Weathering an Unexpected Financial Shock: The Role of Cash Grants on Household Finance and Business Survival

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Abstract

First, we document the impact of being hit by a devastating tornado on household finance and business survival. The tornado paths are random and can't be predicted using risk information. Individuals in severely damaged blocks have a small *reduction* in debt and no change in bill delinquency. The business establishment survival rate declines by 10%. Second, we provide insight on the role of federal cash grants in mitigating the shock. Individuals in severely damaged blocks have 30% less credit card debt post-disaster when cash assistance is available. Credit-constrained victims have lower bill delinquency and increase consumption. The cash grants are a place-based policy and result in 9% more establishments and 12% more employees post-disaster in the average-damaged neighborhood where residents receive grants. Finally, while these effects are concentrated among small non-manufacturing establishments that rely on local demand, we can't rule out that other disaster assistance programs contribute to our findings.

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1 Introduction

Natural disasters in the US are shocks to income, wealth, and capital. In 2017, natural disasters caused at least $100 billion in insured damage losses. Average yearly economic losses from natural disasters in the US more than doubled in real terms from 1981 to 2010, while loss of life from natural disasters remained relatively constant (Munich Re [2013]).

The US government has a long history of federal assistance following natural disasters. Cash grants are a key component of disaster assistance and have been distributed to individuals 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) are insufficient to smooth the negative financial consequences of the natural disaster.

Several recent studies have, for the first time, estimated individual-level financial outcomes following natural disasters in the US using large administrative datasets (Deryugina et al. [2018]; Gallagher and Hartley [2017]; Groen et al. [Forthcoming]). These studies all conclude that the average net financial impact of a large natural disaster is modest and short-lived. None explore the causal role that federal disaster assistance has on post-disaster outcomes.

There are two goals of this study. First, we document the impact of being directly hit by a devastating tornado on household finance and business survival. We study 34 very large US tornadoes that occurred from 2002-2013. The tornadoes cause uninsured property damage and act as unexpected, one-time shocks to wealth and capital. The tornadoes may also lead to lost income if business operations are interrupted or if individuals are displaced. We use credit bureau data to estimate the causal effect of residing in a block with a specific level of tornado damage on post-disaster financial outcomes. We examine the impact on business survival and employment using a proprietary establishment-level database.

The geographic randomness in tornado damage provides identification in our difference-in-differences style (including triple difference and event study) econometric models. We precisely control for block-level damage intensity using detailed damage maps and estimate how outcomes differ for individuals and business in hit blocks to those located in nearby blocks just outside the tornado path.

Figure 1 shows the damage map for an Enhanced Fujita 5 (EF5) tornado that hit Joplin, Missouri on May 22, 2011. The EF ratings are determined by National Weather Service (NWS) employees who conduct on the ground damage inspections. The NWS damage analysis carefully considers the type of structure and building materials, and the local building codes (Edwards et al. [2013]). This guards against the possibility of the tornado damage being overrated due to, for example, damage to pre-fabricated homes.

We find that individuals hit by a tornado have a modest overall post-disaster *reduction* in personal debt. A resident located in a hit block that sustains the average level of damage has approximately 4% lower credit card balances and a 2% reduction in home debt. The estimated impact on the Equifax Risk Score and bill delinquency are economically small in magnitude and statistically insignificant.

Business establishments are vulnerable to natural disasters. Basker and Miranda [2017] estimate a 30 percentage point decrease in the survival rate of businesses damaged by a severe hurricane, relative to those not damaged. FEMA claims that almost 40% of small businesses close after a flood-related natural disaster (FEMA [2019]). We provide, to our knowledge, the first causal evidence on establishment survival from being in the damage path of a very large tornado. Overall, there are fewer business establishments in hit blocks in the four years following the disaster. Establishment closings are highest in severely damaged blocks, where the business survival rate declines by 10% and employment by 21%. To our surprise, the business survival rate is slightly higher in low damaged blocks, relative to nearby non-damaged blocks.

The vast majority of the nascent literature that uses natural disasters as a wealth (or income) shock to study household finance and business outcomes examines the impact from hurricanes and flooding.[1] There are several advantages of using tornadoes as a source of exogenous damage. First, the exact tornado path is completely random. There are areas of the US where tornadoes are prevalent such as the Great Plains. However, it is not possible to predict the exact path of a tornado (e.g. FEMA [2007]). The randomness in the location of a tornado is in sharp contrast to flooding, where flood maps and land characteristics, such as proximity to the ocean, are predictors of property-level flooding (e.g. First Street Foundation [2021]). Second, the tornado location randomness effectively eliminates the ability for individuals and businesses to sort locally based on disaster risk. Disaster risk sorting complicates analyses in other settings such as flooding (e.g. Bakkensen and Barrage [2021]). Third, the tornado location randomness also minimizes the scope for individuals and businesses to use disaster risk information to differentially invest in protective actions such as more durable housing designs and precautionary savings. Measuring the causal impact of a natural disaster is more challenging when victims and non-victims are likely to have different levels of (difficult to observe) protective investments (e.g. Barreca et al. [2016]).

The second goal of this study is to provide insight into how federal disaster assistance

[1] Hurricane and flooding household finance studies include: Billings et al. [2019]; Del Valle et al. [2019]; Deryugina et al. [2018]; Gallagher and Hartley [2017]; Groen et al. [Forthcoming]. Hurricane and flooding business survival studies include: Basker and Miranda [2017]; Collier et al. [2020].

cash grants affect post-disaster outcomes. Our estimates using credit bureau measures for the financial impact of tornadoes imply that individual-level financial outcomes slightly *improve* when a tornado damages your residence. This is consistent with the recent research on flooding (Deryugina et al. [2018]; Gallagher and Hartley [2017]; Groen et al. [Forthcoming]), and underscores the possibility that federal disaster assistance may play an important role in mitigating the negative impact of a natural disaster.[2]

The federal disaster cash assistance program we study is called Individual Assistance. Under Individual Assistance, residents in disaster areas can receive cash grants up to approximately $30,000 (Fed [2010]). The cash grants are linked to incurred damage and expenses caused by the disaster. We test whether cash grants substitute for personal debt and lead to a decrease in the level of debt incurred by disaster victims. We also test whether cash grants reduce the likelihood of negative financial outcomes such as bill delinquency. For example, disaster-related expenses may increase bill delinquency for credit-constrained individuals who are less able to borrow.

The cash grant program is a place-based policy. Cash assistance is provided to individuals, but the distribution of cash assistance is concentrated in the most-damaged neighborhoods by design. We examine business outcomes because we hypothesize that the cash grants act as a targeted stimulus to local businesses. Specifically, we test whether, following the disaster, there is less of a reduction in the number of business establishments and employees in disaster-affected neighborhoods where individuals receive cash grants. The cash grants to individuals could lead to improved local establishment survival rates if there is an increase in spending on local goods and services. The cash grants that go to individuals who happen to be small business owners could also help keep businesses open.

Cash assistance is not provided to individuals in disaster areas following all tornadoes. This facilitates a comparison between individuals (and businesses) located in blocks that suffer the same level of damage, but where cash assistance is provided only to victims of some tornadoes and not to victims of other tornadoes. However, the disaster-level endogeneity of whether cash assistance is made available also provides two related identification challenges. First, cash assistance is more likely to be made available when areas with more vulnerable populations are affected. Second, there are multiple federal disaster assistance programs and the provision of disaster assistance under each program tends to be correlated.

We approach the first identification challenge by estimating a triple difference econometric model. We examine the pre- to post-tornado difference in financial outcomes for hit and

[2]Gregory [2017], in related work, evaluates the impact of a congressionally approved, supplemental disaster housing grant program on the rebuilding and migration decisions of New Orleans residents following Hurricane Katrina.

nearby populations who are affected by tornadoes with and without federal cash assistance ("cash tornadoes" and "no-cash tornadoes", respectively). Differencing with the nearby non-hit groups leverages the randomness of the tornado path, and provides a way of controlling for both divergent pre-existing trends and differing levels in key financial variables among the two groups hit by a tornado.

The second identification challenge is more difficult to definitively address given the available public assistance data. In our view, the spatial pattern of disaster assistance, combined with our estimation results, is most consistent with cash assistance as the underlying mechanism. Still, we can not completely rule out that payments from other federal disaster assistance programs contribute to our findings.

We find that disaster-affected individuals in high damage blocks with access to cash grants have \$774 (30%) less in average quarterly credit card debt after the disaster relative to disaster-affected individuals without access to cash grants. Access to credit markets impacts how tornado victims substitute cash grants for credit card debt. Consistent with the life cycle/permanent income hypothesis, nearly all of the reduction in credit card debt is attributable to less credit-constrained individuals. Immediate cash assistance following a disaster appears to reduce the financial hardship for more vulnerable individuals who are less able to smooth the financial shock. Credit-constrained individuals who have access to cash grants have lower rates of bill delinquency and are more likely to increase consumption on new vehicle purchases.

We estimate that there are approximately 9% more establishments and 13% more employees in blocks that sustain the average level of tornado damage in our sample when residents in the neighborhood have access to cash assistance. The increase in the number of establishments is due to a higher survival rate for existing non-manufacturing establishments. There is no evidence that the cash grants affect the formation of new establishments. Overall, our business results indicate a mechanism whereby the cash stimulus to the local population most benefits businesses that rely on local demand. We estimate that the cost per job retained or created in the disaster areas (provided cash assistance is the primary mechanism) is approximately \$75 thousand.

2 Background and Data

This section describes our main data sources and summarizes the institutional background. Additional details are available in Appendix Section 1.3.

2.1 Tornado Data

There are 34 tornadoes in our sample. To form our sample we start with the list of tornadoes compiled by the Tornado History Project. The main source of the Tornado History Project information is the Storm Prediction Center's historical tornado data file. The Storm Prediction Center is part of the National Weather Service and the National Centers for Environmental Prediction. We use tornado cost, casualty, and maximum intensity information from the Tornado History Project.

Three criteria determine whether a tornado is included in our sample. First, the tornado occurs from 2002-2013 so as to match the period covered by our individual and business financial data. Second, the tornado must have a Fujita (F) or Enhanced Fujita (EF) rating of either a 4 or 5.[3] Third, the tornado must have a high quality damage path map, generally created by the National Weather Service (NWS), that demarcates areas of the tornado path that suffered different levels of damage. Appendix Section 1.1 provides details on how the NWS creates the damage maps using on the ground observations and a detailed engineering model that takes into account the strength of the damaged materials and local building codes. Thirty-five tornadoes satisfy the three criteria. Our sample includes 34 tornadoes, as one tornado violates the pre-trend assumption of our sample design. We provide more details when we discuss the econometric model in Section 3. Appendix Table 1 lists all 35 tornadoes.

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 PDD opens the door to three major types of assistance. The first type is Individual Assistance and is the source of the cash grants we study in this paper. There are two steps to qualify for cash grants. First, Individual Assistance must be available to disaster-affected residents in the county. Second, the exact level of assistance is determined via an application that documents incurred damage (e.g. structural damage to the home) and expenses (e.g. temporary housing and relocation) caused by the disaster. The maximum amount of cash assistance was $30,200 in 2010 and is indexed to inflation (Fed [2010]).

In order to receive cash assistance, an individual usually must first apply for a Small Business Administration (SBA) disaster loan. Individuals who are denied SBA loans are then eligible for cash assistance. Low income individuals are automatically eligible (e.g. Collier and Ellis [2021]). Cash grants are provided based on disaster-related costs not also

[3] Tornado classification 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.

covered by a SBA loan. Many SBA loan applicants are not approved based on past credit and expected repayment ability (e.g. Billings et al. [2019]). Cash grants, when available, are awarded over and above that provided by SBA loans.

SBA disaster loans are available in 99% of the hit blocks in our sample (regardless of cash tornado classification). Overall, the amount of SBA loan assistance provided to individuals located in hit blocks in our sample is very similar between cash and no cash tornadoes. $1.3 million in SBA home loans, on average, are approved for a cash tornado, while $1.4 million are approved for a no cash tornado. The average per-capita amount of approved loans is $297 for a cash tornado and $344 for a no cash tornado (see Appendix Table 4).

Individual Assistance is not declared for all disasters. There is no single minimum eligibility threshold or guideline that must be met in order for FEMA to approve Individual Assistance as part of a PDD. Instead, FEMA is required to consider six criteria (GAO [2018]). The criteria are: concentration of damages, trauma (e.g. casualties and deaths), special populations (e.g. low-income and elderly), voluntary agency assistance (e.g. non-profit, local, and state capacity), access to insurance for the affected population, and the average past amount of Individual Assistance by state. The multiple criteria and lack of numerical thresholds have contributed to the "subjective nature" of Individual Assistance approval following a disaster (GAO [2018], p22).

Appendix Table 2 provides summary information for the tornadoes in our sample. Twenty-five tornadoes are part of disaster declarations where individuals received cash grants. Tornadoes with cash assistance are part of larger state-level disasters as measured by the percent of the state's counties included in the PDD. Cash assistance tornadoes also tend to cause more block-level damage. FEMA's trauma criteria appears to influence whether cash assistance is made available, as the average number of fatalities and casualties are both larger for cash tornadoes. There is no evidence that tornadoes with cash assistance occur in more electorally competitive states. The difference in the overall damage between cash and no-cash tornadoes motivates our econometric models that control for block-level damage.

We obtained information on all cash grants distributed under the Individual Assistance program via a Freedom of Information Act (FOIA) request. Due to privacy considerations, we are only able to access summary cash grant information at the 5 digit ZIP Code level. For this reason, we do not estimate a model that uses the block-level magnitude of cash assistance. Rather, we use these data to confirm that the distribution of cash grants paid out coincides with the tornado path, and as part of a cost per job calculation in Section 6.

ZIP Codes are spatially much larger than blocks in our sample. Even for the largest tornadoes, only a small fraction of a ZIP Code is directly hit (see Appendix Figure 1). At the same time, individuals living outside the tornado path are eligible for cash assistance to cover less severe damage from the storm system that spawned the tornado. As such, the ZIP Code-level cash assistance data obscure the fact that individuals hit by the tornado, and especially those living in highly damaged blocks, receive much higher levels of cash assistance than the average grant recipient.

Public Assistance is the third type of disaster assistance. Public Assistance is available to local and state governments as well as non-profit organizations located in a PDD county. These groups can access grant money to repair infrastructure and to aid in the reconstruction of public buildings. Public Assistance is provided for 22 of the 25 cash tornadoes and 3 of 9 no-cash tornadoes in our main sample.

We interpret the estimated impact of being hit by a cash tornado on household finance and business establishments as due to the cash grants. We can not rule out the possibility that other sources of disaster assistance contribute to our findings. However, the levels and geography of disaster assistance, combined with the pattern of our results, shape our view that cash assistance is the primary mechanism driving our findings. We provide a detailed discussion in Section 6.

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. The panel is quarterly and 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. To form our sample, we take the individuals living in the treatment and control blocks at the end of the quarter before the tornado and set a balanced panel that runs from 12 quarters prior to the quarter of the tornado through 12 quarters after the quarter of the tornado. We can track all individuals even if they move away from the tornado-affected area or were living elsewhere for some portion of the pre-tornado period using anonymous individual identifiers.

Consumer credit account information is divided into five main types: home loans, auto loans, credit card accounts, student loans, and other debt. Home loan information separately tracks first mortgages, home equity loans, and home equity lines of credit. Credit cards include both bank and retail cards. We do not consider student loan debt because the way in which the data are recorded changed during our study period (Brown et al. [2014]). A significant component of other debt (81% of other debt accounts) are consumer finance loans, which are a type of subprime loan typically used by borrowers with lower credit scores. We follow Lee and van der Klaauw [2010] and group consumer finance loans as part of other debt, in part, due to the relatively low consumer finance loan balances. The CCP includes the number of accounts for each debt, the total balance, indicators for whether the individual is behind on payment for each type of debt, and an indicator for foreclosure. The panel also includes the age, Census block of residence, and Equifax Risk Score (TM) for each individual. The Equifax Risk Score is a composite score that represents overall financial risk.

Appendix Table 3 shows financial and socioeconomic information for individuals in our sample. Overall, individuals hit by a tornado are similar to those in nearby neighborhoods outside the tornado path (columns 1 and 2). The CCP financial health measures (Equifax Risk Score, fraction with an account that is 90 days past due, and an indicator for a recent foreclosure) are nearly identical in the quarter before a tornado. US Census Block Group-level economic data show that hit and nearby individuals both live in areas where the median income is $50,000 and the median home value is $103,000. However, individuals hit by tornadoes where cash assistance is available are economically worse off than individuals hit by tornadoes where cash assistance is not available (columns 4 and 7). The economic information in the table is consistent with FEMA using the economic status as part of the calculation when deciding to award cash assistance (McCarthy [2011]).

2.4 Business Data

We use business establishment data from the Infogroup's Historic Business Database (Serrato and Zidar [2016]). The Infogroup database aims to include longitudinal establishment-level data on all business establishments in the US. The database covers approximately 35 million establishments each year for the years 1997 to 2017. The database includes each establishment's exact location (latitude/longitude or address), start date, number of employees, sales volume in dollars, detailed six-digit industry code, and corporate linkages. The appendix contains details on how Infogroup compiles this information.

Our unit of analysis is the census block. We aggregate the establishment-level data to the census block, and match the block-level establishment data with the tornado blocks.[4] On average, there are 2.1 establishments in hit blocks where individuals receive cash assistance, and 3.0 establishments in hit blocks where individuals do not receive cash assistance (see Appendix Table 3). The percent of employment at manufacturing establishments is similar in areas hit by cash and no-cash tornadoes (5% and 4%, respectively).

[4]The database contains identifiers that would allow us to estimate an establishment-level model. We prefer the block-level analysis because it matches the level of treatment variation (tornado damage), and because it allows us to fix the geography and focus on the neighborhood economic recovery within a small geographic unit. The block-level analysis also allows us to look at entry and exit of establishments in a natural way.

3 Empirical Specification

The sample of hit Census blocks includes all Census blocks that are more than 50% contained in a tornado damage path. The control blocks are selected drawing a 0.5 mile buffer and a 1.5 mile buffer around each tornado path and taking the set of Census blocks that are more than 50% contained in the band between the buffer lines. The average hit block sustains EF 1.8 of damage. We exclude the half mile closest to the edge of the tornado path in case there is measurement error in the tornado map boundaries. Results are similar if we use 0.5-1.0 and 0.5-2.0 buffer areas.[5]

Our baseline empirical specification, Equation 1, is a heterogeneous damage difference-in-differences (DD) model that controls for block-level tornado damage (e.g. Gallagher and Hartley [2017]). The exact path of a tornado is not predictable and this randomness provides a source of identification. We first describe the specification that we use to examine individual financial outcomes.

$$y_{i,t} = \delta(Hit_i * Post_{i,t}) + \beta_1(Post_{i,t}) + \alpha_i + \gamma_t + \epsilon_{i,t} \tag{1}$$

$y_{i,t}$ is a credit outcome for individual i in quarter t. Hit_i is a continuous damage variable measuring the average EF damage in the block. $Post_{i,t}$ is a binary variable indicating the post-tornado period (any of the 12 quarters following the quarter of the tornado). δ is our coefficient of interest and represents the effect on credit outcomes for individuals living in hit blocks relative to those individuals who just missed being hit by the tornado. α_i is an individual fixed effect, γ_t is a quarter-by-year fixed effect, and $\epsilon_{i,t}$ is an error term. Note that the non-interacted Hit_i variable is subsumed by the individual fixed effects. We cluster the standard errors by tornado.

We use a triple difference model, Equation 2, to examine the role of cash grants on post-disaster outcomes. The triple difference model augments Equation 1 by including $Cash_i$, a binary variable indicating whether individual i lived in an area either hit by or near a tornado that received cash assistance.[6] ρ is our coefficient of interest and represents the effect on credit outcomes for individuals living in hit blocks where cash assistance is available following a tornado, relative to those individuals who just missed being hit by the tornado, and as

[5]Results are also similar if we use a propensity score model to select non-hit individuals from control blocks anywhere within the same county as the tornado.

[6]The variables $Cash_i$, Hit_i, and the interaction $Cash_i * Hit_i$ are excluded from the model due to the individual fixed effects.

compared to individuals living in hit blocks with no cash assistance.

$$y_{i,t} = \rho(Cash_i * Hit_i * Post_{i,t}) + \beta_1(Cash_i * Post_{i,t}) + \beta_2(Hit_i * Post_{i,t}) + \beta_3(Post_{i,t}) + \alpha_i + \gamma_t + \epsilon_{i,t} \tag{2}$$

The triple difference estimate can be thought of as taking the difference between two DD estimates, where we separately estimate the effect of being hit by a tornado that does and does not result in post-disaster cash assistance. The within tornado difference between the hit and nearby populations controls for selection differences between victims of cash and no-cash tornadoes. Our strategy is similar to Deschenes et al. [2017] who use a triple difference model to control for state-level selection into a voluntary air pollution program.

Figure 2 provides an illustrative example for how the triple difference model makes identification of cash assistance more robust. The figure plots the mean credit card debt levels separately for the hit and nearby individuals for cash and no-cash tornadoes. The means are plotted with respect to the number of quarters since the tornado. It would be wrong to simply compare the hit areas for the tornadoes where victims did and did not receive cash assistance. Doing so would lead to a biased estimate for the causal effect of cash assistance due to the downward trend in credit card balances in hit areas that receive cash assistance. Differencing with the nearby groups provides a way of controlling for divergent pre-existing trends among the two groups hit by a tornado.

We also estimate a binned damage specification for both Equation 1 and Equation 2. In the binned damage specifications we replace Hit_i with a vector of three binary variables indicating low, medium, or high damage. The advantage of this model over the continuous damage model is that it allows for non-linearities in how individuals respond to disaster damage and cash assistance. We classify the block as *low* damage if the mean EF is less than 1, *medium* damage if the mean EF is greater than or equal to 1 but less than 3, and *high* damage if the mean EF is 3 or higher. A damage level of 3 on the original Fujita scale corresponds to "severe damage" (National Weather Service [2014]). A damage level of 3 on the Enhanced Fujita scale implies that the roofs for most types of buildings will be severely damaged and the outer walls of the building may have collapsed. The EF damage analysis is comprehensive and carefully considers the type of structure, the type of building materials, and the local building codes (Edwards et al. [2013]).

Finally, we estimate event study versions of the continuous damage models which allow us to observe temporal dynamics and to examine differences in pre-existing time trends. When we estimate the event study model we replace the $Post_{i,t}$ variable with a set of binary variables that indicate the number of years the observation is either before or after the tornado. The year before the tornado is excluded from the model and serves as the reference time period. We drop the quarter of the tornado from the panel before running the model.[7]

When we consider business outcomes we use a block-by-year panel. The panel is balanced in event time with four years before and after the year of a tornado. We drop the year of the tornado from our panel, since we are not always able to confirm whether the tornado-year business data are collected before or after the tornado. In place of individual and quarter-by-year fixed effects we use block and year fixed effects.

The three tornado and tornado-mapping criteria discussed in Section 2.1 give us a sample of 35 tornadoes. Our preferred sample includes 34 tornadoes. One of the tornadoes, the Wayne, NE tornado, exhibits pretrends for our business outcomes (see Appendix Figure 3). We drop this tornado from our preferred sample. There is little difference between the two samples for the individual financial outcomes. Not surprisingly, there are some differences in the business results. We highlight these differences in the discussion of the results.

Finally, we test the sensitivity of our main estimates by estimating a robustness subsample that more closely matches the average *levels* of key debt and financial health variables for the hit cash and hit no-cash groups. A potential concern is that differences in the levels of the dependent variables between individuals hit by cash and no-cash tornadoes could bias our estimate if there is heterogeneity in the cash grant treatment effect. We set the robustness sample, which we refer to as the "balanced sample," using two steps. First, the balanced sample includes all individuals from the nine no-cash tornadoes in our main sample. Second, the balanced sample includes observations from nine of the 25 cash tornadoes. The underlying logic is that we could consider our main sample as a collection of random tornado events. We select a robustness sample, balanced in the number of tornadoes, that best matches the levels of the key CCP variables at the time of the tornado between hit individuals in the cash and no-cash tornado groups. Specifically, we minimize the sum of the absolute deviations in z-scores for the eight debt and financial health variables in Appendix Table 3. There are 2,042,975 possible subsamples.

4 Overall Tornado Results

In this section, we present evidence on the impact of being hit by a tornado relative to being located in a nearby undamaged block.

[7] We prefer the yearly event study model to the quarterly model. The estimated pattern of the yearly coefficients is more informative. First, pooling the quarterly data increases the statistical precision. Second, our financial distress outcomes are low incidence outcomes, and estimating yearly coefficients smooths out the high quarter-to-quarter variance. Finally, the yearly dynamics match the business establishment panel and help to facilitate an easier comparison between individual and establishment-level outcomes.

4.1 Household Finance

Table 1 shows estimates for four debt categories and two measures of financial distress using our DD model (Equation 1).[8] Overall, individuals hit by a tornado have a modest reduction in post-disaster debt. Table 1 panel A shows DD coefficient estimates from our continuous damage model. Individuals located in a hit block that sustains the average level of damage (EF 1.8) have approximately 4% lower ($104) in average quarterly credit card balances (probability value 0.089) for the three years following the disaster.[9] Total home debt decreases by $1,213 (2%, probability value 0.022) for a homeowner in a block with average damage who has a home loan continuously during the 12 quarters before the tornado. Auto debt increases by $122 (4%, probability value 0.030). In results not shown, the increase in auto debt is attributable to an increase in new auto purchases. We discuss new auto purchases in detail in Section 5.2.3. There is no change in other debt. The binned damage model estimates in panel B are less precise, but show the same pattern of results.

There is no evidence that being hit by a tornado affects overall financial health. The point estimates for a change in the Equifax Risk Score and the change in the number of individuals with a 90 day delinquent account are close to zero and economically small. Using the 95% confidence intervals we can rule out an effect of just over one half of a point in the Equifax Risk Score and a 1.5% change in the number of individuals with a 90 day delinquent account.

Figure 3 plots difference-in-differences event study estimates. The yearly point estimates for each outcome are marked by squares. The vertical lines with the hash marks represent the 95% confidence interval. The estimates are relative to the year before the tornado. The vertical red line indicates the quarter of the tornado (which is dropped from the sample). There is no evidence of any pre-tornado trends. The post-disaster coefficients show that the decrease in home debt and the increase in auto debt are both driven by the effect in the first year following a tornado. The impact on credit card debt is more persistent. The estimated coefficients are statistically significantly lower for the first two post-tornado years.

To summarize, we find that debt slightly deceases post-disaster, while there is no change in two key measure of financial distress. There are two important caveats worth highlighting. First, the credit bureau data show a comprehensive picture of debt, but do not include direct measures of savings. A reduction in debt could be more than offset by a draw down in savings,

[8] Student debt is the only major CCP debt category we don't evaluate. This is due to a change in how these data are recorded during our study period (Brown et al. [2014]). The CCP data also include a quarterly foreclosure variable that indicates whether an individual had a foreclosure in the past seven years. However, the fact that new quarterly foreclosures are not very common prevents us from examining foreclosure rates. The Appendix provides a detailed discussion.

[9] Credit card debt in the CCP is measured at a point in time which means that we cannot distinguish individuals that rollover credit card debt from one month to the next and incur interest charges from those that pay their balance in full each month and do not incur interest charges.

or the destruction of physical property. Still, one advantage of our setting is that individuals in our sample are unable to use disaster risk information to differentially invest in protective actions. Thus, there is no reason to expect that individuals inside the tornado path would have preemptively invested in more durable housing or precautionary savings. Second, the credit bureau data do not cover the entire population. Lower income individuals who are more vulnerable to the disaster shock are less-likely to have a credit history (e.g. Jacob and Schneider [2006]). Our analysis in Section 5 partially addresses this shortcoming by separately examining the disaster impact on individuals who have lower and higher Equifax Credit Scores at the time of a tornado.

4.2 Local Businesses

Table 2 shows DD model estimates for the effect of a tornado on the number of establishments, level of employment, and level of sales. We emphasize the establishment survival results as these data do not rely on a survey response. The employment and sales data are self-reported and more likely to involve measurement error. Nevertheless, the three sets of results tell a similar story.

Overall, there are fewer business establishments in hit blocks in the four years following the disaster. The continuous damage model implies that the number of establishments decreases by around 3% (probability value 0.000) in blocks that sustain the average (EF 1.8) amount of damage. Establishment closings are highest in severely damaged blocks, where the business survival rate declines by 10% (probability value 0.000). To our surprise, the business survival rate is 4.4% higher (probability value 0.004) in low damaged blocks.

The employment and sales findings mirror the survival results. Our continuous model estimates imply that employment and sales decrease by 6% (probability value 0.000) and 19% (probability value 0.000), respectively. The binned model employment and sales estimates follow the same pattern as establishment survival. The point estimates are positive in the low damage blocks, negative in the medium damage blocks, and most negative in the high damage blocks. All coefficients are statistically significant at conventional significance levels.

Figure 4 plots difference-in-differences event study estimates for the log number of establishments (panel A), log employment (panel B), and log sales (panel C). There is no evidence of any pre-tornado trends. The post-disaster coefficients show that the decrease in establishment survival and employment begin in the first year following a tornado (zero lies just inside the number of establishments confidence interval). The coefficients are negative, statistically significant, and fairly stable in years 2-4 following a tornado for each outcome.

5 Cash Tornado Results

In this section, we separately estimate the effect of being hit by cash and no-cash tornadoes (Equation 2) on household finance and business survival.

5.1 Household Finance

Most economic theories of consumption, including the life cycle/permanent income hypothesis (LCPIH), predict that disaster victims will borrow (or use savings) to intertemporally smooth the effect of a temporary, unexpected wealth shock (e.g. Meghir and Pistaferri [2011]). There will be a relatively small reduction in consumption. Disaster victims who receive cash grants will borrow less and consume (slightly) more than victims who do not receive cash grants. Provided individuals are not credit constrained, the LCPIH predicts that the receipt of the cash will have only a limited effect on measures of financial wellbeing. Our household finance results largely confirm these predictions.

Credit card debt is a common type of short-term debt that victims of tornadoes could use to smooth a financial shock. Table 3 panel A column 1 shows that overall there is a statistically insignificant reduction in the average quarterly credit card balances for victims of cash tornadoes. However, residents in high damage blocks show an economically large ($774) and statistically significant reduction in credit card debt (probability value 0.017). For people facing credit constraints, receiving a cash grant will likely need to be used to smooth the shock of the disaster, possibly helping to avoid financial distress. We find that the reduction in credit card debt is due to less credit-constrained individuals reducing their debt levels. More credit-constrained individuals hit by cash tornadoes do not reduce credit card balances, but they do become less likely to be delinquent (see Section 5.1.1).

Total home debt decreases by $3,922 (6%) in the continuous damage model (probability value 0.001) for the typical victim who has a home loan continuously in the 12 quarters before the tornado.[10] The reduction is much larger for individuals in severely damaged blocks who, on average, reduce their mortgage debt by about $19,000 (probability value 0.000).

Difference-in-differences (DD) results for the debt outcomes are presented separately for cash and no-cash tornadoes in Appendix Table 5. There is a reduction in home debt for homeowners hit by tornadoes with grants in the high damage blocks (-$2,697, probability value 0.021). However, an increase in home debt for homeowners hit by tornadoes without cash assistance ($19,308, probability value 0.000) is driving the triple difference result. The DD model estimates help to highlight that the impact of the cash grants estimated in our triple difference model is coming from *a drop in* debt for those disaster victims with access to cash grants, and *an increase in* debt for those disaster victims without access to grants.

[10] Calculated as -$2,179 (panel A column 2) multiplied by 1.8 (average block damage).

We also estimate two additional descriptive DD models so as to better understand what explains the reduction in mortgage debt for hit residents with access to cash grants (Appendix Table 7). First, we estimate the same DD model as above, except that we separately consider hit residents who either move from or stay in the same block following the tornado. The increase in home debt is larger for residents without access to cash grants who move rather than stay. The reduction in home debt is similar for victims of cash tornadoes regardless of whether they move. Second, we estimate a model that separately considers mortgage and home equity debt. The increase in home debt for victims of no-cash tornadoes is due to an increase in first mortgage debt. These results suggest that when residents hit by no-cash tornadoes move, they purchase new homes and dramatically increase their mortgage debt (relative to cash tornado victims). However, we are cautious in our interpretation as we do not have an economic model that links migration and home debt.

Figure 5 plots yearly triple difference event study estimates for the debt outcomes using the continuous model (panels A-D). There is no evidence of any pre-tornado trend for credit card, home, and auto debt. The immediate and persistent reduction in home debt is consistent with the triple difference result in Table 3 column 2 panel A. While the pre-period triple difference estimates for other debt are not statistically distinguishable from zero, there is a hint of a pre-trend in the point estimates. We do not regard this as evidence against our empirical design, since it can be attributed to testing multiple outcomes and sample variation in the hit group for the no cash tornadoes.

Table 3 columns 4-5 show model estimates for the Equifax Risk Score and 90 day delinquency, two measures of financial health. Overall, the effect on credit score and 90-day delinquency are economically small and statistically insignificant. The exception is for victims in medium damage blocks. Access to cash assistance leads to a 25% decrease (probability value 0.006) in the likelihood of having at least one credit account that is 90 or more days delinquent, and an 1.2% (probability value 0.041) increase in the Equifax Risk Score.

Figure 5 shows the triple difference event study analysis for the financial health measures in panels E and F. There is no evidence of any difference in the pre-tornado trends between individuals hit by cash and no-cash tornadoes. The most striking finding is the reduction in the likelihood of having an account that is 90 days delinquent beginning one year after the tornado. The continuous damage triple difference model masked this delayed effect. The delay could be partially mechanical. 90 day delinquency is an outcome measured with a time lag. The delay may also reflect the fact that the worst financial impacts accumulate over time. In Section 5.1.1 we show that the decrease in delinquency rates is completely attributable to more credit constrained individuals.

5.1.1 Heterogeneity by Access to Credit Markets

The LCPIH provides three predictions, based on access to credit markets, for how cash grants affect the finances of disaster victims (e.g. Meghir and Pistaferri [2011]). First, less credit-constrained individuals will reduce their post-disaster debt by more than those who are credit-constrained. The reason is that credit-constrained individuals are largely shut out of credit markets, and there is little opportunity to substitute the grants for forgone borrowing. Second, the impact that cash grants have on preventing financial distress will be greater for credit-constrained victims. The grants are more likely to be pivotal in preventing financial distress for victims with a limited ability to borrow. Third, the cash grants will lead to higher (immediate) post-disaster consumption for credit-constrained individuals. Victims with limited access to credit markets will rely more on reduced spending as a means to manage the financial shock when cash grants are not available.

The effect of the cash grants may also differ by the age of the tornado victim. Younger tornado victims are likely to have less accumulated savings (e.g. Attanasio [1998]) and may need to rely more on new debt. At the same time, younger residents may be more willing to borrow, since the cost of borrowing can be smoothed over a greater number of future time periods.

Table 4 explores how cash grants impact debt and financial health based on the likelihood a victim is credit constrained, and by age. We consider two proxies for whether an individual is credit constrained: Equifax Risk Score and available credit. We define available credit as the difference between total credit card debt and the total credit card debt limit. We separately divide our sample into thirds based on age, Equifax Risk Score, and available credit, and compare outcomes for the lowest third to the highest third using the continuous damage model (Gelman and Park [2008]; Parker et al. [2013]).

Cash grants lead to a larger reduction in credit card debt for less credit-constrained tornado victims. Individuals in severely damaged blocks who have high available credit at the time of the tornado reduce their quarterly credit card debt by $904 (calculated as the product of -$226 and EF damage level 4). We estimate an economically small decrease of $8 for those with low available credit. The coefficients are statistically different at the 0.000 probability level. Cash grants lead younger individuals to reduce their credit card debt by more than older individuals, but the point estimates are too imprecise to reject the null hypothesis that the estimates are equivalent.

Credit constrained individuals with access to cash grants are less likely to forgo paying a bill. A hit resident with a low credit score is 14% less likely (probability value 0.000) to have a 90 day delinquency (calculated as -0.042 times 1.8 divided by 0.525). There is no effect on tornado victims who are less credit constrained. The difference between the estimated effects on delinquency rates for low and high credit constrained tornado victims is statistically significant using both our available credit and credit score proxies.[11]

5.1.2 Robustness

We show robustness analysis for our triple difference model for each of our household finance outcomes in the appendix (Appendix Tables 14 - 17 and Appendix Figures 7 - 8). We estimate two alternative samples for each outcome. First, we show results from the balanced tornado sample. Second, we estimate the model on the full sample that includes the Wayne, NE tornado that is dropped from our preferred sample due to differing pre-trends. Overall, the estimates are qualitatively similar to our main sample. We limit our discussion in the text to a short summary of the balanced tornado sample.

The mean levels of the CCP and Census variables for the hit groups in the balanced tornado sample are much more similar, as compared to in the main sample (see Appendix Table 13). Individuals hit by cash and no-cash tornadoes have identical pre-tornado Equifax Risk Scores. The balanced sample model estimates are less precise, but suggest that there is limited heterogeneity in the response to cash assistance. The most striking differences between the balanced sample and our preferred model are that the estimates for the reduction in home debt and the increase in the propensity to migrate are both larger in the balanced sample, while the reduction in credit card debt is smaller. Our heterogeneity estimates show that the larger reduction in home debt is partially due to larger reductions for older and low credit score individuals. Still, all of the point estimates from our main sample are within the balanced sample confidence intervals.

5.2 Local Businesses

Federal cash grant assistance to individuals can aid local businesses in two important ways. First, when tornado-affected individuals receive cash assistance a portion is spent locally increasing revenues for local establishments. Damaged business establishments may disproportionately benefit from the increased demand for their goods and services following a disaster, relative to nearby undamaged establishments.[12] Second, cash assistance to individ-

[11] Our results are supported by Del Valle et al. [2019] who find that high-quality borrowers are more likely to have new credit card originations after flooding from Hurricane Harvey. Billings et al. [2019] find that financially constrained flooded residents have higher personal bankruptcy rates following Hurricane Harvey. Tran and Sheldon [2017] examine credit outcomes for individuals in declared disaster counties and find that those individuals residing in counties where Individual Assistance (cash grants) was available show few negative impacts.

[12] Recall that identification in our model comes from taking the difference between establishment outcomes in damaged blocks inside the tornado path and in the undamaged buffer blocks. There are at least two underlying mechanisms consistent with the higher business demand channel. First, our model will estimate (a lower bound) on the role of the cash grants provided that individuals spend a higher fraction of the grant money at locally damaged businesses as compared to establishments farther away. Second, even if residents

uals that happen to be small business owners may positively affect establishment outcomes. Many businesses are small. In 2016, 47 percent of establishments employed four or fewer people (SUSB [2018]). The median establishment size in our sample is four. Around half of all establishments are operated out of a home.[13]

5.2.1 Business Growth and Employment

We explore the effect of cash assistance on the number of establishments and the level of employment. Figure 6 shows the trends in the number of establishments and employees for establishments located in a hit Census block at the time of a tornado, and for establishments nearby, but outside the tornado path. The figure plots residual means from a regression of block-level establishment outcomes on year dummy variables. The horizontal axis shows tornado event time. The trends are plotted relative to when the tornado occurred. The vertical line at -1 indicates the last year before the tornado, while points to the right of the vertical line are years after the tornado.

The left side of Figure 6 plots the trends separately for tornadoes where affected residents were able to access cash grants (circles) and where no cash grants were distributed (triangles). Three facts emerge. First, trends for the two outcomes in the years leading up to a tornado are roughly parallel for the hit and nearby establishments affected by a tornado where no cash grants were distributed (dashed lines). The same is true for hit and nearby establishments of cash tornadoes (solid lines). Second, the trends in establishment outcomes are increasing slightly in areas that are later hit by a cash tornado. The trends are flatter for establishments which are later affected by a no-cash tornado. Third, in the four years after a tornado, the trend in the number of establishments and employees is flat for establishments affected by tornadoes where residents received cash grants. During the same post-tornado period there is a reduction in the number of establishments and employees in areas hit by tornadoes where residents did not receive cash assistance. The reduction is greatest in neighborhoods hit by no-cash tornadoes.

The right side of Figure 6 plots the difference in establishment outcomes between blocks hit by and nearby a tornado. This difference is plotted separately for tornadoes where residents did and did not receive cash grants. The triple difference model assumes that in the absence of the grants the difference in outcomes after a tornado would be the same for the two groups. The trends to the left of the vertical line are roughly parallel, providing

who receive cash grants spend the money equally on locally damaged establishments and buffer region establishments, the increased business revenue is likely to be more important for damaged establishments (i.e. higher marginal impact) to, for example, prevent closure.

[13] The SBA reports that 52 percent of all small businesses are home-based (SBA [2012]). The SBA defines a small business as one with fewer than 500 employees. Over 99 percent of businesses have fewer than 500 employees (SUSB [2018]).

evidence for the validity of the key triple difference model identifying assumption.

Table 5 columns (1) and (2) show triple difference estimates of the effect of cash grants on the number of establishments and employment. Establishments in damaged blocks where residents have access to cash grants benefit economically. We estimate that there are 9% more establishments (probability value 0.047) and 12% more employees (probability value 0.095) in blocks with average tornado damage in our sample when cash grants are available to residents. The business survival estimate for medium damage blocks in our binned damage model is 13% (probability value 0.039). This suggests the possibility of a nonlinear response in how cash assistance impacts business survival based on the underlying block damage. However, the three estimates are too imprecise to reject equality in the binned model.

Table 5 columns (3)-(6) show DD model estimates separately for cash and no-cash tornadoes. There are two key patterns in the binned damage level DD model estimates. First, the greater the block-level damage, the worse the establishment outcomes post-tornado. For example, column (3) shows that there is a slight increase (4.7%, probability value 0.002) in the number of establishments located in low damage blocks where there is cash assistance, relative to establishments in the nearby neighborhoods that are not hit by the tornado. In medium damage blocks there is a 6.0% decrease (probability value 0.015) in the number of establishments. The decrease is largest in the most-damaged blocks (-12.7%, probability value 0.000). Second, the reduction in the number of establishments and the level of employment is consistently greater at each damage level for establishments hit by no-cash tornadoes, as compared to establishments and employment in blocks hit by a cash tornado.

5.2.2 Heterogeneity by Industry, Age, and Size

Table 6 presents estimation results from our triple difference continuous damage model that examine how the treatment effects vary by establishment industry, age, and size. The goal is to shed light on how cash assistance to the local population affects business survival and growth.

Panel A of Table 6 estimates the model separately for manufacturing and non-manufacturing establishments. We classify each establishment as manufacturing or non-manufacturing using its two digit SIC. We view manufacturing as a proxy for whether an establishment is likely to rely on a local or non-local consumer base. Manufacturing establishments are more likely to produce goods for consumers outside the local economy. By contrast, non-manufacturing establishments, which include the retail, service, and construction industries, are more likely to rely on local demand.

The positive effect that the cash grants have on the number of establishments and employees is completely attributable to non-manufacturing, local service-driven establishments.

The estimated effect on manufacturing establishments and manufacturing employment is close to zero and not statistically significant. The estimates for non-manufacturing establishments are more than an order of magnitude larger than the manufacturing estimates, and are nearly identical to full sample estimates in Table 5. Appendix Tables 8 and 9 show triple difference estimates for establishments in each of the "1 digit" industries that make up the non-manufacturing category. The largest impacts are observed in the service, construction, and retail sectors. The estimate for public sector employment is small and not statistically different from zero.

Panel B of Table 6 provides evidence that the positive effects on business establishments are due to an improvement in the survival rate of existing businesses, and are not driven by growth in entrepreneurship (new business establishments). We estimate our model separately for establishments in operation for one year or less and for establishments that have been open for at least four years. We estimate a fairly precise zero for new establishments. The effect on existing establishments is positive, an order of magnitude larger, and statistically different from zero (probability value 0.059).

Panel C of Table 6 divides establishments into small and large-sized establishments based on the size distribution in our sample. Roughly one-third of the establishments employ three or fewer employees, while one-third employ greater than seven employees (see Appendix Figure 5). We estimate an increase in the number of establishments of 7.7% (probability value 0.005) and employees of 8.6% (probability value 0.019) at very small establishments at the mean damaged block. The estimates for larger establishments are an order of magnitude smaller, close to zero, and not statistically significant. We interpret the size of establishment results as evidence that smaller establishments are more vulnerable to the economic shock caused by the tornado, and thus benefit more when cash grants are provided to the local population. This finding is consistent with other recent research on the vulnerability of small businesses (e.g. Cole and Sokolyk [2016]; Greenstone et al. [2015]).[14]

5.2.3 New Purchases and Sales

Improvements in establishment survival rates in cash grant tornado-affected areas are driven by small, existing, local service and sales-oriented establishments. Ideally, we would be able to link individual-level purchases (including the home address) with the establishment location of the purchase. We are not aware of any publicly available data that provides this linkage. Instead, we separately show that new vehicle purchases are greater for individuals hit by cash tornadoes, and that sales are larger for local service and sales-oriented establish-

[14] We are not able to provide any insight as to why small businesses are more vulnerable to the economic impact of tornadoes. Possible explanations include lower capital reserves and more difficulty accessing credit markets (e.g. Runyan [2006]; Basker and Miranda [2017]).

ments in these same tornado-affected areas. Large tornadoes often destroy motor vehicles. Auto purchase is a consumption response we can measure using the CCP data. We follow Ganong and Noel [Forthcoming] and use new auto loans as a proxy for new auto purchases. Approximately, 80% of new vehicle purchases use auto loans (Di Maggio et al. [2017]).

New quarterly auto purchases and balances both increase by more than 50% (probability values 0.000 and 0.000, respectively) for individuals in the most-damaged blocks (see Appendix Table 10). The triple difference sales regression results are greater for retail and service establishments located in damaged neighborhoods with cash assistance, and follow the same pattern as the establishment survival estimates in Table 5.[15] Low available credit and low credit score individuals increase their purchases when they have access to cash grants (see Appendix Table 11). These groups are the most credit-constrained, and in the absence of the cash grants, are more likely to reduce consumption. Individuals who are not credit-constrained do not change their consumption based on access to cash assistance.

5.2.4 Robustness

We show business establishment survival and employment regression estimates for the robustness samples in the appendix (Appendix Tables 18 - 21). The balanced tornado sample estimates are very similar to those in our main sample. The coefficient estimates from the 35 tornado sample are somewhat smaller in magnitude. The difference is most stark in the no-cash tornado DD model estimates. When we include the Wayne, NE tornado in the sample (a no-cash tornado) the estimates are much less precise. In our view, the reason for this result is the differing business pre-tornado trends for the Wayne, NE tornado.

6 Discussion

6.1 Cash Grants as the Primary Mechanism

The timing and spatial pattern of the cash grants under the Individual Assistance program supports our interpretation of the cash grants as the primary mechanism driving our cash tornado findings in the previous section. For example, Appendix Figure 1 shows that more than $12 million in cash grants are distributed to the primary ZIP Code hit by the 2011 Joplin, MO tornado. This is an order of magnitude larger than the total amount dispersed to an Adjacent ZIP Code that was also hit, and several orders of magnitude more than all the other surrounding ZIP Codes. The median amount of time between a Presidential Disaster

[15] As discussed in the appendix, the sales data are collected from survey responses at the time Infogroup contacts each establishment which are subject to measurement error that could bias estimates towards zero. However, whether an establishment exists is not based on a survey response.

Declaration and the approval of the first cash grant application in a hit ZIP Code in our sample is just six days.

SBA Disaster loans and Public Assistance are two other federal disaster assistance programs that might also explain (part of) our findings. However, there is little difference in either access to SBA loans, or the dollar amount disbursed to individuals in blocks hit by cash and no cash tornadoes. We believe that the unequal provision of public assistance in our sample does not meaningfully impact the cash tornado findings for two reasons.

First, Public Assistance targets the repair of transportation infrastructure. If Public Assistance facilitates the opening of damaged roadways then this could contribute to greater economic activity in the damaged neighborhood. However, even the most destructive tornadoes tend to only directly hit a small fraction of a community. For example, the 2011 EF5 Joplin, MO tornado is the deadliest US tornado since reliable record keeping began in 1950 (National Weather Service [2018]). Yet the brunt of the tornado hit just 10% of a single ZIP Code (see Appendix Figure 1). Moreover, area roads were immediately serviceable following the tornado. By contrast, severe winds and flooding from Hurricane Katrina in 2005 (the most costly US hurricane) impacted parts of four states, and flooded more than 80% of New Orleans, a city of 450 thousand people (Sills et al. [2008]). Portions of the city were underwater for five weeks. More than $2.4 billion was spent in the six years following Katrina to repair the transportation infrastructure around New Orleans (Lee and Hall [2011]).

Second, Public Assistance can offset the reconstruction cost of public buildings. Public Assistance could lead to higher public sector employment following a tornado if, for example, buildings that employ public sector workers are repaired faster. If this occurs, then these workers may not be laid off or relocated to a different block. However, our employment findings are insensitive to the inclusion of public sector employees. Moreover, when we limit the data to only public sector employees, we estimate a very small, statistically imprecise change in employment.

The credit-constrained household finance results also support the cash grant interpretation. Cash grants, when available for the disaster, are provided over and above SBA loans. Lower credit worthy individuals are more likely to be turned down for SBA loans (e.g. Begley et al. [2018]). Low credit individuals are therefore more likely to receive a disproportionate share of cash assistance, conditional on the same disaster damage. We find that individuals hit by a cash tornado with low Equifax Credit Scores have much lower bill delinquency rates. High Equifax Credit Score individuals have no change in their rate of bill delinquency.

Finally, the disaggregated industry results support an economic channel whereby cash provided to the local population improves business outcomes for those establishments most reliant on local demand.

6.2 Cost per Job Created

The goal of the IA cash grant program is to provide assistance to individuals who incur direct expenses from a natural disaster. At the same time, we show that the cash grants increase business survival and lead to greater employment in damaged tornado blocks where individuals receive cash grants. In this section, we calculate a rough measure for the cost of each job retained or created by the cash grants.[16]

We calculate the cost per job created from cash grants using two approaches. In the first approach, we use the total amount of cash assistance allocated throughout all of the disaster counties in the state. In the second approach, we only consider the cost of the cash grants that went to ZIP codes hit by (part of) a tornado. The second approach is a policy evaluation that narrows the cash assistance to where we observe job creation. On one hand, the cost per job estimates are too low if our cash tornado estimates are partially driven by other disaster assistance programs. On the other hand, the cost per job estimates are also probably too high for two reasons. First, we limit the jobs created calculation to establishments with fewer than three employees. In all likelihood, there are jobs created at larger establishments. Second, we consider cash assistance provided to everyone hit in a ZIP code, even though a tornado typically hits only a very small fraction of the ZIP.

Our calculation follows Brown and Earle [2017], except that we estimate the net job cost inclusive of other program costs and fiscal externalities (e.g. Bastian and Jones [2019]; Hendren [2016]). We estimate a cost of $198 thousand per job when we consider the total amount of cash assistance, and $75 thousand when we limit the evaluation to where we measure job creation (hit blocks).

Brown and Earle [2017] use administrative data to examine two large SBA (non-disaster) business loan programs. The authors are careful to emphasize that their calculation does not include, among other considerations, the effect of increased employment on the government budget from tax revenue and reduced unemployment benefits. As a point of reference, Brown and Earle [2017] report the cost per job created as $25,450 (2010$) using the employment estimate from their preferred model. One thing to keep in mind, is that Brown and Earle [2017] evaluate a program where low cost credit is provided directly to businesses. By contrast, cash grants are provided to residents. The cash grants benefit local businesses

[16] Figure 6 shows a dramatic decrease in the number of employees in damaged blocks that did not receive cash grants (rather than a disproportionate increase in blocks where individuals received grants). The raw trends in the figure, along with the separate model estimates for new versus existing business establishments (Table 6 panel B), suggest that the difference in jobs between cash and no-cash disaster blocks is largely due to "retained" jobs rather than "new" jobs. Unfortunately, the data do not allow us to distinguish between newly created jobs and the retention of existing jobs. We follow the literature and streamline the exposition by (hereafter) referring to our estimates as jobs created.

through increased demand when recipients spend the grant money locally on goods and services and when the recipient is a business owner. The appendix provides a detailed discussion of the cost calculation.

7 Conclusion

We compile a new database that combines individual-level credit bureau data, establishment-level business information, ZIP Code-level disaster assistance, and block-level tornado damage. The 34 tornadoes in our sample cause uninsured property damage and act as shocks to wealth and capital. There are several advantages of using tornadoes as a source of exogenous damage. The damage location is completely random within a community. This randomness effectively eliminates the ability for individuals and businesses to sort locally, or to differentially invest in protective actions based on disaster risk. This is in sharp contrast to flooding where local geography can help predict property-level flood risk.

We are among the first to document the impact of being directly hit by a devastating tornado on household finance and business survival. We find that tornadoes lead to a small reduction in personal debt. The estimated impact on the Equifax Risk Score and bill delinquency, two key indicators of financial distress, are economically small in magnitude and statistically insignificant. Overall, we estimate that there are fewer business establishments in hit blocks in the four years following the disaster. Establishment closings are highest in severely damaged blocks, where the business survival rate declines by 10% and employment by 21%. To our surprise, the business survival rate is slightly higher in low damaged blocks, relative to nearby non-damaged blocks. These findings, together with the existing literature that examines flooding (e.g. Deryugina et al. [2018]; Gallagher and Hartley [2017]; Groen et al. [Forthcoming]), suggest that federal disaster assistance may play a key role in mitigating the financial impact of a natural disaster.

The second half of the paper examines how post-tornado financial outcomes differ based on whether individuals and businesses are located in neighborhoods where federal disaster cash grants are made available following the tornado. The cash grants are distributed to individuals, but are also a targeted place-based policy for damaged neighborhoods. Business establishments could benefit if there is increased spending on local goods and services. There are three main household finance conclusions. First, we find that disaster-affected individuals in high damage blocks with access to cash grants have less credit card debt following a disaster, relative to disaster victims without access to cash grants. Second, cash grants lead to a dramatic reduction in home debt for residents in high damage blocks. Third, consistent with the life cycle/permanent income hypothesis, credit-constrained individuals who have access to cash grants have lower rates of bill delinquency and increase their spending.

Cash grants to residents in disaster impacted neighborhoods increase the survival rate of business establishments in these neighborhoods. The establishments most reliant on local demand benefit the most. Business survival and employment in low, medium, and high damage blocks are consistently lower when local residents do not have access to cash grants. The small increase in business survival in low damage blocks in our baseline results is due to an increase in blocks where individuals have access to cash grants.

In our view, the spatial pattern of disaster assistance, combined with our estimation results, is most consistent with cash assistance as the underlying mechanism. However, we can not completely rule out that payments from other federal disaster assistance programs, such as Public Assistance infrastructure spending, contribute to our findings.

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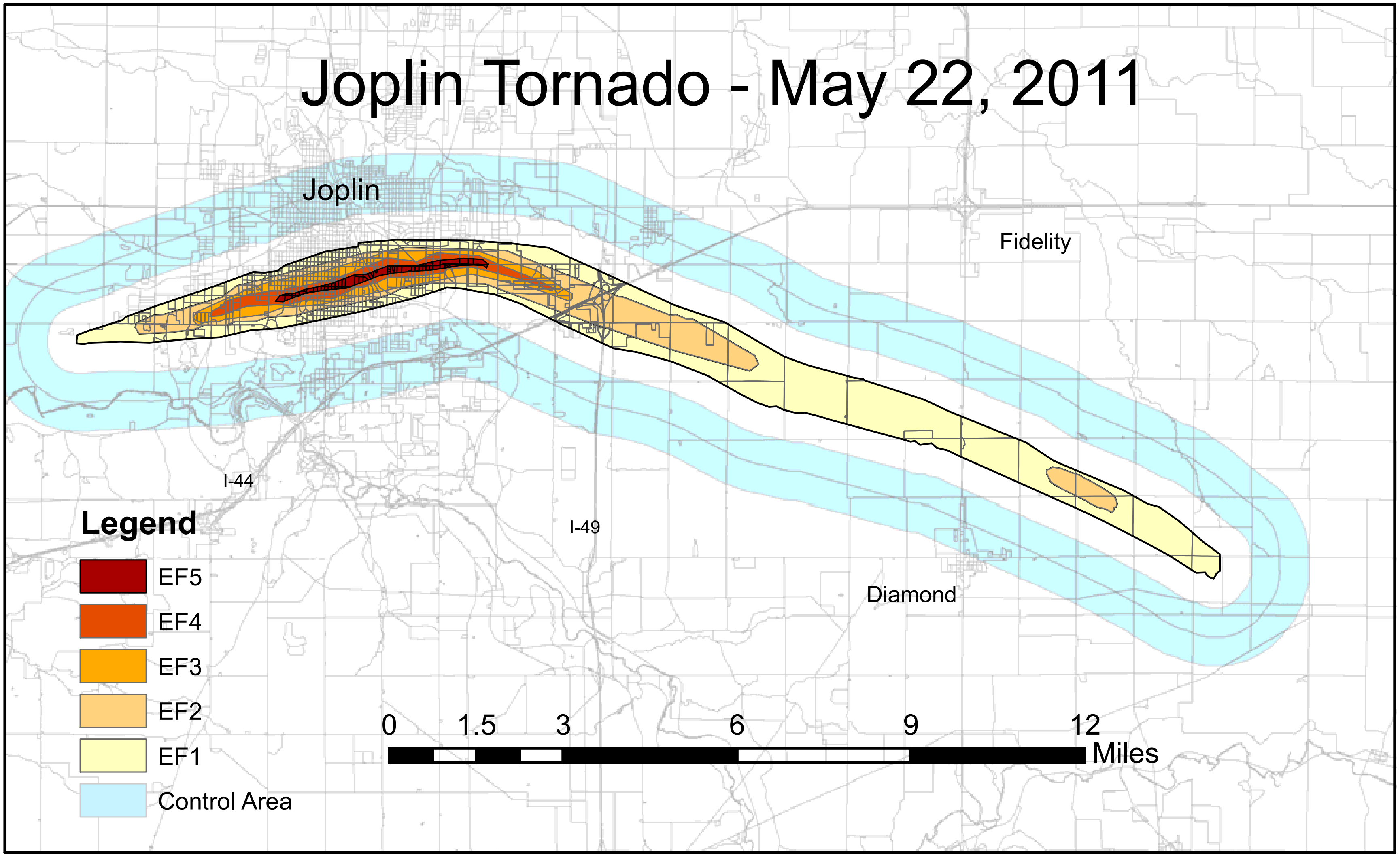
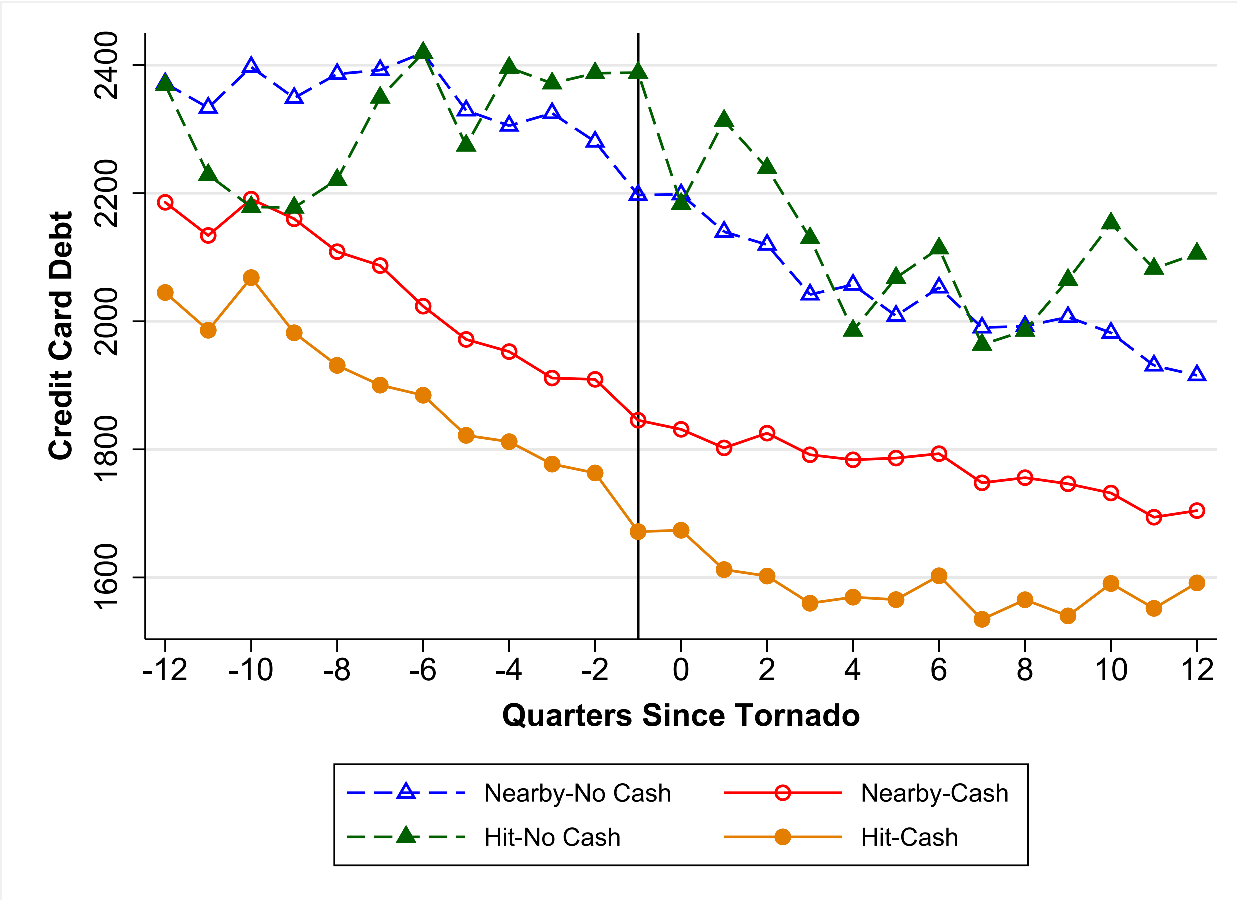
9 Figures and Tables

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



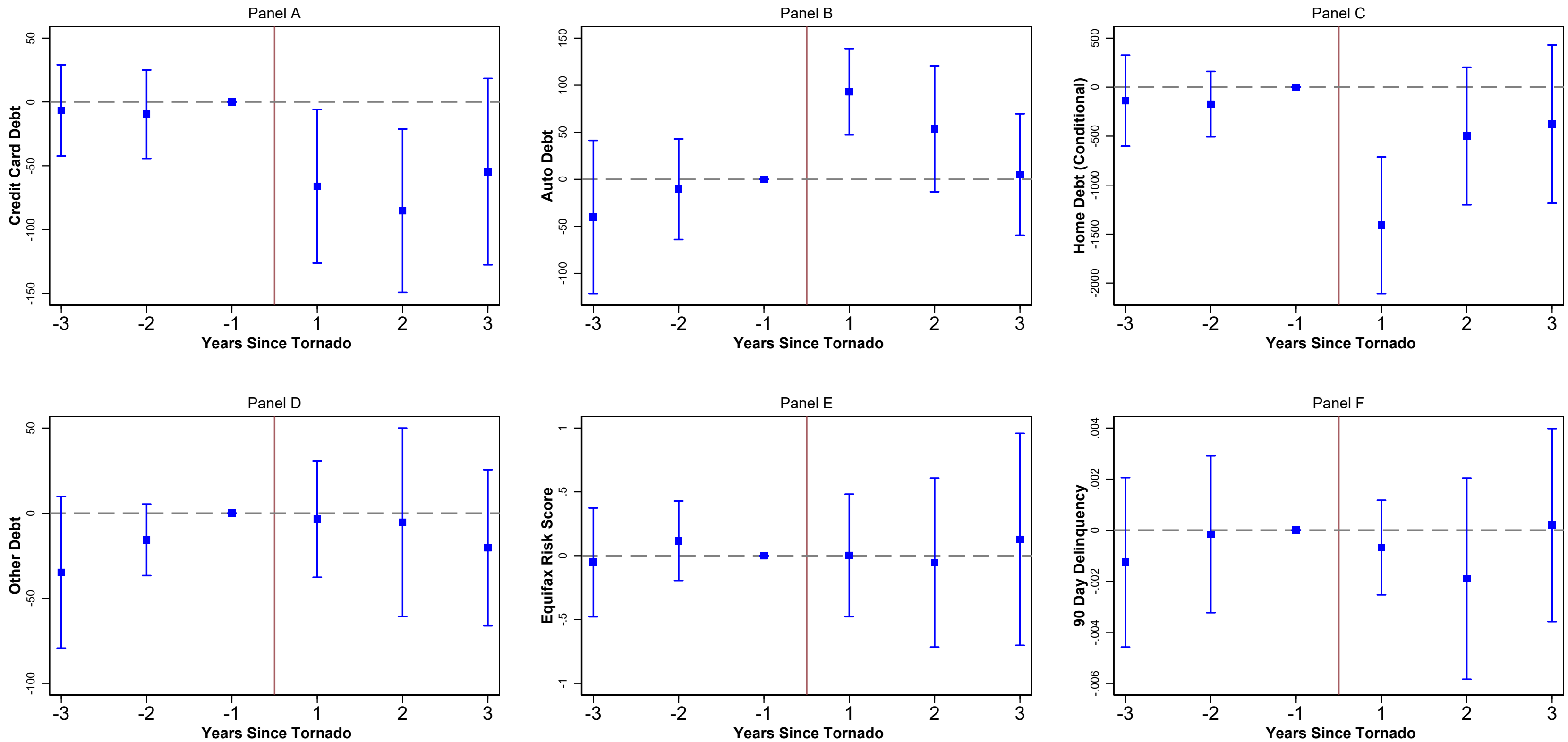
The figure shows the damage map for an EF5 tornado that hit Joplin, Missouri on May 22, 2011. The tornado path is outlined in black. The control area is in blue and located between 0.5 and 1.5 miles from the edge of the damage path. The tornado path and the control area are overlaid on a US Census block map (background grey lines). Sources: National Weather Service, US Census.

Figure 2: Trends in Credit Card Debt



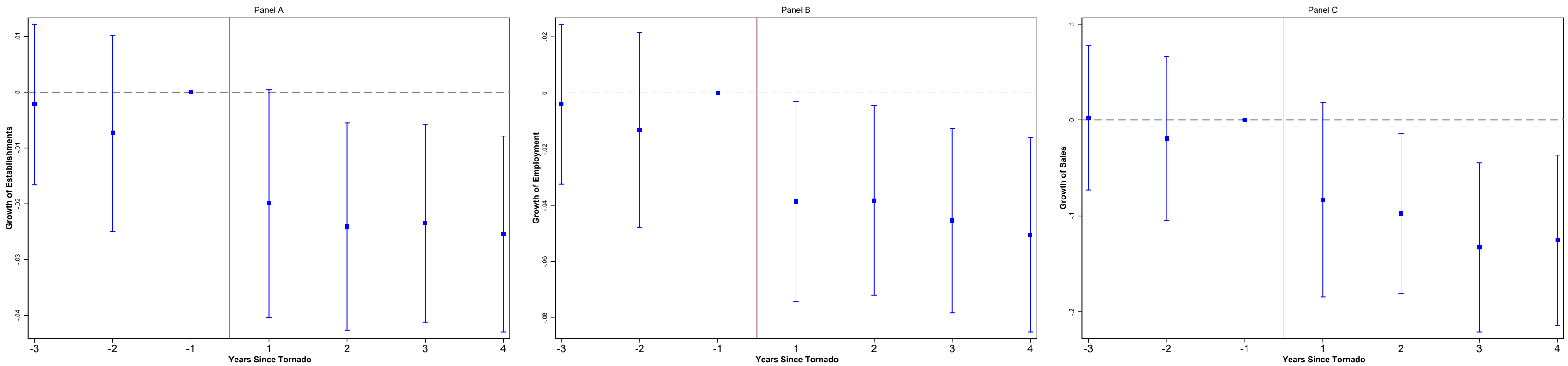
The figure plots the mean credit card balance (bank cards) of four groups of individuals: non-hit residents who lived in the 0.5 to 1.5 mile buffer area around the tornadoes that did not receive cash grants (dashed blue triangles), hit residents who lived in the damage path of tornadoes that did not receive cash grants (dashed green triangles), non-hit residents who lived in in the buffer areas of the tornadoes that did receive cash grants (solid red circles), and hit residents from tornadoes that received cash grants (solid orange circles). All dollar denominated variables are expressed in real terms in 2010 dollars. The vertical line indicates the last quarter before a tornado. Sources: Federal Reserve Bank of New York Consumer Credit Panel / Equifax (CCP), National Weather Service, US Census.

Figure 3: Debt and Financial Wellbeing of being Hit by a Tornado



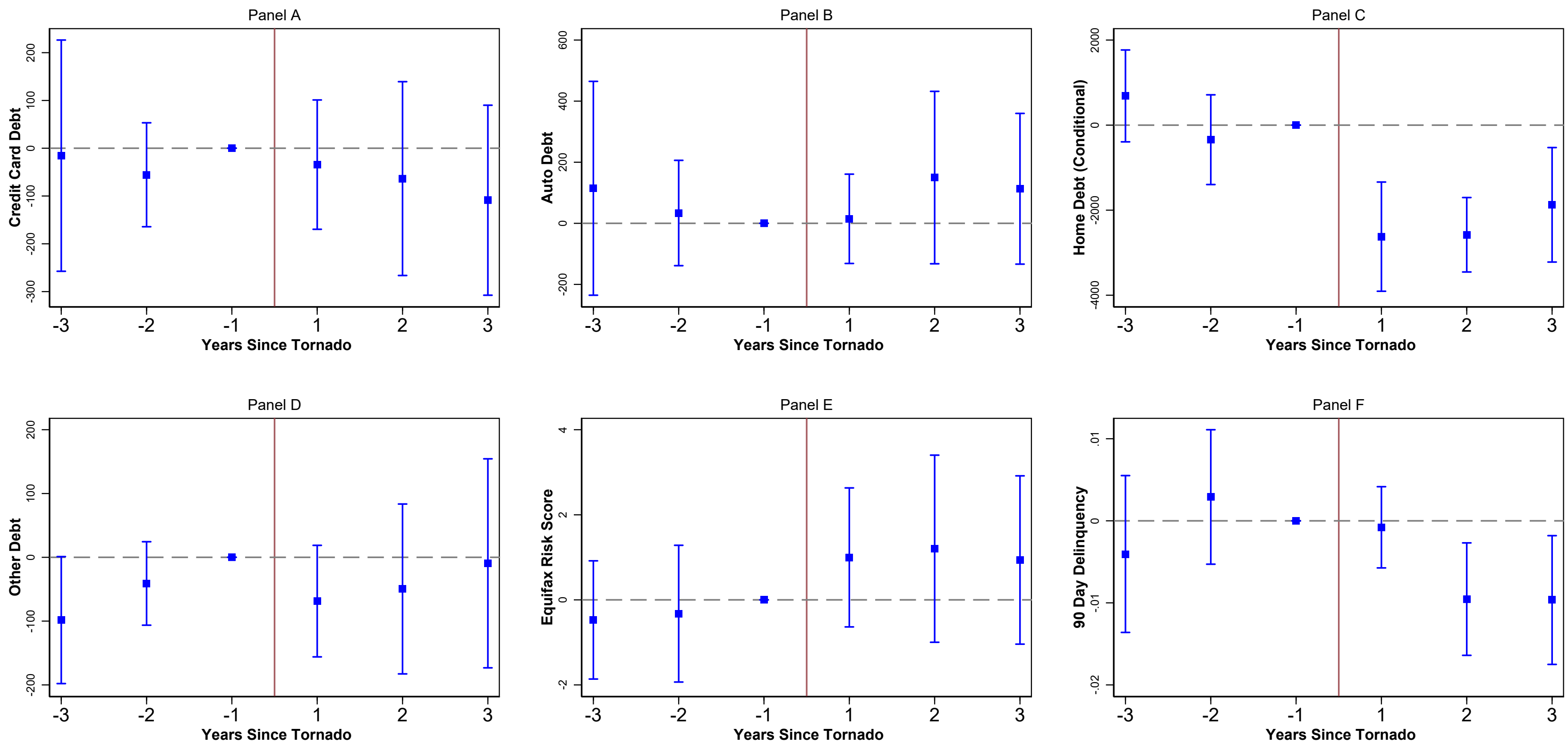
The figure shows yearly difference-in-differences model event study estimates and 95% confidence intervals for the outcomes in Table 1. The year before the tornado is excluded from the model and serves as the reference time period. We drop the quarter of the tornado (red vertical line in each panel) from the panel before running the model. Sources: Federal Reserve Bank of New York Consumer Credit Panel / Equifax (CCP), National Weather Service, US Census.

Figure 4: Business Survival, Employment, and Sales of being Hit by a Tornado



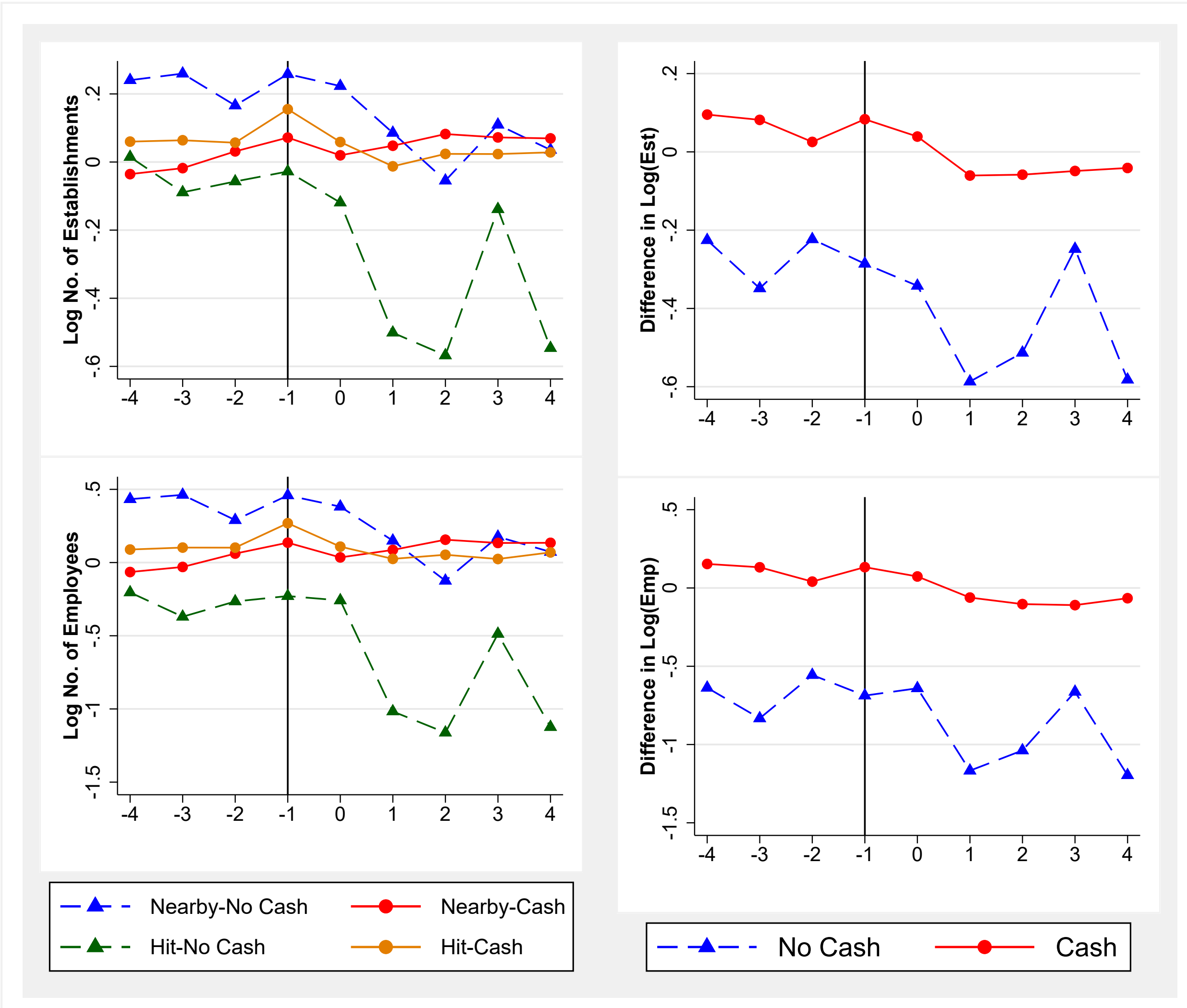
The figure shows yearly difference-in-differences model event study estimates and 95% confidence intervals for the outcomes in Table 2. The year before the tornado is excluded from the model and serves as the reference time period. We drop the quarter of the tornado (red vertical line in each panel) from the panel before running the model. Sources: Infogroup Historic Business Database, National Weather Service, US Census.

Figure 5: Debt and Financial Wellbeing of being Hit by a Cash Tornado



The figure shows yearly triple difference event study estimates and 95% confidence intervals for the outcomes in Table 3. The year before the tornado is excluded from the model and serves as the reference time period. We drop the quarter of the tornado (red vertical line in each panel) from the panel before running the model. Sources: Federal Reserve Bank of New York Consumer Credit Panel / Equifax (CCP), National Weather Service, US Census.

Figure 6: Trends in Business Outcomes



The figure shows the trends in the number of establishments and employees for establishments located in hit Census blocks at the time of a tornado, and for establishments near to the tornado path. The figure plots means of the residuals from a regression of block-level establishment outcomes on year dummy variables. The left side of the figure plots the trends separately for tornadoes where affected residents were able to access cash grants (circles) and where no cash grants were distributed (triangles). The right side of the figure plots the difference in establishment outcomes between blocks hit by and nearby to a tornado. This difference is plotted separately for tornadoes where residents did and did not receive cash grants. Sources: Infogroup Historic Business Database, National Weather Service, US Census.

Table 1: **Household Finance Impact of being Hit by a Tornado**

Dependent Variable:	Credit Card (1)	Home (Conditional) (2)	Auto (3)	Other (4)	Equifax Risk Score (5)	90 Day Delinquency (6)
Panel A: Continuous Damage						
Post x Hit	-58	-674	68	7	-0.03	-0.0002
	(33)	(281)	(30)	(21)	(0.31)	(0.0016)
Dep. Variable Mean	$2,467	$67,404	$3,190	$1,278	674	0.20
R-squared	0.013	0.079	0.003	0.007	0.018	0.001
Observations	496,708	123,602	496,708	496,708	492,439	496,708
Panel B: Binned Damage						
Post x Low	-18	-100	53	-14	0.50	-0.0033
	(80)	(1,340)	(104)	(71)	(0.75)	(0.0199)
Dep. Variable Mean	$2,348	$69,580	$3,157	$1,317	675	0.20
Post x Medium	-128	-4,076	170	-72	0.40	0.0053
	(118)	(947)	(114)	(85)	(1.27)	(0.0068)
Dep. Variable Mean	$2,621	$67,467	$3,506	$1,323	675	0.20
Post x High	-374	-1,064	360	127	-1.39	0.0047
	(265)	(1,990)	(188)	(75)	(1.79)	(0.0074)
Dep. Variable Mean	$2,579	$59,031	$2,630	$1,037	670	0.20
R-squared	0.013	0.079	0.003	0.007	0.018	0.001
Observations	496,708	123,602	496,708	496,708	492,439	496,708

The table shows difference-in-differences estimates for six outcomes. The model includes individual and quarter fixed effects. Only the difference-in-differences coefficients of interest are reported. The binned coefficients in panel B are estimated separately for individuals in blocks with low (F/EF < 1), medium (F/EF ≥ 1 & < 3), and high (F/EF ≥ 3) damage. Dependent variable means are for the last quarter before a tornado for the hit group. The debt variables are winsorized at 99%. Standard errors (in parentheses) are robust to heteroskedasticity and clustered by tornado. Sources: Federal Reserve Bank of New York Consumer Credit Panel / Equifax (CCP), National Weather Service, US Census.

Table 2: **Impact of being Hit by a Tornado on Business Survival, Employment, and Sales**

Dependent Variable:	Log(Establishments)	Log(Employment)	Log(Sales)
	(1)	(2)	(3)
Panel A: Continuous Damage			
Post x Hit	-0.019	-0.036	-0.108
	(0.005)	(0.009)	(0.024)
R-squared	0.550	0.542	0.478
Observations	143,449	143,449	143,449
Panel B: Binned Damage			
Post x Low	0.044	0.066	0.148
	(0.015)	(0.030)	(0.075)
Post x Medium	-0.039	-0.116	-0.273
	(0.024)	(0.046)	(0.116)
Post x High	-0.100	-0.209	-0.497
	(0.026)	(0.052)	(0.132)
R-squared	0.550	0.542	0.478
Observations	143,449	143,449	143,449

The table shows difference-in-differences estimates for three business establishment outcomes. The model includes block and year fixed effects. Only the difference-in-differences coefficients of interest are reported. The binned coefficients in panel B are estimated separately for individuals in blocks with low (F/EF < 1), medium (F/EF ≥ 1 & < 3), and high (F/EF ≥ 3) damage. Standard errors (in parentheses) are robust to heteroskedasticity and clustered by tornado. Sources: Infogroup Historic Business Database, National Weather Service, US Census.

Table 3: **Household Finance Impact of being Hit by a Cash Tornado**

Dependent Variable:	Credit Card	Home (Conditional)	Auto	Other	Equifax Risk Score	90 Day Delinquency
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Continuous Damage						
Cash Tornado x Post x Hit	-39	-2,179	42	7	1.3	-0.0051
	(81)	(574)	(71)	(52)	(0.9)	(0.0035)
Dep. Variable Mean	$2,411	$66,371	$3,143	$1,300	671.7	0.2073
R-squared	0.013	0.079	0.003	0.007	0.018	0.001
Observations	496,708	123,602	496,708	496,708	492,439	496,708
Panel B: Binned Damage						
Cash Tornado x Post x Low	-405	-3,827	440	-227	-2.3	0.0405
	(239)	(2,721)	(386)	(148)	(2.9)	(0.0215)
Dep. Variable Mean	$2,287	$68,614	$3,148	$1,362	672.6	0.2085
Cash Tornado x Post x Medium	425	598	346	240	8.3	-0.0509
	(327)	(2,353)	(385)	(228)	(3.8)	(0.0170)
Dep. Variable Mean	$2,532	$65,659	$3,429	$1,320	672.7	0.2058
Cash Tornado x Post x High	-774	-19,479	-289	-153	1.3	0.0001
	(307)	(2,414)	(295)	(94)	(2.3)	(0.0109)
Dep. Variable Mean	$2,611	$59,365	$2,527	$1,033	666.4	0.2059
R-squared	0.013	0.079	0.003	0.007	0.018	0.001
Observations	496,708	123,602	496,708	496,708	492,439	496,708

The table shows triple difference estimates for six outcomes. The model includes individual and quarter fixed effects. Only the triple difference coefficients of interest are reported. The binned coefficients in panel B are estimated separately for individuals in blocks with low (F/EF < 1), medium (F/EF ≥ 1 & < 3), and high (F/EF ≥ 3) damage. Dependent variable means are for the last quarter before a tornado for the hit group. The debt variables are winsorized at 99%. Standard errors (in parentheses) are robust to heteroskedasticity and clustered by tornado. Sources: Federal Reserve Bank of New York Consumer Credit Panel / Equifax (CCP), National Weather Service, US Census.

Table 4: **Heterogeneity in the Household Finance Impact of being Hit by a Cash Tornado by Access to Credit and Age**

Dependent Variable:	Credit Card (1)	Home (Conditional) (2)	Auto (3)	90 Day Delinquency (4)
Panel A: Available Credit				
Low Available Credit				
Cash Tornado x Post x Hit	-2	-180	161	-0.0102
	(53)	(943)	(59)	(0.0080)
Dependent Variable Mean	$238	$55,950	$1,526	0.3150
Observations	152,278	13,439	152,278	152,278
High Available Credit				
Cash Tornado x Post x Hit	-226	-5,037	76	0.0037
	(116)	(946)	(90)	(0.0039)
Dependent Variable Mean	$4,523	$67,656	$3,797	0.0391
Observations	170,386	67,901	170,386	170,386
Panel B: Credit Score				
Low Equifax Credit Score				
Cash Tornado x Post x Hit	76	1,388	256	-0.0416
	(72)	(1,444)	(179)	(0.0094)
Dependent Variable Mean	$1,556	$57,003	$2,497	0.5249
Observations	161,520	21,380	161,520	161,520
High Equifax Credit Score				
Cash Tornado x Post x Hit	-17	-4,262	9	0.0004
	(90)	(872)	(77)	(0.0004)
Dependent Variable Mean	$2,090	$72,028	$2,747	0.0000
Observations	165,527	55,420	165,527	165,527
Panel C: Age				
Young				
Cash Tornado x Post x Hit	-161	1,138	233	-0.0182
	(130)	(1,119)	(147)	(0.0078)
Dependent Variable Mean	$1,697	$73,944	$3,279	0.2894
Observations	168,246	27,112	168,246	168,246
Old				
Cash Tornado x Post x Hit	-23	-1,516	-236	0.0022
	(92)	(720)	(129)	(0.0063)
Dependent Variable Mean	$2,372	$53,070	$2,378	0.1066
Observations	162,810	39,133	162,810	162,810

The table shows triple difference heterogeneity estimates for four outcomes (omitting credit score, other debt) in Tables 3 using the continuous damage model. The model is estimated separately on two groups of individuals (lower and upper terciles) based on available credit (panel A), Equifax Risk Score (panel B), and age (panel C). The credit card and credit score cutoffs are based on averages across the 12 pre-tornado quarters, while the age is from the quarter before the tornado. The tercile cutoffs are as follows: 40 and 58 for age, $149 and $11,364 for available credit, and 618 and 759 for Equifax Risk Score. Standard errors (in parentheses) are robust to heteroskedasticity and clustered by tornado. Sources: Federal Reserve Bank of New York Consumer Credit Panel / Equifax (CCP), National Weather Service, US Census.

Table 5: **Estimates for the Number of Business Establishments and Employees**

Model:	Triple Difference		Difference-In-Difference			
Dependent Variable:	Log (Establishments)	Log (Employment)	Log(Establishments)		Log(Employment)	
Tornado Type:			Cash	No-Cash	Cash	No-Cash
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Continuous Damage						
Cash Tornado x Post x Hit	0.048	0.069	-0.026	-0.067	-0.048	-0.094
	(0.023)	(0.040)	(0.005)	(0.021)	(0.009)	(0.041)
R-squared	0.561	0.555	0.559	0.516	0.549	0.510
Observations	141,977	141,977	125,016	16,961	125,016	16,961
Panel B: Binned Damage						
Cash Tornado x Post x Low	0.218	0.351	0.047	-0.158	0.066	-0.249
	(0.119)	(0.204)	(0.015)	(0.058)	(0.030)	(0.107)
Cash Tornado x Post x Medium	0.133	0.151	-0.060	-0.178	-0.116	-0.213
	(0.062)	(0.118)	(0.025)	(0.076)	(0.046)	(0.140)
Cash Tornado x Post x High	0.118	0.374	-0.127	-0.208	-0.209	-0.468
	(0.104)	(0.393)	(0.027)	(0.088)	(0.052)	(0.266)
R-Squared	0.561	0.555	0.559	0.516	0.549	0.510
Observations	141,977	141,977	125,016	16,961	125,016	16,961

Columns (1) and (2) show triple difference estimates of the effect of cash grants on the number of establishments and employment. Columns (3)-(6) show difference-in-differences model estimates separately for cash and no-cash tornadoes. The binned coefficients in panel B are estimated separately for individuals in blocks with low (F/EF < 1), medium (F/EF ≥ 1 & < 3), and high (F/EF ≥ 3) damage. Standard errors (in parentheses) are robust to heteroskedasticity and clustered by tornado in the triple-difference model and by census tract in the difference-in-differences model. Sources: Infogroup Historic Business Database, National Weather Service, US Census.

Table 6: **Heterogeneity in Business Establishment Triple Difference Estimates by Industry, Age, and Size**

	(1)	(2)
Dependent Variable:	**Log(Establishments)**	**Log(Employment)**
Panel A: Establishment Industry		
Non-Manufacturing		
Cash Tornado x Post x Hit	0.048	0.070
	(0.023)	(0.041)
R-squared	0.560	0.553
Manufacturing		
Cash Tornado x Post x Hit	-0.002	-0.007
	(0.003)	(0.009)
R-squared	0.513	0.519
Panel B: Establishment Age		
New (1 year or less)		
Cash Tornado x Post x Hit	-0.005	-0.009
	(0.005)	(0.010)
R-squared	0.379	0.318
Existing (4 years or more)		
Cash Tornado x Post x Hit	0.035	0.057
	(0.018)	(0.037)
R-squared	0.538	0.534
Panel C: Establishment Size		
Small (≤ 3 Employees)		
Cash Tornado x Post x Hit	0.043	0.048
	(0.014)	(0.020)
R-squared	0.544	0.529
Large (≥ 7 Employees)		
Cash Tornado x Post x Hit	-0.005	-0.004
	(0.014)	(0.029)
R-squared	0.570	0.571

The table shows triple difference estimates using the same model as in Table 5 panel A, except that we limit the sample by establishment industry (panel A), age (panel B), and size (panel C). Each point estimate in the table is from a separate regression. We classify each establishment as manufacturing or non-manufacturing using the two digit SIC. Standard errors (in parentheses) are robust to heteroskedasticity and clustered by tornado. Sources: Infogroup Historic Business Database, National Weather Service, US Census.