Heterogeneous Expertise and Innovation Resilience: Evidence from Inventors' Green Innovation Response to Hurricane Katrina

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Abstract

This paper studies how exogenous disruptions to knowledge production affect the resilience of innovation when production relies on heterogeneous expertise. I focus on green innovation, an important technology for combating climate change, which draws on diverse knowledge and thus requires collaboration among inventors with heterogeneous expertise. Exploiting physical exposure to Hurricane Katrina, the costliest storm in U.S. history, as a quasi-natural experiment, I combine hazard and patent data for U.S. inventors in a difference-in-differences design. The results show that Katrina reduced the production of green patents by physically exposed inventors, while non-green patents were unaffected. The negative effects are more pronounced for patents produced by teams with greater technological distance and for inventors with more technologically distant collaborators before Katrina. These findings suggest that the heterogeneity of expertise, while beneficial for knowledge creation, can reduce the substitutability of directly disrupted inventors' expertise and thereby undermine the resilience of technological development in the face of disruption.

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1 Introduction

Innovation is often the result of collaboration among individuals with specialized and different expertise working together (Wuchty, Jones, and Uzzi 2007; Jones 2009; Jones 2021). Teams with heterogeneous expertise create more novel knowledge and breakthrough innovation (Fleming 2001; Singh and Fleming 2010; Uzzi et al. 2013; Fortunato et al. 2018). However, productively combining such heterogeneity may also entail costs. For instance, it can increase difficulty in substituting individual specialized expertise when disruptions occur. Prior research shows that disruptions to this knowledge production process, such as the deaths or emigration of collaborators, can significantly reduce inventors' or scientists' innovation productivity (Azoulay, Graff Zivin, and Wang 2010; Oettl 2012; Borjas and Doran 2015; Jaravel, Petkova, and Bell 2018). Yet these studies often do not consider the heterogeneity in expertise among collaborators and therefore do not account for how variation in expertise within teams shapes individual inventors' innovation output responses to disruptions.

Not all types of innovation require the same degree of heterogeneity in knowledge. The focus of this paper is green innovation, which addresses climate change.[1] It is an important and rapidly emerging area of innovation, given the urgency of global environmental challenges. Green technology draws on knowledge from a broader and more diverse range of technological areas (greater knowledge diversity) than its non-green counterpart.[2] To produce green innovation, individual inventors may need to work with collaborators who are more distant from themselves in terms of technological expertise. For example, geothermal technology involves collaboration among experts in geophysics, mechanical engineering, and data science.

The disruptive event used for identification is Hurricane Katrina, which serves as a quasi-natural experiment and provides quasi-exogenous variation in inventors' physical exposure to disruption. The 2005 storm, that resulted in $200 billion in damages, is the costliest tropical cyclone in the US history.[3] Unlike death of star scientists and co-inventors(Azoulay et al. 2010; Jaravel et al. 2018), which causes the permanent loss of top-down knowledge spillover and team-specific capital, such an extremely damaging disaster primarily temporarily disrupts researchers' ability to execute specialized tasks, by damaging homes, labo-

[1] Empirically, I use patent data to measure innovation and focus on Cooperative Patent Classification Y02 class to identify green patents. As robustness, I also use alternative definition of green patents, based on the OECD ENV-TECH classification (Haščič and Migotto 2015).

[2] According to the World Bank (Pigato et al. 2020), green technology tends to be more complex and multifaceted than its non-green counterparts, spanning across all economic sectors. See also De Marchi (2012), Barbieri et al. (2020), Orsatti et al. (2020), and Fusillo (2023) for empirical evidence on the broader technological scope of green innovation.

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

ratories, and local infrastructure. Studying such events is increasingly important today. Scientific evidence suggests that climate change has led to the increased intensity of natural disasters,[4] and hurricanes are becoming stronger and more destructive.[5] As the frequency and severity of such events rise, the potential for disruptions to knowledge production is likely to grow accordingly.

This paper empirically studies how physical exposure to Hurricane Katrina affects individual inventors' green versus non-green innovation outcomes. Direct exposure to natural disasters can significantly constrain inventors' research efforts by damaging their homes and workplaces, thereby disrupting their innovative activities and ultimately reducing innovation output. These negative effects are likely to be more severe for green innovation, which integrates knowledge from a wider range of technological areas than non-green innovation. Because of this greater knowledge diversity, inventors in green innovation teams tend to possess more varied technological expertise and fulfil more distinct roles, resulting in greater technological distance among collaborators.[6] When a disruption event, such as a natural disaster, strikes an individual inventor within a green innovation team, it will be harder for teammates to substitute so as to continue the directly disrupted inventor's technological tasks. Therefore, the development of green technology may be more negatively affected than non-green innovation, where the technological expertise among collaborators tends to be more similar and substitutable.

I use data on individual inventors' location and patenting activities from the United States Patent and Trademark Office (USPTO), combined with data on county-level property damage related to Katrina from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). 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, Grigsby, Nicholas, and Stantcheva 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

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

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

[6] 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.

(Jaravel, Petkova, and Bell 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, inventors in the treatment group produced, on average, 20.0% fewer green patents within a three-year period after 2005,[7] compared to the control group. In the absence of Hurricane Katrina, treated inventors would have produced an additional 0.0375 green patents on average.[8] I find similar effects of Katrina at extensive and intensive margin for green and non-green patents. In addition, I examine whether inventors who migrated after Katrina experienced different effects compared to those who did not migrate. The analysis finds no significant differential effects between migrant and non-migrant inventors. The findings suggests that natural disasters could impede the green transition by adversely affecting inventors' production 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.

I then investigate the mechanism behind the observed differential effects on green and non-green innovation. 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, Klinger, Barabási, and Hausmann 2007; Azoulay et al. 2010), I construct a distance metric in technological expertise. I show 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 investigate the role of firms behind the differential effects. Firms may become financially constrained following an extremely damaging disaster, which could disproportionately depress green innovation (Langer, Lemoine, Martin, and Verhoeven 2022; Aghion, Bergeaud, De Ridder, and Van Reenen 2024). However, I find that Hurricane Katrina did not have differential effects on firms' green and non-green innovation. These findings imply that new technologies,

[7] The outcome variable is measured as the number of patents filed over a three-year window. For details, see Section 3.3.

[8] The absolute number of green patents implied by the counterfactual is small because green patenting has a low baseline rate. Before Katrina, the average number of green patents over a three-year window was 0.05 for both the treatment and control groups. After Katrina, this average was 0.15 for the treatment group and 0.21 for the control group.

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 the literature on knowledge production. A large body of work shows that scientific and inventive output is increasingly produced through collaborations among individual inventors and scientists (Wuchty, Jones, and Uzzi 2007; Jones 2009; Uzzi et al. 2013). Prior work finds that losing collaborators through death or emigration reduces the productivity of surviving team members (Azoulay, Graff Zivin, and Wang 2010; Oettl 2012; Borjas and Doran 2015; Jaravel, Petkova, and Bell 2018), mainly through lost top-down knowledge spillovers and team-specific capital. To the best of my knowledge, this paper is the first to examine how heterogeneous expertise within teams — and the resulting lack of substitutability among collaborators — shapes the response of individual inventors' innovation output with differing knowledge diversity (green versus non-green) to a large-scale disruptive event. Specifically, my results show that physical exposure to disruptions such as Hurricane Katrina can reduce inventors' green patent output, while non-green patents remain unaffected. I measure inventors' technological expertise and the technological distance among collaborators using patent technology classifications and estimate differential effects by this distance, which allows me to establish the unique importance of heterogeneous expertise within teams for the resilience of innovation output to disruptions.

This paper also adds to the literature on the supply of green innovation and complements the broad literature on directed technological change, which has focused on the price mechanism to direct resources from non-green to green innovation and treated environment as exogenous (Acemoglu et al. 2012; Aghion et al. 2016; Dugoua and Gerarden 2024). In addition to financial constraints that limit green innovation (Aghion, Bergeaud, De Ridder, and Van Reenen 2024), this paper identifies an additional supply-side barrier to green innovation: heterogeneous expertise within innovation teams, which limits substitutability and makes green innovation more vulnerable to disruptions. A related strand shows that climate change and natural disasters can redirect innovative effort towards mitigation or adaptation technologies at country or county level (Miao and Popp 2014; Moscona and Sastry 2022). In contrast, I find that climate-related natural disasters reduce green innovation by individual inventors, with heterogeneous team expertise shaping the magnitude of this response, thereby shedding light on the micro foundation for the production of green technology.

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 or higher.[9] 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).

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Insert Figure 1 about here

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Hurricane Katrina is the costliest tropical cyclone in U.S. history, incurring $200 billion in damages according to NOAA.[10] It is also the second deadliest since 1930, claiming 1,833 lives.[11] It developed from a tropical depression southeast of the Bahamas, making its first landfall on August 25th in southern Florida near the Miami area.[12] After crossing southern Florida, Katrina intensified into a Category 5 hurricane on August 28th, located approximately 250 miles south-southeast of the Mississippi River's mouth, with peak winds of 175 miles per hour. By August 29th, when it reached the Louisiana coast, it was a strong Category 3 hurricane with winds exceeding 100 miles per hour, particularly impacting New Orleans. As Katrina moved north-northeast across Mississippi, it gradually weakened but remained at hurricane strength up to 100 miles inland near Laurel, Mississippi. The storm finally downgraded to a tropical depression near Clarksville, Tennessee, on August 30th.

The storm caused extensive storm surge damage, with surges possibly exceeding 30 feet along the

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

[10] 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.

[11] 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)

[12] 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).

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.[13]

The infrastructure damage from Hurricane Katrina was extensive, with over 300,000 homes destroyed.[14] Nearly two years later, over 600,000 individuals had yet to return to their homes in the broader affected areas (Deryugina, Kawano and Levitt 2017). Roads and bridges suffered severe structural damage, and critical public infrastructure, including hospitals, schools, and power stations, was significantly affected.

Beyond the devastation to residential and transportation infrastructure, Hurricane Katrina inflicted severe disruptions on business operations and innovation activities. For example, the storm forced the shutdown of offshore oil and gas production, disrupted petrochemical plant operations, and paralyzed rail, truck, and barge transportation across Mississippi, Alabama, and Louisiana. Similarly, the Southern Regional Research Center (SRRC), an agricultural research laboratory operated by the U.S. Department of Agriculture in New Orleans, suffered approximately $35 million in damages. The facility was closed for a year, necessitating the relocation of about 170 staff members, and only restored full operations two years after the storm. The forced closure disrupted ongoing agricultural research, causing setbacks in the development of new technologies for crop production and pest control.

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,[15] 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

[13] 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).

[14] https://www.fema.gov/sites/default/files/2020-08/fema_548_summary_report_building_performance_hurricane_katrina_2005.pdf

[15] https://patentsview.org/

longitude coordinates, is likely to reflect the actual location where an inventor lives and works (Akcigit et al. 2016; Moretti and Wilson 2017; Akcigit et al. 2022). To get information on each patent's characteristics, such as the application year and technological classes, I merge the inventor data with the patent data from PatentsView by patent number identifier.

I use a 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). 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 location, property damage, crop losses, injuries, and fatalities associated with various natural hazard events in the US. Property damage refers to damage inflicted to private property as well as public infrastructure and facilities. I utilize relevant SHELDUS data to identify counties affected by Katrina and visualize their geographic distribution in Figure 2.

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,[16] which suffered property damage from Katrina, listed as the inventor's address in the patent application. The majority of counties affected by Katrina were concentrated in the Southern US region (Figure 2). Second, their first patent is before the year 2005 when Katrina occurred. Patent data only captures individuals who have already filed patents — it does

[16] 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.

not account for potential inventors who may have entered the innovation landscape later. Due to this data limitation, this study does not examine new inventor entry, i.e., the extensive margin.

Insert Figure 2 about here

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).

Insert Figure 3 about here

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:

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

where i indexes inventors, s denotes the states of inventor i, and t is the year of patent applications as this is the date closest to the actual creation of the innovation (Akcigit et al. 2016; Moretti and Wilson 2017; Akcigit et al. 2022). Y_{ist} denotes the innovation outcome, measured separately for green and non-green patents. My main analysis focuses on patent counts — a discrete, non-negative count variable — estimated using a Poisson pseudo-maximum likelihood (PPML) estimator. To complement the main results

and capture different margins of the effect, I also construct two alternative measures: (i) a binary indicator for having at least one patent (extensive margin); and (ii) the natural logarithm of patent counts, conditional on having any (intensive margin). Both are estimated using ordinary least squares (OLS). All variables are measured over a three-year window between and including years t and $t+2$ (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:

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

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.[17] 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 2004 before Katrina happened for treatment and control group, and across all years for the full sample. By construction, the means and distributions of cumulative patent counts, cumulative green patent counts, and the number of years since the first patent application for the control group exactly match those of the treatment group. The means and distributions of yearly green and non-green patent counts before

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

Katrina are also very similar in these two groups, although this match algorithm did not match exactly on these variables.

Insert Table 1 about here

The treatment and control inventors are 5 years younger than inventors in the full sample, in terms of numbers of years since first patent application. Accordingly, they have much lower yearly and cumulative patent and green patent counts compared to full sample inventors. Therefore, it would not be appropriate to use the full population of inventors as a control group for the treatment inventors, as their life-cycle earnings are likely to be on different trajectories.

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.[18] Before Katrina, treatment and control inventors exhibited similar levels of production in both green and non-green patents. Importantly, the matching algorithm, which only focuses on the stock variables in the year 2004 before Katrina, does not impose that the yearly dynamics before Katrina should be aligned between the treatment and control groups. Following Katrina, green patenting continued to increase over time for both treated and control inventors. This may reflect broader trends such as rising environmental regulation, growing demand for clean technologies, and increasing policy support for green innovation (Popp 2002; Aghion et al. 2016; Popp 2019). However, treated inventors exhibit a slower growth in green patenting relative to the control group, leading to a widening gap after 2005 (Panel A). By contrast, no comparable divergence is observed in non-green patenting (Panel B).

Insert Figure 4 about here

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 20.0% more green patents in the subsequent three years if Hurricane Katrina had not occurred (column 2 in Panel A).[19] Columns 3-4 show that Katrina did

[18] The sample inventors are selected based on their patent applications during 2004-2005, which accounts for an observed spike in patent activity during these years.

[19] Poisson coefficients are transformed as $e^{\beta_1} - 1$ to show percentage changes.

not affect the production of non-green patents by inventors, as the point estimates are neither economically nor statistically significant.

These results are consistent with Zhao, Zheng, and Fu (2022), who find that natural disasters are negatively associated with green innovation in the energy sector at the country level, while showing no relationship with non-green energy innovation. The findings also complement Ballesteros (2024), who shows that counties affected by Hurricane Katrina experienced higher growth in overall patenting.[20] While Ballesteros (2024) studies aggregate patent growth at the county level, this paper focuses on inventor-level green and non-green patent counts. Notably, changes in county-level patenting in Ballesteros (2024) may not fully reflect the innovation activity of inventors who were directly disrupted by Hurricane Katrina. For example, an inventor who resided in one of the Katrina-affected counties and was disrupted by Katrina but did not file a patent in 2005, yet filed at least one patent between 2006 and 2015 in one of these counties, would be excluded from Ballesteros (2024)[21] but remains in the inventor-level panel used in this paper.

The results also align with recent evidence showing that the impact of natural disasters on green innovation depends on disaster severity. Physical exposure to shocks from natural disasters can increase attention, motivation, or effort directed toward green innovation (DellaVigna 2009; Kahn et al. 2021). When inventors' research capacity is not substantially disrupted, such increased attention and motivation may translate into higher green innovation output. For example, Keding and Ritterrath (2025) document higher green patenting in regions exposed to moderate natural disasters relative to unaffected regions in France and Germany. However, the effect is smaller for more economically damaging disasters and disappears when the analysis is restricted to the deadliest events, highlighting that positive green-innovation responses attenuate as disaster severity increases. This is consistent with this paper's finding that an extremely destructive disaster such as Hurricane Katrina reduced green innovation at the inventor level.

Insert Table 2 about here

Insert Figure 5 about here

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

[20] To identify Katrina-affected counties, Ballesteros (2024) uses data from the U.S. National Oceanic and Atmospheric Administration, the Federal Emergency Management Agency (FEMA), and the Department of Housing and Urban Development, while this paper uses SHELDUS data

[21] Ballesteros (2024) identifies and removes post-disaster inventor immigration by excluding inventors who did not file a patent in a Katrina-affected county in 2005 but filed at least one patent in those counties between 2006 and 2015.

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.

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Insert Table 3 about here

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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.

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Insert Table 4 about here

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I also examine whether inventors who migrated after Katrina experienced similar effects compared to those who did not migrate. Migrant inventors are defined as those whose county address prior to Katrina — specifically in 2004 or in 2005 before August 25 — differs from the address listed on their patent applications in the first year they filed any patents after the hurricane. I estimate a triple difference-in-differences (DDD) specification to assess the heterogeneity in Katrina's impact between migrant and non-migrant inventors.[22] I also differentiate whether an inventor moved and moved to a Katrina county and to a non-Katrina

[22] Using the notation in specification (1), the DDD specification is:

$$Y_{ist} = f(\beta_0 + \beta_1 Treatment_i \times Post_t \times Move_i + \beta_2 Treatment_i \times Post_t + \beta_3 Treatment_i \times Move_i + \beta_4 Post_t \times Move_i + \gamma_i + \sigma_s + \tau_t + \sum_j \lambda_j \mathbb{1}_{[tenure_{it}=j]} + \epsilon_{ist}) \quad (3)$$

county. Table 5 show the results which show that there is no differential effects for migrant inventors and non-migrant inventors, also no differential effects for migrant inventors who moved to Katrina counties and non-migrant inventors, and for migrant inventors who moved to non-Katrina counties and non-migrant inventors.

Insert Figure 6 about here

Insert Table 5 about here

5 Does the Difference 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. Next, I construct the measurement of technological distance between inventors, and 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. In addition to the analysis here, I also examine other potential mechanisms in Section 6.

5.1 Motivation

Inventors and scientists are becoming specialised as the expanding knowledge frontier raises the "knowledge burden," requiring individuals to accumulate larger stocks of knowledge within increasingly narrow domains before contributing to innovation (Jones 2009; Jones 2021). As individual expertise narrows, innovation has shifted toward collaborative production, where teams aggregate specialised knowledge. (Wuchty, Jones, and Uzzi 2007; Uzzi et al. 2013). Empirical evidence from science and patenting further shows that teams integrating more diverse technological backgrounds produce more novel and impactful innovations (Fleming 2001; Singh and Fleming 2010; Fortunato et al. 2018).

Green innovation is regarded as an important means of reducing environmental burden and improving environmental performance (Rennings 2000; Popp, Newell and Jaffe 2010; Popp 2019). A large literature shows that green technologies draw on a broader and more diverse set of technological fields

where $Move_i$ is a dummy variable equal to 1 if the county address of inventor i around the time before Katrina, i.e., in 2004 or in 2005 before 25 August, differs from the address listed on their patent applications in the first year they filed any patents after the hurricane. For inventors with filings in both years, the modal county address in the year 2005 before 25 August is used. I estimate the model using a Poisson estimator, as the outcome variable is a count of patents.

(De Marchi 2012; Barbieri et al. 2020; Orsatti et al. 2020; Fusillo 2023), reflecting the need to integrate solutions across multiple environmental and economic dimensions. Because producing such technologies requires combining distant knowledge components, green innovation teams typically consist of collaborators with more heterogeneous technological expertise. As a result, an individual inventor's expertise is less substitutable within the team: if a disruptive event affects an inventor in a green innovation team, replacing the specialised knowledge required to continue that inventor's technological tasks becomes substantially more challenging. Consequently, the development of green technologies may be more negatively affected by disruptions than non-green innovation, where collaborators' expertise tends to be more similar and substitutable.

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 the United States Patent Classification 3-digit level in Akcigit et al. (2022), and focus on classes that are invention information.[23]

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

[23]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. Y section symbols – including Y02 class – are allocated for additional information only.

probabilities of a patent being classified under one given it is classified under the other:

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

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

5.3 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 (white 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. Table 6 additionally presents the summary statistics on average team size and average geographical distance between a sample inventor and collaborators within the research team for green and non-green patents. Green patent teams, on average, have larger team sizes and greater geographical distances compared to non-green patent teams.

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Insert Figure 7 about here

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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):

$$dist_p = \alpha + \eta green_p + \theta X_p + state_p + tech_p + year_p + \epsilon_p \tag{4}$$

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.

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Insert Table 6 about here

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Table 7 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 patent team is, on average, 0.0585 larger than that within a non-green patent 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 patent team.

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Insert Table 7 about here

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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 8 and Figure 8, consistently show that patents with large technological distances suffered significant negative impacts from Hurricane Katrina across green and non-green innovation.[24] 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

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

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).

Insert Table 8 about here

Insert Figure 8 about here

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:

$$\begin{aligned} Y_{ist} =& f(\beta_0 + \sum_{m=1}^{3} \beta_m X_{im} \times Treatment_i \times Post_t + \sum_{m=1}^{2} \beta_m X_{im} \times Post_t + \\ & \gamma_i + \sigma_s + \tau_t + \sum_j \lambda_j \mathbb{1}_{[tenure_{it}=j]} + \epsilon_{ist}) \end{aligned} \tag{5}$$

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 9 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).

Insert Table 9 about here

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

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Insert Figure 9 about here

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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, Bénabou, Martin, and Roulet 2023). Additionally, Inventors' human capital is 5–10 times more important than firm capabilities for explaining the variance in inventor output (Bhaskarabhatla, Chatterji, Higgins, Lin, and Singh 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.[25] In my sample, the vast majority of assignees — 96.8% — are firms. To empirically test this, I estimate the following model:

$$\begin{aligned} Y_{fst} =& f(\beta_0 + \beta_1 Treat_f \times Post_t + X_{ft} + \gamma_f + \sigma_s + \tau_t + \\ & \sum_j \lambda_j \mathbb{1}_{[age_{ft}=j]} + \epsilon_{fst}) \end{aligned} \tag{6}$$

Where f indexes firms, s denotes the states of inventor i, and t is the year of patent applications. Y_{fst} represents the two innovation outcomes: (i) green patents, (ii) non-green patents. Both outcome variables are measured over a three-year window (years to) following Akcigit et al. (2022), and the analysis employs

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

a Poisson estimator.

The key variable, $Treat$, captures the extent to which a firm was affected by Hurricane Katrina, based on inventor locations before August 25, 2005, when Katrina occurred. Specifically, I construct a variable, $mean_treat$, representing the share of a firm's inventors located in Katrina-affected counties, using patents filed in 2004 and up to August 25, 2005.

Figure 10 Panel A displays the distribution of $mean_treat$. There is a pronounced spike near 0, indicating that most firms were not directly affected by Katrina. Panel B of Figure 10 shows the distribution among firms with $mean_treat > 0$; the median for this subset is 0.4. Consequently, I define three alternative treatment variables for robustness: (1) a continuous measure — $mean_treat$; (2) a binary indicator — equal to 1 if $mean_treat > 0$, and 0 otherwise; and (3) a binary indicator — equal to 1 if $mean_treat > 0.4$, and 0 otherwise.

Controls include total accumulated patents and accumulated green patents up to year t. I measure a firm's age_{ft} as the number of years that have passed since the firm f's first successful patent application, and include age fixed effects $\sum_j \lambda_j \mathbb{1}_{[age_{ft}=j]}$. Additionally, I include firm, state, and year fixed effects, denoted by γ_f, σ_s, and τ_t, respectively. Throughout the analysis, standard errors are two-way clustered at the state and year levels to account for serial and spatial correlation.

Table 10 indicates no differential effects on firms' green and non-green innovation across different definitions of $Treat$. Columns 1–4 show no significant impact of Hurricane Katrina on firms' innovation outcomes, regardless of green or non-green. Columns 5 and 6 reveal negative effects on both green and non-green patent outputs for firms with over 40% of their inventors located in Katrina-affected areas.

Insert Table 10 about here

Insert Figure 10 about here

7 Conclusion and Discussion

This paper studies how exogenous disruptions to knowledge production, such as natural disasters, affect inventors' innovation output across green and non-green technologies with differing levels of underlying knowledge diversity. Focusing on Hurricane Katrina — one of the costliest and deadliest storms in U.S. history — I combine hazard data with patent records for US inventors in a difference-in-differences setup. The results show that Katrina significantly reduced inventors' production of green patents, while non-green

patenting activity remained unaffected. Specifically, inventors in the treatment group produced, on average, 20.0% fewer green patents within a three-year period after 2005, compared to the control group. In the absence of Hurricane Katrina, treated inventors would have produced an additional 0.0375 green patents on average

The observed vulnerability of green innovation is consistent with a mechanism rooted in heterogeneity of expertise among collaborators. Green technology tends to be more complex and multifaceted, spanning nearly all economic sectors (Pigato et al. 2020), and draws on a broader range of technological knowledge (De Marchi 2012; Barbieri et al. 2020; Orsatti et al. 2020; Fusillo 2023), requiring collaboration among inventors with more diverse expertise. When a disruption such as a natural disaster strikes one inventor, substituting for the lost expertise becomes more difficult, making green innovation more vulnerable. Consistent with this mechanism, inventors in green patent teams exhibit greater technological distance from collaborators than those in non-green teams, and Katrina's negative effects are more pronounced for patents produced by teams with greater technological distance, and for inventors with more technologically distant collaborators before Katrina. At the firm level, however, no differential effects are observed between green and non-green patents.

These results suggest two broader implications. First, diversity of expertise within innovation teams, while beneficial for knowledge creation, can reduce the substitutability of affected inventors and undermine the resilience of technological development in the face of disruption. Second, natural disasters, whose frequency and/or intensity are increasing with climate change, can slow progress in green innovation, the very type of innovation critical for addressing climate change, by disrupting the collaborative production of specialised knowledge.

Future research could look into whether collaborators of inventors affected by natural disasters produced more green innovation. The indirect exposure to a natural disaster, experienced through professional collaboration 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.

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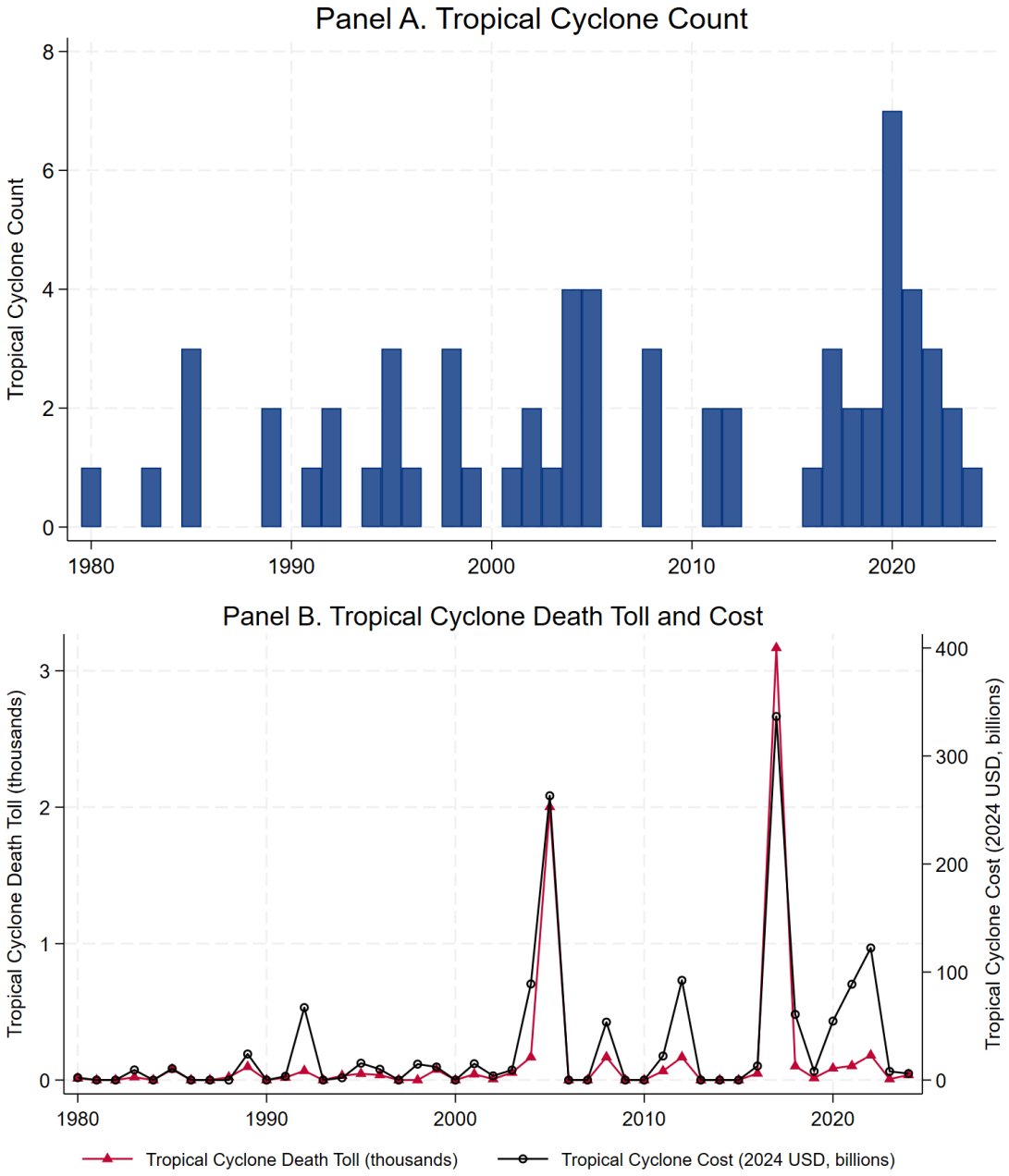
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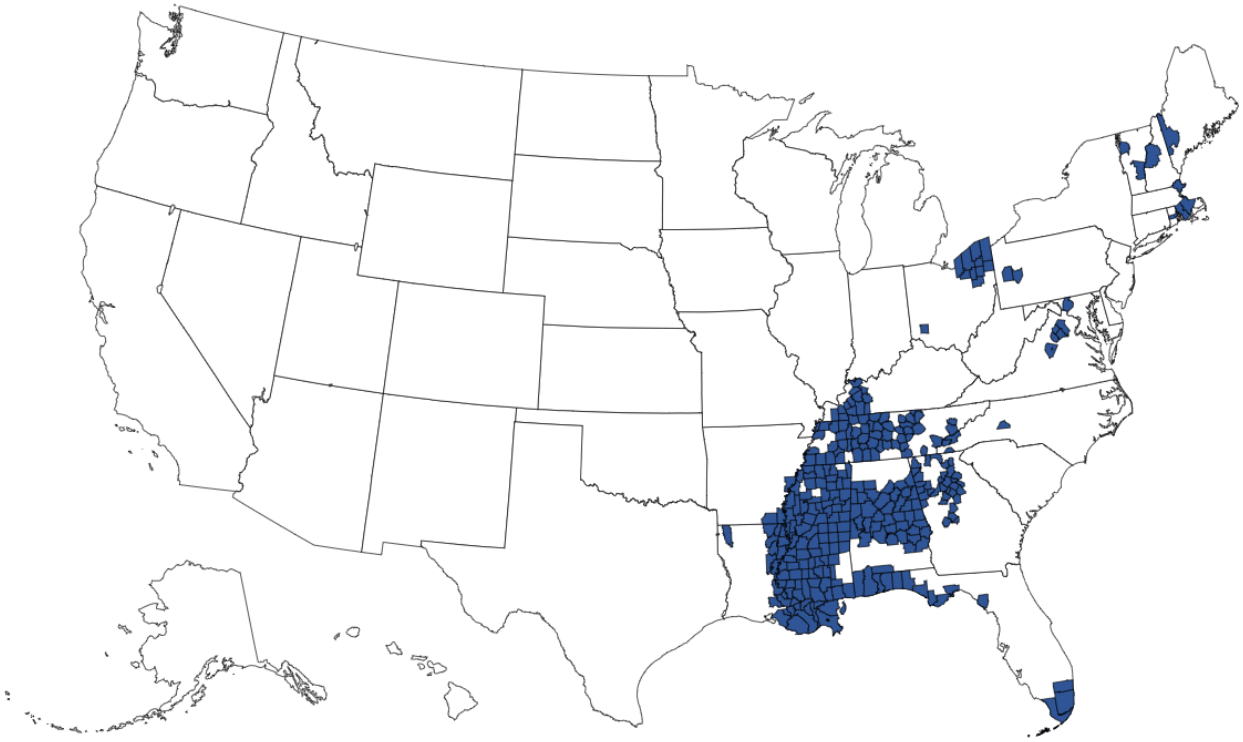
8 Figures

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.

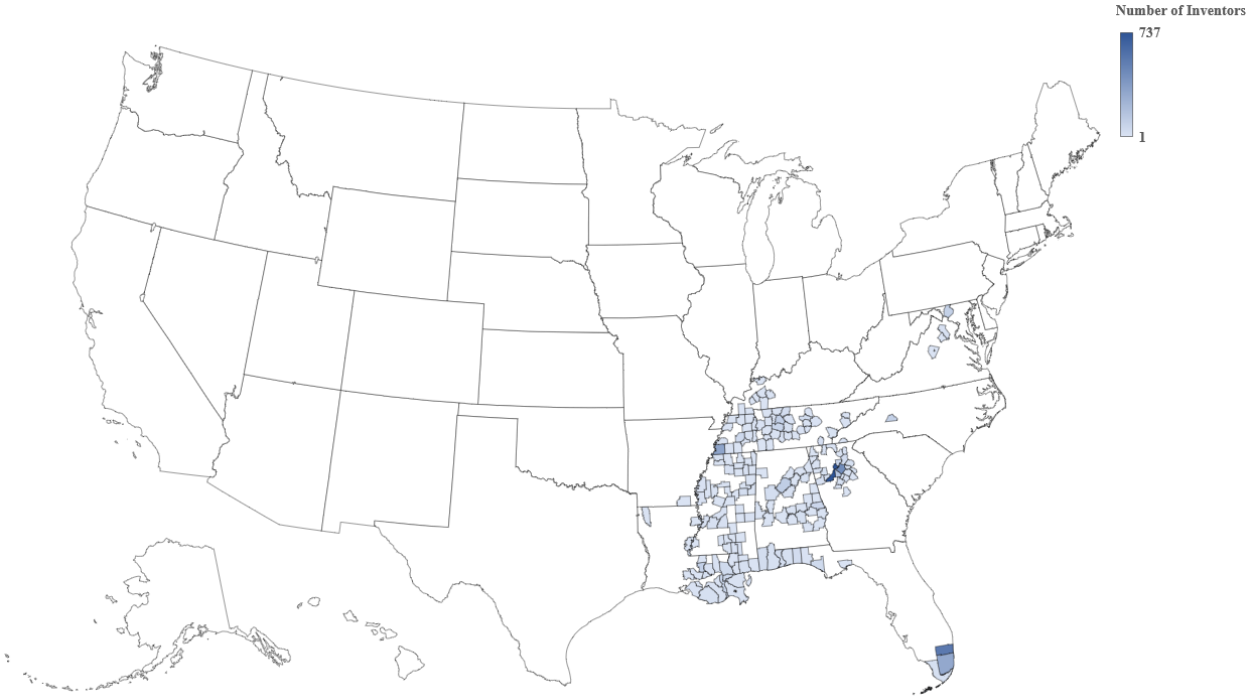
FIGURE 2: GEOGRAPHICAL DISTRIBUTION OF COUNTIES AFFECTED BY KATRINA



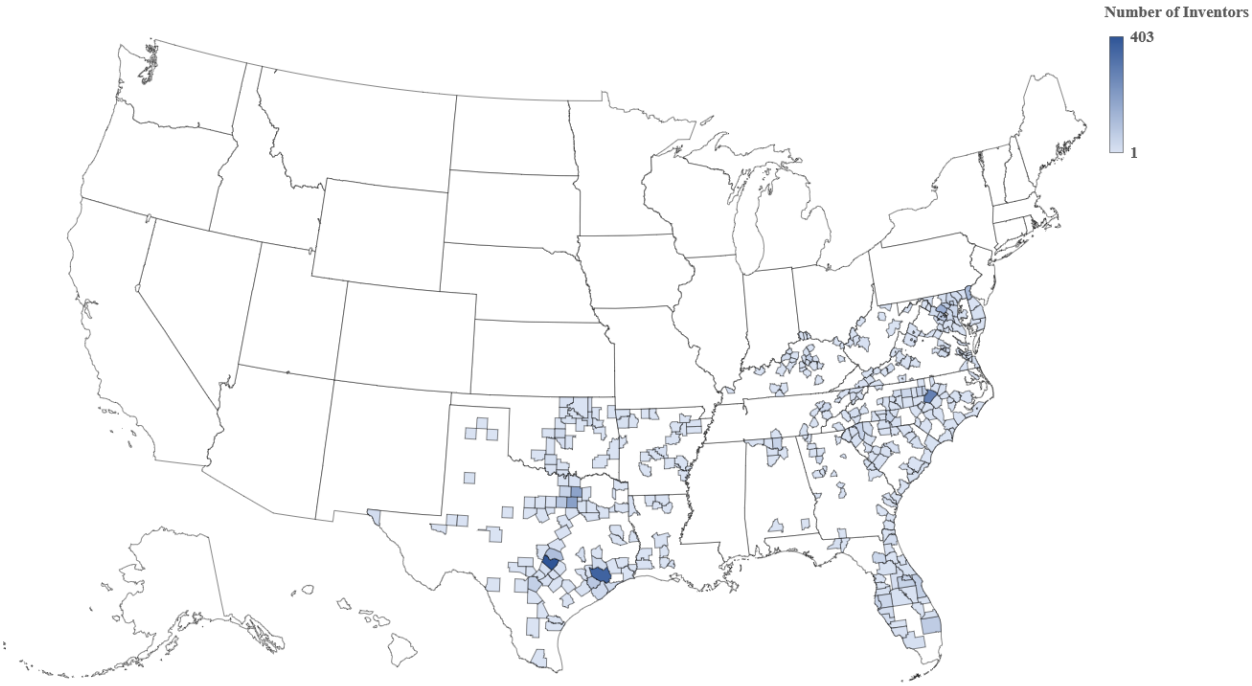
Notes: This figure illustrates the geographical distribution of counties that incurred property damage from Hurricane Katrina, with affected counties highlighted in blue. The majority of the damage is concentrated in the Southern United States, with impacts extending to northeastern regions due to Katrina-related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

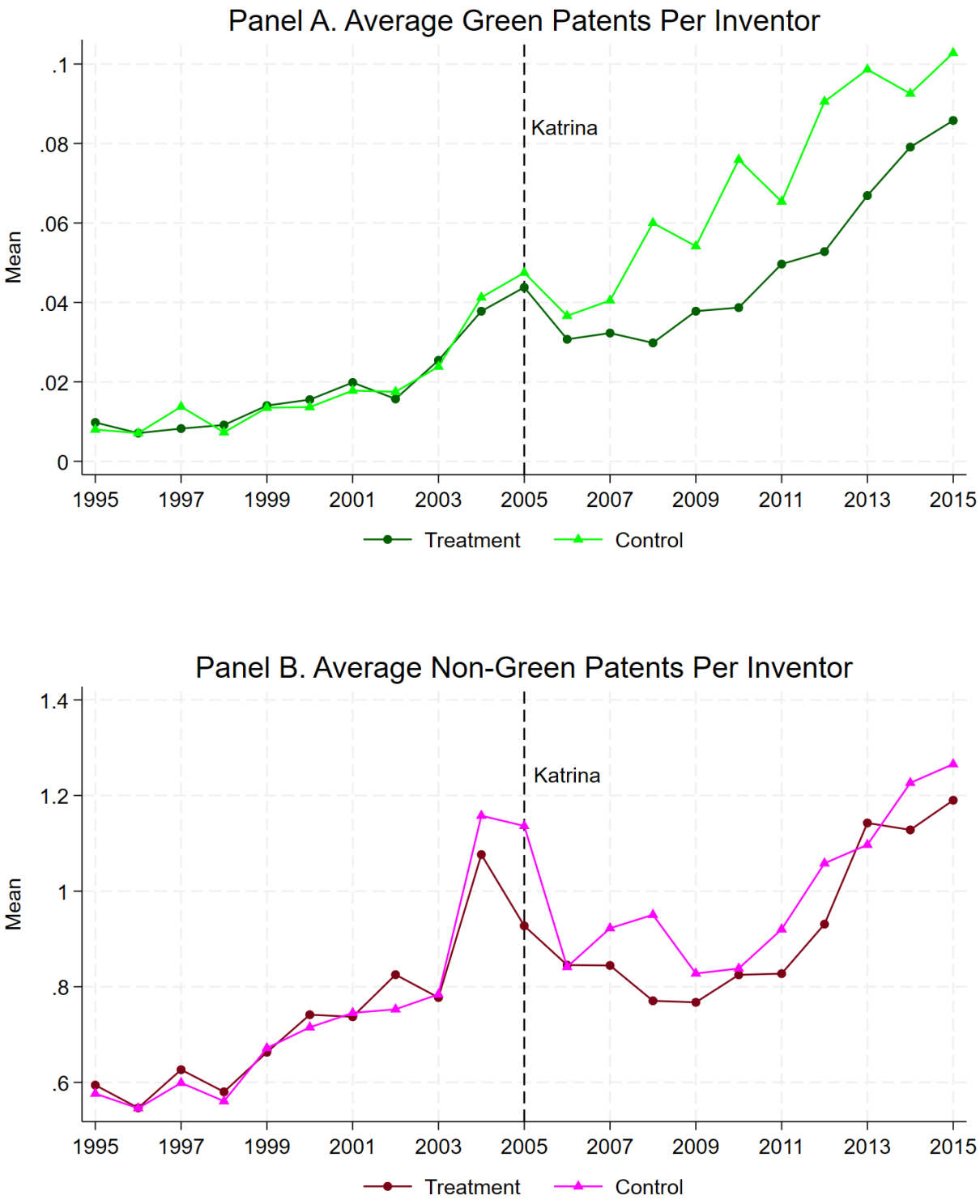


Panel B. Control Group



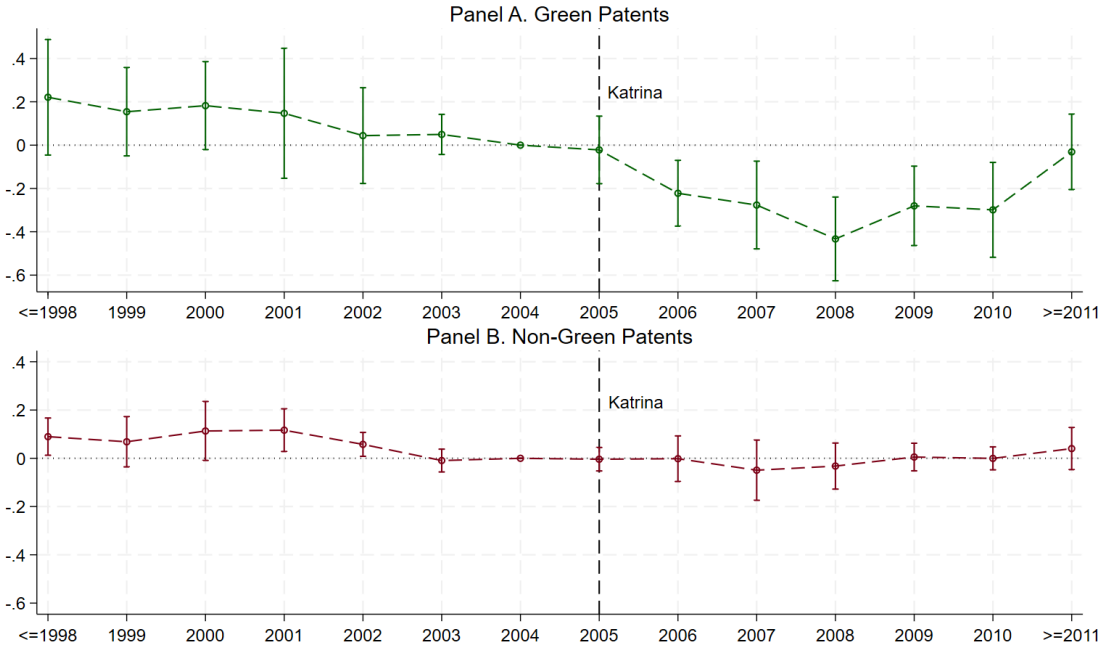
Notes: Panels A and B of this figure show the geographical distribution of treated and control inventors at the county level, respectively. Section 3.2 provides the definitions of the treatment and control groups.

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



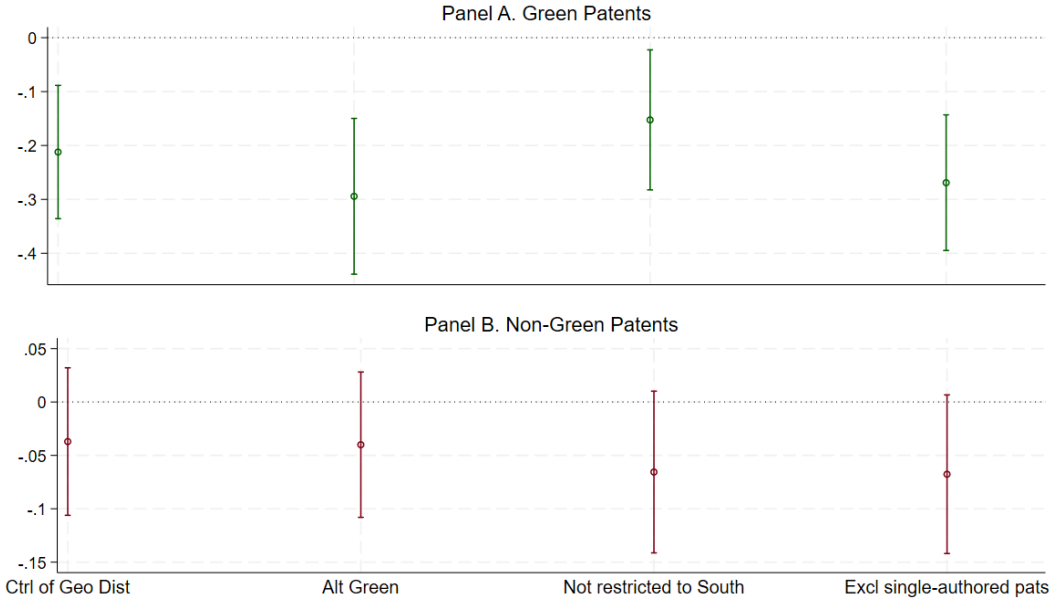
Notes: Panels A and B of this figure display the trends in mean green and non-green patents for treated and control inventors around 2005, the year Hurricane Katrina occurred. The sample inventors are selected based on their patent applications during 2004-2005, which accounts for an observed spike in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



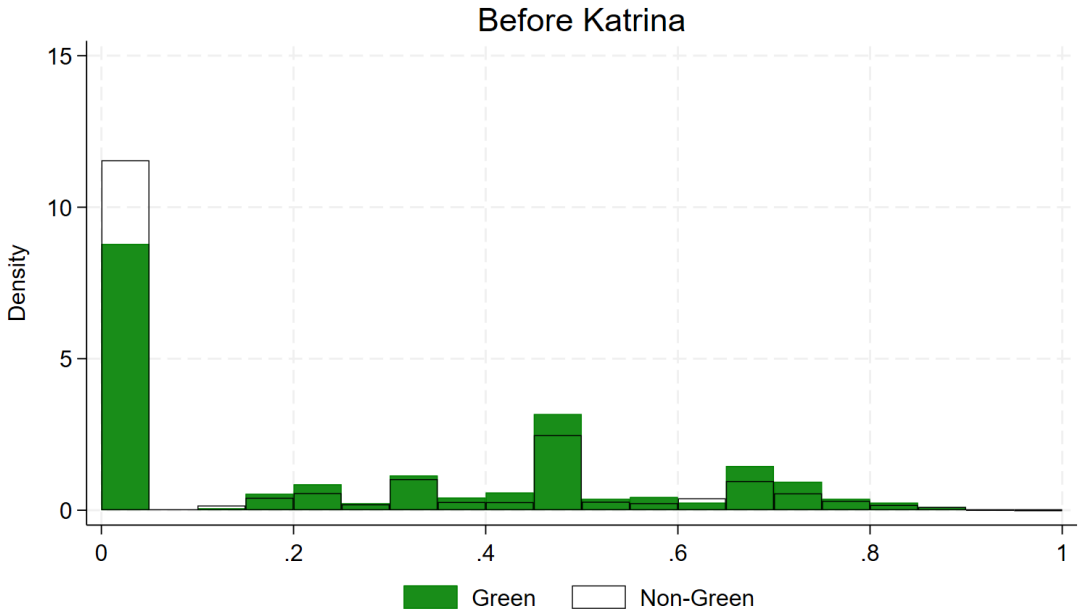
Notes: Panels A and B of this figure show the estimated coefficients β_m, β_{1998} and β_{2011} from Poisson specification (2) for two outcome variables – green and non-green patent counts, which aggregate over three years: between period t and t + 2. This specification includes inventor, tenure, state 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



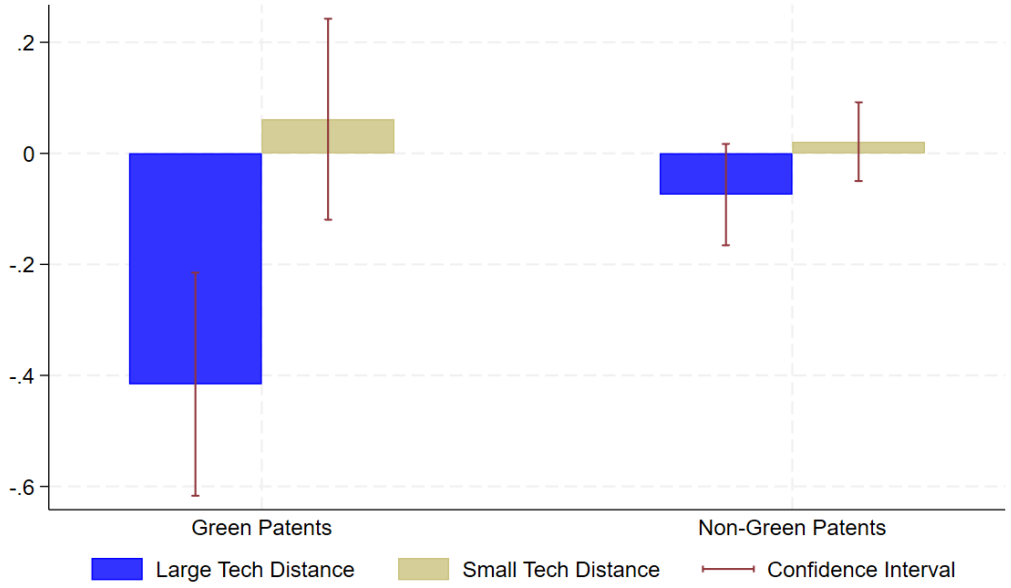
Notes: Panels A and B of this figure plot the estimated coefficient β_1 from Poisson specification (1) for four robustness exercises: 1. Controlling geographical distance of sample inventors with co-inventors; 2. Using the alternative definition of green patents, based on the OECD ENV-TECH classification ((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



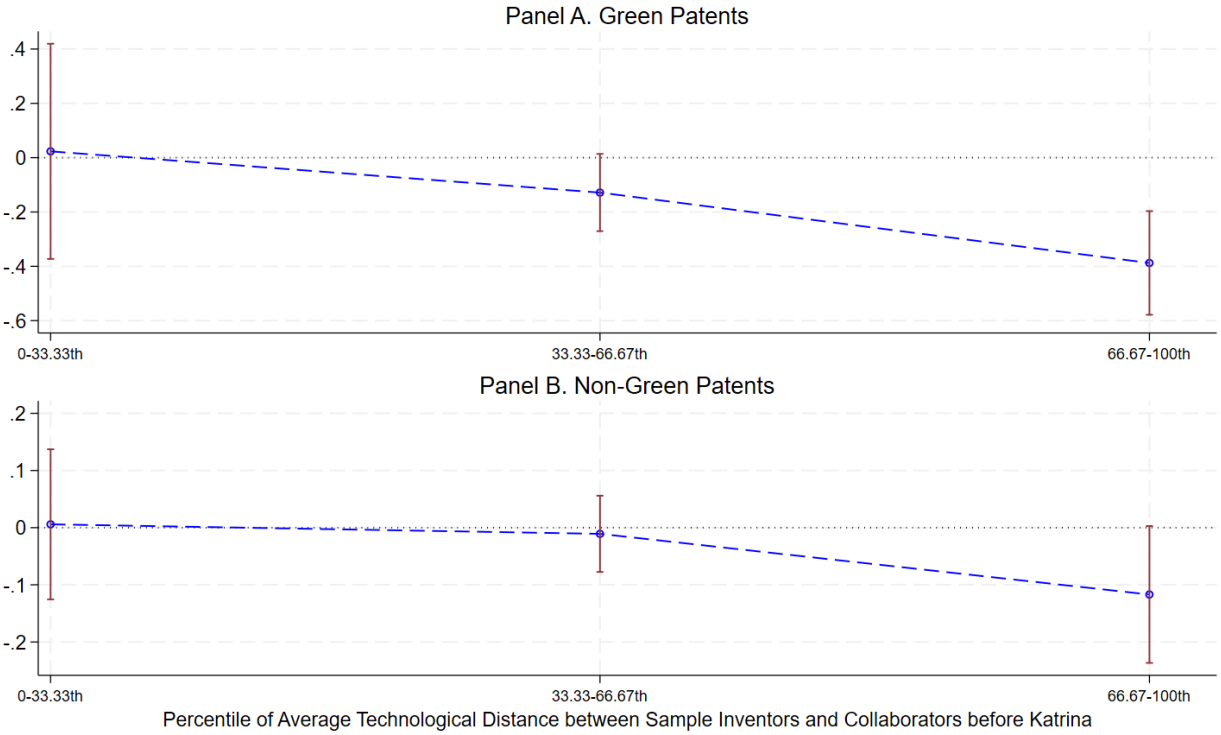
Notes: This figure shows the distribution of average technological distance within a patent team for green and non-green patents produced by sample inventors before Katrina. Section 5.2 details the methodology for measuring technological distance between two inventors. The average technological distance 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.

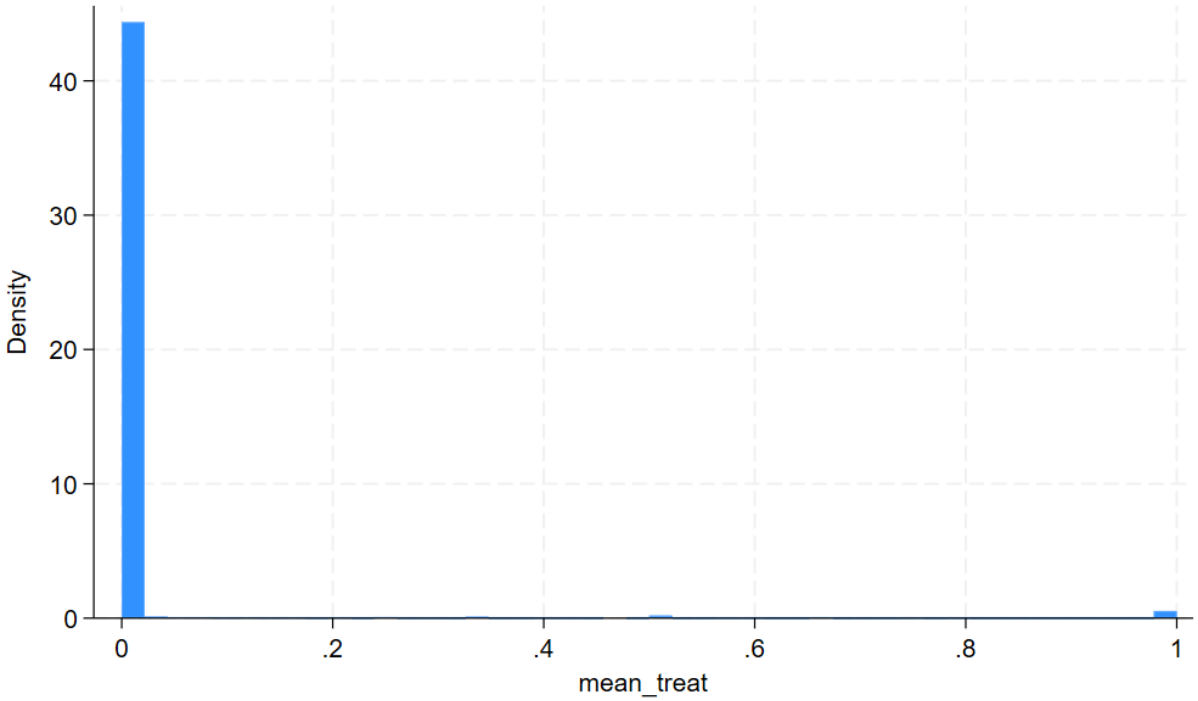
FIGURE 9. HETEROGENEITY BY TECHNOLOGICAL DISTANCE WITH COLLABORATORS BEFORE KATRINA



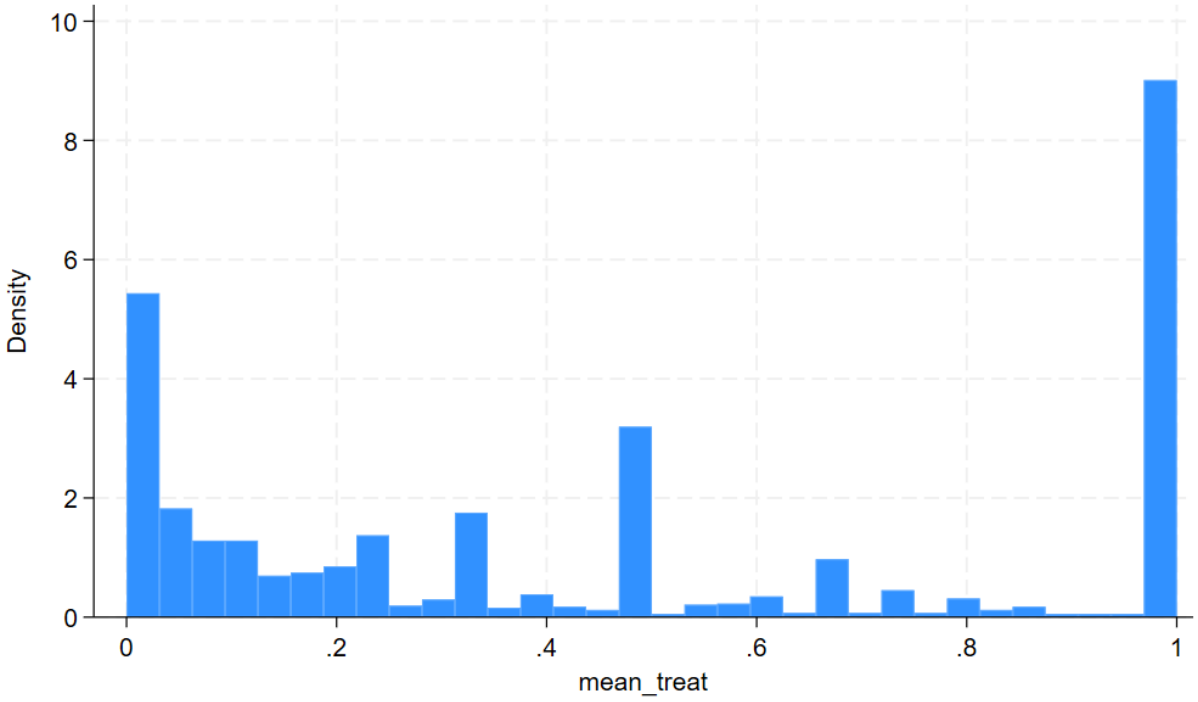
Notes: Panels A and B of this figure plot the estimated coefficients β_m from specification (4) for green and non-green patents, respectively. The estimation is performed using the Poisson method. The tertiles are computed based on the average technological distance between sample inventors and their 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.

FIGURE 10: DISTRIBUTION OF FIRM TREATMENT

Panel A. All Values of $mean_treat$



Panel B. $mean_treat > 0$



Notes: This figure shows the distribution of $mean_treat$. Panel A displays the full distribution, while Panel B focuses on firms with $mean_treat > 0$. $mean_treat$ measures the share of a firm's inventors located in Katrina-affected counties, based on patent filings in 2004 and up to August 25, 2005.

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 2004 — the year before 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. EFFECTS OF KATRINA ON MIGRANT V.S. NON-MIGRANT INVENTORS

	Green Patents		Non-Green Patents	
	(1)	(2)	(3)	(4)
Treatment × Post × Move	-0.194		-0.0386	
	(0.189)		(0.0418)	
Treatment × Post × Move to Katrina counties		0.412		0.247
		(0.843)		(0.198)
Treatment × Post× Move to non_Katrina counties		-0.197		-0.0519
		(0.160)		(0.0554)
Observations	90,398	90,398	90,398	90,398
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes
Tenure FE	Yes	Yes	Yes	Yes

Notes: This table reports the estimated coefficients β_1 from the specification (3) for green patents and non-green patents, respectively. The dependent variable is patent counts aggregated over a three-year period, from year t to t + 2. I estimate the model using a Poisson estimator, as the outcome variable is a count of patents. Move is a dummy variable equal to 1 if the county address of inventor i prior to Katrina — specifically in 2004 or in 2005 before August 25 — differs from the county address listed on their first patent application filed after the hurricane. Move to Katrina counties is a dummy variable equal to 1 if Move is equal to 1 and the address listed on their first patent application filed after the hurricane is in a county that experienced property damage from Hurricane Katrina. Move to non_Katrina counties is a dummy variable equal to 1 if Move is equal to 1 and the address listed on their first patent application filed after the hurricane is in a county that did not experience property damage from Katrina. Standard errors clustered at the state and year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 6. PATENT TEAM CHARACTERISTICS: SIZE AND GEOGRAPHICAL DISTANCE

	Green	Non-Green	p-value of equality of means test
Average team size	6.29	4.95	0.00
Standard deviation	11.48	5.36	
Average geographical distance between collaborators and sample inventors (in km)	539.32	444.82	0.00
Starndard deviation	1276.61	1130.27	

Notes: This table presents the summary statistics on (i) average team size—measured as the number of collaborators within a patent team—and (ii) average geographical distance between a sample inventor and their collaborators within the same research team, separately for green and non-green patents. A two-sample t-test is conducted to assess whether the differences in means between green and non-green patent teams are statistically significant, and the corresponding p-values are reported.

TABLE 7. 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 8. DIFFERENTIAL EFFECTS ON PATENTS OF SMALL VS. LARGE TECHNOLOGICAL DISTANCE

	Green patents		Non-Green patents	
	Large (1)	Small (2)	Large (3)	Small (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 9. 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

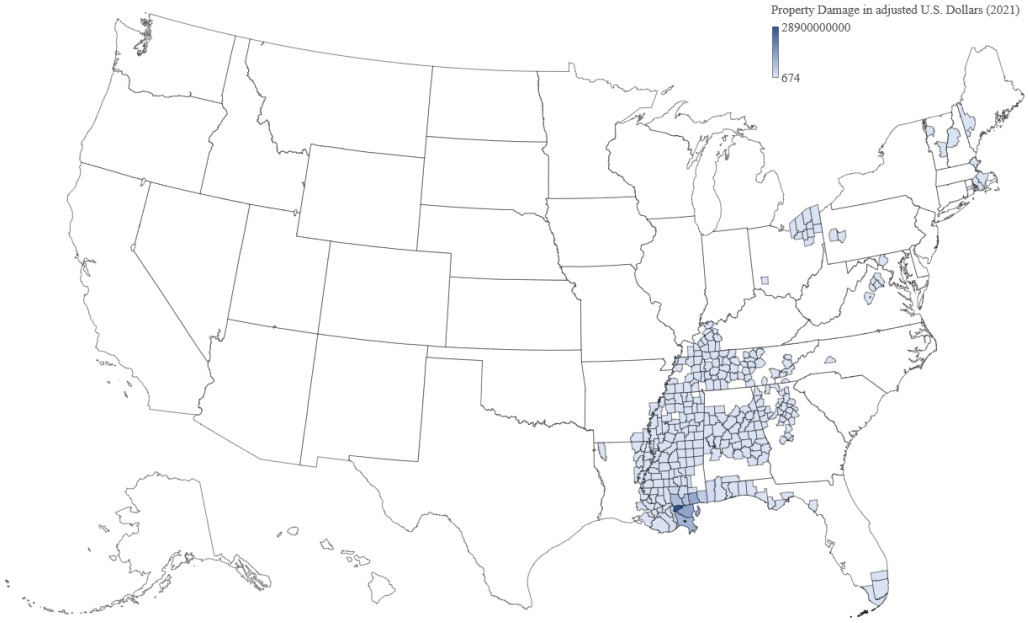
TABLE 10. EFFECTS OF KATRINA ON FIRMS

	mean-treat		Treatment 1		Treatment 2	
	(1)	(2)	(3)	(4)	(5)	(6)
D.V.	Green	Non-Green	Green	Non-Green	Green	Non-Green
Treat X Post	-0.301	-0.175	0.0456	0.0857	-0.359**	-0.277***
	(0.202)	(0.263)	(0.146)	(0.129)	(0.151)	(0.065)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Method	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
Observations	396,308	396,308	396,308	396,308	396,308	396,308

Notes: This table reports the estimated coefficients β_1 from specification (5) for green patents (column 1, 3 and 5) and non-green patents (column 2, 4 and 6), respectively. The dependent variable is patent counts aggregated over a three-year period, from year t to t + 2. The variable age is measured as the number of years that have passed since the firm f's first successful patent application. The full set of fixed effects for age, firm, year, and state are included. Standard errors clustered at the state and year level are reported in parentheses. For more details on the specification, refer to Section 6. *** p<0.01, ** p<0.05, * p<0.1

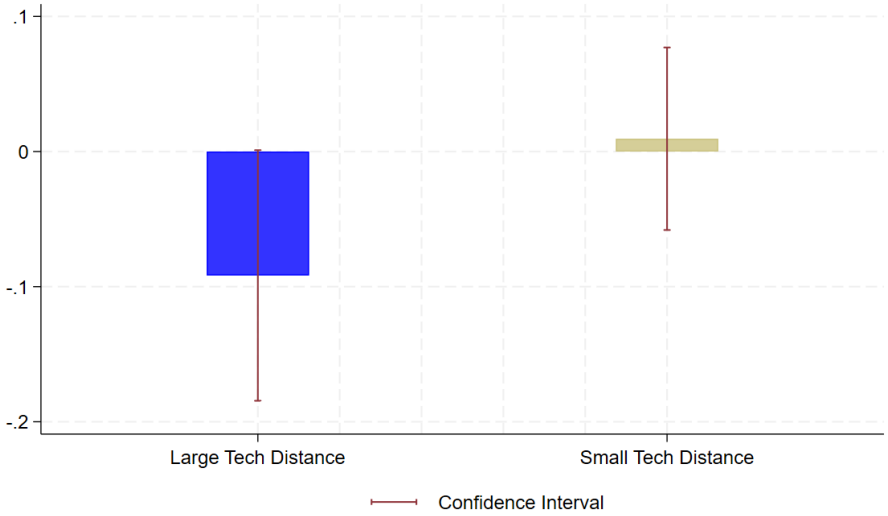
A Appendix Figures

FIGURE A1. GEOGRAPHICAL DISTRIBUTION OF PROPERTY DAMAGE BY KATRINA



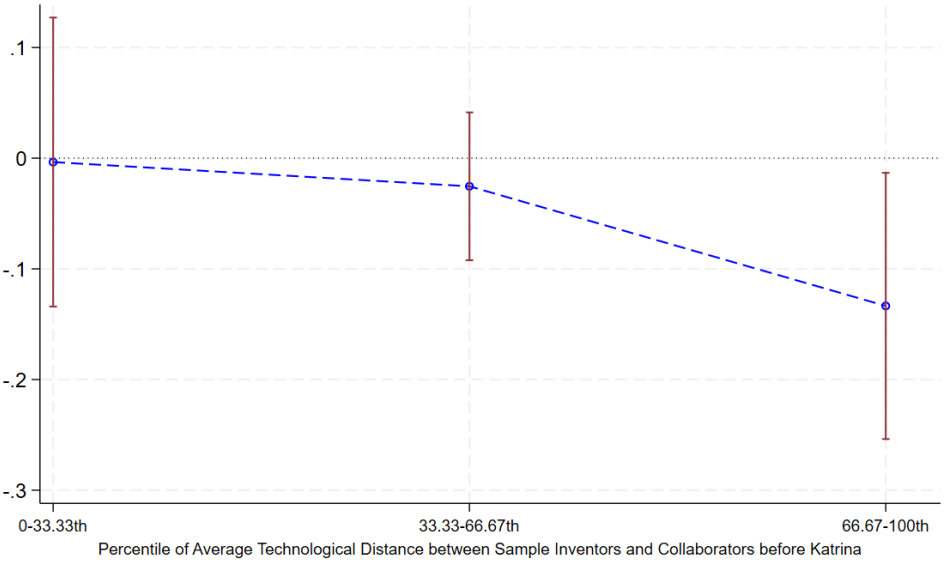
Notes: This figure illustrates the geographical distribution of property damage caused by Hurricane Katrina at the county level, with damage amounts adjusted to 2021 dollars. The shading intensifies from light to dark blue to indicate increasing levels of damage, with the darkest blue representing the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