Same storm, different disasters: Consumer credit access, income inequality, and natural disaster recovery*

Brigitte Roth Tran[†1] and Tamara L. Sheldon[‡2]

[1]Board of Governors of the Federal Reserve System
[2]Department of Economics, University of South Carolina

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Abstract

Natural disasters often produce large income shocks to households. We analyze the impact of natural disasters on household finances. Using a triple differences approach, we estimate the effect of natural disasters on credit card outcomes for individuals in varying financial positions receiving access to different types of FEMA aid. With the exception of those living in low income areas, we find few negative impacts on credit outcomes of most individuals living in areas hit by disasters that qualify for individual and household aid. Though all types of individuals affected by disasters show some signs of increasing credit utilization, the most vulnerable populations are also more likely to declare bankruptcy. While many are able to use credit cards to smooth through negative income shocks from natural disasters, current policy appears to leave the worst off even worse off.

Keywords: household finances; natural disasters

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†Brigitte.RothTran@frb.gov

‡Tamara.Sheldon@moore.sc.edu

1 Introduction

Natural disasters such as floods, tornadoes, and hurricanes often produce large income shocks to households. In addition to property damage, disaster victims suffer injuries resulting in medical costs and lose wages due to workplace shutdowns, transportation disruptions, and daycare and school closures.[1] While insurance may cover property damage and medical expenditures, many households are under- or uninsured. Furthermore, in the U.S., lost wages due to a natural disaster are not typically covered by insurance or eligible for the Federal Emergency Management Administration's (FEMA) or Small Business Administration's (SBA) emergency assistance. We evaluate the impact of natural disasters on personal finances, with a focus on differential impacts based on household credit scores and census tract median household income levels.

Natural disasters may yield different negative income shocks to lower and higher income households. First, lower income households tend to be more vulnerable to natural disasters due to residence location, type, and construction quality (e.g., Fothergill and Peek (2004)). Second, lower income households are less likely to be fully insured if at all (e.g., Browne and Hoyt (2000); Fronstin (2013)). Third, evidence suggests that lower income households tend to lose more wages in the aftermath disasters, probably because they are more likely to work for hourly wages (as opposed to salaried) and less likely to have flexibility to temporarily work from home (Sheldon, Gall, and Collins, 2017). Not only might the relative magnitude of the income shock differ across income groups, but households' abilities to respond to the income shock may also differ due to, for example, differential savings and access to credit.

Indeed, even as climate change projections indicate that natural disasters will likely become more frequent and/or severe, many Americans are woefully unprepared to face

[1] Severe natural disasters also lead to increased out migration and lower housing prices, which may present negative income shocks to some individuals (Boustan et al., 2017).

these catastrophes. In a recent report, the Federal Reserve Board found that 44 percent of individuals reported that they do not have enough cash on hand for a $400 emergency.[2] Twenty-nine percent of these individuals expect that they would simply be unable to cover the expense, while 45 percent would use credit cards, which they would have to pay off slowly, which are likely to charge high interest rates.

While there is a significant literature on natural disaster effects on outcomes ranging from health to consumer behaviors (see for example Beatty, Shimshack, and Volpe (2015)), research on the impacts of natural disasters on personal finances is limited. Two studies that examine impacts of flooding from Hurricane Katrina both find relatively small impacts. Gallagher and Hartley (2017) find that flooded residents took on $700 in additional credit card debt following Katrina, but this was temporary. They also find that total household debt fell post disaster and posit this was due to homeowners using insurance payouts to pay off mortgages. Using data on tax returns, Deryugina, Kawano, and Levitt (2017) find that incomes of households impacted by Katrina recovered fully within a few years. Both studies point to disaster aid as the major factor mitigating impacts of Katrina on household finances. Morse (2011) examines a broader range of disasters and shows that individuals with greater access to payday lenders were less likely to end up in foreclosure after disasters in California.

Recent evidence suggests that non-disaster-based government aid such as unemployment insurance also plays a major role in post-disaster recovery. Using data on US hurricane landfalls from 1979-2002, Deryugina (2017) finds that disaster aid averaged around $160 per capita, while non-disaster social insurance transfers increased around $1,000 per capita in the disaster areas over the ten years following the hurricane.

[2] Board of Governors of Federal Reserve System, 2017. Report on the Economic Well-Being of U.S. Households in 2016. https://www.federalreserve.gov/publications/files/2016-report-economic-well-being-us-households-201705.pdf

We use NY Fed Consumer Credit Panel/Equifax data to analyze the impact of natural disasters on credit card outcomes such as number of new cards, balance as a fraction of limit, and number of bankcards past due, amongst other outcomes. Applying a triple difference approach, we compare these credit card outcomes between households residing in FEMA-declared disaster areas and individuals in neighboring counties before and after natural disasters.[3] We build upon the existing literature in two main ways. First, rather than focusing on a single event, we examine all types of natural disasters for which FEMA has made declarations. Second, we explore differential impacts on low income and low credit score households.

We find heterogeneous effects based on access to disaster aid and financial position prior to the disaster. In particular, we find that credit outcomes for both prime and subprime individuals residing in areas aid do not appear to be significantly impacted by disasters. Subprime individuals with the lowest credit scores who reside in affected areas without access to individual aid are more likely to declare bankruptcy following disasters. We find no negative impacts on credit outcomes of individuals living in high income census tracts in counties that receive individual aid. While individuals in low income areas receiving either individual or public assistance appear to be worse off after the disaster, with more bank cards past due, those in low income areas with no individual assistance are more likely to declare bankruptcy.

In summary, we find that individuals in areas hit by disasters utilize credit more. However, with the exception of those living in low income areas, we find few negative impacts on credit outcomes of most individuals living in areas hit by disasters that qualify for individual aid. The most vulnerable individuals (those with the lowest credit scores

[3] Specifically, we define treated households as those residing in counties that received FEMA aid under the Individuals and Households (IHP) program. This is because IHP aid is a proxy for disaster severity and because we are interested in impact of disasters on households. IHP aid is only granted when there is significant damage to homes and personal property.

and those who reside in low income areas) are more likely to declare bankruptcy. These results highlight the importance of aid to households' financial post-disaster resiliency and suggest that expansion of FEMA aid could help stabilize vulnerable households financially in a meaningful way.

The remainder of this paper is organized as follows. In section 2 we provide additional background. Next in section 3, we describe the data we use. We explain our empirical strategy in section 4, followed by our results in section 5. Finally, we close with a discussion of the implications of this current work as well as plans for future work in section 6.

2 Background

Natural disaster damage is trending upwards both domestically and globally. Direct annual domestic losses from hurricanes and floods tripled between 1960 and 2009, with per capita losses also increasing (Gall et al., 2011). According to Gall et al. (2011), direct economic damage in the United States from natural disasters over this five-decade period was $573 billion. The authors predict that if current trends continue, going forward the US may experience $300 to $400 billion in direct losses from natural disasters per decade. This is consistent with climate scientists' forecasts of increasing frequency and/or severity of many natural disasters (e.g., Mann et al. (2017); Prein et al. (2016); IPCC (2014)).

The Federal Emergency Management Agency (FEMA) is the main source of disaster aid in the United States. According to FEMA's website, "Most emergencies must be borne by the victims of the disaster, but some are large enough to request government assistance. The federal government financially assists local and state governments and its citizens to recover when the emergency is a disaster. Under the Stafford Act (federal law), a community requesting federal assistance must prove they have been overwhelmed by events. Not only must the local government must [sic] be overwhelmed, but state capabilities must be overwhelmed as well."[4]

Specifically, to be declared a presidential disaster zone eligible for FEMA assistance, both a state and county threshold must be met. County damage must exceed \$3.61 per capita and state damage must exceed \$1.43 per capita.[5] FEMA offers four types of aid: individual and household program (IHP) assistance, public assistance (PA), Small Business Administration (SBA) loans, and FEMA grants for hazard mitigation.

FEMA's individual and household disaster assistance "provides money or direct assistance to individuals, families and businesses in an area whose property has been damaged or destroyed and whose losses are not covered by insurance."[6] The IHP program includes Housing Assistance and Other Needs Assistance. All households in a declared disaster area can apply for Housing Assistance, which can provide them with temporary housing assistance. This includes financial assistance for rentals and short term lodging expenses, as well as direct housing assistance where FEMA provides temporary housing units (mobile home or travel trailer). Housing assistance can also cover home repair and replacement up to a cap of approximately \$33,000. This individual FEMA aid can supplement but not duplicate insurance. Individual applications must document insurance.

All households in a declared disaster area can apply for medical, dental, and funeral aid under FEMA's Other Needs Assistance program. However, only those with income below the poverty line or who get rejected from an SBA loan may apply for Other Needs Assistance to cover personal property loss, moving and storage, and transportation. Other households must apply for an SBA low interest rate loan to cover real property (owners only, up to \$200,000) and personal property (owners and renters, up to \$40,000).[7]

[4]http://www.tnema.org/ema/recovery/federaldeclaration.html

[5]These thresholds are adjusted over time by the Consumer Price Index. The \$3.61 and \$1.43 apply to disasters on or after October 1, 2016

[6]See https://www.fema.gov/grants-assistance-programs-individuals.

[7]See http://www.mass.gov/eopss/docs/mema/ihp-flowchart.pdf for more details.

States and local governments can apply for public assistance (PA) following a declared disaster. FEMA's PA is intended to restore community infrastructure affected by a declared disaster. Project categories include debris removal, roads and bridges, water control facilities, public buildings and contents, public utilities, and parks and recreational facilities.[8]

While individual assistance is capped just over $30,000 per household, average payouts are just $5,000 (Associated Press, 2011). Kousky and Shabman (2012) report that individual FEMA assistance is more limited and subject to more restrictions than the popular press may lead us to believe. For example, an applicant may need to show she was rejected after applying for a SBA loan and that she is a US citizen or qualified alien. Furthermore, disaster aid cannot be disbursed more than 18 months after disaster declaration, at which time FEMA starts charging individuals residing in FEMA housing for rent and can garnish their wages for failure to pay rent (Rice, 2012).

According to data released by the Federal Reserve, as of October 2017 Americans had a total of $3.8 trillion in outstanding consumer debt, $1.0 trillion of which is credit card debt (i.e., revolving debt).[9] Assuming a population of 250 million adults (out of a total population of 325 million), this translates to approximately $15,000 in total per capita debt and $4,000 per capita in credit card debt. Assuming a median household income of $55,000, average credit card debt is over 7% of median household income.

Households may respond to income shocks by changing debt, consumption, and/or wealth. Using micro level data from the Great Recession, Baker (2014) finds that consumption is more sensitive to income shocks for highly-indebted households, such that consumption dropped 20% more as a result of the Great Recession than it would have if

[8]See https://www.fema.gov/media-library-data/1497559657642-a01f6ee60e25394fa9a25cae2fd289d5/PublicAssistanceFactSheetJune2017.pdf for more details.

[9]See https://www.federalreserve.gov/releases/g19/current/g19.pdf, accessed on December 14, 2017.

household balance sheets had been similar to the early 1980s. Krueger and Perri (2009) find that labor income shocks result in modest changes to consumption but larger changes to wealth.

Natural disasters may result in substantial income shocks to households who may experience property damage, lost wages, increased medical expenses, increased childcare expenses, and more as a result of the disaster. Although FEMA aid may mitigate the income shock, FEMA aid is limited and restricted. Homeowners, property, and health insurance may also mitigate disaster-related losses, however, many Americans are under- if not uninsured, especially when it comes to extreme weather events not covered by traditional insurance. Furthermore, neither FEMA nor insurance typically cover indirect pecuniary damage, such as lost wages due to a temporary workplace closure or missing work to stay home with children whose schools or daycares are closed as a result of a disaster. In this paper we examine how household credit card debt responds to natural disasters.

3 Data

3.1 Disaster Data

We obtain data on federal disaster declarations from FEMA. These data include the type of disaster, the names and FIPS codes of affected counties, the date of disaster declaration, the types of assistance programs declared (e.g., individual and household assistance, public assistance, etc.), and the assigned identification number of the disaster. While the data set goes back to mid-1953, affected county FIPS codes are not consistently recorded until late 1964. Data are current as of early 2017.

In our analysis we include only natural disasters and exclude non-natural disasters in the data (chemical, fishing losses, human cause, other, terrorist, and toxic substances). The most common types of disasters are severe storms, hurricanes, floods, and fires. We also exclude locations that are not in US states (e.g., territories). Finally, we exclude Hurricane Katrina from our main analysis because it is an outlier. Hurricane Katrina is the disaster with by far the largest amount of damage and FEMA aid in our sample. Furthermore, given the national media coverage, private charitable donations were very large.[10] In future work we will investigate if and how our results change when including Hurricane Katrina.

The FEMA data from 2005 on also include the total amount of money by program type (if any) granted to each county for a disaster declaration. We use individual and public assistance aid to define treatment counties. We do not focus on mitigation and preparedness grants because these funds are not intended for recovery/rebuilding—rather, they are used to fund projects that build resilience against future events. Following a declared disaster, affected individuals may apply for aid from FEMA's Individual and Households Program (IHP).

Over our sample FEMA declared 1,282 natural disasters at the state level, 239 with IHP aid and 738 with PA aid. These statistics are based on FEMA disaster declaration identification numbers. For the same disaster (e.g., Hurricane Sandy) FEMA assigns different numbers to different states. In our analysis, we combine such disasters. Furthermore, since our analysis is quarterly, if a county experiences more than one distinct disaster in a quarter, we also combine these disasters. In total our sample includes 13,904 county-quarters with a declared disaster, 3,165 with IHP aid, and 10,292 with PA aid.

Figure 1 shows the geographic distribution of all FEMA-declared disasters with IHP and/or PA aid. Figure 2 shows the geographic distribution of the most severe FEMA-declared disasters in our sample, as proxied by those with IHP aid over $20 per capita.

[10] Nonprofit organizations tracked by the Washington Post raised over $3 billion within six months of Hurricane Katrina. See http://www.washingtonpost.com/wp-dyn/content/article/2006/02/26/AR2006022601383.html for more details.

Figure 3 shows the distribution of per capita IHP aid for county-quarter observations with non-zero aid. Contingent upon receiving IHP aid, the mean and median per capita amounts received are \$86 and \$12, respectively.

3.2 Census Data

We obtain US Census data on neighboring county boundaries, annual county level population, and census tract 2000 median income levels. The neighboring county data allow us to match treated counties to neighboring control counties and to combine separate state-level disaster declarations. We use annual census county level population figures to calculate per capital IHP and PA aid. Finally, we use census tract level median income from the 2000 Census to define "high" and "low" income observations and to examine the outcomes for individuals living in areas with high rates of poverty.

3.3 Financial Data

We obtain quarterly individual level loan and credit card data from the NY Fed Consumer Credit Panel/Equifax. These data are a representative 5% sample of the US population with a credit record. For computational ease, we utilize a 5% random subsample. Variables include number of bankcards, total bankcard balance, total bankcard limit, number of bankcards past due in the last three months, total amount past due on bankcards, bankruptcy status, Equifax Risk Score, and location down to the census block or zip code level. Summary statistics of the NY Fed Consumer Credit Panel/Equifax variables used in our analysis are shown in Table 2.

The Equifax Risk Score is a proprietary measure of the likelihood of the borrower defaulting. A lower score corresponds to a higher risk of default, while a higher score reflects a lower risk of default. Consistent with the Federal Reserve System's categorization, we use a prime-subprime cutoff of 660. In our analyses we identify individuals with an Equifax Risk Score below 660 as subprime, while those with a score greater or equal to 660 are considered prime. We further identify individuals with Equifax Risk Scores over 760 as "super prime" and those with Equifax Risk Scores below 560 as "deep subprime." For our analyses, we categorize individuals as prime or subprime based on their Equifax Risk Scores at the start of the quarter in which a disaster occurs.

Figure 4 shows the distribution of Equifax Risk Score across our sample. The area to the right of the red subprime cutoff represents the density of the prime observations. The area to left, with a much longer tail, represents the density of the subprime observations.

Figure 5 shows the geographic distribution of the fraction of the population that is subprime. Counties with a higher share of subprime individuals, and thus a lower share of prime, are shaded darker. The South East, south Texas, and pockets of the central South East and Central Plains have the highest subprime share.

Figure 6 shows the probability of prime individuals (in blue) and subprime individuals (in orange) retaining the same status one through eight quarters in the future. Over 80% of subprime individuals remain subprime eight quarters later, while over 90% of prime individuals remain prime.

Figure 7 shows the densities of various credit outcome variables by prime (blue) and subprime (red) status. Prime individuals (shown in light blue) tend to have more bank cards, higher credit limits, and higher balances than subprime individuals (depicted by the unshaded bars with red outlines). However, as might be expected, prime individuals have fewer cards and lower amounts past due and are less likely to have balances near or even above their credit limits.

3.4 Matching Data

Since some people might migrate in response to a disaster, we use an individual's county at the start of a quarter in which a disaster occurs to match the financial data with the FEMA disaster data. We do not match an observation if the individual does not reside in the current county for at least four consecutive quarters.[11] Therefore, if an individual resides in a county when the disaster strikes but subsequently moves, he or she remains in our sample. However, if an individual moves to an affected area after the disaster occurs, he or she will not be in our sample. We exclude individuals with a reported age under 18 or over 100. Our final sample of financial observations consists of quarterly individual observations from the last quarter of 2003 through the fourth quarter of 2016. Each observation includes the individual's credit outcomes as well as whether or not he or she resided in a FEMA-declared disaster county that quarter, and if so, total IHP and PA assistance granted to the county for the disaster. We winsorize continuous variables to limit the influence of potential spurious outliers.

4 Empirical Strategy

We use the following differences-in-differences-in-differences model to compare credit outcomes across prime and subprime households affected by a FEMA-declared disaster county before and after the natural disaster:

[11] Address changes frequently for a small fraction of the NY Fed Consumer Credit Panel/Equifax sample. This four-quarter condition is intended to ensure the individual lived in a treatment/control county when the disaster struck. The individual's four-quarter consecutive streak in a county may begin or end in the quarter of interest.

$$
\begin{aligned}
\Delta y_{ijt} = &\alpha + \boldsymbol{\alpha}_1 post_{jt} + \alpha_2 treat_{ij} + \alpha_3 prime_{ij} \\
&+ \alpha_4 prime_{ij} \times treat_{ij} + \boldsymbol{\alpha}_5 prime_{ij} \times post_{jt} \\
&+ \boldsymbol{\beta}_1 prime_{ij} \times treat_{ij} \times post_{jt} \\
&+ \boldsymbol{\beta}_2 subprime_{ij} \times treat_{ij} \times post_{jt} + \varepsilon_{ijt}
\end{aligned} \tag{1}
$$

where

t:	quarterly period, t=0 at start of quarter with disaster j
Δy_{ijt}:	4-quarter change in credit outcome for individual i
$post_{jt}$:	4-quarter period ending in $t = 4$, $t = 8$, or $t = 12$ for disaster j
$treat_{ij}$:	1 if i in affected county at start of quarter 0 for disaster j
$prime_{ij}$:	1 if Equifax Risk Score ≥ 660 at start of quarter with disaster j
$subprime_{ij}$:	1 if Equifax Risk Score < 660 at start of quarter with disaster j

Our credit outcome variables include log of total bankcard balance, an indicator for if bankcard balance as a fraction of limit is greater than 90%, an indicator for if the individual opened a new bankcard, an indicator for having fewer cards, an indicator for having fewer cards past due conditional on having fewer cards, number of bankcards past due in the last three months conditional on not having fewer cards, log of total amount past due on bankcards conditional on not having fewer cards, an indicator for new bankruptcy status, Equifax Risk Score, and an indicator for if the individual moved to a different county.[12] The first three variables are indicative of credit utilization, while the remaining variables (except for move status) are indicative of negative credit outcomes. The coefficients β_1 and

[12] All continuous variables have been winsorized. The indicator for whether balance exceeds 90% of the limit was created using winsorized variables for balance and limit.

β_2 show the effects of treatment on credit outcomes of prime and subprime individuals, respectively.

We construct our estimation sample by declared disaster. First, to filter out more severe disasters and reduce the frequency of repeat treatment of counties in the sample, we only include disasters for which per capita IHP aid was over $20 for at least one county.[13] In the rare case that more than one disaster is declared in a county in the same quarter, we combine the disasters into a "combined disaster." Furthermore, since the same disaster is assigned different FEMA disaster numbers in different states, we combine disasters that are declared in neighboring counties, across states, into a combined disaster.

Our sample includes a total of 283 combined disasters. For each combined disaster, the treated counties are counties that received FEMA aid. We specify two alternative treatment groups: 1) counties that received IHP aid (and may or may not have received PA aid) and 2) counties that received PA but no IHP aid. The control counties are those that did not receive FEMA aid but neighbor a county that received IHP or PA aid. Therefore, in the first treatment group, damage to private homes and properties was severe enough to quality for IHP. In the second treatment group, the disaster was severe enough to qualify for PA but individual assistance was not granted. Control counties were unaffected by the disaster but also represent "near misses" in that they are located close to the treatment counties and could have been affected by the disaster had the disaster path shifted slightly. If some control counties were affected by disasters but not enough to warrant any FEMA aid, this would bias our estimates toward zero.

We associate all of the treatment and control counties corresponding to each combined disaster number and create a relative time variable set to zero at the start of the quarter

[13] There are still counties in the main sample that receive multiple treatments within four-year periods. Furthermore, some counties that are treated in one quarter serve as control counties for other disasters that occur shortly before or after. Inclusion of counties in the sample both as treatment and control counties is a form of measurement error—thus, there is likely attenuation bias in the results in section 5.

in which the disaster occurred. We then match to each county all of the individuals in the Equifax subsample who resided in the county for four consecutive quarters including at the start of the quarter with the disaster (time 0).

We include observations for each treatment and control individual from 4 quarters prior to 12 quarters post disaster. In particular, we include the changes in a dependent variable over the four quarters before the disaster struck as well as over the the next three four-quarter periods immediately thereafter. This allows us to control both for seasonality effects and pretrends. Finally, we "stack" the disaster-level samples to obtain our estimation sample. Therefore, all observations in our final estimation sample are individuals who resided in either a treatment or control county with a disaster occurring in the quarter that started at time 0.

Figures 8 and 9 show two examples of combined disasters in the sample: Hurricane Sandy in late 2012 and a series of severe storms in the spring of 2008. The orange and blue counties are treated because they received IHP (orange) or PA (blue) aid. The darker the orange, the higher the per capita IHP aid. Gray counties are control counties. They did not receive FEMA aid but neighbor a county that did receive aid.

In estimating Equation 1, there are four observations for each individual: the four quarter period before the disaster strikes and the four quarter period one year, two years, and three years following the disaster. Equation 1 is similar to a standard triple difference set up except rather than having one pre and one post period, there is one pre period and three post periods. This set up allows us to estimate how the dependent variable changes for the treated individuals relative to the untreated individuals one year, two years, and three years following the disaster. Note these changes are not cumulative. The first one year change is the change over the four quarters following the last pre-disaster quarter (i.e. $t = 0$) and thus includes the quarter in which the disaster occurred. The year two change is the one year change over the following four quarters.[14] Standard errors are clustered at the county by combined disaster level.

In a second analysis we compare outcomes of individuals who reside in high versus low income census tracts. Specifically, we categorize a census tract as low income if its 2000 median household income is under $35,000, approximately two times the poverty line for a four-person family in 2000. Otherwise, we categorize a census tract as high income. The estimating equation is the same as Equation 1 except $prime_{ij,0}$ and $subprime_{ij,0}$ are replaced by $high\ income_{ij,0}$ and $low\ income_{ij,0}$, respectively, which refer to whether or not individual i resides in a high or low-income census tract at the start of quarter 0 for disaster j.

Finally, we use the same methodology described above to examine an additional layer of heterogeneity for both the credit rating and income-based analyses by restricting our sample to more extreme parts of the distribution. We examine outcomes for super prime and deep subprime individuals, based on having Equifax Risk Scores above and below 760 and 560, respectively. We also examine outcomes for individuals living in census tracts where the median income is below the poverty line of $17,500, or above triple the poverty line at $52,500.

5 Results

Our results are displayed through a series of graphs (Figures 10–13) in which the point estimates are shown along with 90% confidence intervals (dark bars), 95% confidence intervals (light bars), and 99% confidence intervals (light lines). For each breakdown reflecting

[14]Consider the example of Hurricane Sandy, which hit in late October 2012. The pre-disaster 4-quarter change is for the third quarter of 2011 to the third quarter of 2012. The year one effects would then compare the change from the end of the third quarter of 2012 to the end of the third quarter of 2013 to this pre-disaster change.

varying financial positions (e.g. prime versus subprime and high versus low income) we estimate Equation 1 for ten different outcome variables using two alternative treatments: IHP and PA aid. For each breakdown, the dark blue bars with diamonds for point estimates show effects for individuals in the strongest position (e.g. prime or high income) residing in counties receiving IHP aid. The aqua bars with triangular point estimate markers show effects for these same types of individuals residing instead in counties receiving PA but no IHP aid. On the lower end of the spectrum, the red bars with square markers and yellow bars with circle markers show effects for subprime or low income individuals residing in counties receiving IHP (and possibly PA) aid and PA (but not IHP aid), respectively.

The first set of bars in each graph shows differences in changes in the outcome variable for the four treatment groups relative to the control population for the first year after the disaster. The second and third set of bars show additional changes relative to the control population over the second and third year following the disaster, respectively.

5.1 Prime versus Subprime

Figure 10 displays the results of estimating Equation 1 on ten different outcome variables using two alternative treatments— IHP and PA aid— for prime and subprime individuals. Figure 11 shows results using only “super prime” and “deep subprime” individuals in the sample—that is, those with credit scores above 760 and below 560.

There are no significant impacts (at the 5 percent level) of disasters on credit outcomes of prime and super prime individuals residing in counties receiving IHP aid. Whether due to savings, aid, or insurance payouts (possibly combined with risk aversion), these individuals do not appear to be adversely impacted in terms of credit outcomes. Though some of the point estimates suggest that these individuals may be more likely to add new cards and perhaps increase their balances and amounts past due (conditional on not cutting the number of cards), these effects are not statistically significant.

In contrast, prime and super prime individuals residing in counties that received PA but not IHP aid are less likely to see a drop in the number of credit cards in the second and third year after the disaster than the control. This is likely due to their paying off and closing cards at a slower rate than the control group, which may suggest an increased utilization of credit or a precautionary preservation of access to credit. The positive point estimates for new cards and balance suggest that this may be the case. However, they are not statistically significant.

Subprime individuals residing in counties affected by disasters also see few significant impacts on credit outcomes. Subprime individuals residing in IHP counties, who are therefore eligible for direct assistance, are likely to see a decline in the number of cards in the first and second years after a disaster. If this is due to using aid money to pay off and close credit cards, this could be a positive outcome. However, if this is due to overdue cards being closed out, this could be a negative outcome. These individuals also are more likely to have bankcard balances in excess of 90% of their total limits in the year following the disaster, suggesting greater credit utilization.

Again contrasting individuals with the same credit status but in counties receiving different levels of aid, we now examine subprime individuals in PA counties who are not eligible for individual assistance. In the year immediately following the disaster, these individuals are more likely to have their bankcard balance exceed 90% of the total limit. Those subprime individuals in PA counties who have not reduced the number of cards are likely to see the number of bankcards with past due amounts increase in that first year, a trend which is unlikely to reverse in the following years. Similar to the prime individuals living in PA counties, these individuals are less likely to see a drop in cards a couple of years after a disaster. However, the point estimate for the first year suggests that they may see an initial drop in cards. These individuals are also less likely to have fewer cards past due conditional on having fewer cards (in the third year following the disaster), which could translate to a lower likelihood of having a delinquent card that is closed.

Although there are no significant impacts on deep subprime individuals in areas with IHP aid, those in areas with PA aid are less likely to have fewer cards, less likely to have fewer cards past due conditional on having fewer cards, and more likely to declare a new bankruptcy following the disaster.

In summary, credit outcomes for both prime and subprime individuals residing in areas with IHP aid do not appear to be significantly impacted by disasters. Both prime and subprime individuals in areas with PA but no IHP aid are less likely to own fewer bankcards following the disasters. While it's unclear if this is a positive or negative outcome, it suggests greater utilization of credit, as does their increase in likelihood of having a bankcard balance greater than 90% of the total limit. Since unlike the IHP treated individuals, the PA treated individuals do not receive individual aid, they may rely more on credit. That the deep subprime treated individuals in PA areas but not IHP areas are more likely to declare bankruptcy following the disaster also suggests the importance of aid to individuals with the worst credit worthiness.

Finally, prime and super prime individuals in IHP areas but not PA are more likely to move out of the county following the disaster. It is unclear if this is because disasters qualifying for IHP aid are more destructive, creating greater incentive for out-migration, or because individual aid plays a role in migration decisions. There is no corresponding impact on subprime individuals' propensity to move following a disaster, which could be due to a lesser willingness or ability to move.

5.2 High versus Low Income

In a second analysis we compare outcomes of individuals who reside in high versus low income census tracts. Individuals are defined as living in a high (low) income census tract if the 2000 median income in the census tract is greater (less) than $35,000 (about two times the poverty line for a four-person family in 2000.) Figure 12 shows the results of this treatment. Figure 13 shows results using only "upper" income and "poverty" census tracts in the sample—that is, those with median incomes above $52,500 (about three times the poverty line in 2000) and below $17,500, the 2000 poverty line.

Individuals residing in high and upper income census tracts receiving IHP aid in disasters are more likely to end up with balances exceeding 90 percent of their credit limits. This is a clear indication that these individuals do use credit in the aftermath of disasters, and is consistent with point estimates suggesting that they are more likely to open new credit cards, less likely to close existing credit cards, and likely to increase their balances—though none of these effects are quite statistically significant at the 95 percent level. Whether due to savings, aid, or insurance payouts, these individuals do not appear to be adversely impacted in terms of credit outcomes, as they do not see increases in amounts or cards past due.

Individuals residing in high and upper income census tracts receiving PA but no IHP aid increase their use of credit following the disaster: they are less likely to have fewer cards in the second and third year following the disaster, more likely to increase their bank card balance and to have it exceed 90% of their limit in the year following the disaster, and more likely to open a new bank card in the year following a disaster and again a couple of years later. Furthermore, the individuals in the upper income areas receiving PA appear to be worse off following the disaster, with an increase in the number of cards past due and a decrease in Equifax Risk Score in the first year after a disaster.

Individuals residing in low income census tracts receiving IHP aid have negative outcomes following a disaster. They are more likely to have fewer cards, more likely to have fewer cards past due conditional on having fewer cards, and have an increase in the number of bank cards past due in the first and second year following the disaster. Having fewer cards past due conditional on having fewer cards suggests delinquent cards are closed out. Surprisingly, we do not see corresponding negative impacts for individuals residing in the lowest income census tracts (with median income below the poverty line). This may be because households with income below the poverty line qualify for additional Other Needs Assistance from FEMA, again highlighting the importance of aid. Furthermore, individuals in low income areas receiving only PA experience an increase in number of bank cards past due after the disaster and are more likely to see their balances exceed 90% of their limits. Those in the lowest income areas receiving only PA have a higher probability of declaring bankruptcy following the disaster.

Finally, individuals residing in high and upper income census tracts receiving IHP aid (and high income receiving PA) are more likely to move following a disaster. Those in low income areas with PA are less likely to move.

6 Conclusion

In light of climate change predictions that natural disasters will increase in both severity and frequency, it is increasingly important to understand resilience to natural disasters, which serve as severe income and wealth shocks to many households. While disaster aid and insurance may buffer the shocks for some, aid is limited and many households are under- or uninsured.

We estimate the impact of natural disasters on consumer credit card outcomes using a differences-in-differences-in-differences approach. Unlike previous studies, we consider a panel of nationwide disasters, rather than focusing on one salient disaster, and our analysis attempts to identify differential impacts on prime and subprime individuals as well as on individuals in high and low income areas.

Credit outcomes for both prime and subprime individuals residing in areas with IHP aid do not appear to be significantly impacted by disasters. There is some evidence that PA treated individuals who do not qualify for individual aid may rely more on credit. Subprime individuals with the lowest credit scores who reside in affected areas that do not qualify for individual aid (but not those who do) are more likely to declare bankruptcy following the disaster, highlighting the importance of aid. Prime and super prime individuals in IHP areas but not PA are more likely to move out of the county following the disaster.

We find no negative impacts on credit outcomes of individuals living in high income census tracts in counties that receive IHP aid. Those in high income areas that only receive PA utilize credit more. Individuals in low income areas receiving either IHP or PA appear to be worse off after the disaster, with more bank cards past due. Those in low income areas with only PA are more likely to declare bankruptcy.

In summary, with the exception of those living in low income areas, we find few negative impacts on credit outcomes of most individuals living in areas hit by disasters that qualify for individual aid. We find that individuals in areas hit by disasters utilize credit more. The most vulnerable of these individuals (those with the lowest credit scores and those who reside in low income areas) are more likely to declare bankruptcy after the disaster. These results highlight the importance of aid to households' financial post-disaster resiliency. Our findings suggest that an expansion of FEMA individual and household aid programs—either by granting IHP aid to more counties, expanding Other Needs Assistance to a broader group of low income individuals, or even perhaps by offering low cost credit to subprime individuals—could dramatically help some of the most vulnerable segments of our population weather disasters better.

In future work we will add in Spatial Hazard Events and Losses Database (SHELDUS) disaster damage data. The SHELDUS data will allow us to control for disaster severity (in terms of estimated damage) and thus disentangle damage from aid. We will also analyze different types of disasters, to see what types of events are driving these effects and whether the effects are heterogeneous by disaster type. In particular, we will examine hurricanes, have been predicted to become more severe due to climate change, on their own, with and without Hurricane Katrina.

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7 Tables and Figures

Table 1: Numbers of Disaster Types in Sample

	Declared	with IHP	with PA
Coastal Storm	2	0	2
Earthquake	5	3	5
Fire	462	9	16
Flood	106	27	96
Freezing	1	0	0
Hurricane	109	34	77
Mud/Landslide	3	1	2
Severe Ice Storm	34	0	26
Severe Storm(s)	484	159	443
Snow	57	0	56
Tornado	14	6	11
Tsunami	3	0	3
Volcano	1	0	1

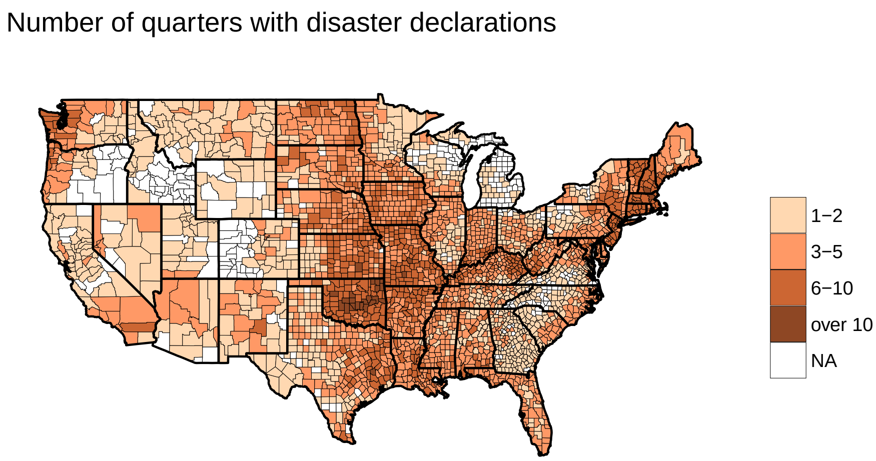
Source: FEMA

Table 2: Summary Statistics of NY Fed Consumer Credit Panel/Equifax Variables

	Obs		Mean		Std. Dev.		Min	Max
	Prime	Subprime	Prime	Subprime	Prime	Subprime	Full	Full
Total Bankcard Balance	20,002,714	7,716,006	4,481	5,185	10,696	10,049	-2,361	5,390,276
Total Credit Limit	20,002,714	7,716,006	23,068	6,967	25,758	13,203	-4,999,500	3,652,500
Number of Cards	24,692,538	13,670,239	2.4	1.4	2.2	2.0	0	69
Equifax Risk Score	24,790,672	13,902,594	758	573	52	69	280	848
Balance / Limit	19,937,163	7,702,174	0.22	1.08	3.72	65.13	-0.25	69,972
Total Past Due Amount: Bankcards	24,396,798	13,636,238	27	674	773	3,014	0	580,000
Num. Bankcards Past Due in Last 3 Mos.	24,404,145	13,685,091	0.011	0.170	0.123	0.593	0	36
New Card	24,790,672	13,902,594	0.045	0.035	0.207	0.185	0	1
County Move	23,543,931	13,025,425	0.018	0.026	0.135	0.160	0	1
Bankruptcy	24,790,672	13,902,594	0.000	0.003	0.015	0.058	0	1
Balance More than 90% of Limit	20,002,714	7,716,006	0.041	0.504	0.199	0.500	0	1

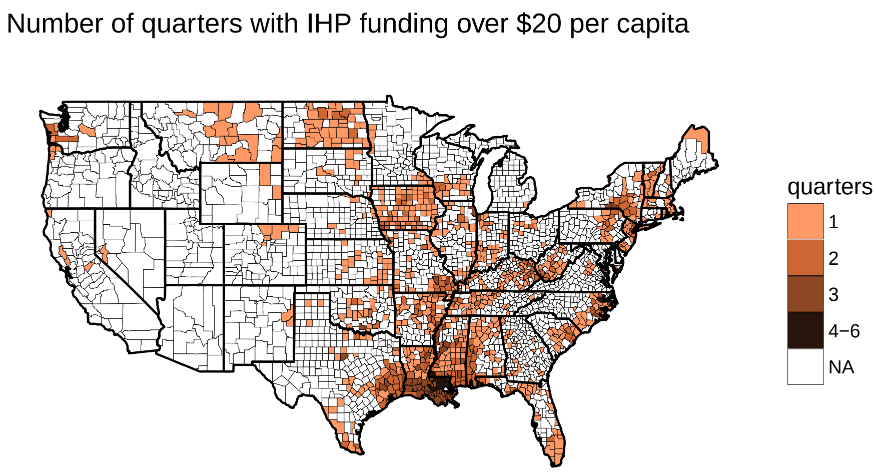
Source: NY Fed Consumer Credit Panel/Equifax
Total Bankcard Balance: Total bankcard balance
Total Credit Limit: Total credit limit across all bankcards
Number of Cards: Number of bankcards
Equifax Risk Score: Proprietary measure of likelihood of borrower defaulting. Ranges from 280 to 850, with a higher score equating to better credit worthiness. Here we consider scores above or equal to 660 to be prime and below 660 to be subprime.
Balance / Limit: Total bankcard balance divided by total credit limit
Total Past Due Amount: Bankcards: Total past due amount for all bankcard accounts
Number of Bankcards Past Due in Last 3 Months: Number of bankcard accounts with 30, 60, 90, or 120-180+ days past due as the worst payment status within the last three months
New Card: Binary variable equal to one if newest bank card less than 3 months old
County Move: Binary variable equal to one if an individual has moved from one location maintained for four subsequent quarters to a location in a new county, where they spent four consecutive quarters
Bankruptcy: Binary variable equal to one if individual files for a new bankruptcy in the current quarter
Balance More than 90% of Limit: Binary variable equal to one if individual's bankcard balance is greater than 90% of his or her total limit, based on winsorized values of balance and limit

Figure 1: Number of FEMA declared natural disasters with IHP and/or PA aid, 2005-2016



Source: FEMA

Figure 2: Number of FEMA declared natural disasters with per capita IHP aid greater than $20, 2005-2016, excluding Hurricane Katrina



Source: FEMA

Figure 3: Distribution of FEMA per capita Individuals and Households Program (IHP) aid (county level), 2005-2016

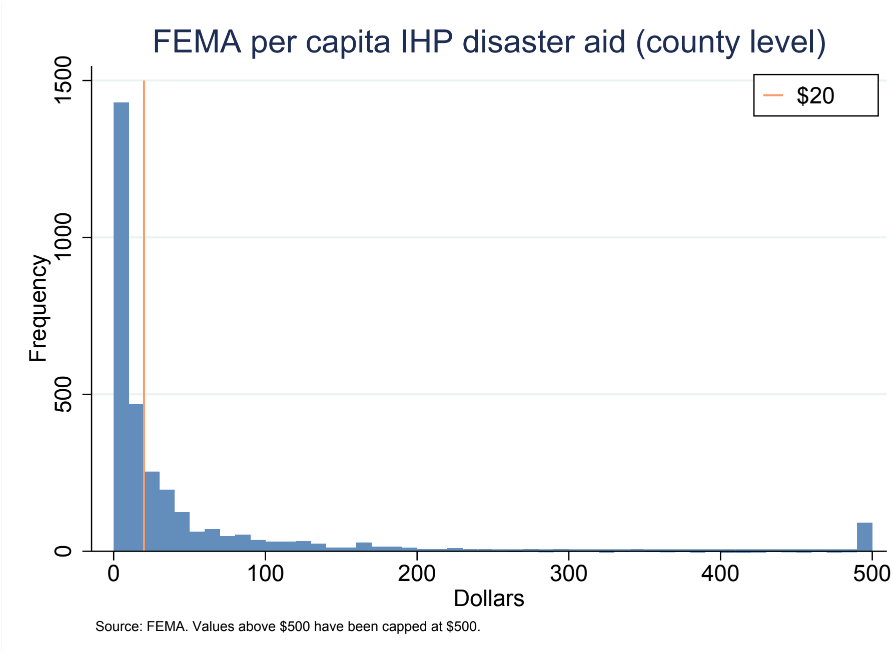
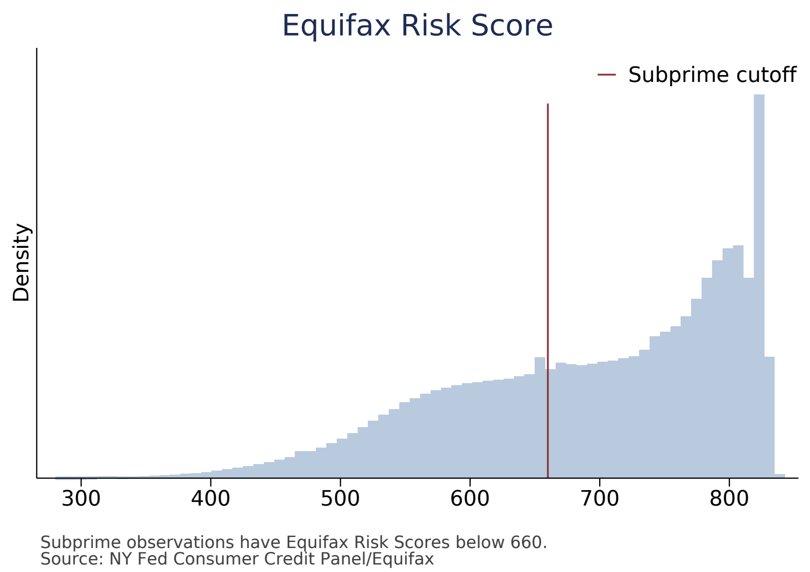
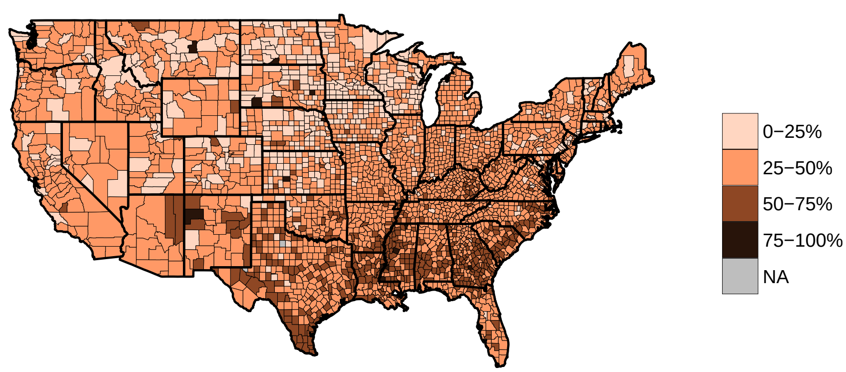


Figure 4: Distribution of Equifax Risk Scores



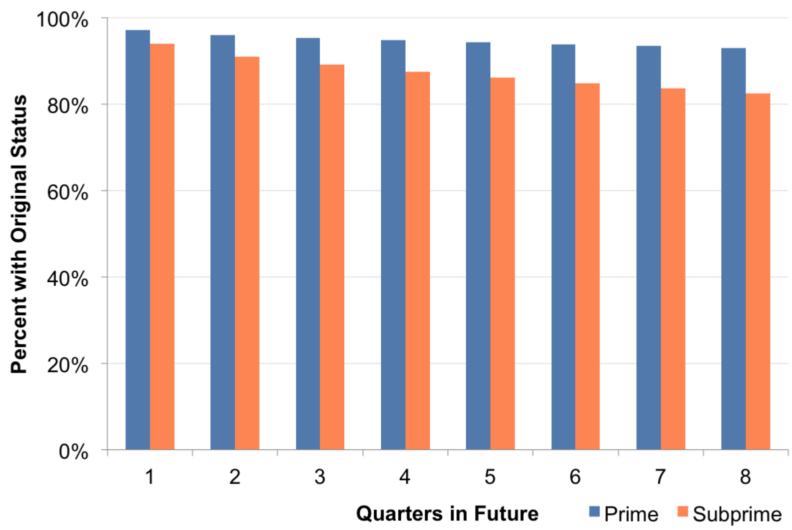
Source: NY Fed Consumer Credit Panel/Equifax

Figure 5: Fraction of Prime Individuals, 2002



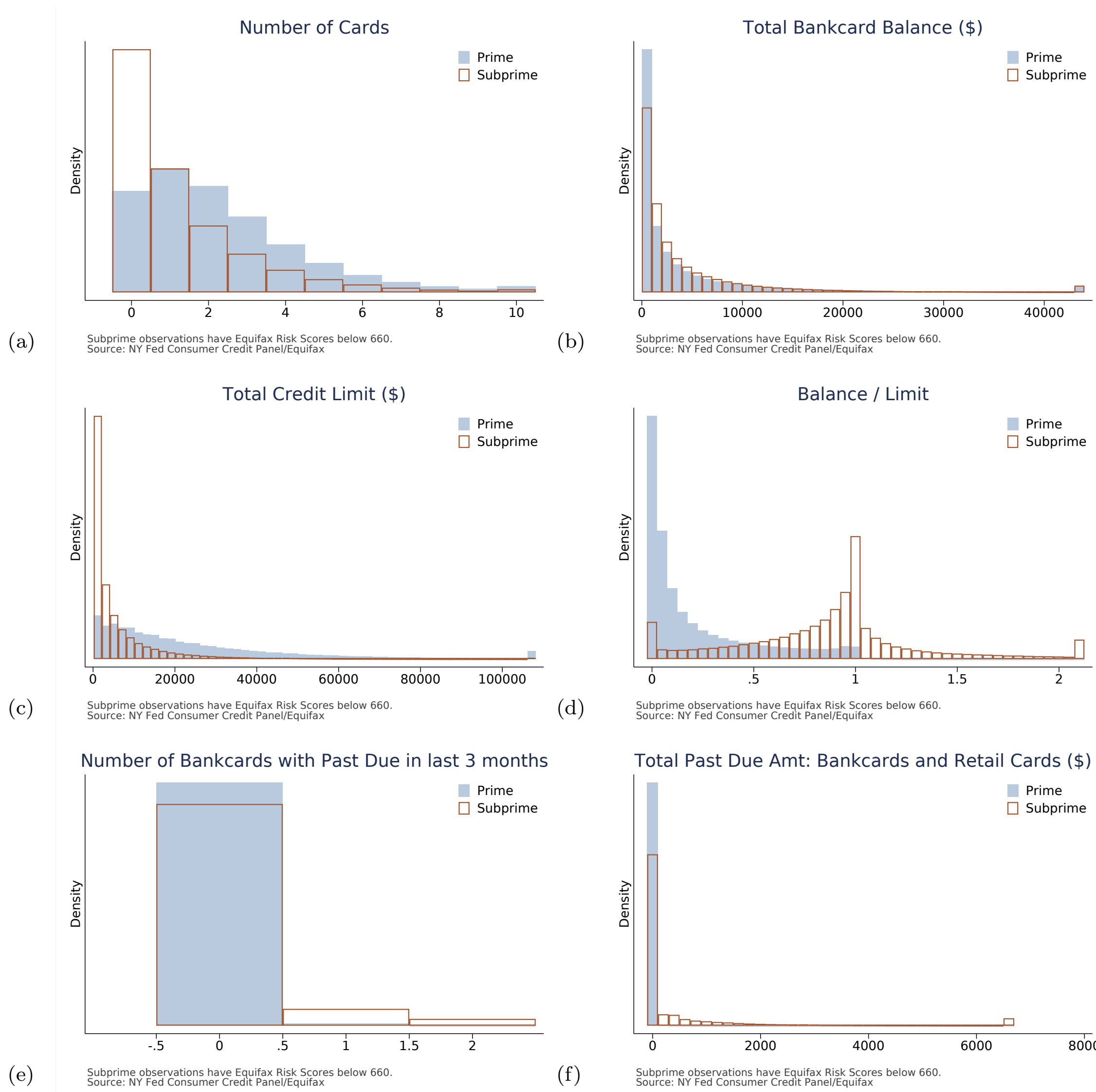
Source: NY Fed Consumer Credit Panel/Equifax

Figure 6: Persistence of Prime Status



Source: NY Fed Consumer Credit Panel/Equifax

Figure 7: Credit outcome variables for prime and subprime observations



Subprime observations have Equifax Risk Scores below 660.
Source: NY Fed Consumer Credit Panel/Equifax

Figure 8: Hurricane Sandy IHP, PA, and Control Counties

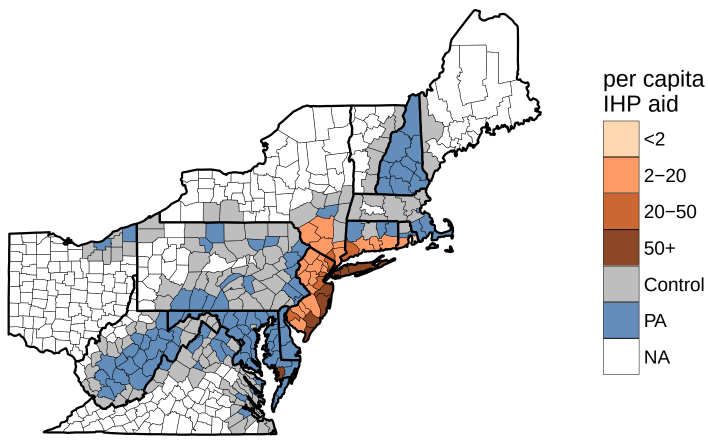


Figure 9: Severe storms, tornadoes, flooding, mudslides, and landslides (spring 2005)

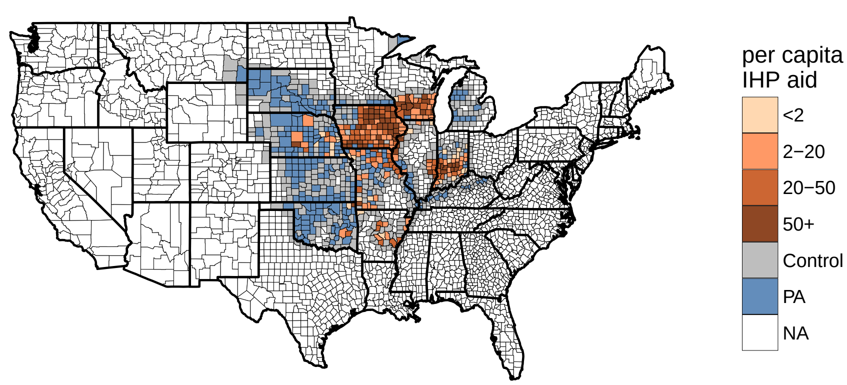
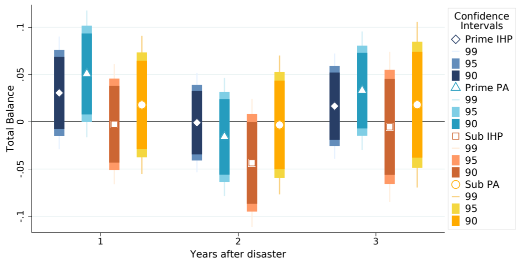
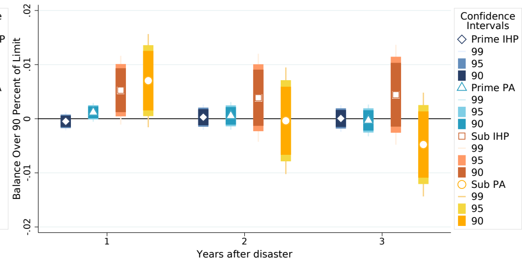


Figure 10: Prime versus Subprime

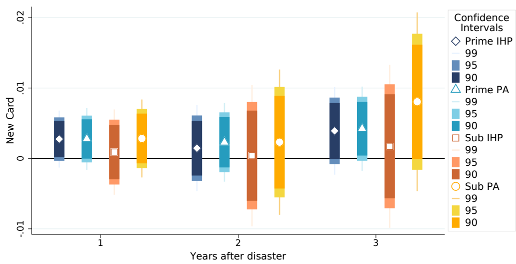
(a) Balance



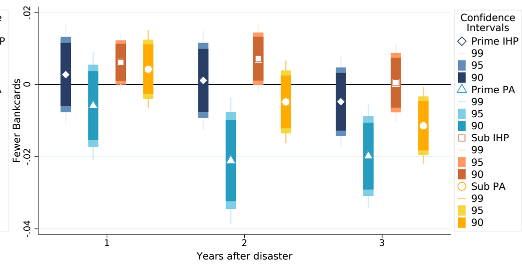
(b) Balance > 90% of limit



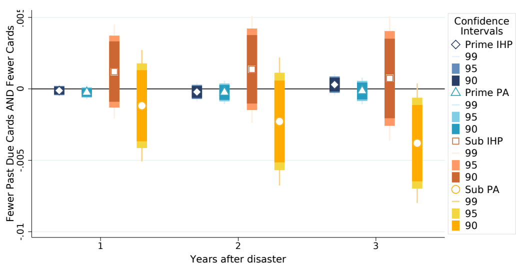
(c) New card



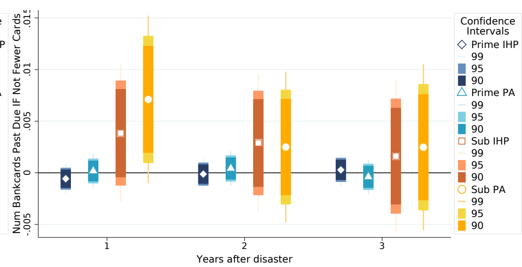
(d) Fewer cards



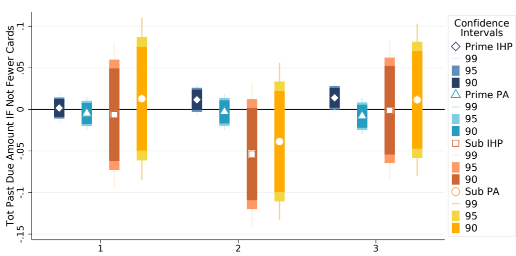
(e) Fewer cards past due AND fewer cards



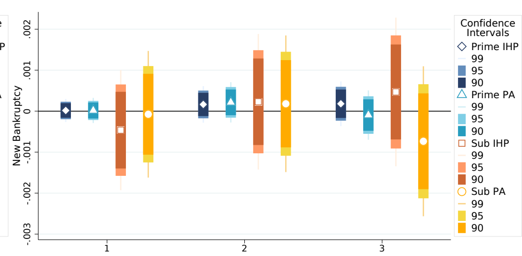
(f) Number of cards past due if not fewer cards



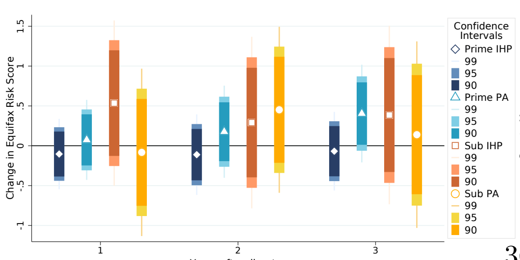
(g) Amount past due if not fewer cards



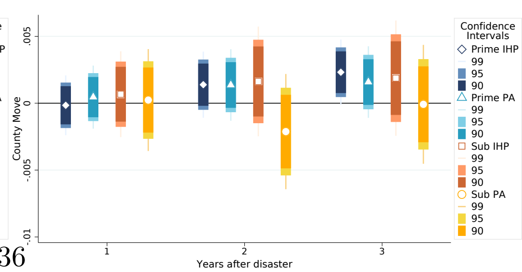
(h) New bankruptcy



(i) Equifax Risk Score

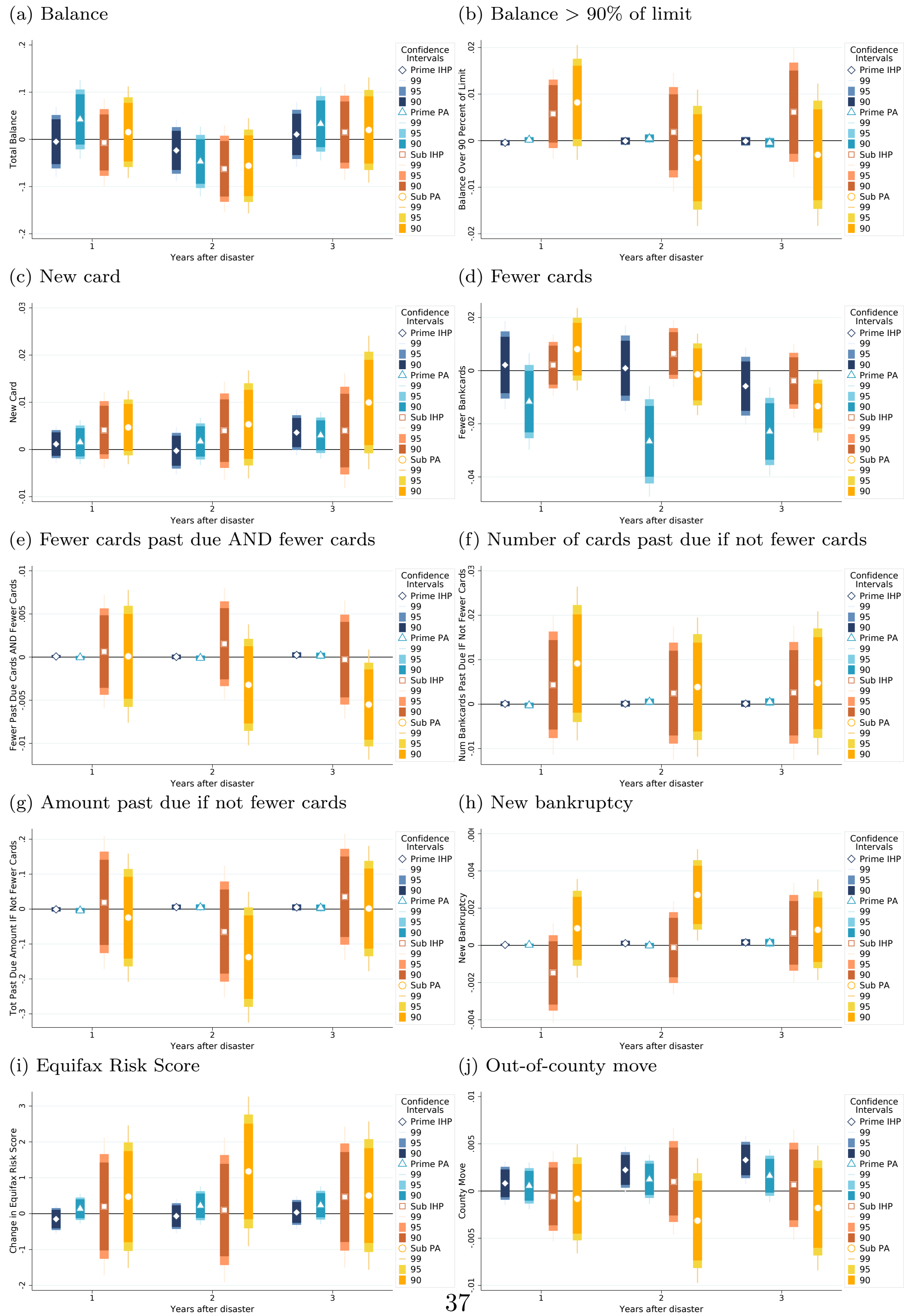


(j) Out-of-county move



Source: NY Fed Consumer Credit Panel/Equifax. Includes disasters with at least one county receiving at least $20 per capita IHP aid. IHP results are for counties that received IHP aid. PA results are for counties that received PA but not IHP aid. Total Balance and Total Past Due Amount are in log form.

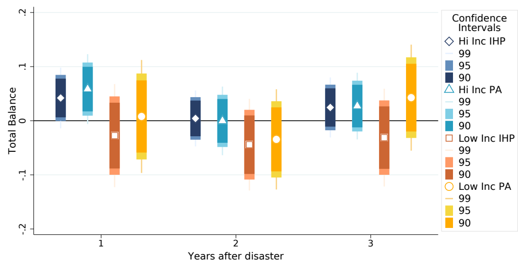
Figure 11: Super Prime versus Deep Subprime



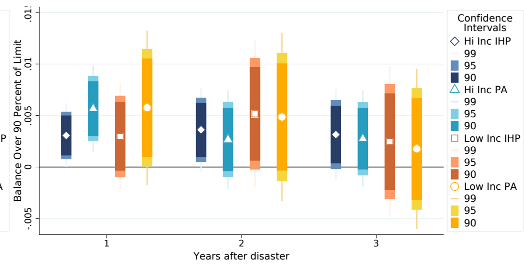
Source: NY Fed Consumer Credit Panel/Equifax. Includes disasters with at least one county receiving at least $20 per capita IHP aid. IHP results are for counties that received IHP aid. PA results are for counties that received PA but not IHP aid. Excludes observations for individuals with Equifax Risk Scores between 560 and 760 at start of quarter with disaster. Balance and Amount Past Due are in log form.

Figure 12: Low versus Middle/Higher Income Census Tracts

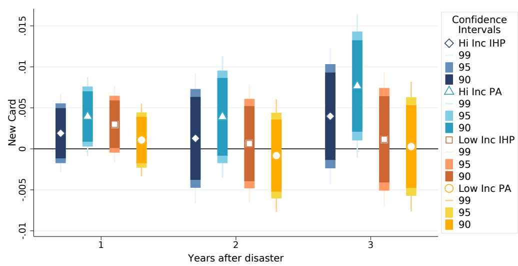
(a) Balance



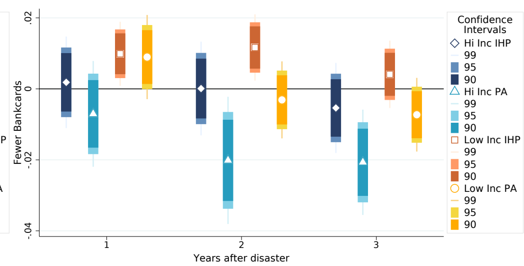
(b) Balance > 90% of limit



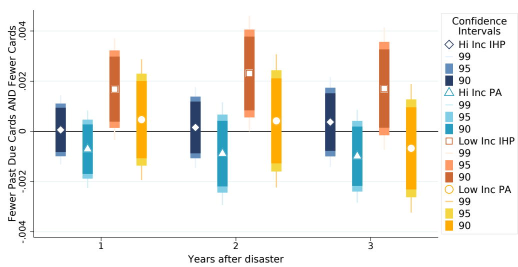
(c) New card



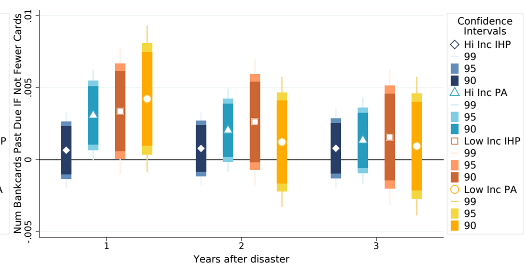
(d) Fewer cards



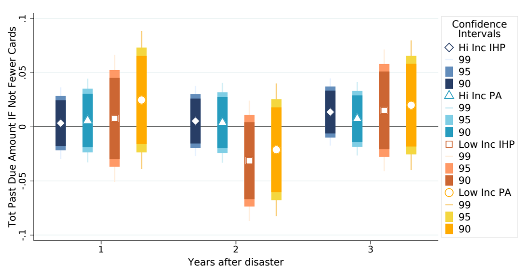
(e) Fewer cards past due AND fewer cards



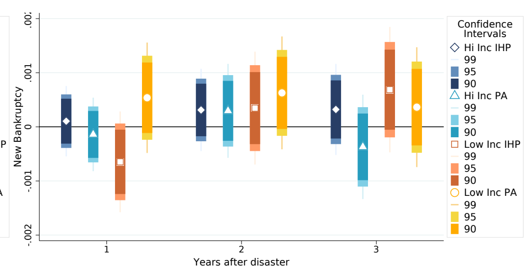
(f) Number of cards past due if not fewer cards



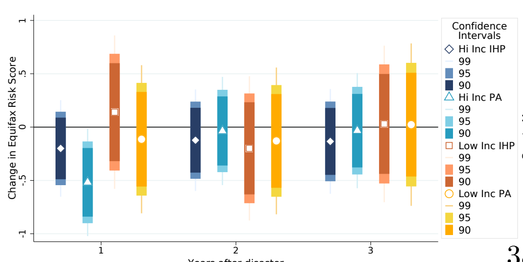
(g) Amount past due if not fewer cards



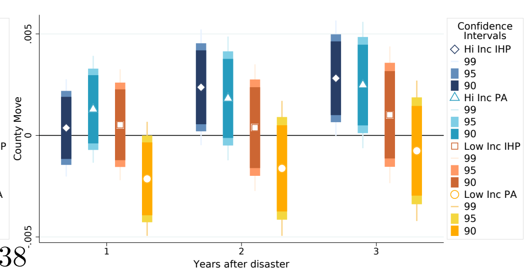
(h) New bankruptcy



(i) Equifax Risk Score



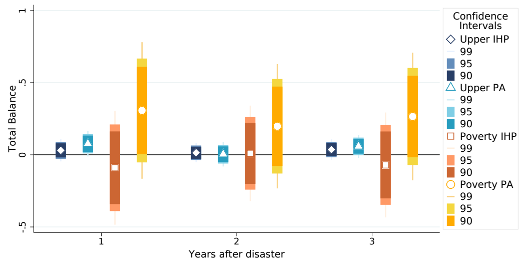
(j) Out-of-county move



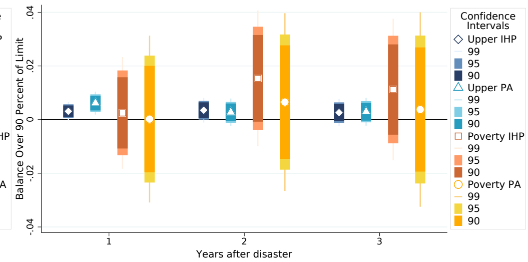
Source: NY Fed Consumer Credit Panel/Equifax. Includes disasters with at least one county receiving at least $20 per capita IHP aid. IHP results are for counties that received IHP aid. PA results are for counties that received PA but not IHP aid. Total Balance and Total Past Due Amount are in log form. High and Low income observations are for individuals residing in census tracts with 2000 median household income above and below $35,000, respectively.

Figure 13: Census Tracts with Median Income Below 1× vs Above 3× Poverty Line

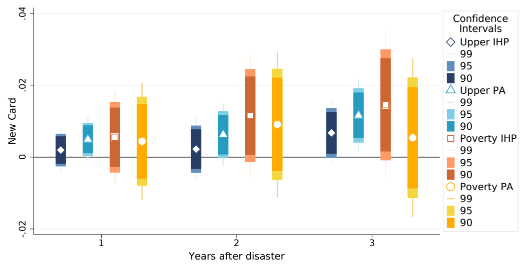
(a) Balance



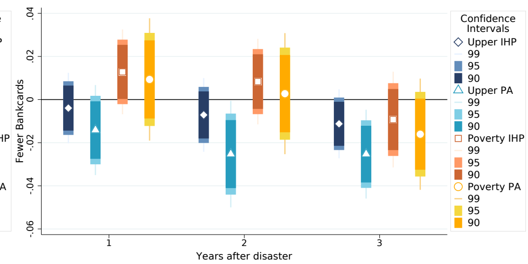
(b) Balance > 90% of limit



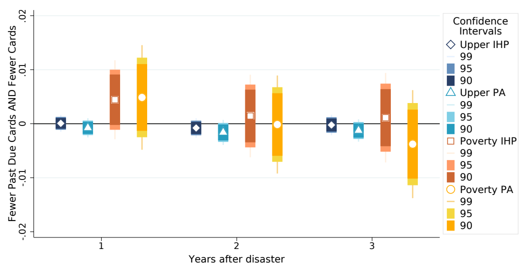
(c) New card



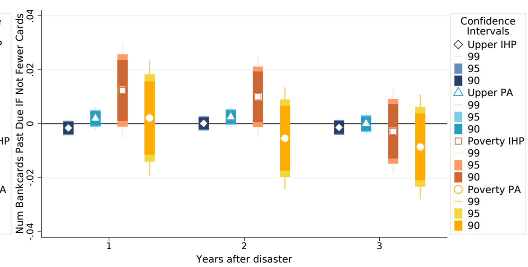
(d) Fewer cards



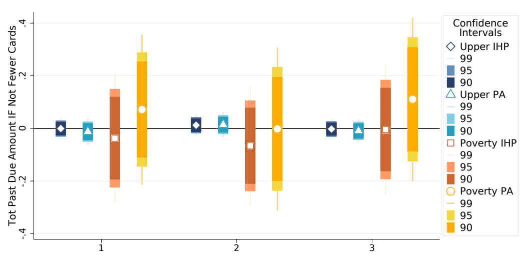
(e) Fewer cards past due AND fewer cards



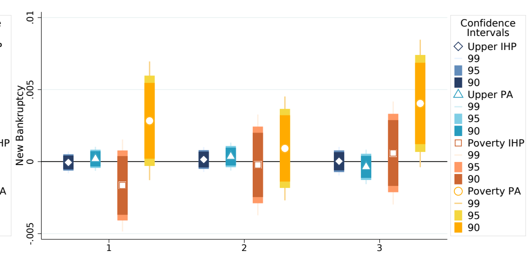
(f) Number of cards past due if not fewer cards



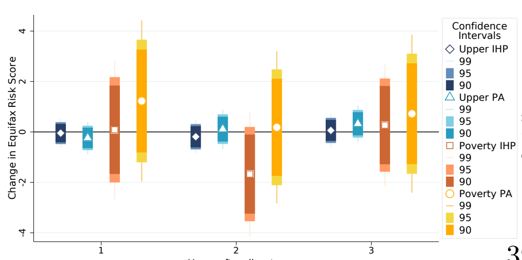
(g) Amount past due if not fewer cards



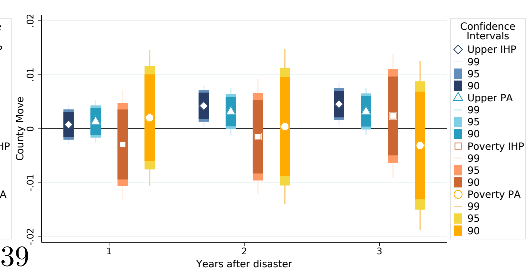
(h) New bankruptcy



(i) Equifax Risk Score



(j) Out-of-county move



Source: NY Fed Consumer Credit Panel/Equifax. Includes disasters with at least one county receiving at least $20 per capita IHP aid. IHP results are for counties that received IHP aid. PA results are for counties that received PA but not IHP aid. Excludes observations in census tracts with median income between $17,500 and $52,500 in 2000. Total Balance and Total Past Due Amount are in log form.