Green Technological Change After Natural Disasters: Evidence from Hurricane Katrina

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Abstract

Climate change intensifies natural disasters. Physical exposure to severe disasters may not only raise the salience of climate change and encourage inventors to produce more green innovation, but also disrupt inventors' ability to carry out research. I leverage Hurricane Katrina, the costliest storm in U.S. history, as a quasi-natural experiment and a difference-in-differences design to test the effects of natural disasters on green patenting. Despite the potential for exposure-based salience to stimulate green innovation, I find Katrina reduced inventors' green patenting. Further, I find evidence of a disruption-to-human-capital mechanism: green innovation requires more heterogeneous, less substitutable expertise among collaborators, which Katrina disrupted. Thus, exposure to severe climate-related disasters may hamper green innovation.

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1 Introduction

Innovation is a key driver of productivity growth, and green innovation is especially crucial for the combat against climate change and the transition to a sustainable economy.[1] Existing literature on directed technical change, which focuses on how the price mechanism can direct resources from non-green to green innovation to tackle climate and environmental challenges, often treats environmental quality as exogenous to innovation supply (e.g., Acemoglu et al. 2012; Aghion et al. 2016; Dugoua and Gerarden 2025). Yet the environment itself may feed back into the innovation process. For example, physical exposure to events that increase individuals' attention to the salience of climate change concerns, such as severe natural disasters, may also encourage individual inventors, who are central to the supply of innovation, to produce more green innovation. At the same time, scientific evidence suggests that climate change has led to the increasing intensity of natural disasters,[2] and hurricanes, in particular, are becoming stronger and more destructive.[3] Physical exposure to these severe disasters may also directly disrupt inventors' ability to carry out research. This disruption may be particularly damaging for green innovation, which draws on a broader range of technological expertise and relies on collaboration among more technologically distant specialists whose contributions are harder to substitute within teams.

The empirical setting of this paper is Hurricane Katrina. The 2005 storm, which is estimated to have caused over $200 billion in direct economic losses,[4] is the costliest tropical cyclone in the US history. Katrina serves as a quasi-natural experiment because its path and intensity were determined by meteorological conditions and largely unanticipated, generating plausibly exogenous variation in inventors' physical exposure to a severe disaster event. Specifically, this paper empirically studies how physical exposure to Katrina affects individual inventors' green innovation output. I use data on county-level property damage related to Katrina from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), combined with data on individual inventors' location and patenting activities from the United States Patent and Trademark Office (USPTO).

I measure treatment at the inventor level. I first 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 as the treatment group. I then construct a matched control group of inventors in unaffected counties who were otherwise identical in terms of their first patent filing year, cumulative patent count, and cumulative green patent count prior to Katrina (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. Counter to expectations from an exposure-based salience view, I find that Hurricane Katrina led to

[1] 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 focus on technologies that tackle climate change and measure innovation using patent data. Specifically, I use Cooperative Patent Classification (CPC) Y02 class to identify green patents. As a robustness check, I also employ an alternative definition of green patents, based on the OECD ENV-TECH classification (Haščič and Migotto 2015). See Section 3.1 for more details

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

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

[4] The figure comes from NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2024). For more details, see Section 2.

fewer green patents, while non-green patents were unaffected. Inventors in the treatment group produced, on average, 20% fewer green patents within a three-year period after 2005,[5] compared to the control group. In the absence of Hurricane Katrina, treated inventors would have produced an additional 0.0375 green patents on average.[6] The negative effects hold across both the extensive and intensive margins of green patenting, while non-green patenting remains unaffected on both margins.

I then investigate the mechanisms behind the observed negative effects of Katrina on green innovation. I consider mechanisms operating on both the demand for and the supply of innovation. On the demand side, the extreme severity of Katrina plausibly increased awareness of climate change, which could have raised demand for green innovation. For example, post-Katrina reconstruction plans in New Orleans emphasized energy-efficient buildings, renewable energy, and green building standards, reflecting increased demand for green technology in housing and public infrastructure.[7] If this demand-side channel dominated, directly exposed inventors would be expected to increase their production of green innovation, which is inconsistent with the documented negative effects. Taken together, these considerations suggest that the negative effects of Katrina on green innovation are unlikely to be driven by demand-side forces.

Therefore, I turn to supply-side disruptions in the innovation process. The analysis first focuses on human capital, followed by physical capital, as key inputs in the innovation production function. Individual inventors play a pivotal role in the production of innovation, contributing their specialized knowledge and skills to develop new technologies. While natural disasters may increase inventors' attention to climate change and encourage green technological development, they also pose significant disruptions that could hinder the production of both green and non-green innovation. In particular, damage to inventors' homes and workplaces can significantly constrain their research efforts and disrupt their innovative activities, ultimately reducing overall innovation output.

The negative impact on innovation output may be more severe for green innovation, which inherently differs from its non-green counterpart. Green technology draws on knowledge from a broader range of technological areas than its non-green counterpart.[8] To produce green innovation, individual inventors may need to work with collaborators who are more distant from themselves in terms of technological expertise.[9] For example, geothermal technology involves collaboration among experts in geophysics, mechanical engineering, and data science. Accordingly, inventors in a green innovation team tend to perform more distinct technological roles and tasks. 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 for and therefore continue

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

[6] The absolute number of green patents implied by the counterfactual is small because green patenting has a low baseline rate. The mean of the dependent variable (green patents over the three-year window) before Katrina is 0.053. See Section 4 for more details.

[7] See U.S. Green Building Council (2005), "The New Orleans Principles: Celebrating the Rich History of New Orleans Through Commitment to a Sustainable Future," developed immediately after Hurricane Katrina, available at https://www.usgbc.org/sites/default/files/new-orleans-charrotte.pdf.

[8] 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, Marzucchi and Rizzo (2020), Orsatti, Quatraro, and Pezzoni (2020), and Fusillo (2023) for empirical evidence on the broader technological scope of green innovation.

[9] Azoulay, Graff Zivin, and Wang (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.

the directly disrupted inventor's technological tasks. Thus, 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.

To test this hypothesis, I measure inventors' technological expertise using their modal CPC subclass prior to Katrina (Akcigit et al. 2022), and construct a measure of technological distance between collaborators using a co-occurrence approach (Hidalgo et al. 2007; Azoulay, Graff Zivin, and Wang 2010). 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. I also examine physical-capital destruction as an alternative supply-side mechanism, but find little evidence that it accounts for the disproportionate decline in green innovation following Hurricane Katrina. Overall, these findings suggest that physical exposure to severe climate-related disasters may hamper rather than stimulate green innovation, by disrupting the specialized, less substitutable expertise that green innovation relies on more heavily. As climate change increases the intensity of such events, the vulnerability of green innovation to supply-side disruptions becomes an increasingly important consideration for policy.

This paper contributes 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 the environment as exogenous (Acemoglu et al. 2012; Aghion et al. 2016; Dugoua and Gerarden 2025). Beyond financial constraints faced by firms (Aghion et al. 2024), this paper shows that the structure of knowledge production itself constitutes a key supply-side constraint on green innovation. Because green technologies rely on highly specialized and less substitutable inventor expertise, disruptive shocks such as Hurricane Katrina can disproportionately stall green innovation, even when demand-side incentives and awareness increase. By providing micro-level evidence on how lack of substitutable human capital constrains the resilience of green innovation, this paper sheds light on a previously underexplored foundation of the green innovation production process.

Relatedly, several strands of literature suggest that natural disasters can stimulate green innovation. Climate change and natural disasters can redirect innovative effort toward mitigation and adaptation technologies at the country or regional level through channels such as increased demand for and returns to such innovation (Miao and Popp 2014; Moscona and Sastry 2023). Complementing this, inventors are driven not only by financial incentives but also by intrinsic and pro-social motivation (Stern 2004; Besley and Ghatak 2005; Bénabou and Tirole 2006), suggesting that physical exposure to severe climate-related events may encourage them to direct effort toward green technologies. In contrast, I show that at the individual inventor level, climate-related disasters reduce green innovation, with heterogeneity in team expertise shaping the magnitude of this response.

This paper also adds to the literature on knowledge production. Prior work documents the rise of teams (Wuchty, Jones, and Uzzi 2007; Jones 2009; Jones 2021) and shows that disruptions such as the deaths of collaborators reduce inventors' or scientists' innovation productivity (Azoulay, Graff Zivin, and Wang 2010; Oettl 2012; Jaravel, Petkova, and Bell 2018). Unlike collaborator deaths which generate

permanent losses of top-down knowledge spillover or team-specific capital (Azoulay, Graff Zivin, and Wang 2010; Jaravel, Petkova, and Bell 2018), extremely damaging disasters may create temporary disruptions to researchers' ability to execute specialized tasks that are hard to substitute within teams — as in green innovation. This is an increasingly important margin as natural disasters become more frequent and severe with climate change.

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 study a human-capital mechanism and show that greater technological distance within green innovation teams is an important explanatory channel. Section 6 discusses and tests the alternative mechanism operating through a physical-capital destruction channel. Section 7 concludes.

2 Background on Hurricane Katrina

Climate change is leading to more destructive hurricanes, which generate profound economic and societal consequences. A hurricane is a tropical cyclone with maximum sustained winds of 74 mph or higher.[10] 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), tropical cyclones dominate the distribution of damage from U.S. billion-dollar disaster events over this period. They have caused the most cumulative damage ($1,418.2 billion), carry the highest average event cost ($22.5 billion per event), and are responsible for the highest number of deaths (6,934) among all disaster categories. Hurricane Katrina is the costliest tropical cyclone in the U.S. historical record, incurring over $200 billion in direct economic losses — including physical damage to residential, commercial, and government buildings, material assets, business interruption losses, vehicles, boats, offshore energy platforms, public infrastructure, and agricultural assets. It also ranks as the third deadliest U.S. hurricane on record, claiming 1,833 lives.[11]

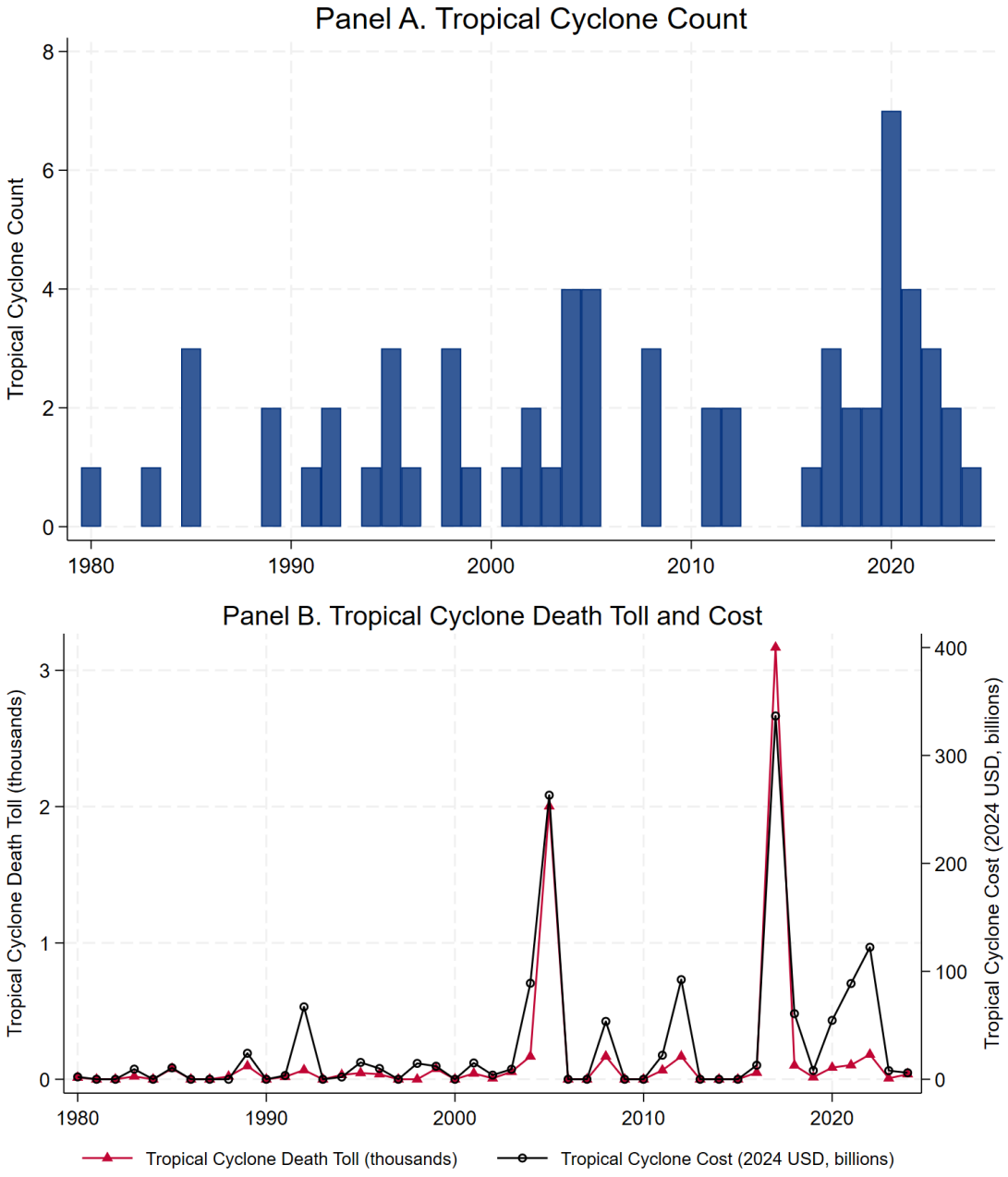
Hurricane Katrina's path and intensity were determined by meteorological conditions, generating variation in local damage exposure that was largely unanticipated and unrelated to the prior innovative activities of affected inventors. Katrina developed from a tropical depression southeast of the Bahamas, making its first landfall on August 25th in southern Florida near Miami.[12] After crossing southern Florida, it intensified rapidly 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 made landfall on the Louisiana coast, it had weakened to a strong Category 3 hurricane with winds exceeding 100 miles per hour, particularly devastating New Orleans. Moving north-northeast across Mississippi, Katrina gradually weakened but remained at hurricane strength up to 100 miles inland near Laurel, Mississippi,

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

[11] Dollar amounts are adjusted based on the 2024 Consumer Price Index. Death toll and cost figures are from NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2024).

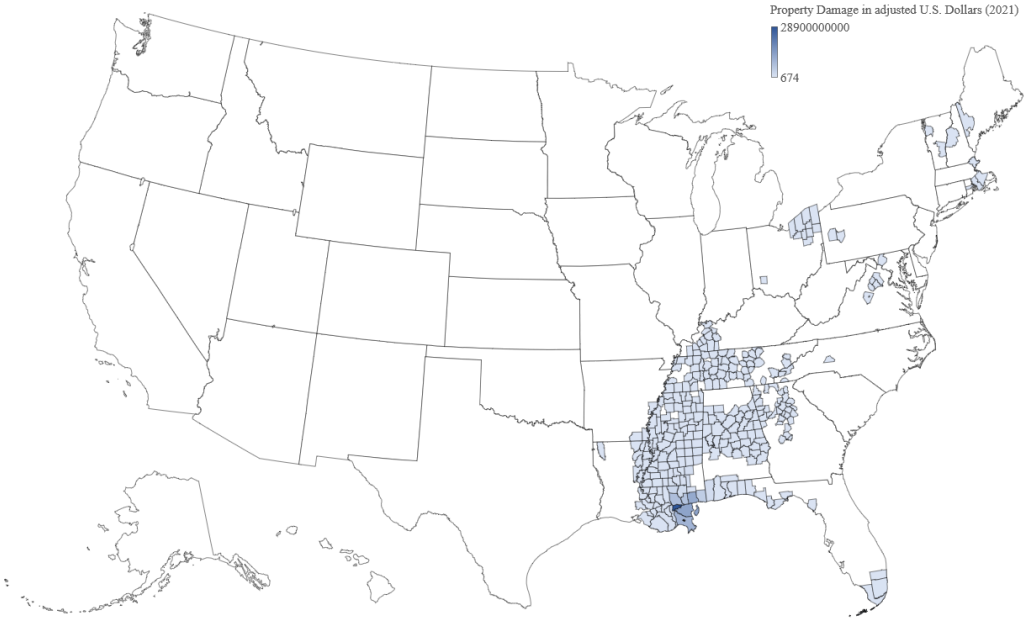
[12] The basic facts about Hurricane Katrina cited throughout are from publications of the National Oceanic and Atmospheric Administration (Graumann et al. 2005; NOAA National Centers for Environmental Information 2005).

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



Notes: Panels A and B display the trends in the count, cumulative deaths, and cumulative cost of billion-dollar tropical cyclones in the United States. Data are 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/). The dataset includes only weather and climate disasters with losses exceeding one billion dollars, adjusted to the 2024 Consumer Price Index.

FIGURE 2. GEOGRAPHICAL DISTRIBUTION OF PROPERTY DAMAGE BY KATRINA



Notes: This figure displays the geographical distribution of property damage caused by Hurricane Katrina at the county level, with damage amounts adjusted to 2021 dollars. Darker shading indicates greater damage. New Orleans, Louisiana, is marked as the epicenter of the damage. Data are sourced from the Spatial Hazard Events and Losses Database for the United States (SHELDUS); further details are provided in Section 3.1.

before finally downgrading to a tropical depression near Clarksville, Tennessee, on August 30th.

The storm caused extensive physical destruction across the affected region and disrupted millions of people's lives. It produced substantial storm-surge damage, reportedly exceeding 30 feet in places along the coasts of Louisiana, Mississippi, and Alabama, along with widespread wind damage and the catastrophic failure of portions of the New Orleans levee system. Inland effects, including high winds and flooding, extended across Alabama, Mississippi, Florida, Tennessee, Kentucky, Indiana, Ohio, and Georgia. Figure 2 illustrates the geographical distribution of property damage, primarily clustered in the Southern United States. Over 300,000 homes were destroyed,[13] and 1.5 million people evacuated or displaced.[14] Roads and bridges suffered severe structural damage, and critical public infrastructure — including hospitals, schools, and power stations — was significantly affected. The destruction extended to workplaces. For example, flooding cut power to research institutions in New Orleans, destroying years of irreplaceable biological samples and severely disrupting ongoing research (Singer 2005).

At the same time, the scale and visibility of Katrina's destruction drew substantial public and institutional attention to climate change. Post-Katrina reconstruction plans in New Orleans prominently emphasized energy-efficient buildings, renewable energy integration, and green building standards, reflecting growing awareness of environmental vulnerability and a desire to rebuild more sustainably.[15] More

[13] See Summary Report on Building Performance Hurricane Katrina 2005 by FEMA https://www.fema.gov/sites/default/files/2020-08/fema_548_summary_report_building_performance_hurricane_katrina_2005.pdf

[14] See, Bureau of Labor Statistics (BLS) report: https://www.bls.gov/opub/mlr/2008/03/art3full.pdf

[15] See U.S. Green Building Council (2005), "The New Orleans Principles: Celebrating the Rich History of New Orleans Through Commitment to a Sustainable Future," developed immediately after Hurricane Katrina, available at

broadly, Katrina appears to have increased scientific attention to the links between climate change and extreme weather, potentially raising the salience of climate change for scientists and inventors. [16]

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

I use a 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. Appendix Table A1 lists the Y02 subclasses and their descriptions. As a robustness check, I also use an alternative definition of green patents based on the OECD ENV-TECH classification (Haščič and Migotto 2015) and find similar results (Column (1) of Appendix Table A2).

Counties Affected by Hurricane Katrina. — The Spatial Hazard Events and Losses Database for the United States (SHELDUS) provides comprehensive data on county-level property damage, crop losses, injuries, and fatalities associated with natural hazard events in the United States. Property damage refers to damage to private property as well as public infrastructure and facilities. Therefore, SHELDUS data allows me to identify counties affected by Katrina, defined as those with positive Katrina-related property damage. Figure 2 shows the geographical distribution of these counties.

https://www.usgbc.org/sites/default/files/new-orleans-charrotte.pdf.

[16] See Andrea Thompson, "From Katrina, an 'Amazing' Decade of Climate Research," Climate Central, August 28, 2015, https://www.climatecentral.org/news/how-katrina-changed-climate-research-19386, which describes how Columbia University scientists Adam Sobel and Suzana Camargo reported a sharp increase in interest in a 2006 workshop on climate change and hurricanes after Katrina.

[17] https://patentsview.org/

3.2 Treatment and Control Group Construction

To ensure comparability, the sample is restricted to inventors located in Southern, hurricane-prone states,[18] where counties affected by Katrina were concentrated (Figure 2), so that treated inventors are compared to inventors in the same hurricane-exposed region rather than to inventors in regions unlikely to experience hurricanes.[19] I use two criteria to identify the treatment group: inventors who were likely to reside in the area affected by Hurricane Katrina at the time of landfall. First, they filed at least one patent in 2004, or in 2005 before 25 August (the date of Katrina's first landfall), listing an address in a Southern U.S. county that experienced Katrina-related property damage. Second, their first patent is before the year 2005 when Katrina occurred. Patent data only captures individuals who have already filed patents — it does 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.

Next, I construct a control group using two analogous criteria to define the pool of potential control inventors. First, they filed at least one patent in 2004, or in 2005 before 25 August, listing an address in a Southern U.S. county. However, none of the inventor locations listed on those patent applications filed during 2004 or in 2005 before August 25, are situated in Southern U.S. counties that experienced Katrina-related property damage. 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, following Jaravel et al. (2018). The matching is based on three observables: year of first patent filing, cumulative patent applications up to 2004, and cumulative green patent applications up to 2004 – the year before Katrina occurred. [20]

Additionally, I restrict the sample to inventors whose first patent was filed in 1983 or later, as data for Louisiana are unreliable before 1983 (Akcigit et al. 2022). The final matched sample contains 4,630 pairs of treated and control patent inventors. Following Akcigit et al. (2022), an inventor is considered active in every year between their first and last patent application; in years without a patent application during this active period, I assign a value of zero to their patent count. Inventors are included in the sample from the year of their first patent application through the year of their last. 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 control inventors are distributed across counties throughout

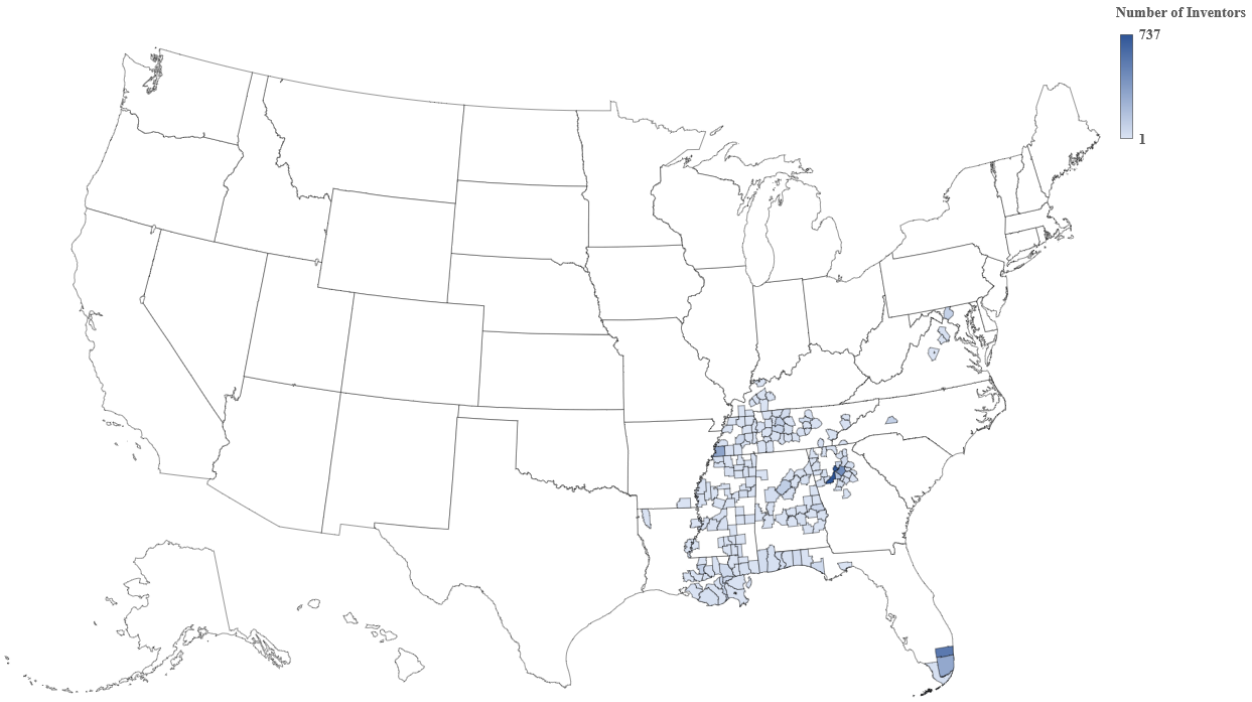
[18] As defined by the U.S. Census Bureau (https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf), the Southern US includes the following states: Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee,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

[19] The baseline results are robust to not restricting the control group to the Southern US; see column 2 of Appendix Table A2.

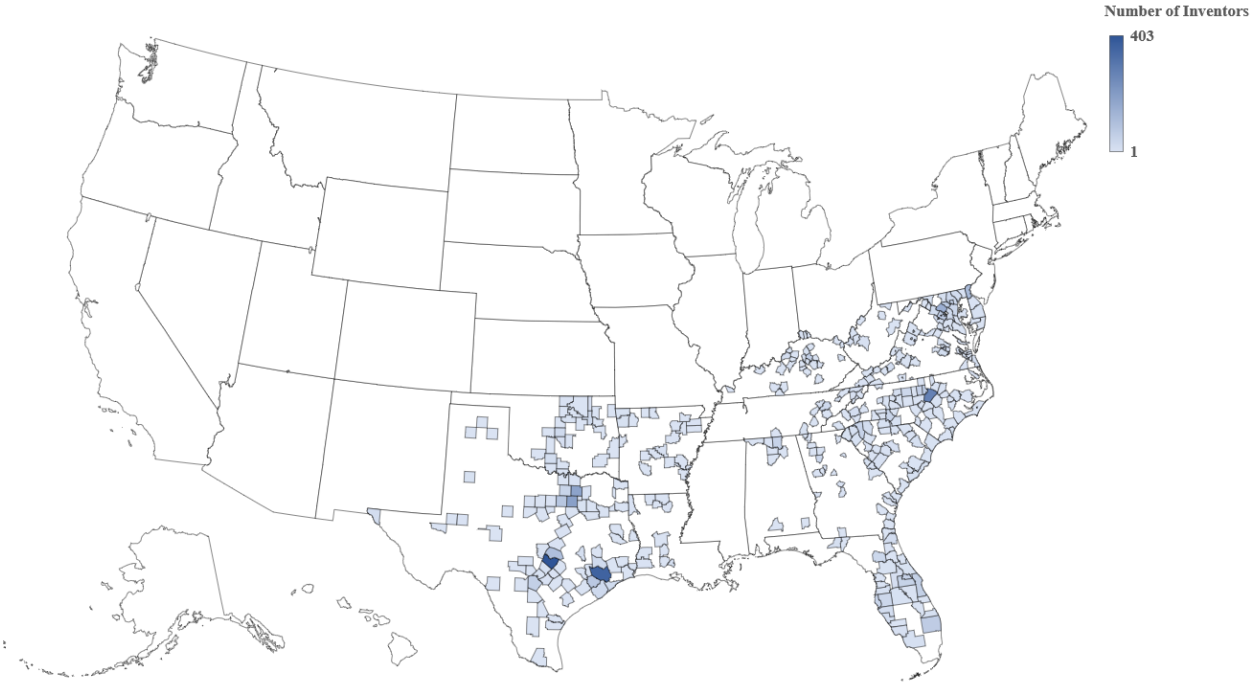
[20] The matching procedure is conducted year by year without replacement, following the approach in Jaravel et al. (2018). I begin by matching inventors who filed at least one patent in 2005 before August 25, seeking exact matches for each treated inventor. An exact match is defined as a control inventor who filed their first patent in the same year and had the same cumulative number of patent applications up to 2004 and of green patent applications up to 2004 as the treated inventor. Matched inventors are then removed, and the procedure is repeated for inventors who filed at least one patent in 2004. Potential control inventors in 2004 are additionally required to have no patent application listing a Katrina-affected county in 2005. If more than one exact match is found, ties are broken at random. In each year, control inventors are restricted to those who did not co-patent with a treated inventor in that year's matched set. There are 84 treated inventors who worked with control inventors before Katrina and 75 control inventors who worked with treated inventors before Katrina. The baseline result is robust to excluding these treated and control inventors. See column 3 in Appendix Table A2.

FIGURE 3. GEOGRAPHICAL DISTRIBUTION OF TREATMENT AND CONTROL GROUPS

Panel A. Treatment Group



Panel B. Control Group



Notes: Panels A and B display the geographical distribution of treated and control inventors at the county level, respectively. Darker shading indicates a higher concentration of inventors. Section 3.2 provides the definitions of the treatment and control groups.

the southern United States.

3.3 Estimation Strategy

In order to study the effect of Hurricane Katrina on inventors' innovation activities, I run a difference-in-differences 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 state[21] 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, Baslandze and Stantcheva 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 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 dependent 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 (Akcigit et al. 2022), 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 remaining 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 main variables used in the analysis. Yearly green and non-green patent counts are computed over the pre-Katrina years for the treated and control groups. Cumula-

[21] An inventor's state s is taken from the inventor address reported on the USPTO patent application. When an inventor files multiple applications in a given year listing different states, I assign the inventor to the modal state across that year's applications; ties are broken at random (Moretti and Wilson 2017; Akcigit et al. 2022). If an inventor does not have a patent application in a given year, the inventor is assigned the state from their most recent prior year in which a location was observed.

tive patent counts, cumulative green patent counts, and the number of years since the first patent application are measured in 2004—the year before Hurricane Katrina—for both groups. By construction, the means and distributions of these cumulative measures and tenure are exactly balanced across the treated and control groups. The means and distributions of yearly green and non-green patent counts in the pre-Katrina period are also very similar across the two groups, although the matching algorithm did not target these variables directly.

TABLE 1. SUMMARY STATISTICS ON INVENTORS

Variable	Sample	Mean	SD
Yearly green patent counts	Treatment	0.018	0.141
	Control	0.018	0.143
Yearly non-green patent counts	Treatment	0.730	1.154
	Control	0.730	1.140
Cumulative patents	Treatment	4.484	5.480
	Control	4.484	5.480
Cumulative green patents	Treatment	0.107	0.422
	Control	0.107	0.422
Number of years since first patent application	Treatment	5.996	5.671
	Control	5.996	5.671
No. inventors	Treatment	4,630	
	Control	4,630	

Notes: This table presents summary statistics for the treatment and control groups of inventors. Yearly green and non-green patent counts are computed over the pre-Katrina years. Cumulative patent counts, cumulative green patent counts, and the number of years since the first patent application are computed in 2004, the year before Hurricane Katrina, for both groups. For details on data sources and sample construction, see Sections 3.1 and 3.2.

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.[22] Before Katrina,

[22]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.

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).

Table 2 reports the estimation results of specification (1). Counter to an exposure-based salience view, Hurricane Katrina reduced green patenting while leaving non-green patenting unchanged.[23] Relative to matched controls, treated inventors produced 20% fewer green patents (column 2).[24] This implies that, absent Katrina, treated inventors would have produced 0.0375 additional green patents on average over the post-period.[25] By contrast, columns 3–4 show no statistically significant effects on non-green patenting. To assess robustness and unpack how Katrina affects patenting, I examine both the extensive and intensive margins for green and non-green patents. Table 3 shows that the decline in green patenting is present on both margins: treated inventors are less likely to file any green patent (column 1) and, conditional on filing, they produce fewer green patents (column 2). By contrast, columns 3–4 indicate no statistically or economically meaningful effects on either margin of non-green patenting.

These results align 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 association with non-green energy innovation. Keding and Ritterrath (2025) document higher green patenting in regions exposed to non-extreme natural disasters relative to unaffected regions in France and Germany, suggesting that moderate disaster exposure can stimulate green innovation. However, they also find that the positive effect attenuates as economic damage increases, which implies that the positive effects observed after non-extreme disasters may not extend to extreme shocks. Consistently, this paper shows that an extremely destructive disaster such as Hurricane Katrina — the costliest and one of the deadliest hurricanes in U.S. history — reduced green patenting among directly disrupted inventors. The findings also complement Ballesteros (2024), who documents that counties affected by Hurricane Katrina experienced a decline in the growth rate of patenting in the disaster year followed by increases in subsequent years. While Ballesteros (2024) studies aggregate patent growth rates at the county level and estimates effects separately by post-shock period,[26] this paper focuses on inventor-level green and non-green patent counts and estimates the average effect over the full post-shock period using a single post-Katrina indicator. The two papers are therefore complementary,

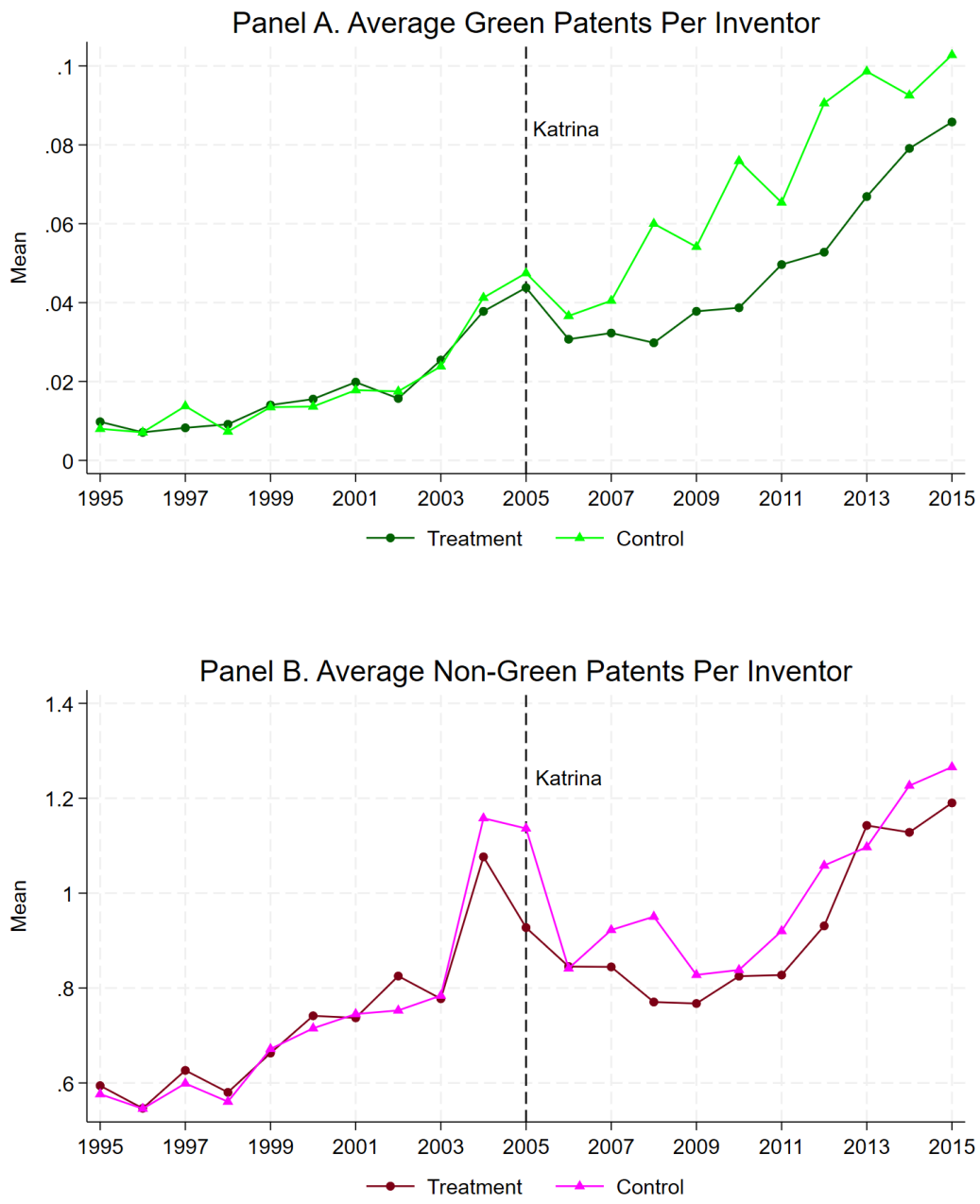
[23] The results for all patents are similar to those for non-green patents, as non-green patents constitute the majority of all patents. See Table A3 for details.

[24] Percentage effects are computed from Poisson estimates as $100 \times (\exp(\hat{\beta}_1) - 1)$.

[25] To translate the estimated effect into levels, I scale the treated group's post-Katrina mean (0.15 green patents over the three-year window) by the percentage effect reported above. Under a 20% reduction, the implied counterfactual mean absent Katrina is $0.15/0.8 = 0.1875$, so the difference is $0.1875 - 0.15 = 0.0375$.

[26] Ballesteros (2024) estimates separate regressions comparing three post-Katrina periods — the disaster year (2005), the short-run period (2006–2010), and the long-run period (2011–2015) — each relative to the pre-Katrina baseline (2000–2004).

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. 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.

capturing different units of analysis, outcome variables, and time horizons.

TABLE 2. EFFECTS OF KATRINA ON INVENTORS' PATENT PRODUCTION

	Green Patents		Non-Green Patents	
	(1)	(2)	(3)	(4)
$Treatment \times Post$	-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	2.051	2.051
Observations	102,622	102,621	102,622	102,621
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 estimates of β_1 from specification (1) for green patents (columns 1–2) and non-green patents (columns 3–4). The dependent variable is the number of patents filed over a three-year window (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. Columns 2 and 4 include the full set of fixed effects for tenure, inventor, year, and state. Standard errors clustered at the state and year levels are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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). For green patents (Panel A), the pre-period coefficients are small and not statistically distinguishable from zero, supporting the parallel-trends assumption. Following Katrina, the estimates turn sharply negative, exhibiting a notable decline in 2006 and reaching their lowest point in 2008, with point estimates significantly below zero throughout 2006–2010. For the period after 2011, the annual coefficient rebounds and approaches zero, suggesting the negative effect is temporary. For non-green patents (Panel B), these estimated coefficients do not show an economically meaningful post-2005 decline. While a few pre-period coefficients are significantly positive, they do not display a systematic trend as 2005 approaches, and the annual means in Panel B of Figure 4 show treated and control inventors evolving similarly in non-green patenting prior to Katrina. Overall, the dynamic patterns reinforce the main findings: Katrina substantially reduced green patenting, with little evidence of a comparable effect on non-green patenting.

The consistent negative effect of Katrina on green patenting makes it unlikely that a demand-side mechanism is the dominant explanation. The extreme severity of Katrina plausibly increased awareness of climate change, which could have raised demand for green innovation. For example, post-Katrina reconstruction plans in New Orleans emphasized energy-efficient buildings, renewable energy, and green building standards, reflecting increased demand for green technology in housing and public infrastructure.[27] If such demand-pull forces dominated, directly exposed inventors would be expected to increase green patenting —

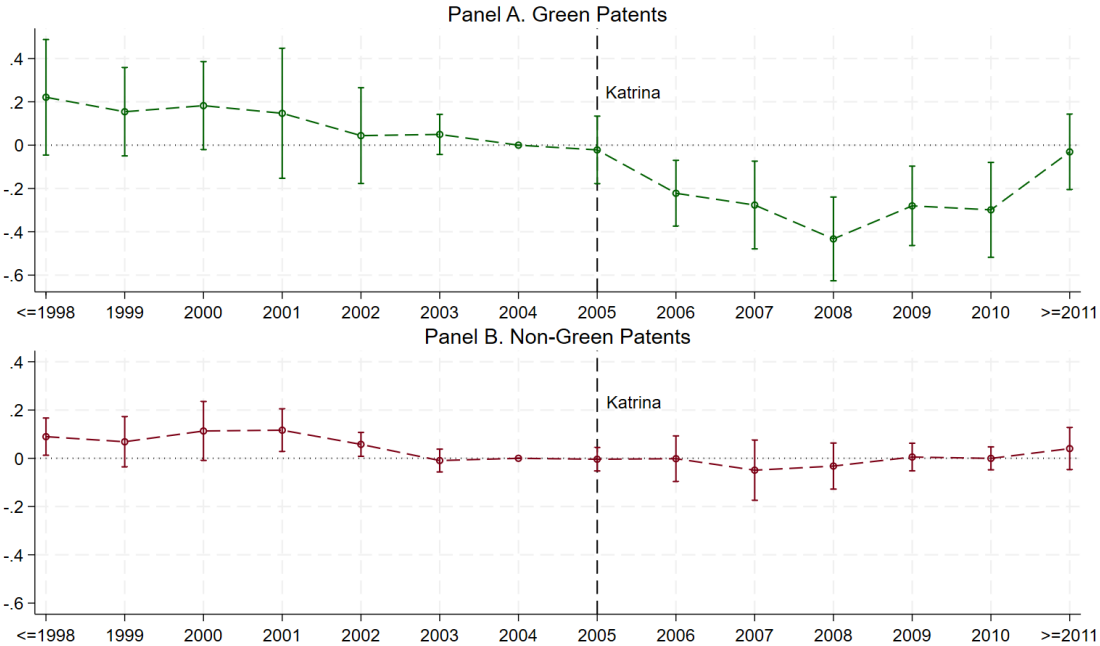
[27] See U.S. Green Building Council (2005), "The New Orleans Principles: Celebrating the Rich History of New Orleans Through Commitment to a Sustainable Future," developed immediately after Hurricane Katrina, available at https://www.usgbc.org/sites/default/files/new-orleans-charrotte.pdf.

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)
Observations	102,621	6,749	102,621	75,126
Inventor FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Tenure FE	Yes	Yes	Yes	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 extensive- and intensive-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

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 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.

the opposite of what I find. I therefore turn to supply-side mechanisms.

5 Disruption to Human Capital: The Role of Technological Distance

In this section, I study a supply-side human-capital disruption mechanism to explain why Hurricane Katrina reduced green innovation but left non-green innovation unaffected. I first develop the argument for why green innovation is less resilient to disruptions. I then construct a measure of technological distance between inventors and show that the average technological distance between a sample inventor (treatment or control) and their collaborators within a patent team is greater for green patents than for non-green ones. Finally, I examine whether the negative effects of Katrina are more pronounced for patents produced by teams with greater technological distance, and for inventors whose pre-Katrina collaborators were more technologically distant. Section 6 considers an alternative supply-side mechanism: physical capital destruction.

5.1 Motivation

Inventors and scientists are becoming increasingly specialized 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 specialized knowledge across individuals (Wuchty, Jones, and Uzzi 2007; Jones 2009; Jones 2021). 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 (De Marchi 2012; Barbieri, Marzucchi and Rizzo 2020; Orsatti, Quatraro, and Pezzoni 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 specialized 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.[28]

After identifying inventors' technological expertise, I construct a measure 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 a 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 the same 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 classifications a and b is the minimum of the pairwise conditional probabilities of a patent being classified under one given it is classified under the other:

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

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

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

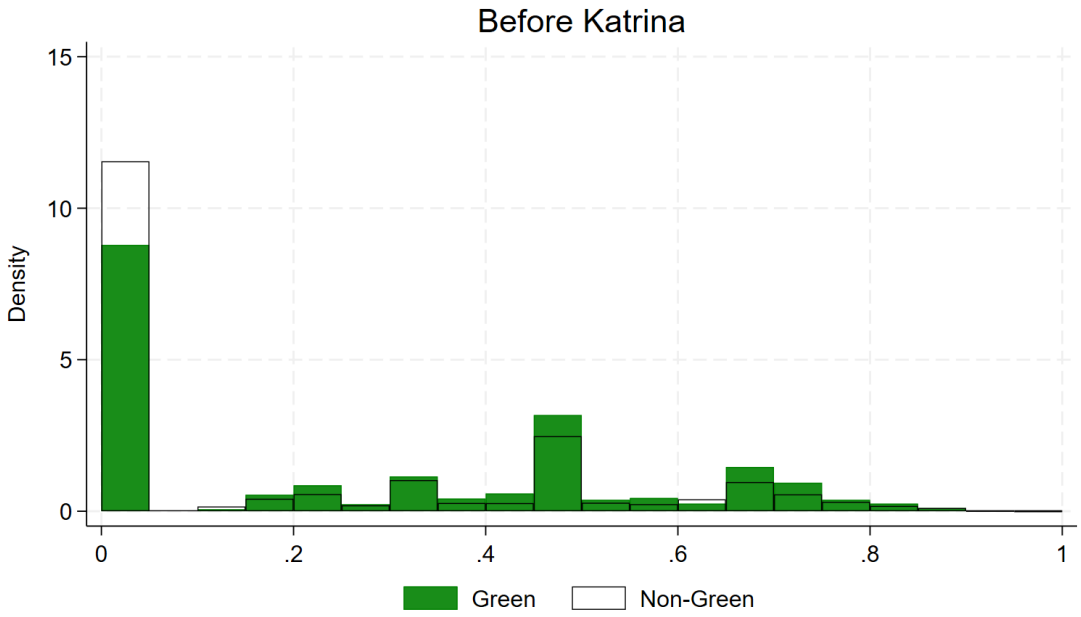
Figure 6 presents the distribution of average technological distance within a patent team for green and non-green patents produced by sample inventors before Katrina. The average technological distance within a patent team is calculated as the mean of all pairwise technological distances between a focal inventor, i.e., a sample inventor, and her collaborators. The distribution for green patent teams (green bars) is more skewed to the right, indicating greater technological distance. In contrast, the distribution for non-green patent teams (white bars) is more concentrated on the left, indicating narrower technological distance. This pattern persists both after Katrina and over the full sample period, with green patents consistently exhibiting greater technological distance. Table 4 additionally reports summary statistics on patent team characteristics for green and non-green patents. Green patent teams are less likely to consist of a single inventor, have larger average team sizes, and exhibit greater geographical distance between collaborators, compared to non-green patent teams.[29] All differences are statistically significant, consistent with green innovation being more reliant on diverse and geographically dispersed collaborative knowledge production.

To empirically test whether technological distance is greater within green than non-green invention

[28] 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.

[29] The baseline results are robust to excluding solo-inventor patents and controlling for the average geographical distance between sample inventors and their co-inventors; see Columns (4)–(5) of Appendix Table A2.

FIGURE 6. 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.

TABLE 4. PATENT TEAM CHARACTERISTICS

	Green	Non-Green	p-value of equality of means test
Likelihood of one-inventor team (%)	12.6	18.7	0.00
Standard deviation	0.331	0.390	
Average team size	3.91	3.51	0.00
Standard deviation	3.54	2.53	
Average geographical distance between collaborators and sample inventors (in km)	865.19	807.29	0.04
Standard deviation	1899.05	1806.18	

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

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 her collaborators within a patent team. Columns 1–3 correspond to the full sample period, the period before Katrina, and the period after Katrina, respectively. Controls include the number of distinct inventors and assignees on each patent and the average geographical distance between a sample inventor and her collaborators. All regressions include state, year, and 3-digit CPC fixed effects. Section 5.2 details the methodology for measuring technological distance. Standard errors clustered at the state-by-3-digit-CPC level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

teams that my sample inventors belong to, I estimate the following specification (Barbieri, Marzucchi, and Rizzo 2020; Fusillo 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 her collaborators within the team that produces patent p. $green_p$ is the focal explanatory variable, a dummy variable equal to 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 on the patent p, and the average geographical distance between a sample inventor and collaborators within the research team that produces patent p. To account for potential geographical heterogeneity and time-varying effects, I include state fixed effects based on sample inventors' locations listed on patents and year fixed effects corresponding to the patent application year. To absorb heterogeneity across technology areas, I include technology class fixed effects at the 3-digit CPC level. Standard errors are clustered at the state-3-digit-CPC level.

Table 5 presents the results. Columns 1–3 correspond to different sample periods: the full sample period, the period before Katrina, and the period after Katrina. The coefficients on the green dummy are positive and statistically significant across all specifications, ranging from 0.0439 to 0.0585. Focusing on Column 2, the average distance between a sample inventor and her collaborators within a green patent team is 0.0585 greater than within a non-green patent team. This difference accounts for 26.35% of the mean technological distance (0.222) before Katrina and 21.67% of the corresponding standard deviation (0.270). These results support my hypothesis: on average, the technological distance within green patent teams is greater than within non-green patent teams.

5.4 Heterogeneous Effects by Technological Distance on Green Patents

If differences in technological distance within patent teams drive the disproportionate negative effect of Hurricane Katrina on green innovation, green patents produced by teams with greater technological distance should suffer more severely, and inventors who worked with more technologically distant collaborators before Katrina should experience a more negative impact on their green patent output.

I first categorize green patents into groups with small and large technological distances based on the distribution of average technological distances before Katrina, using the median value of 0 as the threshold. Green 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 re-estimate the coefficient of interest, β_1, from specification (1) using the Poisson estimator separately for each group. The results, presented in Columns (1) and (2) of Table 6 and Panel A of Figure 7, show that green patents with large technological distances suffered significant negative impacts from Hurricane Katrina, while those with small technological distances show positive but insignificant coefficients. The test confirms that these two effects are statistically different from one another at 0.1% level.[30]

I then categorize inventors into three groups based on tertiles of the average technological distance between inventor i and their collaborators before Katrina, and estimate the following model:

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

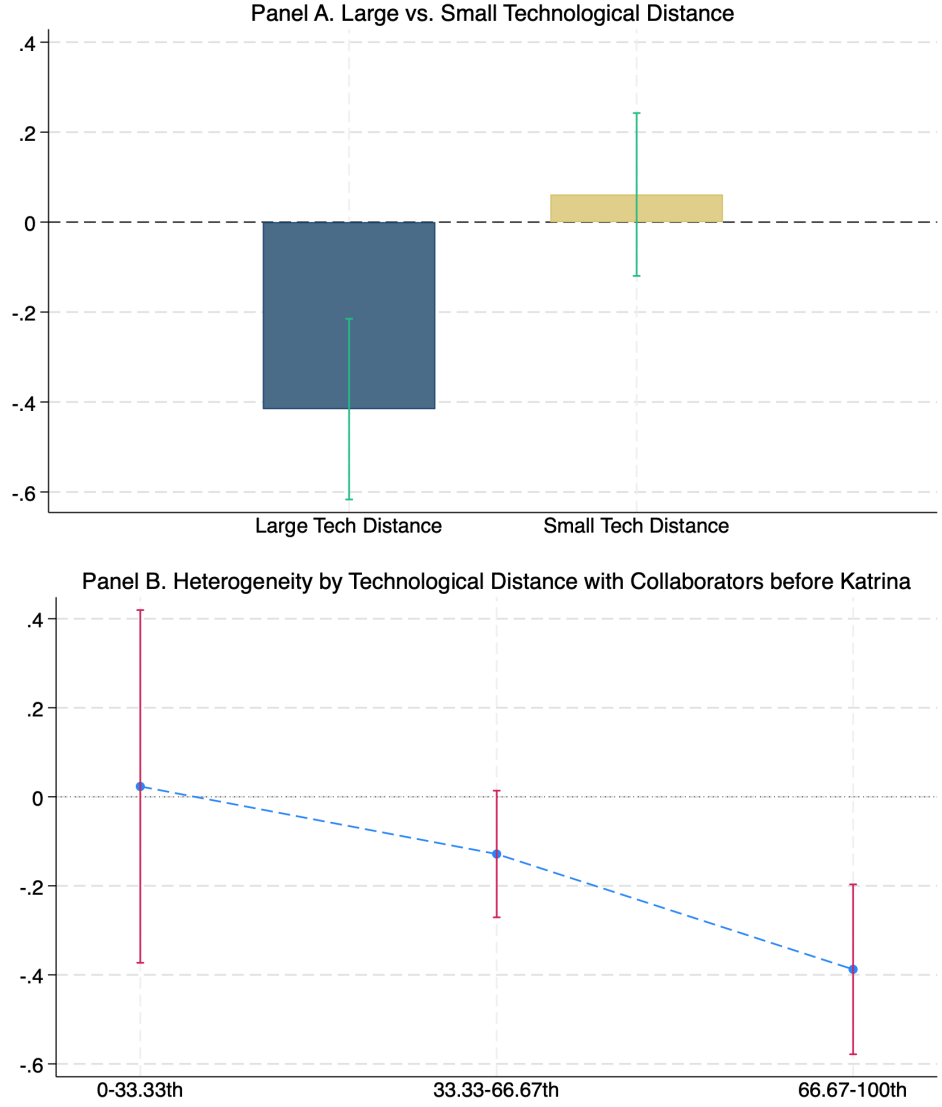
where X_{im} is a dummy variable indicating whether the average technological distance between inventor i and their collaborators before Katrina falls in the mth tertile. All remaining variables are defined as in baseline specification equation (1) in Section 3.3.

Column (3) of Table 6 and Panel B of Figure 7 present the results. The point estimate for the first tertile hovers around zero, while those for the second and third tertiles are significantly negative at the 10% and 1% levels, respectively. The gradient in δ_m is consistent with the hypothesis: the negative effect grows monotonically from the first to the third tertile, and the difference between the second and third tertiles is statistically significant at the 5% level. These findings suggest that inventors who collaborated with more technologically distant partners before Katrina experienced a greater negative impact on their green patent output following the disaster.[31]

[30] I also examine this for non-green patents; results are reported in Columns (1)–(2) of Appendix Table A4 and Panel A of Figure A1. Neither large nor small technological distance non-green patents show significant treatment effects, though the difference between the two groups is statistically significant at the 5% level.

[31] I also examine this for non-green patents. Results are reported in Column 3 in Appendix Table A5 and Panel B in Figure A1. Only the point estimate for third tertiles are significantly negative at the 10% level and the difference between the second and third tertiles is statistically significant at the 10% level.

FIGURE 7. HETEROGENEOUS EFFECTS BY TECHNOLOGICAL DISTANCE ON GREEN PATENTS



Notes: Panel A plots the point estimates for the coefficient β_1 from specification (1), where the dependent variables are the number of green patents with large and small technological distance, respectively. The median average technological distance before Katrina is 0, which serves as the threshold: patents with average technological distance above 0 are classified as large, and those equal to 0 as small. Panel B plots the estimated coefficients δ_m from specification (4), where tertiles are defined based on the average technological distance between sample inventors and their collaborators before Katrina. Both panels use the Poisson estimation method and aggregate outcomes over years t to $t+2$, inclusive. Standard errors are clustered at the state and year levels. Section 5.2 details the methodology for measuring technological distance.

TABLE 6. HETEROGENEOUS EFFECTS BY TECHNOLOGICAL DISTANCE ON GREEN PATENTS

	(1) Patents of large tech distance	(2) Patents of small tech distance	(3) Heterogeneity by tech distance with collaborators before Katrina
$Treatment \times Post$	-0.416^{***}	0.0614	
	(0.103)	(0.0924)	
1st tertile $\times\ Treatment \times Post$			0.0233
			(0.202)
2nd tertile $\times\ Treatment \times Post$			-0.129^{*}
			(0.0726)
3rd tertile $\times\ Treatment \times Post$			-0.388^{***}
			(0.0974)
Tests of coefficient differences (one-sided p-values)			
$\beta_1^{\text{Col 1}} < \beta_1^{\text{Col 2}}$		<0.001	
$\delta_m^{\text{1st tertile}} > \delta_m^{\text{2nd tertile}}$			0.201
$\delta_m^{\text{2nd tertile}} > \delta_m^{\text{3rd tertile}}$			0.015
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: Columns 1 and 2 report the coefficient β_1 from specification (1), where the dependent variables are the number of green patents with large and small technological distance, respectively. Column 3 reports the estimated coefficients δ_m from specification (4), where X_{im} indicates whether inventor i falls in the mth tertile of the pre-Katrina technological distance distribution. Tertiles are computed based on the average technological distance between sample inventors and their collaborators before Katrina. Both analyses use 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. One-sided p-values test whether larger technological distance is associated with more negative treatment effects. Section 5.2 details the methodology for measuring technological distance. *** p<0.01, ** p<0.05, * p<0.1

6 Physical Capital Destruction Is Not the Driving Force

Beyond human capital, physical capital is another key input in the innovation production function. If green innovation relies more heavily on physical capital — such as research laboratories and specialized equipment — than non-green innovation, the destruction of physical capital could disproportionately reduce green patenting while leaving non-green patenting largely unaffected. I investigate this mechanism by exploiting variation in county-level property damage as a proxy for physical capital destruction. I categorize treated inventors into low, medium, and high damage terciles, with control inventors in counties with zero damage serving as the omitted category, and estimate the following specification:

$$Y_{ist} = f\Big(\beta_0 + \beta_1 \,\text{Tercile1}_i \times \text{Post}_t + \beta_2 \,\text{Tercile2}_i \times \text{Post}_t + \beta_3 \,\text{Tercile3}_i \times \text{Post}_t + \gamma_i + \sigma_s + \tau_t + \sum_j \lambda_j \mathbb{1}_{[\text{tenure}_{it}=j]}\Big) + \epsilon_{ist} \tag{5}$$

where Tercile1_i, Tercile2_i, and Tercile3_i are indicator variables equal to 1 if inventor i belongs to the low, medium, or high property damage tercile, respectively. The omitted category is Tercile 0, comprising control inventors located in counties with zero Katrina-related property damage. All other variables are as defined in specification (1). If physical capital destruction were driving the differential decline in green innovation, higher damage intensity should generate progressively larger reductions in green patenting.

Table 7 reports the results for green patents. Green patenting falls by 19.0%, 19.9%, and 20.2% for inventors in low, medium, and high damage terciles, respectively — magnitudes that are remarkably similar across terciles. The gradient tests confirm: I cannot reject the null hypothesis that adjacent tercile coefficients are equal for green patents ($p = 0.485$ and $p = 0.473$). By contrast, Table A5 shows that non-green patenting declines significantly only among inventors in the highest damage tercile (-14.4%, $p < 0.01$), and the gradient tests reject equality of adjacent coefficients ($p = 0.010$ and $p = 0.043$). These results suggest that differential reliance on physical capital is unlikely to explain the disproportionate decline in green innovation following Hurricane Katrina. The absence of a damage-intensity gradient in green patenting is inconsistent with a physical capital destruction mechanism — if destroyed infrastructure were the driving force, inventors located in more severely damaged counties should exhibit larger declines.

7 Conclusion and Discussion

This paper studies how physical exposure to severe climate-related disasters affects green innovation at the individual inventor level. 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% 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

TABLE 7. HETEROGENEITY BY PROPERTY DAMAGE

	(1) Coefficients	(2) Gradient Tests (p-values)	(3)
	Green Patents	Tercile 3 $<$ Tercile 2	Tercile 2 $<$ Tercile 1
Tercile 1 (Low) $\times$ Post	-0.211^{**}		
	(0.0839)		
Tercile 2 (Medium) $\times$ Post	-0.222^{*}		
	(0.129)		
Tercile 3 (High) $\times$ Post	-0.226^{***}		
	(0.0517)		
Constant	0.114^{***}		
	(0.0176)		
Gradient Test p-value		0.485	0.473
Observations	102,621		
Inventor FE	Yes		
Year FE	Yes		
State FE	Yes		
Tenure FE	Yes		

Notes: This table reports Poisson pseudo-maximum likelihood (PPML) estimates of the relationship between Katrina-related property-damage intensity and green patenting. Damage terciles are defined among treated inventors only (i.e., those in counties with positive property damage); the omitted category is Tercile 0 (control inventors in counties with zero damage). Columns 2–3 report p-values from one-sided Chi-squared gradient tests of the null hypothesis that adjacent damage tercile coefficients are equal, against the alternative that higher damage terciles produce more negative effects. The dependent variable is the number of patents filed over a three-year window (t to $t+2$). All regressions include inventor, year, state, and tenure fixed effects. Standard errors are two-way clustered by state and year and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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, Marzucchi and Rizzo 2020; Orsatti, Quatraro, and Pezzoni 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. Moreover, the absence of a damage-intensity gradient in green patenting suggests that physical capital destruction is unlikely to account for the disproportionate decline.

These findings carry two implications. First, as climate change increases the intensity of natural disasters, increasing disruptions from climate-related disasters may constrain green innovation — the very type of innovation critical for addressing climate change. Second, the underlying mechanism may extend beyond green technologies: any innovation that requires collaboration across distant fields faces a tension between knowledge diversity and resilience, as the same expertise heterogeneity that enables novel recombination also reduces the substitutability of individual team members in the face of disruption. Future research could examine whether this trade-off applies more generally to other forms of complex, interdisciplinary innovation.

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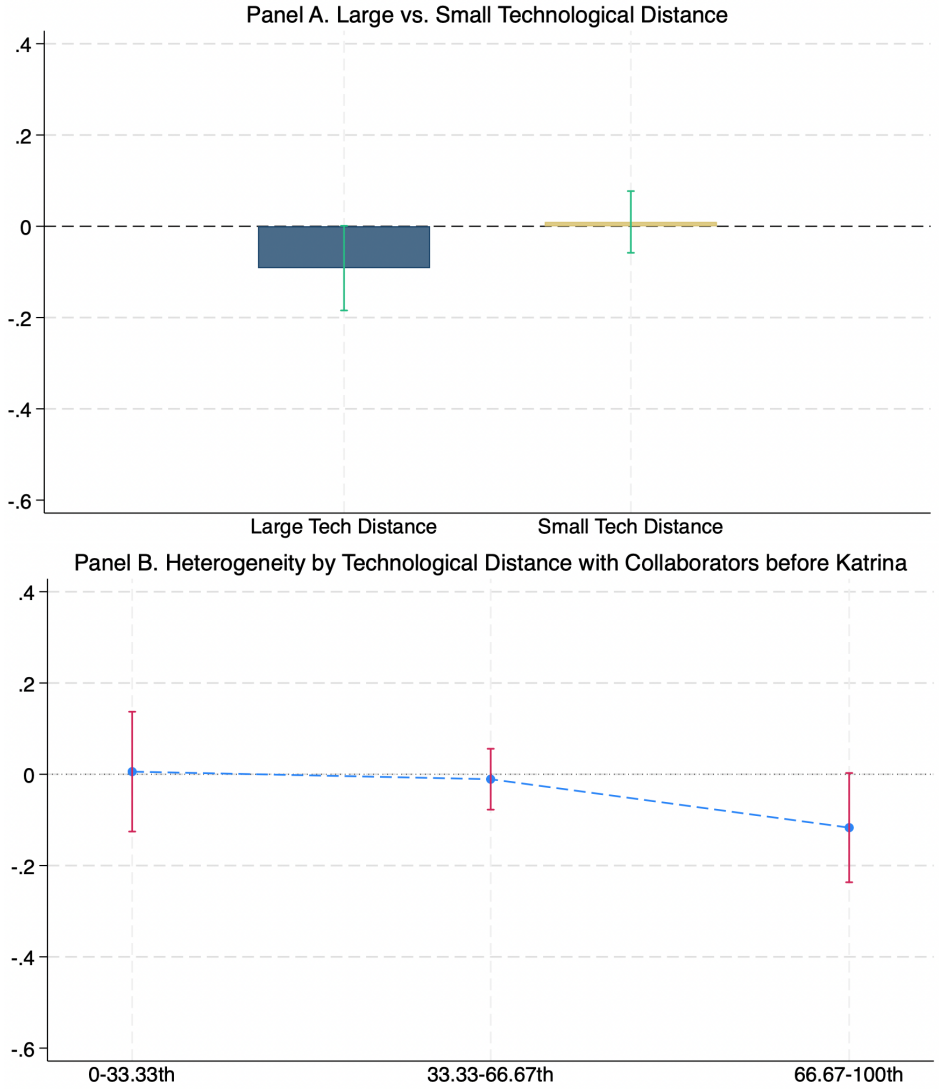
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Appendix Figures

FIGURE A1. HETEROGENEOUS EFFECTS BY TECHNOLOGICAL DISTANCE ON NON-GREEN PATENTS



Notes: Panel A plots the point estimates for the coefficient β_1 from specification (1), where the dependent variables are the number of non-green patents with large and small technological distance, respectively. The median average technological distance before Katrina is 0, which serves as the threshold: patents with average technological distance above 0 are classified as large, and those equal to 0 as small. Panel B plots the estimated coefficients δ_m from specification (4), where tertiles are computed based on the average technological distance between sample inventors and their collaborators before Katrina. Both panels use the Poisson estimation method and aggregate outcomes over years t to $t+2$, inclusive. Standard errors are clustered at the state and year levels. Section 5.2 details the methodology for measuring technological distance.

Appendix Tables

TABLE A1. CPC Y02 GREEN TECHNOLOGY SUBCLASSES AND DESCRIPTIONS

Code	Description
Y02A 10/00	At coastal zones; at river basins
Y02A 20/00	Water conservation; Efficient water supply; Efficient water use
Y02A 30/00	Adapting or protecting infrastructure or their operation
Y02A 40/00	Adaptation technologies in agriculture, forestry, livestock or agroalimentory production
Y02A 50/00	In human health protection, e.g. against extreme weather
Y02A 90/00	Technologies having an indirect contribution to adaptation to climate change
Y02B 10/00	Integration of renewable energy sources in buildings
Y02B 20/00	Energy efficient lighting technologies, e.g. halogen lamps or gas discharge lamps
Y02B 30/00	Energy efficient heating, ventilation or air conditioning [HVAC]
Y02B 40/00	Improving efficiency of home appliances (induction cooking, efficient refrigerators, etc.)
Y02B 50/00	Energy efficient technologies in elevators, escalators and moving walkways
Y02B 70/00	Efficient end-user side electric power management and consumption
Y02B 80/00	Architectural/constructional elements improving thermal performance of buildings
Y02B 90/00	Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation
Y02C 20/00	Capture or disposal of greenhouse gases
Y02C 20/10	Of nitrous oxide (N2O)
Y02C 20/20	Of methane
Y02C 20/30	Of PFC, HFC, or SF6
Y02C 20/40	Of CO2
Y02D 10/00	Energy efficient computing, e.g. low power processors, power/thermal management
Y02D 30/00	Reducing energy consumption in communication networks
Y02E 10/00	Energy generation through renewable energy sources
Y02E 30/00	Energy generation of nuclear origin
Y02E 20/00	Combustion technologies with mitigation potential
Y02E 40/00	Technologies for efficient electrical power generation, transmission or distribution
Y02E 50/00	Production of fuel of non-fossil origin
Y02E 60/00	Enabling technologies with potential/indirect GHG mitigation
Y02E 70/00	Other energy conversion/management systems reducing GHG emissions
Y02P 10/00	Metal processing
Y02P 20/00	Chemical industry
Y02P 30/00	Oil refining/petrochemical industry
Y02P 40/00	Processing of minerals
Y02P 60/00	Agriculture, livestock, agroalimentory industries
Y02P 70/00	Final industrial/consumer products process
Y02P 80/00	Sector-wide applications
Y02P 90/00	Enabling technologies with potential to mitigate GHG emissions
Y02T 10/00	Road transport of goods or passengers
Y02T 30/00	Railways, energy recovery, reducing air resistance
Y02T 50/00	Aeronautics or air transport
Y02T 70/00	Maritime/waterways transport
Y02T 90/00	Enabling technologies or potential for GHG mitigation in transport
Y02W 10/00	Technologies for wastewater treatment
Y02W 30/00	Technologies for solid waste management
Y02W 90/00	Enabling technologies for GHG mitigation in waste management

TABLE A2. ROBUSTNESS

	(1) Alt definition of green	(2) Control group not restricted to South US	(3) Excluding inventors with pre-Katrina cross-group co-inventorship links	(4) Excluding solo-inventor patents	(5) Controlling geo distance with co-inventors
Panel A: Green patents					
$Treatment \times Post$	-0.294^{***}	-0.152^{**}	-0.220^{***}	-0.269^{***}	-0.212^{***}
	(0.074)	(0.066)	(0.0641)	(0.064)	(0.063)
Mean of dep. var before Katrina	0.053	0.053	0.053	0.053	0.053
Observations	102,621	102,621	102,301	102,621	102,621
Year fixed effects	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes
Inventor fixed effects	Yes	Yes	Yes	Yes	Yes
Tenure fixed effects	Yes	Yes	Yes	Yes	Yes
Estimation method	Poisson	Poisson	Poisson	Poisson	Poisson
Panel B: Non-green patents					
$Treatment \times Post$	-0.040	-0.065^{*}	-0.0423	-0.068^{*}	-0.037
	(0.035)	(0.038)	(0.0350)	(0.038)	(0.035)
Mean of dep. var before Katrina	2.084	2.084	2.084	2.084	2.084
Observations	102,621	102,621	102,067	102,621	102,621
Year fixed effects	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes
Inventor fixed effects	Yes	Yes	Yes	Yes	Yes
Tenure fixed effects	Yes	Yes	Yes	Yes	Yes
Estimation method	Poisson	Poisson	Poisson	Poisson	Poisson

Notes: This table reports the estimated coefficient β_1 from specification (1) for five robustness exercises. Column 1 uses the alternative definition of green patents based on the OECD ENV-TECH classification (Haščič and Migotto 2015). Column 2 does not restrict the control group to the Southern US. Column 3 excludes inventors with pre-Katrina cross-group co-inventorship links: 84 treated inventors and 75 control inventors who filed at least one patent with an inventor on the other side of the treatment-control divide before Katrina are dropped. Column 4 excludes patents with a single inventor. Column 5 controls for the geographical distance between sample inventors and their co-inventors. The dependent variable is the number of green (Panel A) or non-green (Panel B) patents filed over years t to $t+2$, inclusive. All columns include fixed effects for tenure, inventor, year, and state. The variable *tenure* is measured 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 A3. 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)
$Treatment \times Post$	-0.0564	-0.00911	-0.00317
	(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. The dependent variables, each aggregated over years t to $t+2$, are: patent counts (column 1), an indicator for filing any patent (column 2), and the natural logarithm of patent counts (column 3). Column 1 is estimated with Poisson and columns 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 levels are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE A4. HETEROGENEOUS EFFECTS BY TECHNOLOGICAL DISTANCE ON NON-GREEN PATENTS

	(1) Patents of large tech distance	(2) Patents of small tech distance	(3) Heterogeneity by tech distance with collaborators before Katrina
$Treatment \times Post$	-0.0744	0.0210	
	(0.0466)	(0.0362)	
1st tertile $\times\ Treatment \times Post$			0.00579
			(0.0670)
2nd tertile $\times\ Treatment \times Post$			-0.0108
			(0.0340)
3rd tertile $\times\ Treatment \times Post$			-0.117^{*}
			(0.0611)
Tests of coefficient differences (one-sided p-values)			
$\beta_1^{\text{Col 1}} < \beta_1^{\text{Col 2}}$		0.040	
$\delta_m^{\text{1st tertile}} > \delta_m^{\text{2nd tertile}}$			0.407
$\delta_m^{\text{2nd tertile}} > \delta_m^{\text{3rd tertile}}$			0.051
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: Columns 1 and 2 report the coefficient β_1 from specification (1), where the dependent variables are the number of non-green patents with large and small technological distance, respectively. The median average technological distance before Katrina is 0, which serves as the threshold: patents with average technological distance above 0 are classified as large, and those equal to 0 as small. Column 3 reports the estimated coefficients δ_m from specification (4), where X_{im} indicates whether inventor i falls in the mth tertile of the pre-Katrina technological distance distribution. Tertiles are computed based on the average technological distance between sample inventors and their collaborators before Katrina. Both analyses use 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. One-sided p-values test whether larger technological distance is associated with more negative treatment effects. Section 5.2 details the methodology for measuring technological distance. *** p<0.01, ** p<0.05, * p<0.1

TABLE A5. HETEROGENEITY BY PROPERTY DAMAGE: NON-GREEN PATENTS

	(1) Coefficients	(2) Gradient Tests (p-values)	(3)
	Non-Green Patents	Tercile 3 $<$ Tercile 2	Tercile 2 $<$ Tercile 1
Tercile 1 (Low) $\times$ Post	0.0546		
	(0.0660)		
Tercile 2 (Medium) $\times$ Post	-0.0459		
	(0.0307)		
Tercile 3 (High) $\times$ Post	-0.155^{***}		
	(0.0470)		
Constant	0.412^{***}		
	(0.021)		
Gradient Test p-value		0.010	0.043
Observations	102,621		
Inventor FE	Yes		
Year FE	Yes		
State FE	Yes		
Tenure FE	Yes		

Notes: This table reports Poisson pseudo-maximum likelihood (PPML) estimates of the relationship between Katrina-related property-damage intensity and non-green patenting. Damage terciles are defined among treated inventors only (i.e., those in counties with positive property damage); the omitted category is Tercile 0 (control inventors in counties with zero damage). Columns 2–3 report p-values from one-sided Chi-squared gradient tests of the null hypothesis that adjacent damage tercile coefficients are equal, against the alternative that higher damage terciles produce more negative effects. The dependent variable is the number of patents filed over a three-year window (t to $t+2$). All regressions include inventor, year, state, and tenure fixed effects. Standard errors are two-way clustered by state and year and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.