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NATURAL DISASTERS, TECHNOLOGY DIVERSITY, AND OPERATING PERFORMANCE

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Abstract—In this paper, we empirically measure the impact of natural disasters on firm-level operating performance and examine if such impact can be mitigated by technology diversification. Using major natural disasters specified by Barrot and Sauvagnat (2015) and factory location data from the toxic release inventory (TRI) database, we first find that firms with factories located in states affected by natural disasters are much less profitable. Second, we find that firms with diversified technologies are significantly less subject to the impact of natural disasters, suggesting that technology diversity enhances firms' sustainability.

I. Introduction

NATURAL disasters are sudden, calamitous events that occur by chance, seriously disrupting the functioning of a society. Standard procedures and regular resources cannot be used to handle such events adequately, as natural disasters often destroy both a society's infrastructure and its environment, causing large-scale loss of human life and property. Unfortunately, most natural disasters are unpredictable and unavoidable; thus, governments have been challenged to make sound preparations to minimize the death toll, property loss, and environmental damage that natural disasters present.[1] According to the Emergency Events Database (EM-DAT), 28 natural disasters were reported in the United States in 2013, and these catastrophes resulted in an estimated 212 deaths and $17.58 billion in economic damage. In addition, the total damage from natural disasters globally was around $118.6 billion in 2013, and the total number of deaths was 21,610.

In addition to causing economic losses and fatalities, natural disasters also disrupt corporate operations.[2] However, few studies explore the impact of natural disasters on corporate profitability and the tools firms use to mitigate these impacts. In this paper, we analyze such impact using U.S. natural disasters' affected locations, which Barrot and Sauvagnat (2015) identify by using the Spatial Hazard and Loss Database (maintained by the University of South Carolina). To assess the impact of these disasters on firms' operating performance, we use the U.S. Environmental Protection Agency's (EPA) toxic release inventory (TRI) database to identify the affected firms' U.S. factory locations.

We find that manufacturing firms with more of their factories located in states that experience natural disasters are associated with significantly lower return on assets (ROA). In particular, a firm that has all of its factories located in one state can experience about a 1-percentage point decrease in its ROA when a natural disaster strikes. When using a subsample of firms that are matched on related control variables, we find that the impact of natural disasters on operating performance is even stronger. Specifically, the point estimate on the measure of natural disasters decreases from –0.012 to –0.020. These analyses quantify an average adverse effect of natural disasters on firm profitability.

We then propose that technology diversity mitigates natural disaster risks. Firms with highly diversified technologies are expected to respond more resiliently to natural disasters, thanks to greater resourcefulness and flexibility, as well as lower costs to develop recovery solutions. These firms are able to diversify their input sources with respect to production and are less subject to operational disruptions (Koren & Tenreyro, 2013). In addition, these firms respond more adaptively to extreme situations, for managers and employees possess different types of expertise and can apply their technologies to different production plans in various scenarios (Garcia-Vega, 2006, Makri & Lane, 2008; Makri, Hitt, & Lane, 2010; Gomez-Mejia et al., 2011); these adaptive responses contribute to firms' ability to respond to rapid environmental changes (Grandstrand, 1998; Gomez-Mejia et al., 2011). Moreover, the cross-fertilization effects and synergies from multiple technologies further lower the R&D costs (Nelson, 1959) that are required to generate new technological solutions to disasters. We thus form our main hypothesis that technology diversification helps firms mitigate adverse effects from catastrophes on firm operations.

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[1] Recent studies suggest that natural disasters have a significant impact on GDP per capita, labor markets, and mental health (Luechinger & Raschky, 2009; Raddatz, 2007). Kahn (2005) shows that countries with better economic development and higher-quality institutional environments suffer fewer fatalities when natural disasters strike.

[2] For example, the world experienced two major supply chain disruptions in 2011: the Great East Japan earthquake and tsunami in March, which seriously harmed many Sendai-based industries and forced Toyota to delay its launch of two new Prius models that were originally scheduled for a late April release, and the Bangkok flooding later that year, which harmed the automobile and hard-drive industries to a great extent. Hard-drive industries in Thailand affected by these natural disasters took approximately a year to fully restore their production lines to normal levels (Fuller, 2011). For Western Digital alone, its losses due to the flooding were estimated at between $225 million and $275 million (Milbourn, 2011).

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To formalize our line of argument, we derive a simple model with one firm operating two product lines with separate inventories and capacities under the threat of natural disasters. In the model, technology diversity enables flexible production (by allowing product lines to produce different goods) and diversifies input sources (by pooling inventories). An important determinant of the firm's optimization is the initial cost of adopting a technology diversity strategy, a cost that depends on the adaptability of workers and the synergies of innovative investments. We provide this model in the online appendix, and its implications are consistent with our argument: given the occurrence of natural disasters, technologically diversified firms perform better than others due to lower adjustment costs and diversifiable input sources.

To construct our proxy for technology diversity, we use the NBER patent database, which includes all details of patents granted by the U.S. Patent and Trademark Office (USPTO). Our empirical tests suggest that technologically diversified firms are barely affected by natural disasters, whereas firms that are not technologically diversified are severely affected by natural disasters. We further address the possible endogeneity of technology diversity by using a propensity-score matching method to select control firms and using changes in the technology diversity of suppliers as a positive shock to the technology diversity of focal firms. We also find similar results when we consider alternative definitions of technology diversity and when we control for firms' geographic diversification, intangible assets, and concentration of suppliers. All of these findings support our hypothesis that firms adopting an innovation strategy with technological diversification are more resilient in responding to natural disasters.

This study adds to the economics literature by presenting firm-level evidence for economic losses stemming from natural disasters. While previous empirical studies mainly focus on country-level economic losses and casualties due to natural disasters (Kahn, 2005; Raddatz, 2007; Luechinger & Raschky, 2009), our paper quantifies the impact on firm-level operating performance by showing that state-level disasters adversely affect firms' ROA. Moreover, we propose and substantiate that by diversifying their technologies, firms better prepare for natural disasters, as the operating performance of firms with more diverse technologies is less affected by natural disasters.

Our investigation may also contribute to the innovation literature by highlighting the economic relevance of innovation strategies. In today's knowledge-based economy, top managers must design and execute innovation strategies that largely determine a given firm's survival and chances for success. Given the severe damage that natural disasters bring, managers who consider shareholders' long-term interests must prepare firms for catastrophes. Our empirical analyses underscore the advantages and benefits associated with developing diverse technologies.

II. Data, Summary Statistics, and Empirical Methodology

To empirically test our hypotheses, we combine state-level natural disaster data, factory-level location data, firm-level patent data, and firm-level accounting data for U.S. public firms in manufacturing industries.

We follow Barrot and Sauvagnat (2015) and define natural disasters as major disasters that last for fewer than thirty days and have a total estimated damage of over $1 billion (in 2013 constant dollars). We obtain the U.S. natural disaster data from the Spatial Hazard and Loss Database, which is maintained by the University of South Carolina. Thirty-seven major disasters (e.g., blizzards, earthquakes, floods, hurricanes) occurred between 1987 and 2013; to align our time line with our factory-level location data, we do not consider disasters before 1987.

To assess the impact of natural disasters on firms' operating performance, we use the U.S. EPA's toxic release inventory (TRI) database to identify U.S. firms' factory locations. The TRI database was established in response to the 1986 Emergency Planning and Community Right-to-Know Act (EPCRA), which requires firms in manufacturing industries with Standard Industrial Classification (SIC) codes between 2000 and 3999 to report their factories' locations as well as their storage, use, and releases of hazardous substances.[3] While this paper does not focus on firms' toxic release data, this database nevertheless provides us with a rich source for identifying factories' locations. Panel A of table 1 lists all the disasters during this period, as well as the state location and number of factories affected by these disasters.

We use the Compustat database to obtain U.S. public firms' accounting data from 1988 to 2014.[4] We measure firm i's operating performance in year t by *ROA*, which is defined as income before depreciation in year t divided by total assets in year $t-1$. Since natural disasters could damage a firm's assets, we use the previous year's assets as a base instead of the current year's assets to avoid misspecification.

A firm is considered affected by natural disasters in a year when at least one of its factories is located in a state that is affected by any disasters in that period. In panel B of table 1, we categorize all 37 major disasters into four groups: (a) hurricanes and floods, (b) blizzards and ice storms, (c) earthquakes, and (d) wildfires. We observe unequal occurrences among these disaster types: among 37 disasters, there are 29 hurricanes and floods, 4 blizzards and ice storms, 2 earthquakes, and 2 wildfires. In panel B of Table 1, we list the average ROA change before and after these disasters occurred. For each affected firm-year observation (in which a firm has at least one factory in an affected state for a

[3] https://www.epa.gov/toxics-release-inventory-tri-program/tri-data-and-tools. We are especially grateful to Xi Xiong for her excellent research assistance in matching the toxic release inventory (TRI) database to the Compustat database.

[4] Disasters are from 1987 to 2013. We have used a one-year lag between natural disasters and ROA.

TABLE 1.—MAJOR DISASTERS AND OPERATING PERFORMANCE

A. List of Major Disasters in the U.S. Territory, 1978–2013

Disaster	Year	Type	Number of Affected Factories	Affected Location
Hugo	1989	Hurricane	621	NC, SC, VA
Loma earthquake	1989	Earthquake	656	CA
Bob	1991	Hurricane	780	MA, ME, NC, NH, NY, RI
Oakland Hills Firestorm	1991	Wildfire	621	CA
Andrew	1992	Hurricane	546	AL, FL, LA, MS
Iniki	1992	Hurricane	11	HI
Blizzard	1993	Blizzard	1,773	AL, CT, FL, GA, MA, MD, NJ, OH, SC, VA, VT
Northridge earthquake	1994	Earthquake	488	CA
Alberto	1994	Hurricane	475	AL, FL, GA
Opal	1995	Hurricane	1,153	AL, FL, GA, LA, MS, NC, SC
Blizzard	1996	Blizzard	1,687	CT, DE, IN, KY, MA, MD, NC, NJ, NY, PA, VA, WV
Fran	1996	Hurricane	310	NC, SC, VA, WV
Ice storm	1998	Ice storm	289	ME, NH, NY, VT
Bonnie	1998	Hurricane	452	NC, VA
Georges	1998	Hurricane	604	AL, FL, LA, MS
Floyd	1999	Hurricane	1,724	CT, DC, DE, FL, MD, ME, NC, NH, NJ, NY, PA, SC, VA, VT
Allison	2001	Hurricane	1,825	AL, FL, GA, LA, MS, PA, TX
Isabel	2003	Hurricane	1,326	DE, MD, NC, NJ, NY, PA, RI, VA, VT, WV
Southern California Wildfires	2003	Wildfire	448	CA
Charley	2004	Hurricane	4	FL, GA, NC, SC
Jeanne	2004	Hurricane	550	AL, FL, GA, KY, MD, NC, NY, OH, PA, SC, VA, WV
Ivan	2004	Hurricane	2,011	AL, FL, GA, KY, LA, MA, MD, MS, NC, NH, NJ, NY, PA, SC, TN, WV
Frances	2004	Hurricane	611	DE, FL, GA, MD, NC, NJ, PA, SC, VA
Dennis	2005	Hurricane	442	AL, FL, GA, MS, NC
Katrina	2005	Hurricane	1,795	AL, AR, FL, GA, IN, KY, LA, MI, MS, OH, TN
Rita	2005	Hurricane	283	AL, AR, FL, LA, MS
Wilma	2005	Hurricane	1	FL
Midwest floods	2008	Floods	1,166	IA, IL, IN, MN, MO, NE, WI
Gustav	2008	Hurricane	212	AR, LA, MS
Ike	2008	Hurricane	1,059	AR, LA, MO, TN, TX
Blizzard Groundhog Day	2011	Blizzard	2,536	CT, IA, IL, IN, KS, MA, MO, NJ, NM, NY, OH, OK, PA, TX, WI
Irene	2011	Hurricane	504	CT, MA, MD, NC, NJ, NY, VA, VT
Tropical Storm Lee	2011	Hurricane	1,096	AL, CT, GA, LA, MD, MS, NJ, NY, PA, TN, VA
Isaac	2012	Hurricane	398	FL, LA, MS
Sandy	2012	Hurricane	1,654	CT, DE, MA, MD, NC, NH, NJ, NY, OH, PA, RI, VA, WV
Flooding and Severe Weather-Illinois	2013	Floods	669	IL, IN, MO
Flooding-Colorado	2013	Floods	76	CO

B. Changes in Operating Performances

	Change in *ROA*	Observations	*t*-statistic
All hit	−1.43%	4,421	−7.10
Types of disaster			
Hurricanes/floods	−1.89%	2,842	−7.16
Earthquakes	−0.52%	252	−0.74
Wildfires	−1.44%	158	−1.32
Blizzards/ice storms	−0.58%	588	−0.98
Nonhurricanes/floods	−0.70%	998	−1.64

Panel A describes the 37 natural disasters that occurred in the U.S. territory from 1989 to 2013. Names, years, and locations of each natural disaster are obtained from table 1 of Barrot and Sauvagnat (2015). The data were originally from the Spatial Hazard and Loss Database for the United States, which is maintained by the University of South Carolina. The number of affected factories equals the total number of factories affected by the disaster. Abbreviations for U.S. states used in the table: AL (Alabama), AK (Alaska), AZ (Arizona), AR (Arkansas), CA (California), CO (Colorado), CT (Connecticut), DE (Delaware), FL (Florida), GA (Georgia), HI (Hawaii), ID (Idaho), IL (Illinois), IN (Indiana), IA (Iowa), KS (Kansas), KY (Kentucky), LA (Louisiana), ME (Maine), MD (Maryland), MA (Massachusetts), MI (Michigan), MN (Minnesota), MS (Mississippi), MO (Missouri), MT (Montana), NE (Nebraska), NV (Nevada), NH (New Hampshire), NJ (New Jersey), NM (New Mexico), NY (New York), NC (North Carolina), ND (North Dakota), OH (Ohio), OK (Oklahoma), OR (Oregon), PA (Pennsylvania), RI (Rhode Island), SC (South Carolina), SD (South Dakota), TN (Tennessee), TX (Texas), UT (Utah), VT (Vermont), VA (Virginia), WA (Washington), WV (West Virginia), WI (Wisconsin), and WY (Wyoming).

Panel B presents the impact of natural disasters on firms' operating performance. Operating performance is measured by return on assets (*ROA*). If at least one of a firm's factories is affected by natural disasters in year $t-1$, then we include the firm in our sample and calculate the changes in *ROA* as the difference between *ROA* in year t minus *ROA* in year $t-1$. We then average the changes of all firms that are affected by natural disasters. For each type of disaster, we perform the same procedure except that we require there be no simultaneous disasters of a different type that occurs. *ROA* is winsorized at 1% at each tail.

particular year), we calculate its ROA change as its ROA in the affected year minus its ROA in the prior year. For the most frequent disaster type (hurricanes and floods that affected 2,842 firm-year observations), the average ROA change is −1.89 percentage points (with a T-statistic of −7.16). These statistics suggest that hurricanes and floods indeed hurt corporate operations, consistent with the U.S. economy's suffering historically from hurricane and flooding more than other disasters in recent decades.[5]

We also find that other disasters damage corporate operations (albeit our results are less statistically significant due

[5] In fact, hurricane and floods have also been the most numerous major disasters across the world (Skidmore & Toya, 2002).

to our smaller sample size). Specifically, blizzards and ice storms affected 588 firm-year observations and are associated with an ROA change of −0.58 percentage points, earthquakes affected only 252 firm-year observations and are associated with an ROA change of −0.52 percentage points, and wildfires affected only 158 firm-year observations, which are associated with an ROA change of −1.44 percentage points. Combined, all three of these disaster types affected 998 firm-year observations and are associated with an ROA change of −0.7 percentage points (around the 10% significance level). Nevertheless, the summary statistics that we provide in panel B of table 1 should be interpreted with caution, for we do not control for other firm and industry characteristics. We will rely on multivariate regression analyses to justify the effect of natural disasters on corporate operations.

Because firms differ in their number of factories, our main explanatory variable in our regression analysis is *HIT_RATIO*, which represents the percentage of factories of firms affected by natural disasters in any given year. We calculate this variable as the ratio of the number of factories affected by natural disasters to the total number of factories that belong to firm *i*. Since a firm's plants are neither equally affected by the same disaster nor of similar importance to firms, we attach various weights to plants when we calculate *HIT_RATIO* in section IV.[6]

We then collect U.S. public firms' patent data from the National Bureau of Economic Research (NBER) patent database, which includes detailed information about each granted patent, such as technology categories in which the patent can be used and the application year of each patent.[7] We define a firm-year observation's technology diversity score as 1 minus the Herfindahl index based on the distribution of technology categories for which a firm's patents are filed in the most recent three years (i.e., 1 minus the sum of the squared percentages of patents in individual technology categories) multiplied by an adjustment factor that is the patent number divided by the patent number minus 1 (see Hall, Jaffe, & Trajtenberg, 2001, appendix 2):[8]

$$Diversity\ score_{i,t} = \frac{\left[1 - \sum_{j=1}^{J} \left(S_j\right)^2\right] N}{N - 1}, \tag{1}$$

for which J denotes the number of technology categories in which firm i has filed patents from year $t - 2$ to year t, S_j denotes the share of filed patents in the jth technology category ($j = 1,\ldots,J$), and N denotes the number of filed patents from year $t - 2$ to year t. In equation (1) based on Hall et al. (2001), we cannot calculate the technology diversity score for firms that have either only one patent or no patents. For firms that have only one patent, it is indeed difficult to decide its technology diversity score, for its patent has only one technology category. Therefore, for this study, we set these firms' technology diversity scores as 0. For firms that have no patents, we cannot calculate their technology diversity scores and therefore also set these firms' technology diversity scores as 0.[9] That said, we find that dropping firm-year observations with 0 technology diversity scores from our sample leads to consistent results.

Our patent-based technology diversity has its limitations. Some firms may choose to keep their technologies secret, and some firms' technologies may not be patentable (Cohen, Nelson, & Walsh, 2000). Nevertheless, since the establishment of a patent-specialized court (the Court of Appeals for the Federal Circuit, CAFC) in 1982 and a few highly publicized patent infringement cases in the mid-1980s, firms have become active in patenting their intellectual property (Kortum & Lerner, 1998; Hall, 2004; Png & Xiong, 2017). Thus, the economics literature often uses patent data to measure firms' innovative activities (Griliches, 1990).

To address possible differences in technology diversity across different industries, we define firm-year observations as "high technology diversity" if the firm-year observation has a technology diversity score (see equation [1]) in the top quartile within an industry (defined by three-digit SIC codes) in a given year. We then use *DIV* as a dummy variable that equals 1 for firms with high technology diversity, and that equals 0 otherwise.[10]

We also consider various ways to define technology diversity in the robustness check section.[11] First, we use a simple count of the number of categories in which a firm participates to measure the diversity score. Second, we vary the technology categories from the six categories to the two-digit subcategories of Hall et al. (2001). Third, we use

[6] Specifically, to measure the importance of plants to firms, we use the waste produced by each plant to proxy for its production level. We also use state location mention in firms' annual reports to calculate the importance of plants by their location. Third, we consider the differentiated effects of disasters on different states by collecting data on economic loss at both the county and state levels and then use these data as weight in calculating *HIT_RATIO*.

[7] The original NBER patent database is developed by Hall et al. (2001) and ends in 2006; Gao, Hsu, and Li (2018) then extend the data to 2010 using the Harvard Patent Inventor Data developed by Li et al. (2014).

[8] For example, if a firm has patent A (assigned to category X), patent B (assigned to category Y), and patent C (assigned to category Y) in the most recent three years, this firm's 1 minus the Herfindahl index based on the distribution of technology categories = 1 − $[(1/3)^2 + (2/3)^2]$ = 0.444. Moreover, given the adjustment suggested in Hall et al. (2001, appendix 2), we multiply 0.444 by 3/2 = 0.667, which will be the firm's diversity score. Such an adjustment aims to correct the downward bias of diversification measures when the number of patents is small. All the patents are classified by Hall et al. (2001) into six technology categories: (a) chemical, (b) computer and communications, (c) drugs and medical, (d) electrical and electronic, (e) mechanical, and (f) others.

[9] We set the technology diversity score of firms with one or zero patents to 0 to keep all manufacturing firms in our sample, since our main explanatory variable in regressions is an indicator variable that equals 1 if a firm's technology diversity score is in the top quartile in each industry-year.

[10] The cutoff point is the 75th percentile. However, the actual cutoff point would be higher if many scores cluster around the 75th percentile. For an industry with 90% of its firms having 0 technology diversity scores, *DIV* equals 1 for the remaining 10%.

[11] For other measures of technology diversity, see Miller (2006) and Hirshleifer, Hsu, and Li (2018).

TABLE 2.—SUMMARY STATISTICS

Variable	N	Mean	SD	Min	P25	P50	P75	Max
ROA	16,709	0.16	0.12	−1.57	0.10	0.15	0.20	1.14
HIT_RATIO	16,709	0.16	0.29	0.00	0.00	0.00	0.22	1.00
DIV (Score)	15,342	0.27	0.32	0.00	0.00	0.00	0.58	1.00
SIZE	16,709	6.71	1.91	0.24	5.43	6.64	7.98	13.08
SIZE2	16,709	48.65	26.44	0.06	29.47	44.04	63.60	171.12
AGE	16,709	2.99	0.87	0.69	2.40	3.18	3.71	4.19
PAGE	16,709	2.10	0.67	0.69	1.61	2.20	2.62	3.33
INTANG	16,709	0.23	0.19	0.00	0.08	0.18	0.33	1.00
S_HHI	16,709	0.12	0.30	0.00	0.00	0.00	0.00	1.00
RDC	16,709	0.07	0.13	0.00	0.00	0.03	0.09	5.59
PATENT	14,851	0.04	0.09	0.00	0.00	0.01	0.05	1.81
SGA	16,709	5.49	2.58	0.00	4.42	5.79	7.17	11.55
AD	16,709	1.12	2.15	0.00	0.00	0.00	1.32	10.24
IND_YEAR	16,709	0.08	0.10	−1.29	0.04	0.10	0.14	0.88
STATE_YEAR	16,709	0.06	0.08	−1.54	0.02	0.07	0.11	0.63

This table presents summary statistics of variables that have been used in the baseline regressions in our paper. *ROA* is defined as income before depreciation in year t divided by total assets in year $t-1$. *HIT_RATIO* is the percentage of a firm's factories affected by natural disasters. *DIV*(*score*) is the raw value of the technology diversity score defined in equation (1). *SIZE* is the natural log of total assets. *SIZE2* is the square of *SIZE*. *AGE* is the number of years a firm has been in the Compustat database. *PAGE* is the average age of plants; the age of a plant is the number of years it has existed in the TRI database. *INTANG* is the percentage of intangible assets defined as total assets minus current assets and net value of property, plants, and equipment scaled by total assets. *S_HHI* is the Herfindahl-Hirschman Index of sales from suppliers and is set to 0 when no information about suppliers is available. *RDC* is the natural log of amortized research and development (R&D) expenses plus 1 in the past five years $\left(i.e., \sum_{k=0}^{4} RD_{t-k}(1-0.2k)\right)$, in which RD_t is R&D expenses at year t. *PATENT* is the log of the ratio of total patents count from year $t-4$ to t scaled by total assets of fiscal year $t-1$. *SGA* and *AD* are amortized sales, general, and administrative expenses and amortized advertisement expenses similarly defined as *RDC*. *IND_YEAR* and *STATE_YEAR* are industry-year and state-year averages of *ROA* without the focal firm itself, respectively. The sample period covers 1987 to 2014. For *DIV* and *PATENT*, the sample ends in 2010.

a logarithmic approach to calculate the diversity score. Fourth, we define firm-year observations as "high technology diversity" if the firm-year observation has a technology diversity score in the 80th, 85th, and 90th percentiles within an industry in a given year.

To examine the pure effect of natural disasters on operating performance, we follow the empirical setting of Giroud and Mueller (2010), who study the impact of the passage of business combination laws on firm-level ROA. We construct the same control variables used in their study. To control for firm size differences, we use the first control variable, *SIZE*, or the natural log of total assets. To account for the possible nonlinear effect of *SIZE*, we also control for *SIZE2* (i.e., the square of *SIZE*). Further, we control for the life cycle differences of firms with *AGE*, defined as the natural log of the number of years a firm has been in the Compustat database. We then add several control variables to the regression, including *PAGE*, which is the average age of plants. We also control for asset intangibility (*INTANG*) and concentration of suppliers (*S_HHI*), as Leiter, Oberhofer, and Raschky (2009) find that the share of intangible assets affects firms' vulnerability under disasters, and both Henriet, Hallegatte, and Tabourier (2012) and Todo, Nakajima, and Matous (2015) show that the network effect of supply chains also matters. We further control for amortized research and development expenses (*RDC*); selling, general, and administrative expenses (*SGA*); advertisement expenses (*AD*); and patents count (*PATENT*) for the effects of intangible assets and potential differences in firm characteristics between high and low technology diversity firms.[12]

[12] We thank two anonymous reviewers for suggesting these alternative explanations. We use selling, general, and administrative expenses (SGA) to measure a firm's organization capital (Eisfeldt & Papanikolaou, 2013).

Finally, given the extent to which local development, institutional quality, income equality, macroeconomic conditions, and levels of corruption might influence a firm's ability to respond to natural disasters, we follow Giroud and Mueller (2010) and use *STATE_YEAR* to control for the time-varying state effect. We calculate *STATE_YEAR* as the state-year average of the dependent variable, *ROA*, without the focal firm itself. In the same way, we control for unobservable industry-level, time-varying shocks with *IND_YEAR*, which is the industry-year average of the dependent variable, *ROA*, without the firm itself. Finally, we define each industry in this paper at the three-digit SIC level; this definition serves as a compromise between an overly coarse partition that may pool together unrelated industries and an overly narrow partition that leads to misclassification (Giroud and Mueller 2010).

We eliminate firm-year observations for which data on *ROA* and factory location are missing. To eliminate the impact of outliers, we require a firm to have at least #1 million in total assets to be included in our study, and we also follow Giroud and Mueller (2010) to trim *ROA* at 1% at each tail. Our main sample starts in 1987, the first year for which our TRI data allow us to identify firms' factory locations. We end our sample period in 2014 because our disaster data end in 2013. In sum, we use a total of 16,709 firm-year observations. For regressions involving technology diversity, the sample ends in 2011 due to our patent data ending in 2010.

In table 2, we present summary statistics for all variables used in this study. ROA is 0.16 on average. For an average firm in the data set, 16% of its factories are affected by natural disasters each year, as reflected by the mean of *HIT_RATIO*, which is 0.16. The *DIV* score is the raw value of technology diversity, which, on average, is 0.27 in the sample.

III. Empirical Results

A. Natural Disasters and Operating Performance

In this section, we first evaluate the negative impact of natural disasters to establish a baseline comparison for section 3.2, in which we explore the ability of technological diversification to mitigate such negative impact.

The impact of natural disasters on operating performance: All manufacturing firms. We follow Giroud and Mueller (2010) to establish our baseline regression:

$$ROA_{i,t} = \beta_0 + \beta_1 HIT\_RATIO_{i,t-1} + \boldsymbol{Xb_{i,t}} + \mu_t + \eta_i + \varepsilon_{it} \quad (2)$$

for which *HIT_RATIO*, the percentage of firm *i*'s factories affected by natural disasters in calendar year $t - 1$, is matched with accounting data with fiscal year end in year *t*. ***Xb*** is a set of control variables that include *SIZE, SIZE2, AGE, PAGE, INTANG, S_HHI, RDC, SGA, AD, PATENT, IND_YEAR*, and *STATE_YEAR* in year *t*, and μ_t and η_i control for year and firm fixed effects, respectively. The standard errors of coefficients are clustered at the state level, given that we use natural disasters at the state level (Rogers, 1993; Petersen, 2009; Giroud & Mueller, 2010; Flammer, & Kacperczyk 2016). Our results are robust to various ways of clustering standard errors, including firm, industry, and year, as well as double clustering based on various combinations of firm, industry, and year. We provide our results in the online appendix, table A.3. We are mainly interested in β_1, the coefficient estimate for *HIT_RATIO*, which reflects the impact of natural disasters on firms' operating performance.

As we show in the first two columns of table 3, the estimates of β_1 are significantly negative across the two columns, which suggests that firms with more factories affected by natural disasters have weaker profits. If a firm has all of its factories located in one state that was affected by a disaster (i.e., *HIT_RATIO* $= 1$), this firm's ROA will be subject to approximately a 1-percentage point decrease after the disaster. Considering that the firm fixed effects have absorbed the firm time-invariant characteristics, this 1-percentage point decrease is significant to firm performance. Although firms located in areas that frequently experience natural disasters might, understandably, endogenously either choose factory locations to avoid these disasters or diversify factories in different locations to deal with natural disasters, our identification strategy is not threatened by these concerns, for they will only bias us against finding any impacts of natural disasters (Barrot & Sauvagnat 2015).

The impact of natural disasters on operating performance: Matched firms. For equation (2), we include all firm-year observations in the regression, including years without natural disasters. We do so to control for firm-fixed effects that account for unobserved firm characteristics. Another way to assess the impact of natural disasters is by using matched firms as controls instead of using all firm-year observations. In particular, we match firms that experience natural disasters with control firms that did not on observed covariates. To ensure the robustness of our results, we use a matched sample in this section to study the impact of natural disasters.

We identify all firm-year observations with nonzero *HIT_RATIO* as treated firms. We select control firms from the same year based on age, size, past operating performance (ROA), asset intangibility, and patents. Given our sample size limitation, we match observations based on a

TABLE 3.—NATURAL DISASTERS AND OPERATING PERFORMANCE

	(1) ROA	(2) ROA	(3) ROA	(4) ROA
Variables	*All Firms*		*Matched Sample*	
HIT_RATIO	−0.009**	−0.012***	−0.024***	−0.020***
	(0.004)	(0.004)	(0.007)	(0.006)
SIZE		0.038**		0.039***
		(0.014)		(0.010)
SIZE2		−0.002*		−0.002***
		(0.001)		(0.001)
AGE		−0.050***		−0.006**
		(0.010)		(0.003)
PAGE		−0.004		−0.007**
		(0.005)		(0.003)
INTANG		−0.078***		−0.079***
		(0.013)		(0.016)
S_HHI		−0.010		−0.008
		(0.007)		(0.006)
RDC		0.040***		0.037
		(0.010)		(0.024)
PATENT		0.079		0.067***
		(0.054)		(0.024)
SGA		−0.003**		−0.002*
		(0.001)		(0.001)
AD		−0.003		0.006***
		(0.002)		(0.001)
IND_YEAR		0.133***		0.032
		(0.027)		(0.034)
STATE_YEAR		0.031		−0.020
		(0.040)		(0.034)
Constant	0.192***	0.166***	0.174***	0.051
	(0.005)	(0.046)	(0.005)	(0.038)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	No	No
Observations	16,709	14,851	5,814	4,916
Adjusted R^2	0.434	0.465	0.061	0.104

This table presents the regression results using the following equation:

$$ROA_{i,t} = \beta_0 + \beta_1 HIT\_RATIO_{i,t-1} + \mathbf{Xb_{i,t}} + \mu_t + \eta_i + \varepsilon_{it}.$$

ROA is defined as a firm's income before depreciation in fiscal year *t* divided by total assets in fiscal year $t - 1$. *HIT_RATIO* is the percentage of a firm's factories affected by natural disasters in calendar year $t - 1$. ***Xb*** is a set of control variables that include *SIZE, SIZE2, AGE, PAGE, INTANG, S_HHI, RDC, SGA, AD, PATENT, IND_YEAR*, and *STATE_YEAR*. *SIZE* is the natural log of total assets. *SIZE2* is the square of *SIZE*. *AGE* is the number of years a firm has been in the Compustat database. *PAGE* is the average age of plants; the age of a plant is the number of years it has existed in the TRI database. *INTANG* is the percentage of intangible assets defined as total assets minus current assets and net value of property, plants, and equipment scaled by total assets. *S_HHI* is the Herfindahl-Hirschman Index of sales from suppliers and is set to 0 when no information about suppliers is available. *RDC* is the natural log of amortized research and development (R&D) expenses plus 1 in the past five years $\left(\sum_{k=0}^{4} RD_{t-k}(1 - 0.2k)\right)$, in which RD_t is R&D expenses at year *t*. *PATENT* is the log of the ratio of total patents count from year $t - 4$ to *t* scaled by total assets of fiscal year $t - 1$. *SGA* and *AD* are amortized sales, general, and administrative expenses and amortized advertisement expenses, similarly defined as *RDC*. *IND_YEAR* and *STATE_YEAR* are industry-year and state-year averages of *ROA* without the focal firm itself, respectively. The sample period covers 1987 to 2014. Columns 1 and 2 use all firms. Columns 3 and 4 are based on a sample with the following matches: age, size, past performance, asset intangibility, and patents. Robust standard errors are clustered at the state level. Statistically significant at ***1%, **5%, and *10%.

25% range (i.e., the selected firm characteristics of a control firm-year observation are between 75% and 125% of those of a treated firm-year observation).

In columns 3 and 4 of table 3, we report the regression results for the matched sample. We include all the control variables as we did in equation (2), except for firm-fixed effects. The results are stronger than what we have found in columns 1 and 2: if a firm has all of its factories located in one state that was affected by a disaster (i.e., $HIT\_RATIO = 1$), this firm's ROA will be subject to approximately a 2-percentage point decrease after the disaster.

B. The Moderating Effect of Technology Diversity

In this section, we examine whether the diversity in technology could moderate the impact of natural disasters on firms. Specifically, we first present the moderating effect of technology diversity and then address the possible endogeneity issue with respect to technology diversity.

The effect of technology diversity: Baseline regression. We regress a firm's operating performance (*ROA*) on disaster impact (*HIT_RATIO*) interacted with the high technology diversity dummy (*DIV*) and all other variables included in equation (2) as follows:

$$\begin{aligned} ROA_{i,t} = {} & \beta_0 + \beta_1 HIT\_RATIO_{i,t-1} \times DIV_{i,t-1} \\ & + \beta_2 HIT\_RATIO_{i,t-1} + \beta_3 DIV_{i,t-1} \\ & + \boldsymbol{Xb_{i,t}} + \mu_t + \eta_i + \varepsilon_{i,t}. \end{aligned} \quad (3)$$

For each firm and year, *DIV* equals 1 if the technology diversity score of firm i in year $t-1$ is within the top quartile in the industry, and equals 0 otherwise. β_1, the variable of interest here, measures the moderating effect of technological diversification. We expect the coefficient to be positive and significant based on our main hypothesis.

Column 1 of table 4 shows that the coefficient on the interaction term is positive and significant as expected. Assuming that all of a firm's factories located in the state are affected by a disaster (i.e., $HIT\_RATIO = 1$), a natural disaster then leads to a decrease of 1.5% in the ROA of firms with low technology diversity but a decrease of only 0.3% in the ROA of technologically diversified firms.[13]

Table 4.—Moderating Role of Technology Diversity

	(1) ROA	(2) ROA	(3) ROA
Variables	*ALL*	*Closest 1*	*Closest 2*
*HIT_RATIO*DIV*	0.020***	0.014*	0.017**
	(0.005)	(0.008)	(0.006)
HIT_RATIO	−0.015***	−0.014**	−0.015***
	(0.004)	(0.006)	(0.005)
DIV	−0.008**	−0.006	−0.007
	(0.004)	(0.005)	(0.004)
SIZE	0.038**	0.024	0.019
	(0.015)	(0.022)	(0.024)
SIZE2	−0.002*	−0.002	−0.001
	(0.001)	(0.001)	(0.002)
AGE	−0.050***	−0.038*	−0.046**
	(0.010)	(0.019)	(0.019)
PAGE	−0.004	0.014*	0.006
	(0.005)	(0.007)	(0.007)
INTANG	−0.079***	−0.046**	−0.064***
	(0.013)	(0.021)	(0.023)
S_HHI	−0.010	−0.003	−0.007
	(0.007)	(0.006)	(0.007)
RDC	0.040***	0.023**	0.030**
	(0.010)	(0.009)	(0.012)
PATENT	0.080	0.127***	0.124**
	(0.054)	(0.034)	(0.048)
SGA	−0.003**	−0.002	−0.003*
	(0.001)	(0.001)	(0.002)
AD	−0.003	−0.002*	−0.004*
	(0.002)	(0.001)	(0.002)
IND_YEAR	0.133***	0.148***	0.149***
	(0.027)	(0.036)	(0.026)
STATE_YEAR	0.032	0.032	0.044
	(0.040)	(0.041)	(0.047)
Constant	0.166***	0.193**	0.235***
	(0.046)	(0.077)	(0.070)
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Observations	14,851	5,444	6,975
Adjusted R^2	0.465	0.506	0.48

This table presents the regression results using the following equation:

$$ROA_{i,t} = \beta_0 + \beta_1 HIT\_RATIO_{i,t-1} \times DIV_{i,t-1} + \beta_2 HIT\_RATIO_{i,t-1} + \beta_3 DIV_{i,t-1} + \boldsymbol{Xb_{i,t}} + \mu_t + \eta_i + \varepsilon_{i,t}.$$

ROA is defined as a firm's income before depreciation in fiscal year t divided by total assets in fiscal year $t-1$. *HIT_RATIO* is the percentage of a firm's factories affected by natural disasters in calendar year $t-1$. *DIV* is a dummy variable that equals 1 if the technology diversity score of firm i is within the top quartile within the SIC three-digit industry in calendar year $t-1$. ***Xb*** is a set of control variables that include *SIZE, SIZE2, AGE, PAGE, INTANG, S_HHI, RDC, SGA, AD, PATENT, IND_YEAR*, and *STATE_YEAR*. *SIZE* is the natural log of total assets. *SIZE2* is the square of *SIZE*. *AGE* is the number of years a firm has been in the Compustat database. *PAGE* is the average age of plants; the age of a plant is the number of years it has existed in the TRI database. *INTANG* is the percentage of intangible assets defined as total assets minus current assets and net value of property, plants, and equipment scaled by total assets. *S_HHI* is the Herfindahl-Hirschman Index of sales from suppliers, and is set to 0 when no information about suppliers is available. *RDC* is the natural log of amortized research and development (R&D) expenses plus 1 in the past five years $\left(i.e., \sum_{k=0}^{4} RD_{t-k}(1-0.2k)\right)$, in which RD_t is R&D expenses at year t. *PATENT* is the log of the ratio of total patents count from year $t-4$ to t scaled by total assets of fiscal year $t-1$. *SGA* and *AD* are amortized sales, general, and administrative expenses and amortized advertisement expenses, similarly defined as *RDC*. *IND_YEAR* and *STATE_YEAR* are industry-year and state-year averages of *ROA* without the focal firm itself, respectively. The sample period covers 1987 to 2011. Column 1 uses all firms, while columns 2 and 3 use samples based on propensity score matching. The propensity score is calculated from a logit model that includes *SIZE, SIZE2, AGE, RDC, INTANG, PATENT*, and industry fixed effects. With the propensity score, we use two criteria to match firms: (a) we use one firm with the nearest propensity score in column 2, and (b) two firms with the closest propensity score in column 3. Robust standard errors are clustered at the state level. Statistically significant at ***1%, **5%, and *10%.

Propensity score matching. Although natural disasters plausibly occur exogenously, technology diversity could be endogenously determined by the choice of firms. Although we have shown that natural disasters seem to affect only firms with low technology diversity, this finding could be the result of omitted variables. Hence, firms that differ in technology diversity might also differ in other dimensions. In this section, we aim to address this endogeneity concern by using a popular matching method: propensity score matching, a widely used and simple method to address endogeneity problems (Roberts & Whited 2013). We

[13] In an unreported test, we perform subsample studies for firms with high and low technology diversity, respectively. The coefficients on *HIT_RATIO* are negative in both regressions. However, the coefficient is significant only for a subsample of firms with low technology diversity, suggesting that natural disasters significantly affect only firms with low technology diversity and have an insignificant impact, though still negative, on firms with high technology diversity. The coefficients on *HIT_RATIO* between the two subsamples are statistically different with a p-value of 0.07, supporting the prediction of our main hypothesis.

conduct propensity score matching to prepare a matched sample in which all sample firms are similar in characteristics. In particular, we conduct the first-stage logit regression to calculate the propensity score of a firm identified as a high technology diversity (treated) firm as follows:

$$\begin{aligned} DIV_{i,t} = \beta_0 &+ \beta_1 SIZE_{i,t} + \beta_2 SIZE2_{i,t} + \beta_3 AGE_{i,t} \\ &+ \beta_4 RDC_{i,t} + \beta_5 INTANG_{i,t} + \beta_6 PATENT_{i,t} \\ &+ \sigma_j + \varepsilon_{i,t}. \end{aligned} \tag{4}$$

Since they are most relevant for technology diversity, we control for *SIZE, SIZE2, AGE, RDC, INTANG*, and *PATENT* as we did in equation (2). We also control for industry effects (σ_j) in the regression. We first estimate equation (4) and calculate a firm's probability for becoming a high-technology diversity firm (i.e., propensity score) from this estimation.

After calculating the propensity score, we match firm-year observations by propensity scores for the treated observations. The treated sample consists of firm-year observations that have high technology diversity. The control sample is selected from the firm-year observations that consist of firms with low technology diversity but with similar characteristics as treated firms. To ensure that the matching results are robust, we use two matching criteria: (a) for each treated firm-year observation, we match only one control firm-year observation with the closest propensity score, and (b) we match the two control firm-year observations with the closest propensity scores. In columns 2 and 3 of table 4, we report the regression results when we use the propensity-matched sample based on one and two control firm-year observations, respectively.

In the two propensity-matched samples based on different matching criteria, we obtain results similar to those in column 1 of table 4. Hence, we confirm that natural disasters negatively affect firms' profitability, but only for firms with low technology diversity.

Changes in suppliers' technology diversity. To further address the concern that technology diversity might be endogenous, we use changes in suppliers' technology diversity as an exogenous substitute variable for a focal firm's technology diversity. When suppliers' technology diversity changes, a focal firm's technology diversity is likely to be positively affected, as the focal firm has more technology variety to source from its suppliers.[14] Using the Compustat Segment data set, we follow the procedures employed in Pandit, Wasley, and Zach (2011), Ellis, Fee, and Thomas (2012), and Patatoukas (2012) to identify major buyer-supplier relationships. We then calculate the changes in technology diversity of suppliers that sell products to a focal firm but are located in different states from that of the focal firm.[15] To assess the impact of natural disasters on firms, we estimate the following regression, using the change in suppliers' technology diversity (*SUP_CH*) to substitute for the focal firms' technology diversity (*DIV*), as the former is an exogenous component of the latter:

$$\begin{aligned} ROA_{i,t} = \beta_0 &+ \beta_1 HIT\_RATIO_{i,t-1} \times SUP\_CH_{i,t-1} \\ &+ \beta_2 HIT\_RATIO_{i,t-1} + \beta_3 SUP\_CH_{i,t-1} \\ &+ \boldsymbol{Xb_{i,t}} + \mu_t + \eta_i + \varepsilon_{i,t}. \end{aligned} \tag{5}$$

If technology diversity does moderate the impact of natural disasters on firms, then we would expect β_1 to be positive, given the expected positive spillover in technology diversity along the supply chain.

As reported in table 5, we obtain results consistent with our hypothesis that technology diversity mitigates the adverse effect of natural disasters. In column 1, the coefficient on the interaction term is 0.147. A 1-standard deviation increase (0.05) in *SUP_CH* will decrease the magnitude of the impact of natural disasters by 0.007. Given that the coefficient on *HIT_RATIO* is –0.012, the moderating effect is strong. In column 1, for the observations without identifiable suppliers from the Compustat Segment data set, we set *SUP_CH* to 0. To address this possible bias, we use a dummy variable (*D_MISS*) that equals 1 when suppliers' information is unavailable and 0 otherwise; doing so is similar to how missing R&D expenditures are handled in the innovation literature (Hall & Ziedonis, 2001). That said, when we include this item in our regression (column 2), our results do not change.

IV. Robustness Tests

A. *The Roles of Network Connectivity, Asset Intangibility, and Technology Intensity*

In this section, we examine if the effect of technology diversity is distinct from the effects of network connectivity and asset intangibility in mitigating the impact of natural disasters. We also examine if our results exist only in high-tech firms.

The network effect. Henriet et al. (2012) argue that the interconnectedness among firms works as an important vari-

[14] As shown in Hui et al. (2018), supply chain spillovers are a driver of supply chains' innovativeness. Indeed, among firms for which we can identify suppliers, the changes in suppliers' technology diversity ($SUP\_CH_{i,t-1}$) are positively correlated with the subsequent changes of a focal firm's technology diversity ($DIV_{i,t}$). When we focus only on nonzero changes in a supplier's technology diversity, the correlation is 0.08 at the 1% significance level.

[15] We calculate the technology diversity score of suppliers in the same way we did with the focal firm (see section II). If there are multiple suppliers, we take the average value of the diversity scores. We thereafter calculate the change in the diversity scores of the suppliers of firm i from year t – 2 to year t – 1 and label this calculation $SUP\_CH_{i,t-1}$. We have 1,044 observations that have nonzero changes on *SUP_CH*, and the mean of *SUP_CH* is 0.00, the standard deviation 0.05.

TABLE 5.—MODERATING ROLE OF TECHNOLOGY DIVERSITY: CHANGE IN SUPPLIERS' TECHNOLOGY DIVERSITY

Variables	(1) ROA	(2) ROA
HIT_RATIO	0.147**	0.145**
	(0.069)	(0.071)
*HIT_RATIO*SUP_CH*	−0.012***	−0.012***
	(0.004)	(0.004)
SUP_CH	−0.016	−0.016
	(0.024)	(0.024)
D_MISS		−0.010
		(0.018)
SIZE	0.038**	0.039***
	(0.014)	(0.014)
SIZE2	−0.002*	−0.002**
	(0.001)	(0.001)
AGE	−0.050***	−0.050***
	(0.010)	(0.010)
PAGE	−0.004	−0.004
	(0.005)	(0.005)
INTANG	−0.078***	−0.077***
	(0.013)	(0.013)
S_HHI	−0.010	−0.020
	(0.007)	(0.013)
RDC	0.040***	0.040***
	(0.010)	(0.010)
PATENT	0.078	0.078
	(0.054)	(0.054)
SGA	−0.003**	−0.003**
	(0.001)	(0.001)
AD	−0.003	−0.003
	(0.002)	(0.002)
IND_YEAR	0.132***	0.133***
	(0.027)	(0.027)
STATE_YEAR	0.031	0.031
	(0.040)	(0.040)
Constant	0.166***	0.175***
	(0.046)	(0.052)
Year fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Observations	14,851	14,851
Adjusted R^2	0.465	0.465

This table presents the regression results using the following equation:

$$ROA_{i,t} = \beta_0 + \beta_1 HIT\_RATIO_{i,t-1} \times SUP\_CH_{i,t-1} + \beta_2 HIT\_RATIO_{i,t-1} + \beta_3 SUP\_CH_{i,t-1} + \beta_4 D\_MISS_{i,t-1} + \boldsymbol{Xb_{i,t}} + \mu_t + \eta_i + \varepsilon_{i,t}.$$

ROA is defined as a firm's income before depreciation in fiscal year t divided by total assets in fiscal year $t-1$. *HIT_RATIO* is the percentage of a firm's factories affected by natural disasters in calendar year $t-1$. *SUP_CH* is the change in the suppliers' technology diversity in year $t-1$. If a firm has multiple suppliers, this variable is calculated as the average value. For firms with missing supply chain information, we set *SUP_CH* to 0. We use *D_MISS*, a dummy variable, for firms with missing supply chain information. ***Xb*** is a set of control variables that include *SIZE*, *SIZE2*, *AGE*, *PAGE*, *INTANG*, *S_HHI*, *RDC*, *SGA*, *AD*, *PATENT*, *IND_YEAR*, and *STATE_YEAR*. *SIZE* is the natural log of total assets. *SIZE2* is the square of *SIZE*. *AGE* is the number of years a firm has been in the Compustat database. *PAGE* is the average age of plants; the age of a plant is the number of years it has existed in the TRI database. *INTANG* is the percentage of intangible assets defined as total assets minus current assets and net value of property, plants, and equipment scaled by total assets. *S_HHI* is the Herfindahl-Hirschman Index of sales from suppliers and is set to 0 when no information about suppliers is available. *RDC* is the natural log of amortized research and development (R&D) expenses plus 1 in the past five years $\left(i.e., \sum_{k=0}^{4} RD_{t-k}(1-0.2k)\right)$, in which RD_t is R&D expenses at year t. *PATENT* is the log of the ratio of total patents count from year $t-4$ to t scaled by total assets of fiscal year $t-1$. *SGA* and *AD* are amortized sales, general, and administrative expenses and amortized advertisement expenses, similarly defined as *RDC*. *IND_YEAR* and *STATE_YEAR* are industry-year and state-year averages of *ROA* without the focal firm itself, respectively. We also include firm and year fixed effects. The sample period covers 1987 to 2011. Robust standard errors are clustered at the state level. Statistically significant at ***1%, **5%, and *10%.

able in explaining how disasters affect firm performance. Using firm-level data related to the Great East Japan earthquake, Todo et al. (2015) show that supply chain networks have both positive and negative effects on firms' resilience when natural disasters strike. One concern for our baseline finding is that firms with high technology diversity also have more extensive networks that enhance their resilience following natural disasters. To show that our results are robust to this concern, we collect data on the geographic locations of plants and suppliers of focal firms. Presumably firms with more geographically diversified plants are more likely to be connected to an extensive network (i.e., connected to more firms). Also, firms that do not rely on any single major supplier are associated with a more extensive network. We collect the geographic information of a focal firm's plants from the TRI data set and collect information about a focal firm's major suppliers from the Compustat Segment data set. We separate our sample by whether firms' plants are all in one state or whether there exists a major supplier, and we then estimate equation (3) for each subsample. We report the results on geographic diversity in columns 1 and 2 of table A.1 and report the results on supplier concentration in columns 3 and 4.

Columns 1 and 2 show that the effect of technology diversity exists not only in firms that are less likely to have an extensive network (low geographic diversity) but also in firms that are more likely to have an extensive network (high geographic diversity). Columns 3 and 4 show that the effect of technology diversity exists not only in firms with less concentrated suppliers but also in firms with more concentrated suppliers, respectively. These results suggest that the presence of extensive networks (or not) does not alter our results.

Asset intangibility. Another concern for our baseline finding is that firms with high technology diversity also have more intangible assets that may mitigate the vulnerability of firms under disasters (Leiter et al., 2009). To show that our results are robust to this concern, we examine the effects of technology diversity in subsamples split by the share of intangible assets. For that purpose, we calculate the share of intangible assets by using total assets less current assets and the net value of property, plants, and equipment, scaled by total assets. We then separate our sample into subsamples based on the share of intangible assets by annual medians. In columns 5 and 6, we report the results for firms with low and high shares of intangible assets, respectively. We observe that in both subsamples, our results that technologically diversified firms are less subject to the impact of natural disasters remain. Our baseline results thus cannot be simply attributed to intangible assets.

High-tech versus non-high-tech industries. The third concern that one may have is that firms with high technology diversity might be simply those in high-tech industries. To mitigate this concern, we follow Li et al. (2008) and assign firms of three-digit SIC codes 357, 365, 366, 367, 381, 382, 384, and 386 to high-tech industries and all other firms to non-high-tech industries. Our results, which we report in columns 7 and 8 of table A.1, suggest that the effect of technology diversity exists not only in high-tech industries but also in non-high-tech industries. It is perhaps unsurprising that this effect is more pronounced in the former group. Nevertheless, our evidence suggests that our baseline results cannot be simply attributed to technology intensity.

B. Alternative Definitions of HIT_RATIO

Our main explanatory variable, *HIT_RATIO*, which represents the percentage of plants affected by natural disasters, is relatively easy to calculate but has drawbacks. Obviously, not all plants are equally important to firms, nor are all plants equally affected by the same disaster. Thus, we try to use available data to construct four alternative measures of *HIT_RATIO* to examine the robustness of our baseline findings. Ideally, if we had the contribution of profits or production levels of each plant, we could use those data to calculate *HIT_RATIO*. However, because we do not have such data, we use two methods to estimate the importance of plants. We first use the waste produced by each plant, which is available in the TRI database, as a proxy for the production level in each plant,[16] and then we calculate a weighted *HIT_RATIO* in the following way. If a plant is hit by disasters in year *t*, we generate a dummy *HIT* that equals 1; *HIT* equals 0 otherwise. We next calculate the weighted average of *HIT* for each firm in a year, with the weight being waste produced by each plant, as our measure of *HIT_RATIO*. Using this weighted measure, we rerun equations (2) and (3) and report the results in columns 1 to 3 of table A.2. We find that, again, firms that experience natural disasters are less profitable than unaffected ones, but their loss is mitigated by technology diversity.

The second alternative measure of *HIT_RATIO* uses state mentioning in annual financial reports (Garcia & Norli, 2012). For example, if California is mentioned more often than Louisiana in the annual report of a firm, then for this firm, plants in California may be more important than those in Louisiana. Thus, the weight of a plant to a firm can be approximated by the percentage of state mentioning within an annual report (i.e., if California consists of 10% of a firm's total state mentioning, then plants located in California receive a weight of 0.1). We thus calculate our second weighted *HIT_RATIO* with the weight being state mentioning. We report the results based on this measure in columns 4 to 6 of table A.2, and these results are consistent with our baseline results.

We next consider the differential impacts of the same disaster on different firms in different areas. Searching online news, we manually collect data on firms' economic losses due to natural disasters at the county level, and we obtain 1,539 county-year economic loss observations. To calculate the loss-weighted *HIT_RATIO*, we attach a weight of 1 (original weight) to plants in locations where we cannot find economic loss data and attach 1 plus the economic loss in billions (the maximum is 17) as the weight for plants in counties for which we can find economic loss data. Using these weights, we calculate our third weighted *HIT_RATIO*. We report our results using this alternative measure in columns 7 to 9 of table A.2, and these results are consistent with our baseline results. Finally, we sum all losses at the county level to the state level and calculate the fourth weighted *HIT_RATIO* using state-level economic losses in the same way as the third one. We report consistent results in columns 10 to 12 of table A.2.

Overall, our baseline results are robust when we use different data sources to analyze the heterogeneity on the impacts of natural disasters on plants.

C. Alternative Definitions of Technology Diversity

In this section, we use three alternative measures of technology diversity to ensure our results do not depend on any single, specific definition of technology diversity. First, instead of using equation (1) to measure the diversity score, we use a simple count of the number of categories in which a firm participates (*J*), so that the robustness does not depend on a specific formula to calculate diversity scores. Second, we vary the technology categories from the one-digit categories to the two-digit subcategories of Hall et al. (2001), denoted by *SUBCAT*, which are finer and more specific. Third, we use the following logarithmic method to calculate technology diversity *CAT2*:

$$CAT2_{i,t} = \sum\nolimits_{j=1}^{J} [S_j ln(1/S_j)], \tag{6}$$

for which *J* denotes the number of technology categories in which firm *i* has filed patents from year $t-2$ to year t, S_j denotes the share of filed patents in the *j*th technology category ($j = 1,\ldots,J$), and *N* denotes the number of filed patents from year $t-2$ to year t. After calculating each of these technology diversity measures for each firm for each year, we again generate the dummy *DIV*, which equals 1 if the technology diversity score of the firm is within the top quartile in the industry.

We present these results in table A.3 in the online appendix. Using alternative definitions of technology diversity, we obtain results similar to those in column 1 of table 4. For firms with high technology diversity, the impact of natural disasters is much weaker, as reflected by the positive and significant coefficients on the interaction term in all columns.

D. Alternative Cutoff Points for High Technology Diversity

Thus far, we have used the top quartile as our cutoff for classifying high and low technology diversity firms. In this section, we show that our findings are robust to this cutoff choice; as long as a firm has relatively high technology diversity in its respective industry, that firm will be less subject to the impact of natural disasters. In table A.4 in the online appendix, we report our regression results using the 80th, 85th, and 90th percentiles as cutoff points for high

[16] Such a design assumes that all plants of a firm operate similarly and that the amount of waste appropriately reflects plants' output levels.

technology diversity firms in columns 1, 2, and 3, respectively. We observe that irrespective of these selected cutoff points, technologically diversified firms always respond more resiliently when natural disasters strike.

E. *Alternative Ways in Clustering Standard Errors*

Finally, we examine if our results are robust to various clustering standard errors. In table A.5 in the online appendix, we estimate equations 2 and 3 under different clustering levels. In columns 1 to 3, we cluster standard errors at the firm level. In columns 4 to 6, we cluster standard errors at the industry level. We then use two-way clustered standard errors by firm and industry (columns 7 to 9), two-way clustered standard errors by firm and year (columns 10 to 12), two-way clustered standard errors by industry and year (columns 13 to 15), and two-way clustered standard errors by state and year (columns 16 to 18). Our results are robust to all levels of clustering.

V. Conclusion

Natural disasters are unpredictable events that not only cause significant fatalities and property losses but also disrupt corporate operations. Our empirical analysis identifies the magnitude of the damage of natural disasters on firms' profitability and highlights how firms might use technologies to mitigate the damage. Our empirical results of the impacts of natural disasters provide new evidence to the economics literature stream that explores this phenomenon. Specifically, we propose that an innovation strategy that emphasizes technological diversification helps firms survive and endure natural disasters, for such a strategy contributes to flexibility, adaptability, and resourcefulness, all associated with technology diversity, that firms require to respond resiliently to natural disasters. This proposition is supported by our empirical results, which confirm that firms with diversified patent portfolios are significantly less subject to the impact of natural disasters. This study highlights the role of innovation strategies with respect to corporate sustainability, and our findings point to the advantage of technology diversity to mitigate operational risks.

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