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Firms' Management of Infrequent Shocks

We examine businesses' financial management of a rare, severe event using detailed firm-level data collected following Hurricane Sandy in the New York area. Credit played a prominent role in financing recovery; more negatively affected firms took on debt because of Sandy (39%) than received insurance payments (15%) in our data. Negatively affected firms were frequently credit constrained after the shock. We also find that the most credit-constrained firms after the event, younger firms, and smaller firms, were the least likely to insure before it. Our findings align with the predictions of dynamic risk management theory (Rampini and Viswanathan 2010, 2013).

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We examine businesses' financial management decisions regarding an infrequent, severe risk. Hurricane Sandy struck the New York area in the fall of 2012. Our data were collected 1 year after the event in the affected area through a survey of businesses, which comprised detailed questions regarding firms' insurance and credit decisions. The surveyed businesses are small and medium enterprises (SMEs), firms with 500 employees or fewer.[1] Nine hundred forty-nine businesses participated in the areas affected most by Sandy. We specifically consider how these businesses financed losses from the event: whether they were insured, if the event increased their demand for credit, and whether they were credit constrained. We find that the storm proved a financial challenge for many firms with smaller firms and younger firms disproportionately bearing the costs of the disaster.

SMEs play an important economic role in the U.S., accounting for 50% of employment (Caruso 2015) and 45% of GDP (Kobe 2012). Recent disasters such as Hurricane Harvey have highlighted their vulnerability to severe events (Simon and McWhirter 2017). Such cases are of concern because the frequency and severity of these events are increasing so that severe weather risks may play a more prominent role in the success and failure of SMEs in the future.[2]

We find that much of businesses' losses from Sandy were not covered by insurance. Hurricane Sandy had a negative financial impact on one-third of the firms in our data. The event damaged firms' assets and disrupted their operations (e.g., through utilities outages and customer relocation). Many negatively affected firms were uninsured: 29% had no insurance of any kind. Moreover, insured businesses often did not have coverage for the kinds of losses that Sandy created: 74% of businesses with property insurance, 72% with business interruption insurance, and 52% of businesses with flood insurance reported that *none* of their losses from the event had been covered by their policies.

Credit played a prominent role in financing recovery for firms negatively affected by Sandy in our data. More negatively affected firms took on debt because of Sandy (39%) than received insurance payments (15%). Negatively affected firms were about twice as likely as unaffected firms to apply for credit following the storm and spent more time completing credit applications. Businesses incurring large losses that were not covered by insurance were significantly more likely to apply for credit than businesses incurring large losses that were fully paid by insurance.

Sandy also tightened credit constraints: negatively affected firms were more than twice as likely to report that their access to financing had decreased relative to the previous year. These firms were 35% more likely to be required to secure loans with collateral and 2.7 times as likely to experience interest rate increases as unaffected firms.

We also find that firms' insurance and credit decisions varied by their age and size. Younger firms and smaller firms are significantly less likely than older firms and

1. SMEs are often called "small businesses" in the U.S. and commonly classified as businesses with fewer than 500 employees (Small Business Administration [SBA] 2014). All the businesses in our study and 99.7% of U.S. businesses fall into this category (Caruso 2015).

2. Cummins, Suher, and Zanjani (2010) estimate that over the next 75 years the U.S. government's exposure alone to the cost of catastrophes could reach $7 trillion.

larger firms to insure. Younger firms and *larger* firms are more likely to apply for credit. Our results are generally consistent with predictions that younger firms and smaller firms are more likely to experience financial frictions. Larger firms are more likely than smaller ones to receive all the credit that they requested, which seems to be explained by their ability to secure loans with collateral. In sum, we find that Sandy increased credit demand and credit constraints across all types of firms, and these Sandy effects combine with age and size effects such that the most constrained firms after the shock were negatively affected, smaller, younger firms.

Our paper contributes to the existing literature in several ways. We add to research on firms' vulnerability to and management of shocks (see, e.g., Bolton, Chen, and Wang 2011, Iyer et al. 2014, Berger, Bouwman, and Kim 2017). The richness of our data regarding firms' credit decisions allows for a more nuanced assessment than is typically possible of how firms address their risk financing needs. Moreover, our sample of SMEs comprises a distinct group from the publicly traded companies typically studied (see, e.g., Nance, Smith, and Smithson 1993, Rampini, Sufi, and Viswanathan 2014) and from studies examining how households manage disasters (see, e.g., Sawada and Shimizutani 2008, Dobridge 2018). Firm heterogeneity is an important topic of our paper. Previous research has recognized that the financial constraints of smaller and younger firms likely increase their vulnerability to shocks, and our analyses further clarify this generalization. Our findings regarding firms' age and size generally align with the predictions of dynamic risk management theory (Rampini and Viswanathan 2010, 2013), that more financially constrained firms were less likely to insure. However, our analyses also contribute to a literature showing important differences between young firms and small firms (see, e.g., Haltiwanger, Jarmin, and Miranda 2013). For example, Sandy seemed to increase the credit demand of young firms, but not necessarily small firms.

The remainder of the paper is structured as follows. Section 1 summarizes relevant research from which we develop hypotheses to guide our analyses. Section 2 describes our data, estimation strategy, and identifying assumptions. Section 3 describes our results. Section 4 provides robustness tests and extensions of our main analyses. Section 5 concludes.

1. RELEVANT RESEARCH AND HYPOTHESES

A substantial literature uses shocks to understand firms' financing constraints (see, e.g., Jiménez et al. 2012, Gilje and Taillard 2016, Berger, Bouwman, and Kim 2017). It has shown financing frictions in a variety of settings and that these frictions can vary across firms. For example, Iyer et al. (2014) examine the effects of an unanticipated freeze in European interbank credit markets on the credit supplied to businesses in Portugal. Large firms found credit at less affected banks; however, smaller firms and younger firms were generally unable to manage this transition and so borrowed less. A few papers examine financing needs and constraints after natural disasters. Chavaz (2015) finds that local banks increase SME lending in communities affected by hurricanes in the U.S. Berg and Schrader (2012) find that loan applications increased for an SME lender in Ecuador following volcanic activity. While approval rates were unaffected for previous borrowers, new applicants were significantly less likely to be approved after a volcanic eruption.

Financial constraints are a common explanation for firms' insurance and hedging decisions. Froot, Scharfstein, and Stein (1993) note that higher financing costs *after* a shock might motivate firms to hedge. In contrast, Rampini and Viswanathan (2010, 2013) posit that *ex ante* financing constraints might more importantly explain firms' risk management decisions. They theorize that financially constrained firms are *less* likely to insure as dedicating resources to risk management (e.g., paying insurance premiums) diverts them from production. As financing frictions tend to be greater for smaller firms and younger firms, their theory predicts that these firms are less likely to insure. Indeed, smaller airlines tend to hedge less (Rampini, Sufi, and Viswanathan 2014), as do smaller banks (Rampini, Viswanathan, and Vuillemey 2017).[3] Nance, Smith, and Smithson (1993) study Fortune 500 and S&P 400 firms and also find that the likelihood that a firm hedges is increasing in size.

Finally, while smaller firms and younger firms are sometimes lumped together, a recent line of research on firm demographics has observed important differences between the small and the young (see, e.g., Adelino, Ma, and Robinson 2017). This research notes that while U.S. public policies have tended to target small firms, it is young firms that increase economic productivity and employment (Foster, Haltiwanger, and Syverson, 2008, 2016, Haltiwanger, Jarmin, and Miranda 2013). Hurst and Pugsley (2011) find that while young firms are often small, many will grow into large firms as they mature. However, some firm owners do not prioritize growth (e.g., their goal is to be self-employed) and these firms are more likely to remain small. Thus, smaller firms and younger firms may differ regarding their demand for and access to credit following a disaster and so we examine both age and size in our analyses.

To organize our analyses, we develop three sets of hypotheses from previous research regarding the insurance decisions (H1), credit demand (H2), and credit constraints (H3) of firms negatively affected by Hurricane Sandy.

1.1 Insurance

H1a: Insuring against disasters is increasing in firm size.
H1b: Insuring against disasters is increasing in firm age.

1.2 Credit Demand

H2: Sandy increased credit demand among negatively affected firms.
H2a: Credit demand is decreasing in firm size.
H2b: Credit demand is decreasing in firm age.

3. These papers examine the use of derivatives such as interest rate swaps rather than the property and business interruption insurance products that we consider.

1.3 Credit Constraints

H3: Sandy increased credit constraints among negatively affected firms.
H3a: Credit constraints are decreasing in firm size.
H3b: Credit constraints are decreasing in firm age.

Regarding insurance, we examine several types of insurance coverage: property, flood, and business interruption. As measures of credit demand, we assess whether firms searched for credit, whether they applied for credit, the types of products for which they applied, and the time spent applying. As measures of credit constraints, we assess whether firms perceive that their access to financing had changed relative to the previous year, their interest rates had increased during this time, they were required to secured loans with collateral, and they received all the financing that they had requested.

2. METHODS

In this section, we first describe how the data were collected. Our data comprise a cross-sectional survey of firms performed by the Federal Reserve Bank of New York (FBNY 2014). The surveyors created an online survey and partnered with civic and nonprofit organizations such as chambers of commerce who contacted businesses in their network to inform them of the survey and ask for their participation. Thus, the participating businesses are associated with the partner organizations and not necessarily representative of all businesses in the New York area. Representativeness relates to the external validity (i.e., generalizability) of our findings, and is secondary to considerations of internal validity. Next, we describe our estimation strategy and identifying assumptions, discussing internal validity and potential selection bias in detail. We conclude this section with descriptive statistics on firms' age and size and on negatively affected firms.

2.1 Data

Since 2010, the FBNY has conducted the Small Business Credit Survey annually (or biannually in some years), polling businesses with fewer than 500 employees about their financing. The survey that was collected in November 2013 included a series of questions regarding Hurricane Sandy, roughly 1 year after the event. Respondents were in Connecticut, New Jersey, New York, and Pennsylvania. The survey and additional details on the data collection methodology are available from the FBNY (2014). We include the specific survey question in a footnote for each outcome variable that we assess below.

We limit our focus to respondents in the disaster areas declared by the U.S. Federal Emergency Management Agency (FEMA), counties that qualify for individual and public assistance from the federal government for Hurricane Sandy, which we call

TABLE 1

COMPARISON OF FIRMS IN THE SAMPLE TO THE REGION

	Total population of firms in region	Total Sample	Disaster County Sample
Firm age			
0–2 years	22.4%	16.7%	15.6%
3–5 years	16.7%	15.1%	14.4%
6–10 years	20.0%	18.2%	19.1%
11–20 years	23.4%	20.3%	22.2%
21+ years	17.6%	29.7%	28.7%
Firm size			
1–4 employees	57.3%	48.6%	50.8%
5–9 employees	18.0%	18.8%	18.9%
10–19 employees	12.0%	14.0%	13.7%
20–99 employees	10.7%	16.0%	14.9%
100–499 employees	2.0%	2.6%	1.8%
Location			
Connecticut	7.8%	5.0%	6.7%
New Jersey	20.0%	15.9%	25.9%
New York (minus NYC)	26.4%	24.7%	13.9%
New York City	19.8%	32.8%	53.4%
Pennsylvania	26.1%	21.6%	-
Industry			
Agriculture	0.1%	1.0%	0.2%
Construction	8.8%	13.3%	16.1%
Manufacturing	3.8%	11.0%	6.4%
Retail	14.7%	10.4%	9.6%
Wholesale/Transportation	8.5%	7.0%	8.6%
Information/Media/Telecom	1.9%	3.9%	4.2%
Finance/Insurance/Real estate	10.3%	4.6%	5.4%
Professional & Business services	11.3%	18.7%	20.4%
Personal services	10.8%	2.7%	3.0%
Education/Healthcare & Soc. Assist.	12.8%	7.2%	6.8%
Leisure & Hospitality	11.0%	7.7%	7.1%
Other	6.2%	12.6%	12.1%
Firm count	1,129,211	1,548	949

NOTE: The table compares firms in the sample to the population of firms in the region. The sample data were collected in the fall of 2013. The data collection procedures used stratified sampling by firm age, size (in employees), location (state), and industry, attempting to match the regional distribution. The Disaster County Sample includes observations from the Total Sample in counties declared disaster areas by FEMA due to Hurricane Sandy. The Disaster County Sample is the data used in our analyses unless noted otherwise. Population age data are from Census Bureau (2011a); all other population data are from Census Bureau (2011b).

the “Disaster County Sample.” On October 29, 2012, Sandy made landfall along the New Jersey coast as a posttropical storm. The storm caused more than $70 billion in damages, becoming the second costliest such event in U.S. history after Hurricane Katrina (NOAA HRD 2014; see the Online Appendix, Section A.1, for more on the effects of Hurricane Sandy). All of New Jersey, New York City, counties in the southeast of Hudson Valley of New York, and the coastal counties in Connecticut were declared disaster areas, 38 counties overall. In total, 1,548 firms completed the survey, and 948 were in counties declared disaster areas qualifying for individual and public assistance. Table 1 compares the Disaster County Sample and the Total Sample to the population of firms in the survey area. The surveyors were largely, but not fully, able to stratify the sample with respect to the distribution of age, size (in employees), location (state), and industry of firms in the area.[4]

2.2 Estimation

This section presents our preferred estimation strategies. Our outcome variables are typically binary and unless otherwise noted we report linear probability models with White's (1980) heteroskedasticity-consistent standard errors clustered by county.[5] Linear probability models facilitate interpreting model intercepts, indicator variables, and interaction terms, which we frequently do in our analyses. We also estimated the presented regressions as logit models, finding consistent results with those presented below.

The regressions related to insurance take two forms. Only firms reporting that they were affected by Sandy answered questions about what insurance they had in place during Sandy. Our analyses of insurance decisions are restricted to negatively affected firms. Specifically, we consider how a firm's age and size (in employees) affected the likelihood that it was insured during Sandy. First, we examine the effects of age and size by binning firms by quartile. We estimate binary outcome y (e.g., whether a firm has property insurance) for firm i

$$y_i = \mathbf{I}\left(\sum_{l=1}^{3} \beta_l \mathbf{I}\left(AgeQuartile_{i,l}\right) + \sum_{m=1}^{3} \lambda_m \mathbf{I}\left(EmployeesQuartile_{i,m}\right) + \delta_j + \eta_k + u_i > 0\right), \tag{1}$$

where, for example, $\mathbf{I}(AgeQuartile_{i,1})$ is the indicator function for whether firm i is in the first age quartile. We examine age and size quartiles to account for possible nonlinear effects. Parameters δ_j and η_k are county and industry fixed effects, respectively, and u_i is an error term. In these regressions, the oldest firms and largest firms serve as reference groups. In a second model of insurance decisions, we interact age and size quartiles

$$Insurance_i = \mathbf{I}\left(\sum_{l=1}^{4}\sum_{m=1}^{4} \beta_{l,m} \mathbf{I}\left(AgeQuartile_{i,l}\right) \times \mathbf{I}\left(EmployeesQuartile_{i,m}\right) + \delta_j + \eta_k + u_i > 0\right), \tag{2}$$

where $Insurance_i$ is an indicator variable for whether firm i has insurance of any kind. In this regression, the oldest, largest firms serve as the reference group.

4. The surveyors stratified the sample by having the partner organizations target businesses that were underrepresented in the survey. For example, if few businesses in a certain industry were in the sample, the partner organizations would send a reminder e-mail to businesses in that industry.

5. Model errors may be correlated by country and/or industry. Our data include 38 counties and only 12 industries so we use county clusters to improve estimation of the coefficients' variance matrix (Cameron and Miller 2015). We examined models without clustering and clustering by industry; each lead to qualitatively similar results.

Our regressions related to credit demand and constraints examine the consequences of being negatively affected by Hurricane Sandy. We estimate outcome y (e.g., whether a firm's interest rates increased) for firm

$$\begin{aligned} y_i = {} & \beta_0 + \beta_1 \mathbf{I}\left(Neg.\,Affected_i\right) + \beta_2 \mathbf{I}\left(Age_i,\ 1st\ Quart\right) \\ & + \beta_3 \mathbf{I}\left(Age_i,\ 2nd\ Quart\right) + \ \beta_4 \mathbf{I}\left(Employees_i,\ 1st\ Quart\right) \\ & + \beta_5 \mathbf{I}\left(Employees_i,\ 2nd\ Quart\right) + \ \beta_6 \mathbf{I}\left(Age_i,\ 1st\ Quart\right) \\ & \times \mathbf{I}\left(Neg.\,Affected_i\right) + \ \beta_7 \mathbf{I}\left(Age_i,\ 2nd\ Quart\right) \times \ \mathbf{I}\left(Neg.\,Affected_i\right) \\ & + \beta_8 \mathbf{I}\left(Employees_i,\ 1st\ Quart\right) \times \mathbf{I}\left(Neg.\,Affected_i\right) \\ & + \beta_9 \mathbf{I}\left(Employees_i,\ 2nd\ Quart\right) \times \mathbf{I}\left(Neg.\,Affected_i\right) + \delta_j + \eta_k + u_i, \end{aligned} \tag{3}$$

where $\mathbf{I}(Neg.Affected_i)$ is an indicator for whether a firm reported being negatively affected by Sandy. Variable $\mathbf{I}(Age_i,\ 1st\ Quart)$ is an indicator for firms in the first age quartile and so on. We include indicators for the first and second age quartiles and first and second size (employees) quartiles as previous research indicates that younger firms and smaller firms tend to be more credit. Thus, the reference group for the age quartiles is firms above the median age; for the size quartiles, it is firms that are above the median size.[6] We interact whether a firm was negatively affected with the age quartiles and with the size quartiles. The models also include county and industry fixed effects. We construct the model's intercept β_0 to facilitate comparisons between negatively affected and other firms (those that were not negatively affected). We constrain the county and industry fixed effects so that $\sum_{j=1}^{J} \delta_j = 0$ and $\sum_{k=1}^{K} \eta_k = 0$. Given this construction, the intercept represents the average (above-median age and size) firm that was not negatively affected in our data. Many of our outcome variables using equation (3) are binary. For consistent notation with equations (1) and (2), we might concisely rewrite equation (3) as $y_i = \mathbf{I}(\mathbf{x_i}\boldsymbol{\beta} + \delta_j + \eta_k + u_i > 0)$ in those cases.[7]

Equation (3) follows a treatment effects structure, which we use to examine the effects of Sandy in three ways. For illustration, consider whether a firm searched for credit in the months following Sandy as the outcome of interest. First, the regression shows the average effect of Sandy across above-median age and size firms, captured in β_1. Thus, a statistically significant $\beta_1 = 0.2$ indicates that being negatively affected increases the likelihood that a firm searched for credit by 20 percentage points relative to firms in the control group. Second, it shows how a firm's age and its size affect whether it searched for credit, captured in β_2 through β_5. Thus, a statistically significant $\beta_2 = 0.18$ would indicate that firms that are in the first age quartile are 18 percentage points more likely to search for credit than firms above the median age. Third, it shows whether the treatment effect varies by a firm's age and size

6. We also tested three-way interaction terms of age, size, and whether firms were negatively affected by Sandy. Those terms were typically insignificant and provided few additional insights. Because of the difficulty of interpreting three-way interaction terms, we have omitted them from these regressions.

7. We also examined these models including indicators for the third quartiles for age and size so that the reference groups become firms in the fourth quartile. Those models were notably more complicated to interpret and provided very few additional insights, and so the estimation in equation (3) is our preferred model.

(i.e., whether Sandy changes the effects of a firm's age and it size), captured in the coefficients for the interaction terms β_6 and β_9. Thus, a statistically significant $\beta_6 = 0.02$ would indicate that negatively affected firms that are in the first age quartile are 2 percentage points more likely to search for credit than the treatment effect β_1 and the age effect β_2 would predict.[8]

While our sample includes 949 firms, our observations differ across regressions. Differences in observations are largely because the questions asked of each firm depend on its prior responses. For example, only firms that applied for credit were asked how much time they spent applying. In a few cases, observations also change because firms elected not to answer certain questions (e.g., 793 businesses answered that they used some form of collateral to secure their loan, but only 790 indicated whether this collateral was business real estates). We cannot identify a pattern in these missing observations that is relevant to our analysis.

2.3 *Identifying Assumptions*

These survey data provide unparalleled detail on firms' insurance and credit characteristics and their experiences during a major natural disaster; however, they are prone to several of the challenges inherent to a retrospective, cross-sectional survey design. We consider our empirical identification strategy for the credit and insurance models described in Section 2.2. Section 4 includes several robustness tests to further examine these assumptions.

Credit hypotheses and treatment effects assumptions. Our estimation approach for the credit outcomes of interest is called "regression adjustment" in the treatment effects literature (Wooldridge 2010, ch. 21). Its identifying assumptions rely on the concept of ignorability of treatment, conditioning on a set of explanatory variables, the credit outcomes of firms that were not negatively affected serve as a counterfactual for those of negatively affected firms. As a specific example, this approach assumes that if it were not for Sandy, negatively affected firms would have applied for credit at the same rate as other firms that were of a similar age and size and in the same industry and county.[9] To illustrate, consider the model of outcome y (e.g., whether a

8. A statistically insignificant β_6 or β_9 should not, however, be interpreted to mean that a negatively affected firm's age or size does not matter, rather they indicate that the effects of age or size operate similarly among negatively affected firms as other firms. For example, suppose that $\beta_1 = 0.20$, $\beta_2 = 0.18$, and $\beta_4 = 0$. We would estimate that, compared to the control group, a negatively affected firm of above-median age is 20 percentage points more likely to search for credit, and a negatively affected firm that is in the first age quartile is 38 percentage points more likely to search for credit. Thus, among negatively affected firms, younger ones may be especially likely to search for credit because of the direct effect of age.

9. An additional consideration for these models is whether the distributions of the variables of interest overlap for treatment and control groups. For example, comparing the effects of a firm's age for negatively affected firms and unaffected firms requires similar variation in age across these groups. Imbens and Rubin (2015, ch. 14) propose measuring normalized differences to assess overlap. The measure is $(\mu_1 - \mu_0)/(s_1^2 + s_0^2)^{1/2}$ where μ is the variable's mean and s its sample standard deviation for groups 0 and 1. Values greater than 0.25 are a cause for concern (Wooldridge 2010, ch. 21). Overlap between treatment and controls groups for age is 0.06 and overlap between groups for size (in employees) is 0.03, indicating sufficient overlap in both cases.

firm searched for credit) for firm i

$$\mathrm{E}\left[y_i|D_i = 1\right] = \beta + \mathbf{C}'_i\boldsymbol{\gamma} + \mathrm{E}\left[u_i|D_i = 1\right],$$
$$\mathrm{E}\left[y_i|D_i = 0\right] = \mathbf{C}'_i\boldsymbol{\gamma} + \mathrm{E}\left[u_i|D_i = 0\right],$$

where D indicates being negatively affected by Sandy, $\mathbf{C}$ is a vector, and u an error term. This model provides the effect of Sandy β, but only if $\mathrm{E}[u_i|D_i = 1] = \mathrm{E}[u_i|D_i = 0]$.

Insurance hypotheses and possible selection bias. Regarding the insurance hypotheses, our insurance models examine the insurance decisions of negatively affected firms as only firms affected by Sandy were asked about their insurance. Analyzing the insurance of firms negatively affected by Sandy is attractive in that we know *ex post* that these firms were exposed to a major hurricane; however, selection bias can result in inconsistent parameter estimates for the relationships of interest—how a firm's age and size affect its insurance decisions—as these relationships may differ in the subpopulation (negatively affected firms) from the total population of firms. We assess this possibility using Heckman selection models (Section 4), which account for nonrandom sample selection as an omitted variable problem.

Measuring firm size. Firms report their size in terms of employees and revenues *at the time of the survey*, but our interest lies in the firm's size at the time of Sandy. This is a limitation of our data as a firm's insurance in place during Sandy or its credit access afterward might affect these measures of size, affecting the amounts reported on the survey. For example, an uninsured firm might need to lay off employees due to its losses from Sandy. We take three steps to address this limitation in our measure of firm size in our analysis. First, we rely on previous research in interpreting our findings, which posits that smaller businesses are less likely to insure and more likely to be credit constrained than larger ones (Section 1). Second, we use employees to measure size as it is likely more persistent than other measures such as revenues (e.g., due to the transaction costs of hiring and firing employees). Finally, our estimations are structured to reduce the influence of small changes in firm size by binning firms by quartile. Thus, the estimations capture the effects of size as long as Sandy is not systematically causing firms to switch quartiles. Using U.S. Census Bureau data, we examine firm demographics and closures in New Jersey before and after Sandy in Section 4.

2.4 Descriptive Statistics on Negatively Affected Firms and Firms' Age and Size

One-third of the firms in the disaster counties report being negatively affected by Hurricane Sandy in our data. Firms in New Jersey and New York City were significantly more likely to be negatively affected than those in Connecticut or New York State. Firms in the leisure and hospitality industries were more likely to be negatively affected than those in other industries. Disasters do increase demand for some goods and services (e.g., consumers need to replace damaged durable goods),

TABLE 2
FIRM LOSS SOURCE AND MAGNITUDE OF LOSS FROM SANDY

		Reported loss amount per employee (by percentile)				
Loss source	Frequency	P10	P25	P50	P75	P90
Customer	61.2%	$1,167	$2,500	$6,250	$17,500	$37,500
Utilities	43.6%	$921	$1,786	$5,000	$11,667	$25,000
Assets	29.7%	$3,289	$4,688	$12,500	$25,000	$75,000
Supplier	12.5%	$1,000	$2,206	$5,417	$9,375	$18,750
Gasoline	11.4%	$1,346	$2,174	$5,000	$8,750	$17,500
Other	8.4%	$438	$1,750	$7,000	$25,000	$75,000

NOTE: Firms negatively affected by Hurricane Sandy. Negatively affected firms estimated the financial loss in dollars that they incurred from Sandy and were asked to select up to two sources of loss. The table shows the frequency that firms reported each loss source. It also shows the distribution of losses (loss amount per employee) for firms reporting each loss source. For example, the median loss per employee for firms reporting asset losses is $12,500; for firms reporting losses from utility disruptions, it is $5,000.

and we find that some firms report being positively affected by Sandy. Firms in construction most commonly reported being positively affected.[10]

Negatively affected firms report a combination of effects on their incomes and balance sheets: 82% report that revenue decreased, 55% that expenses increased, 42% that assets decreased, and 39% that debt increased. Negatively affected firms estimated the financial loss in dollars that they incurred from Sandy and were asked to select up to two causes of loss from a list (categories shown in Table 2). We scale the loss amount by the number of employees to increase the comparability of losses across firms.[11] Firms most frequently cited customer disruptions (e.g., customers evacuating or changing spending habits due to the storm), but the largest magnitude losses stemmed from damage to assets (see Table 2). Firms were also given the opportunity to write in other sources of loss, but no additional categories emerged.

Among negatively affected firms, 77% report an immediate financing need created by the event. Firms were asked to report their most important financing need "experienced in the aftermath of Superstorm Sandy." The most frequent financing needs reported by negatively affect firms were *meeting operating expenses* (34% of firms), *making capital investments* (11%), and *repositioning business to meet changing customer demand* (10%).

Regarding firms' age and size, Table 3 provides summary statistics. The median age is 11 years. The median size is 4 employees, but the average size is 12.6 employees, illustrating that the number of employees is right-skewed. The second part of the

10. Firms that reported being positively affected are included as part of the control group (i.e., firms not negatively affected by Sandy include both unaffected firms and positively affected firms). We also examined including indicators for positively affected firms so that they are not part of the control. Doing so results in almost identical results for the variables of interest in the models presented here.

11. The specific wording of the loss amount question is "What was the total value of your business's estimated financial losses from Superstorm Sandy?" with response options (i) Less than $10,000, (ii) $10,000–$25,000, (iii) $25,001–$50,000, (iv) $50,001–$100,000, (v) $100,001–$250,000, and (vi) Greater than $250,000. To scale the loss amount by the number of employees, we take the midpoint of each bin: if a firm answers (i), we code this value as $5,000; if it answers (vi), we code this as $250,000.

TABLE 3

Summary Statistics for Firm Age and Size

				Percentiles		
	Mean	Std. dev.	Coeff. of variation	25th	50th	75th
Age (years)	16.4	17.8	1.1	4	11	23
Size (employees)	12.6	25.4	2.0	2	4	12

Employee summary statistics by age quartile

Age quartile	Mean	Std. dev.	Coeff. of variation	25th	50th	75th
First	4.1	6.9	1.7	1	2	5
Second	9.3	20.0	2.1	2	4	9
Third	14.4	25.3	1.8	2	6	15
Fourth	24.0	36.9	1.5	4	10	25

Note: The table shows summary statistics for firm age and size. Estimation equations (1) and (2) bin firms by age quartile and size quartile, which correspond to the percentiles reported here. The coefficient of variation is the standard deviation (Std. dev.) divided by the mean. This table illustrates that young firms tend to be small, but as firms age, some grow while others stay small, increasing the coefficient of variation for firm size among older firms.

TABLE 4

Summary of Hypotheses and Conclusions

Hypothesis	Conclusion
H1a: Insuring against disasters is increasing in firm size.	Supported
H1b: Insuring against disasters is increasing in firm age.	Supported
H2: Sandy increased credit demand among negatively affected firms.	Supported
H2a: Credit demand is decreasing in firm size.	Not supported
H2b: Credit demand is decreasing in firm age.	Supported
H3: Sandy increased credit constraints among negatively affected firms.	Supported
H3a: Credit constraints are decreasing in firm size.	Partially supported
H3b: Credit constraints are decreasing in firm age.	Partially supported

table examines the relationship between firm age and size in our data. The youngest firms are almost always small, but small firms are not necessarily young. A firm's age is positively correlated with its size as measured by number of employees (Pearson's $r = 0.34$) and revenues ($r = 0.49$).

3. RESULTS

This section describes our findings related to each of the hypotheses developed in Section 1. Table 4 serves as a guide, summarizing our hypotheses and our conclusions.

TABLE 5
INSURANCE IN PLACE DURING SANDY AND LOSS RECOVERY AMONG NEGATIVELY AFFECTED FIRMS

		Reported fraction of loss recovered through insurance			
Insurance	Frequency	None	Some	Most	All
Property insurance	54.1%	71.6%	18.1%	6.3%	1.6%
Biz. Int. insurance	30.0%	72.2%	16.7%	8.3%	2.8%
Flood insurance	11.9%	51.7%	31.0%	17.2%	0.0%
No insurance	28.9%	100.0%	-	-	-

NOTE: Data on firms negatively affected by Hurricane Sandy. A total of 270 firms reported on their insurance in place during Sandy and 170 specified a recovery amount. For fraction of loss recovered, some/most refers to a loss recovery of less/more than 50%. Only firms that were affected by Sandy were asked about their insurance.

3.1 Insurance Coverage

We find that insurance played a small role in addressing the losses that firms negatively affected by Sandy incurred. Negatively affected firms in our sample were asked the types of insurance that they had in place when the event occurred and the percent of losses recovered through insurance.[12] Among insured firms, property insurance was the most common response. Twenty-nine percent of negatively affected firms reported having no insurance of any kind (Table 5).

Across all types of insurance, negatively affected firms most frequently reported that *none* of their losses from Sandy were recovered through insurance claims (Table 5). This finding does not seem to be the result of slow claims resolution: while some claims may have remained unsettled at the time of the survey (November 2013), 93% of insurance claims in New Jersey and New York had been settled by April 2013 (Insurance Information Institute 2013). Instead, this result seems broadly consistent with repeated findings that a notable proportion of disasters losses remain uninsured even in the most developed insurance markets. For example, Swiss Re (2013) estimates that approximately half ($35 billion) of the total losses from Sandy were uninsured.

The low level of insurance payments seems to be explained by the types of losses created by a severe storm or hurricane, which may differ from the protections provided by the most common forms of insurance. Sandy was not a hurricane when it made landfall and so asset losses were likely from flood. Commercial property insurance policies in the U.S. vary regarding whether they cover flood as businesses can purchase flood insurance from the National Flood Insurance Program (NFIP, Quintero 2014). Flood insurance from the NFIP protects against flood-related property losses; it does not cover flood-related business interruptions. *All* the businesses with flood insurance that did not receive any insurance payments reported that they did not have property damage from Sandy. Their losses came from customer and utility disruptions. While

12. Firms affected by Sandy were asked “Which types of insurance did your business have at the time of Superstorm Sandy? *Select all that apply*” and could choose from response options “property insurance,” “flood insurance,” “business disruption insurance,” “no insurance,” and “other, please specify.”

TABLE 6

Effects of Age and Size on Insurance in Place during Sandy, Negatively Affected Firms

	(1) **I**(Any Insurance)	(2) **I**(Property Insurance)	(3) **I**(Business Interruption Insurance)	(4) **I**(Flood Insurance)
Reference group: Firms in 4th age and employees quartiles				
I(*Age*)				
First quartile	−0.299**	−0.362**	−0.234***	−0.0341
	(0.121)	(0.164)	(0.083)	(0.071)
Second quartile	−0.104	−0.136**	−0.144	0.00619
	(0.066)	(0.066)	(0.089)	(0.067)
Third quartile	−0.157**	−0.238**	−0.103	−0.0126
	(0.072)	(0.115)	(0.079)	(0.061)
I(*Employees*)				
First quartile	−0.252***	−0.240**	−0.184**	−0.117
	(0.087)	(0.099)	(0.072)	(0.081)
Second quartile	−0.245**	−0.211**	−0.161*	−0.135*
	(0.092)	(0.090)	(0.086)	(0.073)
Third quartile	0.0137	−0.00704	−0.0464	−0.0629
	(0.048)	(0.079)	(0.076)	(0.061)
Industry FEs	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes
Obs.	273	273	273	273
R^2	0.31	0.28	0.27	0.27

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses. I(·) is the indicator function. Linear probability models with White's (1980) heteroskedasticity-consistent standard errors clustered at county. These models only include firms negatively affected by Sandy and follow equation (1). Only firms that were affected by Sandy were asked about their insurance. This table shows that among negatively affected firms, older firms and larger firms tended to be more likely to have insurance in place during Sandy.

a variety of business interruption policies exist, many require that the firms' property be physically damaged and that the claimed financial loss from interruption is due to a shutdown from this damage and not other factors such as economic conditions (Lesser 2016). These requirements seem to poorly match the losses stemming from customer and utility disruptions commonly reported by negatively affected firms (Section 2.4).

We examine the insurance that negatively affected firms had in place during Sandy as a function of the firm's age and size. Table 6 reports the results. This table divides firms into quartiles by age and by size (in employees), using the oldest firms and largest firms as reference groups. Firms less than 5 years old (the first age quartile) are 30 percentage points more likely to be uninsured relative to the oldest firms. Younger firms and smaller firms are less likely to insure against property damage and business interruptions. The effects of age seem to be incremental—even firms in the third age quartile (12–24 years old) insure significantly less than the oldest firms. Size tends to divide firms relatively evenly at the median (four employees), such that below-median firms are about 25 percentage points less likely to have any form of insurance than above-median ones. Less than 12% of the firms in our sample insure against floods; those that do tend to be larger. Thus, we find support for Hypotheses 1a and 1b, that the likelihood of insuring increases in firm age and firm size.

TABLE 7

AGE BY SIZE INTERACTION EFFECTS ON THE LIKELIHOOD THAT A FIRM HAD ANY INSURANCE IN PLACE DURING SANDY, NEGATIVELY AFFECTED FIRMS

Dependent variable: **I**(Any Insurance)

			I(Age Quartile)				
			First	Second	Third	Fourth	Total Obs.
I(Employee Quartile)	First	Coeff.	-0.480***	-0.270***	-0.518***	-0.240	
		St. Err.	(0.112)	(0.097)	(0.105)	(0.207)	
		Obs.	27	25	20	8	80
	Second	Coeff.	-0.436**	-0.492**	-0.289*	-0.233	
		St. Err.	(0.204)	(0.191)	(0.155)	(0.207)	
		Obs.	13	11	14	12	50
	Third	Coeff.	-0.416***	-0.041	-0.0244	0.098	
		St. Err.	(0.143)	(0.160)	(0.079)	(0.078)	
		Obs.	19	12	23	19	73
	Fourth	Coeff.	0.127	-0.056	-0.145	Reference	
		St. Err.	(0.107)	(0.078)	(0.109)	Group	
		Obs.	2	11	28	31	72
	Total Obs.		61	59	85	70	275

NOTE: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. I(·) is the indicator function. Output from linear probability model of whether a firm has any form of insurance with White's (1980) heteroskedasticity-consistent standard errors clustered at county. The model follows equation (2), only includes firms negatively affected by Sandy, and includes industry and county fixed effects. The reference group is the oldest, largest firms (fourth quartiles for both age and employees). For each age quartile by employee quartile interaction, the table reports the model coefficient, standard error (in parentheses), and number of observations of firms in that category. Table shading is such that darker cells reflect lower values. The model has an R^2 of 0.34. The table shows, among negatively affected firms, the interaction of firm's age and size on the likelihood that the firm had any insurance in place during Sandy.

Table 7 complements the results from Table 6 by examining age quartile and employee quartile interactions for a model of whether a firm has any form of insurance. The model follows equation (2) and only includes firms negatively affected by Sandy. The reference group is the oldest, largest firms (firms in the fourth quartile for both age and employees). For each age quartile by employee quartile interaction, the table reports the model coefficient, standard error, and number of observations of firms in that category. The table is shaded such that darker cells reflect lower values. The pattern of darker cells in the top-left section of the table confirms the results from Table 6 that age and size each contribute to insurance decisions. For example, among the youngest group of firms, those in the first, second, and third size quartiles (shown in the first column) are all significantly less likely to insure than the reference group; a similar pattern is found for the smallest firms (shown in the first row). Combining size and age effects, the smallest, youngest firms are 50 percentage points less likely to have any form of insurance than the oldest, largest ones.[13]

13. The coefficient value for firms in the first size and second age quartiles (−0.270) appears large relative to its neighbors. These differences are not statistically significant, with one exception. This coefficient is marginally significantly different ($p = 0.09$) from the coefficient for firms in the first size and third age quartiles (−0.518). In the former, 13 of 25 firms are insured while 10 of 20 are insured in the latter. The marginally significant differences may be a sampling anomaly or product of the stratification

3.2 *Credit Demand*

Negatively affected firms were more likely to search and apply for credit and put forth more effort doing so than unaffected firms. We consider whether firms searched for credit, applied for credit, the types of products for which they applied, and the time spent applying.[14] Table 8 provides the results for all outcome variables related to Hypotheses 2 and 3 and follows equation (3). The first row shows the model intercept, which describes the results for the average firm that is above-median age and size and was not negatively affected by Sandy in our data (as described in Section 2.2). The next row shows the consequences of the shock for negatively affected firms. The following rows show the effects of firms' age and size for firms that were not negatively affected. The final rows are interaction terms. These regressions also include county and industry fixed effects.

Being negatively affected by Sandy increased the likelihood that a firm searched for credit by 65% (Table 8, Column (1), $(Intercept + \mathbf{I}[Neg.\ Affected])/Intercept = (0.278 + 0.226)/0.278 = 1.65$). About 28% of firms that were not negatively affected searched for credit compared to half of negatively affected firms $(0.278 + 0.226 = 0.504)$. Younger firms were significantly more likely to search for credit: firms in the first age quartile were 18 percentage points more likely to apply than above-median firms. Thus, using the significant coefficients, we estimate that 69% of negatively affected firms in the first age quartile searched for credit $(0.278 + 0.226 + 0.183 = 0.687)$. Firms in the first size quartile were 17 percentage points *less* likely to search for credit than firms above the median size.

Negatively affected firms were about 60% more likely to apply for credit than other firms (Table 8, Column (2)). The likelihood of applying for credit is 24% for firms in the control group versus 38% of negatively affected firms ($Intercept + \mathbf{I}(Neg.\ Affected) = 0.236 + 0.142 = 0.378$). Firms that did not apply for credit were asked why they did not, and negatively affected and unaffected firms responded similarly: about a third are debt averse, a third believe they are unlikely to be approved, and a third do not need credit.

It is the *younger* firms and the *larger* firms that are more likely to apply for credit. Firms in the first age quartile were 11 percentage points more likely to apply for credit than firms that were above the median age. Thus, the model estimates that 49% of negatively affected firms in the first age quartile applied for credit after Sandy $(0.236 + 0.142 + 0.114 = 0.492)$. Firms in the first size quartile were 21 percentage points *less* likely to apply for credit than firms above the median size.

approach: firms in the first size and second age quartiles were more frequently originally funded by credit cards and located in Queens County than other firms in the first size quartile.

14. Respectively, these survey questions are: (i) "Did your business search for credit in the first half of 2013?," (ii) "Did your business apply for credit in the first half of 2013?,"(iii) "Which types of credit products did your business apply for in the first half of calendar year 2013?" with response options "Business loan," "Line of credit," "Credit card," and "Other, please specify," and (iv) "When applying for credit in the first half of 2013, approximately how many total hours did your business spend researching and completing credit applications?" (FBNY 2014).

TABLE 8

EFFECTS OF SANDY ON CREDIT DEMAND AND ACCESS

	(1) I(Searched for Credit)	(2) I(Applied for Credit)	(3) I(Applied for Loans)	(4) I(Applied for Credit Cards)	(5) Number of hours	(6) I(Access to Financing Decreased)	(7) I(Interest Rate Increased)	(8) I(Collateral)	(9) I(Collateral, Bus. Real Estate)	(10) I(Received all Credit Financing Requested)
Intercept	0.278^{***}	0.236^{***}	0.395^{***}	0.186^{**}	11.38	0.121^{***}	0.0576^{*}	0.365^{***}	0.0920^{**}	0.438^{***}
	(0.0381)	(0.0288)	(0.0789)	(0.0735)	(10.86)	(0.0231)	(0.0317)	(0.0443)	(0.0397)	(0.0700)
I(Neg. Affected)	0.226^{***}	0.142^{**}	0.228^{**}	0.0210	18.09^{*}	0.185^{***}	0.0993^{**}	0.126^{**}	0.100^{**}	−0.00152
	(0.0585)	(0.0603)	(0.112)	(0.0871)	(9.627)	(0.0348)	(0.0482)	(0.0504)	(0.0426)	(0.107)
I(Age, First Quart)	0.183^{***}	0.114^{***}	0.285^{**}	0.230^{**}	9.039	0.0271	0.00114	−0.0726	-0.0423^{**}	-0.241^{**}
	(0.0358)	(0.0324)	(0.111)	(0.0988)	(13.43)	(0.0484)	(0.0469)	(0.0539)	(0.0203)	(0.121)
I(Age, Second Quart)	0.162^{***}	0.132^{***}	0.120	0.143	24.72	−0.00195	0.00155	−0.0363	-0.0349^{*}	−0.0297
	(0.0451)	(0.0450)	(0.106)	(0.133)	(16.45)	(0.0361)	(0.0268)	(0.0488)	(0.0201)	(0.0865)
I(Employees, First Quart)	-0.169^{***}	-0.213^{***}	0.00933	0.158	−4.896	0.0264	0.0326	-0.272^{***}	-0.0645^{***}	-0.151^{*}
	(0.0462)	(0.0268)	(0.0854)	(0.129)	(14.86)	(0.0292)	(0.0371)	(0.0466)	(0.0200)	(0.0865)
I(Employees, Second Quart)	−0.0555	−0.0733	−0.0460	−0.0105	−8.456	0.114^{**}	0.0572	-0.181^{***}	-0.0653^{**}	−0.0271
	(0.0597)	(0.0550)	(0.123)	(0.109)	(15.83)	(0.0488)	(0.0401)	(0.0421)	(0.0265)	(0.113)
I(Age, First Quart) × **I**(Neg. Affected)	0.00428	0.0830	-0.379^{**}	0.0392	−3.140	−0.118	0.0611	−0.0836	-0.0730^{*}	0.135
	(0.0599)	(0.0915)	(0.153)	(0.120)	(16.82)	(0.0773)	(0.0745)	(0.0884)	(0.0426)	(0.182)
I(Age, Second quart) × **I**(Neg. Affected)	−0.0518	−0.00455	−0.219	0.0791	−13.76	0.0493	0.00654	−0.0388	−0.0740	−0.136
	(0.0886)	(0.0905)	(0.167)	(0.158)	(19.28)	(0.0719)	(0.0867)	(0.132)	(0.0452)	(0.100)
I(Emp, First Quart) × **I**(Neg. Affected)	−0.0315	0.0563	0.189^{*}	0.0534	−5.598	0.0530	0.0326	0.0487	−0.0150	0.0289
	(0.0692)	(0.0889)	(0.113)	(0.123)	(23.15)	(0.0562)	(0.0860)	(0.0859)	(0.0269)	(0.136)
I(Emp, Second Quart) × **I**(Neg. Affected)	−0.0557	−0.0191	0.252^{*}	0.110	31.08	−0.0782	−0.0846	0.0683	−0.0630	0.142
	(0.0722)	(0.0732)	(0.139)	(0.199)	(22.36)	(0.0863)	(0.0822)	(0.0913)	(0.0480)	(0.261)
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	829	830	275	275	186	834	808	793	790	273
R^2	0.138	0.142	0.299	0.267	0.308	0.116	0.0769	0.208	0.201	0.248

NOTE: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses. I(·) is the indicator function. All models have binary outcome variables except for "Number of hours" and are linear probability models. All models report White's (1980) heteroskedasticity-consistent standard errors clustered at county and include industry and county fixed effects, as described in equation (3). Models are constructed so that the intercept value represents the average firm that was not negatively affected by Sandy in the data. Columns (3), (4), and (10) only include firms that applied for credit. Column (5) only includes firms that applied for credit but did not get all the credit that they requested. Columns (8) and (9) include all firms with outstanding debt.

Columns (3) and (4) show the types of credit for which firms applied, whether they applied for commercial loans and for credit cards, respectively.[15] Negatively affected firms were about 23 percentage points more likely to apply for commercial loans than other firms, but no more likely to apply for credit cards. A firm's age and whether it was negatively affected interact in Column (3): while firms in the first age quartile are generally more likely to apply for loans than older firms (leading to a point estimate of $0.395 + 0.285 = 0.68$); among negatively affected firms, those in the first age quartile are *less* likely to apply for loans (point estimate of $0.395 + 0.228 + 0.285 - 0.379 = 0.529$). Since young, negatively affected firms applied for credit frequently (as shown in Column (2)), the negative coefficient on $\mathbf{I}$(Age, 1st Quart.) $\times$ $\mathbf{I}$(Neg. Affected) in Column (3) would seem to indicate that these young negatively affected firms tend to apply for types of credit other than commercial loans. We also find that while a firm's size does not typically affect whether it applies for commercial loans, negatively affected firms with employees in the first or second quartile are more likely to apply for commercial loans than negatively affected firms above the median size, at marginally significant rates. This interaction term indicates that among smaller firms, who do not tend to apply for credit, being negatively affected by Sandy increased the likelihood that they pursued commercial loans when applying for credit.

Negatively affected firms also put forth more effort, at marginally significant levels, than unaffected firms when applying for credit, characterized by the hours they spent. Firms that receive all the credit for which they apply may stop searching for credit and so we limit our regression on effort applying to those firms that did not receive all the credit for which they applied. From this regression, we find that negatively affected firms spent 18 hours more than other firms completing applications during the first half of 2013 (Column (5)).

In sum, we conclude that these results support H2 that Sandy increased the credit demand of negatively affected firms. It significantly increased the likelihood that these firms searched and applied for credit and they spent more time doing so. We also find support for H2b, that credit demand is decreasing in firm age. Compared to older firms, younger firms are more likely to search and apply for credit, for both commercial loans and more expensive sources of financing such as credit cards.

We do *not* find support for hypotheses H2a, that credit demand is decreasing in firm size. Instead, firms in the first size quartile were significantly less likely to search and apply for credit than firms above the median size. One plausible explanation follows from Hurst and Pugsley (2011): an important subset of small businesses is guided by nonpecuniary rewards such as the owner's amenity value of being self-employed. Avoiding or limiting the use of credit in this context can be consistent with the behavior of a risk-averse utility maximizing owner.

15. We also examined applications for lines of credit. About 75% of firms applying for credit applied for lines of credit. Among firms applying for credit of any type, a firm's age, size, and being negatively affected by Sandy do not significantly affect its likelihood of applying for a line of credit.

3.3 Credit Constraints

We also find that credit markets tightened for negatively affected firms. We examine whether firms perceive that their access to financing had decreased relative to the previous year, their interest rates had increased during this time, and they were required to secured loans with collateral.[16] Columns (6)–(10) of Table 8 show the results for these regressions, which follow equation (3). Negatively affected firms were more than 2.5 times as likely as other firms to report that their access to financing had decreased relative to the previous year (Column (6), $(Intercept + \mathbf{I}(Neg.\ Affected))/Intercept = (0.121 + 0.184)/0.121 = 2.53$). Almost one-third of negatively affected firms report that their access decreased $(0.121 + 0.184 = 0.306)$.[17]

Firms negatively affected by Sandy also experienced increased interest rates and collateral requirements. Negatively affected firms are more than 2.7 times as likely as unaffected firms to report that their interest rate increased relative to the previous year (Column (7)). Approximately 6% of firms in the control group reported that their rates increased, compared to 16% of negatively affected firms. Small business interest rates were generally declining during this time: the interest rates on Small Business Administration (SBA) 20-year major asset and real estate loans (CDC/504 loans) decreased by 40 basis points from an average rate of 4.7% in the first half of 2012 to 4.3% in the first half of 2013 (Small Business Finances 2016).[18]

We also find that being negatively affected increases the likelihood that a firm is required to secure its loan with collateral by 35% relative to unaffected firms (Column (9)). Approximately 49% of negatively affected, large firms use collateral. Smaller firms were significantly less likely to use collateral: firms in the first size quartile

16. Respectively, these survey questions are: (i) "How has your business's ability to access financing changed when comparing the first half of 2013 to the same period in 2012?"; (ii) "How did the interest rate on your business debt change in the first half of 2013 compared with 2012?"; (iii) "Was collateral required to secure any of your business debt? *Collateral can include inventory, equipment, property, personal real estate or other assets"* and "Which types of collateral were required to secure your business debt? *Select all that apply"* with response options "Inventory or accounts receivable," "Business nonreal estate assets (equipment, vehicles, securities)," "Business real estate," "Personal real estate," "Other, please specify (e.g., *personal assets*)"; (iv) "How much of the credit your business applied for was approved?" with response options "All (100%)," "Most (≥50%)," "Some (<50%)," "None (0%)." The outcome variable in this regression the value 1 if firms answered "All (100%)" and 0 otherwise (FBNY 2014).

17. This difference in credit access is not due to negatively affected firms using significantly more credit: negatively affected and unaffected firms had similar leverage ratios at the time of the survey. We model leverage as both a firm's debt (in $10,000) divided by its revenues and by its number of employees. In both cases, being negatively affected leads to a positive, insignificant coefficient ($Neg.\ Affected = 0.2$, $s.e. = 0.12$ for the debt-to-revenues model and $Neg.\ Affected = 1.3$, $s.e. = 1.01$ for the debt-to-employees model).

Column (6) also shows a positive, significant coefficient, indicating that access to financing decreased for firms in the second size quartile. We do not have an intuitive explanation for this result and so view it with some caution.

18. Our data do not explain what leads firms to report that their interest rates increased after the disaster. One potential explanation is that the additional debt that firms take on to finance recovery reduces the viability of their existing business model, which is reflected in the higher interest rate. Another potential explanation is asymmetric information, that lenders have difficulty evaluating how badly firms were affected by the disaster and these dynamics push firms to higher cost lenders. Asymmetric information has been a frequent explanation for financing frictions (see, e.g., Berg and Schrader 2012, Gilje and Taillard 2016).

were 27 percentage points less likely to secure their loans with collateral. Negatively affected firms are more likely than unaffected firms to collateralize business real estate, business nonreal estate assets, and personal real estate. Some of the largest differences are for business real estate (Column (9)). Smaller firms and younger firms were less likely to use collateral than larger, older firms. A possible explanation for this finding is that smaller and younger firms may not own collateralizable assets. For example, previous research shows that more financially constrained firms are more likely to lease rather than own capital assets (Eisfeldt and Rampini 2009, Rampini and Viswanathan 2013).

This use of collateral may be important for explaining credit constraints, as smaller firms and younger firms are less likely receive all of the credit financing that they requested (Column (10)). For example, firms in the first age quartile are 24 percentage points less likely to receive all of the credit that they requested. These credit constraints are substantial and persistent. Most negatively affected firms (69%) report a financing need specifically related to Sandy 1 year after the event.[19] The median range of these financing needs is $50,000–$100,000.

In sum, we conclude that these results support H3 that Sandy increased credit constraints among negatively affected firms. Negatively affected firms were significantly more likely than other firms to report that their access to financing had decreased, their interest rates had increased, and they were required to secure loans with collateral. We find partial support for H3a and H3b that credit constraints are decreasing in firm size and age, respectively. Age and size did not influence the likelihood that a negatively affected firm reported that its access to financing had decreased or that its interest rates increased. However, the youngest firms and smallest firms were more likely to report that they did not receive all the financing that they requested.

4. EXTENSIONS AND ROBUSTNESS

In this section, we include extensions and robustness tests. Our data allow for several additional analyses beyond our core consideration of how Sandy affected firms, especially smaller and younger firms. First, we examine how a firm's insurance payments affect its demand for and access to credit. Second, we assess whether a firm's initial funding (e.g., personal savings versus a commercial loan) influences its credit outcomes following Sandy. Third, we examine firms in counties that were less severely affected by Sandy. Fourth, we analyze a firm's age versus its size in additional detail as some databases include size or age, but not both. Finally, we describe the role of the Small Business Administration's federal disaster loan program in our data.

Following these extensions, we describe several robustness analyses examining our identifying assumptions discussed in Section 2.3. First, we consider whether negatively affected firms reported different initial funding than other firms. Important

19. "Now, roughly one year later, what type(s) of financing needs related to Superstorm Sandy does your business have?"

preexisting differences might create concern about using firms that were not negatively affected as a counterfactual for negatively affected firms. Second, we examine U.S. Census Bureau data for New Jersey to assess whether Sandy seemed to result in a large amount of firm deaths that might affect our interpretation of the data. Third, we examine whether a firm's insurance payments influenced the likelihood that it reduced its number of employees following Sandy. Finally, we reexamine our insurance outcomes using Heckman selection models.[20]

4.1 Extensions

Insurance payments affect credit demand and access to financing. We examine whether a firm's insurance payments affect its credit demand and access to financing. We find that businesses incurring large losses that were *not* covered by insurance were significantly more likely to apply for credit than businesses incurring large losses that were fully paid by insurance. Also, firms whose losses from Sandy were not covered by insurance were *more* likely to report that their access to financing had decreased, relative to unaffected firms.

Credit would seem to act as an imperfect substitute for insurance following a catastrophe and so we predict that firms without insurance and those receiving small insurance payments relative to their losses would be more likely to search and apply for credit. These regressions follow

$$\begin{aligned} y_i = \mathbf{I}(&\beta_0 + \beta_{1,l}\mathbf{I}\left(Neg.\ Affected_i\right) \times \mathbf{I}\left(Small\ Loss_i\right) \times \mathbf{D}_l\left(Ins.\ Payments_i\right) \\ &+ \beta_{2,l}\mathbf{I}\left(Neg.\ Affected_i\right) \times \mathbf{I}\left(Large\ Loss_i\right) \times \mathbf{D}_l\left(Ins.\ Payments_i\right) \\ &+ \beta_3 Age_i + \beta_4\, Employees_i + \beta_5\, Age_i \times \mathbf{I}\left(Neg.\ Affected_i\right) \\ &+ \beta_6\, Employees_i \times \mathbf{I}\left(Neg.\ Affected_i\right) + \delta_j + \eta_k + u_i > 0). \end{aligned} \tag{4}$$

The term $\mathbf{D}_l(Ins.\ Payments)$ is a dummy set (a set of indicator variables) indicating the percent of losses paid by insurance. Among insured firms, it includes response options (i) None (0%), (ii) Some (<50%), (iii) Most (≥ 50%), or (iv) All (100%).[21] In this dummy set, we also include (v) Uninsured, for firms that do not have any form of insurance. The relationship between insurance payments and credit demand may depend on the magnitude of losses sustained by the firm. Therefore, the regressions include interaction terms, examining the effects separately of insurance payments for negatively affected firms that sustained below-median losses ($Small\ Loss_i$) from those that sustained above-median losses ($Large\ Loss_i$). We use the firm's losses

20. The working paper version of this paper, Collier et al. (2017) includes several alternative model specifications and additional robustness tests that we omit here in the interest of space.

21. "Roughly, what percent of your business's losses was recovered through insurance?" Some firms ($n = 34$) reported that they were negatively financially affected Sandy but answered this question "Business did not suffer any losses." We speculate that these firms were considering a specific type of insured loss (e.g., property damage). We include these firms in the regression as controls, but do not interpret or report their coefficient.

TABLE 9

EFFECTS OF INSURANCE PAYMENTS ON CREDIT DEMAND AND ACCESS

	(1) **I**(Searched for Credit)	(2) **I**(Applied for Credit)	(3) **I**(Access to Financing Decreased)
Intercept	0.296***	0.210***	0.166***
	(0.0234)	(0.0179)	(0.0186
Negatively affected, *Below*-median losses			
I(Uninsured)	0.268***	0.170**	0.227**
	(0.0892)	(0.0817)	(0.0886)
I(Ins. Pay = None (0%))	0.200***	0.238***	0.0766*
	(0.0742)	(0.0834)	(0.0431)
I(Ins. Pay = Some (<50%))	0.127	0.239	0.0562
	(0.179)	(0.18)	(0.131)
I(Ins. Pay = Most (≥ 50%))	−0.0478	0.023	0.0351
	(0.210)	(0.175)	(0.170)
I(Ins. Pay = All (100%))	0.167	0.209	−0.140***
	(0.358)	(0.358)	(0.0237)
Negatively affected, *Above*-median losses			
I(Uninsured)	0.181**	0.0624	0.315***
	(0.0874)	(0.0803)	(0.0627)
I(Ins. Pay = None (0%))	0.223***	0.209***	0.204***
	(0.0677)	(0.0553)	(0.0462)
I(Ins. Pay = Some (< 50%))	0.347***	0.377***	0.216
	(0.105)	(0.126)	(0.141)
I(Ins. Pay = Most (≥ 50%))	0.0115	0.111	−0.200***
	(0.207)	(0.219)	(0.0741)
I(Ins. Pay = All (100%))	−0.242***	−0.235***	−0.103**
	(0.0581)	(0.0602)	(0.0417)
Industry FEs	Yes	Yes	Yes
County FEs	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Obs.	829	830	834
R^2	0.12	0.13	0.12

NOTE: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses. I(·) is the indicator function. Linear probability models with White's (1980) heteroskedasticity-consistent standard errors clustered at county. All models include industry and county fixed effects and control for firms' age and size, as described in equation (4). The loss measure divides the firm's losses from Sandy by its number of employees. The median loss per employee is $5,833. All rows use the intercept, which represents firms that were not negatively affected by Sandy, as a reference group.

from Sandy divided by its number of employees as the measure of losses, but find qualitatively similar results using losses in absolute dollars. The median loss per employee is $5,833. The regressions also include controls for firms' age and size, and industry and county fixed effects.

Table 9 shows the results. The reported interaction terms for negatively affected firms are structured so that firms not negatively affected by Sandy (the intercept) serve as the reference group in each case.[22] Among negatively affected, *below*-median loss firms that received at least some insurance payments were *not* significantly more likely to search or apply for credit than unaffected firms. Insured firms receiving no insurance payments were around 20 percentage points more likely to search and to

22. The fixed effects and firm age and size are demeaned so that the intercept is interpretable as the average firm that was not negatively affected.

apply for credit than the average unaffected firm. Similarly, uninsured firms incurring below-median losses were more likely to search and apply for credit.

Among negatively affected, *above*-median loss firms, insured firms receiving no insurance payments or payments that were less than half of their losses were significantly more likely to search and apply for credit than unaffected firms. Uninsured, negatively affected firms were significantly more likely to search for credit than unaffected firms, but were not necessarily more likely to apply. Insured firms who received insurance payments for "most" of their losses searched and applied for credit at rates similar to unaffected firms. Firms whose losses were fully insured were about 45 percentage points *less* likely to search and apply for credit than firms who received no insurance payments. These fully insured firms were also significantly less likely than unaffected firms to search and apply for credit. We speculate that these firms that received full insurance payments had especially low credit demand as insurance payouts (e.g., cash for business interruptions) may have addressed their financing needs.

We also find the anticipated result regarding access to financing: firms whose losses from Sandy were not covered by insurance were *more* likely to report that their access to financing had decreased, relative to unaffected firms. Firms whose losses were mostly or fully insured were *less* likely than unaffected firms to report that their access to financing had decreased. Uninsured firms were more likely than unaffected firms to report that their access to financing had decreased and so they may not have applied because they did not anticipate being approved. Uninsured firms incurring above-median losses were 32 percentage points more likely than unaffected firms to report that their access to financing had decreased relative to the previous year. We conclude that the results support the prediction that insurance payments reduce credit demand among negatively affected firms.

Initial funding and credit outcomes following sandy. We examine whether a firm's original source of funding affected its demand for and access to credit following Sandy. Previous research finds that following a natural disaster, firms who have a preexisting relationship with a lender are more likely to receive credit than new borrowers (Berg and Schrader 2012), yet firms who were established with credit may have less capacity to take on additional debt (Rampini and Viswanathan 2010). We examine the credit outcomes evaluated in Sections 3.2 and 3.3. These regressions follow

$$\begin{aligned} y_i = \mathbf{I}(&\beta_0 + \beta_1 \mathbf{I}\left(Neg.\,Affected_i\right) + \beta_2 \mathbf{I}\left(Orig.\,Fund_i = Biz\,Loan\right) \\ &+ \beta_3 \mathbf{I}\left(Orig.Fun\,d_i = Credit\,Cards\right) + \beta_4 \mathbf{I}\left(Orig.\,Fund_i = Biz\,Loan\right) \\ &\times \mathbf{I}\left(Neg.\,Affected_i\right) + \beta_5 \mathbf{I}\left(Orig.Fun\,d_i = Cred.\,Cards\right) \times \mathbf{I}\left(Neg.\,Affected_i\right) \\ &+ \beta_5 Age_i + \beta_6\, Employees_i + \beta_7\, Age_i \times \mathbf{I}\left(Neg.\,Affected_i\right) \\ &+ \beta_8\, Employees_i \times \mathbf{I}\left(Neg.\,Affected_i\right) + \delta_j + \eta_k + u_i > 0). \end{aligned} \tag{5}$$

The term $\mathbf{I}(Orig.\,Fund = Biz\,Loan)$ and $\mathbf{I}(Orig.Fund = Credit\,Cards)$ are indicators for firms whose original funding included business loans and credit cards,

TABLE 10

EFFECTS OF ORIGINAL FUNDING ON CREDIT DEMAND AND ACCESS

	(1) I(Searched for Credit)	(2) I(Applied for Credit)	(3) I(Access to Financing Decreased)	(4) I(Interest Rate Increased)	(5) I(Collateral)	(6) I(Collateral, Bus. Real Estate)
Intercept	0.259***	0.222***	0.118***	0.0487	0.288***	0.0659**
	(0.0405)	(0.0295)	(0.0283)	(0.0341)	(0.0460)	(0.0332)
I(Neg. Affected)	0.223***	0.140**	0.152***	0.101*	0.171***	0.117**
	(0.0676)	(0.0684)	(0.0406)	(0.0558)	(0.0593)	(0.0477)
I(Orig. Fund = Biz Loan)	−0.0219	0.00917	0.0224	−0.0147	0.359***	0.119***
	(0.0639)	(0.0749)	(0.0569)	(0.0422)	(0.0713)	(0.0399)
I(Orig. Fund = Credit Cards)	0.205***	0.0965**	−0.00153	0.0897**	0.0242	0.0149
	(0.0332)	(0.0398)	(0.0388)	(0.0397)	(0.0310)	(0.0288)
I(Neg. Affected) x I(Orig. Fund = Biz Loan)	−0.0446	−0.0893	0.0553	0.00963	−0.179*	−0.0582
	(0.134)	(0.119)	(0.121)	(0.0901)	(0.0996)	(0.0839)
I(Neg. Affected) x I(Orig. Fund = Credit Cards)	0.0250	0.103*	0.155**	−0.0473	−0.0297	−0.0278
	(0.0801)	(0.0612)	(0.0671)	(0.0556)	(0.0706)	(0.0592)
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	828	829	833	807	792	789
R^2	0.167	0.157	0.125	0.0852	0.260	0.216

NOTE: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses. I(·) is the indicator function. Linear probability models with White's (1980) heteroskedasticity-consistent standard errors clustered at county. All models include industry and county fixed effects and control for firms' age and size, as described in equation (5). Models are constructed so that the intercept value represents the average unaffected firm in the data.

respectively.[23] The most commonly reported sources of original funding are savings, friends/family, business loans, and credit cards. Thus, the original funding reference group effectively can be considered firms who were established using the personal resources of owners and their friends and family. The model includes the firm's age and size, age and size interacted with whether the firm was negatively affected by Sandy, and industry and county fixed effects as controls. As before, these regressions are structured so that the intercept represents the average firm not negatively affected.

Table 10 shows the results. To conserve space, we only show the credit demand and access outcomes on which a firm's original funding had a significant effect. The results show that firms originally funded by business loans were no more likely to search or apply for credit than the reference group (mainly firms established using personal/friends/family resources). Firms originally funded by credit cards were significantly more likely to search and apply than other firms. As before, the table shows that being negatively affected by Sandy increases the likelihood that a firm searched and applies for credit. We also find a marginally significant interaction term showing that negatively affected firms who were established with credit cards are

23. What type of funding was used to start your business? Select all that apply" with response options "Business loan," "Line of credit," "Credit cards," "Personal savings," "Friends/family," and "Other, please specify (e.g., home equity line)."

especially likely to apply for credit. Similarly, negatively affected firms who were established with credit cards were significantly more likely to report that their access to financing had decreased relative to the previous year. We also find that firms originally funded with credit cards were more likely to report that their interest rates had increased relative to the previous year, and firms originally funded by business loans were more likely to report using collateral, including business real estate. Taken with the previous results regarding a firm's age and size, these findings suggest important heterogeneity across firms regarding how a shock like Sandy affects their need for and access to credit.

Comparison across disaster areas. Thus far, we have limited our analysis to the counties hit hardest by Sandy, federally declared disaster counties that qualified for individual and public assistance ("IA/PA Counties," 35 counties in our data).[24] Our data include firms in two other groups of counties: (i) federally declared disaster counties that qualified for public assistance only ("PA Counties," 18 counties), and (ii) counties that were outside of the federally declared disaster area ("Outside Counties," 75 counties). Here, we compare firms across these groups of counties. Because so many businesses are affected concurrently in the IA/PA disaster counties, lenders in those areas may be constrained in their ability to assess borrowers, potentially contributing to a reduction in credit access. Thus, examining firms in other counties may provide additional insights. These regressions follow

$$\begin{aligned} y_i = \; & \mathbf{I}(\beta_0 + \beta_1 \mathbf{I}\left(Neg.\ Affected_i\right) + \beta_2 \mathbf{I}\left(Neg.\ Affected_i\right) \times \mathbf{I}\left(PA\ County_j\right) \\ & + \beta_3 \mathbf{I}\left(Neg.\ Affected_i\right) \times \mathbf{I}\left(Outside\ County_j\right) + \beta_4 Age_i \\ & + \beta_5\ Employees_i + \delta_j + \eta_k + u_i > 0), \end{aligned} \tag{6}$$

where $\mathbf{I}(PA\ County_J)$ is an indicator for counties that received public assistance, $\mathbf{I}(Outside\ County_j)$ is an indicator for counties that were not declared disaster counties. We interact each of these indicators with $\mathbf{I}(Neg.\ Affected_i)$, the indicator for whether a firm was negatively affected by Sandy. Thus, $\beta_1 \mathbf{I}(Neg.\ Affected_i)$ describes negatively affected firms in IA/PA Counties, and for example, $\beta_2 \mathbf{I}(Neg.\ Affected_i) \times \mathbf{I}(PA\ County_j)$ uses β_1 as a reference, examining whether negatively affected firms in PA countries responded differently. The model includes county and industry fixed effects and age and employees as controls. It is structured so that the intercept describes the average firm that was not negatively affected across all counties.[25]

Table 11 shows the results. In the interest of space, we report the five most important credit variables. As we found before, negatively affected firms in the IA/PA Counties were significantly more likely to report greater credit demand and credit constraints

24. Public assistance describes providing resources to affected local and state government entities. Individual assistance describes providing resources directly to affected populations such as shelter or a grant for an affected household (FEMA 2018).

25. We demean the fixed effects and age and size to facilitate interpretation of the intercept. We do not include uninteracted county indicators **I**(PA County) and **I**(Outside County) as the county fixed effects capture these direct effects. Excluding those uninteracted terms results in the intercept representing the average firm not affected by Sandy across all counties. Regressions including those county indicators are qualitatively consistent with the presented results.

TABLE 11

Examining Negatively Affected Firms in Less Severely Affected Counties

	(1) **I**(Searched for Credit)	(2) **I**(Applied for Credit)	(3) **I**(Access to Financing Decreased)	(4) **I**(Interest Rate Increased)	(5) **I**(Collateral)
Intercept	0.312***	0.246***	0.168***	0.0880***	0.331***
	(0.0140)	(0.0158)	(0.0124)	(0.00877)	(0.0363)
I(Neg. Affected)	0.185***	0.167***	0.170***	0.106***	0.125***
	(0.0494)	(0.0389)	(0.0251)	(0.0228)	(0.0347)
I(Neg. Affected)	0.174	0.0032	−0.216*	0.164	−0.199
x **I**(PA County)	(0.111)	(0.132)	(0.130)	(0.152)	(0.141)
I(Neg. Affected)	0.0007	0.153	0.0130	0.133	0.0364
x **I**(Outside County)	(0.143)	(0.123)	(0.112)	(0.114)	(0.171)
Industry FEs	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	1,353	1,355	1,364	1,321	1,306
R^2	0.148	0.145	0.139	0.130	0.228

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses. I(·) is the indicator function. Linear probability models with White's (1980) heteroskedasticity-consistent standard errors clustered at county. All models include industry and county fixed effects and control for firms' age and size, as described in equation (6). "PA County" refers to federally declared disaster counties that qualified for public assistance only, "Outside County" refers to counties that were outside of the federally declared disaster area. These counties are compared to a reference group of federally declared disaster counties that qualified for both individual and public assistance. Models are constructed so that the intercept value represents the average unaffected firm in the data.

than unaffected firms. Negatively affected firms in the PA Counties and Outside Counties did not tend to differ at statistically significant levels from negatively affected firms in the IA/PA Counties. The table also shows much larger standard errors for negatively affected firms in the PA Counties and Outside Counties. In sum, we do not find consistent significant differences across the three groups of counties; however, one challenge in identifying effects in the PA Counties and Outside Counties appears to be greater idiosyncratic variation in firms' responses in those areas.

Omitting age versus omitting size. Some anonymized databases only report a firm's size or its age (e.g., from the U.S. Census Bureau). In analyzing data in which only age or size is available, an omitted variable problem can emerge such that age and size effects are conflated. We examine this problem by reestimating our credit outcomes models, excluding a firm's age variables (its main effect and its interaction with $\mathbf{I}[Neg.\ Affected]$) and then in a separate regression, omitting its size variables. In the models omitting firm age, the coefficients on firm size appear qualitatively similar to those reported in our main results (Table 8). However, in the models omitting firm size, the coefficients on firm age differ in several cases. The results indicate that for the credit outcomes studied here, controlling for firm size may be especially important for research interested in firm age effects. The Online Appendix (Section A.2.1) includes the detailed results.

Few firms borrow from the federal disaster loan program. We examine the role of the SBA disaster lending program following Hurricane Sandy. In our data, only 8% of negatively affected firms borrowed from the SBA disaster lending program. Given our findings that Sandy increased firms' credit constraints, we anticipated that more firms would borrow from this program. Administrative data on the program shows that one-third of firms that begin the application process never complete it, and 60% of firms completing applications are ultimately rejected by the SBA, reflecting the limited creditworthiness of these businesses. Program rules regarding collateral seem to limit its use, especially in years like 2012 and 2013 when private-sector interest rates are low. The Online Appendix (Section A.2.2) provides additional details.

4.2 Robustness

Potential for participation bias and survivorship bias. Two common sources of survey bias in settings like ours are survivorship bias and participation bias. Regarding survivorship bias, only firms that survived Sandy are included in the survey as it was conducted about 1 year after the event. If Sandy caused firms to fail, systematic differences between failing and surviving firms might introduce bias in our sample selection. We examine U.S. census data on firms in New Jersey, a state severely affected by Sandy. We consider both the total number and the age and size distributions of firm failures, but do not find significant changes in firm failures in 2012 (the year Sandy occurred). Regarding participation bias, surveyors often consider whether certain types of respondents select into a survey based on the topic. In our setting, there could be some concern that firms with extremely bad or good experiences with Sandy might be more likely to participate, potentially skewing the results. This potential participation bias seems to be mitigated by the fact that the survey was a semiregular poll regarding firms' performance and credit following the Great Recession and the Sandy questions were a supplemental topic included in fall 2013. The Online Appendix (Section A.3.1) includes additional details.

Initial funding and ignorability of treatment. Our identification strategy uses an ignorability of treatment assumption, that after conditioning on a set of observable characteristics, firms that were not negatively affected by Sandy provide a counterfactual for negatively affected firms (as discussed in Section 2.3). We assess whether negatively affected firms differed from unaffected ones with respect to their original funding. Differences in original funding might indicate preexisting differences in credit use, challenging the ignorability of treatment assumption. However, we do not find differences in original funding between negatively affected and unaffected firms. The Online Appendix (Section A.3.2) provides additional details.

Size and insurance payments. In our analyses, we use a firm's number of employees of firm size as it is likely persistent across time (as discussed in Section 2.3). We examine whether insurance payouts influenced the likelihood that negatively affected firms reduced their number of employees. Surveyed firms reported whether their number of employees had decreased relative to the previous year. For negatively affected firms, we regress whether a firm reduced its employees on the fraction of its Sandy-related losses that were paid by insurance and a set of control variables (firm age and industry fixed effects and county fixed effects).[26] We find no statistically significant effect of insurance on the likelihood that a firm reduced its employees after Sandy, which seems to provide support for the view that a firm's number of employees is a persistent measure of firm size in our setting.

Insurance coverage and sample selection. Following the discussion of empirical identification in Section 2.3, we examine our primary models (those presented in Table 6), using alternative estimation strategies. As we only observe the insurance decisions of firms affected by Sandy, we employ Heckman selection models due to the possibility that sample selection bias may affect our analyses of insurance decisions. This approach includes a selection equation (modeling the likelihood of being negatively affected in our setting). Then, the equation of interest (whether a firm had insurance in place during Sandy) includes the estimated likelihood of selection from the selection equation as an additional variable to account for potential bias. We pursue two approaches in the Online Appendix (Section A.3.2): (i) using the two-step approach originally proposed by Heckman (1979) and (ii) modeling the two equations as a bivariate probit. Neither approach indicates a sample selection problem, and in both cases, the results are qualitatively consistent with our main findings (Table 6).[27] The Online Appendix (Section A.3.2) includes the detailed results.

5. CONCLUSION

We examine firms' financial management decisions related to an infrequent, severe income and asset shock, Hurricane Sandy. We use data collected 1 year after Sandy from firms in the New York area. We find that a third of the firms negatively affected by the event did not have insurance of any kind. Firms with insurance did not tend to insure against the losses created by Sandy. For example, half of negatively affected firms with flood insurance and almost three quarters with business interruption insurance did not receive *any* payment due to Sandy. Instead, firms turned to credit to finance recovery: firms negatively affected by Sandy were twice as likely to apply for credit as unaffected firms. Negatively affected firms also reported financing constraints such as higher interest rates and increased requirements to secure loans with collateral.

Firms' age and size systematically affect their financial management of Sandy, resulting in increased vulnerability of smaller firms and younger firms as these firms are less likely to insure and more likely to be credit constrained. Our findings

26. The regression model is $\mathit{Reduced\_Employees}_i = \mathbf{I}(\beta_0 + \beta_{1,l}\ \mathbf{D}_l(\mathit{Ins.\ Payments}_i) + \beta_2\ \mathit{Age}_i + \delta_j + \eta_k + u_i > 0)$ where $\mathbf{D}_l(\mathit{Ins.\ Payments})$ is a dummy set (a set of indicator variables) describing the fraction of losses paid by insurance. Among insured firms, it includes responses (i) None (0%), (ii) Some (<50%), (iii) Most (≥ 50%), or (iv) All (100%); the indicator for "None" is used for uninsured firms.

27. The additional distributional assumptions required by the two-stage Heckman model (normally distributed errors in the first stage, Wooldridge 2010, p. 803) and the bivariate probit (bivariate normally distributed errors between the models) motivate us to prefer the linear probability models as our primary estimation strategy.

align with recent research showing that both a firm's age and size matter (see, e.g., Haltiwanger, Jarmin, and Miranda 2013, Berman, Rebeyrol, and Vicard 2018). These findings may improve targeting of market opportunities and public programs.[28]

Our findings provide initial insights that motivate additional. For example, how the outcomes that we observe following a major storm in the New York area generalize to other locations and shocks is unclear. While particularly challenging, collecting detailed data on firms both before and after a severe shock would strengthen comparisons across firms. Also, while our results illustrate a gap in catastrophe coverage for SMEs, designing effective public policy interventions requires more information on what motivates these firms' risk management decisions.

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28. Additional research might clarify age and size effects. Age and size may be effective characteristics for targeting even if they are proxies of unobservable features of the firm (e.g., owner risk aversion or managerial skill).

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.