Creatively Destructive Hurricanes: Do Disasters Spark Innovation?

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Abstract

We investigate whether disasters can lead to innovation. We construct a US county-level panel of hurricane damages using climate data, hurricane tracks, and a wind field model and match these to patent applications by the location of their inventor over the last century in the United States. We examine both general innovation and patents that explicitly mention the terms 'hurricane' or 'storm.' In line with the current literature that hypothesizes innovative activity driven by shocks, in particular innovation intended to mitigate future shocks, we find that hurricanes lead to temporary boost in damage-mitigating patents a few years after the event. However, we also show there is long-term, lasting over two decades, general reduction of innovation after a damaging storm. We conclude that hurricanes, and possibly other types of disasters, cannot be viewed as a 'benefit in disguise,' and that these events are unlikely to generate longer-term beneficial dynamics in an adversely affected location.

Keywords Creative destruction · Hurricanes · Patents · US counties

1 Introduction

Typically, disaster impacts are differentiated between the direct damage that disasters wreak, and the indirect losses that follow them later Botzen et al. (2019). These indirect economic losses can include business interruptions, macroeconomic effects such as falls in aggregate demand, changes in relative prices, long-term consequences for health and education, and social and political turmoil. Maybe counter-intuitively, indirectly disasters can also generate benefits. For example, a demand surge for (re)construction services can lead to a boom in this sector for several years in the aftermath of a disaster Olsen and Porter (2011). Positive long-term dynamics can also occur when technological innovation and investment in better planning and design are generated by the shock event Hallegatte and Dumas (2009). If associated with deliberate policy, these positive dynamics are sometimes referred to as 'Build Back Better' Fernandez and Ahmed (2019), Noy et al. (2020). When

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these arise out of private sector activity and initiative, they can be thought of as a variant of the Schumpeterian 'Creative Destruction' hypothesis.[1]

The common empirical approach employed in assessing the impact of a disaster is to use statistical-econometric techniques to examine whether or how a country's dynamics have changed after the event. A common practice is to use some form of difference-in-difference estimation (e.g., (Cerra and Saxena 2008; Belasen and Polachek 2009), and Husby et al. (2014)), and other methods, such as propensity score matching (e.g., (Deryugina et al. 2018)) or synthetic control (e.g., (Barone and Mocetti 2014), and Cavallo et al. (2013)). Most of this research focuses on macroeconomic variables from national (or regional) income accounts, where typical variables of interest are aggregate production (GDP), consumption, measures of fiscal spending and revenue, exports and imports, and prices Cavallo and Noy (2011).

Importantly, only a few papers find evidence in support of any variant of the positive post-disaster dynamics as described in the build-back-better or creative-destruction hypotheses. For instance, Cuaresma et al. (2008) find some evidence of possible long-run positive effects, but one that is limited to moderate disasters in higher-income regions. Similarly, De Alwis and Noy (2019) and Jiuping and Yi (2013) find some positive longer-term dynamics associated with disasters in which post-disaster assistance was unusually generous (the tsunami in Sri Lanka in 2004 and the Wenchuan earthquake of 2008, respectively). Skidmore and Toya (2002) are atypical in arguing that they identify, on average, a long-run increase in human capital acquisition and total factor productivity in countries hit by disasters. While the broader literature is generally consistent in identifying multiple negative dynamics following disaster shocks, this minority of 'build back better' or 'creative destruction' papers does seem to suggest the possibility of a positive outcome, at least on some dimensions, following some types of catastrophic events, in some countries.

In this paper we further explore the potential positive impact of disasters, particularly on technological progress and innovation, by focusing on patenting activity after hurricanes in the United States. To this end we build a county level panel data set of innovation and hurricane damages over nearly 120 years. Ultimately, if there is to be a long-term benefit post-disaster, it will have to manifest itself through some form of technological innovation (i.e., technological progress). As is common in this literature, we measure innovation by patents Popp (2019).

Miao and Popp (2014) examined global country-level patent data from the Delphion database for the period 1974-2009, and the corresponding experience with disasters therein. In particular they investigated whether these events were followed by "risk-mitigating innovation" (p. 280). They examine whether floods, droughts, and earthquakes generated future innovation in flood control, drought-resistant crops, and seismic resilience in buildings, respectively. Their analysis rests on the hypothesis that the main channel through which a shock generates future innovation is by changing relative prices. Innovation is induced as relative price changes make the resulting patents more beneficial. These changes in relative prices can come about because the availability of inputs has changed, or because as the salience of certain risks increases. Their results show that disasters can result in more risk-mitigation, but that this depends on the type of disaster and the type of technology examined.

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[1] Although, unlike Schumpeter's framing, the destruction that motivates and generates beneficial (creative) change originates from a disaster, rather than from the churn of a dynamic market economy.

In another paper, Hu et al. (2018) examined both recent short-term (2005-2013) province level patents and long-term historic (11 A.D. to 1910 A.D) national level innovation data from patents in China following weather events. They find that mitigating innovative activity in historical and modern times increased as a result of weather events, and that during the modern period these mitigating patents led to more general innovative activity. Similarly, by focusing on a specific sub-sectors (within European agriculture) and patents aimed at climate change adaptation (as identified in the patent text), Auci et al. (2021) are able to investigate both whether climate variability is associated with more patenting activity (it is) and whether that patenting activity is successful in improving productivity (it is as well).[2]

The central contribution of the present paper (relative to the papers described above) is our ability to focus on the longer term impacts on innovation (specific to the hazard, and more generally), and to tie patents with environmental shocks using the exact location of both. We do this within the context of the United States, and without focusing on the agricultural sector and specific crop-related innovations. Focusing on the long-term enables us to potentially, as argued above, observe the full 'benefit' of the shock in terms of generating new innovation (specific and general). At the same time, focusing locally is important for our purposes, since natural disasters are inherently local and their true impact is likely to be blurred when examining national or even broad regional data Strobl (2011).

We focus on local long-term impacts by compiling US data on (ultimately successful) patent applications and the creator(s)'s location (at the county level) since 1900. We match these with localized hurricane damage data constructed from the physical characteristics of the storm, a wind field model, pre-event population exposure, and a stylized damage function. As shown by Strobl (2012) and Felbermayr and Gröschl (2014), such damage data can overcome the endogeneity and measurement problems inherent in using ex-post estimated damages of disasters.[3]

Using a Poisson fixed effects count model we demonstrate that there is indeed some evidence of temporary boosts to disaster mitigation creative activity after a hurricane. But these are dwarfed by a long-term decline, lasting over two decades, of general innovative activity in the damaged area. Thus, while previous research might have identified cross-country or broad regional positive links between disaster events and mitigating innovation, our more localized investigation over a longer time period reveals that, viewed more broadly and over a longer time horizon, disasters are detrimental to general innovation.

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[2] Another recent paper, Moscona (2021) focuses on agriculture as well. He investigates the reaction of farmers to the loss of topsoil associated with the Dust Bowl in the 1930s in the US. Similarly, he finds an increase in the adoption of new crop technologies aimed at adapting to the damage associated with the catastrophe.

[3] Miao and Popp (2014) needed to use a set of instrumental variables to overcome this problem, while (Hu et al. 2018) used lagged values as instruments to try to overcome this issue.

2 Data

2.1 Hurricane Damage Index

2.1.1 Damage Index

We follow the common approach and model the damage due to a hurricane as dependent on the wind speed experienced locally.[4] In terms of the actual functional form, Emanuel (2011) points out that it is reasonable to assume that: The relationship between wind speed experienced and damage incurred is cubic; and that such damage is only likely to occur above a minimum threshold. We incorporate these features and ensure that the percentage of damage varies between 0 and 1 with the following damage function of storms $k = 1..., K$, during time period t, for location m, in county i:

$$f_{mit} = \sum_{k \in t} \frac{v_{mik}^3}{1 + v_{mik}^3} \tag{1}$$

where

$$v_{mik} = \frac{MAX\big[(v_{mik} - v_{thresh}), 0\big]}{v_{half} - v_{thresh}} \tag{2}$$

where v_{mikt} is the maximum wind speed of storm k experienced at point of interest m in county i during year t, v_{thresh} is the threshold below which no damage occurs, and v_{half} is the threshold at which half of the property is damaged. Following Emanuel (2011), we set values of 92 km/h and 204 km/h for v_{thresh} and v_{half}, respectively. One should note that Eq. (1) is defined in terms of the percentage of damage caused per storm. Since any location i could be hit by multiple storms within a year, we assume that damages are cumulative but cannot exceed 100% in a given year.[5]

Equation 1 allow us to calculate local wind speeds within counties. Importantly, in using these to arrive at county level annual damages should take into account the local exposure. To do so we define

$$H_{it} = \sum_{mi \in Mi} w_{mit-1} f_{mit} \tag{3}$$

where w_{mit-1} are shares of total population exposure at point m in county i at time $t - 1$. One should note that we measure the exposure weights a year prior to the damages in order to ensure that these are exogenous to the contemporaneous storm event.

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[4] Damages from hurricanes are caused not only by wind, but also from storm surges and flooding that is associated with rainfall during the storm, as noted by Emanuel (2011). These damages, however, tend to be correlated with the storm's measured wind speed, and direct hydrological data is not available.

[5] This may overstate damages to assets if already damaged assets cannot be damaged further by a subsequent storm within the same year. Alternatively, using the within-year maximum value did not change our regression results in any noticeable manner.

2.1.2 Hurricane Wind Field Model

For the hurricane intensity measure described in Eq. (1), we need to estimate maximum wind speed experienced during a hurricane at each location m. To model these local wind speeds v we employ the Boose et al. (2004) version of the Holland (2008) wind field model, according to which the approximate maximum local wind speed at any point m, for storm k, at hour h is given by:

$$v_{ik} = \max_{h \in k} \left(GF \left[V_{max,kh} - S(1 - sin(T_{imkh})) \frac{v_{imkh}}{2} \right] \right.$$
$$\left. \times \left[\left(\frac{R_{max,kh}}{R_{imkh}} \right)^{B_{kh}} exp \left(1 - \left[\frac{R_{max,kh}}{R_{imkh}} \right] B_{kh} \right) \right]^{\frac{1}{2}} \right) \tag{4}$$

where V_{max} is the maximum sustained wind velocity anywhere in the storm k at time h, T is the clockwise angle between the forward path of the storm and a radial line from the storm center to the point of interest i, V_h is the forward velocity, R_{max} is the radius of maximum winds and R is the radial distance from the center of the tropical storm to point i. G is the gust factor, and F, S, and B are the scaling factors for surface friction, asymmetry due to the forward motion of the storm, and the shape of the wind profile curve, respectively. We set G equal to 1.5 and S equal to 1 following (Paulsen and Schroeder 2005) and Boose et al. (2004), respectively. For the surface friction indicator F, Vickery et al. (2009) suggest that in open water the reduction factor is around 0.7 and that there is a reduction in wind-speed of around 14% on the coast and 28% 50 km inland. Following (Elliott et al. 2015) we linearize the reduction factor to capture the friction effect of the storm as it moves inland. In terms of the pressure profile parameter B we adopt (Holland 2008)'s approximation method. For every storm we take the maximum wind speed experienced during a storm's lifetime at point m for input in Eq. (1).

2.1.3 Hurricane Track Data

Our source for hurricane data is the National Oceanic and Atmospheric Administration (NOAA) Best Track Hurricane Database (HURDAT). HURDAT provides six hourly data on all hurricanes in the North Atlantic Basin, including the position of the eye and the maximum wind speed of the storm. We linearly interpolate these to 3 hourly positions to fit with our rainfall data that is described below. We also restrict the set of storms to those that came within 500 km of the US coast, and that achieved hurricane strength (at least 119 km/hr) at some stage.[6] One should note that the HURDAT database provides storms from 1851, but has been shown to be relatively reliable from 1870 onward Mann et al. (2007), and hence we only use data on storms that fit our criteria from 1870.

2.1.4 Population Data

In order to derive historical population exposure within counties we use the gridded decadal population estimates from the HYDE data-set version 3.2.1. It provides global

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[6] Tropical cyclones generally do not exceed a radius of 500 km.

population maps at a spatial resolution of 0.5 arc minutes for every ten years from 1700 until 2000, and yearly thereafter Klein Goldewijk et al. (2017). For the period prior to 2000, we linearly interpolate the decadal population figures to arrive at annual values. One should note that the cell centroids of the population data serve as points m within counties i for use in Eqs. (1) and (3).

2.2 Patent Data

To construct a spatially (county level) time varying patent database we rely on two sources. From 1976 onward we use information from the USPTO's PatentsView databases, which contains information on all patent activity in the United States (US). In particular we use this data to determine the filing year of granted patents and the geographic location (latitude & longitude) of the inventor(s). We limit our analysis to those US patents in which at least one of the inventors was located in the US so we can allocate their location to the appropriate county. Prior to 1975 we use the county level location attributed to US inventors as constructed by Petralia et al. (2016).[7]

In order to identify hurricane-related inventions we searched each patent's title and text for any occurrence of the words 'hurricane' or 'storm'. A more detailed visual analysis of about a 1000 random patents identified accordingly showed that incidences of the word 'hurricane' accurately highlighted patents that were directly related to hurricane damage mitigation measures. A similar analysis of randomly chosen patents that did not contain the word 'hurricane' and only the word 'storm' was also accurate, although less than the presence of the term 'hurricane', in identifying storm damage related mitigation measures. We thus group patents into those that contain either of the two words, or, more stringently, just the word 'hurricane'.
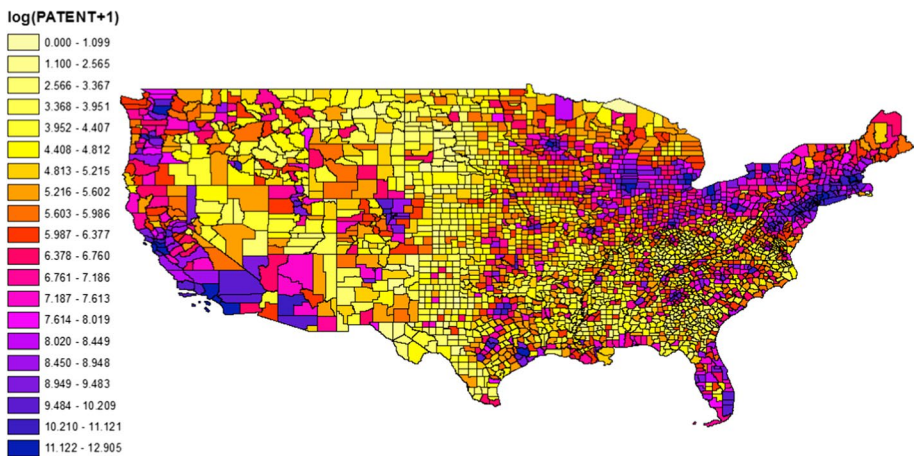
2.3 Climate Controls

We also construct time varying controls for precipitation and temperature. To this end we use the precipitation and temperature measures from the PRISM climate grid, which constructs a small-scale monthly climate history developed by the Spatial Climate Analysis Service at Oregon State University. The data-set's resolution is roughly 4km covering the coterminous United States and is available from 1895 onward. Since the resolution of PRISM is higher than the population data, we attribute the PRISM grid cells to their closest HYDE population cell, and calculate the average across PRISM cells. As with the hurricane destruction index in Eq. (3), we weight the HYDE grid cell averages with the previous year's population share to construct annual averages of monthly precipitation and temperature by county. One should note that we exclude monthly values of precipitation in a county where in that same month the value of $H \neq 0$. This is done in order to ensure that the precipitation measures do not capture some of the damages that may be due to a hurricane in any given year.[8]

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[7] One should note that, when there was more than one inventor for any patent, we attributed the patent to the counties of all inventors, although simply attributing to the first listed inventor made no qualitative and only very marginal quantitative difference in our results. Details available from the authors upon request. Two counties were dropped in the estimation since they had zero patent filing activity throughout our sample period.

[8] Not doing so does not change the estimates very much.

Table 1 Summary statistics

Variable	Avg.	Min.	Max.	St.Dev.
Patent (All)	25.43	0	23105	207.36
Patent (Storm & Hurricane)	0.176	0	181	1.78
Patent (Hurricane)	0.05	0	114	0.86
H	0.013	0	1	0.08
$H(\neq 0)$	0.11	1.23e−18	1	0.21
$Precipitation(mm)$	78.21	0.22	293.66	31.57
$Temperature(°C)$	7.82	− 10.72	25.99	5.96

Fig. 1 Log number of patents (+1) (1900–2017)

2.4 Data Sample and Summary Statistics

Our sample consists of a complete panel of annual patent activity, hurricane damages, and climate controls over 118 years covering 3,084 counties in the the coterminous United States. We define years as going from the 1st May to the following year's April 30th in order to ensure that patent activity before May in any year would not be potentially linked to any hurricane damages that occurs later in that year. We also note that while our total estimation period is restricted by the patent data to be between 1900 to 2017, we need not reduce this sample when including up to 5 year lags for the climatic controls and 31 year lags for the hurricane damage index.

Summary statistics are provided in Table 1. Over our sample period, on average, 25 patents are filed every year per county, but with considerable variation across counties. The average number of patents related to hurricanes, identified by the mention of 'Hurricane' or 'Storm' in the patent text, is substantially smaller, with only 0.2 per year, i.e., one every five years per county. If one narrows the classification further, by focusing on patents that explicitly use the word 'Hurricane', then such a patent is filed every twenty years, on average, per county. As with overall patents, there is considerable variation in terms of county-level filings. Looking at the hurricane destruction index one finds that the average
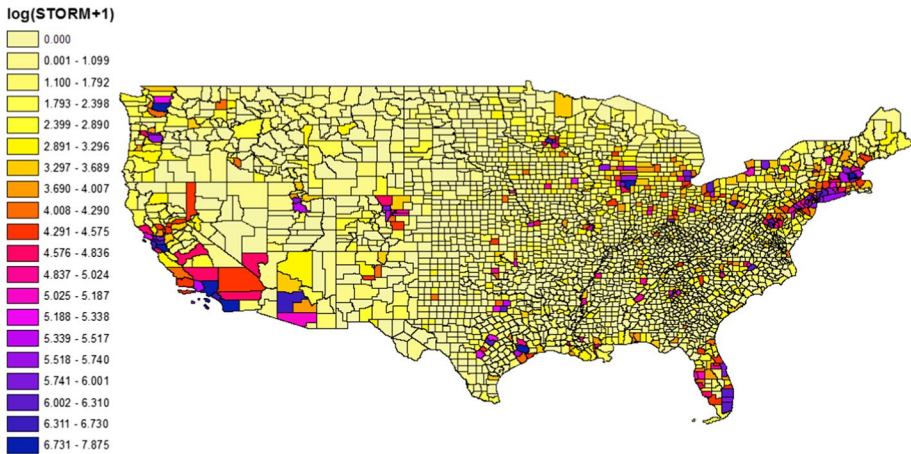
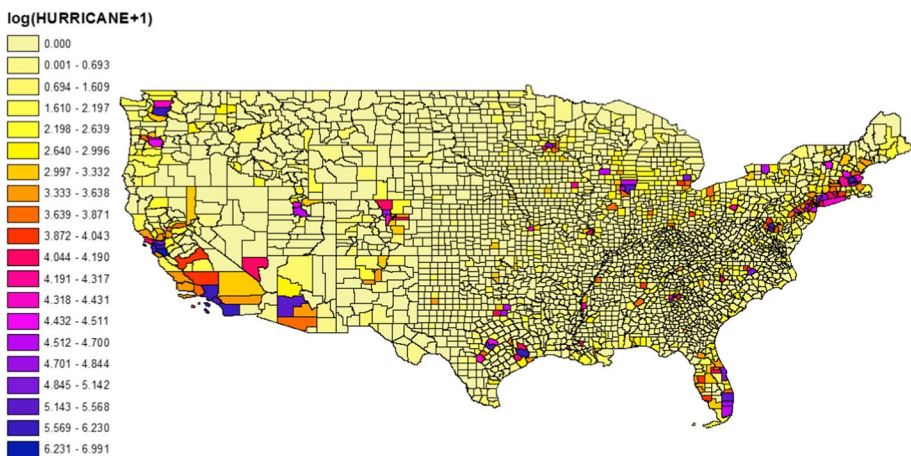**Fig. 2** Log number of storm/hurricane patents (+1)

Fig. 3 Log number of hurricane patents (+1)

damage is 1.3% since the beginning of the 20th century, and as high 100%. Looking at those county-years with positive values of *H* indicates that the average damage is 11%, but again with considerable variation.

We depict the county level distribution of the logged number of counts of patents over our sample period in Fig. 1. As can be seen, these are unevenly distributed, with greater concentrations along both the east and west coasts. Examining the hurricane related sub-categories, more broadly and more narrowly defined in Figs. 2 and 3, patents seem also more concentrated along the coasts, but in particular in Florida and the Northeast.

In Fig. 4 the average value of our hurricane destruction index by county since 1851 is shown. As would be expected given that hurricanes are storms specific to the North Atlantic Basin, damage occurs along eastern coast of the continental US. Average damages are highest for counties closest to the coast and lower for counties further west.
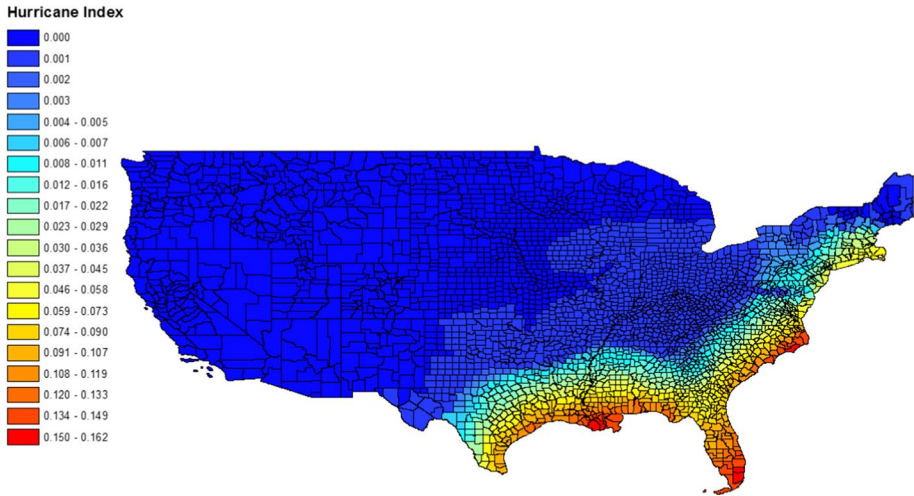
Hurricane Index

	0.000
	0.001
	0.002
	0.003
	0.004 - 0.005
	0.006 - 0.007
	0.008 - 0.011
	0.012 - 0.016
	0.017 - 0.022
	0.023 - 0.029
	0.030 - 0.036
	0.037 - 0.045
	0.046 - 0.058
	0.059 - 0.073
	0.074 - 0.090
	0.091 - 0.107
	0.108 - 0.119
	0.120 - 0.133
	0.134 - 0.149
	0.150 - 0.162

Fig. 4 County level average hurricane destruction index (1851-2017)

3 Econometric Analysis

3.1 Regression Framework

Given the nature of our dependent variable of interest - i.e., a count of patents - we use a Poisson Conditional Fixed Effects Maximum Likelihood Estimator (PCFE):

$$PATENT_{it} = \alpha + \sum_{l=0}^{L} \beta_{H_{t-l}} H_{it-l} + \sum_{l=0}^{L} \lambda_{\mathbf{C_{it-l}}} \mathbf{C_{it-l}} + \pi_t + \mu_i + \epsilon_{it} \tag{5}$$

where *PATENT* is the number of patents in county i filed at year t, H is the hurricane damage index, potentially including its lags (l), and ϵ is the error term. Time fixed effects (π_t) are included, and county level time-invariant unobservables are captured by μ_i. $\mathbf{C}$ is a vector of climatic controls, namely average monthly temperature and average monthly precipitation, which are potentially lagged in line with chosen lags of H. Hubert/White/sandwich robust standard errors are calculated. One should note that coefficients in Eq. (5) are interpreted as semi-elasticities.

The use of PCFE with robust standard errors provides a number of advantages. Firstly, it produces the same coefficients, as well as the associated covariance matrix, as the unconditional Poission fixed effects estimator, and hence does not suffer from the incidental, typical of many non-linear estimators ((Cameron and Trivedi 2013)). Additionally, it is robust to misspecification, such as lack of equidispersion, an excessive amount of zeros, and dependence over time, as long as the conditional mean is correctly specified Wooldridge (1999). However, spatial dependence may change the variance of the PCFE estimator if this dependence is time varying. To test for time varying spatial dependence we employ the test developed by Bertanha and Moser (2016).

One should note that there are a couple of assumptions implicit in Eq. 5 which we need to interrogate. First, we assume that patents are location specific, i.e., that they can be assigned strictly to one county. However, as discussed in Sect. 2, some patents are

Table 2 Regression results - all patents

	(1)	(2)	(3)	(4)	(5)	(6)
H_t	− .126	− .086	− .035	− .064	− .065	− .076
	(0.073)	(0.076)	(0.08)	(0.075)	(0.075)	(0.072)
H_{t-1}		− .161**	− .125*	− .081	− .110	− .110
		(0.061)	(0.064)	(0.067)	(0.063)	(0.064)
H_{t-2}			− .206**	− .164**	− .125*	− .151**
			(0.053)	(0.055)	(0.057)	(0.055)
H_{t-3}				− .222**	− .177**	− .142**
				(0.053)	(0.053)	(0.054)
H_{t-4}					− .212**	− .170**
					(0.055)	(0.052)
H_{t-5}						− .259**
						(0.061)
Obs.	363912	363912	363912	363912	363912	363912

(a) Robust standard errors in parentheses; (b) ** and * indicate 1 and 5 per cent significance levels, respectively; (c) All specifications include year dummies; (d) All specifications include appropriately lagged precipitation and temperature controls

attributed to several inventors located in different counties, and we attribute these patents to each of the relevant locations. In a robustness check, we exclude all such multi-county patents.

Second, Eq. 5 assumes that there are no spatial spillovers through the impact of hurricanes. These spillovers, as noted above, would also undermine the PCFE estimator if they are time varying, and we explicitly test for this. To determine whether there are spillovers of any effect from hurricanes we also explored whether our results are sensitive to including a dummy variable that denotes counties that neighbour a hurricane-impacted county (and zero otherwise) in the base specification (Eq. 5).

3.2 Econometric Results

We first investigated whether there is time-varying spatial correlation, potentially undermining the validity of the PCFE estimator in Eq. (5), using the test developed by Bertanha and Moser (2016). The resultant test statistic (11.7) indicated that this is not the case.

Coefficient estimates of H from Eq. (5) of up to five lags are provided in Table 2. As can be seen, there is no contemporaneous effect of hurricane destruction on local patent filing activity. However, as one increases the number of lags of H, a different picture emerges. More precisely, two years after a damaging hurricane the number of patents filed falls and this effect persists up to $t − 5$ included values of H. Moreover, the coefficient noticeably rises at $t − 4$ and at $t − 5$, and is about 70% higher.[9] Taken at face value the coefficients suggest that a mean damaging hurricane ($H = 0.11$) would cause local patent filing activity to

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[9] This difference is statistically significant at the 5% level.

Table 3 Regression results - hurricane specific patents & robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
H_t	− .170	− .123	− .078	− .076	− .084	− .165	− .068	− .168*	− .075
	(0.101)	(0.218)	(0.073)	(0.074)	(0.068)	(0.099)	(0.213)	(0.069)	(0.072)
H_{t-1}	− .153	0.265	− .113	− .112	− .098	− .126	0.3	− .199**	− .109
	(0.109)	(0.188)	(0.065)	(0.066)	(0.062)	(0.105)	(0.183)	(0.066)	(0.064)
H_{t-2}	0.036	0.16	− .153**	− .153**	− .122*	0.099	0.227	− .249**	− .150**
	(0.1)	(0.145)	(0.056)	(0.057)	(0.058)	(0.101)	(0.143)	(0.07)	(0.056)
H_{t-3}	0.105	0.456**	− .145**	− .147**	− .125*	0.191*	0.504**	− .245**	− .141**
	(0.088)	(0.133)	(0.055)	(0.056)	(0.057)	(0.088)	(0.13)	(0.083)	(0.054)
H_{t-4}	0.022	0.209	− .175**	− .181**	− .109*	0.113	0.243	− .260**	− .169**
	(0.106)	(0.166)	(0.053)	(0.054)	(0.055)	(0.104)	(0.165)	(0.088)	(0.052)
H_{t-5}	− .063	0.121	− .266**	− .275**	− .138*	0.068	0.185	− .288**	− .258**
	(0.103)	(0.194)	(0.062)	(0.064)	(0.059)	(0.101)	(0.186)	(0.095)	(0.061)
$NBNAFF_t$									3.309
									(2.177)
$NBNAFF_{t-1}$									2.786
									(2.191)
$NBNAFF_{t-2}$									3.102
									(1.893)
$NBNAFF_{t-3}$									3.405
									(1.866)
$NBNAFF_{t-4}$									3.439
									(2.031)
$NBNAFF_{t-5}$									2.884
									(1.969)
Sample:	STORM	HURR.	ALL	ALL	ALL	STORM	HURR.	ALL	ALL
C	YES	YES	YES	YES	NO	NO	NO	YES	YES
Obs.	220896	129328	220896	129328	363912	220896	129328	363912	363912

(a) Robust standard errors in parentheses; (b) ** and * indicate 1 and 5 per cent significance levels, respectively; (c) All specifications include year dummies

decrease by 1.6% within two years, and that this would increase to a decline of 2.8% five years after the storm.

In the first two columns of Table 3 we focus specifically on patents related to hurricanes and storms.[10] This entailed dropping a number of counties which had no corresponding patent filing activity over our sample period. To facilitate comparisons between these results and the results from Table 2, we also re-ran our all patents using a more restricted sample of these remaining counties, for both the broader and narrower hurricane/storm patent definitions in columns 3 and 4, respectively. Results, when compared to Table 2,

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[10] As for overall patents, the test by Bertanha and Moser (2016) did not reject the null hypothesis of time invariant spatial correlation, where the corresponding test statistics were 8.77 and 5.02, respectively for the broader and narrower definitions.
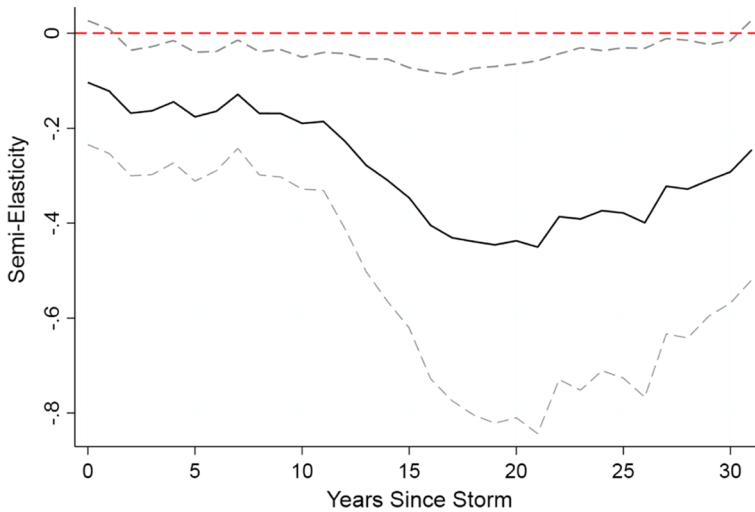
Fig. 5 Long-term impact on patents

do not change qualitatively and only slightly quantitatively when reduced to these two sub-samples.

Turning to the estimated coefficients for the broader definition of hurricane patents in the first column, one discovers that there was no significant impact on these after local hurricane destruction up to five years after the event. For the narrower definition in the subsequent column, one finds a positive boost to patent filing 3 years after the storm, but no impact otherwise. Taking this coefficient at face value suggests that a mean damaging hurricane increases patents related to hurricanes by 5% for one year.

We have thus far restricted any lagged effects to up to five years. Including further lags would mean reducing our sample since the climatic control variables only go back as far as 1895. However, as noted above, we can construct hurricane damages back much further, allowing us to include up to 31 lags of H without having to reduce our sample period if we exclude climate controls. One worry, and the reason for including climatic controls, is that hurricanes may be correlated with other climatic factors that could also affect patent activity Auffhammer et al. (2013). We thus first re-estimated Eq. (5) for our three patent variables without the climatic controls, as depicted in the last three columns of Table 3. As can be seen, the results remain qualitatively the same as with climatic controls. Ooverall patent activity, excluding the climatic controls, produces less precisely estimated and smaller coefficients. At worst, therefore, not including climatic controls when one includes more lags of H is likely to bias the estimated coefficients downward, and consequently more likely fail to reject the null hypothesis of these being equal.

In the second to last column of Table 3, we re-run our main specification but drop those patents for which inventors are located in more than one county. Accordingly, this produces a significant effect both contemporaneously and for the lags. Moreover, the coefficients tend to be higher compared to the last column of Table 2. This further strengthens the argument that the impact of hurricanes on patent activity is local; one is more likely to capture the impact when the location of patenting activity is more precisely identified.

In the final column 3 we include our dummy variables (*NBNAFF*) that indicate counties that were not affected by hurricanes but are adjacent to counties that were. As can be seen,
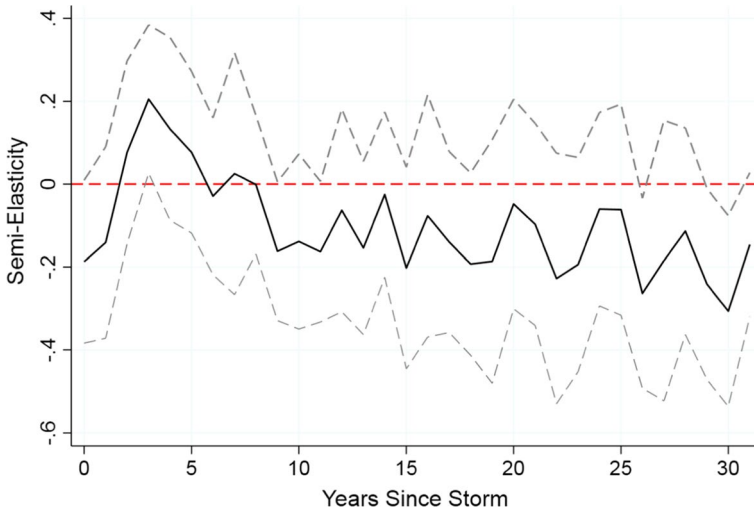
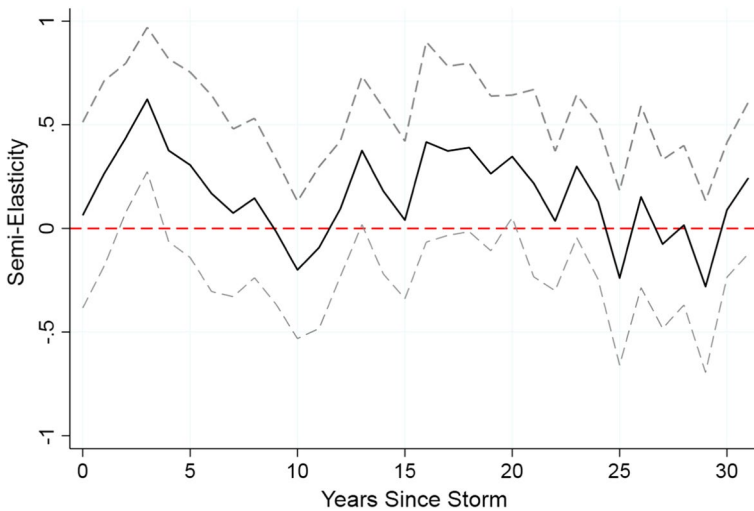**Fig. 6** Long-term impact on storm/hurricane patents

Fig. 7 Long-term impact on hurricane patents

their inclusion does not alter, qualitatively nor quantitatively, the estimated coefficients on the hurricane destruction index, as compared to the last column of Table 2.

The estimated coefficients along with 95% confidence bands from including up to 31 lags of H, but no climatic controls, for total patent filing activity are depicted in Fig. 5. Accordingly, in line with our earlier results, we find no impact until two years after a damaging storm, and the subsequent negative effect lasts until $t - 30$, i.e., up to 30 years after the event. Examining the evolution of the significant coefficients over time one notices that size falls considerably after about ten years after the storm to reach a maximum negative impact at $t - 17$, where it is estimated to be -0.41. Taking at face value this suggests that

seventeen years after an average damaging storm, total patent filing activity is 5.1% lower than it would have been if there had been no storm. After around 22 years the negative effect begins to subside until it becomes insignificant.

We also show the coefficients on the lagged values of *H* for the broader and narrower definition of hurricane related patent activity in Figs. 6 and 7, respectively. For the broader definition one finds that there is a small positive impact at $t − 3$, i.e., three years after the storm, which for an average storm translates into a 4% increase in hurricane mitigating patents. For most of the rest of the lags the coefficient is negative and insignificant, except for a few years near the end. In terms of limiting patent activity to those that contain the word hurricane in their text one discovers positive impacts at $t − 2$, which increases further at $t − 3$. Taken at point value the largest boost to the local filing of patents that likely are mitigating suggests an increase of 6.8%, but this increase is short-lived, as suggested by the remaining insignificant estimated lags.

4 Discussion and Concluding Remarks

Using 120 years of United States county-level data on patents and hurricane damage, we uncover evidence of very limited 'creative destruction' dynamics. These disasters generate new innovations, but only temporary sparks of innovative activity directly related to mitigating this risk of storms and hurricanes. This finding, specifically, is in line with the cross-country evidence presented by Miao and Popp (2014) and the broad regional and historical national findings for China by Hu et al. (2018).

However, while (Hu et al. 2018) show that extreme weather events can also spark short-term non-mitigating innovation, our findings suggest a starkly different picture. Rather, we show that US hurricanes have caused long-term reduction, lasting up to nearly thirty years, in patent awards. There are a number of possible reason that could be driving the long-term negative effect on innovative activity from damages caused by hurricanes.

First, as disasters have been shown to increase risk aversion , and risk aversion is an impediment to innovation and research and development (R &D) activity, hurricanes in the US may have reduced the long-term propensity to innovate because of this increasing reluctance to take on risky activities.[11] Investment in the development of patents has uncertain returns (with very large variance), and if businesses expect a more uncertain commercial environment more generally, and become more risk averse, the amount of R &D investment may decline.

Second, a number of studies have shown that hurricanes in the US have led to emigration from the affected regions. For instance, Boustan et al. (2020) show that over the period 1940 to 2010, a US county's net inward migration rate fell after hurricanes. Also, Strobl (2011) shows that it is higher income individuals that leave a county in the US after a storm. This high-income and presumably more educated population is also more likely to innovate Bell et al. (2019). Thus, emigration reduces the long-term potential for discovery and innovation.

Finally, there may be inertia, in that a lack of exposure to innovative activity in the immediate aftermath of the disaster, because of the damage to facilities and infrastructure,

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[11] See, for example, Cameron and Shah (2015); Bourdeau-Brien and Kryzanowski (2020); Simsons and Åstebro (2010).

may reduce innovation in the long-term Bell et al. (2019). This decline can be associated with the observation that innovation is an increasing-returns activity Aizenman and Noy (2007), more prosaically with some form of status quo bias Samuelson and Zeckhauser (1988), or because of long-term decline in the economic potential of the region hit by the event Noy and duPont (2018).

With regard to the long-term negative effect of hurricanes on patents, we note that this result does not necessarily undermine the general finding that disasters typically entail only short-term aggregate negative economic impacts on output and incomes Cavallo and Noy (2011), Botzen et al. (2019). The literature does often identify longer-term adverse impacts at the local level. Innovation is thus only one of several other local economic dimensions that might be adversely affected by hurricanes. Others include employment Groen et al. (2020), neo-natal health Currie and Rossin-Slater (2013), home ownership Sheldon and Zhan (2019), and business activity Sydnor et al. (2017). Moreover, the spillovers arising from patent activity, while generally shown to be favourable to close proximity, are likely to reach well beyond the usual size of a county Murata et al. (2014).

While this is not directly relevant to the research questions we posed here, it would have been informative to examine the efficacy of risk mitigating innovations, as small as these may be, in actually reducing the damage and loss associated with disasters in the long-term Carrión-Flores and Innes (2010); Miao (2019). In the US case, for example, this might involve examining the efficacy of storm-related patents in reducing the damages wrought by hurricane events.[12] We leave these important questions for future research.

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[12] Moscona and Sastry (2021), for example, examined the impact of temperature patterns and change on innovation and consequently the productivity of US agriculture.

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