Dressing up for stormy weather – Bank lending to SME's in the face of natural disasters

Evidence from the U.S. Market

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A thesis of
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Abstract

My work examines the lending behavior of U.S. banks to SMEs in the aftermath of natural disasters. The study is based on 2016-2019 panel data at bank-county-neighborhood-year level. To identify a causal effect of natural disasters on bank lending, I use an ordinary least squares regression model with group fixed effects. My results demonstrate that there are differences in post shock lending behavior of affected local versus non-local banks. In normal times a strong positive relationship can be observed between SME lending and local bank presence, my results show robust evidence for the existence of a negative disaster lending effect. After a natural disaster, local banks lend significantly less to firms in affected areas than non-local banks. This pattern manifests itself especially for major disasters and hurricanes. My results further show different disaster lending effects based on the income structure of affected regions. I observe positive disaster lending effects for high income regions, negative effects for lower income regions.

Key Words - Disaster Lending – Credit Supply – Natural Disasters – Bank – SME

Curativo para tempestades - Empréstimos bancários às PMEs face a catástrofes naturais

Provas do Mercado dos Estados Unidos

Jil Luca Birgel

Português Abstrato

O meu trabalho examina o comportamento dos bancos dos EUA em matéria de empréstimos às PME na sequência de catástrofes naturais. O estudo baseia-se nos dados compreendidos entre 2016-2019 a nível do ano de vizinhança dos bancos. Para identificar um efeito causal das catástrofes naturais nos empréstimos bancários, utilizo um modelo normal de regressão de mínimos quadrados com efeitos fixos de grupo. Os meus resultados demonstram que existem diferenças no comportamento de empréstimo pós-choque dos bancos locais afectados versus bancos não-locais. Em tempos normais pode ser observada uma forte relação positiva entre os empréstimos às PMEs e a presença de bancos locais, os meus resultados mostram provas robustas da existência de um efeito de empréstimo negativo em caso de catástrofe. Após uma catástrofe natural, os bancos locais emprestam significativamente menos às empresas nas áreas afectadas do que os bancos não locais. Este padrão manifesta-se especialmente no caso de grandes catástrofes e furacões. Os meus resultados mostram ainda diferentes efeitos de empréstimo em caso de catástrofe, com base na estrutura de rendimentos das regiões afectadas. É também possível observar efeitos positivos dos empréstimos em caso de catástrofes para regiões de elevado rendimento, efeitos negativos para regiões de menor rendimento.

Palavras-chave - Crédito a calamidades - Fornecimento de crédito - Catástrofes naturais - Banco - PME

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1 Introduction

Small- and medium-sized enterprises (SME) built the fundament of the U.S.-economy. They generate 43.5 % of GDP, 33.30 % of known export value, 65 % of new net jobs since 2000 and pay 40.7 % of private sector payroll (SBA, 2019). Regarding debt financing, SMEs rely almost exclusively on bank finance because low volumes, high fixed costs and less diversified cashflows prevent them from issuing bonds and stocks (Nouy, 2018). Compared to listed firms, less data is known about SMEs, which makes them subject to stronger information asymmetries and further restricts access to funding (Beck et al., 2005). It follows that SMEs are largely financed by commercial banks, which yield information advantages and stronger relationships to local firms (Berger, Frame, et al., 2005).

In my dissertation I examine empirically if bank lending under adverse market conditions to determine whether local banks continue to serve SMEs' demand for credit. More specifically, my work focuses on small business credit supply after natural disasters. Hazards can cause severe property damage to business and private households in the affected communities. The frequency and expense associated with natural disasters have risen sharply over the past century (Platt et al., 2017). Government aid and insurance policies are incomplete and do not cover the full amount of disaster damage. Hence, banks play a key role by providing additional capital for corporate and public rebuilding after disaster strikes (Froot, 2001).

Numerous studies have shown that natural disasters boost local demand for bank loans dramatically (Berg & Schrader, 2012; Chavaz, 2016; Ivanov et al., 2020). Considering these demand shocks, it is not entirely clear how the credit supply side reacts. Hence, it is relevant to have a closer look on disaster lending provided by (local) banks to SMEs. On the one hand, business opportunities to increase revenue growth arise for (local) banks within the disaster-affected areas (Ivanov et al., 2020). After natural disasters, banks are explicitly forced to lend by their regulatory supervisors (Cortés, 2014). On the other hand, natural disasters destabilize credit markets and might cause market shortfalls (Gilchrist et al., 2014). The loss of collateral to existing credits resulting from disaster losses can increase information asymmetries, reduce credit ratings of borrowers, and increase business risks (Berg & Schrader, 2012; Faiella & Natoli, 2018).

Motivation According to survey data, 66% of disaster-affected SMEs experience notable funding gaps due to funding rejections or insufficient loan volumes (Battisto et al., 2017). After natural disasters, (local) banks seem unable or unwilling to sustain SME financing. Accordingly, SMEs might be unable to recover quickly and experience sales collapses and business difficulties, which in the worst case lead to bankruptcy. Of course, small communities would suffer from that situation, especially in structurally weak and low-income regions.

My work investigates disaster lending provided by (local) banks to SMEs within counties and respective neighborhoods with different income structures. The underlying assumption is that local banks react fundamentally differently to exogenous disaster shocks than non-local banks. They have both more business opportunities and operational risks in the affected regions (Chavaz, 2016). This should have a direct impact on risk management and credit allocation to disaster affected counties. In the context of the special dependency relationship of SMEs to local banks, it is crucial to understand if local banks increase or decrease their lending to disaster affected firms (Berger, Frame, et al., 2005). A significant negative or positive disaster lending effect should be observable, depending on the local disaster exposure of the bank.

Data My analysis is based on yearly reporting data of the Community Reinvestment Act (CRA)[1] from 2016 -2019, which comprises annual bank lending data aggregated at bank-county-neighborhood level. Each county is divided in up to four different neighborhoods along the income structure (low-,moderate-, middle-, high income). Lending data is mapped to annual aggregated disaster losses (property damages) from the Spatial Hazard Events and Losses Database for the United States (SHELDUS)[2]. Additionally, I map Summary of Deposits Database (SOD)[3] to identify the local presence of a bank within a county. To the best of my knowledge, I am the first to investigate disaster lending after natural disasters using this dataset. Most other studies use mortgage lending data because the consequences of catastrophes are immediately visible in the loss of collateral. Moreover, most studies examine credit supply at county-level, whereas I conduct an analysis at the county-neighborhood level.

The constructed baseline panel for the 2016-2019 period includes lending to 2,782 counties, 770 different commercial and saving banks and 0.64 million aggregated loan transactions. I use

[1] https://www.ffiec.gov/cra/craflatfiles.htm

[2] https://cemhs.asu.edu/sheldus

[3] https://www.fdic.gov/bank/statistical

annual lending, natural disasters and banks branch presence data to build the panel. Aggregated loan volume (number) data at bank-county-neighborhood level serves as dependent variable. Disaster severity is expressed as annual disaster losses (property damages) at county level. The local disaster exposure of a bank is estimated by its branch presence and share of branches within an affected county (absolute and relative exposure).

Methodology To identify a causal effect of exogen shocks on SME bank lending, I exploit the exogeneity of the timing, intensity, and distribution of natural disasters (Nordhaus, 2010). To obtain unbiased estimates, I apply a fixed effects ordinary least squares (OLS) regression model (Wooldridge, 2010). I use bank-, county- and year- fixed effects (FE) and the possible two pair combinations (e.g. bank *x* county). The identification strategy is focused on recognizing disaster lending effects of local banks relative to non-local banks. I split my analysis and distinguish *whether* and *to what extent* a bank is locally exposed in a disaster region. In this way, I examine absolute and relative disaster lending effects.

Main Findings First, I examine the individual effects of local exposure and disaster damage on bank credit supply. I define a bank as local if it has at least on branch within a disaster affected area. The results demonstrate a strong positive effect of local exposure and a slightly negative effect of disaster damage on bank lending. After, I test the joint effect of local exposure and disaster damage on bank lending by considering the interaction among both. To this purpose, I verify empirically two opposing strands of argumentation[4]: (1) Profitability Strand - Compared to non-local banks, a local bank has information advantages in a disaster region and a positive disaster lending effect can be observed. (2) Financial Constraints Strand - Compared to a non-local bank, a local bank has greater business risks in a disaster region and a negative disaster lending effect can be observed. I test empirically whether local banks behave differently from non-local banks when disasters occur and trigger a local credit demand shock. Hence, I test for the exitance of a disaster lending effect. Within all model variations, the baseline analysis shows a consistently negative disaster lending effect. However, after adding FE, a statistically significant effect emerges only for one dependent variable, namely number of loans awarded. Either non-local banks substitute for the decline in local bank loans, or there is a credit bottleneck and SMEs experience funding gaps after natural disasters.

[4] The argumentation strands and empiermatic examination are constructed following Chavaz (2016) methodology.

Local Banks I reduce my baseline panel to exclusively local banks to account for relative local disaster exposure (share of branches in affected county). The results are much clearer compared to the baseline. In all FE model variations and for all dependent variables, I find a significant positive (relative) disaster lending effect. This carries the following meaning: The more local a bank is, the more disaster lending it provides to SMEs in disaster affected county-neighborhoods. All else equal, if a banks relative local exposure increases by 1% the disaster lending to disaster county-neighborhoods increases by USD 29 versus 15 (depending on the model specification).

Major Disasters It seems self-evident that severe natural disasters with high disaster losses have a more blatant impact on lending decisions compared to small disasters. To empirically verify it, the panel is split into major and minor natural disasters. For major disasters, I demonstrate a significant and negative disaster lending effect for all dependent variables. This leads to the finding that local banks (in the face of major disasters) lend significantly less in loan number and -volume to disaster affected firms. Compared to the baseline, the results within this panel are much clearer. It raises the question if the explanatory power of the baseline results is mitigated by including disasters that are too weak in losses.

Hazard Type Conducting analyses based on disaster losses caused by individual hazard types leads to the finding of a significant disaster lending effect only for hurricanes. This goes hand in hand with the paragraph above, as hurricanes are by far the most severe (major) disaster types in the U.S.[5].

Neighborhoods The sub-analysis of disaster lending within different income-neighborhoods (low, moderate, middle, high income) shows different disaster lending effects depending on the income level. I find a positive significant disaster lending effect for high-income neighborhoods. For the others, I find a negative effect. The results imply that local banks mainly increase disaster loans to SMEs in high-income neighborhoods at the expense of the other neighborhoods. This raises questions about socio-economic issues, such as worsening economic inequalities and frictions.

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[5] https://www.ncdc.noaa.gov/billions/summary-stats/US/2016-2020

2 Existing Literature & Contributions

Climate change is causing structural changes in the natural environment. In response to this ongoing process, natural hazards are occuring more frequently and with greater intensity, tossing incremental risks to the economy (Platt et al., 2017). Like other extreme and rare events, natural disasters are local phenomena which trigger devastating consequences and damage in the affected regions. According to survey data, SMEs are particularly hard hit by natural disasters. Affected small businesses experience sizable revenue, employment and funding gaps and financial bottlenecks compared to non-affected ones (Battisto et al., 2017).

Banks play an essential role in the refinancing of disaster regions, which is why it makes sense to examine mechanisms related to bank lending and natural disasters in more detail (Ivanov et al., 2020). Especially in the context of SME recovery loans, this study makes sense, as affected small businesses are more likely to apply for bank financing than to seek public disaster aid (Battisto et al., 2017). There are mixed study results on how banks respond to disaster-induced credit demand shock. First, I will review findings on banks and disaster lending in general. Afterwards, I will summarize research on disaster lending to SMEs and the related role of local banks.

There are arguments in favor of a reduction in the supply of credit and thus a short-term collapse of the credit market. Natural disasters can damage properties and disrupt businesses, causing borrowers to be unable to repay their loans, eventually forcing the banks to fire sell assets and ration credit (Faiella & Natoli, 2018) . There is empirical evidence that imperfections in insurance markets can significantly limit the availability of credit by 22 percent for properties in disaster-prone areas (Garmaise & Moskowitz, 2009). Moreover, access to credit can be restricted depending on the degree of bank-borrower relationship (Berg & Schrader, 2012). Brei et al. (2019) show that banks experience deposit withdrawls and negative funding shocks in the aftermath of natural disasters, thus reducing credit supply and drawing on liquid assets.

However, there are numerous studies that show the opposite effect, demonstrating an increase in the supply of credit to disaster-affected regions (Chavaz, 2016; Cortés, 2014; Cortés & Strahan, 2017; Koetter et al., 2020; Schüwer et al., 2018). Evidence shows that banks are able to compensate for the additional negative portfolio risks caused by disaster lending by means of assets wap mechanisms. A majority of studies show a compensation effect in credit allocation, with more credit supply being directed to high-demand disaster markets and credit supply being withdrawn from low-performing unaffected regions (Chavaz, 2016; Cortés, 2014; Cortés & Strahan, 2017; Koetter et al., 2020). In addition, banks offset disaster portfolio risk by increasing brokered deposits[6] and government securities while reducing existing loans (Schüwer et al., 2018). Moreover, studies show that while banks increase the supply of credit after natural disasters, they also increase the financial constraint (in the shape of higher interest rates) attached to these disaster loans (Gilchrist et al., 2014). This is particularly true for SME's , so Holton and McCann (2021) show that interest rates for SMEs rise more sharply in the context of natural disasters than for large firms.

Based on various study results, there is evidence to suggest that local banks react differently to disaster-based credit demand shocks than non-local banks. This is particularly important in the context of disaster lending to SMEs, as they are heavily dependent on financing from local banks.

During normal times, local banks take over most of SME financing due to competitive advantage through better access to information and stronger relationships between borrowers and local institutions (Behr et al., 2013; Berger et al., 2017; Berger, Miller, et al., 2005; Degryse & van Cayseele, 2000; Hasan et al., 2017). Berger et al. (2015) show that local bank presence results in more SME lending and lower failure rates during normal times. Simultaneously they show that these benefits disappear in light of exogenous shocks, substantiated in local banks' nature of less geographic diversification. This is supported by the fact that disaster affected SMEs mostly apply for loans at large banks, not at local institutions as during normal times (Battisto et al., 2017).

This raises the question of whether local banks or non-local banks are more likely to provide disaster lending to businesses and in particular SMEs. The findings of empirical studies are contradictory, but there is a tendency for a bank's local disaster exposure and disaster lending to be positively related to each other. Recent findings suggest that during a natural disaster, banks from the same region lend significantly more to affected firms than banks from unaffected regions (Koetter et al., 2020). Moreover, it has been demonstrated that increase in

[6] In the means of portfolio risk reduction banks sell large deposits to deposit brokers, who divide them into smaller investment pieces, which are then sold to individual investors or smaller banks.

credit supply to affected areas is driven by small, less diversified banks with an asset value below USD 2 billion (Cortés & Strahan, 2017). As in normal times, the informational advantage of local banks is still a critical factor. Because of their close relationship to borrowers, local lenders invest in rebuilding their local economies after a disaster, influencing important economic variables such as employment rates and economic recovery (Cortés, 2014).

On the other hand, there are the advantages of locally unexposed banks. There is research evidence to suggest that community banks constrain lending and diversified banks increase lending in response to external economic shocks (Demyanyk et al., 2007; Deyoung et al., 2015). Everything else kept constant, banks make fewer new business loans when their portfolios contain large fractions of prevailing local loans, and make more new business loans when their portfolios contain large fractions of loans to other sectors that covary negatively with business loans (Deyoung et al., 2015).

This results in a "local lending puzzle" in the aftermath of natural disasters: Local banks in affected areas more vulnerable to losses (tighter financial constrains), but superior local knowledge (advantages in loan screening, monitoring) yield to more business opportunities (Chavaz, 2016).

3 Research Hypotheses

As explained, disasters could have both a positive and a negative effect on banks' credit allocation decisions. The contrast is fueled by the potential impact of regulatory obligations and public aid programs versus increasing uncertainties and portfolio risks of the banks (Noth & Schüwer, 2017). Questions arise as to whether and by which type of banks disaster loans will be provided. In the context of SME lending and its heavy reliance on local banks, it seems necessary to examine the difference in disaster lending between local and non-local banks. While in normal times the demand for credit from SMEs is met almost exclusively by local banks, it is unclear what the situation is in times of exogen market shocks.

H0 - ***Local banks react differently than non-local banks to credit demand shocks induced by natural disasters.***

Based on existing studies outlined within the literature review, there is evidence to suggest that local banks respond differently than non-local banks to the credit demand shock from natural hazards. It should be examined more closely whether the credit offer to affected counties depends on whether the financial institution can be considered as local. It is not obvious whether natural disasters and associated losses are integrated into credit allocation decisions in different ways by local and non-local banks. Moreover, it is not evident whether local or non-local banks have a greater incentive to lend in affected areas.

In general, local banks have specialized in serving information-intensive borrowers such as small businesses (Berger, Frame, et al., 2005). Several studies show that this is due to private information advantages (Behr et al., 2013; Degryse & van Cayseele, 2000; Elsas, 2005; Hasan et al., 2017). The mechanism behind this works as follows: Locally resident banks have more local knowledge and, as a result, more private information about their borrowers. Thus, local banks are viewed as having a comparative information advantage and a greater incentive to lend to small businesses (Berger et al., 2017). The conclusion that arises is that local banks should have greater post shock business opportunities. Due to the information advantage, they might be able to realize greater ex-post benefit through lending to affected areas (Chavaz, 2016). Recent studies have shown that local banks are able to increase their net interest margin through disaster lending in the aftermath of natural disasters (Barth et al., 2019).

H1: ***Profitability* – Local disaster exposure of banks and disaster lending are positively related due to greater post shock business opportunities compared to non-local bank.**

On the opposite side, local banks might have higher operational risks in affected counties. The portfolio of local banks contains a proportion of deposits from the counties affected by natural disasters. This increases the risk profile of the local banks' portfolios, as well as the operational risks in the region, compared to non-local banks. In response to exogenous market shocks, a risk overhang might arise in the loan portfolios of local banks, which could lead these banks to reduce their supply of small business loans to affected regions (Deyoung et al., 2015). Moreover, local banks in affected areas could be more vulnerable to income losses (loss of collateral following a natural disaster) or access to external funding and consequently subject to tighter financial constraints (Berg & Schrader, 2012; Gilchrist et al., 2014).

H2: *Financial Constraints* – Local disaster exposure of banks and disaster lending are negatively related due to greater post shock operational risks compared to non-local bank.

In addition, I test the validity of my hypotheses within different panels:

Local Banks - I reduce my panel to local banks only which allows me to measure the relative local exposure of each bank to natural disasters. Since many studies emphasize the special importance of local banks for refinancing communities and businesses after a natural disaster shock, I would like to take a closer look at this sub-sample.

Major Disaster – I split my baseline panel into Major and Minor Disasters using USD 1 million as critical threshold. I expect to observe a stronger disaster lending effect in the major disasters channel.

Hazard Types - Moreover, I look at different types of disasters within my model. For this purpose, I include additional SHELDUS datasets, on property damages, of the four most common disasters in the U.S. – Hurricanes, Thunder storms, Floods, Wildfires. It seems reasonable to assume that different disasters have a different impact on bank lending, thus yielding different disaster lending effects. Depending on the type, they differ greatly in duration, severity and intensity. In addition, different regulatory rescue packages are activated depending on the type of disaster[7].

Income Neighborhoods - Finally, I split my baseline panel into four parts along the CRA reported income neighborhoods. This enables me to examine disaster lending effects between neighborhoods with different income structures. I suspect that the observed effects vary, depending on the neighborhoods income structures, thus observing negative effects for low- and positive effects for high income neighborhoods. Disaster lending between low- and high income neighborhoods should vary significantly, as the associated borrowers have different risk profiles.

4 Data and Methodology

4.1 Data

This section describes the data sets used to create the baseline panel built on credit supply, natural disasters, and local bank presence. All data considered is reported yearly from 2016-2019. Table 1 provides an overview of all variables used within my research.

[7] FEMA department of homeland security designs different assistance programs to businesses and individuals based on disaster type, severity, and declaration status (state of emergency). https://www.fema.gov

Table 1 – Variable Description

The table provides an overview of all variables used within the empirical analysis. Therefore, the variable name, description and source is provided.

Variable Name	Description	Source
Loan Volume (b,c,n,t)	The Natural Logarithm of yearly amount of small business loans from origination. Amounts of loans are aggrerated at county-neighborhood-bank level and reported in 1000 USD.	Own Calculation based on CRA
Loan Numer (b,c,n,t)	The Natural Logarithm of yearly number of small business loans from origination. Number of loans are aggrerated at county-neighborhood-bank level and reported in total amounts.	Own Calculation based on CRA
Lending Frequency (b,c,n,t)	The absolute loan number of bank b within neighborhood n over the total absolute domestic loan number of bank b.	Own Calculation based on CRA
Lending Size (b,c,n,t)	The absolute loan volume of bank b within neighborhood n over the total absolute domestic loan volume of bank b.	Own Calculation based on CRA
Loan Volume Growth (b,c,n,t)	The one year backward looking growth rate of Loan Volume. Considered growth calculated at county-neighborhood level.	Own Calculation based on CRA
Loan Number Growth (b,c,n,t)	The one year backward looking growth rate of Loan Amount. Considered growth calculated at county-neighborhood level.	Own Calculation based on CRA
Disaster Loss (c,t)	The Natural Logarithm of yearly property damages from weather-related natural disasters, across chosen hazard types. Property Damages are yearly summed across all counties and returned as county totals in 1000 USD.	Own Calculation based on SHELDUS
Absolute Exposure (b,c)	Dummy Variable indicating whether bank b has a branch within a county c.	Own Calculation based on FDIC
Relative Exposure (b,c)	The Sum of Deposits bank b has within county c over the total domestic deposits of bank b.	Own Calculation based on FDIC

4.1.1 Natural Disasters

To identify disaster occurrence, related severity and losses, I use SHELDUS data base[8]. It is a county-level hazard data set for the U.S. and covers different types of natural hazards. The database provides aggregate information on locations (state and county) affected by natural disasters and associated losses such as property damages, injuries and fatalities. For my analyses, I consider natural disasters over the period 2016-2019. I use annual property damages at county level to model the severity and impact of natural disasters. Since the SHELDUS-

[8] https://cemhs.asu.edu/sheldus

student-subscription only allows me to obtain data at aggregate level, all disaster-information examined is clustered at county-year-level. I am given the amount of disaster losses incurred in the form of property damages per county per year. More precise aggregations, for example per city or per month, are not available.

To construct my baseline panel, I follow the hazard selection of Cortés (2014) and aggregate the information on property damages and injuries from 11 different hazard types[9]: Avalanche, Coastal, Earthquake, Flooding, Hail, Hurricane/Tornado, Landslide, Thunderstorms/Severe Storms, Tsunami/seiche, Wildfire.

Per year, natural disasters in my sample caused a total of 18.16 billion USD (2019), 119.29 billion USD (2018), 31.73 billion USD (2017), 5.99 billion USD (2016) in property damage, distributed across all counties in the sample. Disaster losses in form of property damages are the most actuate and direct proxy available to me to measure the impact and severity of a natural disaster. Therefore, I identify county c's disaster exposure in year t as:

$$Disaster\ Loss\ (c,t) = ln\ [Property\ Damages\ (c,t)]$$

The original property damage data is heavily skewed, so I take the natural log, assuming that the original data follows or approximately follows a log-normal distribution.

4.1.2 Bank Lending

In line with the natural disasters data sets, I construct a panel of bank -county-neighborhood - year loan originations for the 2016-2019 period. It includes lending to 2,782 counties which are subject to natural disasters of different severity levels. Each county is split in up to four distinct neighborhoods along the prevailing income structure. The small business loans are originated by 770 different banking institutions.

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[9] Within his studies Cortés (2014) identifies ten disasters that could pose the most risk for bank capital and stability. I am adding to these the additional category "Thunderstorms/Severe Storms" as they are the most common natural disaster in the U.S. in terms of frequency. In the context, the sum of all severe storms causes the highest property damages.

I use the CRA data collected as part of a regulatory initiative by various U.S. agencies including, Federal Banking Authorities, Office of the Comptroller of the Currency (OCC) and the Federal Deposit Insurance Corporation (FDIC). Among others, CRA reports loans originated to SMEs. These loans are aggregated at the bank - county-neighborhood - year level in the publicly available disclosure report files[10]. Therefore, each institution must annually sum up and report the *Loan Volume (in USD)* and *Loan Number* granted to each county-neighborhood in which it does business.

The initiative was launched to foster financial institutions to help meet the credit needs of the communities in which they operate with special focus on low- and moderate-income neighborhoods. Based on the U.S. Medium Family Income[11] each neighborhood within a county is assigned an income tract - low, moderate, middle, high. The objective is to obtain insights into patterns of well-being by neighborhood using geospatial analysis.

The unfiltered CRA sample contains a total of 3.2 million aggregate transactions. After cleaning the sample for empty transactions (*Loan Volume* = 0 USD) and data gaps, 887,845 aggregated transactions remain. It covers lending by 814 national member banks, commercial banks (stock saving and mutual savings banks), public banks and saving associations.

Loan Number (b,c,n,t) and *Loan Volume (b,c,n,t)* of bank *b*, in county *c* and neighborhood *n*, in year *t* serve as dependent variables. Both are highly skewed, which is typical for other bank-specific variables like assets or deposits (Cortés, 2014). Hence, I log-transform both variables, assuming that the original data (approximately) follows a log-normal distribution.

$$Loan\ Number\ (b,c,n,t) = \ln[\ Number\ of\ Aggregate\ SME\ Loans\ (b,c,n,t)]$$
$$Loan\ Volume\ (b,c,n,t) = \ln[\ Amount\ in\ USD\ of\ Aggregate\ SME\ Loans\ \ (b,c,n,t)]$$

4.1.3 Local Finance

To determine the local presence of a bank within a county, I use a data set of the Federal Deposit Insurance Corporation (FDIC), the Summary of Deposits[12]. It is the annual survey of branch

[10] https://www.ffiec.gov/cra/craflatfiles.htm

[11] Census tracts based on income data from the U.S. Census Bureau's American Community Survey (ACS)

[12] https://www.fdic.gov/bank/statistical

office deposits as of June 30 for all FDIC-insured institutions. The detailed reporting at branch level allows me to precisely determine the geographical presence of a bank within a county. To meaure bank b's absolute local exposure to county c, I define the categorical variable *Absolute Exposure (b,c)*. To measure bank b's relative local exposure to county c, I define the metric variable *Relative Exposure (b,c)*.

Bank *b Absolut Exposure* is equal to one if it owns at least one branch in county *c*. At first glance, this condition appears to be too permissive to estimate the local exposure of a bank. Studies often opt for a stricter classification of local lender, for example based on deposit shares or number of branches within a county. However, bank deregulation and acquisition activity had resulted in a massive closure of branches over the last decade (Demyanyk et al., 2007). All geographical constraints on bank branch locations and business areas were abolished by the Dodd-Frank Act of 2010[13]. In recent years, this trend is reinforced by digitalization, a low interest rate environment and outdated business organisation models leading to margin - and cost pressures and, in turn, encourage branch closures(Perez & Martin, 2018). My Sample confirms this trend: Following my definition of *Absolute Exposure (b,c)* only 22.39% of the observed aggregated loan transactions are originated by local institutions. Thus, in most cases, lending and borrowing institutions have no local connection to each other at the county level within my sample. Therefore, I deliberately choose a categorical definition of *Absolute Exposure* in the baseline model.

Nevertheless, the degree of exposure plays an important role for local banks. For this purpose, the variable *Relative Exposure (b,c)* is created. This is only applied to a subsample of local banks, as it has a strong skewness in the baseline model and is not applicable. The FDIC data set is used to built *Relative Exposure*, thus I calculate the relative degree of local exposure in percent based on deposit shares as follows:

$$Relative\ Exposure\ (b,c) = \frac{County\ Deposits\ (b,c)}{Domestic\ Deposits\ (b)}$$

[13] Dodd-Frank reorganized the financial regulatory system after 2008 crisis, protecting consumers against abuses related to credit cards, mortgages, and other financial products and stabilizing the financial system. In that course restrictions on local banks business regions where removed, to enable further portfolio diversification and hedging. https://www.cftc.gov/LawRegulation/DoddFrankAct/index.htm

According to the FDIC Research, banks may open ad hoc branches in areas affected by natural disaster to provide rapid assistance and funding[14]. To preclude this effect, I use branch location and deposit data from the year preceding the disasters (July 30, 2015). Thus, I keep the variables *Absolute Exposure(b,c)* and *Relative Exposure(b,c)* constant over the entire sample period.

The table below provides summary statisticts of the baseline panel for all relevant variables explained in this section.

Table 2 – Descriptive Statistics

This table displays summary statistics of the main dependent and explanatory variables of interest for the analysis.

Variable	N	Mean	SD	Min	50th	Max
(ln) Loan Volume in 1,000 USD	657,145	5.42	2.06	0.69	5.42	13.98
(ln) Loan Numer	657,145	2.25	1.44	0.69	1.79	11.27
(ln) Lending Frequency	657,145	0.00	0.02	0.00	0.00	1.00
(ln) Lending Size	657,145	0.00	0.02	0.00	0.00	1.00
(ln) Loan Volume Growth	262,459	0.07	1.37	-8.27	0.03	10.31
(ln) Loan Number Growth	262,459	0.06	0.89	-6.43	0.00	8.83
(ln) Disaster Loss 1,000 USD	657,145	11.28	3.84	0.00	11.46	23.72
Absolut Exposure	657,145	0.22	0.42	0.00	0.00	1.00
Relative Exposure in %	657,145	0.02	0.10	0.00	0.00	1.00

4.2 Identification Strategy

In the following, an empirical model is developed to examine disaster lending by local and non-local banks in the face of exogen, disaster-induced credit demand shocks. The interaction effect between a counties *Disaster Loss* and a bank's *Absolute Exposure* on disaster lending is examined. A special focus on local banking is set due to the dependency profile of SMEs and local financing.

Identifying the causal effect of natural disasters on bank lending is challenging because disaster-related damages are influenced by the local economic structure, and therefore is endogenous to local economic conditions (Noth & Schüwer, 2017). The resulting endogeneity problem could also have an impact on banks' lending decisions, which also depend on local economic

[14] https://www.fdic.gov/analysis/archived-research/outlook/t4q2005.pdf

circumstances. As previously mentioned, the better or worse income structure of a region could be related to better or worse local disaster-management. This is followed by the possibility that banks could make their local business area decisions based on more or less disaster risk within a county. To account for the endogeneity problem, I exploit the exogeneity of the timing, intensity, and distribution of natural disasters by using a OLS FE regression model. The occurrence of the natural disaster itself can be considered as unambiguously exogenous, since banks are not able to estimate timing, intensity, and distribution of natural disaster shocks (Nordhaus, 2010). A multiple (group) FE setting is the best applicable model in my case due to the heterogeneous panel data structure of my sample. As outlined above, it can be safely assumed that unobservable differences exist between groups (banks, counties, years). FE Models address this heterogeneity issue by applying a within-group estimator to filter out time invariant observable and unobservable variation within groups (Collischon & Eberl, 2020). I apply bank (B), county-neighborhood (CN) and year (Y) FE. Further, I use all possible two-pair combinations of these (B *x* CN, B *x* Y, CN *x* Y) which I will refer to as "paired" FE in the further course.

Regression Models To study the impact of hazard-related damages on bank lending and to test whether disaster lending differs significantly between locally exposed and unexposed banks, I estimate the following OLS regression models:

Core Check

$$Y(b,c,n,t) = \beta 1 \cdot Abs.Exposure(b,c) + \beta 2 \cdot Disaster\ Loss(c,t)$$
$$+B(b,t) + CN(c,n,t) + Y(t) + \in (b,c,n,t)$$

Baseline

$$Y(b,c,n,t) = \beta 1 \cdot Abs.Exposure(b,c) + \beta 2 \cdot Disaster\ Loss(c,t)$$
$$+ \beta 3 \cdot Abs.Exposure(b,c) \cdot Disaster\ Loss(c,t) + \in (b,c,n,t)$$

Model (1)

$$Y(b,c,n,t) = \beta 1 \cdot Abs.Exposure(b,c) + \beta 2 \cdot Disaster\ Loss(c,t)$$
$$+ \beta 3 \cdot Abs.Exposure(b,c) \cdot Disaster\ Loss(c,t) + B(b,t) + CN(c,n,t) + Y(t) + \in (b,c,n,t)$$

Model (2)

$$Y(b,c,n,t) = \beta 1 \cdot Abs.Exposure(b,c) + \beta 2 \cdot Disaster\ Loss(c,t)$$
$$+ \beta 3 \cdot Abs.Exposure(b,c) \cdot Disaster\ Loss(c,t)$$
$$+B(b,t) \cdot Y(t) + CN(c,n,t) \cdot Y(t) + CN(c,n,t) \cdot B(b,t) + \in (b,c,n,t)$$

Y(b,c,n,t) represents two alternative measures for bank lending, namely Bank b's (ln) *Loan Volume* and (ln) *Loan Number* in county c, neighborhood n and year t.

Exploiting the exogeneity of timing, intensity and distribution of disaster losses, I use annual aggregate disaster-related property damages at county level to model the explanatory variable (ln) *Disaster Loss (c,t)*. This allows me to measure the relative degree of affect of a county by natural disasters. Accordingly, major disasters with severe damage weigh more heavily than minor ones.

To measure a bank's local disaster exposure, I include the explanatory variable *Absolute Exposure (b,c)* in my model which is fixed to the year preceding the natural disasters. Thereby, I should additionally counter the endogeneity problem by preventing disaster related changes in branch structure from influencing my results. The dummy variable represents local presence of a bank within a county, thus embodying the *Extensive Local Margin* to determine the absolute exposure to a disaster region.

Following the empirical model of Chavaz (2016), I implement a interaction term *Absolute Exposure (b,c) x Disaster Loss (c,t)* within my model. It is intended to provide evidence on whether banks that are locally exposed to a natural disaster shock conduct their lending differently from banks that are not exposed to it. Based on the prefix and significance of the parameter β3 it could be determined whether the Profitability or Financial Constraints strand outlined in section 3 is predominant. If local exposure increases the tendency of banks to allocate credit to affected counties, the parameter β3 should be positive and significant (Profitability). If in turn the local exposure decreases the tendency of banks to allocate credit to affected counties, the parameter β3 should be negative and significant (Financial Constraints). This relationship is referred to as the disaster lending effect in the following section of this paper.

I include bank, county and year FE in Model (1) to additionally alleviate the described endogeneity problem. They allow me to capture heterogeneity between banks, county-neighborhoods and years, respectively. Hence, these help me control for unobserved time-invariant variables, for example economic structure, local disaster management or institutional risk management (Noth & Schüwer, 2017). In particular, the spatial distribution of natural disasters cannot be considered completely random, as some regions in the U.S. are known to be frequently affected by different types of disasters (Wirtz et al., 2014). The integration of CN(c,t) should alleviate this concern. To account for unobservable differences between bank institutions I implement B(b,t). They should cover issues such as institution type, corporate governance, and disaster risk aversion.

To further control differing risk aversions dependent on the county and changing economic differences I substitute the “single” FE by “paired” FE. For example, they should account for differing credit demand across affected counties and time. These are reflected in Model (2). Here I am only able to estimate the interaction term *Absolute Exposure x Disaster Loss* due to collinearity and ranking deficiency issues.

In settings with several layers of clustering (county, bank, year) default standard errors can greatly overstate estimator precision (Colin Cameron & Miller, 2015). Therefore, I choose a clustered-standard-error approach for all regressions to adjust for heteroskedasticity. Standard errors are clustered by bank to capture within-cluster correlation across institutions.

I reduce my panel to local banks only to be able to determine the impact of disaster damages on bank lending based on the relative local exposure of a bank. I replace the *Absolute Exposure (b,c)* dummy in the baseline model with the metric variable *Relative Exposure (b,c)*. The variable measures the relative degree of a bank local diversification across counties, thus embodying the *Intensive Local Margin*.

5 Results

5.1 Baseline Results (All Banks)

5.1.1 Core Check

First, it is crucial to investigate the individual effects of a bank's local exposure and disaster severity on disaster lending. Disaster Severity is expressed with the variable *Disaster Loss (c,t)* and local exposure with *Absolute Exposure (b,c)*. The analysis aims to show that both parameters individually have an impact on bank lending, expressed by *Loan Volume (b,c,n,t)* and *Loan Number (b,c,n,t)*. Furthermore, it should be shown that it makes a fundamental difference in lending whether a bank has a local presence in a region or not.

Table 3 – Core Check

The Table shows results of OLS estimation of different specifications of the Core Check applied to Loan Volume (Number). Disaster Loss is a metric variable, Absolute Exposure is a dummy variable (see Definition Section 3). Heteroskedasticity-robust standard errors are clustered at the bank level and reported in (). *, ** and *** indicate significance at 10%, 5% and 1%.

	Loan Volume (ln)				**Loan Number (ln)**			
	(1)	(2)	(3)	**(4)**	(5)	(6)	(7)	**(8)**
Coefficients:								
(Intercept)	4.7559*** (0.1299)	-	-	-	1.9578*** (0.1218)	-	-	-
Abs. Exposure (0,1)	2.2319*** (0.1523)	1.9075*** (0.1060)	2.0435*** (0.1639)	1.7817*** (0.0860)	1.0218*** (0.1679)	1.5172*** (0.0860)	0.9714*** (0.1867)	1.4511*** (0.0705)
Disaster Loss (ln)	0.0346*** (0.0039)	0.0337*** (0.0035)	-0.002* (0.0011)	-0.002** (0.0012)	0.0130*** (0.0033)	0.0225*** (0.0036)	-0.0011 (0.0008)	-0.0001* (0.0010)
Fixed Effects:								
Bank	-	YES	-	YES	-	YES	-	YES
County-Neighborhood	-	-	YES	YES	-	-	YES	YES
Year	-	-	YES	YES	-	-	YES	YES
Observations	657,145	657,145	657,145	657,145	657,145	657,145	657,145	657,145
R2	0.2083	0.4072	0.3762	0.578	0.0887	0.4143	0.1573	0.6035
R2 Adjusted	0.2083	0.4065	0.3695	0.573	0.0887	0.4136	0.1483	0.5988
Residual S.E.	1.831	1.586	1.634	1.345	1.374	1.102	1.329	0.9119

The core check regression is applied to *Loan Volume (Number)* in Table 3 and FE are added one after another. Columns 4 and 8 represent the analysis after the FE have been fully added. For *Loan Volume (Number)*, the coefficients of both explanatory variables show similar patterns. β_1 consistently yields a positive effect at 1% significance, capturing a strong positive impact of local exposure on bank lending. For β_2 a flip of sign to negative can be observed after adding *CN*- and *Y*- FE, resulting in a 10% significance. This suggests a slightly negative impact of *Disaster Loss* on *Loan Volume* (*Number)*.

A positive effect of local exposure and a slightly negative effect of disaster severity on bank lending are found. The positive effect of *Absolute Exposure* is substantially stronger and more significant than the negative effect of *Disaster Loss*. The strong positive effect of *Absolute Exposure* is in line with most of existing literature (Barth et al., 2019; Berg & Schrader, 2012; Chavaz, 2016; Cortés, 2014; Cortés & Strahan, 2017; Koetter et al., 2020; Noth & Schüwer, 2017). The negative effect of *Disaster Loss* contributes to recent findings, showing that natural disasters can lower credit supply and restrict borrowers access to credit (Froot, 2001; Gilchrist et al., 2014).

5.1.2 Absolute Disaster Lending Effect

The following section focuses on investigating the interaction effect of a bank's local exposure and disaster loss on disaster lending. The analysis aims to show that local banks behave fundamentally differently from non-local banks when disasters occur and trigger a local credit demand shock. The main explanatory variable of interest within the analysis is *Absolute Exposure (b,c) x Disaster Loss (c,t),* measuring how a bank's *Loan Volume* (*Number*) in affected county-neighborhoods changes with its absolute local exposure to the affected area. The effect of the interaction term is referred to as (absolute) disaster lending effect. I anticipate the related parameter ($\beta 3$) to be negative and significant if the financial constraints strand is predominant (local banks in affected areas have greater business risks smaller lending capacity), and positive if the profitability strand dominates (local banks in affected areas greater business opportunities and larger lending capacity) (Chavaz, 2016).

Loan Number

Table 4 – Baseline Results (Loan Number)

The Table shows results of OLS estimation of different specifications of the baseline model applied to Loan Number. In columns 2 and 3, I add FE from Model (1). Thus, I am able to identify the respective influences of the FE on the explanatory variables. I proceed analogously in columns 5-8 for Model (2). Disaster Loss is a metric variable, Absolute Exposure is a dummy variable (Definition Section 3). Heteroskedasticity-robust standard errors are clustered at the bank level and reported in (). *, ** and *** indicate significance at 10, 5 and 1%.

	Loan Number (ln)							
	Baseline			**Model 1**				**Model 2**
	(1)	(2)	(3)	**(4)**	(5)	(6)	(7)	**(8)**
Coefficients:								
(Intercept)	1.9467***	-	-	-	-	-	-	-
	(0.1197)							
Abs. Exposure	1.0673***	1.5937***	0.9864***	1.4994***	-	1.5085***	1.5194***	-
(0,1)	(0.1563)	(0.0799)	(0.1760)	(0.0604)		(0.0603)	(0.0554)	
Disaster Loss	0.0015***	0.0264***	-0.0003	0.0015	-0.0009	-	0.0009	-
(ln)	(0.0039)	(0.0041)	(0.0018)	(0.0017)	(0.0012)		(0.0015)	
Abs. Exposure x	-0.0092	-0.0156***	-0.0030	-0.0098*	-0.0016	-0.0102*	-0.0100*	-0.0011
Disaster Loss	(0.0063)	(0.0054)	(0.0061)	(0.0052)	(0.0025)	(0.0054)	(0.0051)	(0.0009)
Fixed Effects:								
(B) Bank	-	YES	-	YES	-	YES	-	-
(CN) County-Neighborhood	-	-	YES	YES	-	-	YES	-
(Y) Year	-	-	YES	YES	YES	-	-	-
CN x B	-	-	-	-	YES	-	-	YES
CN x Y	-	-	-	-	-	YES	-	YES
B x Y	-	-	-	-	-	-	YES	YES
Observations	657,145	657,145	657,145	657,145	657,145	657,145	657,145	657,145
R2	0.0888	0.4145	0.1573	0.6036	0.8971	0.6107	0.6398	0.9354
R2 Adjusted	0.0888	0.4138	0.1483	0.5988	0.832	0.5980	0.6344	0.8904
Residual S.E.	1.374	1.102	1.329	0.9119	0.59	0.9128	0.8704	0.4766

Table 4 - Model (1)

The observations for *Absolute Exposure* show a clear pattern for the influence on *Loan Number*. Across all columns, there is a strong positive effect at 1% significance level. After adding all FE, an *Extensive Local Margin* of 4.48 (exp (1.4994) = 4.48) is found. In the absence of natural disasters, local banks on average lend substantially more (around 4.5 x) to SMEs in the respective county relative to non-local banks. For *Disaster Loss*, I initially observe a significance at 1% and a positive effect. If *CN*- and *Y*-FE are added, the significance is lost and the effect turns slightly negative, but close to zero. Hence, on its own *Disaster Loss* does not show an influence on bank lending. Without these FE, the results are driven by collinear, unobservable regional and institutional phenomena, such as institution strategy and risk management or geopolitical factors.

If *Absolute Exposure* is placed into interaction with *Disaster Loss*, a slightly negative effect is observed. Coefficient β3 remains significant at 10% level after adding all FE (Column 4). If a bank has a branch within a affected county and the respective *Disaster Loss* increases by one unit, the *Loan Number* decreases by 0.0098. I am able to demonstrate a negative disaster lending effect: With increasing *Disaster Loss* local banks grant significantly fewer loans compared to non-local banks. Interestingly, β3 only becomes significant when I add bank-FE to the model (Columns 2,4). Unobservable differences across bank institutions probably overshadow the interaction effect before.

The coefficient β2 (close to zero and insignificant) shows that natural disasters do not seem to have an impact on credit supply. Combining this observation with the negative disaster lending effect leads to the conclusion that non-local banks are substituting for the decline in lending by local banks. Thus, lending is maintained at pre-disaster levels, after occurrence of natural hazards.

Table 4 - Model (2) Within the "paired" FE setting the disaster lending effect remains significant and negative in most settings. However, it becomes evident that adding *CN x B*-FE absorbs the significance of the interaction term. Compared to Model (1), the effect captures a relative reduction of *Loan Number* by 0.0011 units, which is comparatively small. Nevertheless, the estimated interaction coefficient should be regarded as conservative. It cannot be ruled out that the elusive *CN x B* - FE absorbs causal effects that might be actually present, since

coefficients could be biased towards zero and might not predict effects that exist due to attenuation bias (Collischon & Eberl, 2020).

In total, the following picture emerges: *Loan Number* is positively related to a bank's *Absolute Exposure* with an *Extensive Local Margin* of 4.48. However, this relationship turns around when *Absolute Exposure* is put into interaction with *Disaster Loss*. A significant and negative disaster lending effect for local banks can be found, which corresponds to the *Financial Constraints* argument (explained in Section 3). My findings correspond to the reasoning, that local banks face a greater portfolio risk in affected counties and are less able to make disaster loans than non-local banks due to their lower portfolio diversification. Issues surrounding access to external finance and income loss vulnerability are consistent with this effect.

These findings contrast the other study results which report a positive disaster lending effect for local compared to non-local banks (Barth et al., 2019; Chavaz, 2016; Cortés, 2014; Cortés & Strahan, 2017; Noth & Rehbein, 2019; Noth & Schüwer, 2017). My findings are based on corporate SME lending whereas most other studies look at mortgage loans. I suspect that this difference in loan nature is a potential reason for the contradictory findings (negative versus positive disaster lending effect). The corresponding risk evaluation of each loan category vary strongly. Mortgages are usually directly linked to tangible collateral value, while corporate SME loans are based on tactic information and firm value (Koetter et al., 2020). In addition, there are large differences in the insurance coverage of an entire company versus a property against disaster losses. The granting of a new loan to a disaster-affected firm may be more complex and associated with greater risks and uncertainties due to limited tangibility. There is empirical evidence that SMEs in disaster affected areas often experience massive post shock losses and revenue declines (Battisto et al., 2017). This makes their income streams more unstable and classifies them as riskier borrowers. A local bank, which is less geographically diversified and more vulnerable to income losses, is less able to absorb these risks. Hence this might explain why local banks show a negative disaster lending effect, compared to non-local.

From my point of view, there are two possible follow-up mechanisms. Either non-local banks substitute for the credit reduction of local banks after natural disasters, or the resulting financing gap is not filled by local banks and supply shortfalls occur. Recent studies prove that (in normal times) SMEs are almost exclusively dependent on local bank finance (Berger et al., 2017; Hasan et al., 2017). They find it less attractive to finance small businesses they don't know much about, so they leave it to local players. Hence, it is questionable whether non-local banks will adapt this strategy in an adverse market situation. On the other hand, they are better able to offset additional disaster risks through portfolio diversification, interest rate adjustments and financial constraints. My study at least shows that non-local banks ensure that credit levels are maintained at pre-disaster levels. However, it is doubtful whether all disaster-induced demand for credit is met.

Loan Volume

Table 5 – Baseline Results (Loan Volume)

The Table shows results of OLS estimation of different specifications of the baseline model applied to Loan Volume. Column 4 of table 5 shows the results of the estimation of Model (1). The Column logic follows the order of table 4. Disaster Loss is a metric variable according, Absolute Exposure is a dummy variable (definition Section 3). Heteroskedasticity-robust standard errors are clustered at the bank level and reported in ( ). *, ** and *** indicate significance at 10, 5 and 1%.

	Loan Volume (ln)							
	Baseline			**Model 1**				**Model 2**
	(1)	(2)	(3)	**(4)**	(5)	(6)	(7)	**(8)**
Coefficients:								
(Intercept)	4.7189***	-	-	-	-	-	-	-
	(0.1332)							
Abs. Exposure	2.3243***	1.9629***	2.0776***	1.7982***	-	1.8106***	1.8086***	-
(0,1)	(0.1521)	(0.1062)	(0.1623)	(0.0853)		(0.0857)	(0.0856)	
Disaster Loss	0.0394***	0.0364***	-0.0003	-0.0015	-0.0024**	-	-0.0019	-
(ln)	(0.0046)	(0.0042)	(0.0020)	(0.0180)	(0.0011)		(0.0017)	
Abs. Exposure	-0.0188***	-0.0113**	-0.0069	-0.0033	0.0015	-0.0039	-0.0040	0.0004
X Disaster Loss	(0.0019)	(0.0478)	(0.0061)	(0.0051)	(0.0022)	(0.0053)	(0.0052)	(0.0015)
Fixed Effects:								
(B) Bank	-	YES	-	YES	-	YES	-	-
(CN) County-Neighborhood	-	-	YES	YES	-	-	YES	-
(Y) Year	-	-	YES	YES	YES	-	-	-
CN x B	-	-	-	-	YES	-	-	YES
CN x Y	-	-	-	-	-	YES	-	YES
B x Y	-	-	-	-	-	-	YES	YES
Observations	657,145	657,145	657,145	657,145	657,145	657,145	657,145	657,145
R2	0.2084	0.4072	0.3763	0.578	0.8666	0.5869	0.5907	0.8849
R2 Adjusted	0.2084	0.4065	0.3696	0.573	0.7823	0.5734	0.5846	0.8049
Residual S.E.	1.8310	1.5850	1.6340	1.3450	0.9603	1.3440	1.3260	0.9090

Table 5 - Model (1) The observations regarding the coefficients β1, β2 and β3 show similar patterns to those already observed for *Loan Number*. After adding all FEs, the result is a high *Extensive Local Margin* of 6.04 which is significant at 1% level. The *Disaster Loss* coefficient changes from positive to negative (close zero) and becomes insignificant after adding CN- and Y-FE. The disaster lending effect in coefficient β3 is also slightly negative, but insignificant for *Loan Volume*.

Table 5 - Model (2) The pattern that appears in Model (1) is reinforced by the application of "paired" FE in Model (2). To the extent that the applied FE allow for parameter estimation, the significance of the *Absolute Exposure* coefficient manifests itself at one percent level. The coefficients of the remaining variables develop similarly as described for Model (1).

In total, the following picture emerges: *Loan Volume* is positively related to a bank's *Absolute Exposure*. Local banks grant higher loan volumes than non-local banks with an *Extensive Local Margin* of 6.04. This is hardly surprising and corresponds to the rationale for the explained informational advantages of local over non-local banks. A significant disaster lending effect captured by the interaction term cannot be found. *Loan Volume* is not statistically significantly related to either disaster loss or the interaction term. This pattern becomes more consistent with the introduction of "paired" FE in Model (2).

5.2 Relative Disaster Lending Effect (Local Banks)

Local banks make their credit allocation decisions partly on basis of different information and according to deviating mechanisms compared to non-local banks (Berger et al., 2017). I observed a negative (absolute) disaster lending effect in the baseline analysis and saw that local banks seem to behave differently in light of disaster shocks than non-local banks. *Absolute Exposure* is highly significant resulting in high *Extensive Local Margins* for both dependent variables, which gives reason to examine local banks and disaster lending in more detail. Therefore, I create a subsample containing only banks whose *Absolute Exposure* is equal to one. Accordingly, I measure a local bank's disaster exposure by its share of deposits per county and build the variable *Relative Exposure* from this[15].

[15] Banks tend to open adhoc branches after a disaster shock to fulfill additional credit needs. I keep the calculated deposits shares constant at one year prior to the first shock.

Table 6 – Local Banks

This table shows the results of OLS estimation in Model (1) and (2) to local banks only applied to Loan Volume (Number). Disaster Loss is a metric variable, Relative Exposure is a metric ratio (definition Section 3). Heteroskedasticity-robust standard errors are clustered at the bank level and reported in ( ). *, ** and *** indicate significance at 10, 5 and 1%.

	Loan Volume (ln)		**Loan Number (ln)**	
	Model (1)	Model (2)	Model (1)	Model (2)
Coeficients:				
Rel. Exposure	2.1700***	-	1.9178***	-
(in %)	(0.1116)		(0.0892)	
Disaster Loss	-0.0084***	-	-0.0048***	-
(ln)	(0.0027)		(0.0018)	
Rel. Exposure x Disaster Loss	0.0293**	0.0153*	0.0180**	0.0082*
	(0.0125)	(0.0095)	(0.0083)	(0.0043)
Fixed Effects:				
Bank (B)	YES	-	YES	-
County-Neighborhood (CN)	YES	-	YES	-
Year (Y)	YES	-	YES	-
CN x B	-	YES	-	YES
CN x Y	-	YES	-	YES
B x Y	-	YES	-	YES
Observations	92,670	92,670	92,670	92,670
R2	0.5504	0.7677	0.7343	0.8969
R2 Adjusted	0.5191	0.6484	0.7159	0.8439
Residual S.E.	1.157	0.9889	0.7935	0.5881

The main explanatory variable of interest in Table 6 is *Relative Exposure (b,c)* × *Disaster Loss(c,t)*, which measures how a bank's *Loan Volume (Number)* in affected county-neighborhoods changes with the share of its deposits in the affected area. The coefficient β_3 is positive and significant in all model variations (Column 1 - 4). The higher a banks relative regional disaster exposure, the more is lent to an affected areas. This parametric relationship applies to both *Loan Volume* and *Number*. Changing from normal to "paired" FE setting, for the significance of the coefficient β_3 decreases from 5% (Column 1, 3) to 10% (Column 2,4) for both dependent variables. This is to be expected, as "paired" FE extract more variation from the data and can also eliminate causal effects that may be present (Collischon & Eberl, 2020). In the "paired" FE setting, however, one can assume that all noisy influences from colinear unobservable factors are eliminated. Thus, I observe a significant positive (relative) disaster lending effect for both dependent variables, capturing economic meaning. As expected, *Relative Exposure* has a positive impact on lending, while *Disaster Loss* has a negative impact. The individual effect of β_1 is positive and β_2 negative, both coefficients being significant at 1% level (Column 1, 3). Resulting from *Relative Exposure* I observe *Intensive Local Margins* of 8.76 and 6.81.

In the "single" FE setting the following relationship results for *Loan Volume* (Column 1): All else equal, if a local banks' *Relative Exposure* increases by 1%, the *Loan Volume* granted increases by 0.0293 units. Within the "paired" FE setting (Colum 2), this relation slightly changes with a *Loan Volume* increase by 0.0153 units. With no change in *Disaster Loss*, the resulting total increase in *Loan Volume* (per 1 % increase in local exposure) would be USD 29,3 (15,3) respectively. The pattern is similar for the *Loan Number*: All else equal, a 1% increase in *Relative Exposure* causes the *Loan Number* to increase by 0.018 units (0.0082 units) respectively.

In the reduced sample, the previously observed confounding differences between *Loan Volume* and *Number* disappear. My results show higher significances and a clear trend for all variables, which leads me to conclude that my estimation model is more relevant for local banks than for non-local ones. This is supported by the fact that disaster loss shows a significant negative impact, which is no longer close to zero. Furthermore, I observe a strong positive (relative) disaster lending effect, which is in line with recent studies (Chavaz, 2016; Cortés & Strahan, 2017). However, the interpretation differs from the observed effect in the baseline: The more local the bank, the more loans it allocates to disaster affected SMEs with a margin of USD 29.3 per percent increase in local exposure.

Following the argumentation of Cortés (2014), a distinction must be made as to whether a bank is "local" or "truly local". He defines "truly local" as banks with a *Relative Exposure* greater than 65%. I choose a less stringent approach to defining local banks, as the nature of the raw data does not lend itself to a strict definition, as explained in the methodology section. As a result, the average local exposure of local banks is around 2.00%. Accordingly, I hypothesize that the observed negative absolute disaster lending effect in the baseline analysis is driven by banks that cannot be considered "truly local". My results suggest that most local banks in my analysis are not locally integrated enough to realize business opportunities based on information advantages in disaster affected counties (Profitability strand). On the other hand, they are exposed to greater business risks after a natural disaster, which they would try to minimize (Financial constraints strand). This would result in the observed post shock reduction in credit supply. In this context, the results in the baseline panel must be questioned and put into perspective.

5.3 Major Disasters

It is logical to assume that severe disasters have a greater effect on banks' credit allocation than small disasters as firm value and associated credit risk scoring are more affected by disasters with high destructive capacity. Thus, I split my sample to *Major* and *Minor Disasters*. *Major Disasters* sample is built with the most severely affected counties with the highest realized disaster losses (Threshold Disaster Loss USD 1 Million). The remaining counties are stored in *Minor Disasters*. This allows me to test the validity of my model under more stringent conditions.

Table 7 – Major Disasters

This Table shows the results of OLS estimation in Model 1 to Major - (1) and Minor Disasters (2) applied to Loan Volume (Number). Disaster Loss is a metric variable, Absolute Exposure is a dummy variable (definition Section 3). Heteroskedasticity-robust standard errors are clustered at the bank level and reported in (). *, ** and *** indicate significance at 10, 5 and 1%.

	Loan Volume (ln)		**Loan Number (ln)**	
	(1)	(2)	(1)	(2)
Coefficients:				
Abs. Exposure	2.2558***	1.7721***	1.9493***	1.4858***
(0,1)	(0.2294)	(0.0866)	(0.1800)	(0.0754)
Disaster Loss	0.0090*	-0.0024*	0.0115***	-0.0001
(ln)	(0.0046)	(0.0013)	(0.0037)	(0.0011)
Abs. Exposure x	-0.0230*	-0.0011	-0.0267**	-0.0049
Disaster Loss	(0.0131)	(0.0044)	(0.0114)	(0.0043)
Fixed Effects:				
Bank	Yes	Yes	Yes	Yes
County-Neighborhood	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	131,754	524,079	131,754	524,079
R2	0.5729	0.5827	0.633	0.6024
R2 Adjusted	0.5626	0.5767	0.6241	0.5966
Residual S.E.	1.369	1.333	0.9454	0.8965

The analysis in Table 7 shows noticeable differences in terms of a (absolute) disaster lending effect between the major and minor sample. For major disasters, *Loan Volume* (*Number)* show a significant and negative disaster lending effect. This results in an effects for β_3 of -0.02 and -0.03 respectively which are significant at 10% and 5% level. Consitent with the baseline analyis, I find a negative effect. However, it is consistently significant across both dependent variables and more negatively pronounced. The results underline the predominance of the financial constraints strand. Operational risks seem to prevent local banks (relative to non-local) from providing small business loans to affected regions. This is in direct contradiction to the findings of Chavaz (2016), who, however, focuses on mortage loans.

The *Absolute Exposure* coefficient behaves analogously to the previous observations, while an interesting change can be observed for *Disaster Loss*. With regard to major disasters $\beta 2$ turns out to be positive and significant at 10% versus 1% level. This implies an increase in *Loan Volume* (*Number)* of approximatly 0.009 (0.0115) when disaster loss increases by USD 1,000. This is interesting as one would expect a negative effect (analogous to the previous regressions). A potential explanation for this difference can be found in the regulatory environment. Banks are obliged by regulatory agencies to lend to SMEs and private individuals in the event of severe natural disasters (Noth & Schüwer, 2017). This is inteded to ensure a quick and efficient post shock recovery. In addition, financial aid programms provided by public banks could form an explanatory basis.

For *Minor* disasters neither a significant relationship to *Disaster Loss* nor a disaster lending effect can be found. As expected, the model is more relevant for major disasters. Compared to the baseline analysis, it raises the question of whether natural hazards and the associated disaster losses need to reach a critical severity level before a robust effect on credit allocation can be identified. Although disaster severity is weighted continuously via the disaster loss (in USD 1,000) value in my baseline model, it cannot be ruled out that uncertainty and noise are included in the model due to smaller hazards.

5.4 Hazard Types

Different natural disasters vary greatly in intensity, duration, severity, and frequency dependent on the related hazard type. Therefore, the associated disaster losses (property damages) as well as regulatory environment, public available disaster aid and insurance coverage very greatly. Wildfires can last for several weeks, while thunderstorms only last a couple of days. Hurricanes are known to be the most severe hazards in the U.S., which caused 67.7% of the total natural disaster losses from 2016-2019[16]. I want to see if there are different disaster lending effects depending on the hazard type classification. I retrieve four additional SHELDUS data sets, to separately get annual property damages for each hazard type. For that, the most common natural disasters in the U.S. are selected, namely hurricanes, thunderstorms, floods and wildfires.

[16] https://www.ncdc.noaa.gov/billions/summary-stats/US/2016-2019

Table 8 – Hazard Type

The table shows the results of OLS estimation in Model 1 to hurricanes (1), thunderstorms (2), floods (3) and wildfires (4) applied to Loan Volume (Number). Disaster Loss is a metric variable, Absolute Exposure is a dummy variable (Definition Section 3). Heteroskedasticity-robust standard errors are clustered at the bank level and reported in (). *, ** and *** indicate significance at 10, 5 and 1%.

	Loan Volume (ln)				**Loan Number (ln)**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Coefficients:								
Abs. Exposure	1.8069***	1.800***	1.7310***	1.5174***	1.4801***	1.4816***	1.4498***	1.4431***
(0,1)	(0.1667)	(0.0926)	(0.1004)	(0.1232)	(0.0869)	(0.0677)	(0.0816)	(0.1170)
Disaster Loss	0.0080**	0.0002	-0.0018	-0.0013	0.0069***	0.0012	-0.0011	0.0042
(ln)	(0.0035)	(0.0018)	(0.0016)	(0.0034)	(0.0024)	(0.0014)	(0.0012)	(0.0044)
Abs.Exposure	-0.0141*	-0.0025	0.0062	0.0015	-0.0138**	-0.0042	0.0015	-0.0078
x Disaster Loss	(0.0076)	(0.0050)	(0.0040)	(0.0058)	(0.0064)	(0.0043)	(0.0027)	(0.0086)
Fixed Effects:								
Bank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Neighborhood	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,317	522,691	315,983	35,475	51,317	522,691	315,983	35,475
R2	0.5967	0.5771	0.5768	0.6154	0.6292	0.6044	0.608	0.7006
R2 Adjusted	0.5838	0.5717	0.5693	0.6035	0.6223	0.5994	0.601	0.6913
Residual S.E.	1.3180	1.3430	1.351	1.3280	0.9262	0.9066	0.9224	0.9305

The results in Table 8 show great differences between the hazard types since I observe positive and negative disaster lending effects. Consistent for both dependent variables is only the negative effects for hurricanes (Column 1, 2) and thunderstorms. A significance can only be observed for hurricanes. For the other hazard types neither a significance for *Disaster Loss* nor for the interaction term is observable. These results correspond to the observation for major disasters (Section 5.3). Hurricanes can be identified as major disasters, as they are by far the most severe typ of hazards in the U.S.[17]. It is not surprising that I observe analogues effects for hurricanes, namely a significant and negative disaster lending effect as well as a positive and significant impact of *Disaster Loss* on bank lending.

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[17] https://www.ncdc.noaa.gov/billions/summary-stats/US/2016-2020

For hurricanes, *Loan Volume* (*Number)* show a negative effect in the interaction term with β_3 of -0.0141 (-0.0138) and significance of 10% (5%), respectively. This corresponds to previous observed pattern of a negative disaster lending effect for local banks and further confirms the financial constraints argumentation, being in contrast to Chavaz (2016). With regards to *Disaster Loss* I observe a positive coefficient value close to zero with 0.008 (0.007) at 5% significance. *Disaster Loss* increase leads to an increase in bank lending, in line with the observations in Table 7.

Potential explanations for these results follow the same argumentative line as within Section 5.3. It also raises the question, whether my results within the baseline panel could be mainly driven by hurricanes. This would correspond insofar to other study results, as many researchers only use hurricanes to model exogenous shocks to the bank credit market (Behr et al., 2013; Brei et al., 2019; Chavaz, 2016; Noth & Schüwer, 2017; Schüwer et al., 2018). However, potential interdependencies between natural disasters and associated property damages get lost. For example, floods often follow-on hurricanes. Therefore, the actual damage caused by hurricanes may be greater, as the associated flood damage is not considered when only hurricanes are used.

5.5 Income Neighborhoods

Due to the composition of the CRA raw data and its special focus on lending disparities between structurally strong and weak regions, I look at disaster lending within individual income neighborhoods. It is evident that in normal times the CRA has significantly reduced the inequality of credit availability between different income neighborhoods (Bates & Robb, 2015). I would like to see if this effect holds up when credit markets are shocked by natural disasters. Arguably, credit availability to small businesses in low- and moderate-income neighborhoods could suffer more from natural disasters than that in high-income neighborhoods. Borrowers in structurally weak areas generally have a higher credit risk profile due to geographical and demographic factors (Getter, 2015).

Table 9 – Income Neighborhood

The table shows the results of OLS estimation in Model 1 to high- (1), middle- (2), moderate- (3) and low-income-neighborhoods (4) applied to Loan Volume (Number)[18]. Disaster Loss is a metric variable, Absolute Exposure is a dummy variable (definition Section 3). Heteroskedasticity-robust standard errors are clustered at the bank level and reported in (). *, ** and *** indicate significance at 10, 5 and 1%.

	Loan Volume (ln)				Loan Number (ln)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Coefficients:								
Abs. Exposure	2.0778***	1.8612***	1.6013**	1.2927***	1.7693***	1.5667***	1.3084***	0.9621***
(0,1)	(0.0702)	(0.0928)	(0.1033)	(0.1075)	(0.0596)	(0.0655)	(0.0723)	(0.0606)
Disaster Loss	-0.0050**	-0.0004	-0.0014	0.0011	-0.0013	0.0023	0.0012	0.0038
(ln)	(0.0023)	(0.0019)	(0.0025)	(0.0030)	(0.0019)	(0.0017)	(0.0021)	(0.0019)
Abs. Exposure	0.0141**	-0.0100*	-0.0023	-0.0041	0.0083	-0.0144**	-0.0103*	-0.0101*
x Disaster Loss	(0.0035)	(0.0060)	(0.0060)	(0.0053)	(0.0058)	(0.0057)	(0.0057)	(0.0046)
Fixed Effects:								
Bank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Neighborhood	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	145,212	282,988	180,489	48,456	145,212	282,988	180,489	48,456
R2	0.6091	0.5823	0.5786	0.5282	0.6278	0.6316	0.5928	0.4959
R2 Adjusted	0.6025	0.5771	0.5722	0.5143	0.6215	0.6270	0.5866	0.4810
Residual S.E.	1.371	1.303	1.335	1.371	0.975	0.8804	0.8800	0.8254

Table 9 shows different results regarding the individual income neighborhoods. For the coefficient of *Absolute Exposure*, a clear trend can be seen for both dependent variables: The weaker the income neighborhood, the smaller the factor β_1 becomes, resulting in strong differences in the *Extensive Local Margin* (e.g. for *Loan Volume* 7.99 versus 3.63). As expected, local banks lend significantly less to low-income neighborhoods compared to high ones.

For *Loan Volume*, I observe a positive disaster lending effect in high-income neighborhoods that is significant at the 5% level. Local banks thus grant significantly higher recovery loans to SMEs if they are situated within a high-income regions. This effect flips to negative when the

[18] The respective neighborhoods are clustered in dependence to the MFI census tract, defined as High (> 120% of MFI), Middle (80% to 120% of MFI), Moderate (50% to 80% of MFI) and Low (< 50% of MFI).

income structure weakens. For middle-, moderate- and low-income neighborhoods I observe a negative disaster lending effect. However, this is only significant (at 10% level) for middle income neighborhoods. My observations confirm the assumption that small businesses in structurally weak regions in particular experience disadvantages in the allocation of disaster credit. It could be possible that firms in income weak neighborhoods suffer from credit supply shortfalls after natural disasters, which would exacerbate the socio-economic inequalities between neighborhoods.

Regarding *Loan Number*, a similar pattern is seen for the disaster lending effect, i.e. a positive effect for high-income neighborhoods and a negative effect for the others. In terms of significance, the picture is diametrically opposed to the *Loan Volume* analysis. I observe significant disaster lending effects for middle-, moderate- and low-income neighborhoods at the 5% and 10% level, respectively.

For both dependent variables, the disaster lending effect is most negative for middle- income neighborhoods. I suspect a regulatory explanation behind the observation that the effects for moderate- and low-income neighborhoods are less negative. Local banks are required by regulation to promote small businesses in small- and moderate-income neighborhoods (Battisto et al., 2017). This seems to happen here at the expense of middle-income neighborhoods.

In sum, a disaster lending premium in high-income neighborhoods after natural hazards can be observed. For all other income neighborhoods, a negative disaster lending effect becomes evident. SMEs in economically weaker regions cannot achieve a significant increase in credit allocation from local banks after disasters. Local banks are increasing disaster loans to high income neighborhoods at the expense of other neighborhoods.

5.6 Robustness Checks

I perform several robustness checks to verify the validity of my results. First, I replace *Loan Volume* and *Number* with two alternative measures, namely the ratios (ln) *Lending Size* and (ln) *Lending Frequency*. Additionally, I look at how my model works in a growth rate setting. I calculate one-year backward looking growth rates (ln) *Loan Volume Growth* and (ln) *Loan Number Growth*.

Table 10 – Robustness Check

The table shows the results of OLS estimation in Model 1 to Loan Volume Growth (1), Loan Number Growth (2), Lending Size (3) and Lending Frequency (4) applied to Loan Volume (Number). Disaster Loss is a metric variable, Absolute Exposure is a dummy variable (definition Section 3). Heteroskedasticity-robust standard errors are clustered at the bank level and reported in (). *, ** and *** indicate significance at 10, 5 and 1%.

	Loan Volume Growth (ln)	Loan Number Growth (ln)	Lending Size	Lending Frequency
	(1)	(2)	(3)	(4)
Coefficients:				
Abs. Exposure	-0.0423***	-0.0131	1.808***	1.6910***
(0,1)	(0.0140)	(0.0145)	(0.0863)	(0.0652)
Disaster Loss	-0.0028**	-0.0016	0.0000*	0.0000**
(ln)	(0.0012)	(0.0011)	(0.0000)	(0.0000)
Abs. Exposure	0.0013	0.0003	-0.0000*	-0.0000***
x Disaster Loss	(0.0015)	(0.0013)	(0.0000)	(0.0000)
Fixed Effects:				
Bank	YES	YES	YES	YES
County-Neighborhood	YES	YES	YES	YES
Year	YES	YES	YES	YES
Observations	262,459	262,459	657,145	657,145
R2	0.0504	0.0851	0.7242	0.8038
R2 Adjusted	0.0289	0.0641	0.7209	0.8015
Residual S.E.	1.3510	0.8578	1.371	1.005

In Table 10 the results for Loan Size (Frequency) show analogous patterns as the baseline analysis. I observe a robust and positive *Extensive Local Margin* at 1% level for both dependent variables. I find a negative and significant coefficient for the disaster lending effect which, however, is very small (close to zero) in terms of impact.

In contrast, the growth rate analysis differs from the observations in the baseline analysis. I observe a negative coefficient for *Absolute Exposure* for both growth rates. It is only significant for *Loan Volume Growth* at 1% level. In addition, a positive (but not significant) positive disaster lending effect is observed. There are several remarks to be made regarding these observations. First, I lose a large part of my data when looking at growth rates (about 60%). Moreover, my analyses so far have followed an in-time-approach, while the growth rates are one year backward looking. The application of growth rates over a period of only four years is problematic due to the short-term horizon, which is why the resulting estimates should be viewed with caution.

Originally, I wanted to check the validity of the disaster impact modelling by replacing the *Disaster Loss* with the public disaster aids granted at county-year level. Unfortunately, the data necessary for this analysis is not publicly available and my request at the regulatory authority FEMA is still pending.

Checks based on time differentiation, such as splitting the sample into two distinct periods, are out of focus for me, as the period under consideration only covers 4 years. Verifications regarding the restriction of affected counties are covered in section *5.3 - Major Disasters*.

6 Conclusion

Within my study, I examine the lending behaviour of (local) banks under disruptive market conditions. Specifically, it focuses on small business credit supply of local banks after natural disasters. Local banks are the primary funding source of SME's, which explains the special focus (Berger et al., 2017; Hasan et al., 2017). Aggregated loans at annual bank-county-neighborhood level are used and related to annual disaster losses at county level. The analysis is conducted solely on the U.S. market and captures the time period 2016-2019. Within a FE regression model, I empirically identifiy a disaster lending effect for local banks. It should indicate if local banks increase or deacrease lending (relative to non-local banks) after natural disasters. It is not clear whether local banks have greater insentives to increase or decrese lending to SMEs in disaster-affected counties. On the one hand, they might have higher profit opportunities (information advantages in the region). On the other hand, they might have higher operational risks (lower portfolio diversification). A positive disaster lending effect should correspond to the former explanation, a negative one to the latter. To the best of my knowledge I am the first one investigating disaster lending effects on the U.S. SME market.

Previous empirical studies focus on mortgage loans in the U.S. market (Barth et al., 2019; Chavaz, 2016; Cortés, 2014; Cortés & Strahan, 2017). Most of them demonstrate a positive disaster lending effect for local banks. However, the majority of my findings point to a negative disaster lending effect for small business loans. This is in direct contrast to the findings of Koetter et al. (2020), which show a positive disaster lending effect for SMEs on the German savings bank market[19].

My baseline analysis provides evidence for a significant negative disaster lending effect. This picture manifests itself when only extreme disasters with high losses are considered (property damages > USD 1 million). Here, a significant negative effect emerges for all dependent variables considered. This finding remains robust when I look only at the most severe disaster type in the U.S., namely hurricanes. Among other disaster types considered, it is the only one where a significant negative disaster lending effect can be identified. The trend emerges that a disaster must reach a critical destructive severity in order to have a significant impact on small business lending. The negative effect might be indicative of potential credit supply shortfall for SMEs after natural disasters. It is unlikely that the emerging gap of local bank lending will be taken over by other players in the market (non-local banks, fintech etc). These are already reluctant to lend to SMEs under normal market conditions. Nevertheless, my studies show that non-local banks (relative to local) increase lending to SMEs under disaster conditions, thus keeping the credit supply at predisaster level. However, given the demand shock triggered by natural disasters, one has to question whether this is enough to support SMEs with necessary recovery funding. Further studies could focus on the credit demand side to examine the acceptance and rejection rates of SME disaster loans.

Furthermore, a (relative) disaster lending effect is identified, depending on the degree of local integration of a bank (in percent). Looking at a subsample only containing local banks, a robust positive (relative) disaster lending effect can be found for all dependet variables. In general, I notice that my model is more relevant for local banks due to the validity and significance of the

[19] The German and American savings bank markets differ greatly in terms of the regulatory environment, the public mandate and the business strategy of the institutions. Therefore, the results are difficult to transfer between the markets.

identified coefficients. All else being equal, a 1% increase in relative local exposure causes the loan volume (number) to increase by 29 USD (15 USD) respectively. The more local the bank, the more disaster loans it gives to disaster affected firms. The result suggests that my baseline results may be driven by local banks with low relative disaster exposure. The question raises whether the negative effects identified are possibly driven by banks that are not local enough to realize information advantages in affected areas.

A third finding within my research is that there is a differences in disaster lending depending on the location of the SME within a high- versus low-income neighbourhood. Thus, I find a significant positive disaster lending effect for local banks in high income neighbourhoods. For all other neighbourhoods, I find a negative one. Thus, I notice a lending premium for SMEs in high-income areas at the expense of other neighbourhoods. It would be interesting to take a closer look at this in future studies, as small businesses in lower-income regions are particularly dependent on recovery funding to secure their business. Credit shortfalls in the aftermath of natural hazards might trigger small business bankruptcy and exacerbate socio-economic issues.

Lastly, my results should be critically questioned due to some limitations. First of all, shocks caused by natural disasters can be considered as non-linear shocks. The identification of a disaster lending effectwithin a linear OLS regression model therefore inevitably leads to distortions. For further research purposes, it would be interesting to consider a longer time period and to work with non-linear techniques (e.g. machine learning, decision tree algorithms). Moreover, as I only have data aggregated annually, it makes it difficult to isolate a clear disaster lending effect in the direct aftermath of the disaster, which could be of interest for future studies. Monthly data would be more accurate for modelling purpuses. In addition, the local disaster exposure is approximated by a dummy variable which is critical because it does not cover the extent of local disaster exposure. Further, the definition of local disaster exposure is problematic, as there are no clear standards how to define a “truly local” bank, which solicits further deep-dive.

Table of References

Barth, J. R., Sun, Y., & Zhang, S. (2019). Banks and Natural Disasters. *Available at: SSRN Electronic Journal*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3438326

Bates, T., & Robb, A. (2015). Has the Community Reinvestment Act increased loan availability among small businesses operating in minority neighbourhoods? *Urban Studies*, *52*(9), 1702–1721.

Battisto, J., Choi, L., Kramer Mills, C., Mattiuzzi, E., Ryder Perlmeter, E., & Storey, S. (2017). Small Business Credit Survey: Report on Disaster-Affected Firms. Federal Reserve Bank. *Available at*: *Https://Www.Newyorkfed.Org/Medialibrary/Media/Smallbusiness/2017/SBCS-Report-on-Disaster-Affected-Firms.Pdf.*

Beck, T., Demirg¨uç, A., Demirg¨uç -Kunt, D., & Maksimovic, V. (2005). Financial and Legal Constraints to Growth: Does Firm Size Matter? *THE JOURNAL OF FINANCE* •, *LX*(1).

Behr, P., Norden, L., & Noth, F. (2013). Financial constraints of private firms and bank lending behavior. *Journal of Banking and Finance*, *37*(9), 3472–3485.

Berg, G., & Schrader, J. (2012). Access to credit, natural disasters, and relationship lending. *Journal of Financial Intermediation*, *21*(4), 549–568.

Berger, A. N., Bouwman, C. H. S., & Kim, D. (2017). Small bank comparative advantages in alleviating financial constraints and providing liquidity insurance over time. *The Review of Financial Studies*, *30*(10), 3416–3454.

Berger, A. N., Cerqueiro, G., & Penas, M. F. (2015). Market size structure and small business lending: Are crisis times different from normal times? *Review of Finance*, *19*(5), 1965–1995.

Berger, A. N., Frame, W. S., & Miller, N. H. (2005). Credit scoring and the availability, price, and risk of small business credit. *Journal of Money, Credit and Banking*, 37(2),191–222.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., & Stein, J. C. (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics*, *76*(2), 237–269.

Brei, M., Mohan, P., & Strobl, E. (2019). The impact of natural disasters on the banking sector: Evidence from hurricane strikes in the Caribbean. *The Quarterly Review of Economics and Finance*, *72*, 323-239

Chavaz, M. (2016). *Dis-integrating credit markets: diversification, securitization, and lending in a recovery*. Staff Working Paper, No. 617

Colin Cameron, A., & Miller, D. L. (2015). A Practitioner's Guide to Cluster-Robust Inference. *Journal of Human Resources*, *50*(2), 317–372.

Collischon, M., & Eberl, A. (2020). Let's Talk About Fixed Effects: Let's Talk About All the Good Things and the Bad Things. *Kolner Zeitschrift Fur Soziologie Und Sozialpsychologie*, *72*(2), 289–299.

Cortés, K. R. (2014). Rebuilding after Disaster Strikes: How Local Lenders Aid in the Recovery. Working Papers of the Federal Reserve Bank of Cleveland, No. 14–28.

Cortés, K. R., & Strahan, P. E. (2017). Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics*, *125*(1), 182-199.

Degryse, H., & van Cayseele, P. (2000). Relationship Lending within a Bank-Based System: Evidence from European Small Business Data. *Journal of Financial Intermediation*, *9*(1), 90–109.

Demyanyk, Y., Ostergaard, C., & Sørensen, B. E. (2007). U.S. Banking Deregulation, Small Businesses, and Interstate Insurance of Personal Income. *THE JOURNAL OF FINANCE •*, *LXII*(6).

Deyoung, R., Gron, A., Torna, G., & Winton, A. (2015). Risk Overhang and Loan Portfolio Decisions: Small Business Loan Supply before and during the Financial Crisis. *Journal of Finance*, *70*(6), 2451–2488.

Elsas, R. (2005). Empirical determinants of relationship lending. *Journal of Financial Intermediation*, *14*(1), 32–57.

Faiella, I., & Natoli, F. (2018). Natural Catastrophes and Bank Lending: The Case of Flood Risk in Italy. Working Paper Questiono DieEconomia e Finanza (No. 457).

Froot, K. (2001). *The Market for Catastrophe Risk: A Clinical Examination*. Journal of Financial Economics, 60(2), 529-571

Garmaise, M. J., & Moskowitz, T. J. (2009). Catastrophic Risk and Credit Markets. *The Journal of Finance*, *64*(2), 657–707.

Getter, D. E. (2015). The Effectiveness of the Community Reinvestment Act. *CRS Report for Congress*. *Available at: https://sgp.fas.org/crs/misc/R43661.pdf*

Gilchrist, S., Sim, J. W., & Zakrajšek, E. (2014). Uncertainty, financial frictions, and investment dynamics. *NBER Working Paper Series, No. 20038*. National Bureau of Economic Research.

Hasan, I., Jackowicz, K., Kowalewski, O., & Kozłowski, Ł. (2017). Do local banking market structures matter for SME financing and performance? New evidence from an emerging economy. *Journal of Banking and Finance*, *79*, 142–158.

Ivanov, I., Macchiavelli, M., & Santos, J. A. C. (2020). Bank Lending Networks and the Propagation of Natural Disasters. *In Federal Reserve Working Paper*.

Koetter, M., Noth, F., & Rehbein, O. (2020). Borrowers under water! Rare disasters, regional banks, and recovery lending. *Journal of Financial Intermediation*, *43 (In Press)*.

Nordhaus, W. D. (2010). The Economics of Hurricanes and Implications of Global Warming. *Climate Change Economics*, *1*(1), 1–20.

Noth, F., & Rehbein, O. (2019). Badly hurt? Natural disasters and direct firm effects. *Finance Research Letters*, *28*, 254–258.

Noth, F., & Schüwer, U. (2017). Natural Disaster and Bank Stability: Evidence from the U.S. Financial System. *SAFE Working Paper , No. 167*. Sustainable Architecture for Finance in Europe.

Nouy, D. (2018). Financing the economy-SMEs, banks and capital markets. *Rede Auf Der von Der Österreichischen Nationalbank Und Der Wirtschaftskammer Österreich Organisierten Konferenz, Linz*, *6*. *Available at: https://www.bankingsupervision.europa.eu/press/speeches/date/2018/html/ssm.sp180706.en.html*

Perez, C., & Martin, F. (2018). Digitalisation and Artificial Intelligence: The New Face of the Retail Banking Sector. Evidence from France and Spain. *Virtuous Circles between Innovations, Job Quality and Employment in Europe? Case Study Evidence from the Manufacturing Sector, Private and Public Service Sector* , 178.

Platt, L., Matthew, B., Kahn, E., Rhode, P. W., Yanguas, M. L., Bailey, M., Bleakley, H., Costa, D., Hornbeck, R., Naidu, S., Palmer, B., Rashid, M., Sutch, R., Walsh, R., Boustan, L. P., & Kahn, M. E. (2017). The Effect of Narural Disasters on Economic Activity in US Counties: A Century of Data. *NBER Working Paper Series*, No. 23410

SBA. (2019). Annual Report of the Office of Economic Research, Fiscal Year 2019. In *Office of Advocacy of the U.S. Small BusinessAdministration (SBA), Available at: https://advocacy.sba.gov/*.

Schüwer, U., Lambert, C., Noth, F., Blum, M., Bremus, F., Brown, M., Chance, D., Entorf, H., Goncharov, I., Heider, F., Krahnen, J. P., Nini, G., Rocholl, J., Santos, J., Schäfer, A., Schmidt, R. H., Schnabel, I., Sunderam, A., Tyrell, M., … Weill, L. (2018). How do banks react to catastrophic events? Evidence from Hurricane Katrina. *Review of Finance*

Wirtz, A., Kron, W., Löw, P., & Steuer, M. (2014). The need for data: Natural disasters and the challenges of database management. *Natural Hazards*, *70*(1), 135–157.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.