters shaping individual inventors' technological direction complements the large literature on directed technological change and the environment. While existing work has mostly focused on the price mechanism to direct resources from non-green to green innovation (Acemoglu et al. 2012; Aghion et al. 2016; Dugoua and Gerarden 2024) to address climate and environmental challenges, my focus is on how climate change and related natural disasters influence technological direction. In this vein, Miao and Popp (2014) find that floods, droughts and earthquakes lead to more innovation of their respective mitigation technologies at the country level; Moscona and Sastry (2022) find that agricultural innovation has shifted towards crops more exposed to extreme temperatures at the county level since the mid-20th century; According to Moscona (2022), agricultural technology development at county level persistently redirected toward more Dust Bowl-exposed crops in the wake of the American Dust Bowl. Different from these papers, I find that Hurricane Katrina not only failed to encourage green innovation but actually reduced inventors' green innovation output, while non-green innovation remained unaffected.

Most close to my work is Zhao et al.(2022), which finds that natural disasters are negatively associated with green innovation in the energy sector at the country level, but shows no correlation with non-green energy innovation. Unlike Zhao et al. (2022), my paper focuses on the causal impact of a specific natural disaster — Hurricane Katrina — on general green innovation at the individual inventor level. Furthermore, 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 new micro-level channel – 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 distinctive dependency suggests that inventors' green innovation output was more negatively impacted by the disruption caused by Hurricane Katrina.

Second, this paper also contributes to the growing literature on scientists and inven-

tors 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 identifies a novel mechanism of knowledge substitutability – an inventor's technological expertise 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 diversity of knowledge areas and the inherent technological characteristics of the team involved.

Third, this paper also adds 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 labour 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 provides background information on Hurricane Katrina. Section 3 describes the data, empirical design and some key summary statistics. Section 4 presents the empirical results. In section 5, I establish that greater knowledge diversity and technological distance within a green innovation team is one important explanatory channel. Section 6 discusses and tests the alternative mechanism operating at firm level. Section 7 concludes.

2 Background on Hurricane Katrina

Climate change is leading to more destructive hurricanes, which can generate great economic and societal impacts. A hurricane is a tropical cyclone with maximum sustained winds of 74 mph (64 knots) or higher.[11] Figure 1 shows the increasing frequency rising death tolls, and escalating monetary losses of billion-dollar tropical cyclones in the United States between 1980 and 2024. 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).

Hurricane Katrina is the costliest tropical cyclone in U.S. history, incurring $200 billion in damages according to NOAA.[12] It is also the second deadliest since 1930, claiming 1,833 lives.[13] It developed from a tropical depression southeast of the Bahamas, making its first landfall on August 25th in southern Florida near the Miami area.[14] After crossing southern Florida, Katrina intensified into a Category 5 hurricane on August 28th, located

[11] See, https://www.nhc.noaa.gov/climo/

[12] 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.

[13] 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)

[14] 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).

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.

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.[15]

3 Data, Empirical Design and Descriptive Statistics

In this section, I describe the various datasets I use, outline my empirical design, and provide some basic descriptive statistics.

3.1 Data Description

Inventors, Patents and Green Patents. — I obtain the disambiguated inventor data from PatentsView,[16] 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 num-

[15] 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).

[16] https://patentsview.org/

ber 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 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.

3.2 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,[17] which suffered property damage from Katrina, listed as the inventor's address in the patent application. The majority of counties affected by Katrina

[17] 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.

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 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. 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.

3.3 Estimation Strategy

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

$$Y_{ist} = \beta_0 + \beta_1 Treatment_i \times Post_t + \gamma_i + \sigma_s + \tau_t + \sum_j \lambda_j \mathbb{1}_{[tenure_{it}=j]} + \epsilon_{ist} \qquad (1)$$

Where i indexes inventors, s denotes the states 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 $tenure_{it}$ as the number of years that have passed since the inventor's first successful patent application, and include tenure fixed effects 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.

To further explore the dynamics of the effects, I 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 as follows:

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

3.4 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.[18] Statistics on yearly 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,

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

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.

4 Results

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 non-green patents by inventors (Panel B).

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 2 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. Columns 3-4 show that Katrina did not affect the production of non-green patents by inventors, as the point estimates are neither economically nor statistically significant.

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.

To further explore the robustness of the results, I estimate the effects of Katrina at extensive and intensive margin for green and non-green patents. Table 3 show similar results. Treated inventors could have been more likely to file a green patent (column 1), and conditional on filing any green patent, they could have produced more green patents (column 2). Columns 3-4 show that Katrina affected neither the extensive nor the intensive margin of non-green patent production by inventors. I also do additional robust exercises: 1. Controlling geographical distance of sample inventors with co-inventors; 2. Using the alternative definition of green patents, based on the OECD ENV-TECH classification (Haščič and Migotto 2015); 3. Not restricting control inventors to the South US; 4. Excluding solo-inventor patents. Table 4 and Figure 6 show the robust results that support the main findings.

5 Do Differences in Technological Distance Matter?

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 present the argument how disruptions to knowledge production affect differently individual inventors' production of green versus non-green innovation. Then, I 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 Motivation

5.1.1 Green Innovation with Greater Knowledge Diversity

Green 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,[19] green technologies, that are fundamentally more complex and multifaceted than their non-green counterparts, have applications that that span all economic sectors.

5.1.2 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, con-

[19] See, Pigato et al. 2020

centrating 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 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.

5.1.3 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.

5.2 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.[20]

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 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.

[20]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.

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

Figure 7 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 5 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.

5.4 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 for green and non-green patents. The results, presented in Table 6 and Figure 8, consistently show that patents with large technological distances suffered significant negative impacts from Hurricane Katrina across green and non-green innovation.[21] 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. I also conduct similar analysis for all patents and find similar results (see Appendix columns 1-2 in Table A2 and Figure A2).

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

5.5 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 patent outcomes. To empirically test this, I estimate the following model:

$$\begin{aligned} Y_{ist} =& \beta_0 + \sum_{m=1}^{3} \beta_m X_{im} \times Treatment_i \times Post_t + \sum_{m=1}^{2} \beta_m X_{im} \times Post_t + \\ & \gamma_i + \sigma_s + \tau_t + \sum_j \lambda_j \mathbb{1}_{[tenure_{it}=j]} + \epsilon_{ist} \end{aligned} \tag{4}$$

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. I conduct this analysis for both green and non-green patents. Table 7 presents the regression results, and Figure 9 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 green and non-green patents. Furthermore, tests confirm that the point estimates for β_m are significantly different between the first and third tertiles for both innovation types. For 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. Similar results also hold for all patents (see Appendix columns 3 in Table A2 and Figure A3).

6 Are Firms behind the Differential Effects of Katrina?

In this section, I seek to understand whether the differential effects of Katrina on inventors' output of green and non-green patents are driven by firm-level decision making. Firms may have been more likely to shy away from green R&D than from non-green R&D if they became financially constrained and more risk-averse following Hurricane Katrina.

Langer, Lemoine, Martin, and Verhoeven (2022) find green innovation has higher but more dispersed returns, making them riskier than the non-green alternative. Their quantitative counterfactual analysis suggests that financial constraints following the Great Recession depressed green innovation, as such restrictions increased risk aversion among investors and innovators, particularly when faced with riskier green projects. Similarly, in the aftermath of Katrina, firms may have faced financial pressures and became more risk averse, pushing them to avoid riskier green innovation.

However, firms may also have the incentives to increase investment in green R&D if they expect the increase in the market demand for green product. 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., 2023). Additionally, Inventors' human capital is 5–10 times more important than firm capabilities for explaining the variance in inventor output (Bhaskarabhatla et al. 2021). Therefore, the decline in inventors' green innovation output following Katrina, while non-green innovation remained unaffected, may not be entirely attributable to firms

To investigate whether firms contributed to the differential effects of Hurricane Katrina on inventors' green and non-green patent output, I examine the assignee information in patent applications. A patent assignee is an entity or individual that receives the rights to a patent or application from the original owner.[22] In my sample, the vast majority of assignees — 96.8% — are firms. To capture the potential firm-level effects, I include assignee or assignee-year fixed effects in the model specification (1).[23]

Panel A and B in Table 8 present the results of including assignee or assignee-year fixed effects for green and non-green patents, respectively. Columns 1-2 show results with assignee fixed effects, while columns 3-4 include assignee-year fixed effects. For green patents, the negative effects are robust to the inclusion of assignee fixed effects (columns 1-2 in Panel A), with an increase in magnitude. When assignee-year fixed effects are included (columns 3-4 in Panel A), the negative estimates become marginally significant. Especially,

[22]Patent assignments are a legal way to transfer ownership of a patent from the inventor to a business or other entity.

[23]If an inventor is associated with multiple assignees in a given year, the modal assignee will be assigned to the inventor for that year.

the standard errors increases substantially. This is due to the inclusion of assignee-year fixed effects, which leads to a drop of over 30% in the number of observations, reducing the sample size from over 100,000 to below 70,000. Additionally, there is also high correlation between the Treatment × Post variable and the assignee-year fixed effects.[24] However, the magnitude of point estimates in columns 3-4 are similar to those in columns 1-2 in Panel A. For non-green patents, all results in Panel B are not statistically significant, except in column 2. However, the estimate -0.084 in column 2 is not economically meaningful, when compared to the mean of non-green patents before Katrina, i.e., 2.084. Therefore, it is hard to look at the evidence presented so far and conclude that firms drive the differential effects of Katrina on inventors' output of green and non-green patents.

7 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

[24] The R^2 from the regression of Treatment X Post on assignee-year fixed effects is 0.7899.

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. Additionally, I find that the differential effects of Hurricane Katrina on inventors' green and non-green patent output are not driven by firms, by estimating with additional assignee or assignee-year fixed effects. These results suggest 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.

In the end, this paper raises as many questions as it answers. It would be interesting to know whether collaborators of inventors affected by Katrina produced more green innovation. The indirect exposure to a natural disaster, experienced through connections with directly impacted inventors, might increase collaborators' environmental awareness without disrupting their capacity to innovate. While I document the negative impact on green innovation of direct exposure to a destructive natural disaster, a comprehensive welfare analysis should also consider the potential benefits that indirect exposure might provide.

All of the evidence I have presented focus on individual inventors, leaving open the question of how firms respond to disruptions, such as destructive natural disasters, in terms of innovation. Large firms, with broader pools of inventors and dispersed R&D

locations, might be more resilient and experience less disruption, whereas smaller, locally concentrated firms may suffer declines in both green and non-green innovation activities. Exploring these dynamics could provide further insights into the broader economic impact of disruptions to knowledge production on innovation and resilience in green technology.

References

[1] Acemoglu, Daron, et al. "The environment and directed technical change." American economic review 102.1 (2012): 131-166.

[2] Acevedo, Sebastian, et al. "The effects of weather shocks on economic activity: what are the channels of impact?." Journal of Macroeconomics 65 (2020): 103207.

[3] Adams, James D., et al. "Scientific teams and institutional collaborations: Evidence from US universities, 1981–1999." Research policy 34.3 (2005): 259-285.

[4] Aghion, Philippe, et al. "Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry." Journal of Political Economy 124.1 (2016): 1-51.

[5] Aghion, Philippe, et al. "Environmental preferences and technological choices: Is market competition clean or dirty?." American Economic Review: Insights 5.1 (2023): 1-19.

[6] Akcigit, Ufuk, et al. "Taxation and innovation in the twentieth century." The Quarterly Journal of Economics 137.1 (2022): 329-385.

[7] Akcigit, Ufuk, Salomé Baslandze, and Stefanie Stantcheva. "Taxation and the international mobility of inventors." American Economic Review 106.10 (2016): 2930-2981.

[8] Azoulay, Pierre, Joshua S. Graff Zivin, and Jialan Wang. "Superstar extinction." The Quarterly Journal of Economics 125.2 (2010): 549-589.

[9] Ballesteros, Luis. "Fluctuations in Innovation after Natural Disasters: Evidence from Hurricane Katrina." Academy of Management Proceedings. Vol. 2022. No. 1. Briarcliff Manor, NY 10510: Academy of Management, 2022.

[10] Barbieri, Nicolò, Alberto Marzucchi, and Ugo Rizzo. "Knowledge sources and impacts on subsequent inventions: Do green technologies differ from non-green ones?." Research Policy 49.2 (2020): 103901.

[11] Bell, Alex, et al. "Who becomes an inventor in America? The importance of exposure to innovation." The Quarterly Journal of Economics 134.2 (2019): 647-713.

[12] Bernile, Gennaro, Vineet Bhagwat, and P. Raghavendra Rau. "What doesn't kill you will only make you more risk-loving: Early-life disasters and CEO behavior." The Journal of Finance 72.1 (2017): 167-206.

[13] Bhaskarabhatla, Ajay, et al. "Are inventors or firms the engines of innovation?." Management Science 67.6 (2021): 3899-3920.

[14] Bordalo, Pedro, et al. "Memory and probability." The Quarterly Journal of Economics 138.1 (2023): 265-311.

[15] Blake, Eric S. et al. "The deadliest, costliest, and most intense United States tropical cyclones from 1851 to 2010 (and other frequently requested hurricane facts)".NOAA technical memorandum NWS NHC (2011)

[16] Botzen, WJ Wouter, Olivier Deschenes, and Mark Sanders. "The economic impacts of natural disasters: A review of models and empirical studies." Review of Environmental Economics and Policy (2019).

[17] Carrillo-Hermosilla, Javier, Pablo Del Río, and Totti Könnölä. "Diversity of eco-innovations: Reflections from selected case studies." Journal of cleaner production 18.10-11 (2010): 1073-1083.

[18] Colmer, Jonathan. "Temperature, labor reallocation, and industrial production: Evidence from India." American Economic Journal: Applied Economics 13.4 (2021): 101-124.

[19] Dechezleprêtre, Antoine, Ralf Martin, and Myra Mohnen. "Knowledge spillovers from clean and dirty technologies: A patent citation analysis." (2022).

[20] Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. "Temperature shocks and economic growth: Evidence from the last half century." American Economic Journal: Macroeconomics 4.3 (2012): 66-95.

[21] De Marchi, Valentina. "Environmental innovation and RD cooperation: Empirical evidence from Spanish manufacturing firms." Research policy 41.3 (2012): 614-623.

[22] de Solla Price, Derek J. Little Science, Big Science. Columbia University Press, 1963.

[23] Dugoua, Eugenie, and Todd Gerarden. Induced innovation, inventors, and the energy transition. No. w31714. National Bureau of Economic Research, 2023.

[24] Elliott, Robert JR, Eric Strobl, and Puyang Sun. "The local impact of typhoons on economic activity in China: A view from outer space." Journal of Urban Economics 88 (2015): 50-66.

[25] Emanuel, Kerry. "Increasing destructiveness of tropical cyclones over the past 30 years." Nature 436.7051 (2005): 686-688.

[26] Florida, Richard. "Lean and green: the move to environmentally conscious manufacturing." California management review 39.1 (1996): 80-105.

[27] Fusillo, Fabrizio. "Green Technologies and diversity in the knowledge search and output phases: Evidence from European Patents." Research Policy 52.4 (2023): 104727.

[28] Ghisetti, Claudia, Alberto Marzucchi, and Sandro Montresor. "The open eco-innovation mode. An empirical investigation of eleven European countries." Research policy 44.5 (2015): 1080-1093.

[29] Goolsbee, Austan. "Does government R&D policy mainly benefit scientists and engineers?." The American Economic Review 88.2 (1998): 298-302.

[30] Gozen, Ruveyda Nur. "Property Rights and Innovation Dynamism: The Role of Women Inventors." (2024)

[31] Graumann, Axel, Tamara Houston, Jay Lawrimore, David Levinson, Neal Lott, Sam McCown, Scott Stephens, and David Wuertz (2005). "Hurricane Katrina: A Climatological Perspective." US Department of Commerce NOAA/NESDIS. Asheville, October.

[32] Haščič, Ivan, and Mauro Migotto. "Measuring environmental innovation using patent data." OECD Environmental Working Papers (2015).

[33] Hidalgo, César A., et al. "The product space conditions the development of nations." Science 317.5837 (2007): 482-487.

[34] Horbach, Jens, Vanessa Oltra, and Jean Belin. "Determinants and specificities of eco-innovations compared to other innovations—an econometric analysis for the French and German industry based on the community innovation survey." Industry and Innovation 20.6 (2013): 523-543.

[35] Hötte, Kerstin, Anton Pichler, and François Lafond. "The rise of science in low-carbon energy technologies." Renewable and sustainable energy reviews 139 (2021): 110654.

[36] Intergovernmental Panel on Climate Change (IPCC). "Weather and Climate Extreme Events in a Changing Climate." Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press, 2023. 1513–1766. Print.

[37] Jaravel, Xavier, Neviana Petkova, and Alex Bell."Team-specific capital and innovation." American Economic Review 108.4-5 (2018): 1034-1073.

[38] Jayachandran, Seema. "Selling labor low: Wage responses to productivity shocks in developing countries." Journal of political Economy 114.3 (2006): 538-575.

[39] Jones, Benjamin F. "The burden of knowledge and the "death of the renaissance man": Is innovation getting harder?." The Review of Economic Studies 76.1 (2009): 283-317.

[40] Jones, Benjamin F. "The rise of research teams: Benefits and costs in economics." Journal of Economic Perspectives 35.2 (2021): 191-216.

[41] Kaplan, Sarah, and Keyvan Vakili. "The double-edged sword of recombination in breakthrough innovation." Strategic Management Journal 36.10 (2015): 1435-1457.

[42] Kocornik-Mina, Adriana, et al. "Flooded cities." American Economic Journal: Applied Economics 12.2 (2020): 35-66.

[43] Koning, Rembrand, Sampsa Samila, and John-Paul Ferguson. "Who do we invent for? Patents by women focus more on women's health, but few women get to invent." Science 372.6548 (2021): 1345-1348.

[44] Langer, Ashley, et al. The Private Value of Clean Energy Innovation. Working Paper, 2022.

[45] Le, Huong, et al. "Natural disasters and corporate innovation." The European Journal of Finance (2023): 1-29.

[46] Malmendier, Ulrike, and Stefan Nagel. "Learning from inflation experiences." The Quarterly Journal of Economics 131.1 (2016): 53-87.

[47] Mealy, Penny, and Alexander Teytelboym. "Economic complexity and the green economy." Research Policy 51.8 (2022): 103948.

[48] Miao, Qing, and David Popp. "Necessity as the mother of invention: Innovative responses to natural disasters." Journal of Environmental Economics and Management 68.2 (2014): 280-295.

[49] Mohnen, Myra. "Stars and brokers: Knowledge spillovers among medical scientists." Management Science 68.4 (2022): 2513-2532.

[50] Moretti, Enrico, and Daniel J. Wilson. "The effect of state taxes on the geographical location of top earners: Evidence from star scientists." American Economic Review 107.7 (2017): 1858-1903.

Moscona, Jacob. "Environmental Catastrophe and the Direction of Invention: Evidence from the American Dust Bowl," Harvard University Working Paper (2022).

[51] Moscona, Jacob, and Karthik A. Sastry. "Does directed innovation mitigate climate damage? Evidence from US agriculture." The Quarterly Journal of Economics 138.2 (2023): 637-701.

[52] Mullainathan, Sendhil. "A memory-based model of bounded rationality." The Quarterly Journal of Economics 117.3 (2002): 735-774.

[53] NOAA National Centers for Environmental Information. "Monthly National Climate Report for August 2005." (2005). Retrieved on September 10, 2024 from https://www.ncei.noaa.gov/access/monitoring/monthly-report/national/200508.

[54] NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2024). https://www.ncei.noaa.gov/access/billions/, DOI: 10.25921/stkw-7w73

[55] Nordhaus, William D. "The economics of hurricanes in the United States." (2006).

[56] Oettl, Alexander. "Reconceptualizing stars: Scientist helpfulness and peer performance." Management science 58.6 (2012): 1122-1140.

[57] Oltra, Vanessa, and Maïder Saint Jean. "The dynamics of environmental innovations: three stylised trajectories of clean technology." Economics of Innovation and New Technology 14.3 (2005): 189-212.

[58] Orsatti, Gianluca, Francesco Quatraro, and Michele Pezzoni. "The antecedents of green technologies: The role of team-level recombinant capabilities." Research Policy 49.3 (2020): 103919.

[59] Pigato, Miria, et al. Technology transfer and innovation for low-carbon development. World Bank Publications, 2020.

[60] Popp, David. "Environmental policy and innovation: a decade of research." (2019).

[61] Popp, David, Richard G. Newell, and Adam B. Jaffe. "Energy, the environment, and technological change." Handbook of the Economics of Innovation 2 (2010): 873-937.

[62] Quatraro, Francesco, and Alessandra Scandura. "Academic inventors and the antecedents of green technologies. A regional analysis of Italian patent data." Ecological Economics 156 (2019): 247-263.

[63] Rennings, Klaus. "Redefining innovation—eco-innovation research and the contribution from ecological economics." Ecological economics 32.2 (2000): 319-332.

[64] Romer, Paul M. "Should the government subsidize supply or demand in the market for scientists and engineers?." Innovation policy and the economy 1 (2000): 221-252.

[65] Schumpeter, Joseph A.. *The Theory of Economic Development*. Harvard University Press, 1934.

[66] Somanathan, Eswaran, et al. "The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing." Journal of Political Economy 129.6 (2021): 1797-1827.

[67] U.S. Census Bureau. "Census Regions and Divisions of the United States." U.S. Census Bureau, 2024, www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf. Accessed 10 Sept. 2024.

[68] Van Reenen, John, and Agnes Norris Keiller. Disaster management. No. w32595. National Bureau of Economic Research, 2024.

[69] Weitzman, Martin L. "Recombinant growth." The Quarterly Journal of Economics 113.2 (1998): 331-360.

[70] Winter, Sidney G. "Schumpeterian competition in alternative technological regimes." Journal of Economic Behavior Organization 5.3-4 (1984): 287-320.

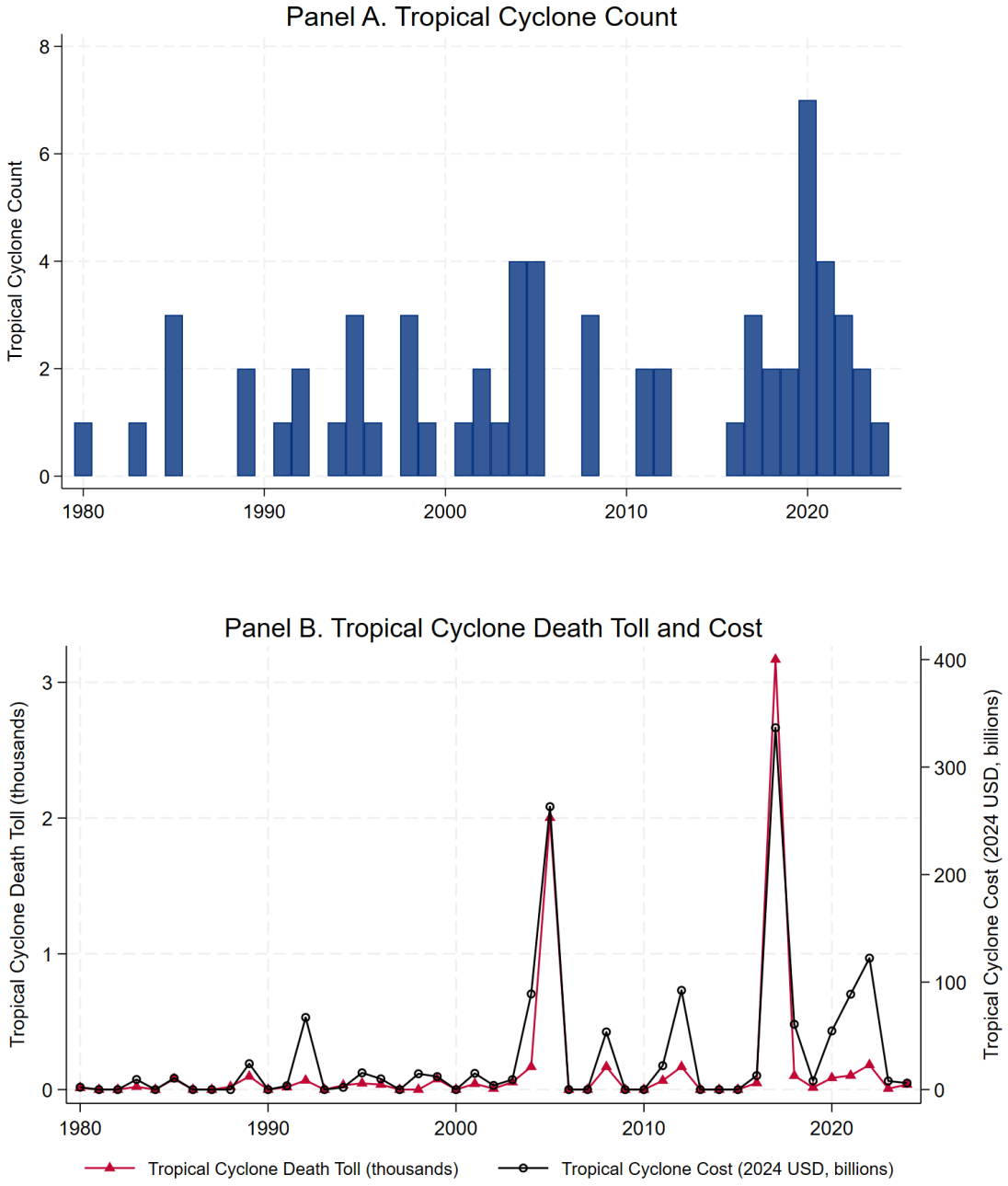
[71] World Meteorological Association. WMO atlas of mortality and economic losses from weather, climate and water extremes (1970–2019). Technical Report, 2021.

[72] Wuchty, Stefan, Benjamin F. Jones, and Brian Uzzi. "The increasing dominance of teams in production of knowledge." Science 316.5827 (2007): 1036-1039.

[73] Zhao, Xin-Xin, Mingbo Zheng, and Qiang Fu. "How natural disasters affect energy innovation? The perspective of environmental sustainability." Energy Economics 109 (2022): 105992.

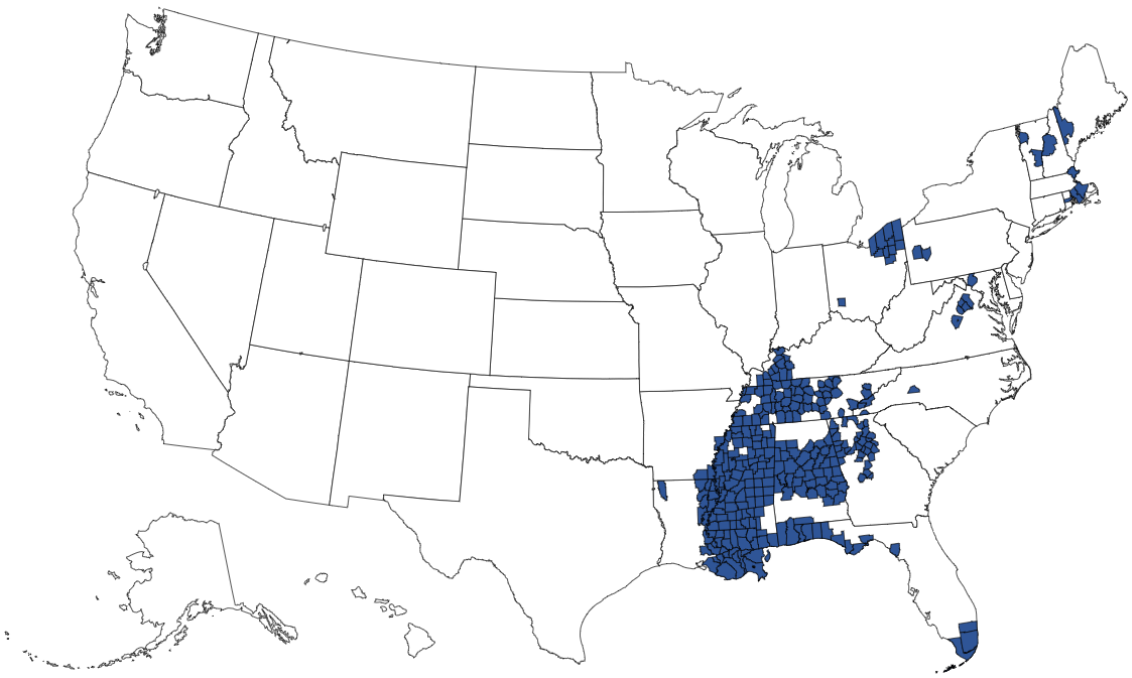
8 Figures

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.

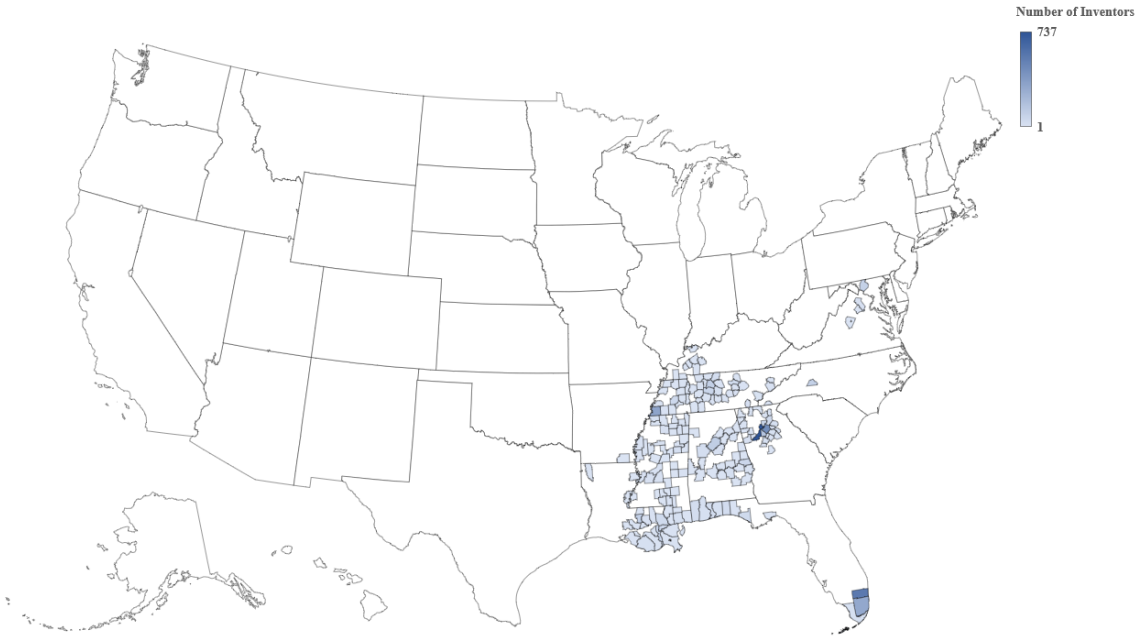
Figure 2: Geographical Distribution of Counties Affected by Katrina



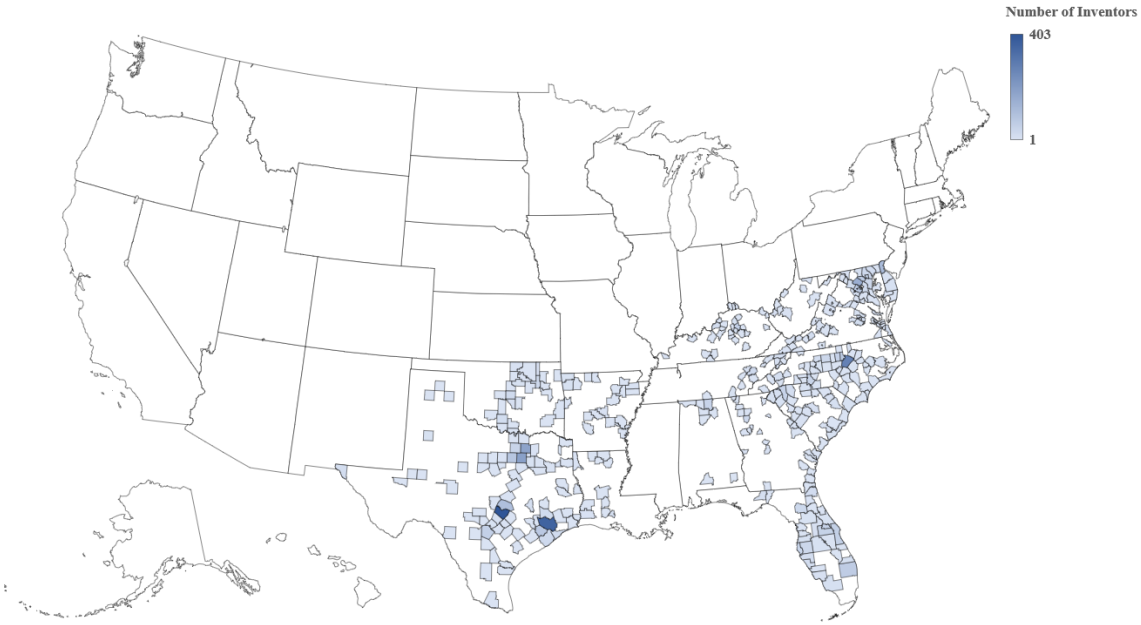
Notes: This figure illustrates the geographical distribution of counties that incurred property damage from Hurricane Katrina, with affected counties highlighted in blue. The majority of the damage is concentrated in the Southern United States, with impacts extending to northeastern regions due to Katrina-related 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 3.1.

Figure 3: Geographical Distribution of Treatment and Control Groups

Panel A. Treatment Group

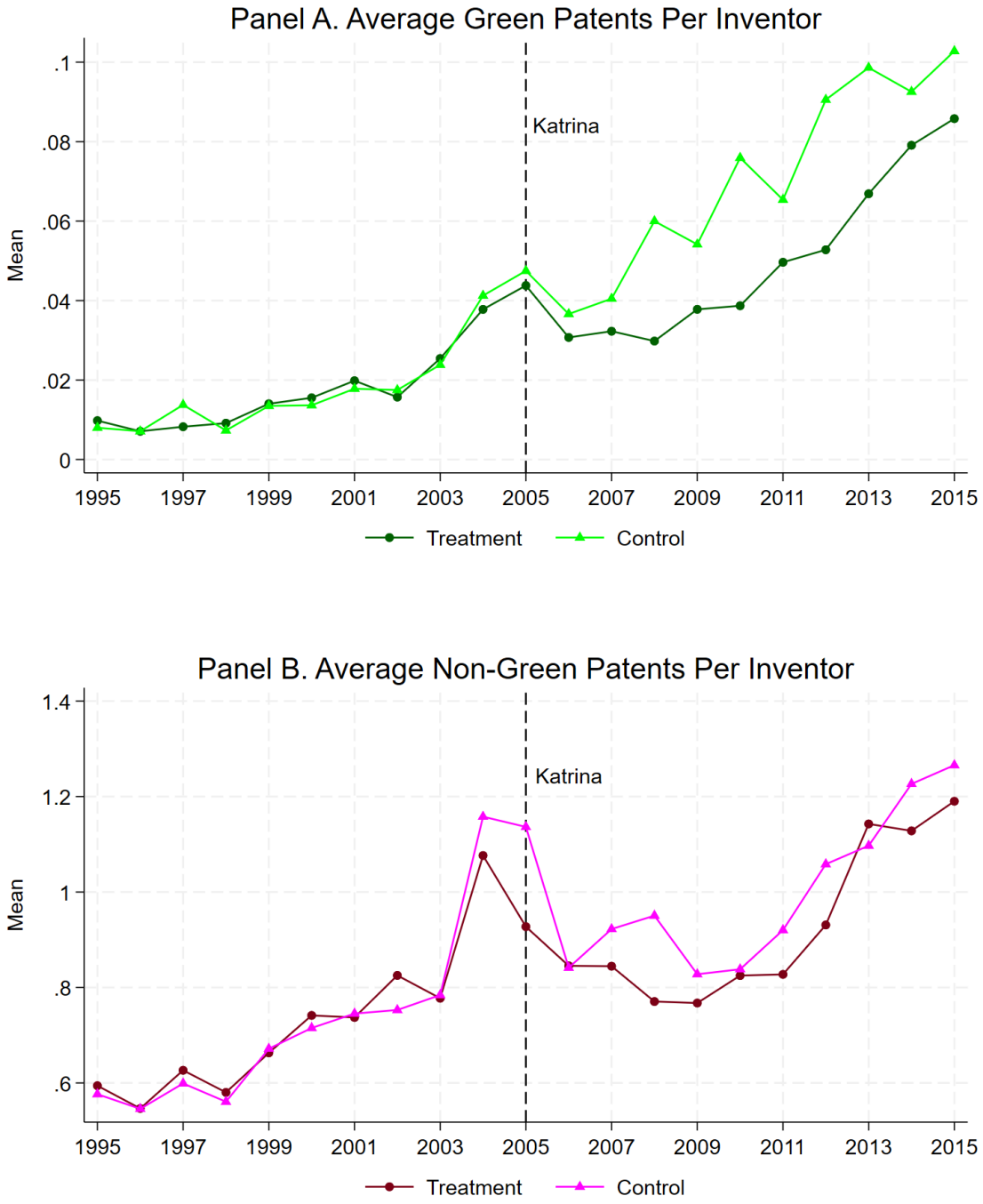


Panel B. Control Group



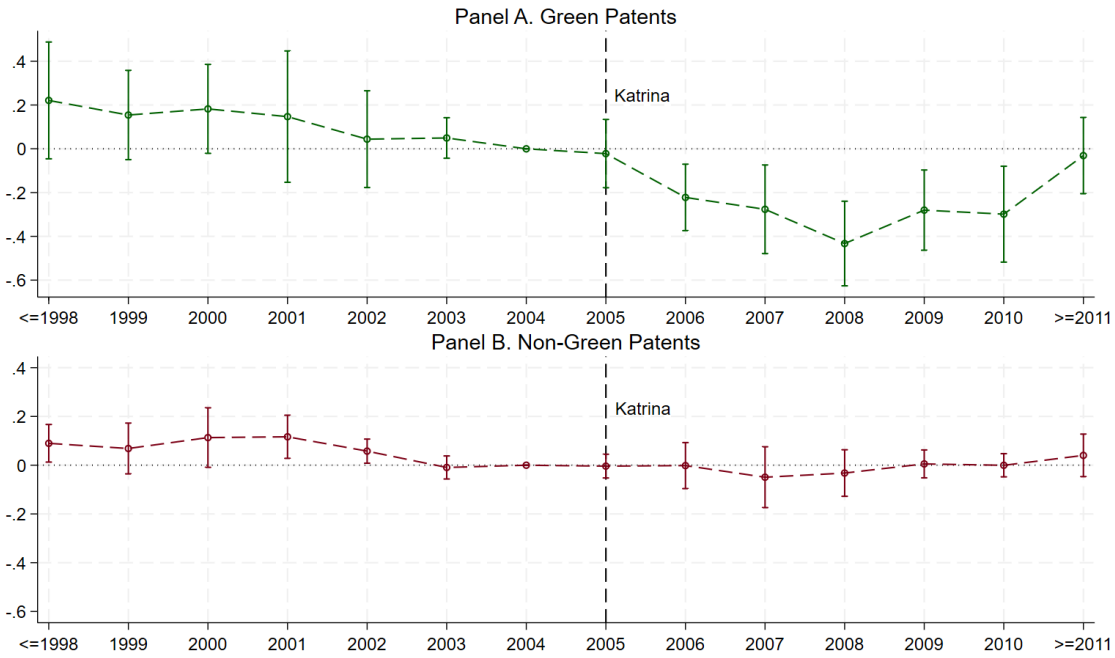
Notes: Panels A and B of this figure show the geographical distribution of treated and control inventors at the county level, respectively. Section 3.2 provides the definitions of the treatment and control groups.

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



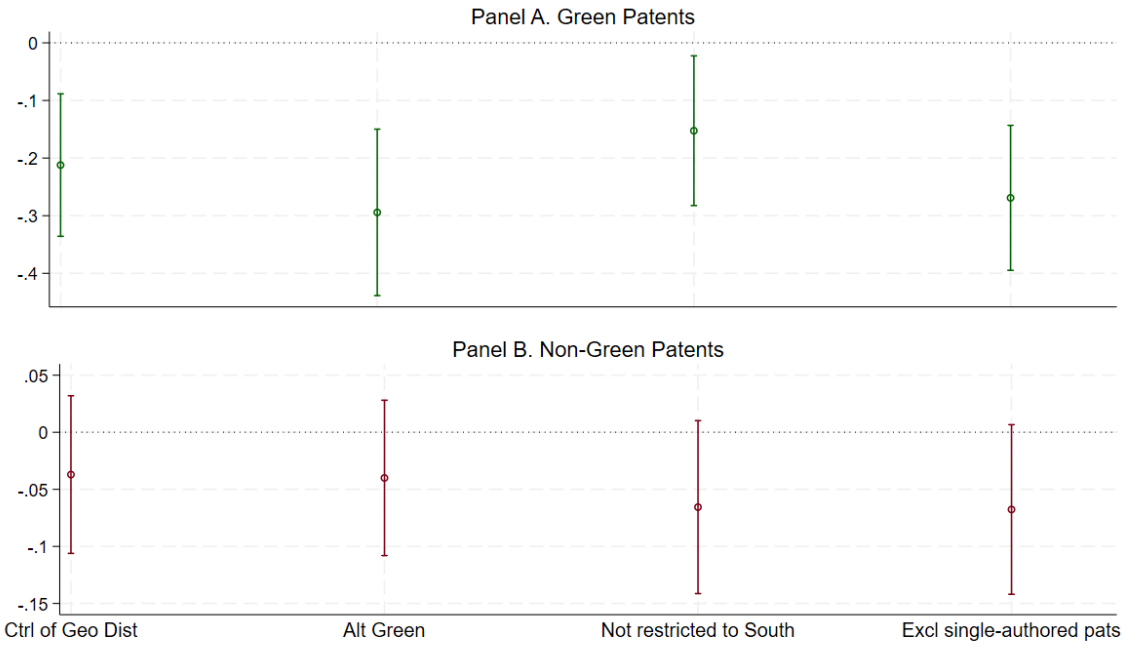
Notes: Panels A and B of this figure display the trends in mean green and non-green patents for treated and control inventors around 2005, the year Hurricane Katrina occurred. The sample inventors were selected based on their patent applications during 2004-2005, which accounts for an observed spike in patent activity during these years. Section 3.2 provides the definitions of the treatment and control groups.

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



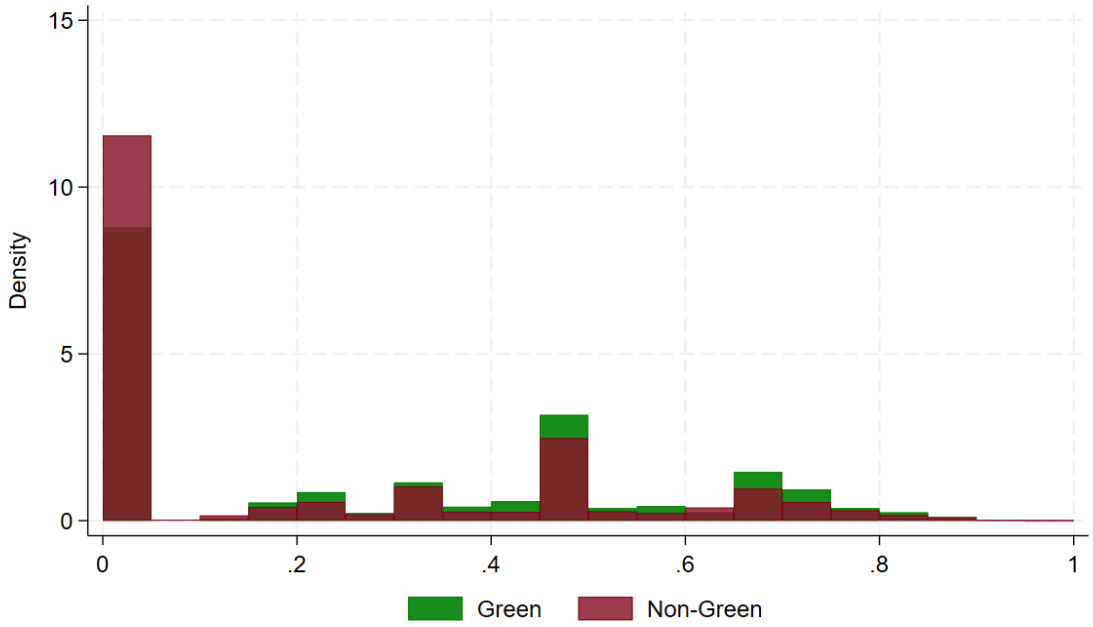
Notes: Panels A and B of this figure show the estimated coefficients β_m, β_{1998} and β_{2011} from Poisson specification (2) for two outcome variables – green and non-green patent counts, which aggregate over three years: between period t and t + 2. This specification includes inventor, tenure, state and year fixed effects. Tenure is measured as as the number of years that have passed since the inventor's first successful patent application. Standard errors are clustered at the state and year level. For more details on the specification, refer to Section 3.3.

FIGURE 6. ROBUSTNESS



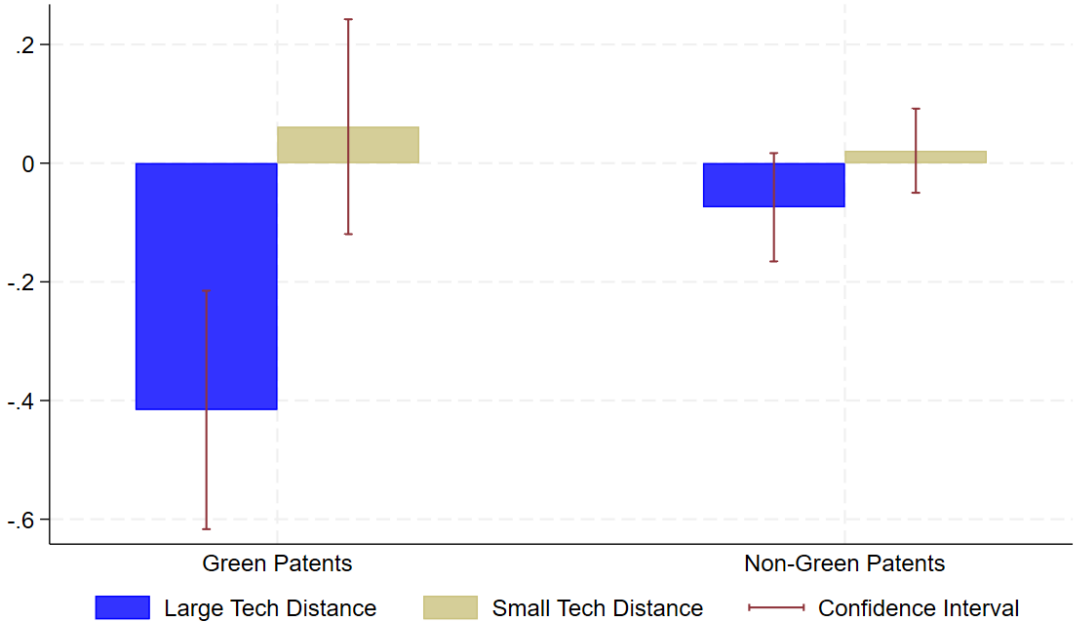
Notes: Panels A and B of this figure plot the estimated coefficient β_1 from Poisson specification (1) for four robustness exercises: 1. Controlling geographical distance of sample inventors with co-inventors; 2. Using the alternative definition of green patents, based on the OECD ENV-TECH classification ((Haščič and Migotto 2015); 3. Not restricting control inventors to the South US; 4. Excluding solo-inventor patents. The outcome variables are 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. Standard errors are clustered at the state and year level. For more details on the specification, refer to Section 3.3.

Figure 7. Distribution of Average Technological Distance within a Patent Team for Green vs Non-Green



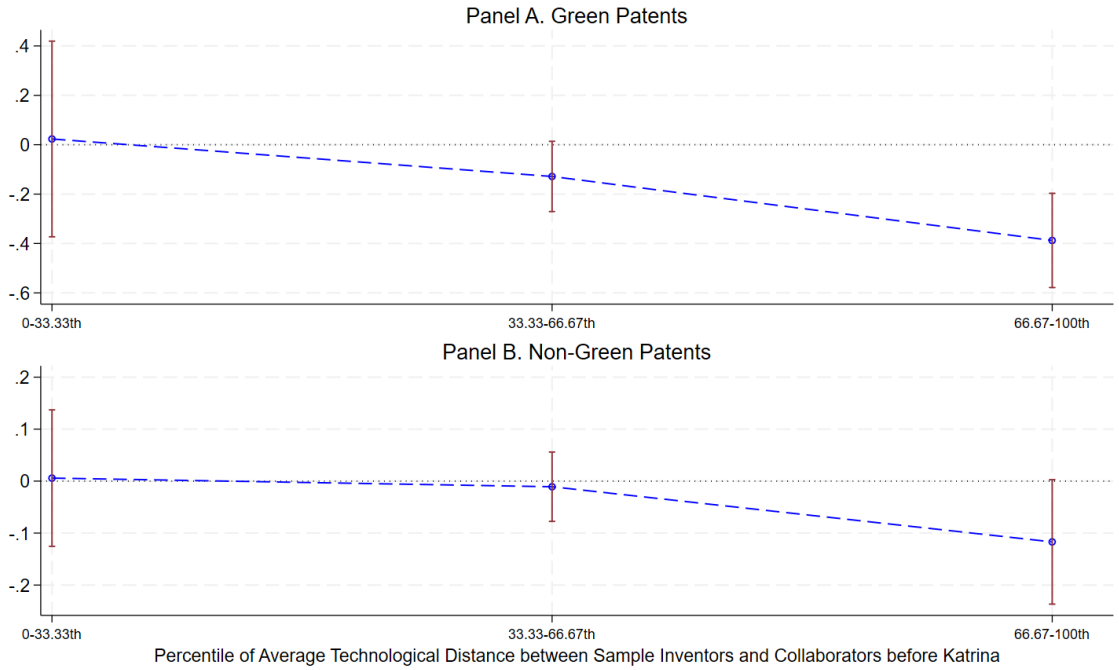
Notes: This figure shows the distribution of average technological distance within a patent team for green and non-green patents produced by sample inventors before Katrina. Section 5.2 details the methodology for measuring technological distance between two inventors. The average technological distance 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 8. Differential Effects on Patents of Large vs. Small 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. Both aggregate over three years: between period t and t + 2. 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 5.2 provides a detailed explanation of the methodology used to measure technological distance between two inventors. The analysis is conducted for both green and non-green patents, using the Poisson estimation method. Standard errors are clustered at the state and year levels. For more details on the specification, refer to Section 3.3.

FIGURE 9. HETEROGENEITY BY TECHNOLOGICAL DISTANCE WITH COLLABORATORS BEFORE KATRINA



Notes: Panels A and B of this figure plot the estimated coefficients β_m from specification (4) for green and non-green patents, 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 5.2 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 5.5.

9 Tables

Table 1. Summary Statistics on Inventors

Variable	Sample	Mean	SD
Yearly green patent counts	Full sample	0.073	0.489
	Treatment	0.019	0.145
	Control	0.019	0.148
Yearly 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 yearly 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 3.1 and 3.2.

Table 2. Effects of Katrina on Inventors' Patent Production

	Green Patents		Non-Green Patents	
	(1)	(2)	(3)	(4)
Treatment × Post	-0.212***	-0.220***	-0.0296	-0.0419
	(0.0404)	(0.0646)	(0.0394)	(0.0349)
Mean of dep. var Before Katrina	0.053	0.053	2.084	2.084
Observations	102,622	102,621	102,378	102,377
Inventor FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes
Tenure FE	No	Yes	No	Yes
Method	Poisson	Poisson	Poisson	Poisson

Notes: This table reports the estimated coefficients β_1 from specification (1) for green patents (column 1-2) and non-green patents (column 3-4), respectively. The dependent variable is patent counts aggregated over a three-year period, from year t to t + 2. The variable *tenure* is measured as the number of years that have passed since the inventor's first successful patent application. Column 2 and 4 include the full set of fixed effects for tenure, inventor, year, and state. Standard errors clustered at the state and year level are reported in parentheses. For more details on the specification, refer to Section 3.3. *** p<0.01, ** p<0.05, * p<0.1

Table 3. Extensive and intensive margin

	Green Patents		Non-Green Patents	
	Has Any Patent over Three Years	Log(Patent Counts over Three Years)	Has Any Patent over Three Years	Log(Patent Counts over Three Years)
	(1)	(2)	(3)	(4)
Treatment × Post	-0.0129**	-0.116**	-0.0098	-0.00317
	(0.00595)	(0.0429)	(0.0119)	(0.031)
Mean of dep. var Before Katrina	0.041	0.166	0.726	0.744
Observations	102,621	6,749	102,621	75,126
Inventor FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes
Tenure FE	No	Yes	No	Yes
Method	OLS	OLS	OLS	OLS

Notes: This table reports the estimated coefficients β_1 from specification (1) for green patents and non-green patents, respectively. To capture intensive- and extensive-margin responses to Hurricane Katrina, I construct two dependent variables, both measured over a three-year window between and including years t and t+2 (Akcigit et al. 2022): (i) having any patent or not; (ii) 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. The estimation method is OLS. Standard errors clustered at the state and year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 4. ROBUSTNESS

	(1) Controlling geo distance with co-inventors	(2) Alt definition of green	(3) Control group not restricted to South	(4) Excluding solo-inventor patents
Panel A: Green patents				
Treatment × Post	-0.212***	-0.294***	-0.152**	-0.269***
	(0.063)	(0.074)	(0.066)	(0.064)
Mean of dep. var before Katrina	0.053	0.053	0.053	0.053
Observations	102,621	102,621	102,621	102,621
Year fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Inventor fixed effects	Yes	Yes	Yes	Yes
Tenure fixed effects	Yes	Yes	Yes	Yes
Estimation method	Poisson	Poisson	Poisson	Poisson
Panel B: Non-green patents				
Treatment × Post	-0.037	-0.040	-0.065*	-.068*
	(0.035)	(0.035)	(0.038)	(0.038)
Mean of dep. var before Katrina	2.084	2.084	2.084	2.084
Observations	102,621	102,621	102,621	102,621
Year fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Inventor fixed effects	Yes	Yes	Yes	Yes
Tenure fixed effects	Yes	Yes	Yes	Yes
Estimation method	Poisson	Poisson	Poisson	Poisson

Notes: This table reports estimated coefficient β_1 from Poisson specification (1) for four robustness exercises: 1. Controlling geographical distance of sample inventors with co-inventors; 2. Using the alternative definition of green patents, based on the OECD ENV-TECH classification ((Haščič and Migotto 2015); 3. Not restricting control inventors to the South US; 4. Excluding solo-inventor patents. The outcome variables are 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. Standard errors clustered at the state and year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Difference in Technological Distance between Green and Non-Green Patents

	(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
Year fixed effects	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
CPC 3-digit fixed effects	Yes	Yes	Yes

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 5.2 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 6. Differential Effects on Patents of Small vs. Large Technological Distance

	Green patents		Non-Green patents	
	Large	Small	Large	Small
	(1)	(2)	(3)	(4)
Treatment × Post	-0.416***	0.0614	-0.0744	0.0210
	(0.103)	(0.0924)	(0.0466)	(0.0362)
Observations	102,621	102,621	102,621	102,621
Year fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Inventor fixed effects	Yes	Yes	Yes	Yes
Tenure fixed effects	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. Both aggregate over three years: between period t and t + 2. 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 5.2 provides a detailed explanation of the methodology used to measure technological distance between two inventors. The analysis is conducted across green and non-green patents, 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 7. Heterogeneity by Technological Distance with Collaborators before Katrina

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

Notes: This table reports the estimated coefficients β_m from specification (4) for green and non-green patents, respectively. The tertiles are computed based on the average technological distance between sample inventors and their collaborators before Katrina. Section 5.2 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

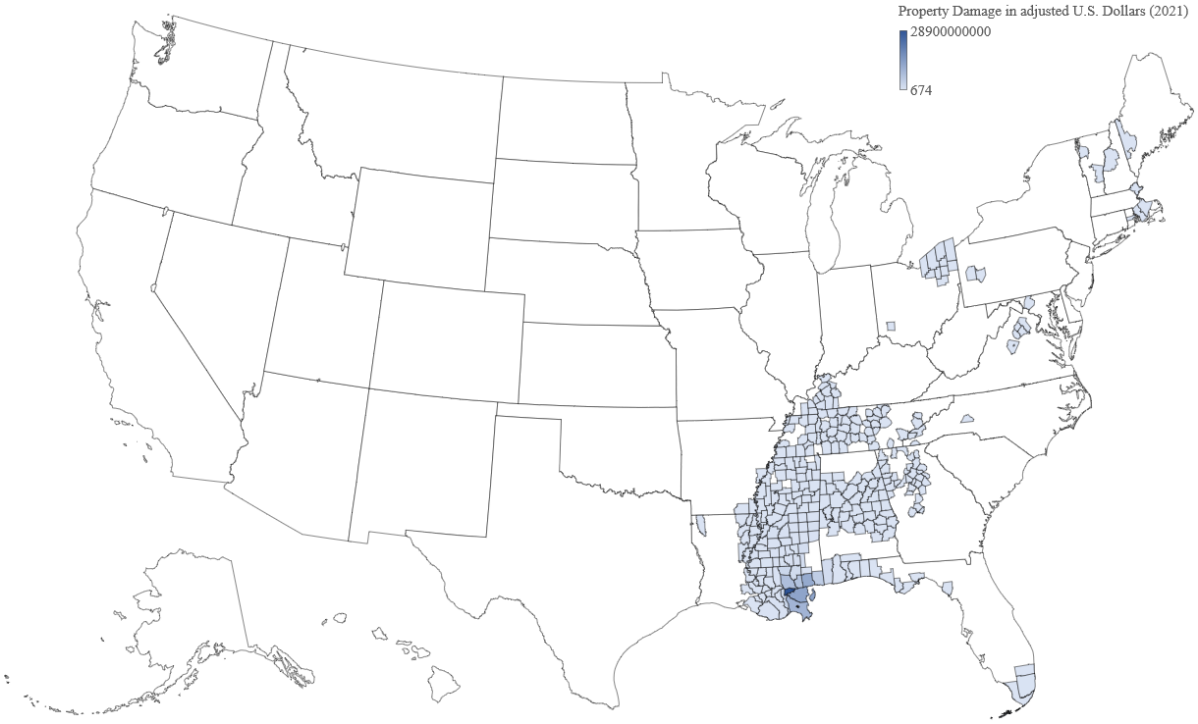
Table 8. Effects of Katrina with Assignee or Assignee-Year Fixed Effects

	(1)	(2)	(3)	(4)
Panel A: Green Patents				
Treatment × Post	-0.390***	-0.347***	-0.303*	-0.310
	(0.0874)	(0.102)	(0.157)	(0.234)
Mean of dep. var Before Katrina	0.053	0.053	0.053	0.053
Observations	102,461	101,280	69,216	67,658
Assignee FE	Yes	Yes	No	No
Assignee-Year FE	No	No	Yes	Yes
Inventor FE	No	Yes	No	Yes
Year FE	No	Yes	No	No
State FE	No	Yes	No	Yes
Tenure FE	No	Yes	No	Yes
Method	Poisson	Poisson	Poisson	Poisson
Panel B: Non-Green Patents				
Treatment × Post	-0.0733	-0.0840**	0.0296	-0.102
	(0.0696)	(0.041)	(0.108)	(0.0871)
Mean of dep. var Before Katrina	2.084	2.084	2.084	2.084
Observations	102,461	101,280	69,216	67,658
Assignee FE	Yes	Yes	No	No
Assignee-Year FE	No	No	Yes	Yes
Inventor FE	No	Yes	No	Yes
Year FE	No	Yes	No	No
State FE	No	Yes	No	Yes
Tenure FE	No	Yes	No	Yes
Method	Poisson	Poisson	Poisson	Poisson

Notes: Panel A and B of this table report the point estimates for the coefficient β_1 from specification (1) with assignee fixed effects (column 1-2) or assignee-year (column 3-4) fixed effects, for green and non-green patents, respectively. The dependent variable is patent counts aggregated over a three-year period, from year t to t + 2. The variable *tenure* is measured as the number of years that have passed since the inventor's first successful patent application. Column 2 and 4 include the full set of fixed effects for tenure, inventor, year, and state. Standard errors clustered at the state and year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

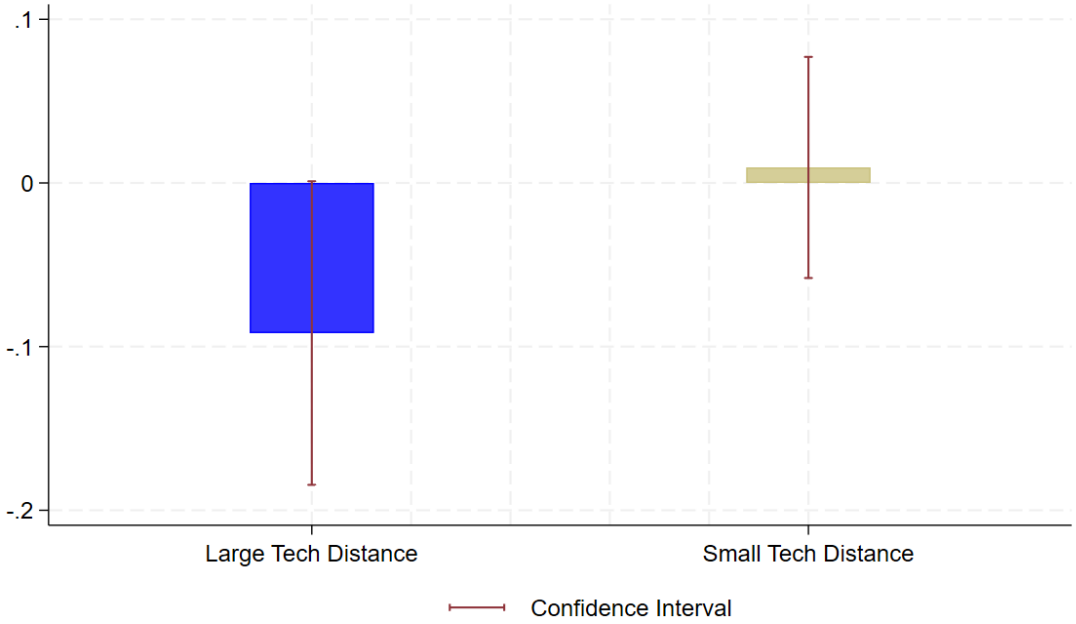
A Appendix Figures

Figure A1. Geographical Distribution of Property Damage by Katrina



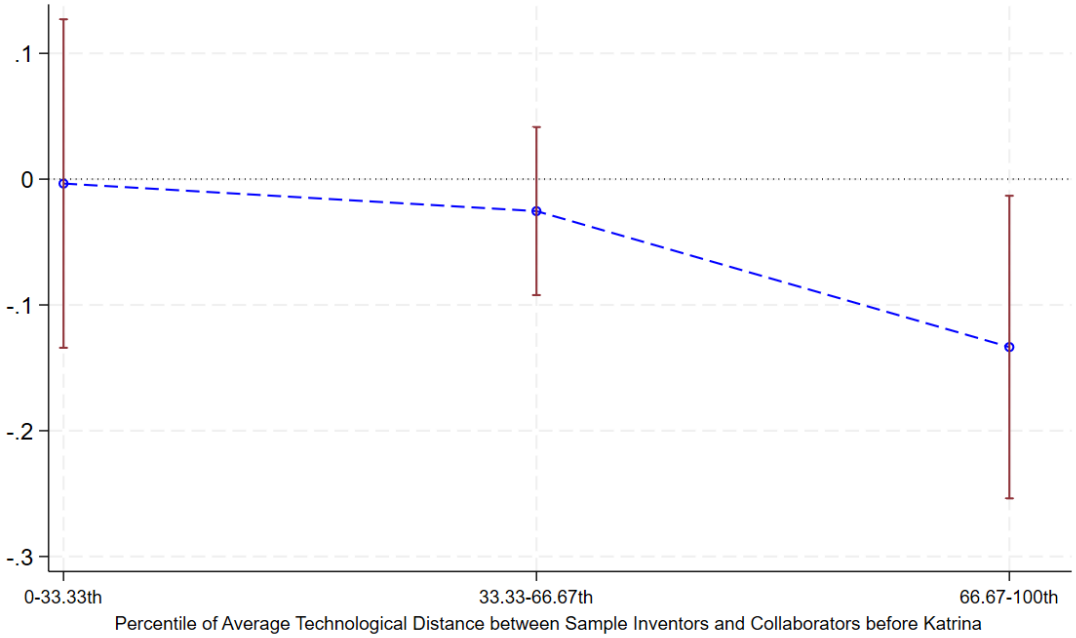
Notes: This figure illustrates the geographical distribution of property damage caused by Hurricane Katrina at the county level, with damage amounts adjusted to 2021 dollars. The shading intensifies from light to dark blue to indicate increasing levels of damage, with the darkest blue representing the 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 3.1.

Figure A2. Differential Effects on Patents of Small vs. Large Technological Distance for All Patents



Notes: This table the estimated coefficients 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. Both aggregate over three years: between period t and t + 2. 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 5.2 provides a detailed explanation of the methodology used to measure technological distance between two inventors. The analysis is performed using the Poisson estimation method. Standard errors are clustered at the state and year levels. For more details on the specification, refer to Section 3.3.

FIGURE A3. HETEROGENEITY BY TECHNOLOGICAL DISTANCE WITH COLLABORATORS BEFORE KATRINA FOR ALL PATENTS



Notes: This figure plots the estimated coefficients β_m from specification (4) for all patents. 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 5.2 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 5.5.

B Appendix Tables

Table A1. Effects of Katrina on All Patents

Dependent variable	(1) Patent counts over three years	(2) Has any patents over three years	(3) Log (patent counts over three years)
Treat × Post	-0.0564	-0.00911	-0.00943
	(0.0344)	(0.0112)	(0.0321)
Observations	102,621	102,621	76,852
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	2.619	0.748	0.853

Notes: This table reports the estimated coefficients β_1 from specification (1) for all patents. 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. Column 1 is estimated with Poisson and column 2-3 with OLS. All columns include the full set of fixed effects for tenure, inventor, year, and state. 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 A2. Heterogeneous Effects of Katrina on All Patents

	(1) Patents of large tech distance	(2) Patents of small tech distance	(3) Heterogeneity by tech distance with collaborators before Katrina
Treatment × Post	-0.0917*	0.00947	
	(0.0473)	(0.0345)	
First tertile × Treatment × Post			-0.00350
			(0.0666)
Second tertile × Treatment × Post			-0.0254
			(0.0341)
Third tertile × Treatment × Post			-0.134**
			(0.0614)
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 heterogeneous effects of Katrina on all patents. All dependent variables aggregate over three years: between period t and t + 2. Column 1-2 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. Column 3 reports estimated coefficients β_m from specification (4). The tertiles are computed based on the average technological distance between sample inventors and their collaborators before Katrina. Section 5.2 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