Post-disaster fluctuations in innovation: Evidence from Hurricane Katrina

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Abstract

Theoretically motivated by evidence that large exogenous shocks can produce enduring fluctuations in economic behavior, this study shows that counties affected by Hurricane Katrina exhibit substantial post-disaster increases in the quantity and quality of patenting compared to unaffected counterfactual counties. The significance of the matched-sample difference-in-differences estimates rises in damage severity, persists up to 10 years, and is robust to factors such as a post-disaster economic rebound, changes in the demand for specific innovation, aid and investment, wealth, education, and traditional explanations of innovative activity, such as firm R&D, institutions and market factors, but enhanced by inventor density and collaboration. Using georeferenced histories of inventors, the analyses trace the "Katrina effect" and control for selective migration and company affiliation. The findings point to an understudied driver of the geography of innovation.

Keywords: innovation, disasters, risk-taking behavior, patents.

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1. Introduction

In comparison with other economic behavior, the pursuit of innovation is highly impacted by localized factors (Alcacer and Chung 2007, Feldman and Kogler 2010). Location affects opportunities to collaborate (Bikard and Marx 2020, Catalini 2018) and share knowledge (Berkes and Gaetani 2021, Gambardella and Giarratana 2010), access factor markets (Acemoglu et al. 2018) and infrastructure that economizes search (Roche 2019). It determines access to financing (González-Uribe 2020), institutional incentives (Flammer and Kacperczyk 2015, Mukherjee et al. 2017, Vakili and Zhang 2018), and intellectual-property protection (Cockburn et al. 2016).

Location also exposes individuals to exogenous shocks that affect their opportunities, resources, and/or willingness to pursue innovation. Natural disasters, for instance, can be a form of Schumpeterian creative destruction by generating opportunities to renovate the capital stock with new technology (Aghion and Howitt 1990). The most direct link is that innovation becomes a strategy for shock mitigation and adaptation (Li 2017). For instance, drought-resistant crops, water-level control, and quake-proof construction are relatively frequent in countries prone to droughts, floods, and earthquakes, respectively (Miao and Popp 2014). Similarly, U.S. counties affected by heat waves often experience increases in patents related to air conditioning within two years (Noy and Strobl 2022). Conversely, other studies document negative correlations between country-level exposure to natural disasters and foreign knowledge spillovers (Crespo Cuaresma et al. 2008) and the rate of some types of technological innovation (Chen et al. 2021, Zhao et al. 2022). Typical explanations point to the scarcity of innovation inputs due to their destruction or reallocation toward reconstruction and recovery. Additionally, theoretical models predict that the high levels of uncertainty created by disasters hinders R&D investment (Bloom 2007).

In the midst of this debate, there is the intuition that if disasters have a sizable effect in innovation that is not directly connected with a demand effect or the perceived need for specific goods, this will be short-lived and explained by the evolution of economic recovery. However, a relatively new albeit fast-growing literature in economics and psychology suggest that natural disasters can have long-lasting consequences on economic behavior (see Schildberg-Hörisch 2018 for a survey). For instance, gambling among men in Japan increased in their proximity to the epicenter of the 2011 earthquake in Japan and this effect is observed years the disaster (Hanaoka et al. 2018). Similarly, CEOs of S&P firms that spent their early life in U.S. counties hit by natural disasters tend to manage their companies comparatively aggressively

regarding decisions such as acquisitions (Bernile et al. 2017). Interestingly, fluctuations in wealth, actual and expected income, the expected distribution of returns, and the macroeconomy do not fully explain these behavioral changes (Guiso et al. 2018).

The prospect that a similar dynamic applies to innovation motivates this study. I focus on the spatial distribution of damage from Hurricane Katrina, the most disruptive disaster in the U.S. to date. This setting allows me to apply different strategies for causal inference that, naturally, is complex given the different factors affecting innovation. The key empirical challenge centers on identifying robust counterfactuals for the innovation patterns of Katrina victims should the disaster have not occurred. Such a comparison must include the individual, organizational, institutional, and socioeconomic factors that may affect the cost and benefits of innovation. To achieve this, I build a database of innovation in the United States proxied by the universe of patents from 1999 to 2015 from the U.S. Patent and Trademark Office (USPTO), which I merge with data of the geolocation of the hurricane's extent and type of damage, and sociodemographic and economic administrative data from different federal agencies.

To identify the spatial distribution of patents, inventors, and assignees, I start by drawing upon the disambiguation procedures of the PatentsView initiative,[1] launched in 2017. I identify the Federal Information Processing Standards (FIPS) county number of street addresses of each of the inventors listed in the patent application to geocode locations for inventors, including frequency of patenting, fields of invention, and patent citations. Then, I define a precise measure of the geographic position of Katrina's direct damage using data from the U.S. National Oceanic and Atmospheric Administration, the Federal Emergency Management Agency (FEMA), and the Department of Housing and Urban Development. With these data, I conceptualize and test a range of treatment effects by classifying counties based on the proportion of households with minor, major, or severe damage, according to FEMA's official assessment. Finally, I construct a panel of control counties that are statistically similar to those affected in the years before the hurricane hit in 2005 using a baseline vector of county socioeconomic and demographic characteristics including education, race and ethnicity, income and wealth, insurance, economically active population, health standards, (un)employment and number of jobs, urbanization, and population size. The

[1] https://www.patentsview.org/.

estimation accounts for disaster-related public and private transfers and economic-recovery programs and acts, county-level institutional differences, and other disasters.

The richness of the data facilitates investigating the role of individual-level factors such as inventor collaboration, firm affiliations, and firm-specific investment and account for confounders such as selective migration. In the studied setting, a comparatively innovative population relocating after the shock could have substituted risk-averse (or less innovative) emigrants. This may result in estimates driven by the invention of individuals who were not affected by Katrina. To address this concern, I document the migration of inventors in the 17-year period in the U.S. Then, I compare the patenting of individuals that resided in 2005 in one of the counties affected by Katrina, were in any of these counties between 2000 and 2004, and were in these counties between 2006 and 2015. This analysis allows to account for the possibility that the shock changed the transaction costs and/or expected values of patenting—including fluctuations in corporate resources for invention and the general equilibrium effects of Katrina that could have impacted collaboration (Teodoridis 2018). In addition to the battery of time-varying variables and single fixed effects used in the county-level models, I use pair combinations of time and county fixed effects. These sets absorb factors that are unique to time and locations that connect individuals with their places of residence (Bikard et al. 2019).

The main results can be summarized as follows. The difference-in-differences estimates show substantial increases in the rate and quality of patenting, starting a year after Hurricane Katrina. In the five years after the disaster, affected counties became 5.8% more likely to patent than counterfactuals and their patents became 10.8% more likely to be cited than similar patents of control counties. The difference rises in proximity to the intensity of the damage and thus counties ranking in the 90^{th} percentile of severe damage were 17.5% more likely to patent than similar non-affected counties. Between 2006 and 2011, inventors in these severely affected counties were, on average, almost 29% more likely to be cited than similar inventors outside the disaster area.

These results are economically important given the Katrina year is an inflection point in innovation outcomes. Before the disaster year, invention coming from the affected counties was, on average, 20% and 23% less likely to patent and generate citations, respectively, than non-affected control counties.

The patenting gaps persist in the period 2011-2015, at 4.6% for the full sample and at 14.7% for severely damaged counties and cannot be explained by business cycles, the demand for specific innovation, inventor density and collaborative patents, and the set of county-specific socioeconomic and demographic characteristics. Likewise, the estimate of innovation quality is not affected by truncation bias in citations (Hall et al. 2001) and accounts for the varying propensity to cite across patent sections and time (Aghion et al. 2019). The results for counties with mostly minor damage are not significant.

At the individual level, inventors residing in Katrina counties—as per the information from patent applications—that did not emigrate during the observation period were 8.2% and 11.8% more likely to patent than similar inventors outside the affected area in the first and second post-shock periods, respectively. These results are similar to studies showing that post-shock changes vary by proximity to intense damage (Callen et al. 2014, Hanaoka et al. 2018).

Of importance, the interpretation of the findings is not that disaster-stricken counties in the U.S. Gulf Coast will become innovation hubs or more important sources of innovation than places like Silicon Valley. Instead, the analyses suggest that a) the uniqueness of the innovation coming from geographical communities can drastically fluctuate after large disasters and that b) these fluctuations may not be determined by post-disaster changes in the physical, policy, sociodemographic, and economic trends of the place.

These findings, first and foremost, contribute to the literature on the environmental determinants of innovation. They suggest that traditional theoretical silos in this scholarship may not sufficiently capture the effects of shocks like Katrina on innovative activity. The correlations survive prominent measures of urban agglomeration (Moretti 2021), business cycles (Berkes and Gaetani 2021), a demand for invention (Agrawal et al. 2014), market size and economic resources (Aghion et al. 2019), firm investment (Bhaskarabhatla et al. 2021), and public policy (Agrawal et al. 2021, Moretti and Wilson 2017). Subsequent testing of mechanisms shows that the county density of inventors and inventor collaboration enhances the effect of the disaster in innovation.

Furthermore, the analyses systematically indicate that an economic channel does not adequately explain patenting differences. In fact, the results are robust to the three most widespread explanations of post-shock changes in economic behavior: income and wealth (Bordalo et al. 2012, Kahneman and Tversky 1979),

background risk or expected income (Guiso and Paiella 2008), and salience theory or the expected distribution of returns (Bordalo et al. 2012). Taken together, the study illuminates opportunities for future research on understudied behavioral drivers of innovation.

This study also connects with the literature studying the economic consequences of natural-disaster experience (Dahan et al. 2010, e.g., Rehse et al. 2019, Salvato et al. 2020, Yi et al. 2022). Past studies have extensively explored the role of this experience on corporate management and investment (Bernile et al. 2017, Dessaint and Matray 2017) and risk-management decisions (Gao et al. 2020). There is less exploration of economic behavior at the micro-community level. A common prediction is that a disaster's temporary high levels of environmental uncertainty will depress innovation when the disaster hits (e.g., Bloom 2007). My study informs on how large shocks can change the economic geography of local communities and their residents in the long run.

The findings have implications for how we model policy instruments that guide investment and intervention in the aftermath of disruptions like Katrina. Prior work has shown the disconnect between public policy support for market recovery and business decision making because policymakers underestimate the long-run consequences of disasters (Baker et al. 2020). Despite their short-lived and low-probability nature, phenomena like Katrina may drastically affect the trajectory of economic behavior of affected communities.

The rest of the paper continues as follows. Section 2 **Error! Reference source not found.**presents a discussion of the potential drivers of the consequences of Hurricane Katrina on innovation and lays out the theoretical baseline for relevant predictions. Section 3 presents the data and Section 4 describes the identification strategy. Section 5 reports the results and their robustness. Section 6 evaluates potential channels of the reported correlations. Section 7 concludes.

2. Hurricane Katrina as a Shock to Innovation

Hurricane Katrina, which hit the U.S. mainland on August 2005, evolved under substantial uncertainty regarding its scale and location. It was downgraded to a tropical storm when approaching Florida and then reached category 5 right before landfall. The projected trajectory maps varied significantly going from Florida, Mississippi, and then New Orleans, where most of the human and economic costs occurred. The

information that residents were receiving from the local, state, and national governments toward preparation was confusing and, ultimately, resulted in fewer than 24 hours to evacuate before the hurricane's landfall (Dye et al. 2014). There were 136 counties across Alabama, Florida, Louisiana, Mississippi, and Texas with direct material damage, according to the U.S. Government's official designation (USHUD and U.S. Department of Housing and Urban Development 2006).

A channel of a potential effect of Katrina on innovation is economic in nature. Being the costliest and one of the deadliest disasters ever to strike the U.S., a common idea points to the persistent negative economic ramifications on the victims. First, it is possible that the disaster increased the opportunity costs of exploiting proximate income-generating opportunities. Affected communities could have switched their focus to activities yielding immediate income to cope with the welfare loss. Katrina could have resulted in selection out of economic behavior whose payoffs are distant in time and uncertain, such as innovation. Of course, the ephemeral nature of economic impacts does not rule out the possibility that the disaster affected background risk. For instance, loss of livelihood or possessions could have made the negative scenario of the financial outcome of innovation more salient (Bordalo et al. 2012).

Regarding the temporality of these fluctuations, a feedback effect between innovation and economic growth may be at place (Galindo and Méndez 2014). After individuals deferred innovative behavior in the aftermath of the disaster, a subsequent rise in innovation outcomes could have mimicked the trajectory of an economic rebound in the stricken communities.

Aid coming from government relief and recovery, private philanthropy, insurance, and tax benefits could have provided a financial cushion for some of the individuals residing in affected communities, particularly those that were less affected by the hurricane. This could have led to greater opportunities to pursue in invention. It is also possible that the hurricane increased the short-run demand for specific technology, such as those goods associated with the reconstruction or the management of disaster risk (Miao and Popp 2014, Noy and Strobl 2022).

Finally, there is a possibility that Katrina affected institutions that are essential for the innovation process (Ballesteros and Magelssen 2021). Hence, patenting became logistically more challenging because of the damage of infrastructure (Roche 2019), the breakdown of mechanisms for collaboration (Catalini et al. 2020), and/or the scarcity of external resources to fund innovative behavior (Zhao et al. 2022).

A different set of explanations come from evidence on the stability of risk-taking behavior after disasters. For instance, Hanaoka, Shigeoka, and Watanabe (2018) find that individuals affected by the 2011 earthquake and tsunami in Japan became risk tolerant and increased risk taking persisted five years after the shock. Bernile et al. (2017) find that experiencing severe natural disasters between the ages of 5 and 15 can predict how risk-loving executives are when managing their corporations.

If Katrina sparked negative emotions (Necker and Ziegelmeyer 2016) or triggered fearful memories on affected population (Lerner and Keltner 2001), it possibly led to lower willingness to take risks, which could have included innovation. Interestingly, Eckel et al. (2009) apply two waves of surveys to Katrina evacuees and document increased risk-loving attitudes that were more pronounced among women than among men. The authors applied the survey to a control group drawn from non-affected residents with similar demographic characteristics to Katrina evacuees and find comparatively large risk aversion among this population.

In practice, predicting whether large shocks will lead to increases or decreases in innovation, or if these changes are sizeable at all, is not trivial. Broadly, the findings of the direction of post-shock fluctuations in economic behavior are equivocal. An interesting pattern that can potentially explain this ambiguity is that the direction of the relationship seems to depend on certain characteristics of the shock, particularly its severity and temporality. Sudden shocks, such as earthquakes and hurricanes and some manmade disruptions like bomb attacks, tend to increase risk-taking behavior; but shocks whose effects evolve over time, such as pandemics, financial crises, and droughts, tend to decrease it (Callen et al. 2014, Guiso et al. 2018, Hanaoka et al. 2018, Schildberg-Hörisch 2018).

3. Data

3.1. Innovation

The innovation proxies comprise the universe of granted patents from the USPTO between 1999 and 2015. Data suggest that novel activity with a relatively high impact on economic development tends to be patented (Griliches 1990). More broadly, patents are an objective indicator of technological novelty that is ubiquitous in the literature on innovation (Lerner and Seru 2017). Nevertheless, it is reasonable to believe that patents offer a conservative estimate for evaluating the relation of interest. If, for instance, Katrina indeed increased the willingness to engage in innovative activity, it is likely that not all of this activity

resulted in patents. Another benefit of using patents is that that whatever measurement error of innovation they entail, it is unrelated to the occurrence of the hurricane and, hence, any underestimation of innovative activity is at a similar magnitude in disaster-stricken and non-affected counties.

Patent data pose challenges that are relevant to the analysis (Lerner and Seru 2017, Magelssen 2020). An important one is right censoring. There is a gap between patent application and granting that recent reports show to be 23 months (USPTO 2021). This creates a mechanical tail-off in the number of patents granted in the years near the end of a patent database. The tail-off not only affects a measure of number of patents but it is also relevant to correctly measuring forward citations, as newer patents are less likely to be cited. Since the last update of patent data for the study was done in January 2022, right censoring is not a significant risk. However, to measure innovation quality, I limit to forward citations reported within the first five years of a patent's file year so that each patent in the dataset has the same number of years to receive a prior art citation.

The second challenge is the accurate mapping of the location of innovation. For this, I draw upon the identity and address disambiguation conducted by the PatentsView initiative,[2] launched in 2017. PatentsView performs entity resolution from patent data to identify inventor and assignee names and their locations. I merge these disambiguated data with patent-specific data tables including different classifications—focusing on the International Patent Classification (IPC), citations, involved government agencies, and foreign interest. Additionally, I use data of inventor's gender that PatentsView predicts with an algorithm.[3]

Additionally, there is a possibility that examiners in the USPTO offices relatively close to Katrina might have been impacted. Thus, factors such as their approval rating and the areas they tend to approve might be different from those that are in other locations. To address this risk, I test and find no differences in the

[2] PatentsView is a patent data visualization and analysis platform intended to increase the value, utility, and transparency of U.S. patent data. The initiative is supported by the Office of Chief Economist in the USPTO. The PatentsView initiative was established in 2012 and is a collaboration between USPTO, U.S. Department of Agriculture, the American Institutes for Research, New York University, the University of California at Berkeley, Twin Arch Technologies, and Periscopic. More information is at available at: https://www.patentsview.org/.
[3] https://patentsview.org/gender-attribution.

characteristics of application approvals in pre- and post-disaster periods in the offices in the states affected by Katrina and in the offices in non-affected states that are within a range of 500 miles of the disaster area.

I construct a panel of county-level patents spanning the 17-year period. To do this, I identify the Federal Information Processing Standards (FIPS) county number of street addresses of each of the inventors listed in the patent application. Similar to Agrawal et al, (2014), when the application lists inventors located in different counties, I record a patent in each of those counties. The baseline observation unit is the county-year. I also create a monthly panel for all the U.S. counties that I use to document innovation fluctuations before and after the disaster month of August 2005.

Additionally, I construct an inventor-specific panel of their residences and mobility across counties for the studied period. These data geolocate inventors anywhere in the U.S. map and allow me to control for selective migration in robustness tests. I increase the patent count for each individual in the application. In robustness tests, I follow Aghion et al. (2019) and split the patent proportionally across coinventors.

3.2. Specification of Hurricane Katrina's Intensity

The causal inference relies on the spatial distribution of direct damage created by Katrina along the U.S. Gulf Coast area. Compared to human damage, which is highly concentrated in a few areas, material damage captures the range of the spatial distribution of intensity and, arguably, the wide variation of negative shocks for affected individuals and their communities (Deryugina et al. 2018).[4] Moreover, focusing on material damage aligns with the extant literature (see Schildberg-Hörisch 2018 for a survey).

I start by geocoding the housing units officially assessed as damaged in the 136 counties across five states (henceforth, Katrina counties) (USHUD and U.S. Department of Housing and Urban Development 2006). The data come from the Office of the Federal Coordinator for Gulf Coast Rebuilding at FEMA, the Small Business Administration, and the Department of Housing and Urban Development Security. I then

[4] Material damage provides a more efficient measure to capture the heterogeneity of Hurricane Katrina's damage. As for other disasters, the loss of health, particularly the 1,836 associated deaths, was highly concentrated in a few counties in the state of Louisiana. Studies on the impact of Katrina correlate this concentration of human loss with complex historical patterns of economic and institutional destitution rooted in sociodemographic and political factors, such as race and local government accountability (Cutter 2006, Gabe et al. 2005, Select Bipartisan Committee to Investigate the Preparation for and Response to Hurricane Katrina 2006).

cutoff points based on the proportion of housing units in the county that suffered minor, major, and severe damage.[5] FEMA creates this categorization for every disaster by conducting physical inspections of the construction. Given that damage does not distribute uniformly, I use quantiles to identify counties according to their proportion of damage severity.

3.3.Other Data

I compile county-level sociodemographic and economic administrative data from the U.S. Census Bureau and the American Community Survey. These data are used for identifying the pool of control counties and as control variables. They include insurance, education attainment, race and ethnicity, (un)employment, population size, gender composition, GDP and average income and earnings. I also code the level of urbanization of each county using data from the Economic Research Service (ERS) at the U.S. Department of Agriculture. Data of disaster aid and assistance come from the Global Database of Disaster Responses. Additionally, I run automated Boolean searches in Python to track changes in a) government programs for economic development including business creation, b) tax incentives after Katrina, including those not associated with the hurricane, and c) private transfers (e.g., company philanthropy, individual charity, and private investment toward economic development) that could have affected innovation. Appendix B has the complete list of found resources.

3.4. Data Facts

I begin by illustrating innovation trends before and after Hurricane Katrina. Figure 1 shows that, from 2000 to 2004, the average annual growth rate of patenting is either negative or neutral for most Katrina counties. In the post-shock period of 2006-2010, the area hit by Katrina is predominantly characterized by growth in patenting. In the five years before the 2005 disaster, the average number of annual patents (44) in Katrina counties was 11% lower than the national average (49.42). In the disaster year, the number of counties with negative rates increased substantially. Between 2006 and 2010, the annual average of patents by Katrina county was 47.7 compared to 58.4 for the rest of U.S. counties. Between 2011 and 2017, these

[5] The associated housing damage by level is as follows: minor—less than $5,200; major—greater than or equal to $5,200 and less than $30,000; and severe—greater than or equal to $30,000. For details, see (USHUD and U.S. Department of Housing and Urban Development 2006).

numbers were 71.6 and 90.6, respectively. The distributions of patenting in the U.S. have long right tails, as per the high maximum values and standard deviations. Figure A.1 in Online Appendix A shows treatment and control counties located in the U.S. Gulf Coast. Counties that rank at the 50th percentile in the proportion of housing units with severe damage present greater post-Katrina increases in the annual growth rate of patenting than counties with mostly minor and major damage in all two-year periods except 2010-2011.

INSERT FIGURE 1 ABOUT HERE

Regarding sociodemographic and economic characteristics, in 2005, Katrina counties ranked below the national average in jobs per capita, personal income, unemployment insurance, and net earnings. College completion among adults was 3 percentage points lower and the proportion of adults with no high school diploma was greater than in the rest of the country.

There are not substantial differences in pre- and post-disaster net earnings and income per capita adjusted by inflation. Systematic studies on the impacts of the disaster found that the economic impacts were negligible or transitory (Deryugina et al. 2018, Groen et al. 2020). Self-employment income grows, but this does not have a substantial impact on total average income. An analysis of individual tax returns of New Orleans residents finds that the probability of having self-employment income drops by 1% and persists until 2010. Increases in Social Security benefit claims did not accompany retirement withdrawals, suggesting that victims used withdrawals to buffer lost income and assets rather than augmenting them. There was an immediate decline in labor market returns followed by a rapid recovery. Three years after the shock, labor incomes are $1,300 greater among affected residents than similar individuals elsewhere. Growth of unemployment benefits is ephemeral. Two years after the disaster and up to 2013, Katrina communities are up to 3.5 percentage points less likely to receive unemployment benefits than similar individuals located in non-disaster areas. Hurricane victims were allowed to withdraw up to $100,000 from their retirement accounts without incurring in a penalty and spread taxes on these withdrawals over a three-year period. Annual withdrawals are higher than those of the similar communities throughout the post-shock period, but the differences are mostly statistically insignificant (see Deryugina et al. 2018 for a systematic evaluation).

The racial and ethnic composition of Katrina counties does not show sizeable changes after the disaster. In the 2000-2004 and the 2006-2010 periods, respectively, 30.3 and 30.8% of the population is Black; 67.3

and 66.1% is White; 0.8 and 1 percent is Asian; and 0.7 and 0.9 is Native American. Regarding ethnicity, 5% and 6.4% are Hispanic or Latino. In comparison, in each of these periods, the composition of the rest of the U.S. is, on average 7.9% and 8% Black; 87.9% and 87% White; 0.91% and 1.1% Asian; 2% and 2.1% Native American; and 6.7% and 8% Hispanic or Latino. Before Katrina, 50.1% of the total population in Katrina counties is female and 50.5% in the post-disaster period. This compares to 50.2% and 50% in the rest of the country. Table 1 presents the unmatched summary statistics for treated and control counties.

INSERT Table 1 ABOUT HERE

4. Empirical Strategy

4.1. Treatment Group Construction and Identification Strategy

I use a difference-in-differences design to capture the effect of Katrina on innovation by comparing the trajectory of patenting in counties with nonzero damage (treatment group) and patenting in counties with zero damage (control group). The assumption is that this trajectory would have been statistically similar in the absence of the disaster. A multivariate panel allows control for time-stable, location-specific omitted variables, as well as time-varying inventor and market trends and county shocks to innovation outcomes. The empirical strategy departs from traditional difference-in-differences models by exploiting the rich data of the georeferenced distribution of hurricane damage. This is important because prior work shows that shock intensity identifies the effects of disasters on economic behavior (Bernile et al. 2017, Brown et al. 2018, Callen et al. 2014, Gao et al. 2020, Hanaoka et al. 2018).

I start with the 136 counties affected by Katrina as per FEMA's official assessment as the baseline treatment group. Then, I use the quantile group of the county proportion of housing units with severe damage as explained in Section 3.2. Finally, I estimate models when the treatment group is affected counties with no severe damage (i.e., those with minor and/or major damage). I identify and remove from the dataset post-disaster inventor immigration. This is proxied by inventors that did not file a patent in 2005 in one of the Katrina counties and have at least one patent between 2006 and 2015 in one of these counties.

In robustness tests, reported in Table A.1. in Online Appendix A, I use an alternative treatment by that splits the sample based on counties whose proportion of houses with minor, major, or severe damage ranks at the 50^{th} percentile.

4.2. Control Group Construction

Katrina counties are socioeconomically and demographically unique. The goal for the control group is to identify a set of counties that closely resemble Katrina counties, as well as the innovation rate trajectory in the period before the disaster. To achieve this, I apply Kernel matching that generate weighted averages of control pools, which allows comparison of innovation outcomes while accounting for differences in observable characteristics that potentially affect them. One cardinal advantage of this matching technique over others is that it uses the full sample of non-affected counties for constructing the pool of counterfactuals and does not require the number of controls to be exactly the number of treated counties. This is important in my setting given the idiosyncrasies of Katrina counties and, thus, finding suitable comparisons may affect statistical power. Furthermore, this technique assesses and considers the degree of similarity between treatment and control units.

For the analysis, I restrict the specification to the common support area and omit units whose propensity scores lie outside the range of scores in the treatment group. The pool of potential counterfactuals are all non-affected counties in the U.S. In robustness tests, I limit to counties in the same state. The first approach controls for potential contamination of the shock effect because limiting the matching to counties within affected states raises the possibility of spillover effects. That is, individuals close to the damage that were spared could have also developed similar risk-aversion patterns. The second approach provides an additional control for omitted institutional drivers and idiosyncratic changes in the outpouring of resources that might have impacted the perceived cost-benefit of innovation.

In choosing the variables to match treatment and control counties, I consider factors that may affect innovation outcomes at the county level. For instance, I use data on unemployment, employment, and retirement to address the concern that some technology fields may be sensitive to business cycles (Aghion et al. 2019). The racial and ethnic composition of the county can affect economic opportunities (Chetty et al. 2020). Its human capital (Choudhury 2017) and average income (Agrawal et al. 2014) affect the ability to pursue invention. Lastly, agglomeration and urbanization can facilitate collaboration and access to relevant infrastructure (Berkes and Gaetani 2021, Carlino and Kerr 2015, Roche 2019). Guided by prior work, the matching algorithm includes: the county's total population, percent of adults completing some college or associate's degree, percent of adults with less than a high school diploma, percent of male, the racial and ethnic composition (percentage of Black, White, Indian, Hawaiian, and Hispanic), per capita

earnings, per capita county GDP, per capita unemployment insurance, per capita personal income, per capita retirement and other, number of jobs per capita, and the urban-rural continuum code. Additionally, given that innovation is concentrated in a few states and regions and substantially heterogeneous across counties, I include in the matching algorithm the growth rate of patenting between the period 2000-2004.

4.3. Estimation Specification

I run regressions of the following form:

$$\Delta Y_{ct} = \sum_{\tau=2000}^{2004} \beta_0 + \beta_1 \times 1[\tau = 2006\text{-}2010] \times K_t^{2005} + \beta_2 \times 1[\tau = 2011\text{-}2015] \times K_t^{2005} + \alpha_c + \lambda_t + \delta_c + \varepsilon_{ct} \quad (1)$$

where c indexes counties at *t* year. The first dependent variable *Y* is the growth rate of patenting. This variable is the proportional change in the number of granted patent filings in period τ with respect to the pre-shock period. Annual changes are averaged for pre- and post-shock periods. Given the substantial agglomeration in the rate of patenting in the U.S. (Berkes and Gaetani 2021, Doehne and Rost 2021), this measure is superior to the absolute count of patents. A growth rate allows for difference-in-differences estimates between counties with substantially diverse frequency distributions of patenting. I use data from 1999 to calculate the first year of observations. The second dependent variable focuses on the quality of innovation by using the forward citations that a patent receives within five years of its filing year from other patents. This measurement is described in Section 5.2.

The indicator K_t^{2005} takes value one when the county was affected by Katrina. The estimation includes a vector of county variables, δ, (those included in the matching algorithm—Section 4.2) and fixed effects, α, and time fixed effects, λ. This is because the geographic distribution of economic activity is concentrated and not random. Thus, there may exist a feedback effect between innovation and market growth that disproportionally affects some counties with relatively large presence of certain industries. In robustness tests, I use section × time fixed effects as another way to account for business cycles that have been idiosyncratic to some counties. I also integrate county-time fixed effects to control for institutional changes, such as fiscal policy adjustments. To further account for changes in three categories of external resources impacting the costs and benefits to innovate described in Section 3.3, I include dummies that take value 1 when a county received any of these resources in the observation period.

The coefficients β_1 and β_2 capture systematic differences in patenting between Katrina counties and control counties for subsequent five-year periods. A short-run period covering from 2006 to 2010 and a long-run period from 2011 to 2015. An efficient construction of control groups will yield pre-shock betas of matching variables close to zero. The equation collapses the time series of the data into pre- and post-Katrina periods, which corrects for traditional bias in difference-in-differences estimators (Bertrand et al. 2004). I also cluster the standard errors at the county level. These corrections are important because it is likely that innovation is serially correlated within the county. Using several years of data may generate inconsistent standard errors and, ultimately, underestimate the standard deviation of the estimators.

To provide a more nuanced characterization of the strength of the Katrina-innovation relation across time, I run comparatively parsimonious forms of Equation (1) for separate post-shock periods and present independent betas. That is:

$$\begin{aligned}\Delta Y_{ct} = \ & \Sigma_{\tau=2000}^{2004}\, \beta_0 + \beta_1 \times 1[\tau = 2005] \times K_t^{\,2005} \\ & + \beta_2 \times 1[\tau = 2006\text{-}2007] \times K_t^{\,2005} \\ & + \beta_3 \times 1[\tau = 2008\text{-}2009] \times K_t^{\,2005} \\ & + \beta_4 \times 1[\tau = 2010\text{-}2011] \times K_t^{\,2005} \\ & + \beta_5 \times 1[\tau = 2012\text{-}2013] \times K_t^{\,2005} \\ & + \beta_6 \times 1[\tau = 2014\text{-}2015] \times K_t^{\,2005} \\ & + \alpha_c + \lambda_t + \delta_c + \varepsilon_{ct}\,,\end{aligned} \tag{2}$$

This specification estimates the shock effect on the growth rate of innovation on the disaster year, in the short run (β_2), the medium run (β_3), and the long run(β_4). Similar to Deryugina et al. (2018), I choose the selection of periods based on the pattern of coefficients for individual years. To calculate these coefficients, I use the following equation:

$$\Delta Y_{ct} = \Sigma_{\tau=2000,\tau\neq2005}^{2015}\, \beta_\tau \times 1[t = \tau] \times K_t^{\,2005} + \alpha_c + \lambda_t + \delta_c + \varepsilon_{ct}\,, \tag{3}$$

Here, the indicator $1[t = \tau]$ takes value one when the observation falls in year τ. Results of Equation (2) are in Appendix A Table A.2. Figure 2 illustrates difference-in-differences estimates in patenting for the full panel and for the data split by the three levels of damage.

INSERT Figure 2 ABOUT HERE

5. Results

5.1. Impact of Hurricane Katrina on the Quantity of Innovation

Table 2 reports the estimates by damage severity, with all the 136 affected counties as the baseline treatment in Panel A. After a drop in the disaster year, the growth rate of patenting in treatment counties is, on average, 5% higher than in counterfactual counties for the five-year post-Katrina period. The gap persists at 4.6% for the period 2011-2015. The findings are robust to the inclusion of the socioeconomic and demographic variables used in the matching algorithm, local and regional policy instruments, disaster-related resources, patent-section demand and business cycles, and year and county fixed effects.

The difference-in-differences estimates rise in material damage severity, which are presented by quantile group in Panel B of Table 2. In the first post-disaster period, counties in the 3rd percentile group (i.e., those whose proportion of housing units severely damage ranged from the 25th percentile to the 50th percentile) became almost 10% percent more likely to patent than counterfactual counties. This gap is 15.3% for the second quantile group of severity and 17.5%, for counties whose severe damage ranks at the 90th percentile. The significance of difference between the latter group of severely affected and their counterfactual counties lasts the second post-shock period at 14.7%.

INSERT Table 2 ABOUT HERE

Overall, the findings resonate those of experimental (e.g., Cahlíková and Cingl 2017, Conte et al. 2018, Lerner et al. 2003) and administrative data (e.g., Brown et al. 2018, Callen et al. 2014, Hanaoka et al. 2018) showing the relevance of shock magnitude on risk-taking behavior. Of note, these studies proxy risk taking by decisions such as smoking or gambling. Although there is not precedent of a study on the direct effect of disasters on an economic behavior like innovation, scholars have documented the association between experience with natural disasters or the financial crisis and corporate financial leverage (Bernile et al. 2017), corporate social performance (O'Sullivan et al. 2021), and investment in stocks (Guiso et al. 2018).

5.2. Impact of Hurricane Katrina on the Quality of Innovation

I now estimate the effect of Katrina on the economic value of innovation. There is a possibility that the disaster entailed a different economic impact unobserved by major systematic analyses, as per the discussion in Section **Error! Reference source not found.**, that reduced the opportunity cost of invention

regardless of the actual and expected values of innovation. This could have meant that increases in patenting in Katrina counties were explained by low-quality innovation (Agrawal et al. 2019).

To assess this heterogeneity, I calculate a measure of innovation quality using the logged number of patents weighted by the number of prior-art citations, i.e., forward citations, that a patent receives within five years of its filing year from other patents. Forward citations strongly correlate with the economic value of innovation (Hall et al. 2005) and they reflect the contextual perception that inventors have of the invention of others (Jaffe et al. 2000). I exclude citations where an inventor listed in the focal patent is a part of and those from the patent filing's examiner. As mentioned above, the five-year citation period is adopted to rule out right censoring. The fixed and varying effects listed in Section 4 account for the propensity to cite that varies across sectors and time (Aghion et al. 2019).

The difference-in-differences coefficients are positive for the two post-disaster periods, but the gap is only sizeable for 2006-2010. In this period, patents in counties affected by Katrina became, on average, were 10.8% more to be cited than similar patents in control counties (Table 3). This gap increases as severity rises, but this relationship is not monotonic. While treatment counties in the first percentile group were 30% more likely to be cited than control counties, treatment counties in the second percentile group were 18% less likely to be cited than similar non-affected counties.

The quality of patenting is greater again for Katrina counties from the third quantile group of severe damage. These counties were 19.4% more likely to have citations in their patents than counterfactual non-affected counties and this probability is 23.4% for the 4^{th}-quartile treatment group and 28.9% for counties whose proportion of severity ranks at the 90^{th} percentile. Once again, these increases are economically important, given the negative growth rate of citations in the pre-shock period. Before Katrina, invention coming from the affected counties was, on average, 23% less likely to generate citations than similar invention from other counties.

INSERT Table 3 ABOUT HERE

5.3. Additional Robustness

5.3.1. Selective Migration

Systematic evaluations of the socioeconomic consequences of Hurricane Katrina have documented a phenomenon of massive emigration. A portion of this loss in population was never replaced (Groen and Polivka 2008, McIntosh 2008, Paxson and Rouse 2008). Deryugina et al., (2018), for example, find that more than one third of the displaced population in New Orleans had not returned eight years after the disaster. Hence, all we know from systematic assessments suggests that selective migration should not be a source of estimate bias. That is, if after 2005 an immigrant population with greater propensity or willingness to innovate than displaced population settled in Katrina counties, the result might be that the analysis reports spurious correlations between the disaster and innovation.

To directly inform whether sorting is an issue, I construct a database with the histories of residence and invention for each individual listed in the patent filings from 1999 to 2015. Location is approximated by an individual's address in the patent filing and thus the measure is far from perfect—albeit widely used in the specialized literature (e.g., Akcigit et al. 2022, Bell et al. 2019, Bhaskarabhatla et al. 2021). There may be, for instance, unaccounted periods during which the individual moved to a different location, and then returned to the residence listed in the patent application. Individuals might also list an address in the patent application that is not their residence. Of note, however, the risk of this measurement error is similar for the treatment and control groups and orthogonal to the disaster. And thus, the individual-level assessment is a stringent test of the influence of selective migration in the county-level analyses. Given that the approach to proxy innovation (patenting) is exactly the same for both individual and county level analyses, isolating the implications of inventor attrition yields relevant information of the causal effect of the shock.

My strategy is to estimate treatment effects contingent on inventor geolocation before, during, and after Katrina—as per the information from patent applications. First, I define the treatment group with all the inventors that i) listed their address in one of the counties affected by Katrina in 2005, ii) were in any of these counties between 2000 and 2004, and iii) were in these counties after between 2006 and 2015. As explained in Section 4.1, post-shock immigrants to the affected area, that is, inventors not located in Katrina counties in the disaster year that file a patent in Katrina counties after 2005 are eliminated from the dataset. Taken together, this sample is the subset of individuals for whom I can certainly isolate the shock effect from the confounder of immigration—within the natural restrictions of the data.

The next step is to match the treatment group with a control pool comprising all inventors whose locations in 2005 and in the pre- and post-shock periods are outside the Katrina counties. Individuals with

patents in the post-shock period in Katrina and non-Katrina counties are eliminated from the analysis. The preferred specification includes the matching variables listed in the county-level analyses in addition to inventor gender and patenting experience (i.e., count of number of patents that the inventor had in the 2000-2004 period). Third, I run a version of Equation (1) with the following model:

$$\Delta Y_{it} = \Sigma_{\tau=2000}^{2004} \beta_0 + \beta_1 \times 1[\tau = 2006\text{-}2010] \times K_t^{2005} + \beta_2 \times 1[\tau = 2011\text{-}2015] \times K_t^{2005} + \mu_i + \alpha_c + \lambda_t + \delta_c + \varepsilon_{ict}, \quad (4)$$

Inventors are indexed by *i*. The control vector μ captures individual fixed effects to account for variation in education, family, social and professional networks. To further account for the effect of firm-related resources, I include dummies when there is an assignee listed in the patent that is not the inventor. In robustness tests, I control for firm affiliation by using including dummies for the companies listed in as assignees in the patent application using data from the Python tracking.[6] I control for patenting experience, which adds to the county-level variable controls in Equation (1).[7] The vector also includes the average annual growth rate of patenting between the period 2000-2004 and 1999 and dummies taking value 1 when the county in which the inventor is listed receive external resources benefiting economic activities as described in Section 3.3. Fixed effects include inventor, county, and time. In combination with the variable controls, the difference-in-differences estimates account for county heterogeneity in density, education, race and ethnicity, background risk (expected income), insurance, income and wealth, and local resources affecting innovation.

Broadly, the results in Table 4 replicate the strength and direction of the correlation between Katrina and county-level innovation. Regarding the quantity of innovation, patents from non-emigrant inventors located in the affected counties in the year of the shock became 8.2% more frequent than from similar inventors located in non-Katrina counties (Model 2). This difference grows to 11.8% in the period 2011-2015 (Model 3). Regarding the quality of innovation, after Katrina, the patents from treated inventors were

[6] I automate searches that extract the history of employment of individuals with a profile on LinkedIn. I use these data to control for company affiliations in alternative models.

[7] The county's total population, percent of adults completing some college or associate's degree, percent of adults with less than a high school diploma, percent of male, the racial and ethnic composition (percentage of Black, White, Indian, Hawaiian, and Hispanic), per capita earnings, per capita county GDP, per capita unemployment insurance, per capita personal income, per capita retirement and other, number of jobs per capita, and the urban-rural continuum code.

12% (Model 5) and 18% (Model 6) more frequently cited than control inventors in the short- and long-run, respectively.

INSERT Table 4 ABOUT HERE

5.3.2. Placebo Katrina

I conduct two types of falsification tests. First, after excluding the disaster year of 2005 from the pool of options, I randomly choose a placebo year for the occurrence of the disaster between 2001 and 2013, which allows me to have at least two post-shock observation years. I run Equation (1) with the original treatment group and matching algorithm, which, obviously, results in different counterfactual counties. Column 1 in Table 5 shows the results. Second, I randomly assign Katrina counties to a different Federal Information Processing Standard Publication (FIPS) code in the studied period. The list of potential FIPS is all the counties in states that were not affected by a major disaster, including terrorist attacks, as per the Global Database of Disaster Responses. I run 100 repetitions of each falsification test and replicate Table 2 with the average coefficients of the repetitions that are statistically significant at the 5% level. Column 2 in Table 5 reports the average differences. Neither of the falsification tests replicate the original results.

INSERT Table 5 ABOUT HERE

5.3.3. Institutional Similarity

If the vector of controls do not adequately capture heterogeneity in institutions (Cockburn et al. 2016, Hall and Harhoff 2012), there may be an omitted driver of innovation whose source is regulation or other public policy idiosyncrasies (Vakili and Zhang 2018). To account for this concern, I restrict the pool of control counties to those within the same state as a given affected county. For instance, the potential counterfactuals for the 12 affected counties in Florida are the rest 55 unaffected counties in the state. While Table A.2 in Online Appendix A is consistent with the original results, I find greater differences in patenting between treatment and control groups. Disaster-stricken counties were 10.8% and 11.5% more likely to observe patents in the first and second post-shock periods, respectively.

5.3.4. Major disasters in non-Katrina counties

If counties in the control group are affected by other systemic shocks during the observation period, their effects may explain drops in innovation outcomes. To better isolate the causal effect of Katrina, I

delete from the sample all those counties in states that had a Major Disaster Declaration between 2005 and 2015, as per FEMA.[8] I present the results in the Online Appendix Table A.3. The point estimates in these analyses are statistically significant and marginally smaller (showing the same direction of effects) than those reported in the full-sample specifications.

6. Evaluating Enhancing Mechanisms

So far, to the extent that the construction of control groups and the combination of fixed and time-varying effects absorb unobserved heterogeneity that might affect the difference-in-differences estimates, it is unclear to me that there exists an alternative explanation to the correlation between Katrina and innovation outcomes. The set of main analyses and robustness tests suggest that widely discussed determinants in the innovation literature do not sufficiently explain the differences in post-disaster fluctuations in the rate and quality of innovation between treatment and control groups. I am interested, however, to explore whether some of these variables moderate the studied causal path. It could be that Katrina affected the economies of patenting in some areas and/or the dynamics behind agglomeration economies and collaboration, thus modifying the costs and benefits of allocating time and resources toward invention or the opportunities to profit from innovation.

6.1. Agglomeration Economies

6.1.1. Urbanization and population density

There is compelling evidence suggesting that innovation benefits from agglomeration economies (Chatterji et al. 2014, Feldman and Kogler 2010, Moretti 2021). Carlino and Kerr (2015) provide a large survey of studies that inform on the argument that innovation is more geographically concentrated than other economic areas, such as production. The first-order rationale is that proximity to densely populated areas fosters, among other factors, the search of novel ways to solve issues (Fleming et al. 2007), the generation of the knowledge flows that feed invention (Moretti 2021) and fuel a demand for novelty (Agrawal et al. 2014), and facilitates access to physical infrastructure that reduces the administrative and transaction costs of patenting (Alcacer and Chung 2014, Roche 2019). Similarly, high-density urban centers

[8] https://www.fema.gov/disaster/declarations.

can foster diversity of knowledge flows that can result in the generation of unconventional ideas (Berkes and Gaetani 2021).

I start by splitting the dataset by counties' rural-urban continuum code. This classification, which I also used in the matching algorithm as explained in Section 4.2, is created by the Economic Research Service (ERS) at the U.S. Department of Agriculture and distinguishes metropolitan counties by the population size of their metro area, and nonmetropolitan counties by degree of urbanization and adjacency to a metro area or areas.[9] I then run Equation (1) for each of the codes with at least one Katrina county—sections 4, 5, and 9 are not represented in by the affected counties. Given that Berkes and Gaetani (2021) find that more radical innovation tends to occur in urban hubs and this type of innovation yields comparatively high number of citations, I use the measure of innovation quality as explained in Section 5.2.

I do not find evidence that the shock-innovation relation is enhanced by proximity to urban hubs (Table A.4 in Online Appendix A). Conversely, counties in metro areas of 250,000 to 1 million population observe substantial drops in cited patents in the disaster year and the two post-shock periods. The difference-in-difference correlations are not statistically sizeable for the other metropolitan counties, including those located in metro areas of 1 million population or more (code 1). Similarly, there is no evidence that the shock-associated difference in innovation between treatment and control counties rises in urbanization for nonmetro counties. Overall, these results connect with work suggesting that the relation between urban density and patenting is non-monotonic (Berkes and Gaetani 2021).

6.1.2. Inventor density

Next, I explore a more direct measure of agglomeration as informed by the specialized literature (e.g., Carlino and Kerr 2015). First, I calculate county inventor density (number of inventors in a county/county population) and split the sample by quantile groups. Then, I match Katrina and counterfactual counties for each group and run the difference-in-differences specification (Equation 1).

[9] According to the ERS "The codes provide researchers working with county data a more detailed residential classification, beyond a simple metro-nonmetro dichotomy, for the analysis of trends related to degree of rurality and metro proximity." Further information is available at https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/documentation/.

The results can be found in the Online Appendix and provide some indication that relatively large levels of inventor density fostered the differences in quality patenting between affected and non-affected counties. Of note, given the positive sign of the coefficients for counties in the quantile groups 1 to 4 (i.e., those than rank at least at the 25th percentile of the share of inventors in the county), being in a county with a substantial proportion of inventors helped cope with the impact of the disaster in citation-weighted patenting.

Similar to the results for urbanization, these findings indicate that the role of inventor density on the quality of innovation is non-monotonic. For instance, in the period 2011-2015, Katrina counties whose inventor density ranges from the 50th to the 74th percentiles were 46% more likely to have patents with citations than non-affected control counties. For counties ranking at the 75th and higher percentiles, the gap between treatment and control groups is 28.2%.

6.2. Collaboration

A central channel in the literature on the antecedents of innovation is collaboration (Agrawal et al. 2014, Ansell and Gash 2008, Catalini 2018, Fleming et al. 2007, Singh 2005). Katrina could have affected the opportunity, costs, and productivity of interacting with other inventors (Singh and Fleming 2010). To examine this prospect, I construct a measure of collaboration by county-year: the proportion of total patents in a county that list more than one inventor. I calculate this variable by year and then average for the respective period as in the baseline specification. Finally, similar to previous models, I split the sample into quantiles groups. This is particularly important for inventor collaboration because previous studies have shown that the geographic distribution of this variable is not uniform (Aghion et al. 2019, Agrawal et al. 2014). In fact, in Katrina counties, the share of patents with more than one inventor is skewed toward the first quantile group (counties whose collaboration is equal or less than the 25th percentile) and the fourth quantile group (where collaboration is at the 75th percentile or higher).

I run the usual difference-in-differences model in Equation (1). The results in Table A.6. in Online Appendix A show greater gaps in post-shock innovation outcomes between treatment and control groups at higher levels of collaboration. This is unsurprising given the information coming from the test of inventor density. Arguably, greater density facilitates collaboration and this moderates the effect of Katrina on citation-weighted patenting. For counties in the fourth quantile group, the gap between counties affected by the hurricane and their control counties is 40% in the short run and 42% in the long run. Conversely, for

the group with the lowest levels of collaboration, treated counties were 20% less likely to observe citation-weighted patents than similar counties outside the disaster area.

6.3. Post-shock Demand for Specific Innovation

There is a possibility that Katrina generated ephemeral switches in the demand for specific goods. Activities such as the construction of roads, railways, or bridges, water supply, or those related with health and life saving, such as medical and veterinary science or hygiene, tend to follow relief and recovery and thus observe spikes in the aftermath of some disasters (Holguín-Veras et al. 2012). For other products, such as those related with basic necessities, the increased demanded quantity comes from a short-run destruction of goods supply following the disaster (Ballesteros and Magelssen 2021). Consequently, the relative benefit of patenting in areas directly affected by the disaster could explain the correlations.

I explore this possibility by disaggregating the data into sections of the IPC. The IPC hierarchically classifies the body of knowledge consider as proper to the field of patents for invention (World Intellectual Property Organization 2020). There are eight sections at the highest level of the hierarchy.[10] Given the substantial heterogeneity in the propensity of patent sections to be cited, I focus on the citation-weighted measure of patenting calculate difference-in-differences estimates in the quality of patenting for each section.

The results in Table A.7 in Online Appendix A show no indication that increases in some types of innovation explain the results in post-disaster fluctuations in citation-weighted patenting. Particularly, the gaps between treatment and control counties in sections that may be associated with disaster recovery, such as A (human necessities) and D (fixed constructions) are not statistically important. On the other hand, the quality of innovation in section B (performing operations and transporting), which include areas such as nanotechnology and microstructural technology, grew higher among Katrina counties than for control counties. The probability that patents filed in treated counties were cited was 10.3% larger, in the short run, and 17%, in the period 2011-2015.

[10] A = Human Necessitates, B = Performing Operations; Transporting, C = Chemistry; Metallurgy, D = Textiles; Paper, E = Fixed Constructions, F = Mechanical Engineering; Lighting; Heating; Weapons; Blasting, G = Physics, H = Electricity.

7. Conclusion

This paper contributes to the understanding of the determinants of the geography of innovation by focusing on effects of Hurricane Katrina in patenting. The motivation comes from recent evidence that large exogenous shocks generate enduring and substantial changes in risk attitudes and risk-taking behavior. In combination with the idea that engagement in innovative behavior entails risk tolerance, the study centers on the argument that Katrina could have affected the intrinsic motivation to innovate. The results are suggestive evidence of such a prospect.

While the role of localized factors on innovation have been noted extensively (Berkes and Gaetani 2021, Feldman and Kogler 2010), this study provides the first account that exogenous shocks can generate economically substantial fluctuations in innovation. In the analyses, I show that exposure to the damage created by Katrina correlates with increases in the frequency and quality of patenting. These changes are not fully explained by traditional theoretical silos in the innovation literature: agglomeration economies, collaboration, firm resources, organizational affiliation, proximity to infrastructure, and public policy. Furthermore, the theoretical model in the study of regional innovation has centered on tangible resources. While more recent work has brought attention to intangible factors, the findings of this study point toward the role of a determinant whose effect is not captured by factors such as knowledge flows (Berkes and Gaetani 2021) and local buzz (Bathelt et al. 2004).

Assembling histories of productivity, mobility, and collaboration of inventors in the 17-year sample period allows me to offer evidence that differences in patenting are not fully explained by education, income, employment and unemployment, insurance, the racial and ethnic composition of the county, its population size and business cycles, or the inventor's gender and firm affiliation. The findings robustly rule out the influence of selective migration, a disaster placebo, and the institutional idiosyncrasies of states across time. Testing of mechanisms provide evidence of the moderating role of inventor density and collaboration in the effect of the disaster on innovation.

The study also contributes to the literature on the effects of exogenous shocks on economic behavior. Naturally, studying shock-related effects outside laboratory settings faces important empirical challenges. The richness of the data on the geospatial distribution of Katrina damage and patenting helps me overcome several of these challenges. The analyses account for the most prominent mechanisms underlying post-

shock fluctuations in risk preferences: changes in wealth and income, changes in background risk, expected income, and the expected distribution of returns. In doing so, the results are indicative that a different channel, such as emotion-based changes, may be at place, which aligns with recent evidence in the economics and psychology literatures (Guiso et al. 2018, Hanaoka et al. 2018, Lerner and Keltner 2001, Schildberg-Hörisch 2018).

While the different baseline and robustness analyses are consistent with a causal effect of Hurricane Katrina on innovation and point to a previously omitted channel in the literature, the description of a particular mechanism, including changes in risk attitudes, remains speculative due to data constraints. This limitation opens opportunities for future work. Most work studying fluctuations in risk attitudes use survey data that do not connect with economic behavior; and risk taking is often proxied by choices such as smoking or gambling. On the other hand, studies based on archival data that document economic choices rarely connect with a direct measure of risk preferences (Guiso et al. 2018 is one of those rare cases). Consequently, studies that link survey or laboratory data with administrative data can inform about the relation between disasters and economic decisions, such as innovation.

The results contribute to important contemporary debates that have both practical and conceptual implications. Extant work has shown that public policy and firm strategy underestimate or neglect the implications of large shocks on economic choices (Aghion et al. 2021, Bloom et al. 2018). This disconnect can have significant welfare implications (Barro 2007). Thus, information on the relation between shocks like Hurricane Katrina on risk-taking behavior can improve how communities and organizations manage the aftermath. This conclusion takes on a special societal connotation, given the influence that innovation often has in income equality and regional development (Aghion et al. 2019, Gambardella 2021).

References

Acemoglu BD, Akcigit U, Alp H, Bloom N, Kerr W (2018) Innovation, Reallocation, and Growth. *Am. Econ. Rev.* 108(11):3450–3491.

Aghion P, Akcigit U, Bergeaud A, Blundell R, Hemous D (2019) Innovation and Top Income Inequality. *Rev. Econ. Stud.* 86(1):1–45.

Aghion P, Bloom N, Lucking B, Sadun R, Van Reenen J (2021) Turbulence, Firm Decentralization, and Growth in Bad Times. *Am. Econ. J. Appl. Econ.* 13(1):133–169.

Aghion P, Howitt P (1990) *A model of growth through creative desctruction*

Agrawal A, Catalini C, Goldfarb A, Luo H (2019) Slack time and innovation. *Organ. Sci.* 29(6):1056–1073.

Agrawal A, Cockburn I, Galasso A, Oettl A (2014) Why are some regions more innovative than others? The role of small firms in the presence of large labs. *J. Urban Econ.* 81:149–165.

Agrawal A, Gans JS, Stern S (2021) Enabling Entrepreneurial Choice. *Manage. Sci.* (March).

Akcigit U, Grigsby J, Nicholas T, Stantcheva S (2022) Taxation and Innovation in the Twentieth Century. *Q. J. Econ.* 137(1):329–385.

Alcacer J, Chung W (2007) Location Strategies and Knowledge Spillovers. *Manage. Sci.* 53(5):760–776.

Alcacer J, Chung W (2014) Location Strategies for Agglomeration. *Strateg. Manag. J.* 35(November):1749–1761.

Ansell C, Gash A (2008) Collaborative governance in theory and practice. *J. Public Adm. Res. Theory* 18(4):543–571.

Baker SR, Bloom N, Terry SJ (2020) Using Disasters to Estimate the Impact of Uncertainty. *NBER Work. Pap. Ser.*:40.

Ballesteros L, Magelssen C (2021) Institutional Disruptions and the Philanthropy of Multinational Firms. *Organ. Sci.* 33(4):1501–1522.

Barro RJ (2007) Rare disasters, asset prices, and welfare costs. *Am. Econ. Rev.* 99(1):243–264.

Bathelt H, Malmberg A, Maskell P (2004) Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation. *Prog. Hum. Geogr.* 28(1):31–56.

Bell A, Chetty R, Jaravel X, Petkova N, Van Reenen J (2019) Who becomes an inventor in America? The

importance of exposure to innovation. *Q. J. Econ.* 134(2):647–713.

Berkes E, Gaetani R (2021) The Geography of Unconventional Innovation. *Econ. J.* 131(636):1466–1514.

Bernile G, Bhagwat V, Rau PR (2017) What Doesn't Kill You Will Only Make You More Risk-Loving: Early-Life Disasters and CEO Behavior. *J. Finance* 72(1):167–206.

Bertrand M, Duflo E, Mullainathan S (2004) How much should we trust differences-in-differences estimates? *Q. J. Econ.* 119(1):249–275. https://academic.oup.com/qje/article/119/1/249/1876068.

Bhaskarabhatla A, Cabral L, Hegde D, Peeters T (2021) Are Inventors or Firms the Engines of Innovation? *Manage. Sci.* (July).

Bikard M, Marx M (2020) Bridging academia and industry: How geographic hubs connect university science and corporate technology. *Manage. Sci.* 66(8):3425–3443.

Bikard M, Vakili K, Teodoridis F (2019) When collaboration bridges institutions: The impact of university–industry collaboration on academic productivity. *Organ. Sci.* 30(2):426–445.

Bloom N (2007) Uncertainty and the Dynamics of R&D. *Am. Econ. Rev.* 97(2):250–255.

Bloom N, Floetotto M, Jaimovich N, Saporta-Eksten I, Terry SJ (2018) Really uncertain business cycles. *Econometrica* 86(3):1031–1065.

Bordalo P, Gennaioli N, Shleifer A (2012) Salience theory of choice under risk. *Q. J. Econ.* 127(3):1243–1285.

Brown R, Montalva V, Thomas D, Velásquez A (2018) Impact of Violent Crime on Risk Aversion: Evidence from the Mexican Drug War. *Rev. Econ. Stat.*:1–13.

Cahlíková J, Cingl L (2017) Risk preferences under acute stress. *Exp. Econ.* 20(1):209–236.

Callen M, Isaqzadeh M, Long JD, Sprenger C (2014) Violence and risk preference: Experimental evidence from Afghanistan. *Am. Econ. Rev.* 104(1):123–148.

Carlino G, Kerr WR (2015) *Agglomeration and Innovation* 1st ed. (Elsevier B.V.).

Catalini C (2018) Microgeography and the direction of inventive activity. *Manage. Sci.* 64(9):4348–4364.

Catalini C, Fons-Rosen C, Gaulé P (2020) How do travel costs shape collaboration. *Manage. Sci.* 66(8):3340–3360.

Chatterji A, Glaeser E, Kerr W (2014) Clusters of Entrepreneurship and Innovation. Lerner J, Stern S, eds. *Innov. Policy Econ.* (University of Chicago Press, Chicago, IL), 129–166.

Chen YE, Li C, Chang CP, Zheng M (2021) Identifying the influence of natural disasters on technological innovation. *Econ. Anal. Policy* 70(20):22–36.

Chetty R, Hendren N, Jones MR, Porter SR (2020) Race and economic opportunity in the United States: An intergenerational perspective. *Q. J. Econ.* 135(2):711–783.

Choudhury P (2017) Innovation outcomes in a distributed organization: Intrafirm mobility and access to resources. *Organ. Sci.* 28(2):339–354.

Cockburn IM, Lanjouw JO, Schankerman M (2016) Patents and the global diffusion of new drugs. *Am. Econ. Rev.* 106(1):136–164.

Conte A, Levati MV, Nardi C (2018) Risk Preferences and the Role of Emotions. *Economica* 85(338):305–328.

Crespo Cuaresma J, Hlouskova J, Obersteiner M (2008) Natural disasters as creative destruction? Evidence from developing countries. *Econ. Inq.* 46(2):214–226.

Cutter S (2006) The geography of social vulnerability: Race, class, and catastrophe. *Underst. Katrina Perspect. from Soc. Sci.*:120–122.

Dahan NM, Doh JP, Oetzel J, Yaziji M (2010) Corporate-NGO collaboration: Co-creating new business models for developing markets. *Long Range Plann.* 43(2–3):326–342.

Deryugina T, Kawano L, Levitt S (2018) The economic impact of hurricane Katrina on its victims: Evidence from individual tax returns. *Am. Econ. J. Appl. Econ.* 10(2):202–233.

Dessaint O, Matray A (2017) Do managers overreact to salient risks? Evidence from hurricane strikes. *J. financ. econ.* 126(1):97–121.

Doehne M, Rost K (2021) Long waves in the geography of innovation: The rise and decline of regional clusters of creativity over time. *Res. Policy* 50(9):104298.

Dye KC, Eggers JP, Shapira Z (2014) Trade-offs in a Tempest: Stakeholder Influence on Hurricane Evacuation Decisions. *Organ. Sci.*

Eckel CC, El-Gamal MA, Wilson RK (2009) Risk loving after the storm: A Bayesian-Network study of Hurricane Katrina evacuees. *J. Econ. Behav. Organ.* 69(2):110–124.

Feldman MP, Kogler DF (2010) *Stylized facts in the geography of innovation* (Elsevier B.V.).

Flammer C, Kacperczyk A (2015) The Impact of Stakeholder Orientation on Innovation: Evidence from a Natural Experiment. *Manage. Sci.* (November):mnsc.2015.2229.

Fleming L, King C, Juda AI (2007) Small worlds and regional innovation. *Organ. Sci.* 18(6):938–954.

Gabe T, Falk G, McCarty M, Mason VW (2005) Hurricane Katrina: Social-demographic characteristics of impacted areas. *Soc. Policy*.

Galindo MÁ, Méndez MT (2014) Entrepreneurship, economic growth, and innovation: Are feedback effects at work? *J. Bus. Res.* 67(5):825–829.

Gambardella A (2021) The functions of patents in our societies: innovation, markets, and new firms. *Available SSRN 3789554*.

Gambardella A, Giarratana MS (2010) Localized knowledge spillovers and skill-biased performance. *Strateg. Entrep. J.* 4(4):323–339.

Gao M, Liu YJ, Shi Y (2020) Do people feel less at risk? Evidence from disaster experience. *J. financ. econ.* 138(3):866–888.

González-Uribe J (2020) Exchanges of innovation resources inside venture capital portfolios. *J. financ. econ.* 135(1):144–168.

Griliches Z (1990) *Patent Statistics as Economic Indicators: A Survey Part II.* (NATIONAL BUREAU OF ECONOMIC RESEARCH (NBER)).

Groen JA, Kutzbach MJ, Polivka AE (2020) Storms and jobs: The effect of hurricanes on individuals' employment and earnings over the long term. *J. Labor Econ.* 38(3):653–685.

Groen JA, Polivka AE (2008) The effect of Hurricane Katrina on the labor market outcomes of evacuees. *Am. Econ. Rev.* 98(2):43–48.

Guiso L, Paiella M (2008) Risk aversion, wealth, and background risk. *J. Eur. Econ. Assoc.* 6(6):1109–1150.

Guiso L, Sapienza P, Zingales L (2018) Time varying risk aversion. *J. financ. econ.* 128(3):403–421.

Hall BH, Harhoff D (2012) Recent research on the economics of patents. *Annu. Rev. Econom.* 4:541–565.

Hall BH, Jaffe A, Trajtenberg M (2005) Market value and patent citations. *RAND J. Econ.* 36(1):16–38.

Hall BH, Jaffe AB, Trajtenberg M (2001) *The NBER patent citation data file: Lessons, insights and methodological tools*

Hanaoka C, Shigeoka H, Watanabe Y (2018) Do Risk Preferences Change? Evidence from the Great Eastern Japan Earthquake. *Am. Econ. J. Appl. Econ.* 10(2)(2):298–330.

Holguín-Veras J, Jaller M, Van Wassenhove LN, Pérez N, Wachtendorf T (2012) On the unique features of post-disaster humanitarian logistics. *J. Oper. Manag.* 30(7):494–506.

Jaffe AB, Trajtenberg M, Fogarty MS (2000) Knowledge Spillovers and Patent Citations: Evidence from a Survey of Inventors. *Am. Econ. Rev.* 90(2):215–218.

Kahneman D, Tversky A (1979) Prospect theory: An analysis of decision under risk. *Econom. J. Econom. Soc.*:263–291.

Lerner J, Seru A (2017) *The use and misuse of patent data*

Lerner JS, Gonzalez RM, Small DA, Fischhoff B (2003) Effects of fear and anger on perceived risks of terrorism: A national field experiment. *Psychol. Sci.* 14(2):144–150.

Lerner JS, Keltner D (2001) Fear, anger, and risk. *J. Pers. Soc. Psychol.* 81(1):146–159.

Li H (2017) Innovation as Adaptation to Natural Disasters. 1(1709).

Magelssen C (2020) Allocation of property rights and technological innovation within firms. *Strateg. Manag. J.* 41(4):758–787.

McIntosh MF (2008) Measuring the labor market impacts of Hurricane Katrina migration: Evidence from Houston, Texas. *Am. Econ. Rev.* 98(2):54–57.

Miao Q, Popp D (2014) Necessity as the mother of invention: Innovative responses to natural disasters. *J. Environ. Econ. Manage.* 68(2):280–295.

Moretti E (2021) The Effect of High-Tech Clusters on the Productivity of Top Inventors. *Am. Econ. Rev.* 111(10):3328–3375.

Moretti E, Wilson DJ (2017) The effect of state taxes on the geographical location of top earners: Evidence from star scientists. *Am. Econ. Rev.* 107(7):1858–1903.

Mukherjee A, Singh M, Žaldokas A (2017) Do corporate taxes hinder innovation? *J. financ. econ.* 124(1):195–221.

Necker S, Ziegelmeyer M (2016) Household risk taking after the financial crisis. *Q. Rev. Econ. Financ.* 59:141–160.

Noy I, Strobl E (2022) Heat Waves and Innovation in Air Conditioning in the United States. *Weather. Clim. Soc.* 14(1):143–154.

O'Sullivan D, Zolotoy L, Fan Q (2021) CEO early-life disaster experience and corporate social performance. *Strateg. Manag. J.* (May):1–25.

Paxson C, Rouse CE (2008) Returning to new orleans after hurricane katrina. *Am. Econ. Rev.* 98(2):38–42.

Rehse D, Riordan R, Rottke N, Zietz J (2019) The effects of uncertainty on market liquidity: Evidence from

Hurricane Sandy. *J. financ. econ.*

Roche MP (2019) Taking Innovation to the Streets: Microgeography, Physical Structure, and Innovation. *Rev. Econ. Stat.*:1–17.

Salvato C, Sargiacomo M, Amore MD, Minichilli A (2020) Natural disasters as a source of entrepreneurial opportunity: Family business resilience after an earthquake. *Strateg. Entrep. J.* 14(4):594–615.

Schildberg-Hörisch H (2018) Are risk preferences stable? *J. Econ. Perspect.* 32(2):135–154.

Select Bipartisan Committee to Investigate the Preparation for and Response to Hurricane Katrina (2006) *A Failure of Initiative: Final Report of the Select Bipartisan Committee to Investigate the Preparation for and Response to Hurricane Katrina*

Singh J (2005) Collaborative networks as determinants of knowledge diffusion patterns. *Manage. Sci.* 51(5):756–770.

Singh J, Fleming L (2010) Lone inventors as sources of breakthroughs: Myth or reality? *Manage. Sci.* 56(1):41–56.

Teodoridis F (2018) Understanding team knowledge production: The interrelated roles of technology and expertise. *Manage. Sci.* 64(8):3625–3648.

USHUD, U.S. Department of Housing and Urban Development (2006) *Current Housing Unit Damage Estimates Hurricanes Katrina and Rita*

USPTO (2021) Patents Dashboard. Retrieved (September 8, 2021), https://www.uspto.gov/dashboard/patents/.

Vakili K, Zhang L (2018) High on creativity: The impact of social liberalization policies on innovation. *Strateg. Manag. J.* (August 2016):1–27.

World Intellectual Property Organization (2020) *Guide to the International Patent Classification IPC*

Yi J, Chu J, Png IPL (2022) Early-life exposure to hardship increased risk tolerance and entrepreneurship in adulthood with gender differences. *Proc. Natl. Acad. Sci.* 119(15):e2104033119.

Zhao XX, Zheng M, Fu Q (2022) How natural disasters affect energy innovation? The perspective of environmental sustainability. *Energy Econ.* 109(March):105992.

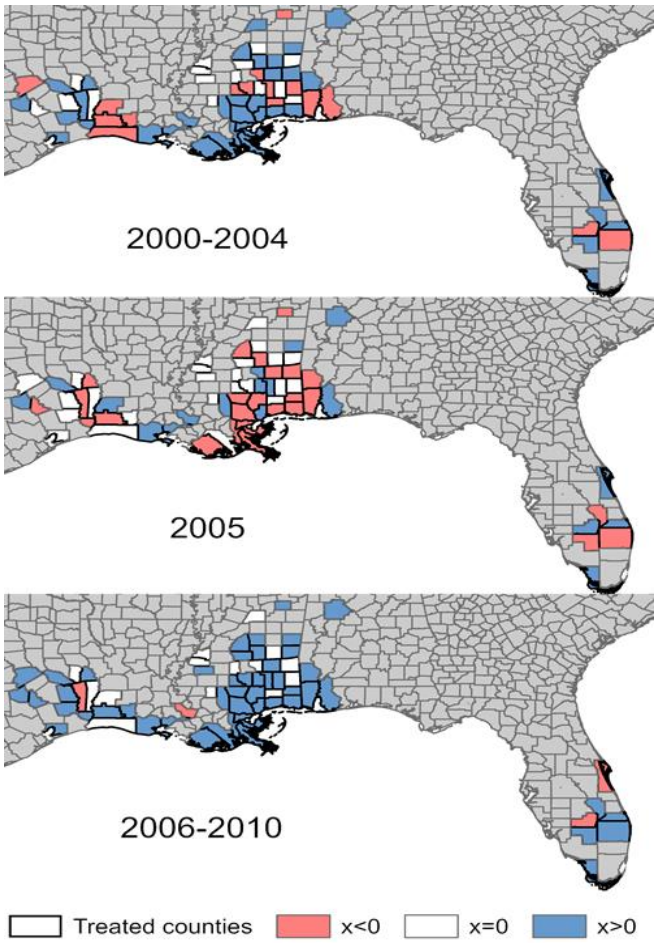
Tables and Figures

Table 1. Summary Statistics for Treatment and Control Counties (Unmatched)

Variable	Mean	Std. Dev.	Min	Max
Pool of Control Counties (1,869)				
Number of patents	45.6	376.71	0	13422.8
Number of citations	921.9	6,323.7	0	267,658.8
Number of inventors	30.5	175.1	0	6,738
Net earnings (PC)	16,013.8	4793.3	6254.4	44,005.6
Unemployment insurance (PC)	92.9	32.3	14.2	244.2
Personal income (PC)	25,407.8	5520.8	13376.6	58,497.4
Retirement and other (PC)	4,218	934.8	1325.6	7653.2
Number of jobs (PC)	0.49	0.13	0.03	1.1
Percent of adults with college	25.6	5.6	9.9	42.5
Percent of adults with less than a high school diploma	23.9	9.1	3	65.3
Rural-urban continuum code	5.1	2.8	1	9
Total population	86,331.7	342,519.4	321.2	9,686,109
GDP (Billion USD)	286.3	531.36	21.35	724.9
Percent of White	86.1	16.69	12.24	99.6
Percent of Black	10.6	15.76	0	84.2
Percent of Hispanic	7.6	13.93	.13	97.1
Percent of Indian	1.4	6.4	0	86.2
Percent of Asian	0.7	1.89	0	32.4
Percent of Men	49.6	2	43	68.7
Treatment Counties [affected by Katrina (136)]				
Number of Patents	44.1	182.6	0	1,890
Number of citations	852.9	4,999.9	0	55,852.8
Number of inventors	28.8	115.3	0	1,189.8
Net Earnings (PC)	14,591.8	4,126.1	7,453.2	29,309
Unemployment Insurance (PC)	82.5	22.4	53.4	173.6
Personal Income (PC)	23,772.4	6,012.5	15,224.4	47,735.2
Retirement and other (PC)	4292.5	888	1766.6	7,462
Number of jobs (PC)	0.4	0.1	0.2	0.7
Percent of adults with college	23.8	4.6	15.1	33.9
Percent of adults with less than a high school diploma	28.2	7.3	13.7	46.7
Rural-urban continuum code	4.3	2.6	1	9
Total population	141,003.6	401,043.3	8,235.2	3,527,706
GDP (Billion USD)	189.6	531.3	31.3	516.9
Percent of White	67.3	18.6	13.5	95.2
Percent of Black	30.3	19.2	3.4	86
Percent of Hispanic	5	8.2	.41	59.4
Percent of Indian	0.7	1.6	.06	14.3
Percent of Asian	0.8	1.3	.03	13.1
Percent of Men	49.26	2.5	45.51	65.67

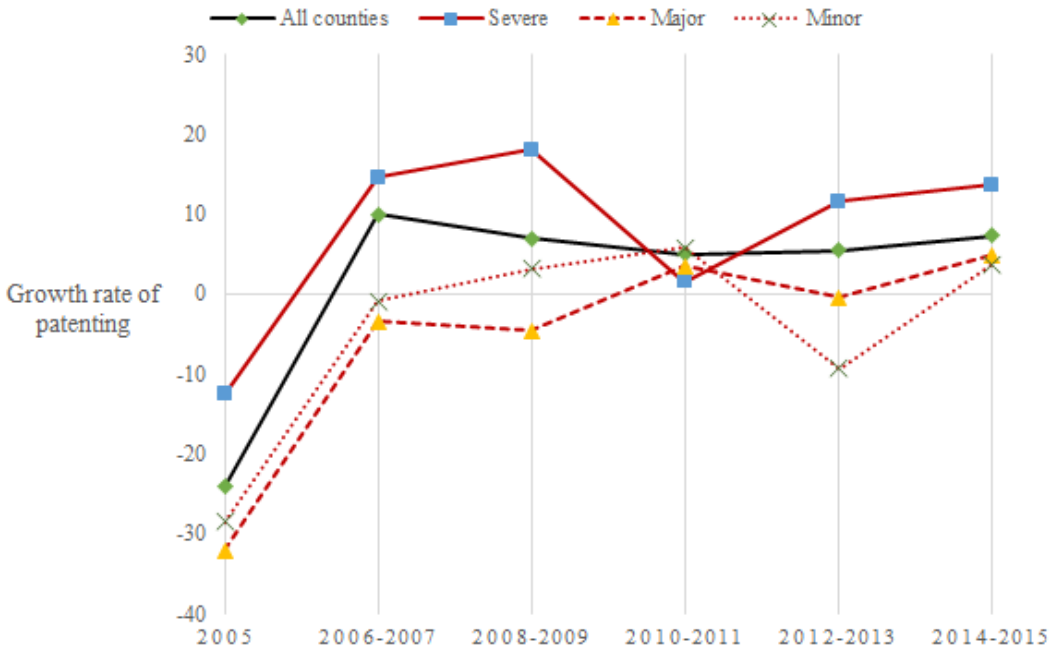
Notes: This table reports descriptive statistics for the period 2000-2004 of the variables used to construct the control group of counties that approximate those in the treatment group. Treated counties are those affected by Hurricane Katrina in 2005 according to the official designation by the Federal Emergency Management Agency that assesses the material damage to each housing unit in a county. The patent data come from the United States Patent and Trademark Office (USTPO) and comprise the universe of granted patents filed in the period 1999-2015. Sociodemographic and economic data come from the U.S. Census Bureau and the American Community Survey and the Economic Research Service (ERS) at the U.S. Department of Agriculture.

Figure 1. Growth Rate of Patenting in Counties Affected by Katrina



Notes: This figure shows the average annual growth rate of patenting in the counties that comprise the treatment group. Treated counties are those affected by Hurricane Katrina in 2005 according to the official designation by the Federal Emergency Management Agency that assesses and reports on the material damage to each housing unit in a county. The counties are identified with their Federal Information Processing Standards (FIPS) number. The growth rate distribution is grouped into increases (>0), decreases (<0), and no change (=0) with respect to the previous year and period. The organization of the dataset responds to the identification strategy that aggregates the analysis in a pre-shock period and post-shock periods. The patent data come from the United States Patent and Trademark Office (USTPO) and comprise the universe of granted patents filed in the period 1999-2015. The first year (1999) is used to calculate the growth rate of patenting of 2000.

Figure 2. Difference-in-differences between Treatment and Control Counties
Growth Rate of Patenting by Damage Level



Notes: This figure shows results of difference-in-differences estimations of the effect of Hurricane Katrina on the rate of innovation calculated using the following specification: $\Delta Yct = \Sigma_{(\tau=2000)}^{2004} \beta 0 + \beta 1 \times 1[t = 2006\text{-}2010] \times Kt\ 2005 + \beta 2 \times 1[t = 2011\text{-}2015] \times Kt\ 2005 + \alpha c + \lambda t + \delta c + \varepsilon ct$. The dependent variable is the average annual growth of patenting at the county level. Treated counties are those affected by Hurricane Katrina according to the official designation by the Federal Emergency Management Agency (FEMA) that assesses and reports on the material damage to each housing unit in a county. Panel A reports the differences between all the 136 counties affected by Katrina (the preferred treatment) and counterfactual counties across the U.S. that were not unaffected. Panel B reports differences by quantile group according to the proportion of housing units in the county with severe damage. FEMA's physical assessment of affected houses categorize them into minor, major, and severe (U.S. Department of Housing and Urban Development, 2006). The counties designation is their Federal Information Processing Standards (FIPS) number. Control counties are identified based on a Kernel propensity score vector that includes: the percent of adults completing some college or associate's degree, the percent of adults with less than a high school diploma, the racial and ethnic composition (percentage of Black, White, Indian, Hawaiian, and Hispanic), percentage of male, total population, per capita earnings, per capita unemployment insurance, per capital personal income, per capita retirement and other, number of jobs per capita, and the urban-rural continuum code. The vector also includes the average annual growth rate of patenting between the period 2000-2004 and 1999. The matching variables are used as control variables, δ, which also include dummies taking value 1 when private and/or public resources benefiting economic activities covered a county. See text for additional variable definitions and constructions. The patent data come from the United States Patent and Trademark Office (USTPO) and comprise the universe of granted patents filed in the period 1999-2015. The first year (1999) is used to calculate the growth rate of patenting of 2000. County-level data come from the U.S. Census Bureau and the American Community Survey and the Economic Research Service (ERS) at the U.S. Department of Agriculture. All the models use county α and time λ fixed effects.

Table 2. The effect of Hurricane Katrina on the Quantity of Innovation

Outcome variable: Growth rate of number of patents by county	(1) **Panel A.** Treatment: All counties with damage	**Panel B.** Treatment: Quantile group of the proportion of severe damage (2) 1st	(3) 2nd	(4) 3rd	(5) 4th	(6) 90th percentile
Disaster Year	-24.03***	-26.24***	-30.00***	-4.927	-14.63***	8.786
	(4.522)	(7.001)	(5.133)	(4.648)	(5.131)	(6.330)
R-squared	0.031	0.033	0.068	0.052	0.054	0.056
2006-2010	5.067***	1.502	-2.758	9.939***	15.25***	17.547***
	(2.250)	(2.805)	(2.539)	(2.411)	(2.643)	(2.441)
R-squared	0.061	0.061	0.043	0.134	0.092	0.158
2011-2015	4.663**	7.627***	4.039	3.716	-2.623	14.727***
	(2.111)	(2.751)	(2.493)	(2.451)	(2.396)	(2.444)
R-squared	0.050	0.115	0.036	0.081	0.062	0.109
Observations	4,010	1,806	2,664	3,172	3,156	2,808
Control	1,869	871	1,298	1,553	1,545	1,391
Treatment	136	32	34	33	33	13

Notes: This table reports results of difference-in-differences estimations of the effect of Hurricane Katrina on the rate of innovation calculated using the following specification: $\Delta Y_{ct} = \Sigma_{\tau=2000}^{2004} \beta_0 + \beta_1 \times 1[t = 2006\text{-}2010] \times K_t^{2005} + \beta_2 \times 1[t = 2011\text{-}2015] \times K_t^{2005} + \alpha_c + \lambda_t + \delta_c + \varepsilon_{ct}$. The dependent variable is the average annual growth of patenting at the county level. Treated counties are those affected by Hurricane Katrina according to the official designation by the Federal Emergency Management Agency (FEMA) that assesses and reports on the material damage to each housing unit in a county. Panel A reports the differences between all the 136 counties affected by Katrina (the preferred treatment) and counterfactual counties across the U.S. that were not unaffected. Panel B reports differences by quantile group according to the proportion of housing units in the county with severe damage. FEMA's physical assessment of affected houses categorize them into minor, major, and severe (USHUD and U.S. Department of Housing and Urban Development 2006). The counties designation is their Federal Information Processing Standards (FIPS) number. Control counties are identified based on a Kernel propensity score vector that includes: the percent of adults completing some college or associate's degree, the percent of adults with less than a high school diploma, the racial and ethnic composition (percentage of Black, White, Indian, Hawaiian, and Hispanic), percentage of male, total population, per capita earnings, per capita unemployment insurance, per capital personal income, per capita retirement and other, number of jobs per capita, and the urban-rural continuum code. The vector also includes the average annual growth rate of patenting between the period 2000-2004 and 1999. The matching variables are used as control variables, δ, which also include dummies taking value 1 when private and/or public resources benefiting economic activities covered a county. See text for additional variable definitions and constructions. The patent data come from the United States Patent and Trademark Office (USTPO) and comprise the universe of granted patents filed in the period 1999-2015. The first year (1999) is used to calculate the growth rate of patenting of 2000. County-level data come from the U.S. Census Bureau and the American Community Survey and the Economic Research Service (ERS) at the U.S. Department of Agriculture. All the models use county α and time λ fixed effects. The standard errors, clustered by county, are in parentheses. **, and *** denote statistical significance at the 5%, and 1% level, respectively.

Table 3. The effect of Hurricane Katrina on the Quality of Innovation

Outcome variable: Logged number of patents weighted by the number of citations by county	(1) **Panel A.** Treatment: All counties with damage	**Panel B.** Treatment: Quantile group of the proportion of severe damage (2) 1st	(3) 2nd	(4) 3rd	(5) 4th	(6) 90th percentile
Disaster Year	-0.0735	0.214**	-0.136	-0.242***	0.143**	-0.258***
	(0.0638)	(0.0940)	(0.0831)	(0.0732)	(0.0728)	(0.0784)
R-squared	0.400	0.498	0.399	0.466	0.347	0.503
2006-2010	0.103**	0.269***	-0.166**	0.178***	0.211***	0.254***
	(0.0517)	(0.0736)	(0.0676)	(0.0600)	(0.0621)	(0.0641)
R-squared	0.503	0.633	0.494	0.541	0.419	0.535
2011-2015	0.0932	0.0930	0.00921	0.134*	0.105	0.0911
	(0.0568)	(0.0874)	(0.0772)	(0.0706)	(0.0677)	(0.0699)
R-squared	0.453	0.557	0.396	0.442	0.379	0.480
Observations	4,136	1,628	2,334	2,704	3,176	2,528
Control	1,933	782	1,133	1,318	1,554	1,250
Treatment	136	32	34	34	34	14

Notes: This table reports results of difference-in-differences estimations of the effect of Hurricane Katrina on the quality of innovation calculated using the following specification: $\Delta Y_{ct} = \Sigma_{\tau=2000}^{2004} \beta_0 + \beta_1 \times 1[t = 2006\text{-}2010] \times K_t^{2005} + \beta_2 \times 1[t = 2011\text{-}2013] \times K_t^{2005} + \alpha_c + \lambda_t + \delta_c + \varepsilon_{ct}$. The dependent variable is the logarithm natural of the number of patents weighted by the number of forward citations a patent receives within five years of its filing year from other patents excluding those where an inventor listed in the original patent is a part of and those citations coming from the patent filing's examiner. The calculation accounts for the different propensity to cite across sectors and time. Treated counties are those affected by Hurricane Katrina according to the official designation by the Federal Emergency Management Agency (FEMA) that assesses and reports on the material damage to each housing unit in a county. Panel A reports the differences between all the 136 counties affected by Katrina (the preferred treatment) and counterfactual counties across the U.S. that were not unaffected. Panel B reports differences by quantile group according to the proportion of housing units in the county with severe damage. FEMA's physical assessment of affected houses categorize them into minor, major, and severe (USHUD and U.S. Department of Housing and Urban Development 2006). The counties designation is their Federal Information Processing Standards (FIPS) number. Control counties are identified based on an a Kernel propensity score vector that includes: the percent of adults completing some college or associate's degree, the percent of adults with less than a high school diploma, the racial and ethnic composition (percentage of Black, White, Indian, Hawaiian, and Hispanic), percentage of male, total population, per capita earnings, per capita unemployment insurance, per capital personal income, per capita retirement and other, number of jobs per capita, and the urban-rural continuum code. The vector also includes the average annual growth rate of patenting between the period 2000-2004 and 1999. The matching variables are used as control variables, δ, which also include dummies taking value 1 when private and/or public resources benefiting economic activities covered a county. See text for additional variable definitions and constructions. The patent data come from the United States Patent and Trademark Office (USTPO) and comprise the universe of granted patents filed in the period 1999-2015. The first year (1999) is used to calculate the growth rate of patenting of 2000. County-level data come from the U.S. Census Bureau and the American Community Survey and the Economic Research Service (ERS) at the U.S. Department of Agriculture. All the models use county α and time λ fixed effects. The standard errors, clustered by county, are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4. Accounting for Selective Migration: Individual-level Evidence of the Effect of Hurricane Katrina on Innovation

	(1)	(2)	(3)
	Disaster Year	2006-2010	2011-2015
Quantity of Innovation	1.916**	8.284***	11.86***
	(0.758)	(0.514)	(0.559)
R-squared	0.206	0.192	0.197
	(4)	(5)	(6)
Quality of Innovation	0.156***	0.119***	0.166***
	(0.0106)	(0.0103)	(0.0115)
R-squared	0.479	0.239	0.188
Observations	136,341	143,685	141,815
Control	72,436	72,436	72,436
Treatment	3,249	3,249	3,249

Notes: This table reports results of difference-in-differences estimations of the effect of Hurricane Katrina on the rate of innovation calculated using the following specification: $\Delta Y_{it} = \Sigma_{\tau=2000}^{2004} \beta_0 + \beta_1 \times 1[t = 2006\text{-}2010] \times K_t^{2005} + \beta_2 \times 1[t = 2011\text{-}2015] \times K_t^{2005} + \mu_i + \alpha_c + \lambda_t + \delta_c + \varepsilon_{ict}$. The dependent variable in models 1, 2, and 3 is the average annual growth of patenting at the individual level; and for models 4,5, and 6 is the logarithm natural of the number of patents weighted by the number of forward citations a patent receives within five years of its filing year from other patents excluding those where an inventor listed in the original patent is a part of and those citations coming from the patent filing's examiner. The calculation accounts for the different propensity to cite across sectors and time. The treatment group are inventors that i) listed their address—as per the information from patent applications—in one of the counties affected by Katrina in 2005, according to the official designation by the Federal Emergency Management Agency (FEMA), ii) were in any of these counties between 2000 and 2004, and iii) were in these counties between 2006 and 2015. Individuals whose data do not show to be residing in one of the affected counties in the disaster year and file a patent in one of these counties after 2005 are not included in the analysis. The control pool comprises all inventors whose locations in 2005 and in the pre- and post-shock periods are outside the Katrina counties. Matching uses a Kernel propensity score vector that includes gender and patenting experience (i.e., count of number of patents that the inventor had in the 2000-2004 period) in addition to the county level percent of adults completing some college or associate's degree, the percent of adults with less than a high school diploma, the racial and ethnic composition (percentage of Black, White, Indian, Hawaiian, and Hispanic), percentage of male, total population, per capita earnings, per capita unemployment insurance, per capital personal income, per capita retirement and other, number of jobs per capita, and the urban-rural continuum code. The vector, δ, controls for the county-level factors in the matching algorithm. It also includes the average annual growth rate of patenting between the period 2000-2004 and 1999 and dummies taking value 1 when the assignee is not the inventor and dummies when private and/or public resources benefiting economic activities covered a county when the inventor resided in time τ. See text for additional variable definitions and constructions. The patent data come from the United States Patent and Trademark Office (USTPO) and comprise the universe of granted patents filed in the period 1999-2015. The first year (1999) is used to calculate the growth rate of patenting of 2000. County-level data come from the U.S. Census Bureau and the American Community Survey and the Economic Research Service (ERS) at the U.S. Department of Agriculture. All the models use inventor, μ, county, α, and time, λ, fixed effects. The standard errors, clustered by county, are in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5. Placebos Katrina

Outcome variable: Growth rate of number of patents by county	(1) Placebo Year	(2) Placebo Disaster Counties
Disaster Year	10.00***	14.62***
	(2.968)	(3.298)
First Post-Disaster Period	2.956	-1.536
	(2.936)	(3.102)
Second Post-Disaster Period	-5.414	4.889*
	(3.315)	(2.913)
Observations	4,010	4,032
Control	1,869	1,880
Treatment	136	136

Notes: This table reports results of difference-in-differences estimations of the effect of Hurricane Katrina (2005) on the rate of innovation calculated using the following specification: $\Delta Y_{ct} = \Sigma_{\tau=2000}^{2004} \beta_0 + \beta_1 \times 1[t = 2006\text{-}2010] \times K_t^{2005} + \beta_2 \times 1[t = 2011\text{-}2015] \times K_t^{2005} + \alpha_c + \lambda_t + \delta_s + \varepsilon_{ct.}$ The dependent variable is the average annual growth of patenting at the county level. Column 1 reports average effects when randomly choosing a placebo year between 2001 and 2013. 2005 is excluded from the pool of options. Column 2 reports analysis after randomly assigning Katrina counties to a different Federal Information Processing Standard Publication (FIPS) code in the studied period. The pool of potential FIPS is all the counties that were not affected by a major disaster, as per FEMA's Disaster Declarations. The official 136 affected by Katrina are identified by the Federal Emergency Management Agency (FEMA). Control counties are those not affected by Katrina and matched based on a Kernel propensity score vector that includes: the percent of adults completing some college or associate's degree, the percent of adults with less than a high school diploma, the racial and ethnic composition (percentage of Black, White, Indian, Hawaiian, and Hispanic), percentage of male, total population, per capita earnings, per capita unemployment insurance, per capital personal income, per capita retirement and other, number of jobs per capita, and the urban-rural continuum code. The vector also includes the average annual growth rate of patenting between the period 2000-2004 and 1999. The matching variables are used as control variables, δ, which also include dummies taking value 1 when private and/or public resources benefiting economic activities covered a county. See text for additional variable definitions and constructions. See text for additional variable definitions and constructions. The patent data come from the United States Patent and Trademark Office (USTPO) and comprise the universe of granted patents filed in the period 1999-2015. The first year (1999) is used to calculate the growth rate of patenting of 2000. County-level data come from the U.S. Census Bureau and the American Community Survey and the Economic Research Service (ERS) at the U.S. Department of Agriculture. All the models use county α and time λ fixed effects. The standard errors, clustered by county, are in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% level, respectively.