Weathering an Unexpected Financial Shock: The Role of Cash Grants on Household Finance and Business Growth following a Natural Disaster

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1 Introduction

Natural disasters in the US are shocks to income, wealth, and capital. Loss of life is relatively rare. Natural disasters caused at least $100 billion in insured damage losses in the US in 2017 (Munich Re [2017]). Average yearly economic losses from natural disasters in the US more than doubled from 1981-2010. Nevertheless, loss of life from natural disasters remained relatively constant during this same time period (Munich Re [2013]).

The US government has a long history of federal assistance following natural disasters. Cash assistance has been distributed to disaster victims immediately following natural disasters via a codified legal process since at least 1953. The implicit assumption is that savings, credit markets, and existing insurance (e.g. homeowners, unemployment, health) are insufficient to smooth the negative financial consequences of the natural disaster. In other words, the aim is to assist with "acts of God" that are of "such severity and magnitude that effective response is beyond the capacities of the state and the affected local governments and that the federal assistance is necessary" (Daniels and Trebilcock [2006]; Disaster Relief Act [1974] [1974]).

Several recent studies have, for the first time, estimated person-level financial outcomes following natural disasters in the US using large administrative datasets (Deryugina et al. [Forthcoming]; Gallagher and Hartley [2017]; Groen et al. [2017]). These studies all conclude that the average net financial impact of a large natural disaster is modest and short-lived, even for the most severely impacted victims. However, none of these papers are able to isolate the role that cash assistance has on post-disaster outcomes.

There are two goals of this study. First, we estimate the causal effect of federal cash grants on post-disaster financial outcomes using credit bureau data. The credit bureau data are from the Federal Reserve Bank of New York Consumer Credit Panel / Equifax (CCP) (Lee and van der Klaauw [2010]). The panel is a random 5% sample of US residents with a Social Security number and any credit history. We hypothesize that the cash grants will substitute for personal debt and lead to a decrease in the level of debt incurred by disaster victims. Cash assistance may also reduce the likelihood of negative financial outcomes such as bill delinquency, personal bankruptcy, and home foreclosure if savings and insurance rates are low and access to credit is limited.

Second, we measure the effect of the cash grants on local businesses. The business data are from Infogroup's Historical Business Database, a proprietary database which seeks to include every US business establishment (Serrato and Zidar [2016]). We use the Infogroup Database to build an annual block-level enumeration of establishments in tornado-affected communities. The panel includes yearly information on the age, number of employees, dollar sales, and a precise (6-digit) industry code for each establishment. We hypothesize that cash grants may act as a targeted stimulus to local businesses directly impacted by a natural disaster. We expect the effect of the cash stimulus to be greatest for those businesses that rely on local demand (e.g. restaurants), rather than non-local demand (e.g. manufacturers that export nationally). Cash grants to households that happen to own a small businesses could also have direct effect on business survival.

The Presidential Disaster Declaration (PDD) process is the main mechanism for direct federal assistance following a natural disaster. The program we study is called Individual Assistance (IA). Under IA, residents in disaster areas can receive cash grants up to approximately $33,000 (GAO [2006]). Assistance is linked to incurred damage (e.g. structural damage to the home) and expenses (e.g. temporary housing and relocation) caused by the disaster. IA grants are an example of an unconditional cash transfer program (e.g. Baird et al. [2011]; Aizer et al. [2016]). Unlike most cash transfer programs, IA is a one time grant and not limited to low socioeconomic residents.

The main identification challenge is that the decision of whether to provide Individual Assistance grants is made following a disaster. Individual Assistance grants are only provided for a subset of Presidential Disaster Declarations. We deal with this endogeneity problem in two ways.

First, since we are concerned that cash grants may be more likely following larger, more damaging disasters, we limit our analysis of natural disasters to very large tornadoes that hit the US between 1999-2013. We show that among this set of the most destructive tornadoes, the mean dollar amount of damage, number of fatalities, and number of casualties are similar for the tornadoes that received IA to those means for the set of tornadoes that did not receive IA.

Further, in our analysis we are able to precisely allow for heterogeneity in block-level damage intensity. Detailed damage maps are available for these large tornadoes. The tornado damage maps are created by the National Weather Service (NWS). There are 32 tornadoes in our sample. All have Enhanced Fujita (EF) ratings of a 4 or 5. The tornado EF ratings are determined by NWS employees who survey post-tornado damage and use an engineering model to relate the observed damage to estimated tornado wind speeds. An EF4 tornado corresponds to a maximum estimated wind speed of between 166 and 200 miles per hour, while an EF5 implies a maximum wind speed of over 200 miles per hour.[1]

Figure 1 shows the damage map for an EF5 tornado that hit Joplin, Missouri on May 22, 2011. The map delineates tornado damage according to EF damage intensity. Only a small fraction of the land within the tornado path incurred EF5 damage. The figure is created using GIS software that overlays the geocoded tornado map on a US Census Block map (light gray). We assign each damaged block a damage intensity equal to the area-weighted average of the block-level EF ratings.

There is still the concern that cash assistance may be made available only when areas with more vulnerable populations are affected. According to the Federal Emergency Management Agency, decision criteria for whether cash grants are provided include whether the affected individuals involve "special populations" such as the economically disadvantaged (McCarthy [2011]). We find evidence that victims of Individual Assistance tornadoes are of lower socioeconomic status than victims of tornadoes without cash assistance.

[1] The official tornado rating scale switched from the Fujita scale to the Enhanced Fujita scale in 2007. The Fujita scale estimated wind speeds are a bit higher for the same numerical rating as compared to the EF scale. For details refer to the National Oceanic and Atmospheric Administration website: http://www.spc.noaa.gov/faq/tornado/ef-scale.html

We address this concern through a triple difference econometric model. Since tornado damage is very localized and the exact path of a tornado is not predictable, geographic areas in close proximity to those affected by a tornado should provide good control groups. Figure 1 illustrates our baseline control group in blue, those living 0.5 to 1.5 miles from the edge of the tornadoes damage path. We examine the pre/post tornado difference in financial outcomes for hit and control populations who are affected by tornadoes with and without federal grant assistance. The hit and control populations for each tornado will be similar provided that the exact location of the tornado path is random. The within tornado difference between the hit and control populations controls for selection differences for victims of tornadoes with and without cash assistance.

We find that disaster-affected individuals who receive cash grants have between \$260 and \$1,400 less in quarterly credit card debt after the disaster relative to disaster-affected individuals who did not receive cash grants. The reduction is largest for residents of blocks that suffered greater property damage from the tornado. The effect lasts for at least three years and is consistent with evidence on the persistence of revolving credit card debt (Telyukova [2013]). There is only limited evidence that the cash grants diminish negative financial outcomes.

Our triple difference estimate of the effect of cash grants on businesses indicates that they ameliorate the negative effects of tornadoes in the worst-affected neighborhoods, resulting in 22 percent more establishments relative to the worst-affected neighborhoods of tornadoes that do not receive cash grants. This effect is concentrated in firms that have two or fewer employees.

Our study examines the financial impact of a one time cash grant on disaster-affected residents in the US. We add to a growing literature on how cash transfers affect household finance and employment (e.g Brudevold-Newman et al. [2017]). Studies in this literature usually examine cash transfers that occur over multiple, scheduled installments (e.g Skoufias and Parker [2001]), and tend to focus on cash transfers to poor residents in developing countries (e.g. Fiszbien and Schady [2009]). Moreover, most of these studies examine cash transfer programs where the receipt of the cash is linked to socioeconomic status such as income or disability (e.g. Aizer et al. [2016]). We are not aware of another study that examines the role of a one time cash grant following a financial shock in a developed country. Thus, the results of our study are likely to be of interest to policymakers in the US and other developed countries considering cash grant policies in a variety of settings.

Finally, we add to the recent literature that uses cross-sectional differences in federal spending to estimate how federal spending affects the local economy (e.g. Chodorow-Reich [2018]). The impact of federal spending on the economy is of great interest to policymakers and there is still no consensus on the size of the fiscal multiplier. In contrast to other work in this area, our setup allows us to investigate whether higher levels of pre-existing household debt mitigate the size of fiscal multipliers. We plan to conduct this analysis in the next version of the paper.

2 Background and Data

2.1 Tornado Data

There are 32 tornadoes in our sample. Three criteria determine whether the tornado is included in our sample. First, the tornadoes occur from 2002-2013 so as to match the period covered by our individual and business financial data. Second, each tornado must have a high quality damage path map created by the National Weather Service (NWS) that demarcates areas of the tornado path that suffered different levels of damage. Third, all tornadoes must have a Fujita (F) or Enhanced Fujita (EF) rating of either a 4 or 5.

Tornado cost, casualty, and maximum intensity information is from the Tornado History Project (http://www.tornadohistoryproject.com/). The main source of the Tornado History Project information is the Storm Prediction Center's historical tornado data file (http://www.spc.noaa.gov/). The Storm Prediction Center is part of the National Weather Service and the National Centers for Environmental Prediction.

2.2 Public Disaster Assistance

The Presidential Disaster Declaration (PDD) system is a formalized process to request and receive federal assistance following large natural disasters. A governor of a US state that experiences a natural disaster must formally request a PDD in a written letter to the US president. Disaster declarations occur at the county-level. The letters must contain a list of proposed counties and preliminary damage estimates. The US president then decides whether or not to grant the request.

A PDD opens the door to three major types of disaster assistance. The largest component of disaster assistance is Public Assistance. Public Assistance is available to local and state governments as well as non-profit organizations located in the impacted area. These groups can access grant money to remove debris, repair infrastructure, and to aid in the reconstruction of public buildings. A second form of assistance comes in the form of subsidized lending. Disaster-affected individuals and businesses can also request subsidized Small Business Administration (SBA) disaster loans. The third type of disaster assistance is Individual Assistance (IA). Residents in disaster areas can receive cash grants of up to approximately $33,000 (GAO [2006]). The level of assistance is linked to incurred damage (e.g. structural damage to the home) and expenses (e.g. temporary housing and relocation) caused by the disaster. Disaster-affected individuals and businesses in counties that receive either Public Assistance or Individual Assistance can also request subsidized Small Business Association (SBA) disaster loans.

Panel A of Table 1 summarizes the overall sample characteristics for our tornadoes. Twenty of the 32 tornadoes are part of disaster declarations which receive Individual Assistance. The vast majority of the tornadoes where victims receive IA grants are also areas that receive Public Assistance.

Panel B of Table 1 provides a comparison between tornadoes where residents receive IA grants (left column) and tornadoes where residents do not receive IA grants (right column). Tornadoes with cash assistance are part of larger state-level disasters as measured by either the percent of state counties included in the PDD or Public Assistance money distributed. However, at the tornado-level and sub-tornado (block-level) tornadoes with and without cash assistance are similar. There is no evidence that tornadoes with cash assistance occur in more electorally competitive states.

Although, not yet included in Table 1, we have obtained data on the number of IA grant recipients and the total dollar amount of grants for each of the 20 tornadoes in our sample that received IA. Across these 20 tornadoes, the mean grant amount is roughly $5,500. We have also compiled preliminary data on SBA disaster lending at the city-zipcode level. These data indicate that SBA disaster lending is available to all of the tornadoes in our sample.

2.3 Credit and Debt Information

We use individual-level credit and debt information from the Federal Reserve Bank of New York Consumer Credit Panel / Equifax (CCP) (Lee and van der Klaauw [2010]). Equifax, one of several large consumer credit repository and credit scoring companies in the US, is the source of the credit and debt data in the CCP. The panel is built using a 5% sample of the US population that is selected based on the last two digits of an individual's social security number. Thus, the sample consists of a random sample of the population that has a social security number who also have a credit history. The CCP has quarterly observations and runs from 1999Q1 to the present.

Consumer credit account information is divided into four main types: home loans, auto loans, credit card accounts, and student loans. Home loan information separately tracks first mortgages, home equity loans, and home equity lines of credit. Bank and retail card accounts (i.e. credit cards) cover all types of issuers: banks, bankcard companies, national credit card companies, credit unions, and savings & loan associations, as well as department store and other retail credit cards.

The CCP includes the number of accounts for each loan/debt type, the balance in each type of account, indicators for whether the individual is behind on payment for each type of account, and indicators for foreclosure and bankruptcy.[2] The panel also includes the age, Census block of residence, and Equifax Risk Score (TM) for each individual.[3] Appendix Table 1 shows how the CCP data compare to information collected from the US Census. WE NEED TO MAKE THIS TABLE. Using the CCP panel and US Census data we show that the implied ratio of adults in the US with a credit history is roughly consistent with that estimated by the Fair Isaac Corporation (FICO) (Jacob and Schneider [2006]).

To form our sample, we take the set of individuals living in the treatment and control blocks in the quarter that the tornado struck and form a balanced panel that runs from 12 quarters prior to the quarter of the tornado through 12 quarters after the quarter of the tornado. Since individuals do not typically enter the CCP until they are 18 years old and we require them to be in the sample for 12 quarters prior to the tornado, our sample will consist only of individuals that are 21 and older in the quarter in which a tornado struck. Using the CCP's individual identifiers, we can track the set of treated and control people even if they move away from the tornado-affected area or were living living elsewhere for some portion of the pre-tornado period.

2.4 Business Data

In order to study the manner in which cash grants and subsidized loans affect local business growth we need detailed establishment-level data containing information about each business's exact location, employment and sales. To examine this, we use the Infogroup's Historical Business Database, which provides longitudinal establishment-level data on all establishments in the United States. The data consists of annual information on every establishment from 1997 to 2017 and are extensive with approximately 35 million establishments

[2]We express all dollar denominated variables in real 2010 dollars. We also winsorize the 99th percentile of all dollar denominated variables so that our estimates are not driven by the presence of extremely large debt balances or credit limits.

[3]The Equifax Risk Score is a trademarked measure of consumer credit risk and ranges from 280-850. A higher score indicates a higher measure of creditworthiness.

each year.[4] These data contain a wealth of establishment information, including exact location (latitude and longitude) or address, its start date, number of employees, sales volume in dollars, detailed six-digit industry code and corporate linkages. Our unit of analysis is the census block; therefore, we aggregate establishment-level data to the census block. In some analysis, we explore how the area's entrepreneurship rate and existing business survival rates are affected. For those analyses, we define a business as "new" if it has been in service for one year or less and a business as "existing" if it has been in business for four or more years.

3 Empirical Specification

Our main goal is to estimate the causal effect of cash grants distributed by FEMA following a tornado on household debt and business survival and employment. We use a triple difference (DDD) empirical strategy to do this. Conceptually, our estimates can be thought of as taking the difference between two difference-in-differences (DD) estimates. The first DD estimates the effect of tornadoes on people and businesses when individual assistance follows. This can be thought of as the composite effect of damage from the tornado, cash grants, and all other sources of assistance (such as Small Business Administration Disaster Loans). The second DD estimates the effect of tornadoes on people and businesses when no individual assistance follows. This is the composite effect of damage from the tornado and all other sources of assistance, but without cash grants.

As we discussed in Section 2, we form a sample of treated Census blocks by taking the set of all Census blocks that are fully contained in a tornado damage path. We form a sample of possible control blocks by drawing a 0.5

[4]The Infogroup compiles this information by first detecting businesses through numerous sources, such as over 4,300 yellow and white pages, county-level public sources, utility connects and disconnects, real estate tax assessor data and web research. It then calls every company in the United States every year. An independent audit found it is similar to, and on many dimensions, of higher quality than other private business-level datasets such as the National Establishment Time-Series dataset. For more information about the data go to http://www.infogroup.com/data .

mile buffer and a 1.5 mile buffer around each tornado damage path and taking the set of Census blocks that are fully contained between those buffer lines. We exclude the half mile closest to the edge to the tornado damage path in case there is measurement error in the placement of the boundary.

While there are areas of the US where tornadoes are prevalent such as the Great Plains, it is not possible to predict the exact path of a tornado. Due to this fact, winding up in the treatment or control set of Census blocks is likely to be as good as random assignment. Comparisons of these blocks using pre-tornado CCP variables or Census block and block group characteristics measured in the 2000 Census support this conjecture (e.g. the difference in means of median household income across the treatment and control blocks is economically small and statistically indistinguishable form zero). This randomness provides a source of identification for the DD estimates.

Identification of the DDD estimates is a bit trickier. This is because the decision of whether or not to give cash grants is determined after the tornado occurs. This means that FEMA can take into consideration the the degree to which the population that is affected by the tornado has the means to recover from the tornado without cash grants. In fact, our data show that tornado-affected areas that subsequently received cash grants had lower median household income in 2000, on average. In particular, cash grants are given to tornado-affected households whose median household income was significantly lower (economically and statistically) than the nearby control group.

Figure 2 shows mean credit card debt levels for 4 groups: the no individual assistance control group (blue triangles), the no individual assistance treatment group (green triangles), the individual assistance control group (red circles), and the individual assistance treatment group (orange circles). The means are plotted with respect to the number of quarters since the tornado, shown on the x-axis. For example, the orange circle above -12, is the mean credit card balance for people that will find themselves living in the damage path of a tornado that subsequently receives individual assistance in 12 quarters. There is a vertical line drawn at -1, indicating the last quarter before the tornadoes strike.

Figure 2 provides an ocular test (statistical tests will come in the next section) of some of the assumptions that need to hold for our identification strategy. The first thing to note is that in the 12 quarters before the tornadoes, the red and orange circle-marked lines are moving in parallel. There is a level difference between the two lines. The tornado-affected group that ends up receiving individual assistance has about $600 less in credit card debt, on average. This could reflect the fact (mentioned above) that they have lower household income than the control group and thus may have less access to credit, or simply cycle a lower amount of spending through their credit cards each month.

The second thing to note in Figure 2 is that the blue and green triangle-marked lines are moving (roughly) in parallel prior to the quarter of the tornadoes. Comparing the upward trend of the blue and green lines to the flat trend of the red and orange lines highlights the necessity of the of the DDD strategy. If one were to simply compare the tornado-affected (treated) areas for the tornadoes that received individual assistance (the orange circle-marked line) to the tornado-affected (treated) areas of the tornadoes that did not receive individual assistance (the green triangle-marked line), then one would mistakenly attribute the continuation of the upward trend in credit card balances in tornado-affected areas that did not receive individual assistance to the effect of the tornado. Differencing out the control groups provides a way of removing the pre-existing trend observed among the tornadoes that did not receive individual assistance.

First we describe the specification that we use with the CCP data. After that we will discuss the differences between the individual and business specifications. Our baseline specification is a regression-based implementation of a a triple difference (DDD) estimator.

$$y_{i,t} = \beta_1 Post_{it} * IA_i * T_i + \beta_2 Post_{i,t} * IA_i + \beta_3 Post_{i,t} * T_i + \beta_4 Post_{i,t} * + \alpha_i + \gamma_t + \epsilon_{i,t} \quad (1)$$

where $y_{i,t}$ is a credit outcome for individual i in quarter t, $Post_{it}$ is a binary variable indicating the post-tornado period (any of the 12 quarters following the quarter of the tornado), IA_i is a binary variable indicating whether individual i lived in either a treatment or control area of a tornado that received individual assistance, T_i is a binary variable indicating whether individual i lived in a treatment (tornado-damaged) or control (nearby) area, α_i is an individual fixed effect, γ_t is a quarter*year fixed effect, and $\epsilon_{i,t}$ is an error term.

To test for differences in pre-existing time trends between the set of tornadoes that get individual assistance versus those that do not, we also estimate a version of the specification shown above where we replace the $Post_{it}$ variable with a set of binary variables that indicate the number of quarters the observation is either before or after the tornado. We include variables indicating 12 quarters before the tornado through 12 quarters after the tornado, but exclude the quarter before the tornado which serves as the reference quarter. Since the variables T_i and IA_i are determined by the Census block of residence in the quarter that the tornado occurs, they do not vary over time and are thus subsumed by the individual fixed effects.

Since the tornado maps show heterogeneity in damage intensity, we also estimate specifications that allow for the effect of individual assistance to vary with the level of damage. Our idea in running this specification is that it is probably the case that a greater share of households receive individual assistance in the most damaged parts of the tornado path. The tornado damage paths are classified according to the Enhanced Fujita (EF) scale (integer values from 0 to 5 corresponding to 6 bins of estimated wind speeds). We find the area-weighted mean EF value for each Census block and classify the block as low damage if the mean EF is less than 1, medium damage if the mean EF greater than or equal to 1 but less than 3, and high damage if the mean EF is 3 or higher. We refer to this specification as our binned damage level specification. The equation for this specification simply replaces each occurrence of the binary variable indicating treatment, T_i in the equation above with a vector of 3 binary variables indicating low, medium, or high treatment.

In all specifications we report standard errors that are clustered by tornado.

4 Results

4.1 Household Finance

Table 2 presents triple difference estimates of the effect of individual assistance on several categories of household debt balances (credit card, mortgage and home loan, auto, other, and total), Equifax Risk Score (a credit score), a binary variable indicating whether the individual has any accounts in their credit file that are 90 or more days delinquent, and an indicator of whether they had a foreclosure in the past 7 years. Panel A presents our baseline triple difference specification estimates of β_1 where IA corresponds to IA_i in Equation 1, after tornado corresponds to $Post_{i,t}$, and Hit corresponds to T_i. Panel B presents triple difference results which allow for variation in the degree of treatment based on the severity of the damage and implied wind speed. While both specifications also contain the other variables shown in Equation 1, we report only the triple difference coefficient or coefficients for the sake of keeping the table simple.

Column 1 in Panel A of Table 2 shows that the estimated mean effect of receiving individual assistance after a tornado is roughly \$400 dollar lower credit card balances over the next 3 years. Looking back to Figure 2 reveals that initially a small part of the drop may have been driven by a reduction in credit card debt for people living in the damage path of tornadoes that received individual assistance (orange line relative to the red line). However, the bulk of the effect toward the end of the period is driven by an increase in credit card balances of the people living in the damage path relative to those in the control group of the tornadoes that did not receive individual assistance. This gap begins to really open up about a year after the tornado. Panel B of Column 1 reveals that the reduction in credit card debt is much higher (about \$1,400) in the most severely damaged Census blocks.

The remainder of outcomes are not economically large or statistically distinguishable from zero in Panel A of Table 2. Panel B shows a marginally (10% level) statistically significant reduction in auto debt in the most severely damaged Census blocks of about \$1,300 and about a \$1,400 reduction in other debt. Our other debt category includes consumer finance loans, student loans, and a category that the CCP labels as "other". There is also a marginally statistically significant increase in the Equifax Risk Score (TM) of about 5 points in the most severely damaged Census blocks and about a one percentage point drop in the propensity to have a foreclosure flag in the medium damaged Census blocks.

The second coefficient estimate shown in Column 1 of Table 2 reveals that in the quarter of a tornado and the 12 quarters following a tornado, mean credit card balances dropped by about $450 on average for tornadoes receiving individual assistance relative to those that did not. Looking back to Figure 2 reveals that initially a small part of the drop may have been driven by a reduction in credit card debt for people living in the damage path of tornadoes that received individual assistance (orange line relative to the red line). However, the bulk of the effect toward the end of the period is driven by an increase in credit card balances of the people living in the damage path relative to those in the control group of the tornadoes that did not receive individual assistance. This gap begins to really open up about a year after the tornado.

Figure 3 plots quarterly triple difference estimates for the pre- and post-tornado periods, using the quarter before a tornado as the reference period. These estimates are for the most severely damaged group of Census blocks. In Panel A, the point estimates in the pre-tornado period are mostly close to zero and cannot be distinguished from zero, statistically (hollow boxes and dotted lines show the upper and lower bounds of the 95% confidence interval). The point estimates drop to around -$1,000 in the first three quarters after the tornado and then fluctuate a bit ending closer to -$2,000 twelve quarters after the tornado.

The remainder of the outcomes shown in Panels B - D of Figure 3 and Panels A - D of Figure 4 do not show statistically significant evidence of pre-existing trend differences between the treatment and control groups of the individual assistance and non-individual assistance tornadoes.

4.2 Business Growth, Employment and Sales

Federal assistance following tornadoes can aid local businesses in two important ways. First, more directly, federal assistance can provide access to subsidized loans to businesses affected by the disaster which may ease liquidity problems while their business and local customers are recovering from the disaster. Second, when tornado-affected individuals receive cash assistance a portion is spent locally increasing revenues for local businesses. We explore the cumulative effect of both the cash assistance and subsidized loans on three important measures of local business growth: number of establishments, employment, and sales of these establishments.

Table 3 presents difference-in-differences estimates separately for tornadoes with and without individual assistance for our three measures of business activity. Columns (1), (3), and (5) include establishments from all blocks hit by a tornado where residents received IA and neighboring blocks between 0.5 and 1.5 miles from the tornado path. Columns (2), (4), and (6) include establishments from all blocks hit by a tornado where residents did not receive IA and neighboring blocks between 0.5 and 1.5 miles of the tornado path. All models include block and calendar year fixed effects. The sample is balanced in event time and because the Infogroup collects the data annually, the model includes establishment observations from 4 years prior to the year of the tornado through 4 years after the tornado. The model drops the year of tornado in order to address possible non-reporting issues as a result the "after tornado" variable indicates being one to four years after the tornado hits. Robust standard errors clustered by tornado area presented in parentheses.

Panel A presents results pooling all areas hit by the tornado regardless of damage intensity. Column (1) shows that the number of establishments in IA tornadoes fell by 0.7 percentage points compared to their counterfactual areas while column (2) indicates a decrease of 4.9 percentage points compared to their counterfactual areas. This pattern continues for both employment (-1.7 for IA compared to -8.6 for non-IA) and sales (-10.5 for IA and -39.5 for non-IA) with progressively larger magnitudes, however none of these point estimates are statically significant at conventional levels. Panel B utilizes our block-level measures of damage by interacting our post tornado indicator with the continuous damage measure and finds a similar pattern of a relatively small decrease in IA tornadoes compared to a larger loss of business activity in non-IA tornadoes compared to their counterfactual areas.

Our preferred specification, Panel C, estimates a non-parametric damage intensity model with three dichotomous damage variables similar to Table 3. Our results suggest that accounting for damage intensity is important. Across all three dependent variables we find that businesses in the tornado path that experienced damage levels below EF1 (low) but received IA had positive economic growth relative to their counterfactual areas while businesses that experienced the same levels of damage but did not receive IA had relatively small decreases in business growth (although not statistically significant). In both medium and high damage areas, regardless of receiving individual assistance the areas experienced substantive decreases in business activity however, areas that received individual assistance had much smaller decreases in business activity. For instance, columns (1) and (2) show that areas that experienced medium (EF1 to EF3) damage with IA had a decrease of 8.4 percentage points compared to a decrease of 21.2 percentage points in areas without IA. Likewise, for areas with high (EF3 or greater) damage, IA areas experienced a decline of 12.8 percentage points compared to a decrease of 31.4 percentage points in non-IA areas. Our findings suggest that the cash assistance and subsidized loans mitigated the financial damage to local businesses in the areas that experienced the worst of the damage.

Table 4 extends the analysis to the triple difference framework. Column (1) shows relatively large point estimates across all three levels of damage but only the high damage is statistically significant. More specifically, we find in areas that experience EF3 damage or higher receiving individual assistance results in 22.1 percentage points more establishments compared to their counterfactual areas than in areas that did not receive individual assistance. Column 2 finds similarly large positive point estimates in employment growth but lacks statistical significance. Lastly, the sales estimates show progressive larger impacts as you increase damage intensity with increasing levels of precision. The sales estimates support the idea that providing cash assistance to individuals affected by the disaster also help the business community in these areas.

Table 5 continues our triple difference model and examines varying sources of heterogeneous treatment effects that can help us understand how the individual assistance is helping local economic growth. Panel A of Table 5 examines the effect across firm size and shows that the smallest establishments (2 or fewer employees) are benefiting the most. This supports the idea that small businesses are the most vulnerable and providing cash assistance and subsidized loans can help them endure a natural disaster. Panel B of Table 5 explores the effect of individual assistance across industries. Comparing the effect between manufacturing firms, who are likely export-oriented to non-manufacturing whose customers are more likely local we see the positive benefits of IA are going to non-manufacturing businesses generally (22.5 percentage point increase compared to a 2.9 percentage point decrease). One may be concerned that construction is driving this result but we find relatively modest positive effects (3.8 percentage point increase in number of establishments) while the retail sector increases are larger (4.9 percentage point increase). Lastly, one may wonder whether the positive effects are driven by growth in entrepreneurship (new businesses) or improving the survival rates of existing businesses. Panel C separately examines new businesses (1 year or less in service) and existing businesses (4 years or more in service) and finds that positive estimates in the business outcomes is driven by improving the survival rate of existing businesses.

The critical concern when using a differencing strategy is the parallel trends assumption. In the triple difference setting the concern is that the difference between the areas hit by the tornado (treated areas) and the near-miss areas (control areas) of the the IA and the same differences for the non-IA tornadoes had different trends prior to the tornado. To examine this we employ an event study framework and plot our estimates in Figure 5. The first column illustrates that these areas were trending quite similarly before the tornado and that after the tornado damaged areas that did not receive IA experienced substantive declines while the damaged areas that did receive assistance seem to follow the same path as the counterfactual areas.

5 References

Hurricanes katrina and rita disaster relief: Improper and potentially fraudulent individual assistance payments estimated to be between $600 million and $1.4 billion. Technical Report Government Accountability Office Report 06-844T, Government Accountability Office (GAO), 2006.

Anna Aizer, Shari Eli, Joseph Ferrie, and Adriana Lleras-Muney. The long-run impact of cash transfers to poor families. *American Economic Review*, 106(4), 2016.

Sarah Baird, Craig McIntosh, and Berk Ozler. Cash or condition? evidence from a cash transfer experiment. *Quarterly Journal of Economics*, 126(4), 2011.

Andrew Brudevold-Newman, Maddalena Honorati, Pamela Jakiela, and Owen Ozier. A firm of one's own, experimental evidence on credit constraints and occupational choice. *World Bank Working Paper*, February 2017.

Gabriel Chodorow-Reich. Geographic cross-sectional fiscal spending multipliers: what have we learned? *Working Paper*, March 2018.

Ronald J. Daniels and Michael J. Trebilcock. Rationales and instruments for government intervention in natural disasters. *University of Pennsylvania ScholarlyCommons*, January 2006. URL http://repository.upenn.edu/law_series/19.

Tatyana Deryugina, Laura Kawano, and Steven Levitt. The economic impact of hurricane katrina on its victims: Evidence from individual tax returns. *American Economic Journal: Applied Economics*, Forthcoming.

Disaster Relief Act [1974]. Public law 93-288: Disaster relief act of 1974. Technical report, United States Government, May 1974.

Ariel Fiszbien and Norbert Schady. Conditional cash transfers: Reducing present and future poverty. *World Bank*, 2009.

Justin Gallagher and Daniel Hartley. Household finance after a natural disaster: The case of hurricane katrina. *American Economic Journal: Economic Policy*, 9 (3), 2017.

Jeffrey A. Groen, Mark J. Kutzbach, and Anne E. Polivka. Storms and jobs: The effect of hurricanes on individuals' employment and earnings over the long term. *Working Paper*, September 2017.

Katy Jacob and Rachel Schneider. Market interest in alternative data sources and credit scoring. *The Center for Financial Services Innovation*, December 2006.

Donghoon Lee and Wilbert van der Klaauw. An introduction to the frbny consumer credit panel. Technical Report 479, Federal Reserve Bank of New York, November 2010.

Francis X. McCarthy. Fema's disaster declaration process: A primer. Technical Report 18, Congressional Research Service, May 2011.

Munich Re. Topics geo natural catastrophes 2012, report. Technical report, Munich Re, 2013.

Munich Re. Preliminary sigma estimates for 2017: global insured losses of usd 136 billion are third highest on sigma records. Technical report, Munich Re, 2017. URL http://www.swissre.com/media/news_releases/nr20171220_sigma_estimates.html.

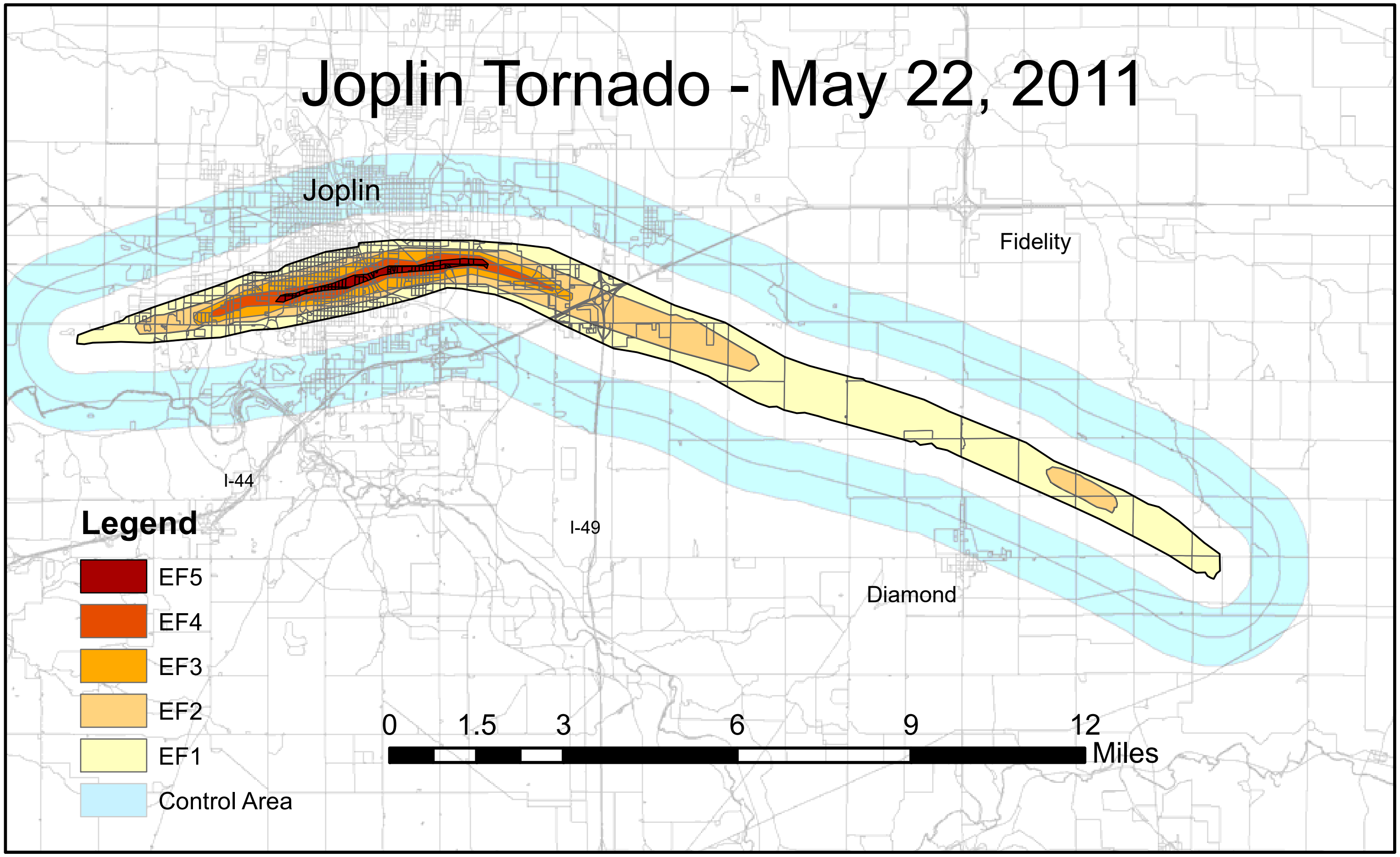
Juan Carlos Serrato and Owen Zidar. Who benefits from state corporate tax cuts? a local labor markets approach with heterogeneous firms. *American Economic Review*, 106(9), 2016.

Emmanuel Skoufias and Susan W. Parker. Conditional cash transfers and their impact on child work and schooling: Evidence from the progresa program in mexico. *Economia*, 2(1), 2001.

Irina A. Telyukova. Household need for liquidity and the credit card debt puzzle. *The Review of Economic Studies*, 80, July 2013.

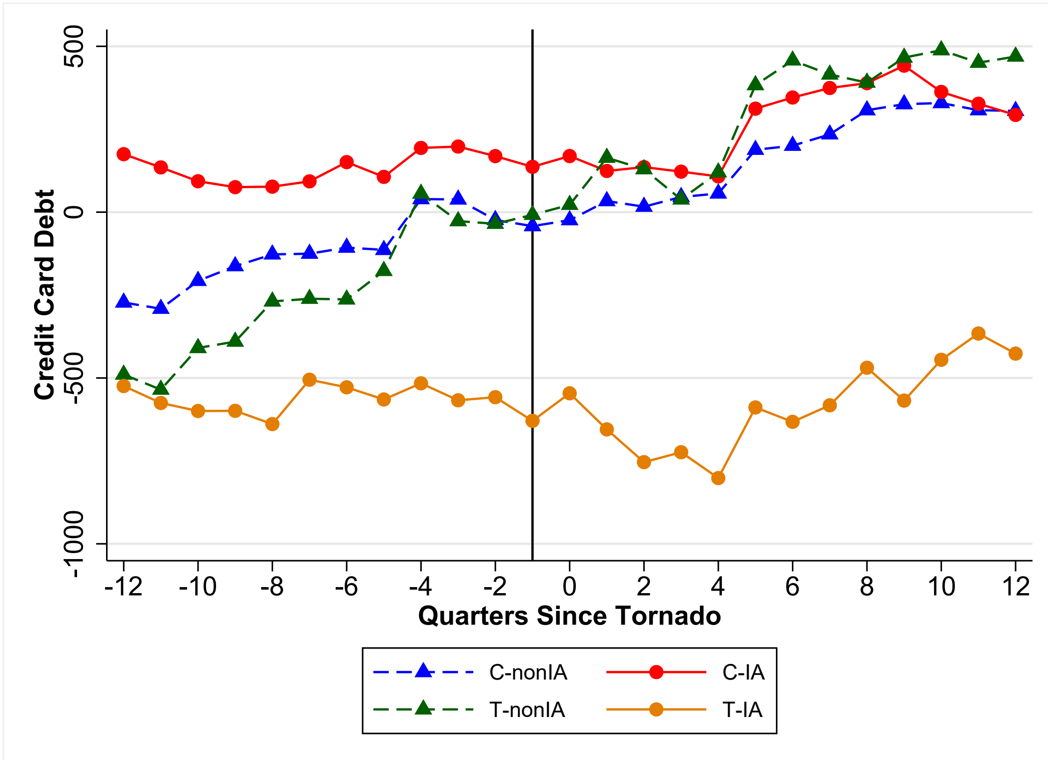
6 Figures and Tables

Figure 1: Tornado Damage Map for Joplin, MO 2011 Tornado



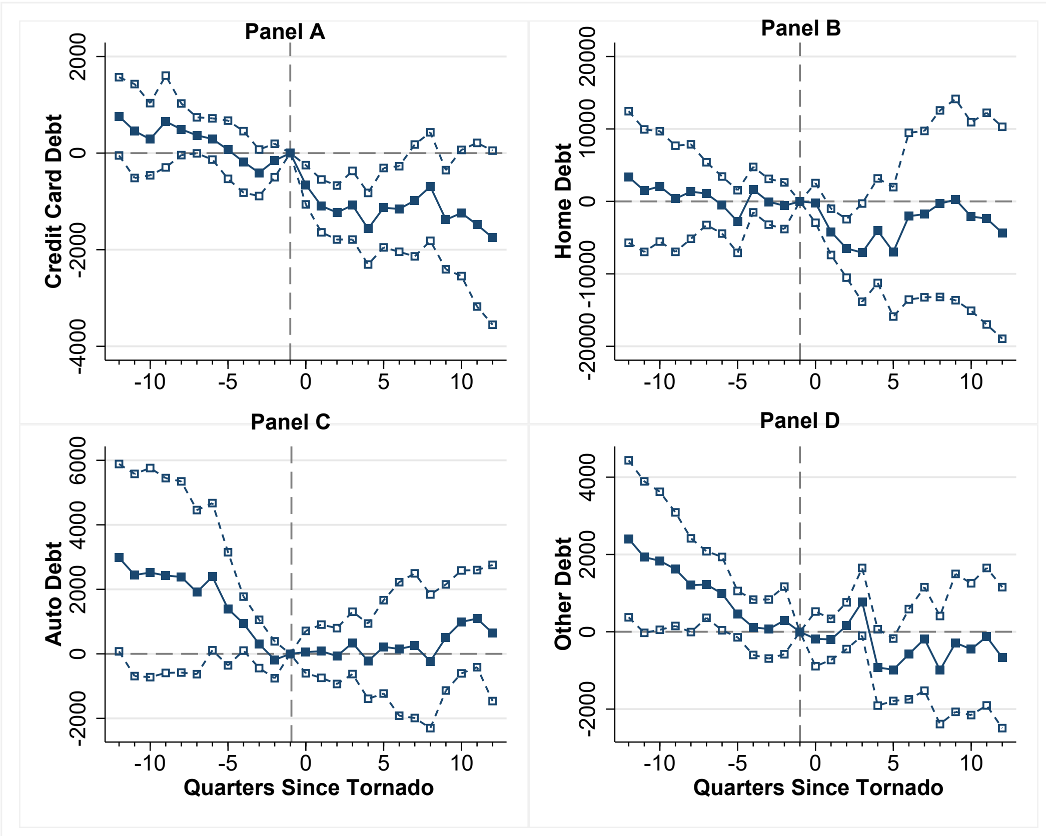
The figure shows the damage map for an EF5 tornado that hit Joplin, Missouri on May 22, 2011. The Figure shows Census block-level tornado damage levels for and a control area 0.5 - 1.5 miles from the edge of the damage path. Sources: US Census, National Weather Service

Figure 2: Trends in Credit Card Debt



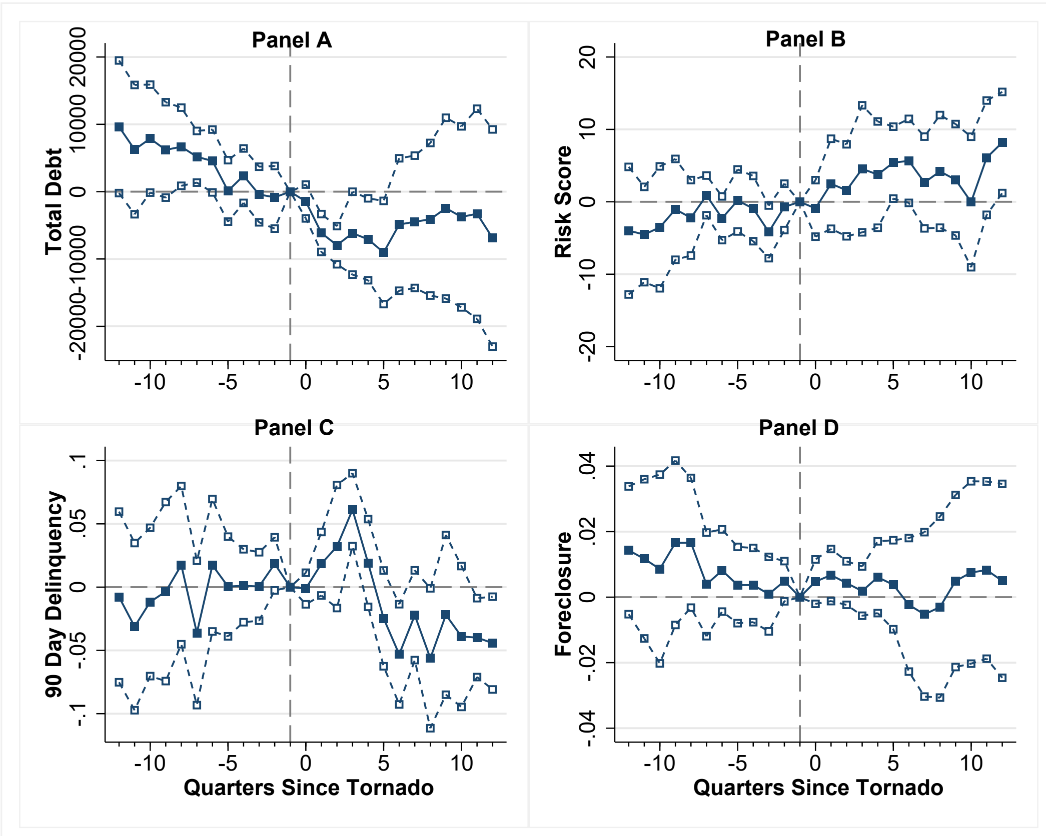
The figure plots the mean credit card balance of four groups of individuals: non-hit residents who lived in the 0.5 to 1.5 mile buffer area around the tornadoes that did not receive cash grants (blue), hit residents who lived in the damage path of tornadoes that did not receive cash grants (green), non-hit residents who lived in in the buffer areas of the tornadoes that did receive cash grants (red), and hit residents from tornadoes that received cash grants (orange). The plotted data are residuals from a regression of credit card debt on quarter-by-year dummy variables. All dollar denominated variables are expressed in real terms in 2010 dollars. The vertical line indicates the last quarter before a tornado. Source: Federal Reserve Bank of New York Consumer Credit Panel / Equifax (CCP).

Figure 3: Quarterly Analysis of Debt by Subcategory



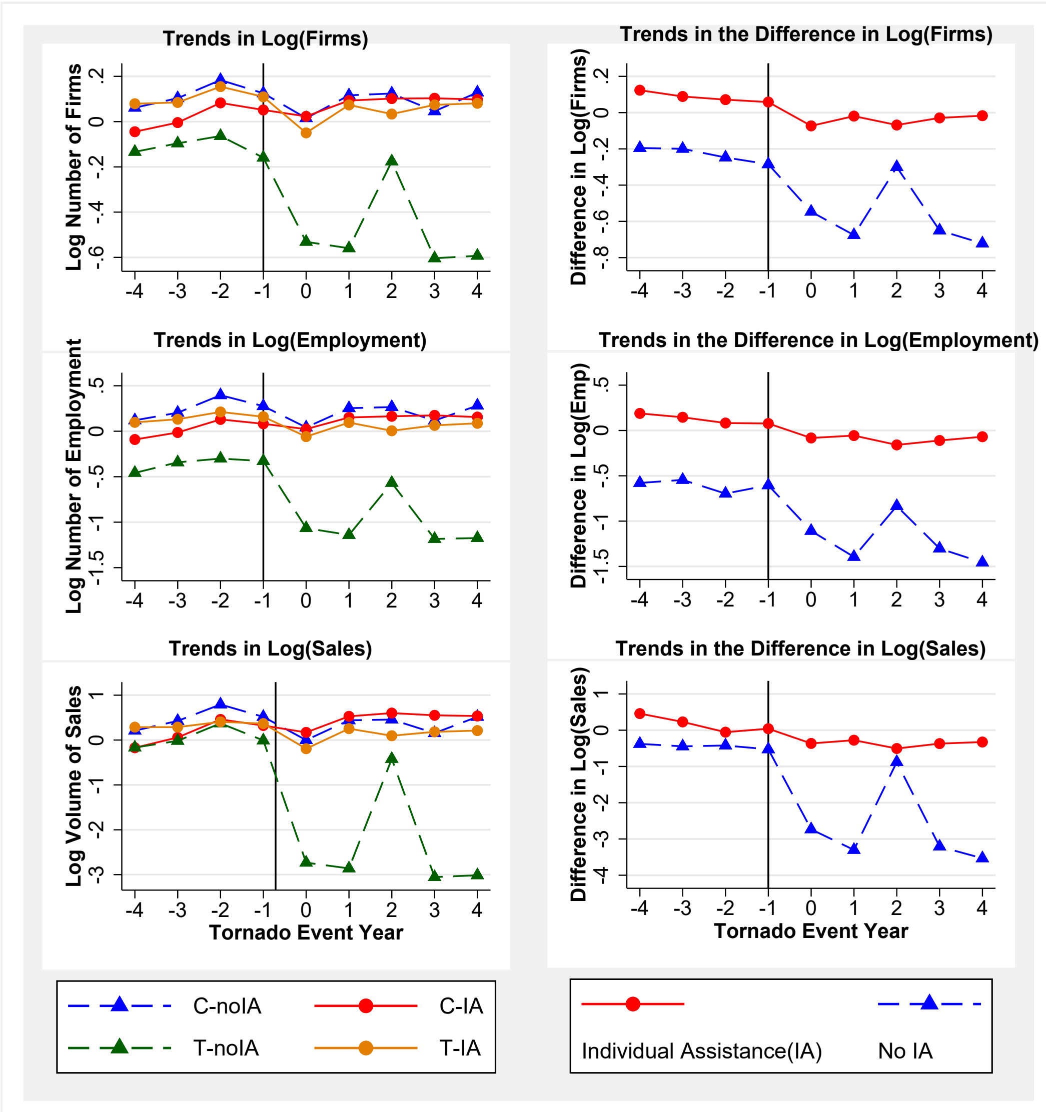
Source: Federal Reserve Bank of New York Consumer Credit Panel / Equifax (CCP).

Figure 4: Quarterly Analysis of Negative Consumer Financial Outcomes



Source: Federal Reserve Bank of New York Consumer Credit Panel / Equifax (CCP).

Figure 5: Trends in Business Outcomes



Source: Infogroup Historical Business Database

Table 1: **Tornado Damage Characteristics**

Panel A: Overall Sample Characteristics

States hit by Tornado	15
Total Number of Tornadoes	32
Presidential Disaster Declaration Tornadoes	
Public Assistance	21
Individual Assistance (Cash Grants)	20
Public Assistance and Individual Assistance	18
Tornado Damage Severity	
F5/EF5 Tornadoes	6
F4/EF4 Tornadoes	26

Panel B: Characteristics by Assistance Status

	Cash Assistance Mean (Median)	No Cash Assistance Mean (Median)
Disaster-Level[1]		
Number of Counties in Disaster Declaration	41 (40)	22 (9)
Percent State Counties in Disaster Declaration	50 (38)	21 (8)
Public Assistance (Millions $)	69.2 (20.6)	25.1 (10.7)
Electoral Competitiveness of State[4]	42.4 (41.9)	43.9 (43.0)
Tornado-Level[2,3]		
Tornado F/EF Rating	4.3 (4)	4.1 (4)
Number of Damaged Blocks	294 (224)	329 (54)
Estimated Tornado Damage (Millions $)	458 (161)	369 (71)
Fatalities	16 (7)	13 (2)
Casualties	129 (54)	166 (20)
Block-Level[2,3]		
Average Block F/EF Rating	1.46 (1.45)	1.05 (0.87)
Average Tornado Damage per Block (Millions $)	1.65 (0.65)	1.29 (0.62)

Tornadoes occur from 2002-2013. A Presidential Disaster Declaration event can include either Public Assistance and/or Individual Assistance. Public Assistance is allocated to communities to repair public infrastructure. Individual Assistance provides cash grants directly to residents. *Cash Assistance* includes information from the 20 Individual Assistance tornadoes (18 were also allocated Public Assistance). *No Cash Assistance* includes 3 tornadoes where Public Assistance was allocated and 9 tornadoes that were not part of a Presidential Disaster Declaration. Damages in 2013$. *Electorial Competitiveness* follows Reeves (2011) and measures the 2-way voteshare of the losing political party at the midpoint of our sample (2007) averaged over 3 presidential elections (2004, 2000, and 1996). Sources: [1]Federal Emergency Management Agency, [2]Tornado History Project, [3]US Census, [4]uselectionatlas.org

Table 2. **Tornado Damage Characteristics**

Dependent Variable:	Credit Card Debt (1)	Home Debt (2)	Auto Debt (3)	Other Debt (4)	Total Debt (5)	Risk Score (6)	90 Day Delinquency (7)	Foreclosure (8)
Panel A: Pooled								
IA x After Tornado x Hit	-223	-3,909*	-157	-462	-5,014**	1.0	-0.002	-0.000
	(137)	(1,985)	(189)	(327)	(1,834)	(1.3)	(0.005)	(0.003)
R-squared	0.743	0.799	0.624	0.730	0.818	0.880	0.603	0.608
Observations	513,410	513,410	513,410	513,410	513,410	509,800	513,410	524,113
Panel B: Binned Damage Levels								
IA x After Tornado x Low	-264	-625	292	-509	-569	2.0	-0.006	-0.005
	(238)	(3,004)	(345)	(385)	(2,943)	(2.3)	(0.014)	(0.005)
IA x After Tornado x Medium	-364	-2,971	-45	175	-3,870	4.3	0.003	-0.013**
	(369)	(2,678)	(444)	(493)	(3,159)	(4.0)	(0.015)	(0.006)
IA x After Tornado x High	-1,403***	-3,756	-1,339*	-1,368**	-9,100*	5.4*	-0.010	-0.005
	(401)	(3,820)	(739)	(639)	(4,512)	(3.0)	(0.021)	(0.011)
R-squared	0.743	0.799	0.624	0.730	0.818	0.880	0.603	0.608
Observations	513,410	513,410	513,410	513,410	513,410	509,800	513,410	524,113

Source: Federal Reserve Bank of New York Consumer Credit Panel / Equifax (CCP).

Table 3: **The Effect of Cash Grants and Subsidized Loans on the Number of Business Establishments, Employment, and Sales**

Difference-in-Differences Model Estimates

	Log(Firms)		Log(Employment)		Log(Sales)	
	(1) IA	(2) non-IA	(3) IA	(4) non-IA	(5) IA	(6) non-IA
Panel A: Pooled						
After Tornado × Hit	-0.007	-0.049	-0.017	-0.086	-0.105	-0.395
	(0.044)	(0.116)	(0.081)	(0.204)	(0.236)	(0.619)
Panel B: Heterogenous Damage Level						
After Tornado × Damage Level	-0.029**	-0.067	-0.054**	-0.121**	-0.140**	-0.541***
	(0.010)	(0.037)	(0.020)	(0.051)	(0.052)	(0.159)
Panel C: Binned Damage Levels						
After Tornado × Low	0.051	-0.028	0.079	-0.047	0.129	-0.224
	(0.044)	(0.104)	(0.081)	(0.187)	(0.245)	(0.515)
After Tornado × Medium	-0.084*	-0.212	-0.135	-0.343	-0.437*	-1.795**
	(0.045)	(0.148)	(0.082)	(0.218)	(0.237)	(0.600)
After Tornado × High	-0.128**	-0.314***	-0.230**	-0.753*	-0.567**	-2.503**
	(0.045)	(0.093)	(0.082)	(0.386)	(0.204)	(0.792)
R-squared	0.642	0.578	0.638	0.573	0.560	0.504
Observations	54648	29488	54648	29488	54648	29488

The table represents difference-in-differences estimates of the effect of Individual Assistance (IA) cash grants and subsidized loans on the percent change in the number of establishments, employment, and sales. All models include block and calendar year fixed effects. Panel A reports the coefficient of interest for a model that uses a dichotomous variable to measure whether a business establishment is located in the tornado path. In panel B, the variable of interest is the interaction term of post-tornado and the continuous variable of block-level damage. Panel C estimates a non-parametric damage intensity model with 3 dichotomous damage variables. The low damage group includes blocks with average damage levels below EF1. The medium group includes hit blocks with an average damage of at least EF1 but less than EF3. The high group includes blocks with at least EF3 damage. The model drops the year of tornado in order to address non-reporting issues. The sample is balanced in event time and includes establishment observations from 4 years prior to the year of the tornado through 4 years after the tornado. The model drops the year of tornado in order to address possible non-reporting issues. The table estimates the same model on two samples for three dependent variables. Column (1), (3), and (5) include establishments from all hit blocks and neighboring blocks between 0.5 and 1.5 miles from the tornado path where residents in the hit blocks receive IA. Column (2), (4), and (6) include establishments from hit blocks where residents did not receive IA and neighboring blocks between 0.5 and 1.5 miles of the tornado path. Reported R-squared values are for regressions in Panel C. Cluster-robust standard errors by tornado are in parentheses. *** $p<0.01$, ** $p<0.05$, *$p<0.1$. Source: Infogroup Historical Business Database

Table 4: **The Effect of Cash Grants and Subsidized Loans on the Number of Business Establishments, Employment, and Sales**

Triple Difference Model Estimates

	(1) Log(Firms)	(2) Log(Employment)	(3) Log(Sales)
IA Grant × After Tornado × Low	0.110	0.181	0.490
	(0.106)	(0.190)	(0.526)
IA Grant × After Tornado × Medium	0.108	0.190	1.271*
	(0.157)	(0.258)	(0.687)
IA Grant × After Tornado × High	0.221**	0.650	2.177**
	(0.097)	(0.383)	(0.792)
R-squared	0.622	0.621	0.547
Observations	84136	84136	84136

Source: Infogroup Historical Business Database

Table 5: **The Effect of Cash Grants and Subsidized Loans on the Number of Business Establishments, Employment, and Sales**

Heterogeneity by Firm Size, Industry, and Firm Age

	(1) Log(Firms)	(2) Log(Employment)	(3) Log(Sales)
Panel A: Firm Size			
2 or Less Employees			
IA Grant×After Tornado×High	0.262***	0.282***	1.530***
	(0.076)	(0.090)	(0.408)
Observations	64528	64528	64528
3-5 Employees			
IA Grant × After Tornado × High	0.041	0.115	0.506
	(0.066)	(0.113)	(0.340)
Observations	56136	56136	56136
More Than 5 Employees			
IA Grant×After Tornado×High	-0.025	0.514	1.211
	(0.099)	(0.537)	(1.132)
Observations	59072	59072	59072
Panel B: Industry			
Manufacturing			
IA Grant × After Tornado × High	-0.029***	-0.058***	-0.224***
	(0.007)	(0.019)	(0.063)
Non-manufacturing			
IA Grant×After Tornado×High	0.225**	0.646	2.196**
	(0.096)	(0.380)	(0.788)
Retail			
IA Grant×After Tornado×High	0.049*	0.091*	0.484***
	(0.027)	(0.052)	(0.141)
Construction			
IA Grant×After Tornado×High	0.038**	0.035	0.280*
	(0.018)	(0.034)	(0.161)
Panel C: New or Existing Firms			
New Firms			
IA Grant×After Tornado×High	-0.006	0.004	-0.009
	(0.025)	(0.040)	(0.136)
Existing Firms			
IA Grant×After Tornado×High	0.192*	0.584	2.032**
	(0.093)	(0.386)	(0.800)
Observations	84136	84136	84136

Source: Infogroup Historical Business Database