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Natural disasters and corporate innovation

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ABSTRACT
We examine how natural disasters affect corporate innovation. Using a comprehensive sample of U.S. firms and inventors, we find that natural disasters significantly drop innovation quantity and quality. The results are robust to include a broad set of regional characteristics, matching analysis, and alternative proxies for innovation. These effects persist for up to three years after the disaster. We also provide suggestive evidence that financial constraints due to natural disasters give firms less incentive to innovate. Further analysis shows that natural disasters have impacts on inventor relocation, innovation productivity, and innovation risk.

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1. Introduction

Climate change is making natural disasters more frequent and more intense. According to the Emergency Events Database (EM-DAT), the number of climate-related disasters has tripled in the last 30 years. In addition, there are 396 disasters reported in 2019, and they led to 11,755 deaths, 95 million people affected, and 103 billion US$ in economic losses across the world.[1] This increased risk of natural disasters has thus captured the attention of academics. A vast amount of research has been devoted to estimating their impact on the economy.[2] However, the research on how businesses and workers react to natural disasters is fairly limited.[3] This paper investigates the impact of natural disasters on corporate innovation and the human capital responsible for it. Our motive for focusing on corporate innovation is because of its central role as the primary driver of long-term economic growth (Solow 1957).

We propose that natural disasters have a negative effect on corporate innovation because of financially constrained situations. First, firms experience stronger financial constraints due to the severe financial loss caused by natural disasters. Firms located in the affected areas suffer huge damage to real estate and physical capital, followed by the interruption in production and delay in cash income. Following Statista.com, the economic loss from natural disasters globally is 232 billion US dollars in 2019 and this figure in 2020 is 268 billion US dollars.[4] Hsu et al. (2018) provide evidence that the profitability is declined for firms hit by natural disasters. The literature also suggests that the ability to generate cash flow strongly affects corporate investment expenditures (Hovakimian and Titman 2006). For instance, Campbell et al. (2012) show that the decline in internal funds is responsible for the decrease in corporate investment. Consequently, the financial losses due to natural disasters may affect the ability of a firm to finance new or ongoing innovation investments.

Second, natural disasters lead to a decline in the firm's incentive to innovate and thereby reduce corporate innovation through the banking sector. Schüwer, Lambert, and Noth (2018) argue that independent banks based in disaster areas increase their risk-based capital ratios after the hurricane and reduce their total loan exposures to non-financial firms. Local natural disasters may adversely affect local deposit levels and loan performance.

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This article has been corrected with minor changes. These changes do not impact the academic content of the article.

As a result, local banks may tighten the credit supply in the local area. When a firm can not access the external capital and raise enough funds, it has to suspend the innovation investment. This suspension may lead to an increase in the likelihood of an unfinished project. Xu (2020) shows evidence that investments in innovation and the quantity and quality of innovation outcomes are declined when the cost of capital increases.

To test this hypothesis, we conduct a sample dataset encompassing 4443 unique firms and 70,125 firm-year observations over the period 1986–2018. We consider only natural disasters affecting U.S. territory, classified as 'Major Disasters' in the SHELDUS database of the University of South Carolina, resulting in total direct estimated damages above $1 billion 2017 constant dollars and lasting less than 30 days. Our study thus encompasses 41 major natural disasters. Our dataset makes it possible to examine the temporal changes in metrics of corporate innovation for firms affected by natural disasters. To track natural disasters, we construct a dummy variable, *Natural Disaster*, which equals one if firms are located in a county struck by the natural disaster and zero otherwise. We use different innovation metrics to measure corporate innovations, similar to previous studies in the literature (Fang, Tian, and Tice 2014; Gao et al. 2020), such as the number of patents, the number of patent citations and the number of citations per patent. We also assess the quality (value) of the innovation with the method outlined by Kogan et al. (2017).

Using difference-in-difference regression analysis, we find a robust negative relationship between natural disasters and corporate innovation. On average, firms hit by natural disasters experience a decrease in the number of patents, citations, citations per patent, and innovation value of 6.39%, 10.95%, 7.32%, and 11.40%, respectively. The difference-in-differences estimation assumes that treated and control firms share parallel trends before natural disasters, and our tests provide evidence that their pre-treatment trends are indistinguishable. Our results also indicate that innovation outputs remain depressed for up to three years following a major natural disaster.

Then, we control for several variables to allay concerns that our findings are influenced by effects other than natural disasters. Our findings remain valid when; (i) we control for county-level characteristics; (ii) we use alternative measures of natural disasters; (iii) we use alternate innovation measures; (iv) we exclude firms whose main customers or suppliers are also affected by the natural disaster. Following Barrot and Sauvagnat (2016), we test whether firms' innovation outputs are reduced because the natural disasters also strike their main customers and suppliers by excluding those firms from the sample. We identify firms whose suppliers or main customers are also affected by the same natural disaster, using Customer Segment data from COMPUSTAT. Our results, however, indicate that firms that do possess close connections with other stricken firms yield comparable results to our main tests.

If the impact of natural disasters on corporate innovation is true because of financially constrained situations, we expect that the negative effect is stronger for firms with financial constraints, which is measured by three dummy variables including the KZ index (Kaplan and Zingales 1997), HP index (Garcia and Norli 2012) and WW index (Whited and Wu 2006). KZ index, HP index, and WW index are indicators of whether a firm is financially constrained or not according to each financial constraint measure. We interact *Natural disaster* with financial constraints variables, and then test whether the interaction effect negatively affects innovation of firms. First, we find a negative and significant interaction term on the number of patents and citations. This result indicates that the adverse effect of natural disasters on corporate innovation is stronger for firms with high levels of financial constraints. In addition, the firm's incentive to innovate following a natural disaster is examined in the form of Research and Development (R&D) spending. We report that the coefficients of the interaction term are also negative and statistically significant. This suggests that disaster is negatively correlated with R&D investment scales by total assets and this effect is worse for financially constrained firms.

We next investigate other possible channels that may drive the adverse impact of natural disasters on corporate innovation: human capital, innovation productivity, and innovation risk. In terms of the first channel-human capital, we expect that natural disasters affect corporate innovation due to the reduction of inventors' assessment of their safety. Thus, we test the inventor mobility and relocation after the occurrence of disasters. We observe that there are significant falls in the numbers of new hires and staff engaged in innovation, accompanied by a significant increase in innovation staff leaving the firm. Second, we provide evidence that for affected firms, the number of patents and citations per employee, the number of patents and citations per inventor, is significantly negatively affected following a natural disaster. Finally, natural disasters may affect innovation output through innovation risk. Firms may reduce the incentive to engage in a risky innovation project, and thus they have fewer high-value projects or they are not valuable at all. This channel is in line with Mukherjee, Singh, and Žaldokas (2017) that there is an uncertain nature of innovation investments, making returns to innovation risky.

Our paper contributes to the literature in several ways. First, the results reported in this paper add to the emerging literature on finance and climate risk. Recent studies have shown evidence of the relationship between climate change risk and corporate finance (Chava 2014; Huynh, Nguyen, and Truong 2020; Hugon and Law 2019; Barrot and Sauvagnat 2016; Addoum, Ng, and Ortiz-Bobea 2021); financial risks (Painter 2020) and stock market inefficiency (Ameli et al. 2019; Semieniuk et al. 2021). Specifically, some studies focus on the impact of natural disasters on a firm's performance and policy (e.g. Dessaint and Matray 2017; Hsu et al. 2018; He 2019; Elnahas, Kim, and Kim 2018). For instance, Dessaint and Matray (2017) suggest salient risk associated with hurricane strikes results in an increase in cash holdings. More studies are required to investigate the impact of climate-related risks on firms' long-term performance. This paper aims to fill the gap, suggesting that natural disasters have an adverse effect on firms' R&D investments and their subsequent innovation activities. This study also contributes to the climate finance literature by providing evidence on the role of the financial constraints in transmitting the impact of natural disasters to corporate innovation.

Second, our paper adds to the literature on driven factors of firm innovation. Previous studies indicate that corporate innovation is associated with some types of uncertainty such as national election uncertainty (Bhattacharya et al. 2017); economic policy uncertainty (Xu 2020); market uncertainty (Czarnitzki and Toole 2011); policy uncertainty (Gulen and Ion 2016) and cash flow volatility (Minton and Schrand 1999). Under uncertainty, firms are more cautious in innovation investments when they face an increase in risk (Bloom, Bond, and Van Reenen 2007). Li, Lin, and Lin (2021) show that country climate vulnerability is negatively affected to firms' R&D investment and innovation. Unlike those focusing on the country-level climate vulnerability index from the Notre Dame Global Adaptation Initiative (ND-GAIN), we are interested in the direct impact of uncertainty and climate-related risk inherent in natural disasters and innovation. We find that natural disasters suppress both the inputs and outputs for firms' innovation for up to three years, and financial constraints due to natural disasters give firms less incentive to innovate. Globally, human activities are being increasingly affected by natural disasters due to population growth, migration, and climate change. Considering the importance of innovation for maintaining economic growth and firm value, our findings are relevant to the firm's managers, investors, and local and national policymakers. For example, our paper suggests that the negative impact of natural disasters on corporate innovation persists for up to three years, hence local policymakers could develop better innovation policies to encourage innovation investments for firms in affected areas. Our findings also provide more information for investors before investing in a corporation hit by natural disasters.

The remainder of the paper is organized as follows; Section 2 reviews the related literature and develops our main testable hypotheses. Section 3 describes the data used and explains our choice of metrics of corporate innovation. Section 4 reports our main empirical analysis. Mechanisms for the impact of natural disasters on corporate innovation are discussed in Section 5. We provide further analysis in Section 6. Finally, section 7 contains our summary, conclusions, and suggestions for further work. The variables used in our study are defined in Appendix 1.

2. Related literature and hypothesis development

This section reviews prior literature on the possible effects (and associated mechanisms) of natural disasters on firm innovation and develops a testable hypothesis for our empirical tests.

Recently, there is a growing body of literature on the financing of innovation. Studies have shown evidence of the effects of financial constraints on the firm-level (Brown, Fazzari, and Petersen 2009; Brown, Martinsson, and Petersen 2012; Nanda and Nicholas 2014). Innovation investments usually take a long time to get results and require substantial input resources and both internal and external capital sources. Natural disasters come with a wide range of consequences including both human and economic losses. These consequences can put firms in danger of financial constraints, which negatively affects corporate innovation. First, firms affected by natural disasters may experience financial losses due to the delay in production and cash income. Natural disasters destroy the real estate and physical capital of a firm and these economic losses are expected to increase as a result of the rise in economic exposure and climate change (Botzen, Deschenes, and Sanders 2019). Hsu et al. (2018) find that firms with factories set in affected states are much less profitable, compared to others. Hence, the sharp drop in internal capital source affects corporate ability to keep workers and make R&D investments.

Second, firms affected by natural disasters could not access external finance from the bank, leading to less investment in R&D and thus less innovation after disasters. Previous studies have shown that the supply of credit from banks is reduced in disaster-affected areas (Schüwer, Lambert, and Noth 2018; Nguyen and Wilson 2020). Local natural disasters may affect local deposit levels and loan performance, which will tighten the credit constraints in the local area. For instance, Schüwer, Lambert, and Noth (2018) argue that independent banks based in disaster areas increase their risk-based capital ratios after the hurricane and reduce their total loan exposures to non-financial firms. As a consequence, firms may face higher external financing costs and thus have less motivation to invest in innovation. Supporting this argument, Gilchrist and Zakrajšek (2007) show evidence that a firm's investment spending is affected by the bond price and the weighted average cost of capital. Xu (2020) also suggests that investment in innovation and the quantity and quality of innovation outcomes are declined when the cost of capital increases. This effect is stronger for financially constrained firms and firms are more dependent on external funds. Other studies show evidence of the important role of banks in the financing of innovation (see e.g. Chava et al. 2013; Kerr and Nanda 2014; Mann 2018; Robb and Robinson 2014). For instance, Nanda and Nicholas (2014) study the impact of financing constraints on innovation investments and find that the disruption in external bank finance adversely affects the rate of innovation. This unavailable capital leads to a change in the nature of innovation by firms from experimental, radical innovations to incremental and sustaining innovations.

Based on the above discussion, natural disasters are expected to reduce firms' incentive to engage in innovative projects.

3. Data and experimental design

3.1. Data and sample

The data for this study is collected from multiple sources. We obtain data on major natural disasters striking U.S. territory from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) at the University of South Carolina. From this database, we collect information on the start date, the end date, and the Federal Information Processing Standards (FIPS) code of all affected counties. We follow Barrot and Sauvagnat (2016) and Hsu et al. (2018) by defining natural disasters as major disasters where total direct estimated damages are above \$1 billion (in 2017 constant dollars) and last less than 30 days. We also restrict the data to hurricanes that occurred before 2019 to align our timeline with our innovation data. This selection procedure leaves us with 41 major natural disasters (e.g. blizzards, floods, hurricanes, etc.) over the 1985–2017 period.

We gather patent and citation information from the dataset of Kogan et al. (2017) (KPSS), which contains information on all patent applications filed with (or eventually granted by) the U.S. Patent and Trademark Office (USPTO) from 1926 to 2020.[5] Each filing firm's identifiers allow us to merge this data with the Center for Research in Security Prices (CSRP) and COMPUSTAT databases. We focus on the patent filing year rather than the grant year as Griliches, Pakes, and Hall (1987) argue that the filing year is superior in capturing the actual year of innovation. It also eliminates the potential bias due to the lag between application and granting dates. Given the typical 2-year lag between application and granting (Hall, Jaffe, and Trajtenberg 2005), patents applied for in 2019 and 2020 may not be awarded but may exist in the database. We, therefore, end our sample of patents applied for in 2018 to further alleviate the application-grant lag issue. As a result, our innovation sample spans over the period of 1986–2018.

We acquire financial information from COMPUSTAT and stock price information from the CRSP. In addition, data on the location of headquarters are obtained from the CRSP/Compustat merged database. This database provides historical headquarters data going back to 1994. If a firm does not have historical data, we use the Compustat header information. In the base case analysis, we assign zero patents to firm-year observations without any patenting activity. The final SHELDUS-KPSS-COMPUSTAT-CRSP merged file leaves us with 4443 unique firms (representing 70,125 firm-year observations).

3.2. Measures of innovation

We follow previous innovation literature (e.g. Aghion, Reenen, and Zingales 2013; Fang, Tian, and Tice 2014; Seru 2014) by employing four measures for innovation output. The first measure is the total number of patent applications filed by a firm or an inventor in a year that is eventually granted. Patent counts are the most natural and measurable output from the process of innovation. However, they do not provide information to distinguish breakthrough innovations from incremental technological discoveries. Hence, alternative measures are also considered in this study. The second measure is the total number of forward citation counts received by all patents of a firm or an inventor in a given year. As suggested by Hall, Jaffe, and Trajtenberg (2001, 2005), the third measure is the average number of citations per patent for all patents that a given firm or an inventor applies for in a specific year. These measures are more relevant and important to capture the quality of its innovation outcome (Trajtenberg 1990; Hall, Jaffe, and Trajtenberg 2005). Finally, as an additional way to measure the economic importance of innovation, we follow Kogan et al. (2017) by utilizing the market value (in millions of nominal US dollars) of patents that a firm or an inventor applies for in a given year.[6]

There are two truncation problems associated with the patent data. First, the truncation problem arises because patents are not recorded in the database until they are granted. The second truncation problem is related to citation counts. Patents tend to accumulate citations over a long time period, so the citation counts of more recent patents are significantly downward biased. To address these concerns, we follow the recommendations of Hall, Jaffe, and Trajtenberg (2001, 2005) by modifying patent counts using 'weight factors' calculated from the application-grant empirical distribution and adjusting citation counts by estimating the shape of the citation-lag distribution. In addition, patent and citation data exhibit high levels of skewness, so we use natural logarithms of the amended patent counts and citations in the regressions.

3.3. Descriptive statistics

Table 1 presents descriptive statistics for key characteristics of our firm-level sample. The sample consists of 70,125 firm-year observations and 4443 unique firms. On average, the mean (median) values of the number of patents are 13.688 (0.000). The number of *Citations and Citations/Patents* are 267.886 (0.000) and 8.799 (1.000), respectively. Meanwhile, the mean innovation value is U.S. $290.417 million. Regarding control variables, the average firms exhibit a size of U.S. $5.415 billion, cash holdings of 19.6%, and leverage of 20.5%. In terms of performance, firms perform well with the mean value of return on asset (*ROA*) of 6.7% and *Tobin's Q* of 2.102. On average, these firms have ratios of tangible assets and capital expenditures of 48.8% and 5.5%, respectively. The average Herfindahl index for 3-digit SIC industries in our sample is close to 1.8%.

Table 1. Summary statistics. The table presents the summary statistics of firm-level innovation, output measures and firm characteristics. The sample consists of 70,125 firm-year observations and 4443 unique firms. Detailed definitions of all variables appear in the Appendix.

	Obs.	Mean	Std. dev.	p10	p50	p90
Dependent variables						
#Patents	70,125	13.688	95.372	0.000	0.000	15.000
#Citations	70,125	267.886	1862.433	0.000	0.000	306.726
Citations/Patents	70,125	8.799	17.777	1.000	1.000	23.640
Innovation Value ($M)	70,125	290.417	2798.505	0.000	0.000	121.060
Firm-level control variables						
Size ($M)	70,125	2000.118	5111.971	16.015	178.286	4977.000
Tobin's Q	70,125	2.102	1.622	0.924	1.511	4.054
Cash Holdings	70,125	0.196	0.223	0.009	0.100	0.561
Leverage	70,125	0.205	0.194	0.000	0.171	0.465
ROA	70,125	0.067	0.194	−0.159	0.112	0.232
Tangible Assets	70,125	0.488	0.340	0.109	0.416	0.987
Capital Expenditures	70,125	0.055	0.050	0.010	0.041	0.115
Firm Age	70,125	17.051	16.698	2.000	12.000	38.000
H-Index	70,125	0.018	0.045	0.001	0.004	0.044
H-Index^2	70,125	0.002	0.018	0.000	0.000	0.002

3.4. Experimental design

Following Bertrand and Mullainathan (2003) and Dessaint and Matray (2017), we use a difference-in-difference model (DiD) in our main tests to capture the impact of natural disasters on corporate innovation. The basic regression we estimate is the following:

$$Innovation_{i,\,l,\,t+1} = \alpha_t + \beta_i + \gamma Natural\ Disaster_{i,\,l,\,t} + \delta X_{i,\,l,\,t} + \in_{i,\,l,\,t+1} \tag{1}$$

where i indexes firm, l indexes the county in which the firm headquarter is settled, and t indexes time. The dependent variable, *Innovation*, is one of our four main innovation variables. Patent counts, citation counts, the number of citations per patent, and innovation value. The variable of interest is *Natural Disaster*, which is a binary variable that equals one if firms are located in a county struck by the natural disaster and zero if not. X is a vector of control variables that are commonly used in the innovation literature. Specifically, X includes the natural logarithm of total assets (*Size*), growth opportunities (*Tobin's Q*), cash (Cash Holdings), leverage (Leverage), profitability (ROA), asset tangibility (*Tangible Assets*), leverage (*Leverage*), capital expenditures (*Capital Expenditures*), firm age (*Ln(Firm Age)*), Herfindahl–Hirschman index (*H-Index*), and Herfindahl–Hirschman Index squared (*H-Index*^{2}). All these control variables are lagged by 1 year. To minimize the effect of outliers, we winsorize all variables at the 1st and 99th percentiles. Detailed variable definitions are provided in Appendix 1.

Following Gormley and Matsa (2014), we also estimate Equation (1) with higher-order fixed effects to control for unobserved firm heterogeneity, time-varying differences across states, and time-varying differences across industries by including firm (β_i) and year (t), state-by-year ($\omega_{s,t}$), and 2-digit SIC industry-by-year ($\lambda_{z,t}$) fixed effects for firm i, located in state s, operating in industry z, at time t. Angrist and Pischke (2009) and Gormley and Matsa (2014) argue that including control variables in the presence of fixed effects may lead to biased parameter estimates. Therefore, in the estimations that use the high order fixed effects, we suppress all control variables. In all tests, we follow Petersen's (2009) recommendation by controlling for serial correlation with robust Rogers (1993) standard errors clustered at the firm level.

4. The impact of natural disasters on corporate innovation

4.1. Baseline results

Table 2 reports the results for our eight different regressions based on Equation (1) to assess the impact of natural disasters on corporate innovation. The independent variable of interest is *Natural Disaster*. The main dependents are as follows: The natural logarithm of the number of patents plus one in columns (1) and (2), the natural logarithm of the number of citations plus one in columns (3) and (4), the natural logarithm of the number of citation counts scaled by patents plus one in columns (5) and (6), and the natural logarithm of the number of the cumulative dollar value (in millions of 2005 nominal U.S. dollars) of patents that a firm applies for in a given year plus one in columns (7) and (8).

The coefficient estimates for *Natural Disaster* are significant at the 5% level and negative in all cases, confirming the negative impact of natural disasters on our innovation measures. According to the results in columns (1) and (2), where the dependent variable is *Ln(#Patents + 1)*, the coefficients of *Natural Disaster* are −0.080 and −0.074, respectively. The economic magnitude of the impact of natural disasters is also sizeable. The occurrence of such disasters causes a decline in the number of patents by approximately 7.69% ($= e^{-0.080} - 1$) and 7.13% ($= e^{-0.074} - 1$) after controlling for some variables, compared to firms located in counties without natural disasters.

Columns (3) and (4) also suggest similar findings when using *Ln(#Citations + 1)* as the dependent variable. The coefficient of *Natural Disaster* is −0.143 and −0.138, which are significant at the 5% level. In terms of economic significance, firms affected by natural disasters exhibit 13.32% ($= e^{-0.143} - 1$) and 12.89% ($= e^{-0.138} - 1$) decreases in the number of citations. Meanwhile, we report that the coefficients of *Natural Disaster* in columns (5) and (6) where the dependent variables are Ln (*Citations/Patents + 1)* are −0.072 for both

Table 2. The impact of natural disasters on corporate innovation. This table reports coefficients from difference-in-difference (DiD) regressions of the impact of natural disasters on corporate innovation. The main variable of interest is *Natural Disaster*. The dependent variable in columns (1) and (2) is the natural logarithm of the number of patent counts plus one. The dependent variable in columns (3) and (4) is the natural logarithm of citation counts plus one. The dependent variable in columns (5) and (6) is the natural logarithm of citation counts scaled by patents plus one. The dependent variable in columns (7) and (8) is the natural logarithm of the cumulative dollar value (in millions of 2005 nominal US dollars) of patents that a firm applies for in a given year plus one. All control variables are lagged by one year. The detailed definitions of all variables are provided in Appendix 1. The odd-numbered columns omit the control variables and contain both standard and multiplicative fixed effects (i.e. firm and year fixed effects, state∗year fixed effects, and industry∗year fixed effects whose coefficients are suppressed), while the even-numbered columns include control variables and standard fixed effects (i.e. firm and year fixed effects, whose coefficients are suppressed). Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Ln (#Patents + 1)		Ln (#Citations + 1)		Ln (Citations/Patents + 1)		Ln (Innovation Value + 1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Natural Disaster	−0.080**	−0.074**	−0.143**	−0.138**	−0.072**	−0.072**	−0.123**	−0.116**
	(0.033)	(0.032)	(0.064)	(0.062)	(0.030)	(0.030)	(0.053)	(0.049)
Size		0.281***		0.487***		0.156***		0.380***
		(0.018)		(0.031)		(0.014)		(0.026)
Tobin's Q		0.037***		0.076***		0.032***		0.094***
		(0.004)		(0.010)		(0.006)		(0.008)
Cash Holdings		0.147***		0.452***		0.248***		0.114
		(0.049)		(0.109)		(0.057)		(0.076)
Leverage		−0.284***		−0.547***		−0.203***		−0.451***
		(0.048)		(0.099)		(0.050)		(0.074)
ROA		−0.171***		−0.216**		−0.039		−0.117**
		(0.042)		(0.099)		(0.053)		(0.057)
Tangible Assets		0.186***		0.290***		0.072		0.269***
		(0.046)		(0.092)		(0.044)		(0.069)
Capital Expenditures		0.092		0.530**		0.407***		0.163
		(0.117)		(0.270)		(0.144)		(0.180)
Ln (Firm Age)		−0.011		−0.099***		−0.068***		−0.015
		(0.018)		(0.036)		(0.017)		(0.030)
H-Index		0.488		1.849		1.227*		−0.002
		(0.566)		(1.236)		(0.647)		(0.790)
H-Index^2		0.304		−1.209		−1.349		0.930
		(1.576)		(2.354)		(1.020)		(1.907)
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State∗Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Industry∗Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
No. of Obs.	70,125	70,125	70,125	70,125	70,125	70,125	70,125	70,125
Adjusted R^2	0.758	0.770	0.639	0.649	0.491	0.498	0.774	0.783

cases. These results indicate that the number of citations per patent drops by approximately 6.94%. Interestingly, the estimates of columns (7) and (8) indicate that the innovation value decreases by 12.22% and 10.95% due to natural disasters. In terms of control variables, we observe that the coefficient estimates for *Size, Tobin's Q, Cash Holdings, Tangible Assets,* and *Capital Expenditure* are all positive for our innovation outputs and are significant at the 1% or 5% levels. This is consistent with the notion that large firms with sizable cash holdings, tangible assets, and capital expenditure are more likely to sustain innovation. On the other hand, it can be seen that the coefficient estimates for *Leverage, ROA,* and *Firm Age,* are uniformly negative, and again mostly significant, with *Leverage* being uniformly significant at the 1% level. Again, this is consistent with highly indebted firms, older firms, and those that sweat their assets, being less capable of sustaining innovation in the face of natural disasters.

In addition, the coefficient estimates for the variable *Natural Disaster*, in regressions which omit individual firm's characteristics, but include State Year Fixed Effects and Industry Year Fixed effects in addition to Firm and Year Fixed Effects, while still statistically significant at the 5% level, are negative with a larger absolute magnitude, compared to those seen in the even-numbered columns. This suggests that the negative effect of natural disasters is greater when we omit the control variables and consider both standard and multiplicative fixed effects.

4.2. Robustness tests

We conduct several tests to ensure our baseline results are robust to county-level characteristics, an alternative data source of firm's headquarters location, different innovation measures, and excluding firms with main customers or suppliers also affected by natural disasters. The results are presented in Table 3. In addition to the set of control variables used in Table 2, we also capture the impact of county-level characteristics and show the estimates in Panel A. Richer and larger counties can have more resources for a higher innovation level. Thus, the natural logarithm of county population and county personal income is included in the regression. Education is another factor that may affect innovation, so we include an educational attainment variable using the number of enrollment in institutions of higher education to control for the county's intellectual resources. To control for the labor force demographics, we incorporate the ratio of seniors in the local labor market.[7] This information is collected from the U.S. Bureau of Economic Analysis and the U.S. Census Bureau. The variable of interest, *Natural Disaster*, remains negative for innovation output and statistically significant at the 5% level. This confirms that our basic results are unaffected by county population characteristics. In terms of control variables, we show that educational attainment is positively related to the number of patents filed in column (1) and the value of innovation output in column (4). Local seniors are found to harm innovation in column (3). Other control variables do not have significant impacts on corporate innovation.

In Panel B, we use alternative data source to obtain a firm's headquarters location. We follow Kubick et al. (2017) to use the firm's historical business address from its 10-K filings to identify its headquarters location. We obtain a firm's historical headquarters locations from 'The Notre Dame Software Repository for Accounting and Finance' database.[8] We find that our main result that natural disasters negatively affect is robust to using an alternative data source of firm's headquarters location.[9]

In Panel C, we use alternative innovation measures as our dependent variables, namely; *Originality, Generality, New Products, and New Product Value*, to examine the impact of natural disasters on corporate innovation (Hsu, Tian, and Xu 2014; Kogan et al. 2017; Gao et al. 2020; Huang and Yuan 2020). The independent and the control variables are the same as in Table 2, plus Firm and Year fixed effects. Our findings for the variable of interest, *Natural Disaster*, are effectively unchanged and remain statistically significant at the 10% and 5% levels. Finally, Barrot and Sauvagnat (2016) suggest that strong supply-chain links to other firms struck by natural disasters should be particularly sensitive to economic uncertainty.

Although our setting in the paper has been applied in some papers, such as Aretz, Banerjee, and Pryshchepa (2019), Dessaint and Matray (2017), there is still a concern about the impact of natural disasters on firms operating in multiple counties. Therefore, we follow Hsu et al. (2018) and use an alternative variable to the variable *Natural Disaster* to capture the effect of natural disasters. Specifically, we construct a variable *Affected Facilities*, which represents the percentage of facilities of firms affected by natural disasters in any given year. We use the U.S. EPA's toxic release inventory (TRI) database to identify U.S. firms' factory locations.[10] Given that noconsistent linkingkeys are available to connect the EPA TRI database and Compustat databases, we follow to employ a string-matching process based on company names to match these datasets.[11] We then calculate the ratio of the number of factories affected by natural disasters to the total number of factories that belong to firm. We run the same regression as in the baseline models of Table 2. We find that natural disasters significantly reduce corporate innovation. We report this result in Table 3 – Panel D. This result confirms the robustness of our finding that natural disasters have negative impacts on corporate innovation. Although the EPA TRI database provides us with a rich source for identifying factories' locations, there are still drawbacks in the use of this source. In particular, this database only includes firms in manufacturing industries with Standard Industrial Classification (SIC) codes between 2000 and 3999. In addition, Toxics Release Inventory (TRI) Program only requires reporting if a facility has at least 10 full-time employees and uses one of nearly 600 chemicals. Thus, the use of EPA TRI data potentially underestimates the true geographical diversification of firm operation and hence, the impact of natural disaster on innovation.

In addition, to control for potential selection bias, we implement a coarsened exact matching analysis. We report the results in Table A1 in Appendix 2. Furthermore, we conduct additional tests to control for corporate governance and address potential concerns with firms located in neighboring counties. We report the results in Table A2 in Appendix 2.

Table 3. The impact of natural disasters on corporate innovation – robustness checks. This table reports different robustness checks on the impact of natural disasters on corporate innovation. In Panel A, we control for county-level characteristics, including population, personal income, educational attainment, and local seniors. In Panel B, we examine the impact of natural disasters on corporate innovation, using an alternative sample using 10-K-based firm location data. In Panel C, we examine the impact of natural disasters on corporate innovation using alternative innovation measures. In Panel D, we replace the variable *Natural Disaster* by the variable *Affected Facilities*, which represents the percentage of facilities of firms affected by natural disasters in any given year. All the control variables used in Table 2 are also included in this regression but unreported for brevity. The detailed definitions of all variables are provided in Appendix 1. Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Controlling for county-level characteristics

	Ln (#Patents + 1)	Ln (#Citations + 1)	Ln (Citations/Patents + 1)	Ln (Innovation Value + 1)
	(1)	(2)	(3)	(4)
Natural Disaster	−0.082***	−0.138**	−0.065**	−0.127***
	(0.030)	(0.058)	(0.028)	(0.048)
Ln (County Population)	−0.080	0.331	0.343*	0.155
	(0.187)	(0.372)	(0.180)	(0.297)
Ln (County Personal Income)	0.157	0.101	−0.068	0.109
	(0.166)	(0.320)	(0.152)	(0.270)
Educational Attainment	2.148**	1.405	−0.752	2.541*
	(0.884)	(1.581)	(0.694)	(1.381)
Local Seniors	0.659	−4.287	−4.471***	−3.089
	(1.738)	(3.159)	(1.420)	(2.699)
Control Variables of Table 2	Yes	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes
No. of Obs.	70,125	70,125	70,125	70,125
Adjusted R^2	0.781	0.662	0.507	0.792

Panel B: Alternative sample using 10-K-based firm location data

	Ln (#Patents + 1)	Ln (#Citations + 1)	Ln (Citations/Patents + 1)	Ln (Innovation Value + 1)
	(1)	(2)	(3)	(4)
Natural Disaster	−0.075**	−0.156***	−0.074***	−0.129**
	(0.034)	(0.056)	(0.026)	(0.059)
Control Variables of Table 2	Yes	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes
No. of Obs.	68,963	68,963	8,963	68,963
Adjusted R^2	0.743	0.612	0.487	0.738

Panel C: Using alternative innovation measures

	Originality	Generality	New Products	New Product Value
	(1)	(2)	(3)	(4)
Natural Disaster	−0.019**	−0.012**	−0.014*	−0.003*
	(0.009)	(0.006)	(0.008)	(0.002)
Control Variables of Table 2	Yes	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes
No. of Obs.	70,125	70,125	70,125	70,125
Adjusted R^2	0.405	0.417	0.442	0.432

Panel D: Using alternative measure of natural disaster

	Ln (#Patents + 1)	Ln (#Citations + 1)	Ln (Citations/Patents + 1)	Ln (Innovation Value + 1)
	(1)	(2)	(3)	(4)
Affected Facilities	−0.035***	−0.602**	−0.032**	−0.051**
	(0.012)	(0.262)	(0.015)	(0.024)
Control Variables of Table 2	Yes	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes
No. of Obs.	19,783	19,783	19,783	19,783
Adjusted R^2	0.642	0.573	0.432	0.615

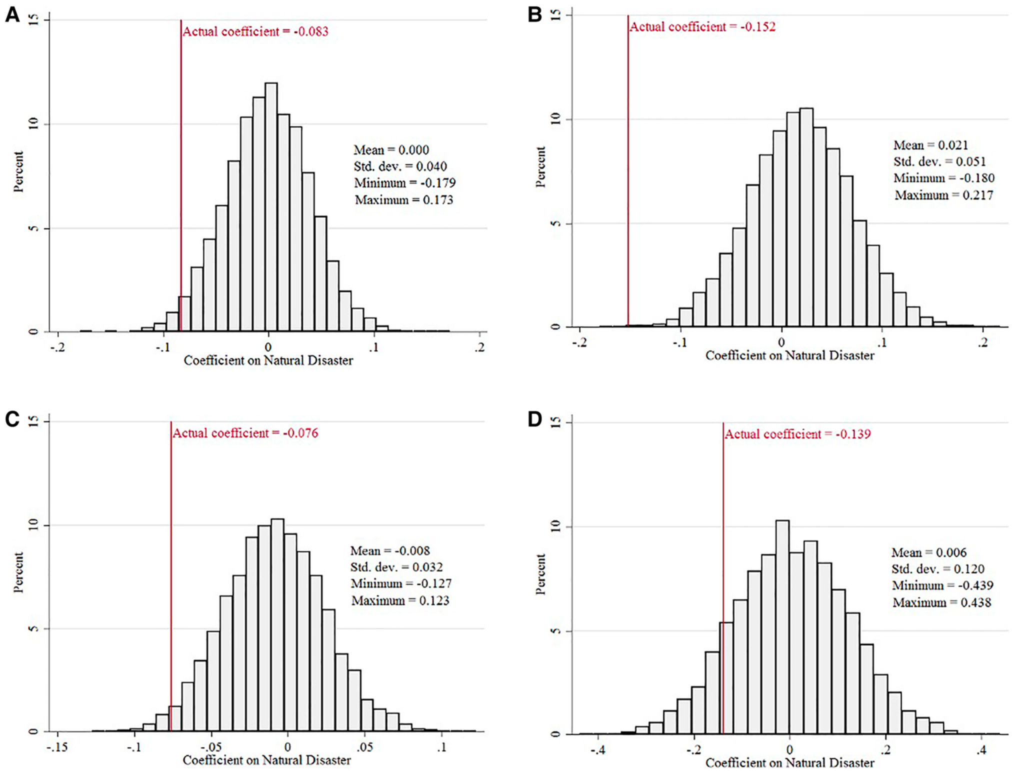

Figure 1. Bootstrap tests. The figure shows the bootstrap distributions for the coefficients on *Natural Disaster* from 10,000 bootstrap simulations of the model in Table 2. For each iteration, we randomly assign a group of 4443 firm-year observations as pseudo treated group and the remaining firms as pseudo control firms. Based on these pseudos treated and control groups, we re-estimate columns 2, 4, 6, and 8 of Table 2 and save the coefficients on *Natural Disaster*. The figure reports the distribution of the coefficients when the dependent variable is Ln (#Patents + 1) in Panel A, Ln (#Citations + 1) in Panel B, Ln (Citations/Patents + 1) in Panel C, and Ln (Innovation Value + 1) in Panel D. The vertical line signifies the coefficients estimated using the real natural disaster treatment.

4.3. Time issues

4.3.1. Placebo tests

In this section, we test whether our results are driven purely by chance by running placebo tests. In particular, we perform a bootstrap procedure for the coefficients on *Natural Disaster* from 5000 bootstrap simulations of the model in Table 2. For each iteration, 3415 firm-year observations were randomly assigned as a ‘treated’ group, with the remainder allocated to a ‘control’ group. The regressions in the even-numbered columns of Table 2 were re-estimated in each iteration of the process, and the coefficients of *Natural Disaster* are saved. We were then able to construct the estimated sampling distributions of the coefficients of *Natural Disaster* seen in Figure 1. In the cases of Panel A and Panel C, where the dependent variables were *Ln(#Patents + 1)* and *Ln(#Citations/Patents + 1)*, the actual coefficients estimated from the data have Z scores of −2.075 and −2.125, respectively, indicating statistical significance at the 1% level. In panel D, where the dependent variable is *Ln(Innovation Value + 1)*, the actual coefficient estimated from the data has a Z score of −1.208, which is statistically significant at the 5% level. However, as shown in Panel B, when the dependent variable is *Ln(#Citations + 1)*, the Z score is −3.392, indicating a significance of $<$ 0.001% or insignificant at all conventional levels. These findings suggest that our baseline results are driven by natural disasters and are not likely to be occurring by chance.

4.3.2. Is the impact of natural disasters permanent?

In the spirit of Bertrand and Mullainathan (2003), we perform an additional test to check the validity of the parallel trend assumption of the DiD model and the dynamic impact of natural disasters. To do so, we

Table 4. Is the impact of natural disasters permanent? This table examines whether the impact of natural disasters on corporate innovation is permanent. The indicator variables *Natural Disaster*$_{t-3}$, *Natural Disaster*$_{t-2}$, *Natural Disaster*$_{t-1}$, *Natural Disaster*$_t$, *Natural Disaster*$_{t+1}$, *Natural Disaster*$_{t+2}$, *Natural Disaster*$_{t+3}$, *Natural Disaster*$_{t+4}$ indicate the year relative to the occurrence of natural disasters. For example, the indicator variable *Natural Disaster*$_{t-1}$ equals 1 if it is 1 year before a county struck by a natural disaster. The dependent variable in column (1) is the natural logarithm of the number of patent counts plus one. The dependent variable in column (2) is the natural logarithm of citation counts plus one. The dependent variable in column (3) is the natural logarithm of citation counts scaled by patents plus one. The dependent variable in column (4) is the natural logarithm of the cumulative dollar value (in millions of 2005 nominal US dollars) of patents that a firm applies for in a given year plus one. All the control variables used in Table 2 are also included in this regression but unreported for brevity. The detailed definitions of all variables are provided in Appendix 1. Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Ln (#Patents + 1)	Ln (#Citations + 1)	Ln (Citations/Patents + 1)	Ln (Innovation Value + 1)
	(1)	(2)	(3)	(4)
Natural Disaster$_{t-3}$	0.039	0.090	0.045	0.066
	(0.026)	(0.061)	(0.034)	(0.043)
Natural Disaster $_{t-2}$	−0.010	−0.021	−0.003	−0.053
	(0.028)	(0.061)	(0.033)	(0.044)
Natural Disaster$_{t-1}$	−0.014	−0.013	0.008	−0.036
	(0.028)	(0.060)	(0.032)	(0.041)
Natural Disaster$_t$	−0.023	−0.082*	−0.035	−0.035*
	(0.030)	(0.049)	(0.032)	(0.021)
Natural Disaster$_{t+1}$	−0.072**	−0.143**	−0.086**	−0.119**
	(0.032)	(0.067)	(0.034)	(0.053)
Natural Disaster$_{t+2}$	−0.053*	−0.101*	−0.074**	−0.114*
	(0.031)	(0.059)	(0.037)	(0.059)
Natural Disaster$_{t+3}$	−0.069*	−0.114*	−0.065*	−0.076*
	(0.037)	(0.067)	(0.033)	(0.045)
Natural Disaster$_{t+4}$	−0.059	−0.107	−0.055	−0.094
	(0.039)	(0.082)	(0.041)	(0.065)
Control Variables of Table 2	Yes	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes
No. of Obs.	70,125	70,125	70,125	70,125
Adjusted R^2	0.775	0.649	0.503	0.788

re-estimate Equation (1) by replacing the indicator *Natural Disaster* with dummy variables (*Natural Disaster*$_{t-3}$, *Natural Disaster*$_{t-2}$, *Natural Disaster*$_{t-1}$, *Natural Disaster*$_t$, *Natural Disaster*$_{t+1}$, *Natural Disaster*$_{t+2}$, *Natural Disaster*$_{t+3}$, *Natural Disaster*$_{t+4}$) indicating the year relative to the natural disaster strikes, for up to three years before and four years after the strike. For example, the indicator variable *Natural Disaster*$_{t-1}$ equals 1 if it is 1 year before a county struck by a natural disaster.

We show that across all 4 columns of Table 4, the coefficients on all 3 indicators (*Natural Disaster*$_{t-3}$, *Natural Disaster*$_{t-2}$, *Natural Disaster*$_{t-1}$) are close to zero and not statistically significant, suggesting that the parallel trends assumption of the difference-in-differences tests is likely met. We further show that across all 4 columns of Table 4, the coefficients on the indicators *Natural Disaster*$_t$ is small in magnitude and statistically significant at the 10% level in columns 1 and 4 and statistically insignificant in columns 2 and 3. The effect of natural disasters shows up 3 years after the strike: The coefficients on the indicator *Natural Disaster*$_{t+1}$ are negative and significant for all innovation measures at the 5% level, while the coefficients on the indicator *Natural Disaster*$_{t+2}$, *Natural Disaster*$_{t+3}$ are negative and significant at the 10% level. This finding shows that across regressions, innovation variables are not statistically different between treated and control firms before the natural disaster strike, suggesting that the parallel trends assumption of the difference-in-differences tests is likely met.[12] Moreover, we also show that the adverse impact of natural disasters on innovation lasts for up to three years after the strikes.

5. Mechanism for the impact of natural disasters on corporate innovation

5.1. Natural disasters, financial constraints, and corporate innovation

To provide a more thorough understanding of the mechanisms for natural disasters to influence innovation, in this subsection we implement the analysis to examine the heterogeneous treatment effects. In particular, we look at the cross-sectional variation in financial constraints to examine how well financial constraints can explain the negative relation between natural disasters and corporate innovation. We thus condition the impact of natural disasters on corporate innovation on variables which capture dependence on firms' financial constraints.

As discussed in Section 2, if a firm's decreased innovation after the strike of natural disasters is due to scarce financial resources being diverted from research and development toward regulation compliance, we expect this effect to be stronger for firms that face greater financial constraints. We construct the variables to capture whether a firm is financially constrained or not according to alternative financial constraint measures. First, we use the Kaplan-Zingales (KZ) index, which is developed by Kaplan and Zingales (1997). This index is estimated based on a logit regression of the firm's financial constraint levels and five accounting variables including cash flow, the Tobin's Q, total debt, dividend and cash holdings. Firms with a higher KZ index are more constrained. The alternative index is Hadlock-Pierce (HP) index created by Hadlock and Pierce (2010). This index takes into account of size, size squared and age of firms. Finally, Whited and Wu (2006) construct a financial constraint index by using the generalized method of moments (GMM) estimation of an investment Euler equation. The details of the regression equation of these measures are in Appendix 2.

Additionally, the control variables of Table 2, plus Firm and Year Fixed Effects, are included as independent variables. The dependent variables are those in Table 2. Table 5 reports the results of this analysis. The coefficients on *Natural Disaster∗KZ index*, *Natural Disaster∗HP index*, *Natural Disaster∗WW* index are significantly negative in all columns, indicating that the negative association between natural disasters and innovation is more pronounced for firms that face greater financial constraints.

5.2. Natural disasters, financial constraints, and R&D investment

So far, we show evidence that firms hit by natural disasters have lower innovation output than other firms after controlling for various firm characteristics. If corporate innovation is reduced following a natural disaster, we should also observe a negative impact of the disaster on the firm's innovation input. We thus examine the direct effect of natural disasters on R&D investment. We regress R&D scaled by total assets on the *Natural Disaster* variable and other control variables. In addition, we examine whether the effect of natural disasters on innovation input is stronger in firms that face greater financial constraints. We regress R&D scaled by total assets on the interaction of *Natural Disaster* and the financial constraint variable (Kaplan-Zingales (KZ) index, Hadlock-Pierce (HP) index, Whited-Wu (WW) index).

Table 6 reports the results. In columns 1 and 2, the variable of interest is *Natural Disaster* and the remaining independent variables are individual firm characteristics and fixed effects, as in Table 2. As expected, we find that the coefficients of *Natural Disaster* are negative and significant at the 1% level in both columns 1 and 2. In economic terms, firms hit by natural disasters exhibit 1% (in column 1) and 0.6% (in column 2) decreases in the R&D investment. Specifications (3), (4) and (5) in Table 6 display the results of regressions after augmenting the baseline model with financial constraints and its interaction with the *Natural Disaster* variable. We find that the interaction of the natural disasters with financial constraints is negative and significant at the 1% level in all specifications. This suggests that the negative impact of natural disasters on R&D investment increases in firms that face higher financial constraints.

Our findings support the conclusion that our measures of a firm's innovation input are depressed following a natural disaster as with innovation outputs. Again, as with Table 2, we find evidence that large firms with cash holdings, tangible assets, and significant capital expenditure are better positioned to recover following a natural disaster. Nevertheless, firms with significant leverage that sweat their assets and are old are negatively affected. We also suggest that financial constraints resulting from natural disasters negatively impact corporate innovation.

6. Natural disasters and corporate innovation: further analysis

6.1. Natural disasters and human capital

6.1.1. Natural disasters and inventor mobility

Bernstein, Korteweg, and Laws (2017) argue that human capital has a strong effect on firm performance. It is possible that our main results are partly due to employees engaged in innovation relocating, because of safety

Table 5. Natural disasters, financial constraints, and corporate innovation. This table presents the impact of natural disasters on corporate innovation, conditioning on firms' financial constraints (i.e. KZ index, HP index, and WW index). The dependent variable in columns (1)–(3) is the natural logarithm of the number of patent counts plus one. The dependent variable in columns (4)–(6) is the natural logarithm of citation counts plus one. The dependent variable in columns (7)–(9) is the natural logarithm of citation counts scaled by patents plus one. The dependent variable in columns (10)–(12) is the natural logarithm of the cumulative dollar value (in millions of 2005 nominal US dollars) of patents that a firm applies for in a given year plus one. All the control variables used in Table 2 are also included in this regression but unreported for brevity. The detailed definitions of all variables are provided in Appendix 1. Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Ln (#Patents + 1)			Ln (#Citations + 1)			Ln (Citations/Patents + 1)			Ln (Innovation Value + 1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Natural Disaster	−0.014	−0.017	−0.013	−0.031	−0.025	−0.035	−0.021	−0.015	−0.019	−0.035	−0.033	−0.032
	(0.026)	(0.050)	(0.070)	(0.041)	(0.049)	(0.111)	(0.018)	(0.017)	(0.023)	(0.026)	(0.027)	(0.026)
Natural Disaster∗KZ index	−0.089***			−0.159***			−0.076***			−0.146***		
	(0.032)			(0.060)			(0.028)			(0.051)		
KZ index	−0.071			−0.085			−0.080			−0.075		
	(0.161)			(0.162)			(0.187)			(0.077)		
Natural Disaster∗HP index		−0.086***			−0.154***			−0.075***			−0.141***	
		(0.031)			(0.059)			(0.028)			(0.048)	
HP index		−0.028			−0.071			−0.046			−0.051	
		(0.202)			(0.115)			(0.055)			(0.072)	
Natural Disaster∗WW index			−0.091***			−0.148**			−0.075***			−0.133***
			(0.032)			(0.059)			(0.028)			(0.048)
WW index			−0.039			−0.109			−0.052			−0.055
			(0.035)			(0.139)			(0.175)			(0.067)
Control Variables of Table 2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	70,125	70,125	70,125	70,125	70,125	70,125	70,125	70,125	70,125	70,125	70,125	70,125
Adjusted R^2	0.766	0.775	0.762	0.648	0.656	0.656	0.497	0.502	0.503	0.781	0.788	0.788

Table 6. Natural disasters, financial constraints, and R&D investment. This table examines the impact of natural disasters on R&D investment, conditioning on firms' financial constraints (i.e. KZ index, HP index, and WW index). KZ index, HP index, and WW index are indicators for whether a firm is financially constrained or not according to each financial constraint measure, i.e. the Kaplan-Zingales (KZ) index, Hadlock-Pierce (HP) index, Whited-Wu (WW) index, respectively. The dependent variable in regressions is research and development (R&D) investments scaled by total assets. All control variables are lagged by one year. The detailed definitions of all variables are provided in Appendix 1. Column (1) omits the control variables and contain both standard and multiplicative fixed effects (i.e. firm and year fixed effects, state∗year fixed effects, and industry∗year fixed effects whose coefficients are suppressed), while Columns (2)–(5) include control variables and standard fixed effects (i.e. firm and year fixed effects, whose coefficients are suppressed). Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	R&D				
	(1)	(2)	(3)	(4)	(5)
Natural Disaster	−0.016***	−0.011***	−0.010*	−0.012*	−0.011*
	(0.006)	(0.003)	(0.006)	(0.007)	(0.006)
Natural Disaster∗KZ index			−0.073***		
			(0.024)		
KZ index			−0.041**		
			(0.020)		
Natural Disaster∗HP index				−0.069***	
				(0.022)	
HP index				−0.035*	
				(0.018)	
Natural Disaster∗WW index					−0.065**
					(0.033)
WW index					−0.031*
					(0.017)
Size		0.008***	0.009***	0.008***	0.009***
		(0.002)	(0.002)	(0.002)	(0.002)
Tobin's Q		0.001	0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)	(0.001)
Cash Holdings		0.024***	0.022***	0.025***	0.026***
		(0.007)	(0.007)	(0.007)	(0.008)
Leverage		−0.041***	−0.040***	−0.041***	−0.043***
		(0.008)	(0.008)	(0.008)	(0.008)
ROA		−0.063***	−0.063***	−0.062***	−0.063***
		(0.010)	(0.010)	(0.010)	(0.011)
Tangible Assets		0.011*	0.011*	0.012*	0.015**
		(0.006)	(0.006)	(0.007)	(0.007)
Capital Expenditures		0.074***	0.073***	0.073***	0.075***
		(0.023)	(0.023)	(0.023)	(0.025)
Ln (Firm Age)		−0.012***	−0.012***	−0.012***	−0.013***
		(0.002)	(0.002)	(0.002)	(0.003)
H-Index		0.098**	0.100**	0.103**	0.127**
		(0.048)	(0.048)	(0.049)	(0.053)
H-Index^2		−0.161**	−0.162*	−0.165**	−0.202**
		(0.082)	(0.083)	(0.083)	(0.088)
Number of bank branches		0.021**	0.027**	0.025**	0.026**
		(0.010)	(0.012)	(0.011)	(0.012)
Bank density		0.007	0.011*	0.010	0.009*
		(0.004)	(0.006)	(0.007)	(0.005)
Neighboring Dummy		0.014	0.011	0.012	0.010
		(0.025)	(0.020)	(0.019)	(0.023)
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State∗Year Fixed Effects	Yes	No	No	No	No
Industry∗Year Fixed Effects	Yes	No	No	No	No
No. of Obs.	70,125	70,125	70,125	70,125	70,125
Adjusted R^2	0.482	0.458	0.457	0.457	0.454

concerns, or infrastructure destruction, following a natural disaster. The results may also reflect firms not taking on new hires following a natural disaster. We address these issues by running DiD regressions of the impact of natural disasters on inventor mobility and report the results in Table 7. Following Gao and Zhang (2017) and Brav et al. (2018), we use three different proxies to measure employee mobility, including *Ln(#Inventors + 1)*, *Ln(#Leavers + 1)*, and *Ln(#New Hires + 1)*. The results follow the same scheme as our basic regressions in Table 2. In columns (1) and (2), the natural logarithm of the number of firm's inventors each year plus one is the dependent variable. In columns (3) and (4), the dependent variable is the natural logarithm of the number of firm's inventors who move to other firms in a given year plus one. In columns (5) and (6), the dependent variable is the natural logarithm of the number of newly inventors firms hire in a given year plus one. As shown in columns (1) and (2), the coefficient of the variable of interest, *Natural Disaster* is negative and statistically significant at the 5% level in both cases. Its absolute value is also smaller in column (2) due to the influence of the control variables. This result confirms that the number of inventors at firms falls following a natural disaster. Moving on to the results in columns (3) and (4), we observe that the coefficient of *Natural Disaster* is positive in both cases and significant at the 5% level in column (3) and at the 1% level in column (4). This result indicates that the number of leavers increases at a firm following a natural disaster. Interestingly, the coefficient is larger and at a greater significance level after controlling for individual firm characteristics. It can also be seen that *Cash Holdings* negatively and significantly impacts the number of inventors and new hires. *Capital Expenditures*, however, negatively affect the number of leavers and is significant at the 10% level. On the other hand, the coefficient of *Firm Age* is positive and statistically significant at the 1% level in column (4). We conclude from this that the number of employees relocating increases after a major natural disaster. They are more likely to leave if the firm is old but less likely to leave if the firm's capital expenditure is high. Next, we consider the regressions in columns (5) and (6). Here, we observe that the coefficients for *Natural Disaster* are negative for new hires in both cases. They are statistically significant at the 10% level in column (5) and the 5% level in column (6) after controlling for individual firm characteristics. Concerning firm characteristics, we observe the coefficient of *Cash Holdings* is positive for new hires and statistically significant at the 10% level, while for *Firm Age* it is negative and statistically significant at the 1% level. The findings confirm that major natural disasters result in a reduction in the figure of inventors in a firm and the number of new hires. However, the number of employees leaving increases. Firms that engage in large capital expenditure tend to reduce the number of employees leaving. Employees, though, are more likely to leave an old firm. Firms with cash holding are more likely to take on new hires. However, older firms are less likely to hire them.

6.1.2. Natural disasters and inventor relocation

We consider the impact of natural disasters on inventor mobility in the regression results presented in Table 8. In this section, we provide further evidence for the human capital channel by focusing on inventor relocation. The results are reported in Table 8. Here the dependent variables capture inventor relocation following a natural disaster. Specifically, in columns (1) and (2), the dependent variable '*Ln (Moving Distance + 1)*' is the natural logarithm of the moving distance of an inventor from her previous employer plus one. In columns (3) and (4), the dependent variable '*Within County Move*' is an indicator variable that takes the value of one if an inventor moves to another employer located in the same county as her previous employer and zero otherwise. In columns (5) through (6), the dependent variable, '*Affected-county Move*' is an indicator variable that takes the value of one if an inventor moves to another employer located in a county, which is affected by a natural disaster in the last five years and zero otherwise. The regressions reported in the even-numbered columns include the firm-level control variables and the year Fixed Effects and Firm Fixed Effects, plus the measures of Inventor Experience as independent variables. The regressions in the odd-numbered columns include the same independent variables but omit the measures of Inventor experience.

We first consider the results for moving distance, presented in columns (1) and (2). The coefficients of *Natural Disaster*, our variable of interest, are positive and statistically significant at the 1% level. The coefficient of *Cash Holdings* is also positive and significant at the 10% level. The coefficient of *Inventor Experience* is negative and significant at the 1% level. The results strongly suggest that, after the natural disasters, some inventors are significantly more likely to relocate to faraway companies if they had worked near the strike's scene. In columns (3) and (4), where the dependent variable is *Within County Move*, the coefficients of *Natural Disaster* are negative and statistically significant at the 5% level. This suggests that inventors are less likely to move within counties hit by natural disasters. The results presented in columns (5) and (6) suggest moves from affected counties to other counties affected by natural disasters are also reduced after natural disasters. Here, the coefficients on our variable of interest are negative and statistically significant at the 10% level.

Table 7. Natural disasters and inventor mobility. This table reports coefficients from difference-in-difference (DiD) regressions of the impact of natural disaster on inventor productivity. The main variable of interest is *Natural Disaster*. In columns (1) and (2) the dependent variable is the natural logarithm of the number of firm's inventors each year plus one. In columns (3) and (4) the dependent variable is the natural logarithm of the number of firm's inventors who leave for other firms in a given year plus one. In columns (5) and (6) the dependent variable is the natural logarithm of the number of firm's newly hired inventors in a given year plus one. All control variables are lagged by one year. The detailed definitions of all variables are provided in Appendix 1. The odd-numbered columns omit the control variables and contain both standard and multiplicative fixed effects (i.e. firm and year fixed effects, state∗year fixed effects, and industry∗year fixed effects whose coefficients are suppressed), while the even-numbered columns include control variables and standard fixed effects (i.e. firm and year fixed effects, whose coefficients are suppressed). Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Ln (#Inventors + 1)		Ln (#Leavers + 1)		Ln (#New Hires + 1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Natural Disaster	−0.066**	−0.060**	0.052**	0.055***	−0.020*	−0.018**
	(0.033)	(0.029)	(0.021)	(0.021)	(0.012)	(0.008)
Size		0.314***		0.104***		0.102***
		(0.020)		(0.010)		(0.010)
Tobin's Q		0.039***		0.014***		0.021***
		(0.005)		(0.003)		(0.003)
Cash Holdings		0.176***		−0.012		0.044*
		(0.056)		(0.027)		(0.027)
Leverage		−0.308***		−0.032		−0.084***
		(0.053)		(0.025)		(0.024)
ROA		−0.196***		−0.118***		−0.082***
		(0.049)		(0.023)		(0.021)
Tangible Assets		0.198***		0.105***		0.094***
		(0.051)		(0.026)		(0.024)
Capital Expenditures		0.035		−0.132*		−0.005
		(0.133)		(0.071)		(0.067)
Ln (Firm Age)		−0.023		0.024***		−0.062***
		(0.020)		(0.008)		(0.009)
H-Index		0.929		0.225		0.128
		(0.625)		(0.341)		(0.347)
H-Index^2		−0.194		0.705		0.486
		(1.657)		(1.120)		(1.215)
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State∗Year Fixed Effects	Yes	No	Yes	No	Yes	No
Industry∗Year Fixed Effects	Yes	No	Yes	No	Yes	No
No. of Obs.	70,125	70,125	70,125	70,125	70,125	70,125
Adjusted R^2	0.727	0.739	0.641	0.649	0.645	0.653

6.2. Natural disasters and innovation productivity

Next, we examine whether there is a decline in the productivity of employees (inventors) who remain in the firm after the occurrence of natural disasters. We repeat the baseline regression using inventor productivity as the dependent variable. In Table 9, the dependent variable in columns (1) and (2) is the natural logarithm of the number of patents per 1000 firm employees (EMP) plus one – *Ln(#Patents/Employees + 1)*. The dependent variable in columns (3) and (4) is the natural logarithm of the number of patents per the number of inventors plus one – *Ln(#Patents/Inventors + 1)*. The dependent variable in columns (5) and (6) is the natural logarithm of the number of citations per 1000 firm employees (EMP) plus one – *Ln(#Citations/Employees + 1)*. The dependent variable in columns (7) and (8) is the natural logarithm of the number of citations per the number of inventors plus one – *Ln(#Citations/Inventors + 1)*. The coefficients of *Natural Disaster*, are negative and statistically significant at the 1% level in all cases for the odd-numbered columns. For the even-numbered columns, the coefficients are negative in all cases and statistically significant. Our previous remarks concerning the influence of individual firm characteristics also hold in this instance. These findings confirm that the firm's employees and those engaged in innovation are negatively affected, and our measures of innovation output fall following natural disasters.

Table 8. Natural disasters and inventor relocation. This table reports coefficients from regressions of the impact of natural disaster on labor market relocation. The main variable of interest is *Natural Disaster*. In columns (1) and (2) the dependent variable '*Ln (Moving Distance + 1)*' is the natural logarithm of moving distance of an inventor from her previous employer plus one. In columns (3) and (4) the dependent variable '*Within County Move*' is an indicator variable that takes the value of one if an inventor moves to another employer located in the same county as her previous employer, and zero otherwise. In columns (5) through (6) the dependent variable, '*Affected-county Move*' is an indicator variable that takes the value of one if an inventor moves to another employer located in a county, which is affected by a natural disaster in the last five years, and zero otherwise. All control variables are lagged by one year. Detailed definitions of all variables appear in Appendix 1. Inventor, Year, and Firm fixed effects, whose coefficients are suppressed, are included in all regressions. Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Ln (Moving Distance + 1)		Within County Move		Affected-county Move	
	(1)	(2)	(3)	(4)	(5)	(6)
Natural Disaster	1.273***	1.263***	−0.021**	−0.019**	−0.041*	−0.041*
	(0.483)	(0.480)	(0.010)	(0.010)	(0.024)	(0.024)
Size	0.032	0.027	−0.002	−0.002	−0.075***	−0.075***
	(0.087)	(0.087)	(0.009)	(0.010)	(0.016)	(0.016)
Tobin's Q	0.013	0.011	−0.001	−0.001	−0.019***	−0.019***
	(0.028)	(0.028)	(0.003)	(0.003)	(0.004)	(0.004)
Cash Holdings	0.652*	0.642*	−0.008	−0.007	−0.109**	−0.109**
	(0.381)	(0.380)	(0.036)	(0.036)	(0.049)	(0.049)
Leverage	0.327	0.329	−0.010	−0.010	−0.105**	−0.104**
	(0.280)	(0.280)	(0.036)	(0.036)	(0.050)	(0.050)
ROA	0.277	0.275	0.004	0.005	0.167***	0.167***
	(0.365)	(0.365)	(0.042)	(0.042)	(0.055)	(0.055)
Tangible Assets	0.314	0.323	0.050	0.049	0.011	0.012
	(0.514)	(0.515)	(0.034)	(0.034)	(0.041)	(0.041)
Capital Expenditures	1.004	0.994	−0.082	−0.081	−0.123	−0.123
	(0.760)	(0.759)	(0.084)	(0.084)	(0.148)	(0.147)
Ln (Firm Age)	−0.144	−0.145	0.016*	0.016*	−0.002	−0.002
	(0.111)	(0.112)	(0.009)	(0.009)	(0.015)	(0.015)
H-Index	−0.474	−0.345	0.047	0.028	0.389	0.384
	(2.374)	(2.382)	(0.246)	(0.250)	(0.480)	(0.481)
H-Index^2	4.146	3.926	−0.394	−0.362	−0.724	−0.716
	(3.361)	(3.375)	(0.350)	(0.357)	(0.805)	(0.806)
Experience		−0.266***		0.033**		−0.009
		(0.093)		(0.014)		(0.013)
Experience^2		0.075***		−0.009***		0.004
		(0.023)		(0.003)		(0.003)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	30,709	30,709	30,709	30,709	30,709	30,709
Adjusted R^2	0.439	0.440	0.459	0.460	0.229	0.229

6.3. Natural disasters and innovation risk

The risk of natural disasters may reduce the incentive of firms to engage in risky innovation projects. Thus, natural disaster-affected firms should have fewer projects which are highly valuable and not valuable at all. Following Mukherjee, Singh, and Žaldokas (2017) and Huang and Yuan (2020), we use the standard deviation of citations in the next five years of patents applied for by firms, the number of top 10% most cited patents in a year, and the number of patents applied for by firm with zero citations as measures of innovation risk. We again follow the scheme of Table 2. Our findings are presented in Table 10. As previously, the variable of interest is *Natural Disaster*. First, we consider the results in columns (1) and (2). Here, the coefficients for *Natural Disaster* are significant at the 5% level. In column (2), controlling for firm characteristics reduces the absolute value of the coefficient considerably. Coefficients for *Tangible Assets* and *Firm Age* are negative and statistically significant at the 10% and 1% levels, respectively for the standard deviation of citations. In summary, this confirms that major natural disasters reduce the standard deviation of citations of patents applied for by a firm in the 5 years following a natural disaster. In columns (3) and (4), *Natural Disaster*'s coefficients are also negative and statistically significant at the 10% and 1% levels, respectively. Here, including the control variables increases the absolute value and significance of the coefficient. The coefficients of independent variables *Cash Holdings* and *Tangible Assets* are positive and statistically significant at the 5% and 1% levels, respectively, while *Leverage* is negative and

Table 9. Natural disasters and inventor productivity. This table reports coefficients from difference-in-difference (DiD) regressions of the impact of natural disaster on inventor productivity. The main variable of interest is *Natural Disaster*. The dependent variable in columns (1) and (2) is the natural logarithm of the number of patents per 1000 firm employees (EMP) plus one. The dependent variable in columns (3) and (4) is the natural logarithm of the number of patents per the number of inventors plus one. The dependent variable in columns (5) and (6) is the natural logarithm of the number of citations per 1000 firm employees (EMP) plus one. The dependent variable in columns (7) and (8) is the natural logarithm of the number of citations per the number of inventors plus one. All control variables are lagged by one year. The detailed definitions of all variables are provided in Appendix 1. The odd-numbered columns omit the control variables and contain both standard and multiplicative fixed effects (i.e. firm and year fixed effects, state∗year fixed effects, and industry∗year fixed effects whose coefficients are suppressed), while the even-numbered columns include control variables and standard fixed effects (i.e. firm and year fixed effects, whose coefficients are suppressed). Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Ln (#Patents/ Employees + 1)		Ln (#Patents/ Inventors + 1)		Ln (#Citations/ Employees + 1)		Ln (#Citations/ Inventors + 1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Natural Disaster	−0.061*	−0.065**	−0.026***	−0.025***	−0.114*	−0.120*	−0.096**	−0.096***
	(0.032)	(0.031)	(0.009)	(0.009)	(0.064)	(0.063)	(0.037)	(0.037)
Size		0.072***		0.050***		0.231***		0.201***
		(0.015)		(0.004)		(0.030)		(0.017)
Tobin's Q		0.042***		0.009***		0.080***		0.044***
		(0.006)		(0.001)		(0.013)		(0.007)
Cash Holdings		0.540***		0.042***		0.850***		0.259***
		(0.068)		(0.015)		(0.134)		(0.070)
Leverage		−0.333***		−0.067***		−0.577***		−0.272***
		(0.055)		(0.014)		(0.110)		(0.062)
ROA		−0.135*		−0.004		−0.154		−0.034
		(0.069)		(0.014)		(0.132)		(0.064)
Tangible Assets		−0.051		0.026*		−0.027		0.096*
		(0.049)		(0.014)		(0.098)		(0.056)
Capital Expenditures		0.181		0.095**		0.606*		0.509***
		(0.150)		(0.041)		(0.311)		(0.180)
Ln (Firm Age)		−0.129***		−0.012**		−0.265***		−0.080***
		(0.016)		(0.005)		(0.034)		(0.021)
H-Index		2.131***		0.055		4.020***		1.212
		(0.650)		(0.170)		(1.403)		(0.813)
H-Index^2		−2.674**		0.058		−4.851**		−1.267
		(1.127)		(0.299)		(2.291)		(1.284)
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State∗Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Industry∗Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
No. of Obs.	70,125	70,125	70,125	70,125	70,125	70,125	70,125	70,125
Adjusted R^2	0.563	0.573	0.398	0.406	0.522	0.531	0.457	0.465

statistically significant at the 1% level. We can conclude from these results that major natural disasters reduce the number of highly cited patents in the 3 years following a natural disaster. Firms with large cash holdings and tangible assets are less likely to be badly affected than those with high leverage and older firms. Coefficients for the variable of interest in columns (5) and (6) are also negative and statistically significant at the 5% level. The finding confirms that natural disasters reduce the number of patents applied by firms with zero citations in the following 3 years. Controlling for firm characteristics suggests older firms, those with high capital expenditure, and those that sweat their assets are likely to have fewer patents applied for in the following 3 years. In summary, these results imply natural disasters suppress the numbers of patents applied for in the top 10% of most cited patents and the numbers of patents applied for by uncited firms in the 3 years following a natural disaster. Moreover, the standard deviation of patents applied for in the following 3 years is also repressed. Overall this is indicative of a reduction in innovation activity and hence an increase in innovation risk.

7. Summary and conclusions

Our research is the first to focus on the impact of major natural disasters on innovation, using firm-level data in the US. Our reason for focusing on innovation is its importance with respect to increasing and maintaining firm

Table 10. Natural disasters and innovation risk. This table reports coefficients from difference-in-difference (DiD) regressions of the impact of natural disaster on innovation risk. The main variable of interest is *Natural Disaster*. In columns (1) and (2) the dependent variable is the natural logarithm of standard deviation of citations in the next five years of patents applied for by firm plus one. In columns (3) and (4) the dependent variable is the natural logarithm of the number of top 10% most cited patents in a year applied for by firm plus one. In columns (5) and (6) the dependent variable is the natural logarithm of the number of patents applied for by firm with zero citations in the following five years plus one. All control variables are lagged by one year. The detailed definitions of all variables are provided in Appendix 1. The odd-numbered columns omit the control variables and contain both standard and multiplicative fixed effects (i.e. firm and year fixed effects, state∗year fixed effects, and industry∗year fixed effects whose coefficients are suppressed), while the even-numbered columns include control variables and standard fixed effects (i.e. firm and year fixed effects, whose coefficients are suppressed). Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Ln (1+ σ(Citations))		Ln (1+#Highly Cited Patents)		Ln (1+#Zero-cite Patents)	
	(1)	(2)	(3)	(4)	(5)	(6)
Natural Disaster	−0.091**	−0.096**	−0.104***	−0.090***	−0.102**	−0.091**
	(0.041)	(0.042)	(0.033)	(0.031)	(0.050)	(0.041)
Size		−0.116***		0.227***		0.227***
		(0.025)		(0.021)		(0.027)
Tobin's Q		−0.011		0.019***		0.018***
		(0.007)		(0.005)		(0.006)
Cash Holdings		0.134		0.106**		−0.015
		(0.086)		(0.049)		(0.062)
Leverage		0.122		−0.194***		−0.110
		(0.075)		(0.052)		(0.068)
ROA		0.104		−0.324***		−0.287***
		(0.075)		(0.047)		(0.057)
Tangible Assets		−0.149*		0.179***		0.115
		(0.088)		(0.054)		(0.085)
Capital Expenditures		0.145		−0.239*		−0.428**
		(0.207)		(0.142)		(0.167)
Ln (Firm Age)		−0.158***		−0.031		−0.150***
		(0.037)		(0.020)		(0.026)
H-Index		0.878		0.622		2.119***
		(0.991)		(0.617)		(0.779)
H-Index^2		−0.390		−0.324		−2.038
		(1.464)		(1.667)		(2.185)
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State∗Year Fixed Effects	Yes	No	Yes	No	Yes	No
Industry∗Year Fixed Effects	Yes	No	Yes	No	Yes	No
No. of Obs.	22,325	22,325	33,836	33,836	33,836	33,836
Adjusted R^2	0.694	0.644	0.776	0.758	0.772	0.742

value and its centrality to the achievement of long-term economic growth. Evidence suggests that major natural disasters are occurring more frequently and are more severe in their effects. This makes the issue of their impact on innovation even more relevant.

Our principal finding is that following a major natural disaster, firms in affected counties file fewer patents, have fewer citations on the patents they do apply for, fewer citations scaled by patents applied for, and reduced dollar value of patents. These results are robust to fixed effects and individual firm characteristics. There is a decline in these innovation outputs for two years following a natural disaster. Thereafter a recovery sets in. However, innovation outputs remain suppressed below their pre-disaster level for up to three years. We perform a variety of robustness tests to validate these empirical results.

We also suggest the mechanism that explains the adverse impact of natural disasters on corporate innovation is financial constraints. Firms hit by natural disasters experience financial loss and difficulty in raising external funds due to the tightening the credit constraints in the local area of local banks. We find that the negative impact of natural disasters on innovation activities is stronger for financially constrained firms.

We also provide evidence for other possible channels that may drive the adverse impact of natural disasters on corporate innovation, including human capital, innovation productivity, and innovation risk. Our findings show that natural disasters cause a higher inventor mobility, a significant reduction in inventor productivity, and a lower firm's incentive in risky innovation projects.

Our empirical results will be of interest to the firm's management and investors, as well as local and national government officials and NGOs. Given that countries operate differing disaster relief and recovery policies and different policies to promote innovation, similar studies of the impact of major natural disasters on innovation in other countries comparable to the US would be a natural extension of this work. Moreover, the study shows additional evidence about the impact of financial constraints on corporate innovation. Finally, our research suggests that natural disasters promote the mobility of productive employees and their allocation due to the reduction of inventors' assessment of their own safety. This finding on the adverse impact of disasters on employee psychology is important for firm managers to sustain the long-run growth and value of firms.

Notes

1. http://www.un-spider.org/news-and-events/news/cred-publishes-2019-disaster-statistics.
2. See, e.g. Strömberg (2007); Toya and Skidmore (2007); and Cavallo et al. (2013).
3. Exceptions are the papers by Barrot and Sauvagnat (2016) on the propagation of natural disasters in production networks, by Dessaint and Matray (2017) on the reaction of managers to hurricane risks, by Hsu et al. (2018) on firm operating performance, and a recent study by Aretz, Banerjee, and Pryshchepa (2019) on the industrial firm risk-shift caused by hurricanes.
4. https://www.statista.com/statistics/510894/natural-disasters-globally-and-economic-losses/.
5. We use the KPSS rather than the NBER patent data because the KPSS patent data comprehensively covers patent portfolios with all patents granted by the United States Patent and Trademark Office (USPTO) over the time period 1926 and 2010. Meanwhile, the NBER patent data contains patents that have been awarded up to 2006.
6. According to Kogan et al. (2017), the market value of a patent is defined as the firm's market-adjusted stock return estimated from the day of the patent approval announcement date until two days after (t, $t+2$), multiplied by the firm's market capitalization on the day before the announcement ($t-1$).
7. Derrien, Kecskes, and Nguyen (2019) report that firms in younger labor markets produce more innovation. Prior studies find that for younger labor markets, the labor force demographic has an impact on corporate policies (Becker, Ivković, and Weisbenner 2011; Ouimet and Zarutskie 2014).
8. Data source: https://sraf.nd.edu/data/augmented-10-x-header-data/.
9. We thank the Associate Editor for providing us with the data concerning headquarter changes and suggesting an alternative data source.
10. Data source: https://www.epa.gov/toxics-release-inventory-tri-program.
11. Please refer to the Appendix Section A.1.4. for a detailed description of the company name string-matching process.
12. Panel A for Ln (#Patents+1), Panel B for Ln (#Citations+1), Panel C for Ln (Citations/Patents+1), and Panel D for Ln (Innovation Value+1).

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendices

Appendix 1. Variable definitions

A.1.1. Dependent variables

Ln (#Patents + 1) – The natural logarithm of the total number of patents that a firm applies for (and are subsequently granted) each year plus one. This variable is created using data from Kogan et al. (2017). (see, https://iu.app.box.com/v/patents).

Ln (#Citations + 1) – The natural logarithm of the total number of citations obtained on all patents that a firm applies for (and are subsequently granted) each year plus one. This variable is created using data from Kogan et al. (2017).

Ln (Citations/Patents + 1) – The natural logarithm of the number of patents scaled by the number of citations plus one. This variable is created using data from Kogan et al. (2017).

Ln (Innovation Value + 1) – The natural logarithm of the cumulative dollar value of patents (in millions of 2005 nominal US dollars) that a firm applies for each year plus one. A patent's value is measured as the firm stock return in excess of the market over the three-day window around the date of patent approval (t, $t+2$), multiplied by the firm's market capitalization on the day prior to the announcement of the patent issuance. The dollar value of each patent is obtained from Kogan et al. (2017).

R&D/Assets – Research and development (R&D) investments scaled by total assets, using the full sample. This variable is created using data from COMPUSTAT.

Exclude missing R&D – Research and development (R&D) investments scaled by total assets, excluding observations with missing or zero R&D. This variable is created using data from COMPUSTAT.

Ln (R&D + 1) – The natural logarithm of research and development (R&D) investments plus one. This variable is created using data from COMPUSTAT.

Ln (#Patents/ Employees + 1) – The natural logarithm of the number of patents per 1000 firm employees (EMP) plus one. This variable is created using data from Kogan et al. (2017) and COMPUSTAT.

Ln (#Patents/ Inventors + 1) – The natural logarithm of the ratio of the number of patents scaled by the number of inventors who applied for a patent at the firm each year and have not yet filed any patent for a different firm plus one. Inventor data are from Li et al. (2014) (see, https://funginstitute.berkeley.edu/research/innovation-in-tech/tools-and-data/).

Ln (#Citations/ Employees + 1) – The natural logarithm of the number of citations per 1000 firm employees (EMP) plus one. This variable is created using data from Kogan et al. (2017) and COMPUSTAT.

Ln (#Citations/ Inventors + 1) – The natural logarithm of the ratio of the number of patents scaled by the number of inventors who applied for a patent at the firm each year and have not yet filed any patent for a different firm plus one. This variable is created using data from Li et al. (2014) and COMPUSTAT.

Ln (#Inventors + 1) – The natural logarithm of the number of firm inventors each year plus one. We define 'Inventors' as those who produce at least one patent in a firm in our sample period. This variable is created using data from Li et al. (2014).

Ln (#Leavers + 1) – The natural logarithm of the number of inventors who leave for other firms each year plus one. We define 'Leavers' as those inventors who stop filing patents at a sample firm where they had previously produced a patent and file at least one patent in a new firm in our sample within one year after producing a patent at the firm they were previously producing patents. This variable is created using data from Li et al. (2014).

Ln (#New Hires + 1) – The natural logarithm of the number of newly hired inventors each year plus one. We define 'New Hires' as those inventors who produce at least one patent at a new assignee firm in our sample within one year after producing a patent at a different assignee. This variable is created using data from Li et al. (2014).

Ln (1+ σ (Citations)) – The natural logarithm of standard deviation of citations in the next five years of patents applied for by firm plus one. This variable is created using data from Kogan et al. (2017).

Ln (1+#Highly Cited Patents) – The natural logarithm of the number of top 10% most cited patents in a year applied for by firm plus one. This variable is created using data from Kogan et al. (2017).

Ln (1+#Zero-cite Patents) – The natural logarithm of the number of patents applied for by firm with zero citations in the following five years plus one. This variable is created using data from Kogan et al. (2017).

Ln (Moving Distance + 1) – The natural logarithm of moving distance of an inventor from her previous employer plus one. This variable is created using data from Li et al. (2014).

Within County Move – An indicator variable that takes the value of one if an inventor moves to another employer located in the same county as her previous employer, and zero otherwise. This variable is created using data from Li et al. (2014).

Affected-county Move – An indicator variable that takes the value of one if an inventor moves to another employer located in a county, which is affected by a natural disaster in last five years, and zero otherwise. This variable is created using data from Li et al. (2014).

A.1.2. Firm- and inventor-level control variables

Natural Disaster – A binary variable that equals one if firms are located in a county struck by the natural disaster and have not experienced other natural disasters three years before and after the current year.

Size – The natural logarithm of total assets (AT). This variable is created using data from COMPUSTAT.

Tobin's Q – The market value of equity (CSHO∗PRCC_F) plus book value of assets (AT) minus book value of equity (CEQ) minus balance sheet deferred taxes (TXDB), scaled by total assets (AT). This variable is created using data from COMPUSTAT.

Cash Holdings – Cash and short–term investments (CHE) scaled by total assets (AT). This variable is created using data from COMPUSTAT.

Leverage – The sum of long-term debt (DLTT) and debt in current liabilities (DLC) scaled by total assets (AT). This variable is created using data from COMPUSTAT.

ROA – Income before extraordinary items (IB) plus interest expense (item XINT) plus income taxes (item XINT), divided by total assets (item AT). This variable is created using data from COMPUSTAT.

Tangible Assets – Property, plant, and equipment (PPEGT) scaled by total assets (AT). This variable is created using data from COMPUSTAT.

Capital Expenditures – Capital expenditures (CAPX) scaled by total assets (AT). This variable is created using data from COMPUSTAT.

Ln (Firm Age) – The natural logarithm of one plus the number of years since the firm's first appearance in the Center for Research in Security Prices (CRSP). This variable is created using data from CRSP.

H-Index – This is the Herfindahl index which represents the sum of squares of the market shares of all firms in a given year and three–digit SIC industry, where market share is defined as sales of the firm divided by the sum of the sales in the industry. This variable is created using data from COMPUSTAT.

Kaplan-Zingales Index: $-1.002 \times$ Cash flow $+ 0.283 \times$ Tobin's Q $+ 3.139 \times$ Total debt $- 39.368 \times$ Dividends $- 1.315 \times$ Cash.

Hadlock-Pierce Index: $-0.737 \times$ Size $+ 0.043 \times$ Size2 $- 0.040 \times$ Age, where Size is the log of Min(AT, $4.5 billion) and Age is Min(Firm age, 37 years).

Whited-Wu Index: $-0.091 \times$ Cash flow $- 0.062 \times$ Positive dividend dummy $+ 0.021 \times$ Long-term debt $- 0.044 \times$ Size $+ 0.102 \times$ Industry sales growth $- 0.035 \times$ Sales growth.

Experience: The number of years between the current year and the year of the first patent filed by a given inventor.

Neighboring Dummy: An indicator variable that takes the value of one if a firm locates in the five counties closest to county struck by the natural disaster, and zero otherwise. This variable is created using data for counties' geographical locations from the 2010 U.S. Censuses.

Affected Facilities: The percentage of facilities of firms affected by natural disasters in any given year, which is calculated as the ratio of the number of factories affected by natural disasters to the total number of factories that belong to firm. This variable is created using data from the U.S. EPA's toxic release inventory (TRI) database to identify U.S. firms' factory locations and.

A.1.3. County control variables

Ln (Population): The natural logarithm of the county-level population. This variable is created using data from the Census Bureau.

Ln (Income Per Capita): The natural logarithm of the county-level income per capita. This variable is created using data from the U.S. Bureau of Economic Analysis (BEA).

Education: The ratio of people with a bachelor's degree or higher to the population aged 25 years or older in one county. This variable is created using data from the Census Bureau.

Seniors: The number of individuals aged 65 or older living in a county divided by the total population of that county. This variable is created using data from the Census Bureau.

Number of bank branches: the number of bank branches in a county. This variable is created using data from the Federal Deposit Insurance Corporation (FDIC).

Bank density: the number of bank branches in a county divided by its population in a given year. This variable is created using data from the Federal Deposit Insurance Corporation (FDIC).

A.1.4. Company name string-matching process

We match the TRI database to Compustat to identify facilities owned by public companies. Specifically, we employ a string-matching process to match parent names in the TRI database to the names of U.S. public companies in the Compustat database. We first clean parent firm names in the TRI database and firm names in the Compustat database by dropping suffixes such as 'Corp.', 'Incorp', etc. To elaborate, we remove all punctuation marks, clean special characters, and convert the historical names of parent companies to uppercase. Next, we use a string-matching command (i.e. – reclink-package) in Stata to generate matching scores for all name pairs of parent names in TRI and firms in CRSP/Compustat. We keep unique matches with similarity scores equal to 1. For other cases, we then rank the potential matches according to similarity scores (from high to low) and manually checked matches with reclink score exceeding 0.95.

Appendix 2

Table A1. The coarsened exact matching analysis. This table reports the regression results of the impact of natural disasters on corporate innovation, using the coarsened exact matching sample. The treatment group consists of firms located in counties hit by natural disasters and there was not no hit by other natural disasters three years before and after the current year. The control group consists of firms that are located in counties that were not hit by natural disasters (excluding the five counties closest to each struck county). We match the treated firms to control firms exactly by year and industry, and stratified matches on firm characteristics (Size, Tobin's Q, Cash Holdings, Leverage, ROA, Tangible Assets, Capital Expenditures, Ln (Firm Age)). The dependent variable in column (1) is the natural logarithm of citation counts plus one. The dependent variable in column (2) is the natural logarithm of the number of patent counts plus one. The dependent variable in column (3) is the natural logarithm of citation counts scaled by patents plus one. The dependent variable in columns (4) is the natural logarithm of the cumulative dollar value (in millions of 2005 nominal US dollars) of patents that a firm applies for in a given year plus one. All control variables are lagged by one year. The detailed definitions of all variables are provided in Appendix 1. All models include firm and year fixed effects, whose coefficients are suppressed. Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Ln (#Patents + 1)	Ln (#Citations + 1)	Ln (Citations/Patents + 1)	Ln (Innovation Value + 1)
	(1)	(2)	(3)	(4)
Natural Disaster	−0.057*	−0.168**	−0.128***	−0.119**
	(0.033)	(0.065)	(0.033)	(0.053)
Size	0.252***	0.413***	0.124***	0.379***
	(0.026)	(0.042)	(0.020)	(0.037)
Tobin's *Q*	0.033***	0.057***	0.020**	0.092***
	(0.007)	(0.015)	(0.008)	(0.013)
Cash Holdings	0.038	0.188	0.123	−0.099
	(0.074)	(0.154)	(0.080)	(0.112)
Leverage	−0.324***	−0.568***	−0.196***	−0.533***
	(0.071)	(0.144)	(0.074)	(0.108)
ROA	−0.173***	−0.270*	−0.082	−0.156*
	(0.064)	(0.148)	(0.082)	(0.088)
Tangible Assets	0.089	0.051	−0.035	0.151
	(0.062)	(0.127)	(0.062)	(0.102)
Capital Expenditures	0.210	0.632	0.426**	0.114
	(0.169)	(0.388)	(0.210)	(0.277)
Ln (Firm Age)	0.030	0.030	0.008	0.047
	(0.026)	(0.051)	(0.025)	(0.044)
H-Index	−0.801	0.000	0.837	−1.351
	(0.618)	(1.572)	(0.893)	(0.980)
H-Index^2	6.102***	4.355	−1.674	6.157***
	(1.339)	(3.164)	(1.707)	(2.144)
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes
No. of Obs.	30,234	30,234	30,234	30,234
Adjusted R^2	0.788	0.661	0.501	0.796

Table A2. Additional robustness checks. This table reports additional robustness checks on the impact of natural disasters on corporate innovation. In Panel A, we controlling for corporate governance. E-Index is defined as the sum of six dummies reflecting the following antitakeover provisions: (i) a staggered board, (ii) limits to amend the charter, (iii) limits to amend bylaws, (iv) supermajority voting requirements, (v) golden parachutes for executives, and (vi) the ability to adopt a poison pill. Board Independence is defined as the number of unaffiliated independent directors divided by the total number of board members. Board Size is defined as the total number of board members. CEO Is Not the Chairman is defined as a dummy variable equal to one if the CEO is not the chairman of the board. Board Ownership is defined as the percent of the firm's stock owned by all directors. In Panel B, we include a dummy of neighboring firms in the model. *Neighboring Dummy* is an indicator variable that takes the value of one if a firm locates in the five counties closest to county struck by the natural disaster, and zero otherwise. This variable is created using data for counties' geographical locations from the 2010 U.S. Censuses. In Panel C, we replace the variable *Natural Disaster* by the measure of natural disaster losses. In Panel C, we exclude firms with main customers or suppliers also affected by natural disasters. All the control variables used in Table 2 are also included in this regression but unreported for brevity. The detailed definitions of all variables are provided in Appendix 1. Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Ln (#Patents + 1)	Ln (#Citations + 1)	Ln (Citations/Patents + 1)	Ln (Innovation Value + 1)
	(1)	(2)	(3)	(4)
Panel A: Controlling for corporate governance				
Natural Disaster	−0.066**	−0.103**	−0.064**	−0.111**
	−0.03	−0.049	−0.028	−0.047
E-Index	−0.021*	−0.027**	−0.023*	−0.015
	(0.011)	(0.013)	(0.014)	(0.019)
Board Independence	−0.015	−0.014	−0.161	−0.009
	(0.010)	(0.010)	(0.213)	(0.020)
Board Size	0.003	0.014	−0.023	−0.003
	(0.003)	(0.013)	(0.065)	(0.005)
CEO/Chairman Split	0.004	0.024	−0.048	−0.007
	(0.005)	(0.034)	(0.088)	(0.007)
Board Ownership	−0.013	−0.013	−0.083	0.015
	(0.010)	(0.010)	(0.150)	(0.018)
Control Variables of Table 2	Yes	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes
No. of Obs.	70,125	70,125	70,125	70,125
Adjusted R^2	0.781	0.662	0.506	0.792
Panel B: Controlling for neighboring firms				
Natural Disaster	−0.084***	−0.162***	−0.084***	−0.138***
	(0.031)	(0.060)	(0.029)	(0.048)
Neighboring Dummy	−0.007	−0.008	−0.006	0.007
	(0.018)	(0.035)	(0.016)	(0.030)
Control Variables of Table 2	Yes	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes
No. of Obs.	70,125	70,125	70,125	70,125
Adjusted R^2	0.773	0.653	0.501	0.785
Panel C: Using alternative measure of natural disaster				
Ln (Natural Disaster Losses)	−0.004*	−0.008*	−0.004**	−0.007*
	(0.002)	(0.004)	(0.002)	(0.003)
Control Variables of Table 2	Yes	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes
No. of Obs.	70,125	70,125	70,125	70,125
Adjusted R^2	0.770	0.649	0.498	0.783
Panel C: Using alternative measure of natural disaster				
Ln (Natural Disaster Losses)	−0.004*	−0.008*	−0.004**	−0.007*
	(0.002)	(0.004)	(0.002)	(0.003)
Control Variables of Table 2	Yes	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes
No. of Obs.	70,125	70,125	70,125	70,125
Adjusted R^2	0.770	0.649	0.498	0.783
Panel D: Excluding firms with main customers or suppliers also affected by natural disasters				
Natural Disaster	−0.067**	−0.125**	−0.067**	−0.104**
	(0.032)	(0.063)	(0.031)	(0.050)
Control Variables of Table 2	Yes	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes
No. of Obs.	67,486	67,486	67,486	67,486
Adjusted R^2	0.770	0.650	0.499	0.784

Table A3. Natural disasters, operations concentration, and corporate innovation. This table reports heterogeneous treatment impacts of natural disaster on corporate innovation in firms with high and low operations concentration. The indicator variable *High Concentration* takes the value of one if the firm's measure of operations concentration, following Garcia and Norli (2012), is above the sample median, and zero otherwise. All the control variables used in Table 3 are also included in this regression but unreported for brevity. The detailed definitions of all variables are provided in Appendix 1. Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Ln (#Patents + 1)	Ln (#Citations + 1)	Ln (Citations/Patents + 1)	Ln (Innovation Value + 1)
	(1)	(2)	(3)	(4)
Natural Disaster	−0.020	−0.027	−0.026	−0.078
	(0.039)	(0.072)	(0.034)	(0.062)
Natural Disaster∗High Concentration	−0.138***	−0.273***	−0.108***	−0.137**
	(0.044)	(0.087)	(0.042)	(0.065)
Concentration	−0.028	−0.013	0.015	−0.061*
	(0.023)	(0.044)	(0.021)	(0.036)
Control Variables of Table 2	Yes	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes
No. of Obs.	70,125	70,125	70,125	70,125
Adjusted R^2	0.779	0.660	0.505	0.791

Table A4. Some cross-sectional analysis by firm characteristics. This table reports heterogeneous treatment impacts of natural disaster on corporate innovation, using some different firm characteristics. The main variable of interest is *Natural Disaster*. Small Firms is defined as a dummy that equal to one if the size of firms is below the median of the year's firm size, and zero otherwise. Young Firms is defined as a dummy that equal to one if a firm was present for less than ten years in Compustat, and zero otherwise. High Financial Dependence set equal to one if he four-digit SIC industry's net change in capital is greater than the median net change in capital across all industries in a given year, and zero otherwise. The dependent variable in columns (1)–(3) is the natural logarithm of the number of patent counts plus one. The dependent variable in columns (4)–(6) is the natural logarithm of citation counts plus one. The dependent variable in columns (7)–(9) is the natural logarithm of citation counts scaled by patents plus one. The dependent variable in columns (10)–(12) is the natural logarithm of the cumulative dollar value (in millions of 2005 nominal US dollars) of patents that a firm applies for in a given year plus one. All the control variables used in Table 2 are also included in this regression but unreported for brevity. The detailed definitions of all variables are provided in Appendix 1. Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Ln (#Patents + 1)			Ln (#Citations + 1)			Ln (Citations/Patents + 1)			Ln (Innovation Value + 1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Natural Disaster	−0.077**	−0.071**	−0.077**	−0.125*	−0.120*	−0.120*	−0.058*	−0.059*	−0.059*	−0.111**	−0.104**	−0.104**
	(0.034)	(0.033)	(0.034)	(0.066)	(0.064)	(0.064)	(0.031)	(0.031)	(0.031)	(0.054)	(0.051)	(0.051)
Natural Disaster∗Small Firms	−0.090*			−0.170**			−0.086**			−0.165**		
	(0.049)			(0.083)			(0.036)			(0.078)		
Small firms	0.002			0.001			0.250			−0.001		
	(0.010)			(0.011)			(0.225)			(0.028)		
Natural Disaster∗Young Firms		−0.107***			−0.158***			−0.094***			−0.110**	
		(0.037)			(0.014)			(0.008)			(0.055)	
Young Firms		0.028			0.053			0.025			0.032	
		(0.023)			(0.041)			(0.047)			(0.036)	
Natural Disaster∗High Financial Dependence			−0.170***			−0.211**			−0.127**			−0.158***
			(0.043)			(0.100)			(0.057)			(0.014)
High Financial Dependence			−0.028			−0.013			0.015			−0.061*
			(0.023)			(0.044)			(0.021)			(0.036)
Control Variables of Table 2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	70,125	70,125	70,125	70,125	70,125	70,125	70,125	70,125	70,125	70,125	70,125	70,125
Adjusted R^2	0.757	0.770	0.757	0.638	0.649	0.649	0.491	0.498	0.498	0.774	0.784	0.784

Table A5. The Impact of natural disaster on corporate innovation – the inventor level analysis. This table reports coefficients from difference-in-difference (DiD) regressions of the impact of natural disaster on corporate innovation using inventor-level data. The main variable of interest is *Natural Disaster*. The dependent variable in columns (1) and (2) is the natural logarithm of the number of patent counts plus one. The dependent variable in columns (3) and (4) is the natural logarithm of citation counts plus one. The dependent variable in columns (5) and (6) is the natural logarithm of citation counts scaled by patents plus one. The dependent variable in columns (7) and (8) is the natural logarithm of the cumulative dollar value (in millions of 2005 nominal US dollars) of patents that a firm applies for in a given year plus one. All control variables are lagged by one year. The detailed definitions of all variables are provided in Appendix 1. Inventor, Year, and Firm fixed effects, whose coefficients are suppressed, are included in all regressions. Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Ln (#Patents + 1)		Ln (#Citations + 1)		Ln (Citations/Patents + 1)		Ln (Innovation Value + 1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Natural Disaster	−0.036***	−0.036***	−0.043***	−0.043***	−0.074***	−0.075***	−0.025**	−0.026**
	(0.010)	(0.009)	(0.012)	(0.013)	(0.023)	(0.024)	(0.012)	(0.011)
Size	0.014	0.012	−0.078***	−0.076***	−0.102***	−0.095***	0.002	0.003
	(0.012)	(0.012)	(0.023)	(0.023)	(0.027)	(0.026)	(0.069)	(0.068)
Tobin's *Q*	0.005	0.006	0.017*	0.017*	0.009	0.009	0.050***	0.050***
	(0.004)	(0.004)	(0.010)	(0.009)	(0.013)	(0.012)	(0.015)	(0.015)
Cash Holdings	0.026	0.024	−0.020	−0.018	−0.053	−0.048	0.134	0.134
	(0.038)	(0.037)	(0.097)	(0.096)	(0.073)	(0.073)	(0.201)	(0.201)
Leverage	−0.007	−0.005	0.072	0.069	0.066	0.060	0.154	0.152
	(0.026)	(0.025)	(0.084)	(0.083)	(0.083)	(0.081)	(0.142)	(0.141)
ROA	−0.043	−0.036	−0.076	−0.081	−0.022	−0.038	0.373**	0.373**
	(0.040)	(0.040)	(0.084)	(0.083)	(0.075)	(0.074)	(0.148)	(0.147)
Tangible Assets	−0.049*	−0.052*	−0.214**	−0.209**	−0.149*	−0.140*	−0.168	−0.164
	(0.029)	(0.029)	(0.090)	(0.088)	(0.088)	(0.085)	(0.228)	(0.227)
Capital Expenditures	0.276***	0.287***	0.677***	0.661***	0.310*	0.277	0.526	0.518
	(0.100)	(0.099)	(0.215)	(0.213)	(0.180)	(0.176)	(0.510)	(0.507)
Ln (Firm Age)	−0.020*	−0.025**	−0.138***	−0.135***	−0.118***	−0.109***	−0.077	−0.077
	(0.011)	(0.012)	(0.033)	(0.032)	(0.028)	(0.027)	(0.078)	(0.078)
H-Index	−0.622	−0.604	0.877	0.861	1.817	1.772	1.742	1.740
	(0.545)	(0.523)	(1.117)	(1.089)	(1.604)	(1.529)	(4.536)	(4.520)
H-Index^2	0.787	0.753	−0.682	−0.658	−1.951	−1.874	−3.625	−3.629
	(0.815)	(0.783)	(1.646)	(1.604)	(2.350)	(2.240)	(6.465)	(6.440)
Experience		0.052***		−0.004		−0.081***		0.047***
		(0.005)		(0.014)		(0.012)		(0.014)
Experience^2		−0.015***		−0.028***		−0.009		−0.051***
		(0.004)		(0.010)		(0.009)		(0.015)
Inventor Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	651,712	651,712	651,712	651,712	651,712	651,712	651,712	651,712
Adjusted R^2	0.429	0.430	0.650	0.650	0.695	0.696	0.747	0.747