NBER WORKING PAPER SERIES

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Working Paper 22612
http://www.nber.org/papers/w22612

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2016

We thank James Orr for facilitating the research collaboration, Gregory Niehaus and Vish Viswanathan for helpful comments and suggestions, the Outreach and Education Function at the Federal Reserve Bank of New York for providing the data, and the U.S. Small Business Administration for its data and insights. This work is partially supported by the Zurich Insurance Foundation, the Center for Risk and Economic Analysis of Terrorism Events (CREATE) at the University of Southern California (U.S. Department of Homeland Security's Center of Excellence), the Travelers-Wharton Partnership for Risk Management Fund, and the Wharton Risk Management and Decision Processes Center. The views and opinions presented here are those of the authors, and do not necessarily reflect those of the Federal Reserve Bank of New York, the Federal Reserve System, or the National Bureau of Economic Research.

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NBER Working Paper No. 22612
September 2016
JEL No. D22,G22,G28,G32,L25,Q54

ABSTRACT

Age and size distinctly affect firms' financial management of infrequent risks. We examine a rare, severe event using detailed firm-level data collected following Hurricane Sandy in the New York area. Our results follow recent contributions from dynamic risk management theory, namely that larger firms are more likely to insure and to use credit after a shock. We build on this theory, showing tradeoffs between managing frequent versus infrequent risks: young firms, exposed to many risks, do not insure against infrequent events and are ex post credit constrained. Consequently, younger firms and smaller firms disproportionately bore the costs of the shock.

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1 Introduction

Managing rare events has opportunity costs. These costs are highest for small firms, which tend to be more productive than larger ones, and for young firms, which are exposed to many hazards.[2] These forces increase the vulnerability of small and young firms to severe events. We exploit a rich new data set on the effect of a major shock – Hurricane Sandy, which struck the New York area on October 29, 2012 – on the finances of a set of businesses in the affected area.[3] The storm proved a financial challenge for many firms with small firms and young firms disproportionately bearing the costs of the disaster.

Age and size distinctly affect firms' financial management of infrequent risks. Size proxies a firm's marginal productivity: controlling for age, small firms grow faster than large ones (Dunne et al., 1989; Evans, 1987a,b). Rampini and Viswanathan (2010, 2013) and Rampini, Sufi and Viswanathan (2014) note that financial risk management diverts resources from production. This tradeoff motivates more productive firms to curtail risk management in order to operate more intensively. Consequently, small firms may be 1) less likely to insure and 2) have greater credit demand than larger firms, but are also 3) less likely to be approved for credit following a shock as they have less uncommitted capital.

We additionally recognize that managing specific rare risks (e.g., disaster, interest rate, or oil price shocks through insurance or hedging) reduces the financial resources available to address other risks, including more frequent hazards. We posit that this tradeoff motivates riskier firms to set a threshold of concern, managing more frequent hazards and gambling that infrequent events

[2] As examples from recent research of what constitutes young and small, Foster et al. (2008) consider firms young if they are less than five years old; Hurst and Pugsley (2011) consider firms small if they have fewer than 20 employees. 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.

[3] The surveyed businesses are stratified by age, size, industry, and state to reflect the profile of firms in the New York area.

will not occur.[4] The threshold point is endogenous to the firms' risk profile; firms with more uncertain earnings will have a higher threshold, investing less in managing rare shocks.

Age proxies earnings uncertainty: young firms grow faster but also fail at higher rates (Caves, 1998; Haltiwanger et al., 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. The broad distribution of outcomes for young firms may also influence their financing: 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 financial institutions' willingness to lend to them. Thus, young firms can be expected to 1) insure against rare events less often than older firms, 2) have greater credit demand, and 3) face greater credit constraints.

Hurricane Sandy had a negative financial impact on about one-third of the firms in our data by damaging their assets and disrupting their operations (e.g., through utilities outages and customer relocation). The event significantly increased their demand for credit. Negatively affected firms were about twice as likely as unaffected firms to apply for credit following the storm and exerted more effort by applying to more financial institutions and spending more time completing credit applications.

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 60 percent more likely to be required to secure loans with collateral and 2.5 times more likely to experience interest rate increases than unaffected firms.

[4] The idea that decision makers may ignore low probability has a strong empirical foundation (e.g., Slovic et al., 1977; Kunreuther and Slovic, 1978). We build on that work through consideration that this threshold point may be a function of the opportunity cost of managing infrequent events and how such tradeoffs influence firms' decisions.

Regarding age and size, we find that 1) young and small firms are significantly less likely than older and larger firms to purchase insurance, 2) young firms and *large* firms are more likely to apply for credit, and 3) large firms are more likely to receive it. This increased access to credit for large firms seems to be explained, at least in part, by their ability to secure loans with collateral.

We find one important deviation from model predictions: small, negatively affected firms are actually *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 young firms, some of which will grow quickly, and a set of firms with owners for whom growth is not a priority.[5] Rather than maximizing expected returns as the models above predict, the behavior of this latter group, sometimes called "lifestyle firms," is consistent with a risk averse owner.[6]

Our primary contribution is to the theory of dynamic risk management, which has focused on productivity-related opportunity costs of managing risk (e.g., Amaya, Gauthier, and Léautier, 2015; Froot, Scharfstein, and Stein, 1993; Rampini, Sufi and Viswanathan, 2014; Rampini and Viswanathan, 2010, 2013), by examining how firms' decisions are affected by the multiple risks that they face. Our focus on tradeoffs related to both age and size complements recent research on firms and growth, which draws distinctions between firms' age and size, showing that *young* firms in particular play a critical role in increasing economic productivity and employment (Adelino et al., 2014; Foster et al., 2008, 2016; Haltiwanger et al., 2013; Hurst and Pugsley,

[5] A number of studies have documented that some firms do not borrow even when expected returns suggest that they should (e.g., Bertrand and Schoar, 2006; Graham, 2000; Strebulaev and Yang, 2013). For example, Strebulaev and Yang (2013), examining publicly listed firms, find that firms with no or little debt tend to be smaller and family owned, age is unrelated to whether a firm has debt, and neither a firm's industry nor size fully explain these financing decisions.

[6] We also show in our theoretical model that even these risk averse lifestyle firms may not insure against rare events since it reduces the financial resources available to address more frequent, moderate 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.

2011; Pugsley and Sahin, 2014).[7] While much of United States public policy has targeted firms by size[8], appropriate policies for the young may differ from those of the small. For example, current U.S. disaster assistance to firms generally takes the form of *ex post* lending through 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 programs that facilitate preparedness and provide a broader set of financing mechanisms characterized by both *ex ante* and *ex post* grants and loans.

Our data provide several benefits for this resarch. They allow for a more nuanced assessment than is typically possible of how firms manage their financing needs and how constraints differ depending on firms' characteristics. Moreover, our data were stratified during their collection to represent the age and size of the population of firms in the geographic area that we study and so offer evidence from a different set of firms than the large corporations typically studied.[9] In the U.S., 99.7 percent of firms have fewer than 500 employees (Caruso, 2015). Additionally, in contrast to some exogenous shocks to firms' financing, the risk of a major storm in the New York area is known.[10] For example, Hurricane Irene, a much less destructive storm, affected the New York area roughly one year prior to Sandy. These shocks can be insured against, at least in part, and so provide an additional opportunity to study how firms' characteristics affect their financial preparation for such risks *ex ante*. Finally, not only do disasters serve as a source of

[7] For example, Adelino et al. (2014) show that the primary mechanism by which local economies respond to positive demand shocks is firm entry, finding that it is firm age, not size, that matters in explaining job creation. Also, Foster et al. (2008) find that increases in economic productivity are driven by young firms (those up to five years old), which produce at lower costs than older competitors and exert downward pressure on prices.

[8] In the U.S., "small" firms are often defined using an inclusive standard: firms with fewer than 500 employees (SBA, 2014). By this definition, 99.7 percent of all firms with employees are small (Caruso, 2015). Those firms account for 50 percent of employment (Caruso, 2015) and 45 percent of GDP (Kobe, 2012).

[9] Recent empirical examples apply dynamic risk management theories to airlines (Rampini, Sufi, and Viswanathan, 2014) and financial institions (Rampini, Viswanathan, and Vuillemey, 2015).

[10] Other recent papers that use natural disasters to examine credit market frictions include Berg and Schrader (2012), Chavaz (2015) and Cortés and Strahan (2015), which we discuss below.

exogenous variation to help us identify financial frictions, but a better understanding of their consequences is important in its own right.[11]

The remainder of this section provides a literature review and outlines the hypotheses guiding our analyses. Section 2 describes our data and methodological approach for testing these hypotheses; Section 3 details the results. The concluding section explores the policy implications of our findings.

1.1 Literature Review

A substantial literature shows how shocks influence firms' credit constraints (e.g., Gilje and Taillard, 2015; Jiménez et al., 2012; Kerr and Nanda, 2009; Khwaja and Mian, 2008; Nguyen, 2015; Sapienza, 2002). Asymmetric information is a frequent theme: lenders have difficulty evaluating the risk of firms' projects. For example, Gilje and Taillard (2015) compare the investment responses of firms based on their informational transparency, using the premise that privately owned firms are less transparent than publicly listed ones. They find that, following the discovery of shale deposits, publicly listed firms make the capital intensive investments needed to extract these deposits while privately held firms do not. They conclude that publicly listed firms can address unanticipated financing needs in ways unavailable to privately owned, less transparent, firms.

Banks frequently embed themselves in communities, developing localized expertise and personal relationships to overcome asymmetric information in lending to privately owned firms (DeYoung et al., 2004). Nguyen (2015) tests how a loss of this specialized information affects small business lending. She examines bank mergers which led to branch closures in markets where multiple banks were previously present, finding that branch closures reduce small

[11] 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 et al. (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 in damages, becoming the second costliest such event in U.S. history, after Hurricane Katrina (NOAA HRD, 2014).

business lending by an average of eight percent. This effect persists for several years. Effects are highly localized such that branch closures do not affect lending beyond a radius of six to eight miles. Her results hold even in dense banking markets.

A firm's size often serves as a proxy for its financial opacity, leading to similar results. For example, Khwaja and Mian (2008) assess lending 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. These small firms were more likely to enter financial distress following the nuclear tests.

Research on credit market frictions has often focused on small business lending (e.g., Agarwal and Hauswald, 2010; Berger et al., 2005; Stein, 2002), but has not fully disentangled the roles of age and size. Research indicates that age influences credit outcomes. For example, Petersen and Rajan (2002) show that as firms age and the duration of the borrower-lender relationship grows, lenders are willing to extend credit at greater distances, suggesting that they feel a reduced need to tightly monitor these borrowers. Demirguk-Kunt, Love, and Maksimovic (2006) find that young firms and small firms are both more likely to report that access to financing is an obstacle to firms' operations and growth. We know of no previous study that exploits an exogenous shock to differentiate the effects of age and size on firms' need for and access to credit.

1.2 Hypotheses

We develop specific hypotheses on firms' financial preparation for and management of Hurricane Sandy. These hypotheses are informed by previous research. In particular, Rampini and Viswanathan (2010) model a firm's risk management and financing decisions in which size influences the firm's decisions given that its marginal productivity is decreasing in assets. Also, Jovanovic (1982) proposes a Bayesian learning model in which the firm's distribution of returns narrows with age. While Jovanovic considers stochastic production costs, we model demand risk, following Foster et al. (2015): young firms are uncertain of the prices at which they can sell the goods that they produce, leading to uncertainty in profit.[12] We develop a simple model to illustrate some of the mechanics of their models in our context, which can be found in Online Appendix 1; however, we describe its insights for each hypothesis below.

Our model considers the problem of a representative owner/manager whose firm is exposed to market-oriented demand risk (which we model as fluctuations in the price at which it can sell its goods) as well as a less probable but more severe disaster risk. If losses from either the demand risk or the disaster risk are sufficiently severe, the firm cannot meet its liabilities and becomes insolvent. The firm has a production technology and can borrow to expand its operations. The firm can also insure against the natural disaster risk. The firm's problem is to maximize its expected returns through its decisions about borrowing and insuring. We also consider the lender's problem, who bears the insolvency risk of the firm.

H1: The majority of firms' losses from Hurricane Sandy were not insured. We predict that firms will not tend to insure against disasters such as Sandy. Firms prepare little for infrequent, high consequence events (e.g., see Webb et al., 2000, for a literature review related to natural disasters). Bankruptcy protection reduces incentives to insure against rare events; moreover, insuring has two opportunity costs. First, it reduces resources that could be dedicated to productivity. Rampini and Viswanathan (2010) predict that small firms are less likely to hedge risks because the opportunity cost is particularly high for them. Second, insuring against rare events reduces the stock of uncommitted financial resources available to the firm to address other risks. Whether firms choose to insure depends in part on the risk of a disaster relative to other shocks. Thus, we predict that, in addition to small firms, young firms will be less likely to insure because they experience greater likelihood of failure due to many risks (Haltiwanger et al., 2013).

[12] Firms begin with an uninformed prior distribution of returns based on the experiences of a broad set of firms, which operate using a variety of imperfectly comparable goods. Older firms have more observations of their returns and so can better estimate their actual distribution.

H2: Sandy increased credit demand among negatively affected firms. We predict that Sandy increased demand for credit as it provides a means to finance recovery. Previous research indicates that disasters increase demand for credit among firms: Berg and Schrader (2012) find that loan applications increased for a small business lender in Ecuador following volcanic activity, and Chavaz (2015) finds that local banks increase small business lending in communities affected by hurricanes in the United States. Variables measuring demand in our data include whether a firm searched for credit, whether it applied for credit, the amount of time it invested in applying, and the number of financial institutions to which it applied.

H3: Sandy decreased access to credit among negatively affected firms. Sandy likely made negatively affected firms less creditworthy by reducing their income and assets. Our survey asked firms whether their access to financing has changed, whether interest rates have changed, and what constitutes their primary source of financing.

The disaster may have also affected firms in ways difficult for lenders to assess, thereby increasing information 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, Cerquiero, 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. Ono and Uesugi (2009) also find a positive relationship between monitoring and collateral by showing that the likelihood of pledging collateral increases with the duration of the lending relationship and the size of the borrower. Following these results, we posit that negatively affected firms will increase their use of collateral to secure loans. Such requirements would be expected to channel credit toward larger firms with more collateralizable assets.[13]

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[13] Lenders might also lend less following disaster due to capital or liquidity constraints; however, recent evidence suggests that even local lenders in U.S markets are able to adjust to increase lending in affected markets. Chavaz (2015) examines the responses of local banks and large diversified banks. He finds that local lenders increase both small business and mortgage lending in affected areas. Similarly, Cortés and Strahan (2015) examine mortgage lending following natural disasters find that banks increase mortgage lending in affected counties by making

Rampini and Viswanathan (2010) predict that small firms will have a greater demand for credit following a shock, but also that these small firms will have less capacity to borrow and so face credit constraints. Large firms are less likely to exhaust their debt capacity and so will be better able to borrow after a shock.

The large variance in returns for young firms affects both their demand for and access to credit, which we observe in our theoretical model. We predict that, betting on their success, younger firms demand more credit following a disaster than the average older firm. Betting on their failure, lenders supply relatively less credit to younger firms. Young firms are also especially prone to information asymmetries, increasing credit supply constraints in ways consistent with Stiglitz and Weiss (1981).

2 Methods

2.1 Data

Our data comprise a survey of firms performed by the Federal Reserve Bank of New York (2014). The survey was conducted online and distributed by civic and non-profit institutions such as chambers of commerce. Respondents were located in Connecticut, New Jersey, New York, and Pennsylvania. The survey focuses on firm financing and performance and includes a series of questions regarding Hurricane Sandy. It was conducted in November 2013, roughly one year after Sandy.

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 Online Appendix 2 for more on the

adjustments in unaffected counties where their market shares are low. In the unaffected counties, these banks lend less, are more likely to securitize new mortgages, and increase short-term interest rates on deposits.

effects of Hurricane Sandy). We limit our focus to respondents in the FEMA-declared disaster area, counties that qualify for individual and public assistance from the federal government. All of 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 area. The survey, descriptive results, and additional details on the data collection methodology are available from the Federal Reserve Bank of New York (2014).

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%
Geography		
Connecticut	6.7%	7.8%
New Jersey	25.9%	20.0%
New York (minus NYC)	13.9%	26.4%
New York City	53.4%	19.7%
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 Services	20.4%	11.3%
Personal Services	3.0%	10.8%
Education/Healthcare & Soc. Assist.	6.8%	12.8%
Leisure & Hospitality	7.1%	11.0%
Other	12.1%	6.2%

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), location, 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 Federal Reserve Bank of New York 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.

2.2 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 for firm i

$$\mathrm{E}[y_i|D_i = 1] = \alpha + \beta + \mathbf{C}_i'\boldsymbol{\gamma} + \mathrm{E}[\varepsilon_i|D_i = 1]$$
$$\mathrm{E}[y_i|D_i = 0] = \alpha + \mathbf{C}_i'\boldsymbol{\gamma} + \mathrm{E}[\varepsilon_i|D_i = 0]$$

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 $\mathrm{E}[\varepsilon_i|D_i = 1] = \mathrm{E}[\varepsilon_i|D_i = 0]$. One could imagine that, in contrast to Sandy being an exogenous event, firms relying on expensive financing products such as credit cards are 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 affected by Sandy. Firms were asked to identify all sources of funding they used to start their business (e.g., business loans, personal savings, etc.). Using data from firms outside the disaster area that reported being unaffected by Sandy, Columns 1 through 5 of Table 2 show that a firm's original funding is related to the primary financing variables that we consider and so these variables would seem to be a relevant proxy for pre-event financing for firms in the disaster area.[15]

[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."

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

Column 6 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 6 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 effect may be due to unexplained differences in location. For example, firms directly on the beach may be older than ones farther inland. Alternatively, this result would be explained if younger negatively affected firms were censored 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.

Table 2. Negatively Affected By Sandy and Original Funding Type

	Outside Disaster Area					In Disaster Area
	(1)	(2)	(3)	(4)	(5)	(6)
	Applied for Credit	Access to Financing Decreased	Interest Rate Increased	Collateral	Primary Financing: Personal Savings	Negatively Affected
Original Funding: Business Loan	0.0349	0.00142	-0.00575	0.307***	-0.0835	0.000523
	(0.048)	(0.046)	(0.031)	(0.076)	(0.052)	(0.054)
Original Funding: Credit Cards	0.169**	0.138**	0.0702	0.0131	-0.0590	0.00332
	(0.078)	(0.068)	(0.51)	(0.059)	(0.070)	(0.053)
Original Funding: Personal Savings	-0.00823	0.000870	-0.0481	-0.0873	0.120	-0.0100
	(0.062)	(0.049)	(0.060)	(0.072)	(0.078)	(0.058)
Original Funding: Friends and Family	-0.0215	0.0691	0.121**	0.0609	-0.0249	-0.000979
	(0.067)	(0.047)	(0.053)	(0.068)	(0.050)	(0.034)
Original Funding: Other	0.0712	-0.00996	-0.00332	0.133*	-0.0715	0.0840
	(0.079)	(0.058)	(0.057)	(0.080)	(0.072)	(0.077)
Age	-0.000981	-0.000255	0.000104	0.00119	-0.00204**	0.00241*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.0009)	(0.0012)
Employees	0.000976	0.0000527	-0.000673	0.00264***	-0.000761	-0.000293
	(0.001)	(0.001)	(0.001)	(0.0007)	(0.001)	(0.001)
Obs.	479	485	468	469	484	776
Rsq	0.240	0.261	0.298	0.386	0.324	0.0892

Note: Standard errors in parentheses. Lindar probability models with White’s (1980) heteroskedastically-consistent standard errors culstered at county. Models include industry and county fixed effects. Columns 1 through 5 use data from firms outside the disater area that reported being unaffected by Sandy; Column 6 uses responses from firms in the disaster area. In Column 1, respondents reported on their firms’ access to financing comparing 2013 to 2012.

2.3 Estimation

Unless otherwise noted we report linear probability models with White's (1980) heteroskedastically-consistent standard errors clustered by county.[16] We also estimated the regressions below as logit models. Those results support the narrative below and conclusions with respect to our hypotheses, but to facilitate interpretation we present linear probability models throughout.

The regressions related to insurance take two forms. Only firms that were affected by Sandy were asked about their insurance protection; these models 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)

$$y_i = \sum_{l=1}^{3} \beta_l \, I(AgeQuartile_{i,l}) + \sum_{m=1}^{3} \lambda_m \, I(EmployeesQuartile_{i,m}) + \delta_j + \eta_k + \varepsilon_i \quad (1)$$

where, for example, $I(AgeQuartile_{i,1})$ is the indicator function for whether firm i is in the first age quartile. Parameters and δ_j and η_k are county industry fixed effects. 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

$$I(Insurance_i) = \sum_{l=1}^{3} \sum_{m=1}^{3} \beta_{l,m} I(AgeQuartile_{i,l}) \times \, I(EmployeesQuartile_{i,m}) \, + \delta_j + \eta_k + \varepsilon_i \quad (2)$$

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

[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, clustering standard errors by county, and clustering by industry; each leads to qualitatively similar results.

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 applied for credit)

$$y_i = \alpha + \beta_1\, I(NA_i) + \beta_2\, Age_i + \beta_3\, Age_i \times I(NA_i) + \beta_4\, Employees_i + \beta_5\, Employees_i \times I(NA_i)$$
$$+ \beta_6\, Age_i \times Employees_i + \beta_7\, Age_i \times Employees_i \times I(NA_i)$$
$$+ \beta_8\, I(PA_i) + \beta_9\, Age_i \times I(PA_i) + \beta_{10}\, Employees_i \times I(PA_i) + \beta_{11}\, Age_i \times Employees_i \times I(PA_i)$$
$$+ \delta_{\boldsymbol{j}} + \eta_k + \varepsilon_i \qquad (3)$$

where $I(NA_i)$ and $I(PA_i)$ are indicators, respectively, for whether affirm was negatively affected or positively affected by Sandy. Our regressions include positively affected firms for completeness, but these firms are not a focus of our analysis.

The credit models also examine the effects of size (here measured by the number of employees) and age (in years) on variables related to firm financing (e.g., whether firms apply for credit, use of collateral, etc.). We allow these effects to differ for negatively affected and unaffected firms through interaction terms. To facilitate comparisons, the age and size variables are standardized. We also examined three-way interactions of age, size and a dummy indicating whether a firm was affected by the event.

We construct the model's intercept α to facilitate comparisons between negatively affected and unaffected firms. The county and industry fixed effects are set so that $\sum_{j=1}^{J} \delta_j = 0$ and $\sum_{k=1}^{K} \eta_k = 0$. Given this construction and that the continuous variables are standardized, the intercept represents the average unaffected firm in our data.

While our sample includes 949 firms, our observations notably differ across regressions. These differences are largely because the questions asked of each firm depends 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.

Firm size is typically measured in number of employees or, sometimes, revenues (e.g., SBA, 2014); we use number of employees. We show in the Appendix that Sandy influenced both revenues and the number of employees for negatively affected firms. 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. Table 3 examines the relationship between firm age and size using firms in the sample that were *unaffected* by Sandy. 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).

Table 3. Firm Size by Age Quartiles

	Employee Summary Statistics			
Age Quartile	**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.

2.4 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. 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.

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 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.[17] 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

		Reported Loss Amount per Employee (by Percentile)				
Loss Source	**Frequency**	**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).

3 Results

This section describes our findings related to each of the three hypotheses developed in the Introduction. In the Appendix, we show that negatively affected firms continued to report reduced profitability and income and employment growth months after the event, and the effects

[17] 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 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."

are largest for young firms and small firms. As these data are cross-section, whether credit constraints cause these effects on profitability and growth is unclear; rather, we include them as a complementary set of outcomes to the financing variables discussed in this section.

3.1 H1: The Majority of Firms' Losses from Sandy Were Not Insured

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 "Roughly, what percent of your business's losses was recovered through insurance?"[18] Among insured firms, property insurance was the most common response. Twenty-nine percent of negatively affected firms reported not having insurance (see Table 5).

Table 5. Insurance and Loss Recovery After Sandy Among Negatively Affected Firms

		Reported Fraction of Loss Recovered through Insurance			
Insurance	**Frequency**	**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.

Younger and smaller firms are more likely to be uninsured. Table 6 (Columns 1-4) reports results for negatively affected firms. This table divides firms into quartiles by age and by size (employees), using the oldest firms and largest firms as reference groups.[19] Firms less than five years old are 30 percentage points more likely to be uninsured relative to the oldest firms. Young

[18] 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."

[19] 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.

firms and small firms are less likely to insure against property damage and business interruptions. These results follow both the prediction of Rampini and Viswanathan (2010) and our own: age and size each help explain firms' insurance decisions. The effects of age seem to be incremental – even firms in the third age quartile (12 to 23 years old) insure 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 and above-median ones. Less than 12 percent of the firms in our sample insure against floods; those that do tend to be larger.

Table 6. Effect of Age on Insurance Uptake and Financing Needs Among Negatively Affected Firms

	(1) Insurance (any)	(2) Property Insurance	(3) Business Interruption Insurance	(4) Flood Insurance
Reference group: Firms in 4th Age and Employees Quartiles				
Age				
1st quartile	-0.299**	-0.362**	-0.234***	-0.0341
	(0.121)	(0.164)	(0.083)	(0.071)
2nd quartile	-0.104	-0.136**	-0.144	0.00619
	(0.066)	(0.066)	(0.089)	(0.067)
3rd quartile	-0.157**	-0.238**	-0.103	-0.0126
	(0.072)	(0.115)	(0.079)	(0.061)
Employees				
1st quartile	-0.252**	-0.240**	-0.184**	-0.117
	(0.087)	(0.099)	(0.072)	(0.081)
2nd quartile	-0.245**	-0.211**	-0.161*	-0.135*
	(0.092)	(0.090)	(0.086)	(0.073)
3rd quartile	0.0137	-0.00704	-0.0464	-0.0629
	(0.0897)	(0.079)	(0.076)	(0.061)
Obs	273	273	273	273
Rsq	0.314	0.278	0.270	0.272

Note: Standard errors in parentheses. 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 1. All models include industry and county fixed effects.

Table 7 complements the results from Table 6 by examing 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 2 and only includes firms negatively affected by Sandy. The reference group is the oldest, largest firms (firms in the fourth quartile for both age and employees). For each age quartile by employee quartile interaction, the table reports the model coefficient, standard error (in parentheses), and number of observations of firms in that category. The table is shaded such that darker cells reflect the lower values. The pattern of darker cells in the top-left section of the table confirms the results from Table 6 that age and size each contribute to insurance decisions. For example, among the youngest group of firms, those in the first, second, and third size quartiles 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.[20]

Across all types of insurance, firms most frequently reported that *none* of their losses were recovered through insurance claims (Table 5). We are surprised that so many firms reported "none." 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 by April 2013 (Insurance Information Institute, 2013). Instead, we speculate that the losses from this event were a blend of flood-related asset damage and business disruptions against which firms do not tend to insure.[21]

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[20] Old, small firms serve as a proxy for lifestyle firms. In Online Appendix 1 (Section 5.2.4), 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.

[21] While the majority of firms had property insurance, Sandy was not a hurricane when it made landfall and so assets losses were likely from flood, a hazard typically not covered by property insurance (Quintero, 2014). 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 shutdown from this damage and not other factors such as economic conditions (Lesser, 2016). These requirements seem to poorly match the losses stemming from customer and utility disruptions commonly reported by negatively affected firms (Section 2.5). The prevalence of customer

Table 7 Age and Size Interactions from Model of Whether a Firm Has Any Insurance

Dependent variable: Insurance (any)

Employees Quartile		Age Quartile: First	Second	Third	Fourth	Total Obs.
First	Coeff.	-0.48***	-0.27***	-0.518***	-0.24	
	St. Err.	(0.112)	(0.097)	(0.105)	(0.207)	
	Obs.	27	25	20	8	80
Second	Coeff.	-0.436**	-0.492**	-0.289*	-0.233	
	St. Err.	(0.204)	(0.191)	(0.155)	(0.207)	
	Obs.	13	11	14	12	50
Third	Coeff.	-0.416***	-0.041	-0.0244	0.098	
	St. Err.	(0.143)	(0.160)	(0.079)	(0.078)	
	Obs.	19	11	23	19	72
Fourth	Coeff.	0.127	-0.0555	-0.145	0	
	St. Err.	(0.107)	(0.078)	(0.109)		
	Obs.	2	11	27	31	71
Total Obs.		61	58	84	70	273

Note: 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 2, 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 the lower values. The model has an R squared of 0.34.

3.2 H2: Sandy Increased Credit Demand

Negatively affected firms were more likely to search for and apply for credit and put forth more effort doing so. Firms were asked "did your business search for credit in the first half of 2013?" and similarly whether they ultimately applied for credit. Those that applied for credit were asked about the products for which they applied: loans, lines of credit, and credit cards. They were also asked about their effort applying, characterized by the hours they spent applying and the number of different financial institutions to which they applied. Firms that receive all of 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 of the credit for which they applied.

and utility disruptions may also explain why flood insurance did not address more of firms' losses as it only covers flood-related property damage.

Table 8 provides these results for all outcome variables related to Hypotheses 2 and 3. The first row shows the model intercept, which describes the results for the average unaffected firm in our data (as described in Section 2.3). 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. Often these interaction terms are significant. 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 a particular outcome (e.g., applied for credit) than older firms ($H_0\colon \beta_{Age\times Neg.Affected} = 0$) . We understand that the shock disproportionately challenged young firms in this context. In some cases, the event may operate through pre-existing differences: all negatively affected firms are more likely to apply for credit ($\beta_{Neg.Affected}$) and young firms, which apply at greater rates than olders ones under normal conditions, apply at similarly greater rates after the shock ($\beta_{Age} = \beta_{Age\times Neg.Affected}$). In a few cases, we find that age (or size) influences unaffected and negatively affected firms differently (such that $\beta_{Age} \neq \beta_{Age\times Neg.Affected}$). In these cases, the shock seems to exacerbate pre-existing dynamics observed among unaffected firms. Finally, we account for the possibility of three-way interactions between age, size and whether Sandy affected firms.

Being negatively affected by Sandy increased the likelihood that a firm searched for credit by 70 percent (Table 8, Column 1). About 29 percent of unaffected firms searched for credit compared to half of negatively affected firms ($Intercept + Neg.Affected = 0.288 + 0.208 = 0.496$). Among those negatively affected, firms of all ages and sizes searched for credit at similar rates.

Negatively affected firms were almost twice as likely to apply for credit. About 21 percent of unaffected firms applied for credit compared to 40 percent of negatively affected firms ($Intercept + Neg.Affected = 0.212 + 0.184 = 0.396$). Among those negatively affected, it is the *young* firms and the *large* firms that are more likely to apply for credit (Table 8, Column 2). For example, being one standard deviation larger than the average firm increases a firm's likelihood of applying for credit by 10 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 13 percentage points (Column 3). Sandy did not increase applications for credit cards; however, negatively affected and unaffected *young* firms alike are significantly more likely to apply for credit cards to address their financing needs (Column 4).[22]

Negatively affected firms also put forth more effort when applying for credit. During the first half of 2013, the median unaffected firm spent 10 hours completing applications and applied to two financial institutions. Among firms that did not receive all of the financing they requested, negatively affected ones spent 68 percent longer applying and applied to 36 percent more financial institutions than unaffected firms (Columns 5 and 6. These are negative binomial count regressions, reporting incidence rate ratios.) Younger firms and larger firms tended to spend more time applying for credit than older ones and smaller ones. Firms' age and size interact such that negatively affected young, small firms spend even more time applying than the incremental contributions of age and size predict.

The result regarding young firms is consistent with our models' predictions, building on Jovanovic (1982). Younger firms perceive the possibility of windfall gains, which increases their credit demand relative to older firms. Thus, compared to older negatively affected firms, young negatively affected firms are more likely to search and apply for credit, to invest more hours applying, and to adopt more expensive sources of financing such as credit cards.

That *small* negatively affected firms do not apply for credit goes against our prediction based on the insights of Rampini and Vinswanathan (2010). We predicted that, because small firms tend to

[22] 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.

have greater marginal productivity, maximizing expected returns would lead them to demand more credit after a shock. Large negatively affected firms are more likely to apply, which may be a function of their likelihood of being approved, as we show in the next section. One plausible explanation for these surprises related to size and credit demand follows from the demographic research of Hurst and Pugsley (2011): after controlling for age, an important subset of small firms are those that operate with an objective function that does not seek to maximize returns. For example, owning and managing a business may be a non-financial amenity for the owners of these firms. As shown in Online Appendix 1 (Section 5.2.4), avoiding or limiting the use of credit in this context is consistent with the behavior of a risk averse utility maximizing owner.

Table 8 Effects of Sandy on Credit Demand and Access

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Searched for Credit	Applied for Credit	Applied for Loans	Applied for Credit Cards	Number of hours	Number of financial institutions	Access to Financing Decreased	Interest Rate Increased	Collateral	Collateral, Bus. Real Estate	Received All Credit Financing Requested	Primary Financing: Personal Savings
Intercept	0.288***	0.212***	0.524***	0.306***			0.160***	0.0739***	0.235***	0.0348	0.336***	0.202***
	(0.025)	(0.023)	(0.030)	(0.049)			(0.021)	(0.017)	(0.034)	(0.028)	(0.044)	(0.024)
Neg. Affected	0.208***	0.184***	0.133**	0.0650	1.676**	1.362*	0.167***	0.114***	0.142***	0.0701***	0.0394	-0.0319
	(0.051)	(0.042)	(0.054)	(0.075)	(0.358)	(0.237)	(0.027)	(0.024)	(0.031)	(0.020)	(0.063)	(0.033)
Age	-0.0669**	-0.0164	-0.0708*	-0.117***	0.670***	1.155**	-0.00989	-0.000366	0.0353	0.0123	0.102**	-0.0288
	(0.027)	(0.027)	(0.040)	(0.034)	(0.088)	(0.070)	(0.0248)	(0.018)	(0.027)	(0.012)	(0.043)	(0.018)
Age x Neg. Affected	-0.0646	-0.0646*	-0.00979	-0.173***	0.588***	1.109	-0.0145	-0.0547**	0.0350	0.0404**	0.0689	-0.0527**
	(0.040)	(0.035)	(0.071)	(0.057)	(0.079)	(0.234)	(0.041)	(0.023)	(0.025)	(0.020)	(0.054)	(0.027)
Employees	0.00928	0.0246	0.0751	-0.0358	2.096*	0.853*	-0.0247	-0.0335**	0.148***	0.0479*	0.0851**	-0.0418***
	(0.030)	(0.030)	(0.078)	(0.066)	(0.917)	(0.071)	(0.027)	(0.012)	(0.036)	(0.027)	(0.042)	(0.010)
Employees x Neg. Affected	0.0138	0.101***	-0.0691	0.0274	1.561**	0.885	-0.0279	0.00363	0.140***	0.158***	0.173**	-0.0592***
	(0.035)	(0.030)	(0.044)	(0.080)	(0.313)	(0.151)	(0.032)	(0.056)	(0.023)	(0.027)	(0.076)	(0.024)
Age x Employees	0.00722	0.00366	-0.0102	0.0339	0.697	1.251***	0.0102	0.00664**	-0.0450***	-0.00400	-0.0187	0.00924**
	(0.013)	(0.009)	(0.022)	(0.022)	(0.211)	(0.083)	(0.010)	(0.003)	(0.0094)	(0.007)	(0.020)	(0.004)
Age x Employees x Neg. Affected	-0.0151	-0.0256	0.0702	0.0206	1.347**	0.865	0.00489	0.00627	-0.0265**	-0.00756	-0.165**	0.0238***
	(0.018)	(0.020)	(0.061)	(0.072)	(0.196)	(0.157)	(0.014)	(0.013)	(0.013)	(0.010)	(0.061)	(0.011)
Obs	829	830	275	275	188	190	834	808	793	790	273	838
Rsqr	0.119	0.122	0.300	0.255	--	--	0.113	0.081	0.199	0.268	0.280	0.135

Note: Standard errors in parentheses. Linear probability models with White's (1980) heteroskedastically-consistent standard errors clustered at county. All models include industry and county fixed effects and full interactions for positively affected firms, as described in Equation 3. Models are constructed so that the intercept value represents the average unaffected firm in our data. Columns 3, 4 and 11 only includes firms that applied for credit. Columns 5 and 6 only include firms that applied for credit but did not get all of the credit that they requested and are negative binomial regressions, reporting coefficients in incidence rate ratios. Columns 9 and 10 include all firms with outstanding debt.

3.3 H3: Sandy Decreased Credit Access

We also find that credit markets tightened for negatively affected firms. While 40 percent of these firms report taking on more debt because of Sandy, negatively affected firms were also more than twice as likely as unaffected firms to report that their access to financing had decreased relative to the previous year (Table 8, Column 7).[23] About one-third of negatively affected firms report that their access decreased ($Intercept + Neg.Affected = 0.160 + 0.167 = 0.327$). 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.[24]

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 8, Column 8).[25] Approximately 7 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 percent in the first half of 2012 to 4.3 percent in the first half of 2013 (Small Business Finances, 2016). Among young firms, negatively affected ones were significantly more likely than unaffected firms to report interest rate increases ($H_0: \beta_{Age} = \beta_{Age \times Neg.Affected}$, $F = 5.28$, $p = 0.02$)

[23] Firms were asked, "How has your business's ability to access financing changed when comparing the first half of 2013 to the same period in 2012?"

[24] 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).

[25] Firms were asked "How did the interest rate on your business debt change in the first half of 2013 compared with 2012?"

We also find evidence that lenders were less willing to rely on soft information from relationship-based lending to provide credit to negatively affected firms.[26] Being negatively affected increases the likelihood that a firm secures its loan with collateral by 60 percent (Table 8, Column 9): approximately 37 percent of negatively affected firms use collateral. Large firms are especially likely to use collateral. Moreover, size and age interact such that larger, older firms are more likely to use collateral compared to larger, younger ones. 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 10). The effect of size on using business real estate for collateral is significantly greater for negatively affected firms than unaffected ones ($H_0\colon \beta_{Employees} = \beta_{Employees \times Neg.Affected}, F = 12.10, p = 0.0005$). About 8 percent of unaffected firm that are one standard deviation larger than the average secures their loans with business real estate, compared to 26 percent of their negatively affected counterparts.

This use of collateral seems important for explaining credit constraints, as larger firms are more likely to receive all of the financing they requested (Column 11). A one standard deviation increase in size increases the likelihood by 17 percentage points of a negatively affected firm receiving all the credit for which it applies. Age and size interact so that older, larger firms are more likely to receive all of the financing that they requested relative to younger, larger firms. In contrast, negatively affected young firms and small firms were ultimately more likely to report that they are primarily financed through the personal savings of their owners (Column 12).[27] Lee and Persson’s (2016) work suggests that financing recovery through personal savings may have

[26] Using data from another survey conducted by same unit at the Federal Reserve (see Federal Reserve Bank of New York, 2013) in the spring of 2013, we find that negatively affected and unaffected firms were equally likely to use a community bank rather than a commercial bank as their primary lender.

[27] Age and size interact so that the younger, smaller firms are especially likely to report being financed by personal savings. For example, compared to firms that are above-median age and size, firms that are below-median age and size are 15 percentage points more likely to report that they are financed by the personal savings of their owners.

longer term consequences for the firm. They find that familial financing reduces entrepreneurial risk taking as it diminishes the owner's personal financial safety net.

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.[28] The median range of these financing needs is $50,000 to $100,000.

These findings regarding credit access align with our predictions. Following the insights of Jovanovic (1982) and Stiglitz and Weiss (1981), we predict that the greater variability in returns of young firms will lead them to be credit constrained. These younger firms experienced interest rate increases and were ultimately more likely to be financed by the personal savings of their owners than older, negatively affected firms. Regarding firm size, Rampini and Viswanathan (2010) identify theoretically a connection that we now observe empirically. They note that collateral constraints fundamentally link access to financing and hedging for risk management among corporations. Firms with financial slack, those that have not exhausted their debt capacity, have a greater ability to manage shocks through borrowing after the event. Firms that are less productive, such as larger firms, are more likely to operate with financial slack and to hedge risks because they face lower opportunity costs. We observe evidence of these mechanisms among the firms in our study: larger firms are much more likely than smaller firms to insure and to have the capacity to secure loans with collateral such as business real estate after a shock.

3.4 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 a public intervention to correct market failures. Toward policy recommendations, we consider the performance of the disaster lending

[28] Firms were also asked "Now, roughly one year later, what type(s) of financing needs related to Superstorm Sandy does your business have?"

program of the U.S. Small Business Administration. 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 borrow from this program given its current lending rules. In our data, 8 percent of negatively affected firms borrowed from the SBA disaster lending program. 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 present) as requirements for borrowing.

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 eligble to apply, SBA, 2015b). Table 9 shows the completion and approval rates for all firms (not just those in our survey) that applied for SBA disaster loans due to Hurricane Sandy. Ninety-nine percent of the value of Sandy-related SBA approved loans went to firms in the three states covered in our survey: CT, NJ and NY. Many of the SBA applicants are referred by FEMA, which suggested to 90,000 firms that they contact the SBA. One-third of firms that began the application process withdrew their application before completing it. Managers at the SBA report that as firms learn more about the program (interest rates, collateral requirements, etc.) through the application process, some choose not to continue. Almost 60 percent of firms that completed the application process were rejected by the SBA.[29]

[29] We speculate that the low acceptance rate may be a function of who enters the program given the low interest rate environment in 2012 and 2013. Interest rates in the disaster lending 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).

Table 9. Applications for SBA Disaster Loans among firms following Hurricane Sandy.

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

Note: Data provided by SBA.

Assuming the experience of the negatively affected firms in our data is consistent with these completion and approval rates, the result that 8 percent used SBA loans suggests that approximately 30 percent of the firms in our data began the SBA application process and 20 percent completed it. Our data on the SBA program are insufficient to explain what prevents more firms from borrowing from this program.

4 Conclusion

We examine the effect on firm financing of an infrequent income and asset shock, Hurricane Sandy. The shock significantly increased demand for credit and reduced access to it among negatively affected firms. Relative to small firms, larger firms in our data were more likely to be insured and to have the capacity to meet the collateral requirements to borrow after the shock, following the predictions of Rampini and Viswanathan (2010, 2013). We build on their work through an extension of the Bayesian learning model proposed by Jovanovic (1982) to account for the influence of firms' age on their financing decisions. Insuring against specific rare events reduces financial resources available to manage other risks. The behaviors of young firms, which face many risks and do not tend to insure against rare events in our data, are consistent with our predictions. Younger firms were more likely to turn to external financing to cope with the event than older ones; however, the young were frequently credit constrained, as the event seems to have exacerbated capital market frictions. For example, credit access is more strongly linked to use of collateral for negatively affected firms than their unaffected counterparts in the period after the event.

These results provide initial insights that warrant additional research to clarify the generalizability of our results, 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 effects of capital market imperfections on the survival and prosperity of young 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 City area generalize to other locations and shockss.

4.1 Policy Recommendations

We close by discussing some public policy recommendations based on our findings that relate to a broad range of disasters: rare but consequential events including severe weather, recessions, terrorism, cyber-security, etc. Young and small firms play an important role in contributing to job creation and productivity growth. These recommendations are intended to deal with the negative externalities caused by the poor health and failure of these firms due to an infrequent, severe event. First, we suggest a greater emphasis on programs that facilitates preparing for shocks. The costs of assessing infrequent risks and developing strategies to address them is nontrivial, and we propose a voluntary federal disaster preparedness program to assist in these tasks Our results on the persistent effects of a disaster on firm performance suggest that the private sector counterparts (e.g., lenders, other firms in a supply chain) of vulnerable firms have a vested interest in reducing the consequences of a disaster on a firm's operations. A firm's preparedness assessment and participation in training might act as a signal to these counterparts, improving access to credit, insurance, supplier contracts, lease agreements, and other private-sector contracts exposed to disaster risk.

The government might also reward participation in the preparedness program by committing to a certain level of immediate, initial dedicated funding for program-compliant firms following a shock, thereby reducing the uncertainty and delays of relying on *ex post* appropriations. Participating in the program might also include expedited review for other forms of federal assistance, e.g., pre-approval from the SBA disaster lending program.

Second, we suggest a broader set of financing mechanisms structured to overcome the capital market frictions constraining vulnerable and affected firms. Firms differ on the types of financing they need. Some firms need more credit after a severe event. Our results suggest a need for targeted improvements to the SBA disaster lending program (especially Section 3.4). 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.

Other firms need more equity after a severe event. Firms with the greatest financing needs may require additional equity, yet many are unlikely to obtain it. Two market failures are at play here: asymmetric information in capital markets limits access to equity investments (especially for young and small firms), but simultaneously, the negative externalities related to firm failure from a systemic shock lead current owners to underinvest in ailing firms. Young firms are some of the least equipped to rely on credit as a substitute for equity. To this end, we suggest public disaster funding that would include loans and/or grants (as a substitute for equity) depending on means testing based on firm preparedness scores, repayment capacity, presence in socially vulnerable communities, among other criteria.

5 Appendices

5.1 Appendix. Sandy Challenges Profitability and Growth for Negatively Affected Firms

Our data are cross-sectional and so limit our ability to assess the causes of reduced profitability and growth; however, our theoretical model highlights that disaster losses may create changes in the financial structures of negatively affected firms that have longer-term implications for their performance. Such losses can put firms in the difficult position of delaying needed investments, or if possible, financing those investments through additional debt that reduces a firm's operating margins. Either response hurts its growth potential. The implications of these financing challenges for profitability may be greatest for younger firms, which frequently must grow to survive.

We examine Sandy's effects on firm's profitability and growth, finding persistent effects. Firms were asked "For the first half of calendar year 2013, did your business operate at a profit, break even, or at a loss?" They also answered questions about their revenues, net profit, and employment growth: "Comparing the first half of calendar year 2013 with the same time period in 2012, did the following increase, decrease, or stay the same for your business?"

We use these items to compare firms that reported being negatively affected by Sandy to those that were not. As Sandy occurred at the end of October 2012, practically all disruptions created by the event such as electricity outages and customer relocations were resolved before January 2013 (see Online Appendix 2 for more on Sandy and the timing of recovery). Thus, these questions would seem to allow for a comparison of profitability and growth before (the first half of 2012) and distinctly after (the first half of 2013) the event.

Firms negatively affected by Sandy reported reduced profitability and growth in the first half of 2013 (Table 10). These regressions follow our model with the full set of age and size interaction terms described in Equation 3; however, we instead show the full results as age and size for profit and employment increases, which are more informative and discussed next. Our model estimates that 30 percent of unaffected firms operated at a loss; being negatively affected by Sandy increases the likelihood to 45 percent ($Intercept + Neg.Affected = 0.308 + 0.142 = 0.45$). Sandy similarly affected the likelihood that a firm experienced decreased revenues, profits and employment, in each case increasing the likelihood by more than 50 percent. Consequently, we estimate that half of negatively affected firms report reduced profits and one quarter reduced their number of employees relative to the same period in 2012.

Table 10. Effects of Sandy on Firm Performance

	(1) Operated at a Loss	(2) Net Profit Decreased	(3) Net Revenue Decreased	(4) Employment Decreased
Intercept	0.308***	0.326***	0.247***	0.152***
	(0.019)	(0.0212)	(0.021)	(0.016)
Neg. Affected	0.142***	0.171***	0.202***	0.108***
	(0.035)	(0.041)	(0.034)	(0.028)
Obs	837	797	800	789
Rsq	0.143	0.118	0.131	0.109

Note: Standard errors in parentheses. Linear probability models with White's (1980) heteroskedastically-consistent standard errors clustered at county. All models include industry and county fixed effects and full interactions for positively affected firms, as described in Equation 3. Models are constructed so that the intercept value represents the average unaffected firm in our data.

Hurricane Sandy had a particularly deleterious impact on the profitability and growth of negatively affected young firms and small firms, as shown in Table 11. For example, among negatively affected firms, a firm that has one standard deviation fewer employees than the average firm is 22 percentage points less likely to report employment growth following Sandy (Column 4). The consequences of age and size are additive and can result in large effects. Compared to an *unaffected* firm of average age and size, a negatively affected firm that is one standard deviation younger and smaller is 36 percentage points more likely to operate at a loss in the first half of 2013 (Column 1).

Similar to our analyses of firm financing, being negatively affected by Sandy seems to exacerbate the pre-existing effects of size. Among negatively affected firms, a firm with one standard deviation fewer employees than the average firm is 15 percentage points more likely to operate at a loss. The effect of size is significantly different and four times larger for negatively affected firms than unaffected ones (H_0: $\beta_{Employees} = \beta_{Employees \times Neg.Aff}$, $F = 4.20$, $p = 0.04$). Age and size also interact in explaining employment growth among negatively affected firms: both you and old large firms report similar employment growth and old, small firms are the least likely to report employment growth.

Sandy also seems to attenuate the benefits of firm age in terms of profit growth. Young, unaffected firms are significantly more likely to report profit growth than older firms; an unaffected firm that is one standard deviation below the average firm is five percentage points more likely to report that its profits have increased relative to the same period the previous year. Among negatively affected firms, the profits of young firms grew no faster than those of their older peers. As the effects of age are similar for unaffected and negatively affected firms regarding net revenue, we conclude that additional costs (e.g., expensive financing such as through credit cards) seem to explain the lower profit growth for negatively affected, young firms.

Table 11. Sandy, Age, Size and Performance

	(1) Operated at a Loss	(2) Net Profit Increased	(3) Net Revenue Increased	(4) Employment Increased
Intercept	0.308***	0.315***	0.408***	0.251***
	(0.019)	(0.014)	(0.018)	(0.022)
Neg. Affected	0.142***	-0.0486	-0.0959**	-0.0526*
	(0.035)	(0.035)	(0.041)	(0.029)
Age	-0.0469*	-0.0483**	-0.0586***	-0.0290
	(0.025)	(0.019)	(0.021)	(0.019)
Age x Neg. Affected	-0.0631	0.000899	-0.0535	-0.0294**
	(0.0421)	(0.0244)	(0.058)	(0.015)
Employees	-0.0388	0.0332	0.0347	0.0997***
	(0.027)	(0.023)	(0.025)	(0.036)
Employees x Neg. Affected	-0.154***	0.0686	0.106*	0.217***
	(0.038)	(0.078)	(0.057)	(0.036)
Age x Employees	0.00107	-0.00276	-0.00988	-0.0133
	(0.010)	(0.008)	(0.010)	(0.011)
Age x Employees x Neg. Affected	0.0230	-0.0201	-0.00955	-0.0513***
	(0.019)	(0.026)	(0.028)	(0.010)
Obs	837	797	800	789
Rsq	0.143	0.099	0.113	0.194

Note: Standard errors in parentheses. Linear probability models with White's (1980) heteroskedastically-consistent standard errors clustered at county. All models include industry and county fixed effects and full interactions for positively affected firms, as described in Equation 3. Models are constructed so that the intercept value represents the average unaffected firm in our data.

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

We develop a theoretical model that complements the literature review to formulate hypotheses related to firm financing and natural disaster risk in Section 1.2. Following Foster et al. (2015), 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.[30] This model

[30] Jovanovic (1982) reaches similar results using stochastic production costs.

leverages the work of Jovanovic (1982), Rampini and Viswanathan (2010) and Stiglitz and Weiss (1981) but uses some simplifications tailored to our research questions. In particular, 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.

5.2.1 Firm's financing problem

A representative firm attempts to maximize its expected returns and is endowed with an initial stock of equity $\underline{k}$ and a unique production technology $f(\cdot)$ that is increasing and concave $(f' > 0, f'' < 0)$. Its output is perishable; what is not sold cannot be saved. 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 ($c' > 0, c'' \geq 0$). The firm also incurs a fixed operating cost h.

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; the variance of these market prices is greater than $\mathrm{var}(p)$.[31] Data on market prices are truncated: firms producing goods with low demand exit the market and so are not observed. The stationary distribution of market prices p_m, adjusted for exiting, is π_m. 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.

[31] For example, consider a restaurant that introduces an ethnic cuisine that was previously unavailable in its community.

Firm rewards are positive as long as 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 its expected return by solving the problem

$$\max_{\bar{k}\geq 0} \mathrm{E}[g] = \int_{p_c}^{\infty} \left(pf(k) - c(\bar{k}) - h + \underline{k}\right)\pi_d(p) \quad dp \qquad (A1)$$
$$\text{s.t.,} \qquad k = \bar{k} + \underline{k}.$$

The critical price p_c is the price below which the firm would be insolvent, its revenues and equity are insufficient to meet its liabilities. This price is a function of the firm's financial structure

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

The critical price is decreasing in equity (firms with more equity can withstand a less advantageous price draw) and is increasing in firm debt.[32]

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

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

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

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

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

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, $\partial p_c/\partial \bar{k} > 0$.

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

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.[33]

5.2.2 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 $c(\bar{k})$.[34] 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

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

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

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

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

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.

[34] The assumption that lenders take interest rates as given facilitates our exposition. Our 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

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

where 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.

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

5.2.3 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 (shown in Section 5.1.1), 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 $\pi_d^O$is converging toward its actual price distribution $\pi_i, \lim_{d\to\infty} \pi_d \Longrightarrow \pi_i$. Thus, the variance for the estimated price variance for the younger firm is greater than that of the older firm, $\mathrm{var}(p^Y) > \mathrm{var}(p^O)$ (following from Section 5.2.1). Assume for comparison a mean-preserving spread, that the old firm is the average firm in the market such that the young and old firm have the same expected price, $\mathrm{E}[p_m] = \mathrm{E}[p^Y] = \mathrm{E}[p^O]$. 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 above). 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 $l^* = (1-\delta)\underline{k}$.

This loss increases demand for credit for all firms as it universally increases returns on borrowing. 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.

5.2.4 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. This lifestyle firm is the same in every way to the entrepreneurial one described in Section 1.1.1 except that it maximizes the expected *utility* of its returns. The firm owner is risk averse ($U' > 0, U' < 0$) such that $\lim_{x\to\infty} U'(x) = 0$ and $\lim_{x\to 0} U'(x) = \infty$. This leads to the lifestyle firm's first order condition

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

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.

5.2.5 Insuring against rare events

We extend the firm's problem to examine decision making with respect to investing in protection *ex ante*. The analysis is relevant to a variety of ways a firm might prepare for rare events through investments in loss reduction measures. However, we consider the concrete example of insuring against a disaster. While in our initial analysis we assumed a risk neutral firm that did not consider its disaster exposure in the above, we now assume the manager of the firm is risk averse and aware of its exposure so that our model more closely aligns with standard insurance models. Moreover, this assumption of risk aversion increases linkages to the lifestyle firm described in Section 5.2.4. We show that even this risk averse firm may not insure against rare events.

Besides demand risk, the firm is also vulnerable to a natural disaster, leading to losses l. The variable l^* above is one example from a continuum of potential disaster losses. The firm can insure an amount q against the disaster, paying premiums $a(q)$ for a contract with payout function $I(q,l)$. The firm's problem is now

$$\max_{\bar{k}\geq 0, q\geq 0} \mathrm{E}[U(g_l)] = \int_{p_c}^{\infty}\int_{0}^{l_c} U\big(pf(k) - c(\bar{k}) - h - a(q) + I(q,l) - l + \underline{k}\big)\, \pi_d(p,l)\ \ dl\, dp$$

$$\text{s.t.,} \qquad k + a(q) = \bar{k} + \underline{k}$$

where l_c is the critical loss, the level of losses from the disaster above which the firm would be insolvent, and $\pi_d(p,l)$ represents the firm's estimated joint density of price and loss risks. We assume that the firm's estimated marginal distribution of disaster probabilities $\pi_d(l)$ is based on publicly available information such that the insurer and firm use the same distribution.

The effect of insuring on the critical price is

$$\frac{\partial p_c}{\partial q} = \frac{\int_0^{l_c}\big((1+c')a' - I'\big)\pi_d(l)\, dl - \frac{\partial l_c}{\partial q}\big(p_c f - c - h - a + I - l_c + \underline{k}\big)\pi_d(l_c)}{\int_0^{l_c} f(k)\pi_d(l)\, dl}.$$

As shown in the first term of the numerator, insurance generally increases the critical price by dedicating resources to manage disaster risk, thereby reducing the capacity of the firm to manage demand risk. The first term increases the critical price. First, the cost of insurance tends to be greater than the expected payout to cover the expenses of the insurer, $a > \int_0^{k+pf} I(l)\pi_d(l)\, dl$. Second, in addition to the premium loading, the firm must incur the added cost of funding the insurance, either through financing or reducing resources dedicated to production.[35] Shown in the second term of the numerator, insuring also puts downward pressure on the critical price by reducing the likelihood of failure due to the disaster.

[35] The equation shown for the critical price here implicitly assumes that the firm finances the insurance. While we omit it here for ease of exposition, it is straightforward to show that for firms taking on less debt or no debt, paying for insurance comes at the opportunity cost of reduced production.

The firm's first order condition extends the discussion of the critical price,

$$\frac{\partial \mathrm{E}[U(g_I)]}{\partial q} = \int_{p_c}^{\infty}\int_{0}^{l_c} (I' - (1 + c')a')U'\pi(p,l)\, dl\, dp + \frac{\partial l_c}{\partial q}\int_{p_c}^{\infty} U\big(pf - c - h - a + I(l_c) - l_c + \underline{k}\big)\pi(p,l_c)\, dp$$
$$- \frac{\partial p_c}{\partial q}\int_{0}^{l_c} U\big(p_c f - c - h - a + I - l + \underline{k}\big)\pi(p_c,l)\, dl \ \leq 0.$$

The first element shows that the optimal level at which to insure depends on the cost relative the expected value of the contract. The second two elements illustrate the tradeoff that insuring against a disaster reduces the likelihood of failure due to that event, but increases the risk of failure due to another event.

The first term is most relevant for the average firm in the data. As just described, administrative loadings and borrowing costs tend to lead to insurance premiums that exceed expected payouts. While risk aversion might motivate firms to partially insure, in practice, insurance contracts are written to discourage partially insuring. First, insurance tends to include a "co-insurance penalty," a condition that if a firm partially insures its assets, payouts will be proportional to the level of the partial insurance (see Zurich Insurance, 2011).[36] Bankruptcy protection additionally reduces incentives to insure. While the firm's total resources are $k + pf$, firm owners do not have an incentive to insure an amount larger than l_c. In summary, whether the firm fully insures, or chooses to partially insure and incur co-insurance penalties, it does not capture the total benefits of the premiums it pays.[37]

[36] Typically, co-insurance penalties occur when insureds select coverage limits that are less than 80 percent of the value of the insured property. For example, if a firm purchases property insurance with a coverage limit equal to 50 percent of its property, a loss equivalent to 50 percent of the property value from an insured event would result in a payout for half of the loss, or 25 percent of the property value.

[37] These insurance-specific arguments can be made more generally with respect to a broader set of risk reducing investments. In many cases, positive returns on risk reduction investments require planning horizons longer than that of a young firm (Mechler et al., 2014). Additionally, many risk reduction investments are indivisible (e.g., elevating a property). Along these lines, Boyd and Kunreuther (1997) consider an indivisible pollution abatement cost and show that smaller firms will not tend to abate. In our model, we might assume an indivisible cost of hiring a chief risk officer that would produce a similar effect.

Age and size influence firms' insurance decisions. The influence of these factors come from the second and third terms of the first order conditions as they are relevant to the tradeoffs between protecting against rare events versus other shocks. As young firms have greater estimated price risk than the average older firm (discussed in Section 5.1.3), they are less likely to insure against disasters. In contrast, large firms have a lower critical price than the average sized firm and so are more likely to insure against disasters.

5.3 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 et al., 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, in particular, may suffer longer-term impacts (Henry et al., 2013). The construction industry, in contrast, has experienced a marked increase in employment and revenues as communities rebuild and repair 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. 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.[38]

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 the Department of Housing and Urban Development. 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).

Two programs available directly to firms are flood-specific insurance through the National Flood Insurance Program (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

[38] 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).

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, 2015b). 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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