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FIRMS' MANAGEMENT OF INFREQUENT SHOCKS

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ABSTRACT

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 (38%) than received insurance payments (15%) in our data. Negatively affected firms were often credit constrained after the shock. While firms' demand for insurance is often explained by financing frictions, we find that the most credit constrained firms after the event, younger firms and smaller firms, were the least likely to insure before it.

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1 Introduction

We examine businesses' financial management decisions regarding an infrequent, severe risk. Hurricane Sandy struck the New York area in the fall of 2012, and our data were collected one 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, and the data collection procedures used stratified sampling by age, size, and industry so that the businesses in our sample reflect the profile of firms in the New York area. 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 could access credit. 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., these businesses account for 50 percent of employment (Caruso, 2015) and 45 percent of GDP (Kobe, 2012).² Recent media reports highlight the vulnerability of these businesses to severe events (e.g., to major floods in North Carolina, Price, 2016; in Louisiana, McWhirter and Simon, 2016; in the United Kingdom, BBC, 2015; and in Chennai, Ghosh and Kondapalli, 2016). Such cases are concerning not only for these affected communities, but also because the frequency and severity of these events are increasing.³ Severe weather risks may play a more prominent role in the success and failure of SMEs in the future.

² SMEs are often called "small businesses" in the U.S. and commonly classified as businesses with fewer than 500 employees (SBA, 2014). All the businesses in our study and 99.7 percent of U.S. businesses fall into this category (Caruso, 2015).

³ Globally, natural disasters have caused \$2.11 trillion in economic losses and 760,000 fatalities in the last decade (2004 – 2013, Aon Benfield, 2015). The Intergovernmental Panel on Climate Change (2013) cites increasing evidence that extreme events including heat waves, severe rainfall, drought, and tropical cyclones are all expected to increase by the late 21st century. 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. Sandy caused more than \$70 billion

Several aspects of the enterprise would seem to motivate SMEs to finance severe risks through insurance; however, research on the topic is surprisingly limited. First, while bankruptcy laws transfer some of the consequences of failure from the owner, the wealth and livelihoods of many SME owners are frequently tied to the well-being of the business (Herranz, Krasa, and Villamil, 2015). Thus, the firm's risk management decisions may be heavily influenced by the owner's personal financial considerations, which we would expect to be guided by risk aversion. Second, while large corporations are typically assumed to be risk-neutral, they often manage risk through hedging and/or insuring, a practice that is frequently explained by financial frictions (e.g., higher external financing costs in unfavorable states of the world, Froot, Scharfstein, and Stein, 1993; Bolton, Chen, Wang, 2011; Amaya, Gauthier, and Léautier, 2015). Such financial frictions are almost certainly greater for SMEs than large corporations and so would be expected to increase their demand for insurance.⁴

We find that much of businesses' losses from Sandy were not financed through insurance. Hurricane Sandy had a negative financial impact on about 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 percent had no insurance of any kind. Moreover, insured businesses often did not have coverage for the kinds of losses that Sandy created: 74 percent of businesses with property insurance, 72 percent with business interruption insurance, and 52 percent of businesses with flood insurance reported that *none* of their losses from the event had been covered by their insurance.

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 (38 percent) than

in damages, making it the second costliest natural catastrophe in U.S. history, after Hurricane Katrina (NOAA HRD, 2014).

⁴ For example, Khwaja and Mian (2008) assess businesses' access to credit following an unanticipated liquidity shortage: the government of Pakistan restricted withdrawals of dollar-denominated deposits following its nuclear tests in 1998. Dollarized banks reduced lending. Large firms responded by finding credit at less affected banks; however, smaller firms were generally unable to manage this transition and so borrowed less.

received insurance payments (15 percent). Negatively affected firms were about twice as likely as unaffected firms to apply for credit following the storm and exerted more effort, spending more time completing credit applications. Businesses incurring large losses that were not financed by insurance were significantly more likely to apply for credit than their counterparts who received insurance payments.

We also find that Sandy tightened credit constraints: negatively affected firms were twice as likely to report that their access to financing had decreased relative to the previous year. They were 73 percent more likely to be required to secure loans with collateral and 2.5 times as likely to experience interest rate increases as unaffected firms.

Thus, we find evidence of the financial frictions following Sandy that have been used to explain why large corporations insure, but do not find that *ex ante* those frictions led SMEs to insure against the risk of a severe storm. Recent research posits that it is opportunity costs rather than financial frictions that most saliently explain firms' risk management decisions (e.g., Rampini and Viswanathan, 2010, 2013). Specifically in our context, insurance premiums dedicate firm resources to managing a specific risk (e.g., property damage from a named peril) that preclude their use in production or to manage other risks. The opportunity costs of insuring against rare events are likely highest for smaller firms, which tend to be more productive than larger ones, and for younger firms, which are exposed to many risks.⁵ Financial frictions also tend to be greater for smaller firms and younger firms (e.g., Demircuc-Kunt, Love, and Maksimovic, 2006) and so these two mechanisms create competing hypotheses regarding who is most likely to insure – frictions predict that the small/young would insure while opportunity costs predict the large/old. We exploit cross-firm variation in our data along the dimensions of age and size to gain additional insights regarding firms' risk management strategies.

⁵ Young firms are often small (Caves, 1998); we find a Pearson correlation $r = 0.34$ between a firms' age and number of employees in our data.

Size proxies a firm's marginal productivity: controlling for age, smaller firms grow faster than larger ones (Dunne, Roberts, and Samuelson, 1989; Evans, 1987a, b). Rampini and Viswanathan (2010) argue that more productive firms tend to curtail risk management in order to operate more intensively, noting that "smaller firms, which are likely to be financially constrained, hedge less" (p. 2294). Consequently, we predict that in our data, smaller firms will 1) be less likely to insure and 2) have greater credit demand than larger firms, but also 3) face greater credit constraints following a shock as they have less uncommitted capital.

Age proxies earnings uncertainty: young firms grow faster but also fail at higher rates than older firms (Caves, 1998; Haltiwanger, Jarmin, and Miranda, 2013; Thornhill and Amit, 2003). Young firms face many existential threats related to managing internal financial and human resources and external relationships with customers, suppliers, investors, and competitors (Thornhill and Amit, 2003). We adopt Jovanovic's (1982) learning model to explain how a firm's earnings expectations evolve. New firms do not know how profitable they will be relative to other firms; however, experience over time clarifies these expectations thus reducing firms' uncertainty. We posit that younger firms will choose not to insure against rare events, which increases the resources available to address the many, frequent risks that they face.⁶ The riskiness of young firms may also affect their credit demand following a crisis: the prospect of a highly successful start-up increases their willingness to borrow relative to their older counterparts, yet the greater possibility of their failure decreases lenders' willingness to fund them. Thus, we predict that younger firms will 1) insure against rare events less often than older firms, 2) have greater credit demand, and 3) face greater credit constraints.

We find that younger firms and smaller firms are significantly less likely than older firms and larger firms to purchase insurance. For example, half of firms that were less than five years old

⁶ Our predictions are consistent with Rochet and Villeneuve (2011) who develop a dynamic, theoretical model to examine the liquidity risk of a firm with costly external financing and exposure to two risks, a Brownian risk that can be hedged and a Poisson risk that can be insured. They show that firms that are vulnerable to liquidation due to both risks will tend to hedge but not insure. Our theory adds to this by positing that the firm's risk distribution evolves systematically with age due to the dynamics identified by Jovanovic.

reported having no insurance of any kind. Younger firms and *larger* firms are more likely to apply for credit.⁷ Our results are generally consistent with predictions that younger firms and smaller firms are more likely to experience financial frictions, though we find that age and size affect different credit constraints. Larger, negatively affected firms are more likely than smaller ones to receive all the credit that they requested, which seems to be explained, at least in part, by their ability to secure loans with collateral. Younger, negatively affected firms are significantly more likely than older ones to report higher external financing costs as their interest rates had increased relative to the previous year. In sum, our findings on differences in insurance demand across firms are more consistent with opportunity costs theory (Rampini and Viswanathan, 2010) than financial frictions theory (Froot, Scharfstein, and Stein, 1993): the most financially constrained firms after the event were the least likely to insure before it.

Our primary contribution is empirical: we provide detailed results on firms' management of a rare, severe event. The richness of our data allows for a more nuanced assessment than is typically possible of how firms address their risk financing needs and how constraints differ after a shock depending on firms' characteristics. Moreover, our sample of SMEs comprises a distinct group from the corporations typically studied regarding firms' risk management. Our results add to research on the opportunity costs of managing risk, finding size effects that have been shown in other contexts⁸ and identifying age effects that help explain firms' risk management decisions. The age versus size distinction that we identify also complement recent findings on firms and

⁷ We find one important deviation from model predictions: smaller, negatively affected firms are less likely to apply for credit than larger ones in our sample. The empirical findings of Hurst and Pugsley (2011) provide a potential explanation as they note that small firms comprise a combination of younger firms, some of which will grow quickly, and a set of firms with owners for whom growth is not a priority. Rather than maximizing expected returns, the behavior of this latter group, sometimes called "lifestyle firms," is consistent with a risk averse owner. We show that even these risk averse lifestyle firms may not insure against rare events since it reduces the financial resources available to address more frequent shocks. Indeed, we find empirically that small, old firms, which act as a proxy for lifestyle firms, are not more likely than other old firms to insure against catastrophes.

⁸ For example, Nance, Smith, and Smithson (1993) use a survey of CEOs of Fortune 500 and S&P 400 firms and COMPUSTAT data and find that the likelihood that firm uses financial hedges is increasing in size. Rampini, Sufi, and Viswanathan (2014) examine fuel price hedging in the airline industry. They show in both between-firm and within-firm models that hedging is increasing in an airline's net worth.

growth, which shows that young firms play a critical role in increasing economic productivity and employment (e.g., Adelino, Ma, and Robinson, 2017; Foster, Haltiwanger, and Syverson, 2008, 2016; Haltiwanger, Jarmin, and Miranda, 2013; Hurst and Pugsley, 2011). While much of United States public policy has targeted firms by size, appropriate policies for the young may differ from those of the small. For example, current U.S. disaster assistance to firms typically occurs through *ex post* lending from the Small Business Administration (SBA), yet the volatile earnings of young firms may preclude financing recovery through debt. Our results suggest that the public sector could better meet firms' needs through recognition of these distinctions, and we conclude with several policy recommendations.

2 Theoretical Model and Hypotheses

We develop specific hypotheses on firms' financial preparation for and management of Hurricane Sandy. Here, we model a representative firm's decision to insure against natural disasters and expand this model in the Online Appendix to consider the firm's borrowing decisions. The firm is vulnerable to natural disaster losses as well as background risks, which for concreteness we model as price risk, fluctuations in the price at which the firm can sell its goods. Our model leverages the work of Jovanovic (1982) and Rampini and Viswanathan (2010) among others but uses some simplifications tailored to our research questions. While we consider the specific case of a severe disaster risk, our predictions related to firm size follow Rampini and Viswanathan's (2010) more general results. We extend Jovanovic's model by showing that as firms' earnings uncertainty falls, their demand for insurance against rare events increases.

2.1 Model Setup

A representative firm is endowed with an initial stock of equity \underline{k} and a unique production technology $f(\cdot)$ that is increasing and concave ($f' > 0, f'' < 0$). The firm is a price taker, facing demand risk as it sells its output at price $p \in P$, which is unknown to the firm when it makes its production decisions. The price is drawn randomly and follows the stationary probability density function π_i . The firm does not observe its firm-specific price distribution, but observes market

prices for a broad class of similar goods.⁹ The stationary distribution of market prices is π_m , and the variance of these market prices is greater than the variance of the firm's price distribution. Beginning with this market distribution as a prior, the firm updates its estimate of its price distribution π_d as it observes draws from its actual price distribution π_i . The firm's price and market prices are normally distributed and truncated at zero. The firm also incurs a fixed operating cost h .

Besides price risk, the firm is also vulnerable to natural disasters, leading to losses l . This variable l represents all losses from the disaster – property damage and business interruptions (including effects on prices). Consequently, this disaster risk should be understood as independent of the non-disaster price risk already discussed. The firm's disaster risk distribution is known and provided to the firm. The firm can insure an amount q against the disaster, paying premiums $a(q)$ for a contract with payout function $I(q, l)$. Any resources used to purchase insurance cannot be used in production, leading to the constraint $k + a(q) = \underline{k}$ where k is the assets used in production.

Firm rewards are positive if firm equity, revenues, and insurance payments are greater than the firm's costs and losses, $\underline{k} + pf + I > h + a + l$. If not, the firm is insolvent, declares bankruptcy, and closes. The firm selects a sum insured to maximize the expectation of its value function

$$\max_{q \geq 0} E[V] = \int_{p_c}^{\infty} \int_0^{l_c} V(pf(k) - h - l - a(q) + I(q, l) + \underline{k}) \pi_d(p, l) \, dl \, dp \quad (1a)$$

$$\text{s. t. ,} \quad k + a(q) = \underline{k} \quad (1b)$$

$$p_c f + I + \underline{k} - h - a - l = 0 \quad (1c)$$

$$p f + I + \underline{k} - h - a - l_c = 0 \quad (1d)$$

⁹ The observed market prices include businesses that have exited the market because the demand for their goods was too low.

Where $\pi_d(p, l)$ is the joint density of the firm's estimated price distribution and the disaster loss distribution. The critical price p_c is the price below which the firm would be insolvent. Similarly, the critical loss l_c is the loss above which the firm would be insolvent.

2.2 Modeling Size and Age

Let a firm's size be measured by its equity endowment so that a large firm has equity $\underline{k}^L > \underline{k}^A$ where \underline{k}^A is the endowment of the average sized firm. Let a firm's age be measured by the number of price draws that it has observed. A young firm, which has observed few price draws, has an estimated price distribution closely resembling the market distribution, $\pi_d^Y \approx \pi_m$. An older firm, which has observed more price draws, has an estimated price distribution π_d^O , which is converging toward its actual price distribution π_i , $\lim_{d \rightarrow \infty} \pi_d \Rightarrow \pi_i$. Thus, the estimated price variance for the younger firm is greater than that of the older firm, $\text{var}(p^Y) > \text{var}(p^O)$. Assume for comparison that the old firm is the average firm in the market such that the young and old firm have the same expected price, $E[p_m] = E[p^Y] = E[p^O]$.

2.3 First Order Condition

The representative firm's first order condition is

$$\begin{aligned} \frac{\partial E[V]}{\partial q} = & \int_{p_c}^{\infty} \int_0^{l_c} V'(I' - a'(1 + pf')) \pi_d(p, l) dl dp + \frac{\partial l_c}{\partial q} \int_{p_c}^{\infty} V(pf - h - l_c - a + I(l_c) + \underline{k}) \pi_d(p, l_c) dp \\ & - \frac{\partial p_c}{\partial q} \int_0^{l_c} V(p_c f - h - l - a + I + \underline{k}) \pi_d(p_c, l) dl \leq 0. \end{aligned} \quad (2)$$

It identifies three effects of the disaster insurance. In the first term, the firm considers the marginal benefits relative to the marginal cost of insuring. This marginal cost includes premiums (a') and foregone investments ($pf'a'$). The second and third terms show that insuring also changes the firm's expected value by affecting the critical disaster loss l_c and critical price p_c . The intuitive result emerging from the second term is that increasing the sum insured allows the

firm to survive a more severe disaster due to insurance payments.¹⁰ The third term indicates that insuring also reduces the firm's resources available to manage price shocks; the critical price is increasing in the coverage limit of the disaster insurance.¹¹ Thus, purchasing natural disaster insurance increases the likelihood that the firm will become insolvent from a price shock.

2.4 Hypotheses

The presented model guides the three insurance-related hypotheses.

H1: Firms were insured against losses created by Hurricane Sandy. The first and second terms of the model's first order condition suggest that SMEs are likely to insure, with some caveats. SMEs have several reasons to act as if they are risk averse such as the close connection between the personal finances of the owner and those of the SME and because of financial frictions that lead to risk averse actions in larger corporations. Still, risk aversion may be insufficient to motivate insuring against disasters due to the third term, which shows that purchasing disaster insurance increases its vulnerability to background risks such as the price shock. To illustrate, consider the following value function, which is in the spirit of Roy's (1952) safety-first criterion

$$V(x) = \begin{cases} \alpha x^\gamma & \text{if } x > 0 \\ -\beta & \text{if } x = 0 \end{cases}$$

where $\beta > \alpha > 0$ and $\gamma < 1$. This value function is concave in returns x , but results in a disutility if the firm fails. If this disutility of failure is large, whether the firm will insure against

¹⁰ By the implicit function theorem, $\frac{\partial l_c}{\partial q} = -\frac{\frac{\partial W}{\partial q}}{\frac{\partial W}{\partial l_c}} = \frac{\frac{\partial a(1+\frac{p\partial f}{\partial a})}{\partial q} - \frac{\partial I}{\partial q}}{\frac{\partial I}{\partial l_c} - 1}$ where $W = pf + I + \underline{k} - h - a - l_c$, from Equation 1d.

This derivative is positive when evaluated at the critical loss, $\frac{\partial l_c}{\partial q} \Big|_{l=l_c} > 0$. The numerator is negative: for an outcome with a large disaster loss (l_c), increasing the sum insured would increase insurance indemnities (I) at a greater rate than insurance premiums (a). The denominator is also negative: a one-unit increase in the critical loss will not result in an increase in insurance indemnities that is greater than one.

¹¹ From Equation 1c, $\frac{\partial p_c}{\partial q} = \frac{a'(1+p_c f') - I'}{f}$. As f , f' , and p_c are positive, this derivative is also positive as long as any increase in the sum insured is priced at or above the actuarially fair rate.

the disaster largely depends on the likelihood of failure due to a disaster relative to the likelihood of failure due to background risks – a firm with large disaster exposures relative to other risks would be likely to insure while others would not.

While frictions in the form of higher external financing costs during unfavorable states of the world are perhaps the most commonly cited explanation for why firms insure, another important literature notes that a firm's debtholders may induce the firm to insure (e.g., Mayers and Smith, 1987; Caillaud, Dionne, and Jullien, 2000). Thus, a firm's insurance purchases might not reflect the risk management decisions of its owners, but serve as a financing requirement. Consequently, we examine several types of insurance coverage: property, flood, and business interruption. While mortgages and equipment loans often require property insurance on financed asset, we are unaware of any borrowing requirements that firms insure against business interruptions.

H1a: Insuring against disasters is increasing in firm size. From the theoretical model, marginal returns to production (f') are larger for smaller firms, due to the concavity of the production function, and so the first term in the first order condition replicates previous findings that smaller firms have a higher opportunity cost of investing in risk management (Rampini and Viswanathan, 2010).

H1b: Insuring against disasters is increasing in firm age. As younger firms experience greater likelihood of failure due to many risks (Haltiwanger, Jarmin, and Miranda, 2013; Thornhill and Amit, 2003), we predict that younger firms are less likely to insure against infrequent events. Doing so reduces their capacity to address more frequent shocks. In the theoretical model, the probability of experiencing the critical price is higher for younger firms. Consequently, insuring against natural disasters more meaningfully influences the likelihood of failure from a price shock for younger firms than older ones.

We extend the presented model to consider the firm's demand for credit and the lender's problem. While many readers may find these extensions intuitive from the mechanics described above, we provide a detailed exposition in the Online Appendix.

H2: Sandy increased credit demand among negatively affected firms. As measures of credit demand, we assess whether firms searched for credit, applied for credit, the types of products for which they applied, and the time spent applying.

We predict that Sandy increased demand for credit as it provides a means to finance recovery. Our model shows that firms borrow to replace assets that were lost in the disaster. Previous research also indicates that disasters increase demand for credit among firms: Berg and Schrader (2012) find that loan applications increased for an SME lender in Ecuador following volcanic activity, and Chavaz (2015) finds that local banks increase SME lending in communities affected by hurricanes in the United States.

H2a: Credit demand is decreasing in firm size. We predict that *smaller*, negatively affected firms will have a greater demand for credit due to their higher marginal productivity relative to larger ones.

H2b: Credit demand is decreasing in firm age. We predict that *younger*, negatively affected firms will have a greater demand for credit than older ones. This demand among younger firms is due to their greater perceived earnings risk. At a given interest rate, younger firms' potential success combined with bankruptcy protections if they fail increase the expected returns on borrowing for younger firms relative to older ones.

H3: Sandy increased credit constraints among negatively affected firms. 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.

In the lender's problem, Sandy increases the default risk of negatively affected firms as it reduces their income and assets. We also consider the potential of a delay in the information available to the lender (e.g., it is using the firm's most recent earnings reports or tax filings), leading to informational asymmetries. The disaster may have affected firms in ways difficult for lenders to assess, thereby increasing informational asymmetries. Lenders wanting to monitor

borrowers more closely may also increase their use of collateral to achieve this objective (Rajan and Winton, 1995). For example, Cerquiere, Ongena, and Roszbach (2016) find that, in response to a reduction in the value of collateral, lenders monitor borrowers less, reduce the amount that they lend to them, and increase their interest rates. Following these results, we posit that negatively affected firms will increase their use of collateral to secure loans.¹²

H3a: Credit constraints are decreasing in firm size. We predict that *smaller*, negatively affected firms will have less capacity to borrow than older firms. This prediction is also a result of the higher marginal productivity of smaller firms, which motivates them to operate more intensively. Larger firms are less likely to exhaust their debt capacity and so will be better able to borrow after a shock.

H3b: Credit constraints are decreasing in firm age. We predict that *younger*, negatively affected firms will experience greater credit constraints. The greater earnings risks of young firms reduce their access to credit. Young firms are also especially prone to the information asymmetries that we model, increasing credit constraints. Our disaster-specific predictions follow more general, established theoretical findings (e.g., Stiglitz and Weiss, 1981) and are consistent with empirical research suggesting that younger businesses are more sensitive to changes in credit market conditions (Fort et al., 2013).

¹² Lenders might also lend less following disaster due to capital or liquidity constraints; however, recent evidence suggests that local lenders in U.S markets are able to adjust to increase lending in affected markets (Chavaz, 2015; Cortés and Strahan, 2015). For example, Cortés and Strahan (2015) examine mortgage lending following natural disasters and find that banks increase mortgage lending in affected counties by adjusting in unaffected counties where their market shares are low. These adjustments include lending less, increasing securitization of new mortgages, and increasing short-term interest rates on deposits in unaffected counties.

3 Methods

3.1 Data

Our data comprise a cross-sectional survey of firms performed by the Federal Reserve Bank of New York (FBNY, 2014). Since 2010, the FBNY has conducted periodically the Small Business Credit Survey, polling businesses with fewer than 500 employees in the New York area about their financing. The survey included a series of questions regarding Hurricane Sandy in November 2013, roughly one year after the event. The survey was administered online and distributed by civic and non-profit institutions such as chambers of commerce. 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 dependent variable that we assess below.

On October 29, 2012, Sandy made landfall along the New Jersey coast as a post-tropical 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 for more on the effects of Hurricane Sandy). 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. All New Jersey, New York City, counties in the southeast of Hudson Valley, and the coastal counties in Connecticut were considered disaster areas, a total of 38 counties overall. In these counties, 949 firms completed the survey.

Table 1 provides descriptive statistics, comparing our sample to the population of firms in the survey area (which includes both disaster and nondisaster counties). The degree to which our sample represents the population of firms in the affected region is unclear and so warrants additional consideration with respect to how our results generalize. The surveyors were largely, but not fully, able to stratify the sample with respect to the distribution of age, size (in employees), and industry of firms in the area. Firm participation may have been influenced by the data collection process, as surveys were distributed by organizations such as chambers of

commerce and business and industry associations and participating firms were told that the FBNY administered the survey. Also, the sample includes only firms that survived Sandy, as the survey was conducted after the event. To the extent that Sandy caused firms to exit, our results would tend to underestimate its effect.

Table 1. Selected Characteristics of Firms in the Sample Compared to the Population of Firms in the Region, Fall 2013

	Disaster County Sample	Total Weighted Population
Firm Count	949	1,129,211
Firm Age		
0-2 years	15.6%	22.4%
3-5 years	14.4%	16.7%
6-10 years	19.1%	20.0%
11-20 years	22.2%	23.4%
20+ years	28.7%	17.6%
Firm Size		
1-4 employees	50.8%	57.3%
5-9 employees	18.9%	18.0%
10-19 employees	13.7%	12.0%
20-99 employees	14.9%	10.7%
100-499 employees	1.8%	2.0%
Industry		
Agriculture	0.2%	0.1%
Construction	16.1%	8.8%
Manufacturing	6.4%	3.8%
Retail	9.6%	14.7%
Wholesale/Transportation	8.6%	8.5%
Information/Media/Telecom	4.2%	1.9%
Finance/Insurance/Real Estate	5.4%	10.3%
Professional & Business	20.4%	11.3%
Services		
Personal Services	3.0%	10.8%
Education/Healthcare & Soc.	6.8%	12.8%
Assist.		
Leisure & Hospitality	7.1%	11.0%
Other	12.1%	6.2%

Table 2. Firm Size by Age Quartiles

Age Quartile	Employee Summary Statistics			
	Mean	Median	S.D.	Coeff. of Variation
First	3.6	2.0	4.0	1.1
Second	8.9	3.0	25.0	2.8
Third	12.9	5.0	25.5	2.0
Fourth	24.9	9.5	43.1	1.7

Note: Firms unaffected by Hurricane Sandy. The coefficient of variation is the S.D. divided by the mean.

Table 2 examines the relationship between firm age and size in our data using firms in the sample that were *unaffected* by Sandy. Firm size is typically measured in number of employees or, sometimes, revenues (e.g., SBA, 2014); we use number of employees.¹³ 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 ($r = 0.49$).

3.2 Identification

Firms report whether they were financially positively affected, negatively affected, or unaffected by Hurricane Sandy.¹⁴ We take being negatively affected by Hurricane Sandy to be an exogenous shock to the firm financing outcomes that we study here. Consider the model of outcome y (e.g., whether a firm applied for credit) for firm i

$$\begin{aligned} E[y_i|D_i = 1] &= \beta + \mathbf{C}'_i\boldsymbol{\gamma} + E[\varepsilon_i|D_i = 1] \\ E[y_i|D_i = 0] &= \mathbf{C}'_i\boldsymbol{\gamma} + E[\varepsilon_i|D_i = 0] \end{aligned}$$

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

One could imagine that, in contrast to Sandy being an exogenous event, firms relying on expensive financing products such as credit cards before the event might be more likely to report being negatively affected. As a proxy for pre-event firm financing, we use the firm's original funding profile and test whether a firm's original funding is related to whether it was negatively

¹³ A firm's number of employees are likely less volatile than its revenues for several reasons, including the transaction costs of hiring and firing employees.

¹⁴ The specific wording is "Was your business financially affected by Superstorm Sandy?" with response options "Yes, overall positively affected," "Yes, overall negatively affected," and "No, not significantly affected."

affected by Sandy. Firms were asked to identify all sources of funding that they used to start their business (e.g., business loans, personal savings, etc.). The financing outcome variables in Columns 1 through 4 of Table 3 are the focus of our analyses of credit demand and credit access. Each is binary and discussed in Section 4. Using data from firms outside the disaster area that reported they were unaffected by Sandy, we find that a firm's original funding is related to these financing outcomes and so a firm's original funding would seem to be a relevant proxy for pre-event financing for firms in the disaster area.¹⁵

Column 5 shows that, in FEMA disaster counties, a firm's original funding source is unrelated to whether it was negatively affected by Hurricane Sandy. Based on these analyses, we conclude that being negatively affected by Sandy is unrelated to a firm's financing before the event, and so treat the group of firms in the disaster counties that reported that they were unaffected by Sandy as a control group for testing our hypotheses.

Column 5 also shows that older firms are more likely to report being negatively affected at marginally significant levels. On average, each year a firm operates increases its likelihood of being negatively affected by Sandy by 0.2 percentage points. This result could occur if younger negatively affected firms were truncated from the data because they did not survive. Such censoring would make our estimates of the effect of age in these data a lower bound.

¹⁵ Ninety-two percent of firms outside the disaster area reported that they were unaffected by Sandy.

Table 3. *Negatively Affected By Sandy and Original Funding Type*

	Outside Disaster Area				In Disaster Area
	(1)	(2)	(3)	(4)	(6)
	I(Applied for Credit)	I(Access to Financing Decreased)	I(Interest Rate Increased)	I(Collateral)	I(Negatively Affected)
I(Original Funding: Business Loan)	0.0349 (0.048)	0.00142 (0.046)	-0.00575 (0.031)	0.307*** (0.076)	0.000523 (0.054)
I(Original Funding: Credit Cards)	0.169** (0.078)	0.138** (0.068)	0.0702 (0.51)	0.0131 (0.059)	0.00332 (0.053)
I(Original Funding: Personal Savings)	-0.00823 (0.062)	0.000870 (0.049)	-0.0481 (0.060)	-0.0873 (0.072)	-0.0100 (0.058)
I(Original Funding: Friends and Family)	-0.0215 (0.067)	0.0691 (0.047)	0.121** (0.053)	0.0609 (0.068)	-0.000979 (0.034)
I(Original Funding: Other)	0.0712 (0.079)	-0.00996 (0.058)	-0.00332 (0.057)	0.133* (0.080)	0.0840 (0.077)
Age	-0.000981 (0.001)	-0.000255 (0.001)	0.000104 (0.001)	0.00119 (0.002)	0.00241* (0.0012)
Employees	0.000976 (0.001)	0.0000527 (0.001)	-0.000673 (0.001)	0.00264*** (0.0007)	-0.000293 (0.001)
Obs.	479	485	468	469	776
Rsqr	0.240	0.261	0.298	0.386	0.089

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Linear probability models with White's (1980) heteroskedastically-consistent standard errors clustered at county. Models include industry and county fixed effects. Columns 1 through 4 use data from firms outside the disaster area that reported being unaffected by Sandy; Column 5 uses responses from firms in the disaster area. In Column 2, respondents reported on their firms' access to financing comparing 2013 to 2012.

3.3 Estimation

Our outcome variables are typically binary and unless otherwise noted we report linear probability models with White's (1980) heteroskedastically-consistent standard errors clustered by county.¹⁶ Linear probability models provide a straightforward way of interpreting model intercepts, indicator variables, and interaction terms, which we frequently do in our analyses. We

¹⁶ 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.

also estimated the regressions below as logit models, and those results support the narrative below and conclusions with respect to our hypotheses.

The regressions related to insurance take two forms. Only firms that were affected by Sandy were asked about their insurance protection; our models of insurance decisions only include negatively affected firms. First, we examine the effects of age and size, binning firms by quartile for firm i and outcome y (e.g., whether a firm has property insurance)

$$y_i = \sum_{l=1}^3 \beta_l \mathbf{I}(\text{AgeQuartile}_{i,l}) + \sum_{m=1}^3 \lambda_m \mathbf{I}(\text{EmployeesQuartile}_{i,m}) + \delta_j + \eta_k + \varepsilon_i \quad (3)$$

where, for example, $\mathbf{I}(\text{AgeQuartile}_{i,1})$ is the indicator function for whether firm i is in the first age quartile. Parameters δ_j and η_k are county and industry fixed effects, respectively. In these regressions, the oldest firms and largest firms serve as reference groups. In a second model of insurance decisions, we include a full set of age by employee quartile interactions

$$I(\text{Insurance}_i) = \sum_{l=1}^4 \sum_{m=1}^4 \beta_{l,m} \mathbf{I}(\text{AgeQuartile}_{i,l}) \times \mathbf{I}(\text{EmployeesQuartile}_{i,m}) + \delta_j + \eta_k + \varepsilon_i \quad (4)$$

where $I(\text{Insurance}_i)$ is the indicator function for whether firm i has insurance of any kind. In this regression, the oldest, largest firms serve as the reference group.

Our regressions related to credit demand and constraints rely primarily on the following estimation model to examine the consequences of being negatively affected by Hurricane Sandy for firm i and outcome y (e.g., whether a firm's interest rates increased)

$$\begin{aligned} y_i = & \alpha + \beta_1 \mathbf{I}(\text{NA}_i) + \beta_2 \text{Age}_i \times \mathbf{I}(\text{UA}_i) + \beta_3 \text{Age}_i \times \mathbf{I}(\text{NA}_i) + \beta_4 \text{Employees}_i \times \mathbf{I}(\text{UA}_i) \\ & + \beta_5 \text{Employees}_i \times \mathbf{I}(\text{NA}_i) + \beta_6 \mathbf{I}(\text{PA}_i) + \beta_7 \text{Age}_i \times \mathbf{I}(\text{PA}_i) + \beta_8 \text{Employees}_i \\ & \times \mathbf{I}(\text{PA}_i) + \delta_j + \eta_k + \varepsilon_i \end{aligned} \quad (5)$$

where $\mathbf{I}(NA_i)$, $\mathbf{I}(UA_i)$, and $\mathbf{I}(PA_i)$ are indicators, respectively, for whether a firm was negatively affected, unaffected, or positively affected by Sandy. Our regressions include an indicator for positively affected firms for completeness, but these firms are not a focus of our analysis.

We are interested in two aspects of these interaction terms. First, we consider whether the interaction term is different from zero. For example, a negative and significant interaction of age and negatively affected indicates that, among negatively affected firms, young ones are more likely to report an outcome (e.g., applied for credit) than older firms ($H_0: \beta_3 = 0$). We would understand from this result that the shock disproportionately challenged young firms. In some cases, the event may operate through pre-existing differences: all negatively affected firms are more likely to apply for credit (captured in β_1) and young firms, which apply at greater rates than older ones under normal conditions, apply at similarly greater rates after the shock (i.e., $\beta_2 = \beta_3$). Second, we consider whether age (or size) influences unaffected and negatively affected firms differently (such that $\beta_2 \neq \beta_3$). In these cases, the shock would seem to exacerbate pre-existing dynamics observed among unaffected firms.

We construct the model's intercept α to facilitate comparisons between negatively affected and unaffected firms. We constrain the county and industry fixed effects so that $\sum_{j=1}^J \delta_j = 0$ and $\sum_{k=1}^K \eta_k = 0$. Also, we standardize age and size (i.e., they are demeaned and divided by their standard deviation). Given this construction, the intercept represents the average unaffected firm in our data.

Finally, in the Appendix, we consider whether a firm's insurance payments affect its credit demand following Sandy. These regressions extend the model described in Equation 5 and compare the credit demand of mutually-exclusive subgroups of negatively affected firms. The relationship between insurance payment and credit demand may depend on the magnitude of loss sustained by the firm. Therefore, we include additional terms interacting the magnitude of the loss with whether insured firms received an insurance payment

$$\begin{aligned}
y_i = \dots + \beta_9 \mathbf{I}(NA_i) \times D(Payouts_i) + \beta_{10} \mathbf{I}(NA_i) \times \mathbf{I}(No\ Insurance_i) + \beta_{11} \mathbf{I}(NA_i) \\
\times \mathbf{I}(Large\ Loss_i) + \beta_{12} \mathbf{I}(NA_i) \times \mathbf{I}(Large\ Loss_i) \times D(Payouts_i) \\
+ \beta_{13} \mathbf{I}(NA_i) \times \mathbf{I}(Large\ Loss_i) \times \mathbf{I}(No\ Insurance_i) \quad (6)
\end{aligned}$$

where “...” represents all the elements on the right-hand side of Equation 5. Negatively affected firms reported a median loss amount of around \$25,000. We divide the sample at \$25,000, calling firms that sustained losses of less than or equal to this amount “small loss” firms and those with losses greater than this amount “large loss” firms. The term $D(Payouts)$ is a dummy set indicating the percent of losses paid by insurance (None (0%), Some (<50%), etc.). “No Insurance” is an indicator for firms reporting that they do not have any form of insurance.

While our sample includes 949 firms, our observations notably 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 some cases, observations also change because firms elected not to answer certain questions; however, we cannot identify a pattern in these missing observations that is relevant to our analysis.

3.4 Firms Negatively Affected by Sandy and Their Financing Needs

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.¹⁷

Negatively affected firms report a combination of effects on their incomes and balance sheets: 82 percent report that revenue decreased, 55 percent that expenses increased, 42 percent that assets decreased, and 39 percent 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

¹⁷ Firms in construction most commonly reported being positively affected by Sandy.

from a list (categories shown in Table 4). We scale the loss amount by the number of employees to increase the comparability of losses across firms.¹⁸ 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 4). Firms were also given the opportunity to write in other sources of loss, but no additional categories emerged.

Table 4. Firm Loss Source and Magnitude of Loss from Sandy

Loss Source	Frequency	Reported Loss Amount per Employee (by Percentile)				
		P10	P25	P50	P75	P90
Assets	29.7%	\$3,289	\$4,688	\$12,500	\$25,000	\$75,000
Utilities	43.6%	\$921	\$1,786	\$5,000	\$11,667	\$25,000
Supplier	12.5%	\$1,000	\$2,206	\$5,417	\$9,375	\$18,750
Customer	61.2%	\$1,167	\$2,500	\$6,250	\$17,500	\$37,500
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

Among negatively affected firms, 77 percent 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 percent of firms), *making capital investments* (11 percent), and *repositioning business to meet changing customer demand* (10 percent).

¹⁸ 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 (1) Less than \$10,000, (2) \$10,000 - \$25,000, (3) \$25,001 - \$50,000, (4) \$50,001 - \$100,000, (5) \$100,001 - \$250,000, and (6) 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 (1), we code this value as \$5,000. In any regression in which we include our transformed debt (which has a similar response set) or loss amount variables, we include dummies to identify top-coded firms (if the firm answers (6) in the above), called “top loss.”

4 Results

This section describes our findings related to each of the hypotheses developed in Section 2. Table 5 serves as a guide, summarizing our hypotheses and our conclusions.

Table 5. Summary of Hypotheses and Conclusions

Hypothesis	Conclusion
H1: Firms were insured against losses created by Hurricane Sandy.	Not supported
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 increasing in firm size.	Partially supported
H3b: Credit constraints are decreasing in firm age.	Partially supported

4.1 H1: Firms Were Insured Against Losses Created by Sandy

We find that insurance played a small role in addressing losses these firms incurred from Sandy. Firms affected by Sandy 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.¹⁹ Among insured firms, property insurance was the most common response. Twenty-nine percent of negatively affected firms reported not having insurance (Table 6).

Across all types of insurance, firms most frequently reported that *none* of their losses were recovered through insurance claims (Table 6). 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 percent of insurance claims in New Jersey and New York had been settled

¹⁹ 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.”

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 assets 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 a variety of business interruption policies exist, many types 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 also seem to poorly match the losses stemming from customer and utility disruptions commonly reported by negatively affected firms (Section 3.4).

Table 6. Insurance and Loss Recovery After Sandy Among Negatively Affected Firms

Insurance	Frequency	Reported Fraction of Loss Recovered Through Insurance			
		None	Some	Most	All
Property Insurance	54.1%	73.8%	18.3%	6.3%	1.6%
Flood Insurance	11.9%	51.7%	31.0%	17.2%	0.0%
Biz. Dis. Insurance	30.0%	72.2%	16.7%	8.3%	2.8%
No Insurance	28.9%	100.0%	-	-	-

Note: 270 firms reported having insurance and 170 specified a recovery amount. For fraction of loss recovered, some/most refers to a loss recovery of less/more than 50%. Data on firms negatively affected by Hurricane Sandy.

While we do not find support for Hypothesis 1 that firms tended to insure against losses created by Sandy, we do find support for Hypotheses 1a and 1b, that the likelihood of insuring increases

in firm age and firm size. Table 7 (Columns 1-4) reports results for negatively affected firms. This table divides firms into quartiles by age and by size (the number of employees), using the oldest firms and largest firms as reference groups.²⁰ Firms less than five years old are 30 percentage points more likely to be uninsured relative to the oldest firms. Young firms and small 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 to 23 years old) insure significantly less than the oldest firms. Size tends to divide firms relatively evenly at the median, 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 percent of the firms in our sample insure against floods; those that do tend to be larger.

²⁰ The four age categories are 1) firms less than 5 years old, 2) firms 5 to 11 years old, 3) firms 12 to 23 years old, and 4) firms greater than 23 years old. Similarly, the four employee (firm size) categories are 1) firms with 1 employee, 2) firms with 2 or 3 employees, 3) firms with 4 to 11 employees, and 4) firms with more than 11 employees.

Table 7. Effects of Age and Size on Insurance Uptake Among Negatively Affected Firms

	(1)	(2)	(3)	(4)
	I(Insurance (Any))	I(Property Insurance)	I(Business Interruption Insurance)	I(Flood Insurance)
Reference Group: Firms in 4 th Age and Employees Quartiles				
I(Age)				
1st Quartile	-0.299** (0.121)	-0.362** (0.164)	-0.234*** (0.083)	-0.0341 (0.071)
2nd Quartile	-0.104 (0.066)	-0.136** (0.066)	-0.144 (0.089)	0.00619 (0.067)
3rd Quartile	-0.157** (0.072)	-0.238** (0.115)	-0.103 (0.079)	-0.0126 (0.061)
I(Employees)				
1st Quartile	-0.252** (0.087)	-0.240** (0.099)	-0.184** (0.072)	-0.117 (0.081)
2nd Quartile	-0.245** (0.092)	-0.211** (0.090)	-0.161* (0.086)	-0.135* (0.073)
3rd Quartile	0.0137 (0.0897)	-0.00704 (0.079)	-0.0464 (0.076)	-0.0629 (0.061)
Obs.	273	273	273	273
Rsq.	0.31	0.28	0.27	0.27

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. $I(\cdot)$ is the indicator function. Linear probability models with White's (1980) heteroskedastically-consistent standard errors clustered at county. These models only include firms negatively affected by Sandy and follow Equation 3. All models include industry and county fixed effects.

Table 8 complements the results from Table 7 by examining the full set of age quartile and employee quartile interactions for a model of whether a firm has any form of insurance. The model follows Equation 4 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 7 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 are all significantly less likely to insure than the reference group (shown in the first column); 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.²¹

²¹ Old, small firms serve as a proxy for lifestyle firms. In the Online Appendix, we model these lifestyle firms as risk averse and show that even these firms may choose not to insure against infrequent events because doing so reduces resources available for more moderate shocks. Consistent with our predictions, we find that these old, small firms are no more likely to insure than old firms that are larger.

The coefficient value for firms in the first size and second age quartiles (-0.270) appears large relative to its neighbors. It 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 out of 25 firms are insured while 10 out of 20 are insured in the latter. The former is otherwise not significantly different from its neighbors.

Table 8. Age and Size Interactions from Model of Whether a Firm Has Any Insurance

Dependent variable: $I(\text{Insurance (any)})$

		$I(\text{Age Quartile})$				Total Obs.		
		First	Second	Third	Fourth			
$I(\text{Employee Quartile})$	First	Coeff.	-0.480***	-0.270***	-0.518***	-0.240	71	
		St. Err.	(0.112)	(0.097)	(0.105)	(0.207)		
		Obs.	27	25	20	8		
	Second	Coeff.	-0.436**	-0.492**	-0.289*	-0.233		50
		St. Err.	(0.204)	(0.191)	(0.155)	(0.207)		
		Obs.	13	11	14	12		
	Third	Coeff.	-0.416***	-0.041	-0.0244	0.098		72
		St. Err.	(0.143)	(0.160)	(0.079)	(0.078)		
		Obs.	19	11	23	19		
	Fourth	Coeff.	0.127	-0.056	-0.145	Reference		71
		St. Err.	(0.107)	(0.078)	(0.109)	Group		
		Obs.	2	11	27	31		
Total Obs.		61	58	84	70	273		

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $I(\cdot)$ is the indicator function. Output from linear probability model of whether a firm has any form of insurance with White's (1980) heteroskedastically-consistent standard errors clustered at county. The model follows Equation 4, only includes firms negatively affected by Sandy, and includes industry and county fixed effects. This regression model has a full set of interaction terms. 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 squared of 0.34.

4.2 H2: Sandy Increased Credit Demand

Negatively affected firms were more likely to search and apply for credit and put forth more effort doing so. We consider whether firms searched for credit, applied for credit, the types of products for which they applied, and the time spent applying. Table 9 provides the results for all outcome variables related to Hypotheses 2 and 3 and follow Equation 5. The first row shows the model intercept, which describes the results for the average unaffected firm in our data (as described in Section 3.3). 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 unaffected and

negatively affected firms. These regressions also include controls for positively affected firms and county and industry fixed effects.²²

Being negatively affected by Sandy increased the likelihood that a firm searched for credit by 70 percent (Table 9, Column 1, $(Intercept + I(Neg. Affected))/Intercept = (0.29 + 0.20) / 0.29 = 1.69$).²³ About 29 percent of unaffected firms searched for credit compared to half of negatively affected firms ($0.29 + 0.20 = 0.49$). Younger, negatively affected firms were marginally significantly more likely to search for credit than older ones.

Negatively affected firms were also almost twice as likely to apply for credit (Table 9, Column 2).²⁴ The likelihood of applying for credit is 21 percent for unaffected firms compared to 39 percent of negatively affected firms ($Intercept + I(Neg. Affected) = 0.21 + 0.18 = 0.39$). Among those negatively affected, it is the *young* firms and the *large* firms that are more likely to apply for credit. For example, being one standard deviation larger than the average firm increases a negatively affected firm's likelihood of applying for credit by 8 percentage points. Firms that did not apply for credit were asked why they did not, and negatively affected and unaffected firms reported similar responses: about a third are debt averse, a third believe they are unlikely to be approved, and a third do not need credit.

Regarding types of credit, negatively affected firms were significantly more likely to apply for commercial loans, increasing the likelihood by about 15 percentage points (Column 3).²⁵ Sandy did not increase applications for credit cards; however, negatively affected and unaffected *young*

²² We also tested three-way interaction terms of age, size, and whether firms were negatively affected by Sandy. Those terms had almost no impact on the age and size coefficients reported in Table 9 and provided few additional insights. Because of the difficulty of interpreting three-way interaction terms, we have omitted them from the regressions reported here.

²³ "Did your business search for credit in the first half of 2013?"

²⁴ "Did your business apply for credit in the first half of 2013?"

²⁵ "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."

firms alike are significantly more likely to apply for credit cards to address their financing needs (Column 4).²⁶

Negatively affected firms also put forth more effort when applying for credit, characterized by the hours they spent.²⁷ Firms that receive all the credit for which they apply may stop searching for credit and so we limit our regressions on effort applying to those firms that did not receive all the credit for which they applied. During the first half of 2013, the average unaffected firm spent about 15 hours completing applications. Among firms that did not receive all the financing they requested, negatively affected ones spent more than twice as long (Column 5). Younger firms and larger firms tended to spend more time applying for credit than older ones and smaller ones.

In the Appendix, we examine whether insurance payments affect credit demand. We find that insurance payments significantly reduced the likelihood that firms incurring above-median losses searched and applied for credit. Insurance payments did not significantly affect credit demand among firms that experienced below-median losses.

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 the age of negatively firms. Compared to older negatively affected firms, young negatively affected firms are more likely to apply for credit, to invest more hours applying, and to adopt more expensive sources of financing such as credit cards.

²⁶ We also examined applications for lines of credit. About 75 percent of firms applying for credit applied for lines of credit. Among firms applying for credit, a firm's age, size, and being negatively affected by Sandy do not significantly affect a firm's likelihood of applying for a line of credit.

²⁷ "When applying for credit in the first half of 2013, approximately how many total hours did your business spend researching and completing credit applications?"

We do *not* find support for hypotheses H2a, that credit demand is decreasing in the size of negatively affected firms. Instead, compared to smaller negatively affected firms, larger negatively affected firms are more likely to apply for credit and spend more time doing so, which may be a function of their likelihood of being approved, as we show in the next section. That *small* negatively affected firms do not apply for credit goes against our prediction based on the insights of Rampini and Viswanathan (2010). One plausible explanation follows from the demographic research of Hurst and Pugsley (2011): an important subset of small businesses is guided by non-pecuniary rewards such as the owner's amenity value of being self-employed. As shown in the Online Appendix, avoiding or limiting the use of credit in this context can be consistent with the behavior of a risk averse utility maximizing owner.

Table 9 Effects of Sandy on Credit Demand and Access

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	I(Searched for Credit)	I(Applied for Credit)	I(Applied for Loans)	I(Applied for Credit Cards)	Number of Hours	I(Access to Financing Decreased)	I(Interest Rate Increased)	I(Collateral)	I(Collateral, Bus. Real Estate)	I(Received All Credit Financing Requested)
Intercept	0.291*** (0.0234)	0.214*** (0.0209)	0.515*** (0.0300)	0.322*** (0.0464)	15.26* (8.383)	0.165*** (0.0195)	0.0769*** (0.0168)	0.215*** (0.0344)	0.0332 (0.0279)	0.333*** (0.0396)
I(Neg. Affected)	0.201*** (0.0517)	0.177*** (0.0391)	0.150** (0.0588)	0.0525 (0.0664)	20.36** (9.858)	0.164*** (0.0280)	0.113*** (0.0229)	0.156*** (0.0290)	0.0703*** (0.0187)	0.0187 (0.0578)
Age x I(Unaffected)	-0.0654** (0.0284)	-0.0154 (0.0274)	-0.0739* (0.0388)	-0.107*** (0.0377)	-10.65 (6.918)	-0.00609 (0.0264)	0.00113 (0.0170)	0.0251 (0.0255)	0.0116 (0.0123)	0.0975** (0.0391)
Age x I(Neg. Affected)	-0.0698* (0.0381)	-0.0736** (0.0333)	0.00791 (0.0649)	-0.165*** (0.0573)	-12.67** (5.662)	-0.0122 (0.0383)	-0.0521** (0.0230)	0.0245 (0.0225)	0.0378* (0.0199)	0.0251 (0.0753)
Employees x I(Unaffected)	0.0188 (0.0240)	0.0307 (0.0228)	0.0504 (0.0451)	0.0456 (0.0499)	18.83 (23.77)	-0.0122 (0.0155)	-0.0226* (0.0128)	0.0740** (0.0303)	0.0413** (0.0181)	0.0410** (0.0184)
Employees x I(Neg. Affected)	0.00296 (0.0309)	0.0824** (0.0373)	-0.0592 (0.0481)	0.0270 (0.0747)	16.71** (8.188)	-0.0256 (0.0287)	0.00790 (0.0493)	0.123*** (0.0237)	0.152*** (0.0233)	0.154** (0.0665)
Obs.	829	830	275	275	188	834	808	793	790	273
Rsqr	0.12	0.12	0.29	0.25	0.32	0.11	0.08	0.179	0.28	0.26

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. $I(\cdot)$ is the indicator function. All models have binary dependent variables except for “Number of Hours” and are linear probability models. All models report White’s (1980) heteroskedastically-consistent standard errors clustered at county, include industry and county fixed effects, and full interactions for positively affected firms, as described in Equation 5. Models are constructed so that the intercept value represents the average unaffected firm 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.

4.3 H3: Sandy Increased Credit Constraints

We also find that credit markets tightened for negatively affected firms. We consider 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.

Table 9 shows the results for these regressions, which follow Equation 5. While 39 percent of these firms report taking on more debt because of Sandy, negatively affected firms were also more twice as likely as unaffected firms to report that their access to financing had decreased relative to the previous year (Table 9, Column 6, $(Intercept + I(Neg.Affected))/Intercept = (0.165 + 0.164)/0.165 = 1.99$).²⁸ About one-third of negatively affected firms report that their access decreased ($Intercept + I(Neg.Affected) = 0.165 + 0.164 = 0.329$). This difference in credit access is not explained by negatively affected firms using significantly more credit: negatively affected and unaffected firms had similar leverage ratios at the time of the survey.²⁹

These credit constraints seem to be caused by several factors, including higher interest rates and collateral requirements for negatively affected firms. Negatively affected firms are more than twice as likely as unaffected firms to report that their interest rate increased relative to the previous year (Table 9, Column 7).³⁰ Approximately 8 percent of unaffected firms report that their rates increased, compared to 19 percent of negatively affected firms. Small business interest rates were generally declining during this time: the interest rates on SBA 20-year major asset and real estate loans (CDC/504 loans) decreased by 40 basis points from an average rate of 4.7

²⁸ “How has your business’s ability to access financing changed when comparing the first half of 2013 to the same period in 2012?”

²⁹ 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).

³⁰ “How did the interest rate on your business debt change in the first half of 2013 compared with 2012?”

percent in the first half of 2012 to 4.3 percent in the first half of 2013 (Small Business Finances, 2016). Younger, negatively affected firms are significantly more likely to report that their interest rates had increased relative to the previous year. ($H_0: \beta_{Age \times I(Unaffected)} = \beta_{Age \times I(Neg.Affected)}$, $F = 5.63$, $p = 0.02$)

We also find that being negatively affected increases the likelihood that a firm is required to secure its loan with collateral by 73 percent (Table 9, Column 9): approximately 37 percent of negatively affected firms use collateral.³¹ Large firms are especially likely to use collateral. Negatively affected firms are more likely to collateralize business real estate, business non-real estate assets, and personal real estate. Some of the largest differences are for business real estate (Column 9). The effect of size on using business real estate for collateral is significantly greater for negatively affected firms than unaffected ones ($H_0: \beta_{Employees \times I(Unaffected)} = \beta_{Employees \times I(Neg.Affected)}$, $F = 19.41$, $p < 0.01$). About 7 percent of unaffected firms that are one standard deviation larger than the average secures their loans with business real estate ($0.033 + 0.041 = 0.074$), compared to 26 percent of their negatively affected counterparts ($0.033 + 0.070 + 0.152 = 0.255$).

This use of collateral seems important for explaining credit constraints, as larger firms are more likely to receive all the financing they requested (Column 10).³² A one standard deviation increase in size increases the likelihood by 15 percentage points of a negatively affected firm receiving all the credit for which it applies. The effect of size on whether a business receives all

³¹ “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 non-real estate assets (equipment, vehicles, securities),” “Business real estate,” “Personal real estate,” “Other, please specify (*e.g., personal assets*).”

³² “How much of the credit your business applied for was approved?” with response options “All (100%),” “Most ($\geq 50\%$),” “Some ($< 50\%$),” “None (0%).” The dependent variable takes the value 1 if firms answered “All (100%)” and 0 otherwise.

the credit for which it applies is greater for negatively affected firms than unaffected ones at marginally significant levels ($H_0: \beta_{Employees \times I(Unaffected)} = \beta_{Employees \times I(Neg.Affected)}$, $F = 2.96, p = 0.087$).

These credit constraints are substantial and persistent. Most negatively affected firms (69 percent) report a financing need specifically related to Sandy one year after the event.³³ The median range of these financing needs is \$50,000 to \$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 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. Still, smaller, negatively affected firms were less likely to report than larger ones that they had received all the credit financing that they had requested, and younger, negatively affected firms were more likely to report interest rate increases than older ones.

4.4 Few Firms Borrow from the U.S. Small Business Administration's Disaster Lending Program.

Our results indicate that financial frictions may play an important role in small and young firms' recovery after a disaster, suggesting the potential for public intervention to address market failures. Toward policy recommendations, we consider the performance of the disaster lending program of the SBA. Firms are eligible to apply for SBA disaster loans if they incur physical damage or an economic loss from a federally declared disaster. This program seems well-suited to address the types of credit market gaps identified above; however, we find that few firms

³³ "Now, roughly one year later, what type(s) of financing needs related to Superstorm Sandy does your business have?"

borrow from this program. In our data, 8 percent of negatively affected firms borrowed from the SBA disaster lending program.

Table 10 shows the loan application completion and approval rates for all firms (not just those in our survey) that applied for SBA disaster loans due to Hurricane Sandy.³⁴ Ninety-nine percent of the value of Sandy-related SBA approved loans to businesses were in the three states covered in our survey: CT, NJ, and NY. FEMA referred many of the SBA applicants, suggesting that about 90,000 firms, overall, contact the SBA. One-third of firms that began the application process withdrew their application before completing it. Almost 60 percent of firms that completed the application process were rejected by the SBA.

In our communications with managers of the SBA program, they cite several demand and supply-side factors explaining this relatively low take-up. For example, SBA (2015a) identifies acceptable credit history, ability to repay, and collateral (when it is available) as requirements for borrowing. Managers at the SBA report that as firms learn more about these requirements through the application process, some choose not to continue. We also speculate that the program's prescribed interest rates affected participation. Interest rates in the program do not exceed 4 percent for businesses that cannot obtain credit elsewhere; for businesses that already have access to credit, interest rates do not exceed 8 percent (SBA, 2015a). These rates are generally higher than the unprecedentedly low market rates in 2012 and 2013 and so the high rejection rate of applicants by the SBA likely results from the types of firms selecting into the program at that time.

³⁴ Federal disaster appropriations for Hurricane Sandy allowed the SBA to provide up to \$5 billion in disaster loans (Rivera, 2013); over \$500 million was eventually approved by the SBA for lending to firms (about 80 percent of approved SBA loans were to households, who are also eligible to apply, SBA, 2015b).

Table 10. Applications for SBA Disaster Loans Among Firms Following Hurricane Sandy

	Number of Firms	Percent of Started Apps Ending in Outcome	Percent of Completed Apps Ending in Outcome
FEMA Referrals to SBA	89,423	---	---
SBA Applications Received	14,970	---	---
Withdraw	4,926	33%	---
Declined	5,808	39%	58%
Approved	4,236	28%	42%
Approved Amount	\$513,458,100		

Note: Data provided by SBA.

5 Conclusion

We examine firms' financial management decisions related to an infrequent, severe income and asset shock, Hurricane Sandy. We use firm-level data, collected one year after Sandy and stratified by age, size, and industry to represent the population of firms in the New York area. We find that about 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. Recent research on firm size (e.g., Rampini and Viswanathan, 2010) indicates that the high productivity of smaller firms motivates them to invest more heavily in production, reducing their capacity to manage shocks relative to larger firms. Consistent with these predictions, larger firms in our data were more likely than smaller firms to be insured and to have the capacity to meet collateral requirements to borrow after the event. We build on that work through recognition that insuring against rare events

reduces resources to manage more frequent shocks. Many of the risks to which firms are exposed decline with age (Haltiwanger, Jarmin, Miranda, 2013). Consequently, we posit that insuring against specific, rare events such as natural disasters becomes more attractive as firms age. Consistent with these predictions, we find that younger firms are significantly less likely to insure than older ones. Also, younger, negatively affected firms were more likely than older ones to apply for credit, especially credit cards, and to experience interest rate increases after the shock.

Our findings provide initial insights that warrant additional research to clarify their generalizability, as the potential influence of survivorship and survey response bias in our sample is unclear. While particularly challenging, collecting detailed data on firms both before and after a severe shock would strengthen causal interpretations of the observed differences across firms. We gain some confidence in the generalizability of our results from the research of Basker and Miranda (2014) who study Hurricane Katrina using census data, rather than post-event surveys. They find that young and small firms were more likely to fail following that event; our results complement this finding through additional information regarding firms' financial management of a similar shock. Our findings also warrant additional research regarding how the outcomes that we observe following a major storm in the New York area generalize to other locations and shocks.

6 Market and Policy Recommendations

We close by discussing market opportunities and public policy recommendations based on our findings. Regarding market opportunities, our theoretical model helps explain why even fully-informed, disaster-prone, risk-averse businesses might not insure, yet we expect that the many insured businesses who received no payments from Sandy were surprised and disappointed to learn that they were not better protected. The exposure of businesses in our study to shocks such as Sandy suggest a need for innovative insurance products. For example, parametric insurance bases claims payments on an objective measure of a catastrophe such as windspeed or rainfall. Parametric insurance may be especially relevant for younger and smaller firms, as this type of

insurance reduces the problems of asymmetric information that may be substantial for insuring these firms through traditional products.

Regarding public policy, we first suggest a greater emphasis on programs that encourage preparing for shocks. We propose a voluntary federal disaster preparedness program to assist firms in the nontrivial tasks of assessing infrequent risks and developing strategies to address them. A firm's preparedness assessment might act as a signal to its counterparts (e.g., lenders, supply chain partners), improving access to credit, insurance, supplier contracts, lease agreements, and other private-sector contracts exposed to disaster risk.

Second, we suggest a broader set of financing mechanisms structured to overcome the financial frictions constraining vulnerable and affected firms. Our results suggest a need for targeted improvements to the SBA disaster lending program. Despite strong evidence that negatively affected firms do not have access to sufficient credit, only 8 percent of negatively affected firms borrowed from the SBA program. Firms with the greatest financing needs may require additional equity investments rather than credit. Young firms are some of the least equipped to finance recovery with credit. To this end, we suggest public disaster funding that would also include means-tested grants (as a substitute for equity) depending on firm preparedness scores, repayment capacity, presence in socially vulnerable communities, among other criteria.

Appendix: Large Insurance Payments Reduce Credit Demand

We also assess whether a firm's insurance payments affect its demand for credit following Sandy.³⁵ 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.

³⁵ "Roughly, what percent of your business's losses was recovered through insurance?" with response options "None (0%)," "Some (<50%)," "Most (≥50 %)," "All (100%)," and "Business did not suffer any losses."

These regressions follow Equation 6. 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 from those that sustained above-median losses – the median loss amount was \$25,000. The regressions also include controls for firms’ age and size, positively affected firms, and industry and county fixed effects.

Table 11 shows the results. The intercept provides the estimate for the average unaffected firm. For these regressions, the term $\mathbf{I}(\text{Neg. Affected})$ serves as a reference group for several interaction terms. It describes negatively affected, insured firms that incurred *below-median losses* and received no claims payments. These firms were around 25 percentage points more likely to search and apply for credit than the average unaffected firm.

Insurance payments did not significantly affect whether firms searched and applied for credit when their *losses were small*. The terms under $\mathbf{I}(\text{Neg. Affected}) \times \mathbf{D}(\text{Insurance Payments})$ show the effects of insurance payments for negatively affected firms that sustained below-median losses, which do not significantly differ from the reference group of firms that received no payments ($\mathbf{I}(\text{Neg. Affected})$). Uninsured firms sustaining small losses also did not differ from this reference group.

Insurance payments significantly reduced the likelihood that firms searched and applied for credit when their *losses were large*. The term $\mathbf{I}(\text{Neg. Affected}) \times \mathbf{I}(\text{Large Loss})$ describes negatively affected, insured firms that sustained *above-median losses* and received no claims payments. The likelihood that these firms searched or applied for credit did not significantly differ from their small-loss counterparts ($\mathbf{I}(\text{Neg. Affected})$), which serve as their reference group. The terms under $\mathbf{I}(\text{Neg. Affected}) \times \mathbf{I}(\text{Large Loss}) \times \mathbf{D}(\text{Insurance Payments})$ show the effects of insurance payments for negatively affected firms sustaining above-median losses. Negatively affected, above-median-loss, insured firms that were fully covered by claims payments were significantly less likely to search and apply for credit than those that received no claims payments (their reference group is $\mathbf{I}(\text{Neg. Affected}) \times \mathbf{I}(\text{Large Loss})$). They were about 60

percentage points less likely, making them even less likely to search and apply for credit than unaffected firms. We speculate that these firms that received full payments had especially low credit demand as insurance payments (e.g., cash for business interruptions) may have addressed their financing needs. Finally in the final row, uninsured firms sustaining large losses did not differ from their reference group of insured firms that sustained large losses but did not receive insurance payments ($\mathbf{I}(\text{Neg. Affected}) \times \mathbf{I}(\text{Large Loss})$).

Table 11 Effects of Insurance Payments on Credit Demand

	(1) I(Searched for Credit)	(2) I(Applied for Credit)
Intercept	0.311*** (0.0307)	0.248*** (0.0205)
Negatively Affected, Below-Median Losses		
I(Neg. Affected)	0.235*** (0.0619)	0.258*** (0.0640)
I(Neg. Affected) x D(Insurance Payments)		
Reference Group: I(None (0%))		
I(Some (< 50%))	-0.158 (0.254)	-0.128 (0.262)
I(Most (≥ 50%))	0.124 (0.377)	-0.117 (0.309)
I(All)	-0.0343 (0.341)	-0.00482 (0.334)
I(Neg. Affected) x I(No Insurance)	-0.0492 (0.159)	0.0200 (0.142)
Negatively Affected, Above-Median Losses		
I(Neg. Affected) x I(Large Loss)	-0.0558 (0.0966)	-0.0684 (0.115)
I(Neg. Affected) x I(Large Loss) x D(Insurance Payments)		
Reference Group: I(None (0%))		
I(Some (< 50%))	0.0667 (0.0870)	0.0956 (0.100)
I(Most (≥ 50%))	-0.362*** (0.124)	-0.241 (0.158)
I(All)	-0.580*** (0.0819)	-0.614*** (0.0723)
I(Neg. Affected) x I(Large Loss) x I(No Insurance)	-0.00246 (0.0719)	-0.150 (0.0989)
Obs.	835	835
Rsqr.	0.12	0.12

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. $I(\cdot)$ is the indicator function; $D(\cdot)$ indicates a dummy set. Linear probability models with White's (1980) heteroskedastically-consistent standard errors clustered at county. All models include industry and county fixed effects and control for firms' age and size and being positively affected, as described in Equation 6. Models are constructed so that the intercept value represents the average unaffected firm in the data.

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FOR ONLINE PUBLICATION

7 Online Appendices

7.1 Online Appendix 1. A Model of Firm Financing and Natural Disaster Risk

We develop a theoretical model to formulate hypotheses related to firm financing and natural disaster risk in Section 2. In the interest of completeness, we repeat portions of the model setup included there. Following Foster, Haltiwanger, and Syverson (2016), who identify a relationship between demand and firms' age and size, we introduce risk to returns via demand risk that influences the price at which the firm can sell its goods.³⁶ Our model leverages the work of Jovanovic (1982), Rampini and Viswanathan (2010), and Stiglitz and Weiss (1981) but uses some simplifications tailored to our research questions. Our model is static, which allows us to examine cross-sectional exogenous differences in firms related to their age and size, but does not facilitate analyses of how firms evolve as is done by Jovanovic and Rampini and Viswanathan.

7.1.1 Firm's financing problem

A representative firm is endowed with an initial stock of equity \underline{k} and a unique production technology $f(\cdot)$ that is increasing and concave ($f' > 0, f'' < 0$). The firm is a price taker, facing demand risk as it sells its output at price $p \in P$, which is unknown to the firm when it makes its production decisions. The price is drawn randomly and follows the stationary probability density function π_i . The firm does not observe its firm-specific price distribution, but observes market prices for a broad class of similar goods.³⁷ The stationary distribution of market prices is π_m , and the variance of these market prices is greater than the variance of the firm's price distribution. Beginning with this market distribution as a prior, the firm updates its estimate of its price

³⁶ Jovanovic (1982) reaches similar results using stochastic production costs.

³⁷ The observed market prices include businesses that have exited the market because the demand for their goods was too low.

distribution π_d as it observes draws from its actual price distribution π_i . The firm's price and market prices are normally distributed and truncated at zero. The firm also incurs a fixed operating cost h .

The firm selects a level of assets k to be used in production. If $k > \underline{k}$, the firm can borrow the residual ($\bar{k} = k - \underline{k}$) at prices governed by the cost function $c(\cdot)$, which is increasing and quasi-convex ($c' > 0, c'' \geq 0$).

Firm rewards are positive if firm equity and revenues are greater than liabilities, $pf + \underline{k} > c + h$. If not, the firm is insolvent and declares bankruptcy, receiving a reward of zero. The firm maximizes the expectation of its value function

$$\begin{aligned} \max_{\bar{k} \geq 0} E[V] &= \int_{p_c}^{\infty} V(pf(k) - c(\bar{k}) - h + \underline{k})\pi_d(p) dp \quad (A1) \\ \text{s. t.,} \quad & k = \bar{k} + \underline{k} \\ & p_c f + \underline{k} - c - h = 0 \end{aligned}$$

The critical price p_c is the price below which the firm would be insolvent. This price is a function of the firm's financial structure

$$p_c f(k) - c(\bar{k}) - h + \underline{k} = 0 \implies p_c = \frac{c(\bar{k}) + h - \underline{k}}{f(k)}. \quad (A2)$$

The critical price is decreasing in equity (firms with more equity can withstand a less advantageous price draw) and is increasing in firm debt.³⁸

³⁸ We identify the effects of equity \underline{k} and debt \bar{k} on the critical price using the implicit function theorem. Let $W = p_c f(k) - c(k - \underline{k}) + \underline{k}$. By the implicit function theorem

$$\frac{\partial p_c}{\partial \underline{k}} = -\frac{\partial v / \partial \underline{k}}{\partial v / \partial p_c} = -\frac{p_c f' + c' + 1}{f} < 0.$$

The critical price is decreasing in equity. Similarly, for debt

$$\frac{\partial p_c}{\partial \bar{k}} = -\frac{p_c f' - c'}{f}.$$

Borrowing both increases the firm's expected returns (should it survive) and increases its chance of failure. The firm's first order condition is

$$\frac{\partial E[V]}{\partial \bar{k}} = \int_{p_c}^{\infty} V'(pf' - c')\pi_d(p) dp - \frac{\partial p_c}{\partial \bar{k}} V(p_c f - c - h + \underline{k})\pi_d(p_c) \leq 0. \quad (A3)$$

The first term shows that when the firm is operating above the critical price level, borrowing increases the expected marginal returns of production, motivating the firm to borrow until expected marginal revenues equal marginal costs. The second term shows that borrowing also reduces expected returns by reducing the size of shock that the firm can survive because debt increases the critical price.³⁹

7.1.2 Lender's problem

The lender's problem follows from that of the firm. The firm's borrowing costs are revenues to the lender. The lender is a price-taker, following an interest rate menu $c(\bar{k})$.⁴⁰ The firm borrows from a single lender so that the lender loses some portion of its initial principal, the amount $c + h - pf - \underline{k}$, if the firm declares bankruptcy. That is, the lender takes control of the firm's

Since $p_c f - c + \underline{k} = 0$ and $\underline{k} > 0$ for operating firms, liabilities are larger than revenues $c > p_c f$. Because the production function f is concave and cost function c quasi-convex, marginal revenues are less than marginal costs $p_c f' < c'$ and so the numerator is negative. The critical price is increasing in debt, $\partial p_c / \partial \bar{k} > 0$.

³⁹ To see this derivation, rewrite the firm's expected return (A1) as

$$\max_{\bar{k} \geq 0} E[V] = - \left(\int_{\infty}^{p_c} V(pf(k) - c(\bar{k}) - h + \underline{k})\pi_d(p) dp \right).$$

Following Leibniz's rule, the derivative of expected returns with respect to debt is

$$\frac{\partial E[V]}{\partial \bar{k}} = - \left(\int_{\infty}^{p_c} V' \left(p \frac{\partial f}{\partial \bar{k}} - \frac{\partial c}{\partial \bar{k}} \right) \pi_d(p) dp + \frac{\partial p_c}{\partial \bar{k}} V(p_c f - c - h + \underline{k})\pi_d(p_c) \right) \leq 0.$$

The term in the integrand is the derivative of the function when the price is above the critical price. The term in the second bracket comes from the fundamental theorem of calculus and evaluates how a change in debt affects returns through a change in the boundary of the integral. The lender's problem and the firm's problem that includes natural disaster risk below follow a similar structure to that above and also rely on Leibniz's rule.

⁴⁰ The assumption that lenders take interest rates as given facilitates our exposition. Our lender model focuses exclusively on supply adjustments. Stiglitz and Weiss (1981) allow lenders to set interest rates and show that asymmetric information can still lead to credit rationing.

resources, $pf + \underline{k}$, which are less than the firms' liability $c + h$ because of bankruptcy. The lender's problem is to maximize

$$\max_{\bar{k} \geq 0} E[g] = c(\bar{k}) - \int_0^{p_c} (c(\bar{k}) + h - pf(\bar{k} + \underline{k}) - \underline{k}) \pi_{d-b}(p) dp.$$

where g is the lender's returns, π_{d-b} is the lender's estimate of the firm's price risk. The lender observes a subset $d - b$ of the firm's price draws. For example, the lender observes the firm's tax filings but not firm revenues since the most recent filing.

From the lender's first order condition, lending more increases 1) the revenue of the lender, 2) the loss of the lender if the firm fails, and 3) the risk of firm failure.

$$\frac{\partial E[g]}{\partial \bar{k}} = c' - \int_0^{p_c} (c' - pf') \pi_{d-b}(p) dp - \frac{\partial p_c}{\partial \bar{k}} (c + h - p_c f - \underline{k}) \pi_{d-b}(p_c) \leq 0. \quad (A4)$$

7.1.3 Firms' age and size, financing and shocks

Firms' financing needs and access to financing are distinctly influenced by their age and size. For the exercise, the compared firms are identical (e.g., have comparable production technologies) except for their age and size characteristics. Let a large firm be one with a large equity endowment $\underline{k}^L > \underline{k}^A$ where \underline{k}^A is the endowment of the average sized firm. This large firm will demand less credit than the average firm as its marginal product of borrowing is lower, $\partial f(\bar{k} + \underline{k}^L) / \partial \bar{k} < \partial f(\bar{k} + \underline{k}^A) / \partial \bar{k}$. Consequently, the large firm will tend to produce more, borrow less, and be less leveraged (have a lower ratio of debt to equity) than the average firm. Additionally, the larger firm can withstand larger price shocks than the average firm as the critical price is decreasing in equity, leading lenders to supply more credit to the large firm (Equation A4).

Let a young firm be one whose estimated price distribution closely resembles its uninformed prior of the market distribution, $\pi_d^Y \approx \pi_m$. Let an older firm be one that operates with more observed price draws d and so its estimated price distribution π_d^O is converging toward its actual

price distribution π_i , $\lim_{d \rightarrow \infty} \pi_d \Rightarrow \pi_i$. Thus, the variance for the estimated price variance for the younger firm is greater than that of the older firm, $\text{var}(p^Y) > \text{var}(p^O)$. Assume for comparison a mean-preserving spread, that the old firm is the average firm in the market such that the young and old firms have the same expected price, $E[p_m] = E[p^Y] = E[p^O]$. The larger estimated variance of the younger firm's price distribution has two effects: it increases the likelihood of failure and of windfall gains. The younger firm would reap the benefit of a windfall and is protected by bankruptcy in the case of failure and so has a larger demand for credit than the older firm.

The increased likelihood of failure reduces the amount of credit provided by the lender to young firms relative to older ones (Equation A4). Asymmetric information, the difference between the firm's price distribution estimate π_d and that of the lender π_{d-b} , intensifies this problem for the young firm as emerging information about its quality is unavailable to the lender, motivating credit rationing. As the number of price draws grows, the discrepancy between information available to the borrower π_d and that available to the bank π_{d-b} decreases.

Consider a scenario in which this firm experiences a financial loss created by an unanticipated disaster l^* . This variable l is general, representing all disaster losses – property damage and business interruptions, including effects on demand. Consequently, this disaster risk should be understood as completely independent of the non-disaster price risk already discussed. This loss occurs just before the firm makes financing and investment decisions. For comparisons across firms, we assume that the losses destroy some portion $1 - \delta$ of the firm's endowment $l^* = (1 - \delta)k$.

This loss increases demand for credit for all firms as borrowing universally increases firms' expected returns. The loss also reduces the lender's optimal credit supply for all firms as all firms have less equity, less capacity to manage a shock following the disaster. The event heightens the demand and supply conditions already in play such that young and small firms are most at risk of being unable to access the financing that they demand.

7.1.4 Lifestyle firms

We also consider a specific type of firm that differs from the entrepreneurial one we describe above and instead is a firm intended to meet the lifestyle objectives of its owners. Hurst and Pugsley (2011) describe a set of firms that do not intend to grow, and we speculate that owning and managing a business is a non-financial amenity for the owners of these firms. For comparison, assume that the lifestyle firm is more risk averse (in the sense of Pratt, 1964) than the entrepreneurial ones previously described. Comparison to the entrepreneurial firm's first order condition (Equation A3) shows that the lifestyle firm is less influenced by the potential of larger returns of borrowing (due to the concavity of the utility function) and more influenced by the risk of failure. Both conditions motivate the lifestyle firm to demand less credit than the entrepreneurial one, including after a shock.

7.2 Online Appendix 2. Hurricane Sandy: Consequences and Public Assistance

On October 29, 2012, Sandy made landfall along the New Jersey coast as a post-tropical 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). Sandy's high winds and powerful storm surge each contributed to the magnitude of the disaster (NOAA NWS, 2012). In addition to the infrastructure and property damage, Sandy created several sources of business interruption, including electricity and transportation disruptions. Across New York and New Jersey, roughly four million customers remained without power two days after the event (Department of Energy, 2012). By November 9, over 250,000 customers in New Jersey were still without electricity (Spoto and Livio, 2012).

Regarding transportation disruptions, on November 2 as many as 60 percent of New Jersey's gas stations were closed due to lack of fuel or damage (Muskal and Carcano, 2012), and state mandated rationing in some counties persisted until November 13 (Spoto, 2012). Sandy was also the worst disaster in the history of the New York City subway system, complicating the commutes of many employees (Keane, Tomesco, and Levin, 2012). Five days after Sandy hit, 80 percent of the subway system was back on line. However, it took one month to restore even

partial service to the PATH trains from NY to NJ, and full service did not return until March 2013. Some subway lines took more than a year to fully return to service (Davies, 2013).

The Department of Commerce (DOC) reported business disruptions for most industries, but noted that the New Jersey tourism industry may suffer longer-term impacts (Henry et al., 2013). In contrast, the construction industry experienced a marked increase in employment and revenues as communities rebuilt and repaired damaged infrastructure (Henry et al., 2013).

The DOC also reported that claims for unemployment insurance in New York and New Jersey spiked dramatically in the weeks after Sandy but returned to pre-event levels within a month. Regional payroll employment and industrial production also rebounded rapidly after the storm (Henry et al., 2013).

Over \$60 billion in federal aid was appropriated for Sandy disaster relief efforts (Hernandez, 2013). These funds included appropriations for several federal agencies. The U.S. Department of Housing and Urban Development (HUD) received the most funding: over \$10 billion for its Community Development Block Grant program. About \$1.3 billion of federal assistance was provided directly to firms: the SBA approved \$500 million in lending to firms, and the National Flood Insurance Program (NFIP) paid approximately \$780 million in *non-residential* claims.⁴¹

A major component of U.S. federal assistance is provided to state and local governments and disbursed via congressional appropriations following a disaster. One example of this relief is Community Development Block Grants provided by HUD. Risk mitigation grants are also available through a competitive process from the Federal Emergency Management Agency. While firms may benefit from these programs, it is local governments that apply for, receive, and determine the uses of these funds (FEMA, 2015; HUD, 2015).

⁴¹ We calculate claims using data provided to us by the NFIP. Sandy led to 5,804 claims, the vast majority of which were in NJ (3,093) and NY (1,934).

Two programs available directly to firms are flood-specific insurance through the NFIP and disaster loans through the Small Business Administration (SBA). Firms can insure against flood events and are eligible for up to \$500,000 in building coverage and \$500,000 in contents coverage through the NFIP. Small firms that can demonstrate physical damage and/or economic injury (e.g., from business interruptions) from a federally declared disaster can borrow up to \$2 million, contingent on credit approval from the SBA.

Sandy appropriations allowed for the SBA to provide up to \$5 billion in disaster loans (Rivera, 2013); over \$500 million was eventually approved by the SBA for lending to firms (about 80 percent of approved SBA loans were to households; SBA, 2015). One year after Sandy, the SBA had approved almost \$2.5 billion in loans to roughly 36,000 borrowers (Hulit, 2013).

The timing of loans may have created additional challenges for firms borrowing from the SBA. The bulk of congressional appropriations (\$50 billion) were approved three months after Hurricane Sandy made landfall (Hernandez, 2013). The SBA can begin lending before full congressional appropriations have been approved. As of April 2013, almost 3,000 loans totaling \$279 million had been approved, yet only \$39 million had been disbursed, leaving many individuals and firms short on needed liquidity six months after the disaster (Clark, 2013).

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