

RESEARCH REPORT

Insult to Injury

Natural Disasters and Residents' Financial Health

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Executive Summary

Images of climate change—driven destruction—coastal communities swept away by storm surge and hurricane-force winds, wildfires and tornadoes erasing whole neighborhoods—increasingly fill newspapers and TV screens. These disasters lead to injury and loss of life, can displace entire communities overnight, and destroy homes and businesses. These consequences, combined with other economic, social, and environmental impacts, can lead to both immediate and longer-term financial setbacks for residents of affected areas. Damaged or destroyed personal property can be expensive to replace or repair, health care costs for bodily injury and mental health may rise, and housing and any relocation expenses must be covered. At the same time, local businesses and employment opportunities may suffer, leaving families with a reduced capacity to meet even routine expenses such as rent or mortgage payments, utilities, auto loans, and other bills.

A wide range of public, private, and charitable recovery assistance programs and temporary financial relief help to mitigate the financial consequences of disasters. But because these programs are often targeted toward the most severe disasters, not readily available to all affected residents, and limited in scope and duration, they may leave many affected residents vulnerable to financial hardship. Especially for families that are already financially fragile, the additional shock from a natural disaster of any size or type could be a recipe for short-term financial hardship that leads to long-term declines in financial health.

Using Federal Emergency Management Agency (FEMA) data on multiple natural disasters across the United States, combined with Census and credit bureau data, we address three questions:

- What are the effects of natural disasters on residents' financial health, as measured by credit scores, credit card debt, debt in collections, bankruptcies, foreclosures, and auto debt?
- How do the effects differ by severity of the disaster, which can result in variations in the provision of financial relief and recovery assistance?
- How do the effects differ by the demographic and economic characteristics of residents and the communities they live in?

The results of this study provide empirical evidence on the impact of natural disasters of differing magnitudes on residents' financial health along a number of dimensions. Four general themes emerge:

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- Disasters lead to broad, and often substantial, negative impacts on financial health. We find
 evidence of negative impacts across most measures of financial health, including credit scores,
 debt in collections, bankruptcy, credit card debt, and mortgage delinquency and foreclosures.
- The negative effects of disasters persist, or even grow over time, for important financial outcomes. For example, while living in a community hit by a medium-sized natural disaster leads to a 5 percentage-point increase in the share of people with debt in collections after one year, this negative effect doubles to 10 percentage points by after four years.
- Medium-sized disasters, which are less likely to receive long-term public recovery funding, appear to lead to larger and more consistently negative effects on financial health than large disasters. For example, we find more substantial credit-score declines among residents hit by medium-sized disasters (average 22-point decline by the fourth year following the disaster) than large disasters such as Hurricane Sandy (average 10-point decline four years out). Note that, in our data, most individuals affected by medium-sized disasters were affected by a 2014 storm that hit urban areas in and around Detroit that did not receive a special congressional appropriation for recovery. Because Southeastern Michigan is a dense urban environment that has faced significant economic challenges, this finding may not be generalizable, and the effects of medium-sized disasters deserve additional study.
- Individuals and communities more likely to be struggling financially before disasters strike, such as low-income communities and communities of color, are often the hardest hit by the disaster. For example, we found that people living in communities of color hit by medium-sized disasters experienced an average 31-point decline in credit score, compared with a 4-point decline for affected people in majority-white communities.

These results suggest that, in general, existing disaster relief programs and other forms of assistance, along with private sources of insurance and support, do not fully protect those affected by natural disasters from their financial consequences. The pattern of results is also broadly suggestive that disasters may be not only harmful for affected residents on average, but may also have the effect of widening already existing inequalities.

Implications of Findings for Disaster Preparation and Recovery Strategies

Our findings provide insight into strategies to promote resilience and recovery for multiple actors—regulators and government (local, state, federal), philanthropy, and nonprofit leaders focused on financial health. For example, our main findings suggest post-disaster programs and resources should consider long-term financial needs, in addition to more immediate needs. Also, a larger share of

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recovery resources should be aimed at communities struggling before the disaster hit. Similarly, the evidence we find of long-term negative impacts on credit scores indicates a need for changes to rules and guidance around how natural disasters and subsequent delinquencies are identified on consumers' credit reports and incorporated into credit scores. These and other recommended strategies were informed by interviews with experts in the field and are discussed in more detail in the concluding section of this report.

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Introduction

Images of climate change-driven destruction—coastal communities swept away by storm surge and hurricane-force winds, populations displaced overnight, wildfires and tornadoes erasing whole neighborhoods—have been filling newspapers and TV screens. In fact, last year, there were 14 "billion-dollar" disasters costing a total of \$91 billion (NOAA 2019). These events run the gamut from wildfires in California and drought in the southwest to tornadoes in the south and hurricanes and winter storms in the east. Beyond these large, widely publicized events are dozens of smaller disasters that disrupt communities and their residents (US Global Change Research Program 2018).

At the same time, many families live on the financial edge and lack the means to absorb even small financial setbacks. For example, over 40 percent of Americans report that they cannot cover a \$400 unplanned expense (Board of Governors of the Federal Reserve System 2018), and it's not just low-income Americans. Middle-income families, and even some high-income families, struggle to meet their basic expenses after an unexpected shock (McKernan et al. 2016).

The combination of devastating natural disasters with financially fragile families can be a recipe for not only short-term financial hardship, but also long-term declines in financial health. These negative effects may be particularly pronounced after smaller-scale disasters, which are vastly more frequent but do not receive a massive infusion of federal assistance dollars or temporary relief from lenders, financial institutions, and other service providers typical of the most severe events.

Using data on multiple natural disasters across the United States, this paper provides empirical evidence on the impact of natural disasters on residents' financial health and addresses the following research questions:

- What are the effects of natural disasters on residents' financial health, as measured by credit scores, debt in collections, credit card debt, bankruptcies, foreclosures, and auto debt?
- How do the effects differ by severity of the disaster, which can result in variations in the provision of financial relief and recovery assistance?
- How do the effects differ by the demographic and economic characteristics of residents and the communities they live in?

The results from these analyses are then used to highlight strategies that can help residents build resilience before a disaster hits and better cope afterward.

When we compare the financial health of residents in affected communities (defined by zip code) to otherwise similar people in unaffected areas, four general themes emerge:

- Disasters lead to broad, and often substantial, negative impacts on financial health.
- The negative effects of disasters persist, or even grow over time, for important financial outcomes (e.g., credit score, debt in collections).
- Medium-sized disasters appear to lead to larger and more consistently negative effects on financial health than large disasters, though this conclusion is tempered somewhat by the fact that most people affected by medium-sized disasters in our analysis were hit by storms and flooding in urban areas in and around Detroit.
- Individuals and communities more likely to be struggling financially before disasters strike are
 often the hardest hit by the disaster.

The overall pattern of results also broadly suggests that disasters do more than harm residents; they also widen existing inequalities.

We next provide background on the link between natural disasters and financial health, including a discussion of disaster recovery and relief policies and programs, what we know from the literature, and the contributions of this paper. We then describe our data and approach, followed by a discussion of key findings. We conclude by highlighting strategies for addressing residents' financial health in light of the increasing and destructive nature of natural disasters (US Global Change Research Program 2018).

Background: Natural Disasters and Financial Health

Natural disasters can harm people's finances through various channels. Personal property, such as the belongings inside a home and/or an automobile, can be damaged or destroyed. A flooded home can leave a homeowner with both a mortgage and a rent payment until the home is habitable. A damaged car can leave the owner with a loan to pay, but no way to get to work. These losses can also leave people struggling to pay deductibles for insurance claims, assuming the rare condition that a household has the appropriate hazard policy coverage for its property and possessions (Kousky and Cooke 2012) and that the coverage applies in that instance. Bodily injury and mental trauma can lead to additional health care costs not necessarily covered by individual health insurance (Rudowitz, Rowland, and Shartzer 2006). At the same time, businesses may be shuttered for days, if not weeks, leaving employees without paychecks.

The consequence of multiple and simultaneous financial setbacks can leave residents struggling to meet their financial obligations in the short term (e.g., rent/mortgage, utility bills, credit card bills, auto loans) and jeopardize their longer-term financial security. After Hurricanes Harvey and Irma, an analysis of checking account data suggests a decline in income, as checking account inflows fell by over 20 percent (Farrell and Greig 2018). Additionally, 12 weeks after these disasters, spending on home expenses had risen by 9 percent in Miami and by 33 percent in Houston, while spending on debt payments and health care had dropped in both locations (Farrell and Grieg 2018).

The federal government—in coordination with state and local governments—provides various disaster recovery and relief policies and programs designed to help mitigate the effects of natural disasters on residents' financial well-being. These programs help pay for vital services immediately following a disaster, help households navigate through tough economic circumstances, and provide some financing for households to rebuild or recoup some of the economic losses caused by the disaster.

Some of the largest governmental disaster relief and recovery programs are listed in box 1. Key among these are assistance from the Federal Emergency Management Agency (FEMA), the US Department of Housing and Urban Development (HUD), and the Small Business Administration (SBA). FEMA's Individual Assistance (IA) program funds direct disaster assistance to individuals through the Individuals and Households Program (IHP), and SBA provides loans for homeowners to repair or rebuild, for example, Additionally, Congress can appropriate funds for the Community Development

BOX 1

Major Public-Sector Assistance Programs for Individuals Affected by Disasters

Here we list the major public public-sector assistance programs for people affected by disasters. For details about each program, see appendix A.

Relief for immediate needs:

- Mass Care/Emergency Assistance is provided by FEMA to all residents in an affected region in the immediate aftermath of a disaster.
- Transitional Shelter Assistance (TSA) is funded by FEMA and available to people unable to return to their residence after a disaster and temporary shelter closures.
- Low Income Home Energy Assistance Program (LIHEAP) Emergency Contingency Funds are distributed at the discretion of the Department of Health and Human Services to states to supplement annual formula grants.

Relief for home repair and replacement of personal property:

- FEMA Individuals and Households Program (IHP—a component of, and also referred to as, Individual Assistance or IA) provides various financial assistance channels to people affected by disasters with unmet needs—that is, needs not covered after insurance claims—for temporary housing, repair, replacement, and reconstruction and for other needs such as disaster-related medical costs, funeral expenses, or personal property loss.
- Disaster Loan Assistance (SBA loans) is a program from the US Small Business Administration that provides low-interest loans to eligible homeowners and businesses.
- Community Development Block Grant Disaster Recovery (CDBG-DR) provides additional funding for unmet housing needs, targeted especially for low- and moderate-income households with remaining uninsured needs in the most severely affected regions.

Relief for economic hardship:

- Disaster Unemployment Assistance (DUA) is also funded by FEMA and provides funds to states and local, tribal, and territorial governments for unemployment benefits and reemployment services to people who become unemployed as a result of a disaster but are not eligible for traditional unemployment insurance.
- Disaster Supplemental Nutrition Assistance Program (D-SNAP) is an extension of the SNAP program that gives food assistance to low-income households following a natural disaster.
- Disaster Housing Assistance Program (DHAP) was a housing assistance program (after Hurricanes Rita and Katrina and Superstorm Sandy) that provided a rental subsidy with case management.
- Disaster Tax Relief is often provided by the Internal Revenue Service in the form of delayed payment or filing deadlines.

Relief for homeowners with mortgages:

- The Federal Housing Administration (FHA) provides a foreclosure moratorium on FHA-insured mortgages and instructs lenders to allow forbearance plans and loan modifications to all affected borrowers.
- Fannie Mae provides a Disaster Response Network offering credit counseling; assistance filing FEMA, insurance, and SBA claims; and credit reporting moratoria, forbearance plans, loan modifications, and relaxed regulations for homeowners with Fannie Mae-owned mortgages.
- Freddie Mac provides forbearance programs, modifications, credit reporting moratoria, and the waiving of late charges for homeowners with Freddie Mac-owned mortgages.

Block Grant Disaster Recovery (CDBG-DR) program. CDBG-DR is administered by HUD to grant state and local governments additional funds to fulfill unmet housing needs in disaster-affected areas. Other smaller assistance programs are also generally available; for example, the Low-Income Home Energy Assistance Program (LIHEAP) allows states to use funds to aid in disaster relief and recovery for households' utility bills.

Concurrently, various other federal and quasi-governmental programs have provisions that adapt to the needs of households affected by disasters through financial relief, as opposed to direct assistance. For example, the Federal Housing Administration (FHA), Fannie Mae, and Freddie Mac all have policies in place to relieve short-term burdens on mortgage holders. In the 2017 hurricane season, this included forbearance programs, restructuring, and moratoria on credit reporting, foreclosure, and eviction.⁴

However helpful to those suffering the effects of natural disasters, assistance and relief from these federal sources are unable to fully protect affected residents from financial hardship. First and foremost, not every form of assistance is available after every disaster. For example, some level of assistance for all federally declared disasters is part of FEMA's normal budget, but HUD requires special appropriations to fund CDBG-DR; such special action by Congress typically follows the most severe disaster events only, though the resulting appropriation may cover a wide range of disasters, large and small. The Disaster Housing Assistance Program, in the form of rental assistance, has been made available only sporadically. This program and other assistance were funded after Hurricanes Katrina and Rita and Superstorm Sandy, for example, but not after Hurricanes Harvey and Maria. Variability in programs' availability across disasters reduces the ability to evaluate their effects, in addition to causing confusion among service providers and households.

Further, most federal programs are targeted at specific subpopulations. For example, HUD dollars have traditionally focused on homeowners, though they are increasingly targeted to residents that are renters. SBA dollars are similarly earmarked for repairing owner-occupied homes and replacing damaged personal property. Moreover, many eligible applicants do not pursue assistance or relief, and significant shares of applications for disaster-related assistance are turned down. In 2017, for example, FEMA rejected two-thirds of IHP applications in the aftermath of Hurricanes Harvey, Irma, and Maria, and the California wildfires (Martín and Teles 2018).

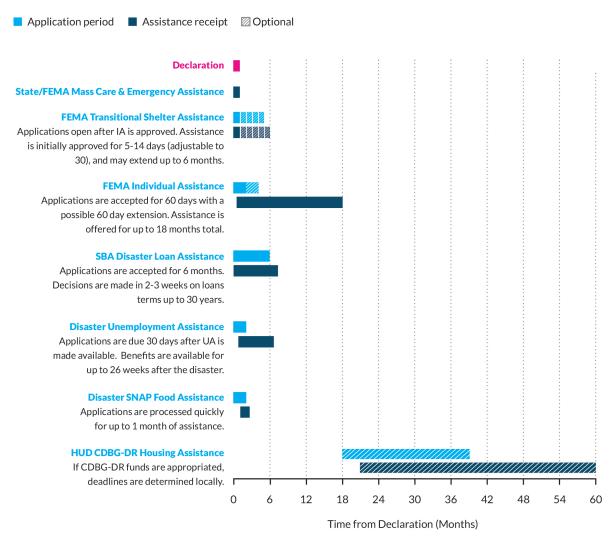
Beyond these large federal programs, there are a host of private- and quasi-public-sector responses to disasters. Private banks, lenders, and other financial institutions often create special relief programs, though there are no consistent triggers or eligibility criteria employed across these entities, or within

the same entity across different disasters. Recent examples of these efforts include moratoria on credit score reporting, forbearance, or direct financial counseling and fraud alerts.⁶

Finally, local charitable resources are deployed to help victims of natural disasters meet their immediate and evolving needs. To understand more about local responses to natural disasters, our research team spoke to several organizations with direct-service experience in areas affected by recent natural disasters (see appendix C for more detail on these conversations). Respondents described various services aimed at helping residents and communities recover that were delivered by local nonprofits, other community- and faith- based organizations, and local governments. In the immediate aftermath, the focus of these efforts tended to be providing quick assistance around basic needs including distributing food, water, clothing, and hygiene products. For example, after major disasters, the Red Cross has provided small grants to families to help with relocation and immediate basic needs. Organizations work to match services to residents' evolving needs, and after a disaster, by providing assistance such as small grants to help cover rent and utilities, help navigating applications for federal aid and other relief programs, and distributing information aimed at helping residents identify and avoid fraud. Despite the importance of the nonprofit sector in the response to natural disasters, local organizations and their staff are many times themselves affected by the disaster and may lack the experience and capacity to meet residents' and community needs.

Ultimately, even for those receiving assistance, the amount, timing, or form of relief might leave important financial needs unmet. In particular, there can be a mismatch between when individuals experience needs and when public disaster assistance is provided. For example, temporary shelter and assistance for disaster-related unemployment and food insecurity generally expire within six months. Yet, it frequently takes more than a year for state and local governments to launch CDBG-DR programs for households with unmet needs, and families may wait up to three years or longer before receiving CDBG-DR funded assistance. See figure 1 for a typical timeline of disaster aid.

FIGURE 1
Federal Disaster Assistance Programs Prioritize Immediate Needs



Notes: LIHEAP, Tax Relief, FHA Foreclosure Moratoria, and Fannie Mae/Freddie Mac Forbearance are not tied to specific or estimated timeframes because of either provider discretion or the nature of the relief actions. The Disaster Housing Assistance Program, which is not shown here, was available one and two years after a disaster for a one- and two-year period, respectively, both times it was enacted.

What Do We Know from the Literature?

Natural disasters harm people's finances, among many other tragic outcomes. Yet, the uncertainty surrounding the nature and magnitude of these effects is exacerbated by the myriad programs and policies designed to ameliorate them. A growing but still small body of research investigates the impacts of natural disasters on individuals' economic well-being. One recent strand of this literature, to which

our study adds, is distinguished by the use of administrative data on credit and employment outcomes to look at the effects of disasters on the economic well-being of individuals for up to several years following the disaster.

Recent papers by Gallagher and Hartley (2015) and Edminston (2017) use the Federal Reserve Bank of New York's Consumer Credit Panel to consider impacts of disasters on measures of financial health similar to those used in this study, including credit score, debt (credit card, auto, home loan), and delinquencies. Gallagher and Hartley (2015) study the effects after Hurricane Katrina, finding small reductions in credit scores, increases in credit card debt and delinquencies, and evidence that financially vulnerable consumers are less able to access credit in the year following the hurricane. These effects are generally modest in size. For example, Katrina is estimated to have lowered credit scores by 4.3 points in the fourth quarter following the storm, on average. They also find that the negative effects fade and even reverse by the third year following the storm, estimating, for example, that Katrina led to reductions in total debt among those in the most flooded regions of New Orleans, driven by individuals' use of insurance payments to pay down mortgages.

Edminston (2017) considers the impacts of a larger set of disasters—major hurricanes, tornados, and floods in the southeastern United States between 2000 and 2014—on a similar set of outcomes using the same source of credit bureau data. The results also link hurricanes to reductions in credit scores, particularly among people who were more financially vulnerable before the storm (measured by unpaid bills and high bank card utilization rates). Interestingly, in looking at effects across a range of disaster sizes, Edminston (2017) shows some evidence that negative effects of natural disasters on financial health may be smallest for the least and most severe events—a finding the author attributes potentially to variations in the levels of public aid and private relief across disasters.

Since job loss is a likely key contributor to financial duress after a hurricane, studies regarding disasters' employment effects are also relevant. Recent studies by Deryugina, Kawano, and Levitt (2018) and Groen, Kutzback, and Polivka (2017) use tax return data and wage records, respectively, to estimate the effects of hurricanes on labor market outcomes including employment and earnings. Although these outcomes are different from those we consider in this study, they are central to individuals' financial health, and so inform how we understand and interpret effects of disasters on credit outcomes. Using tax return data to estimate the effects of Hurricane Katrina, Deryugina, Kawano, and Levitt (2018) find initial reductions in economic well-being that fade out and even turn into improvements over the longer term. For example, in the period closely following Katrina, the authors find evidence of reduced earnings. However, these reductions fade after two years, and by year three average earnings increase. Looking by age and pre-storm level of income, the authors find few

differences in the first two years but find smaller gains in year three for younger residents and people with lower pre-storm income.

Groen, Kutzback, and Polivka (2017) use administrative wage records matched to survey data to estimate the effects of Hurricanes Katrina and Rita on earnings and employment over the subsequent nine years. They, too, find that negative initial impacts of the storms on earnings and employment not only fade but reverse over time, with affected individuals eventually earning more than unaffected individuals. They interpret their findings as suggestive that workers' wages rose as affected labor markets adjusted following the storms.

Contributions of This Study

In this study, we build on and extend the literature on the links between natural disasters and residents' financial health in several ways. We do this primarily by looking at effects over a wider range of people, financial outcomes, and disasters. We also examine how the effects of natural disasters on financial health differ for disadvantaged individuals and communities, including residents of low-income communities and communities of color. In addition, we give attention to a broader range of financial health outcomes, including outcomes not reported in prior research but suggested by our qualitative research (e.g., debt in collections, including utility debt; bankruptcy; mortgage delinquency; and foreclosure). Finally, we also contribute evidence on a point where the prior literature is thin by, similarly to Edminston (2017), examining effects across multiple disasters, rather than a single, large event. In doing so, we generate comparative evidence on how the effects of disasters on financial health vary by the magnitude of the disaster.

Data and Approach

Data for our empirical analyses come from three major sources: FEMA, a major credit bureau, and the Census Bureau's American Community Survey (ACS). Specifically, FEMA data identify which communities have been hit by a natural disaster, credit bureau data are used to measure people's financial health, and ACS data provide contextual information about communities included in our analysis. Together, these data allow us to locate zip codes affected by natural disasters and observe the financial health of people living in these affected zip codes. Our empirical approach compares the financial health of residents in areas affected by natural disasters with the financial health of people with similar characteristics living in unaffected areas. Below we describe the three data sources in turn, followed by a discussion of our empirical approach.

Data

Federal Emergency Management Agency data: To identify places affected by natural disasters, we draw on FEMA's Housing Assistance Data. FEMA creates these data as a part of administering IHP and makes them available to the public at the zip code level. ¹¹ These data provide information on the number of applications for and the number of recipients of IHP assistance for both homeowners and renters affected by natural disasters, including FEMA's damage assessments.

Given the availability of credit bureau data (2010–17), we focus on disasters that hit from 2011 through the summer of 2014. This allows us to observe people's financial health the year before the disaster hit and at least four years afterwards. We identify a zip code as being impacted by a natural disaster if at least one household in the zip code applied for IHP assistance. ¹² Of these, our analysis is restricted to zip codes where at least 20 percent of households in the zip code were assessed has having damage under IHP; this focuses the analysis on places where a meaningful share of residents was impacted by the natural disaster. ¹³

To explore differences in results by disaster size we look at the effects of disasters separately for three groups of disasters. The first group includes only Hurricane Sandy. Because this disaster is by far the largest in the study period, as measured by total assessed damage, we choose to consider it separately. The next group of disasters—which we label "large" disasters—includes those disasters where FEMA assessed \$200 million or more in damage under IHP. The final group, labeled "medium-

sized" disasters, includes disasters with less than \$200 million in assessed damage under IHP that were nevertheless large enough to trigger FEMA Individual Assistance.

Table 1 shows the disasters included in each group. Hurricanes, tropical storms, and severe storms are the most common types of disasters included, but tornadoes and flood events are also represented. Table 1 also displays total assessed damage to owner-occupied housing, which is a proxy for the magnitude of the disaster. Included disasters have damage assessments ranging from around \$3.3 million (2012 West Virginia severe storms, flooding, mudslides, and landslides) to \$2.2 billion (Hurricane Sandy). Finally, table 1 notes whether the disasters received CDBG-DR funding. Each large disaster spurred a federal appropriation that included CDBG-DR. Only three of the nine medium-sized disasters received CDBG-DR funding for recovery.

Notably, no wildfires met the study inclusion criteria—primarily because the largest fires have occurred more recently, so we are not yet able to estimate effects over the four-year follow-up period. An important direction for future analyses will be to explore the effects of these fires.

TABLE 1
Characteristics of Disasters Included in Our Analysis

| | | Total damage to owner-occupied | |
|--|----------------|-----------------------------------|---------|
| Disaster | Date | housing (\$) | CDBG-DR |
| Hurricane Sandy | October 2012 | 2,221,449,984 | Yes |
| Other large disasters | | | |
| Super Outbreak 2011 and Related Storms | April 2011 | 321,538,592 | Yes |
| Severe Storms, Mississippi Basin Floods 2011 | May 2011 | 206,973,664 | Yes |
| Hurricane Irene | August 2011 | 540,736,832 | Yes |
| Tropical Storm Lee | September 2011 | 236,229,136 | Yes |
| Hurricane Isaac | August 2012 | 210,514,752 | Yes |
| Medium-sized disasters | | | |
| Super Outbreak and MS Basin Floods | April 2011 | 68,953,592 | Yes |
| Leap Day Tornado 2012 | February 2012 | 31,894,916 | No |
| West Virginia Severe Storms, Flooding, | | | |
| Mudslides, and Landslides 2012 | March 2012 | 3,308,837 | No |
| West Virginia Severe Storms and | | | |
| Straight-Line Winds 2012 | June 2012 | 3,981,028 | No |
| Illinois Severe Storms 2013 | April 2013 | 140,227,104 | Yes |
| Alaska Flooding 2013 | May 2013 | 4,050,355 | No |
| Colorado Severe Storm 2013 | September 2013 | 60,373,224 | Yes |
| Tornado Outbreak 2014 | April 2014 | 80,140,904 | No |
| Michigan Severe Storms and Flooding 2014 | August 2014 | 111,254,824 | No |

Source: Urban Institute analysis of FEMA's Housing Assistance data and review of federal appropriations and HUD grantee action plans.

Notes: Total damage to owner-occupied housing is calculated using assessments reported in FEMA's Housing Assistance data and do not include the assessed value of damage to rental units. CDBG-DR is funded through special congressional appropriations. Even where CDBG-DR is funded, not every state with an affected population received a housing grant. In the case of Hurricane Sandy, some housing grants were given to states that are not included in our analysis.

Table 2 presents the distribution of our sample of affected people, zip codes, and states across disasters. The states represented in our sample are those with at least one zip code where at least 20 percent of households were assessed as having damage under IHP. These disasters occurred in regions across the US, including the Southeast, Midwest, West, and Gulf Coast.

Table 2 also lists the number of affected zip codes we observe in our sample and the total people we observe in affected zip codes. Most people in our sample for medium-sized disasters were affected by the severe storms and flooding in Michigan in 2014. Our analysis of medium-sized disasters is therefore weighted heavily by the experiences of people in the affected zip codes in the Detroit metropolitan area. Like the majority of the areas affected by medium-sized disasters, Michigan did not receive special congressional appropriations for additional recovery funds.

TABLE 2
Distribution of States, Zip Codes, and People in Our Sample Affect by a Natural Disaster, by Disaster

| | States | Number of zip codes | Number of people |
|--|------------------------|---------------------|------------------|
| Hurricane Sandy | MD, NJ, NY | 56 | 14,966 |
| Other large disasters | | | |
| Super Outbreak 2011 and Related Storms | AL, AR, MS | 11 | 124 |
| Severe Storms, Mississippi Basin Floods 2011 | IA, IL, MO, MS, ND, SD | 20 | 688 |
| Hurricane Irene | MA, NC, NJ, NY, VT | 39 | 611 |
| Tropical Storm Lee | NY, PA | 8 | 310 |
| Hurricane Isaac | LA, MS | 31 | 1,917 |
| Medium-sized disasters | | | |
| Super Outbreak and MS Basin Floods | MO | 2 | 16 |
| Leap Day Tornado 2012 | KY, WV | 3 | 24 |
| West Virginia Severe Storms, Flooding, | | | |
| Mudslides, and Landslides 2012 | WV | 1 | 27 |
| West Virginia Severe Storms and | | | |
| Straight-Line Winds 2012 | WV | 3 | 26 |
| Illinois Severe Storms 2013 | IL | 5 | 325 |
| Alaska Flooding 2013 | AK | 3 | 20 |
| Colorado Severe Storm 2013 | CO | 5 | 118 |
| Tornado Outbreak 2014 | AL | 1 | 24 |
| Michigan Severe Storms and Flooding 2014 | MI | 13 | 7,402 |

Source: Urban Institute tabulations of credit bureau, FEMA's Housing Assistance, and American Community Survey data.

Notes: We define affected zips as those in which at least 20 percent of households, both owners and renters, were found to have natural disaster-related damage by a FEMA inspection. States included in our analysis are those with at least one zip code where at least 20 percent of households were assessed as having damage under IHP. Affected people are the residents of these zips who are also present in the credit bureau data.

Note, finally, that there are some additional differences across these groups on observed aspects of disasters other than their overall magnitude. Hurricanes, which are summer and fall events, are confined to the large disaster group, while the medium group includes a range of spring and summer

storm and flood events. Medium-sized disasters in our set also are observed across a wider range of years and somewhat more dispersed geographies.

Credit bureau data: The credit bureau data are from a nationally representative longitudinal sample of anonymized data on more than 5 million US consumers obtained from one of the three major credit bureaus. ¹⁴ These data are available at annual intervals (August of each year) from 2010 through 2017. Geographic information on the zip code people live in, combined with FEMA data on zip codes impacted by natural disasters, allow us to identify people living in an area when the natural disaster hit. ¹⁵ Further, with data on the same people over time, we observe people's pre- and post-disaster financial health (even if they move out of the disaster impacted area).

The credit bureau data have an array of information on consumers' credit profiles, including the amount of debt and delinquencies related to credit cards, auto loans, and mortgages. We also have people's credit scores, which are essentially a composite indicator of overall financial health. Beyond credit-related measures, we have age, but no other demographic characteristics are available.

We focus on five sets of outcomes: (1) credit score; (2) general financial distress (debt in collections, utility debt in collections, bankruptcy); (3) credit card access and utilization; (4) housing-related distress (mortgage delinquency, foreclosure); and (5) auto debt (see table 3 for details). Overall, we expect that natural disasters lead to declines in residents' financial health. Specifically, we hypothesize that natural disasters reduce credit scores, increase debt levels, and increase rates of delinquency, bankruptcy, and foreclosure.

TABLE 3

Definitions of Financial Health Outcomes

| Variable | Definition |
|---------------------|--|
| Credit score | VantageScore credit score. The VantageScore ranges from 300 to 850. "Poor" scores range from 300 to 649, "fair" from 650 to 699, and "good" from 700 to 850. |
| Debt in collections | Has debt in internal or external collections or is charged off |
| | Total balance of debt in internal or external collections or is charged off |
| Bankruptcy | Bankruptcy on public record in the last 24 months |
| Credit card debt | Has an open credit card |
| | Total balance on open credit cards |
| Delinquent mortgage | Has mortgage (1st or 2nd) or home equity line of credit that is at least $60\mathrm{days}$ past due or derogatory |
| Foreclosure | Mortgage foreclosure in the last two years |
| Auto debt | Has an open auto loan or lease trades |
| | Total balance on open auto loan or lease trades |

Our focus on these outcomes was informed by interviews with local service providers who dealt with the aftermath of the California wildfires and Hurricanes Sandy, Harvey, and Irma. For example, auto debt was identified as a particular concern in places with flooding. In the case of delinquent utility debt, we learned that in some instances hurricane victims were having their utilities disconnected because they could not pay their bills.

This set of outcomes also captures a range of debt types, which may be indicative of different financial circumstances. For people to have credit card debt, auto debt, or a mortgage, they were extended credit (i.e., someone was willing to lend to them). Utility debt, on the other hand, is present in a credit bureau file if the person failed to pay their bill (i.e., was delinquent). Our broader measure of debt in collections includes a combination of unpaid bills (e.g., medical bills, parking tickets, gym memberships, utility bills) and delinquent loans (e.g., credit cards, auto).

Table 4 shows summary statistics for our credit bureau variables, by disaster group, prior to the disaster. Across disasters, these indicate an overall sample of affected individuals among whom financial vulnerability is common. The share of people with debt in collections, for example, ranges upward from 30 percent over these groups. More severe levels of financial distress remain relatively uncommon, however, with 1 to 2 percent of people recording a bankruptcy or foreclosure in the prior two years.

There are also apparent differences across disaster groups, with those affected by medium-sized disasters exhibiting somewhat worse credit characteristics, including lower credit scores and a greater incidence of delinquency. These differences reflect, in large part, the particular economic circumstances of people living in neighborhoods in and around Detroit, Michigan in 2014, who, as noted above, compose the preponderance of all people affected by medium-sized disasters in our data.

A similar issue is reflected in the differences in our sample sizes across groups, shown in the bottom row of table 4. Hurricane Sandy, which affected New York City and surrounding regions, affected more people in our sample than either large or medium-sized disasters, collectively. We also observe more people affected by medium-sized disasters than large disasters. This also appears to be because the Michigan storms in 2014 affected urban areas in and around Detroit.

TABLE 4
Characteristics of People Living in Areas Hit by a Natural Disaster, by Disaster Size

| | | | | | Medi | um-Sized |
|---|-----------------|-----------|-----------------|-----------|-----------|-----------|
| | Hurricane Sandy | | Large Disasters | | Disasters | |
| | Standard | | Standard | | | Standard |
| | Mean | deviation | Mean | deviation | Mean | deviation |
| Individual-level credit characteristics | | | | | | |
| Age | 47.0 | 17.0 | 48.2 | 17.6 | 44.2 | 16.9 |
| Credit score | 676 | 116 | 668 | 120 | 611 | 112 |
| Financial distress | | | | | | |
| Has debt in collections (%) | 29.5 | 45.6 | 33.3 | 47.1 | 53.7 | 49.9 |
| Total debt in collections (\$) | 2,696 | 16,282 | 2,345 | 10,869 | 3,958 | 17,744 |
| Utility debt in collections (\$) | 56 | 282 | 34 | 217 | 156 | 464 |
| Bankruptcy in last two years (%) | 1.4 | 11.6 | 1.2 | 11.0 | 1.5 | 12.1 |
| Credit card access and debt | | | | | | |
| Has credit card (%) | 61.4 | 48.7 | 34.4 | 19.3 | 51.3 | 13.5 |
| Amount of credit card debt (\$) | 4,029 | 9,215 | 3,112 | 7,966 | 1,798 | 5,349 |
| Mortgage delinquency and foreclosures | | | | | | |
| Has delinquent mortgage (%) | 4.5 | 20.8 | 3.6 | 18.7 | 3.8 | 19.1 |
| Foreclosure in last two years (%) | 1.2 | 10.8 | 1 | 10.1 | 0.9 | 9.3 |
| Auto debt | | | | | | |
| Has auto debt (%) | 24.5 | 43.0 | 5.2 | 22.1 | 22.6 | 41.8 |
| Amount of auto debt (\$) | 3,889 | 9,452 | 3,593 | 8,684 | 2,884 | 8,089 |
| Zip code-level demographic | | | | | | |
| characteristics | | | | | | |
| Share of residents of color (%) | 38.0 | 26.5 | 24.6 | 29.1 | 82.2 | 22.5 |
| Unemployment rate | 8.0 | 3.1 | 9.3 | 7.8 | 16.0 | 7.2 |
| Poverty rate | 9.8 | 5.9 | 15.2 | 13.4 | 24.8 | 10.6 |
| Share with income below 200% | | | | | | |
| of poverty level | 24.0 | 11.4 | 34.4 | 19.3 | 51.3 | 13.5 |
| Number of observations | 1 | 4,966 | | 3,650 | | 7,970 |

Source: Urban Institute tabulations of credit bureau and American Community Survey data.

American Community Survey: We supplement the credit bureau and FEMA data with zip code-level demographic and economic characteristics from the ACS. We use ACS zip-level five-year estimates to identify low-income communities (zip codes where more than half of all households have incomes less than twice the federal poverty level) and communities of color (zip codes where at least half of residents are people of color). We use these indicators to estimate the effects of natural disasters on financial outcomes separately for people living in these communities, in order to investigate whether those effects play out differently across communities with different economic and demographic characteristics.

Table 4 shows mean values (across individuals in the respective disaster group samples) of selected neighborhood characteristics. Consistent with the tabulations of credit bureau data, we see that people in our sample hit by medium-sized disasters live in more disadvantaged areas.

Empirical Approach

We estimate the effects of natural disasters on financial health by comparing financial outcomes of residents in affected areas to financial outcomes of otherwise similar individuals in comparison communities that were not affected by natural disasters.

To do this, we first identify, for each disaster, a set of comparison communities following the approach of Deryugina, Kawano, and Levitt (2018) and Groen, Kutzbach, and Polivka (2017). We identify comparison communities using propensity score matching to identify the five nearest neighbor zip codes for each zip code affected by a disaster (where affected zip codes are identified, as above, as those where 20 percent or more of residents applied for FEMA IHP assistance following the disaster). The comparison set of zip codes is drawn from the universe of zip codes in our data that were not affected by a natural disaster in any year in our data (2010 to 2017). We predict propensity scores based on a set of zip-level credit and demographic characteristics. ¹⁶

To estimate the effects of natural disasters on the financial health of individuals, we then compare financial outcomes, such as credit scores, of people residing in affected areas in the year of the disaster with those of otherwise similar people in comparison areas. We estimate these effects using a propensity score matching model using nearest-neighbor matching. The Because we cannot identify which residents in affected areas suffered direct financial (or other) losses due to the disaster, this analysis compares all individuals in affected areas to individuals in unaffected areas. As a result, these estimates show the effects of living in affected areas, averaged over directly affected people and other people. This likely leads our estimates to understate the effects of a disaster on those directly affected. On the other hand, natural disasters are intrinsically spatial events in ways that are likely to generate substantial spillovers; even people not suffering property damage, personal injury, or other direct effects might still suffer financially if their communities and local economies are negatively affected by the disaster.

We examine effects separately by disaster group for four years following the disaster and for a set of subgroups defined by individual-level and community-level characteristics:

Disaster magnitude: We look at the effects of disasters separately for three groups of disasters: (a) Hurricane Sandy, by far the largest disaster in our analysis; (b) other disasters causing over \$200 million in damage (large disasters); and (c) disasters with less than \$200 million in damage but large enough to trigger FEMA individual assistance (medium-sized disasters). Because public attention and relief tend to flow to the largest disasters, we expect these negative effects to be more pronounced for people in areas affected by medium-sized versus very large disasters. Individuals and communities affected by

medium-sized disasters are also, in our data, more financially vulnerable before those disasters, which may magnify the negative effects of disasters on credit outcomes.

Effects over time: Our analyses focus on disasters that hit from 2011 through the summer of 2014, allowing us to observe people's financial health the year before the disaster hit and for four years afterward (up to 2017). On the one hand, time may allow people to repair and recover their financial lives. On the other hand, as post-disaster relief tends to be time-limited and because damage to financial health may spiral downward, people affected by a natural disaster may face greater challenges as time passes.

Subgroups: We look separately at effects by age and pre-disaster financial health (as captured by people's credit scores in the year before the disaster). We also estimate separate effects by whether people live in communities of color or low-income neighborhoods. We expect those people and communities that face greater pre-disaster economic disadvantage—communities of color and low-income communities, and individuals who are older (elderly) and who have lower levels of pre-disaster financial health—to experience greater negative effects.

How Do Natural Disasters Affect Financial Health?

We compare the financial health of residents of areas affected by natural disasters to otherwise similar people in unaffected areas—looking across results for each of our three disaster groups, over all four years in our follow-up period, our full set of outcomes, and for each of our populations of interest. Four general themes emerge in our findings:

- Disasters lead to broad, and often substantial, negative impacts on financial health. While the patterns vary by disaster magnitude and affected populations, we find evidence of negative impacts across most measures of financial health, including on credit scores, collections debt, bankruptcy, mortgage delinquency and foreclosures, and credit card debt. In many instances these effects are of meaningful magnitudes; the largest effects on credit scores, for example, would typically indicate substantial deteriorations in access to and the cost of credit.
- The negative effects of disasters persist, or even grow over time, for important financial outcomes.
 For many important financial health outcomes, these negative effects do not abate over the four years following the disaster, and for key outcomes the effects grow larger over this period.
 The negative effect of disasters on credit scores, for example, is, on average, substantially larger in the fourth year after the disaster than in the first year after the disaster.
- Medium-sized disasters typically appear to cause larger and more consistently negative effects on financial health than large disasters. For most financial health outcomes, in most years, and for most populations, we find that the effects of medium-sized disasters—disasters large enough to trigger FEMA individual assistance, but causing less than \$200 million in total damage—are more substantial than the effects of larger disasters. These smaller-scale disasters were less likely to receive a special congressional appropriation for additional recovery funds. Four years following a disaster, for example, the effect of the disaster on credit scores is roughly twice as large for those affected by medium-sized disasters as for those affected by Hurricane Sandy. In our data, most of the individuals affected by medium-sized disasters are affected by the 2014 storms and flooding in Michigan, which hit urban areas in and around Detroit but did not receive additional long-term recovery funds.
- Individuals and communities more likely to be struggling financially before disasters strike are often
 the hardest hit by the disaster. In particular, we see relatively consistent evidence that

individuals with lower credit scores before the disaster experience larger negative effects than other groups. Individuals with poor initial credit, for example, see larger declines in their credit score and a loss of access to credit cards that other groups do not, on average. For some disasters and outcomes, we also see larger effects in low-income communities and communities of color. Overall, these results are suggestive that disasters may be not just harmful for affected residents on average, but may also have the effect of widening already existing inequalities.

Below, we discuss our results in more detail, taking each of our five sets of financial health outcomes in turn: (1) credit score; (2) general financial distress (debt in collections, utility debt in collections, bankruptcy); (3) credit card access and utilization; (4) housing-related distress (mortgage delinquency, foreclosure); and (5) auto debt. To supplement the figures and estimates presented below, appendix tables D.1 through D.20 present complete results for each of these outcomes, as well as for selected subgroups.

How Do Natural Disasters Affect Credit Scores?

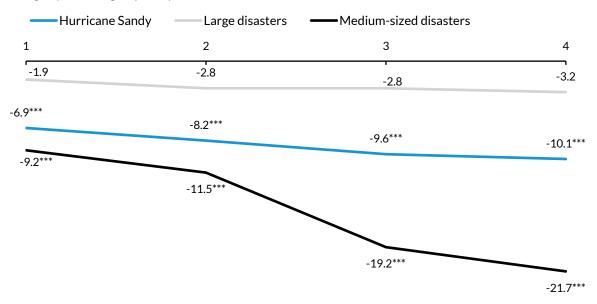
Credit scores are both a composite indicator of residents' overall financial health and determine access to credit and the price of credit (e.g., the ability to obtain credit cards or auto loans, and on what terms). Having good credit reduces the cost of borrowing and can save residents hundreds or even thousands of dollars (Elliott and Lowitz 2018). If natural disasters reduce credit scores, a reduction in the score is not only a general indicator of reduced financial health, but it can also be a central mechanism by which natural disasters lead to other harmful financial outcomes.

We find that living in an area affected by a natural disaster leads to significant and persistent *reductions in credit scores*, on average, compared with living in an unaffected area with otherwise similar residents. These effects are evident in the first year after disasters strike, persist for all four years after the disasters hit, and tend to grow over time. Figure 2 shows the declines in credit score for Hurricane Sandy, other large disasters, and medium-sized disasters.

We also find more substantial credit-score declines among residents hit by medium-sized disasters (up to 22 points by the fourth year following the disaster) than large disasters such as Hurricane Sandy (10 points in year four). Most individuals affected by the medium-sized disasters were affected by a storm that hit urban areas in and around Detroit. For other large disasters, we see credit scores declines that are not as strong and are not statistically significant. For this and most other outcomes, we find effects of large disasters that are generally consistent with but attenuated relative to Hurricane Sandy,

but by and large are not statistically significant. In addition, our sample of people affected by large disasters is smaller than Sandy or medium-sized disasters, making our estimates for this group less precise. For this reason, we do not discuss results for large disasters in what follows, although the results are reported in appendix D.

FIGURE 2
Natural Disasters Lead to Declines in Credit Scores, and These Declines Increase Over Time
Change by disaster group and year(s) after disaster



Source: Urban Institute calculations based on credit bureau, FEMA, and ACS data.

Notes: Values represent estimates of average differences in credit scores between individuals affected by the indicated disaster (or set of disasters) and matched individuals from unaffected areas. Effects are estimated separately for each disaster for each of the four years following the disaster.

This pattern of results, showing greater effects of medium-sized disasters than for larger disasters, is consistent with our expectation that residents hit by medium-sized disasters may experience greater financial struggles because these disasters do not receive the influx of federal support that large disasters receive. However, as noted above, people hit by medium-sized disasters in our data differ from those affected by large disasters; in particular, those affected by medium-sized disasters tend to have worse credit outcomes and be from more disadvantaged areas. In subgroup analyses below, we show that the differences in the effects of disasters of different magnitudes persist even when we condition on some of these characteristics.

For both Hurricane Sandy and medium-sized disasters we also see that the negative effects on credit scores grow larger over time: the initial effect of Hurricane Sandy is a 7-point decline in scores, but this rises to about 10 points by year three (where it remains in year four). This trend is even more pronounced for medium-sized disasters, where an initial decline of 9 points more than doubles by the third year following the disaster (19 points), and reaches 22 points after four years. In fact, the difference between the disaster groups only emerges over time. The initial impacts on credit scores are similar, but by the fourth year after the disaster the effects are much larger—more than twice as large—for medium-sized disasters than for Sandy. The growth in the magnitude of the effects over the four years after Sandy and the medium-sized disasters is consistent with credit scores exhibiting a degree of path dependency; that is, once individuals' credit begins to deteriorate due to a disaster, that initial decline leads to further deterioration as they lose access to or face higher costs for traditional credit.

The 22-point decline for residents affected by medium-sized disasters is substantial and could impact people's ability to access well-priced credit. Credit scores range from 300 to 850, with scores below 650 considered "poor" (includes very poor), scores between 650 and 699 considered "fair," and scores of 700 and above considered "good" (includes excellent). ¹⁸ In our data, the average credit score in year four is 647—near the borderline of what is considered fair and poor—for people in our comparison group for medium-sized disasters. Declines of 22 points for people in this range could make them solidly poor credit risks, which severely constricts their access to traditional credit, can limit their ability to recover from natural disasters, and translates into higher costs if they seek credit from alternative sources.

We also look at declines in credit scores by individual characteristics (pre-disaster credit scores and age) and community characteristics (low-income and communities of color).

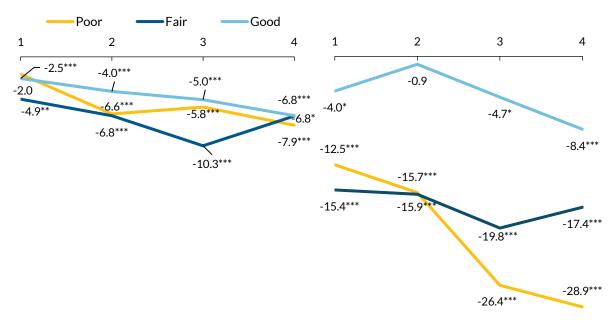
People with poor credit before a disaster hits (credit score below 650) experience a substantial decline in credit scores after a disaster hits, which can have broad impacts for these residents' financial stability. Four years after being hit by a medium-sized disaster, we find that that the average credit score fell by 29 points for those with initially poor credit, 17 points for those with fair credit, and 8 points for those with good credit (figure 3). In our data, the average credit score in year four is 585 for people in our comparison group for medium-sized disasters with scores below 650 before the disaster; an effect of 29 points pushes these individuals toward the "very poor" range of credit scores. For people with fair or good credit before the disaster, the decline is not as sharp.

FIGURE 3

Larger Declines in Credit Scores for Those with Poor Credit before the Disaster Hit

Change by pre-disaster credit score group and year(s) after disaster

Hurricane Sandy Medium-sized disasters



Source: Urban Institute calculations based on credit bureau, FEMA, and ACS data.

Notes: Values represent estimates of average differences in credit scores between individuals affected by the indicated disaster (or set of disasters) and matched individuals from unaffected areas. Effects are estimated separately for each disaster for each of the four years following the disaster. The VantageScore credit scores used here range from 300 to 850. Poor scores range from 300 to 649, fair from 650 to 699, and good from 700 to 850.

People with poor credit hit by Hurricane Sandy did not experience the same sharp decline in credit scores. Four years after being hit by Sandy, the average credit score fell by 8 points for those with initially poor credit and by 7 points for those who initially had good and fair credit. Note that this pattern of results, showing larger credit-score declines for medium-sized disasters, even for similar populations (e.g., those with poor credit), is an additional piece of evidence consistent with differences in effects by disaster magnitude being due, at least in part, to differences in policy responses.

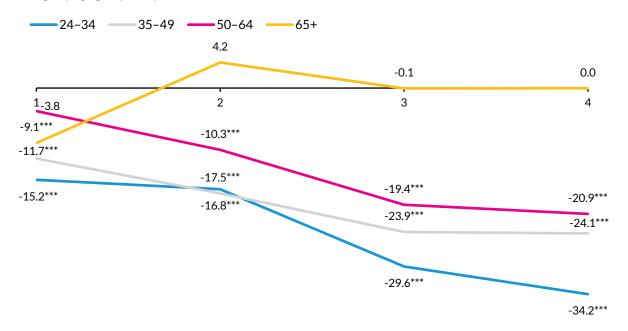
Looking at differences in the effects of disasters across age groups (ages 24–34, 35–49, 50–64, and 65 and older), for medium-sized disasters we see negative effects that grow in magnitude over time, with one exception: for those 65 and older, after an initial decline in credit scores of around 9 points, the estimated effects in years two through four are negligible. For medium-sized disasters, we find the largest declines among young adults ages 24–35—a 34-point credit score decline in year four (figure 4). By way of contrast, for Hurricane Sandy, we see negative effects on credit scores in each year and for

each age group (appendix table D.3). If anything, we see slightly larger credit score declines after four years for those 65 and older (12 points) than for other the age groups (7 to 10 points). Elderly individuals, who may have fixed or no income, could find it particularly challenging to recover financially from the shock of a natural disaster. Additionally, as qualitative interviews with service providers underscored, the elderly may also be especially susceptible to scams and fraud in the wake of a disaster.

FIGURE 4

Larger Credit Score Declines for Younger Residents Hit by Medium-Sized Disasters

Change by age group and year(s) after disaster



Source: Urban Institute calculations based on credit bureau, ACS, and FEMA data.

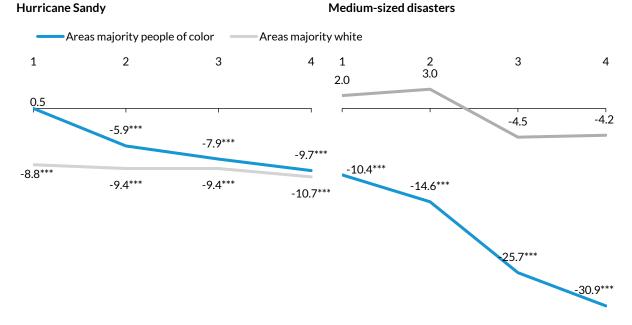
Notes: Values represent estimates of average differences in credit scores between individuals affected by medium-sized disasters and matched individuals from unaffected areas. Effects are estimated separately for each of the four years following the disaster. *p < 0.1, **p < 0.05, ***p < 0.01

For people affected by medium-sized disasters, we see effects that are larger, and emerge earlier, for people in low-income communities and communities of color (than for people in higher-income and predominantly white communities). ¹⁹ The pattern of effects in communities of color is similar to the overall results for medium-sized disasters, but the magnitudes are larger, rising from a 10-point decline in scores in year one to a 31-point decline in year four (figure 5). In our data, the average credit score in year four is 646 for people in our comparison group for medium-sized disasters in communities of color; as for the overall estimates, an effect of 31 points in this range could make affected residents solidly poor credit risks. Our estimates for the effects in predominantly white communities are much smaller and are not statistically significant, which is due in part to a relatively small sample size. Specifically, the

large majority (roughly 85 percent) of people affected by medium-sized disasters in our sample live in communities of color, with only 15 percent living in predominantly white communities.

For Hurricane Sandy we also look at effects separately for individuals in communities of color compared with individuals in predominantly white communities, where we find effects that are qualitatively similar between the two groups by year four: the decline in credit scores for individuals in predominantly white communities was 11 points in year four, while for individuals in communities of color the decline was 8 points. The resources that flowed into Sandy-affected areas may have helped mitigate the declines.

FIGURE 5
Credit Score Declines Are Larger in Communities of Color Hit by Medium-Sized Disasters
Change by area composition and year(s) after disaster



Source: Urban Institute calculations based on credit bureau, ACS, and FEMA data.

Notes: Values represent estimates of average differences in credit scores between individuals affected by the indicated disaster (or set of disasters) and matched individuals from unaffected areas. Effects are estimated separately for each of the four years following the disaster.

*p < 0.1, **p < 0.05, ***p < 0.01

Do Natural Disasters Increase Financial Distress?

The specific financial activities and measures that are recorded by credit agencies can provide a nuanced picture of how people are affected by and respond to natural disasters. To examine the extent to which natural disasters lead people to experience financial distress, we examine two measures of debt in collections (all and utility) and a "yes/no" indicator of having recently filed for bankruptcy (in the past two years). Having debt in collections is suggestive of people suffering from cash flow challenges that are leading them to fall behind on their obligations. Having declared bankruptcy represents the experience of more extreme financial distress. Accruing debt in collections and filing for bankruptcy both can, in turn, lead to further financial challenges.

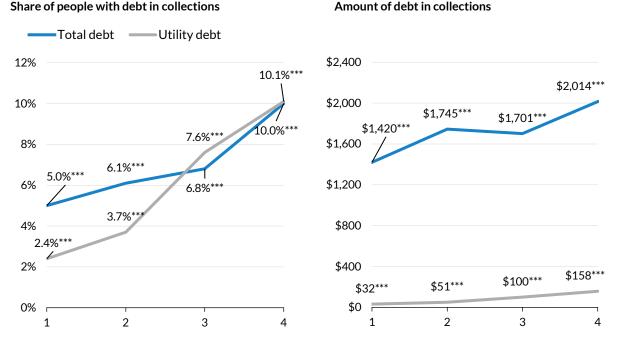
Overall, we find that living in an area affected by a natural disaster leads to *increases in debt in collections and rates of bankruptcy* in the years following a disaster, compared with otherwise similar people in unaffected areas. These effects are most pronounced for those affected by medium-sized disasters, where we see strong and persistent negative effects, as shown below.

The share of people with any debt in collections is 5 percentage points higher in the first year after the disaster, and the effect rises to 10 percentage points by year four (figure 6). These effects are substantial; the share with debt in collections is nearly 25 percent higher by year four than for comparable people not hit by a disaster. ²⁰ The average amount of debt in collections is \$1,420 higher in year one, and this rises to \$2,014 in year four. This is also a correspondingly large effect; the comparison group mean amount of debt in collections in year four is about \$2,700.

Our qualitative interviews suggest that some people struggle to stay current on utility payments following a natural disaster, so we also look at the effects of disasters on utility debt in collections. We see effects that are consistent with this hypothesis, and with the overall collections results. For example, the fraction of people with any utility debt in collections is 2 percentage points higher in the first year after the disaster and the effect rises to 10 percentage points by year four. Because the measure is narrower, the amounts represented are correspondingly smaller: the average amount of debt in collections is \$32 higher in year one and the difference rises to \$158 in year four.

When we look at effects for debt in collections for different groups, while there are some differences, the overall pattern of results indicates negative effects that are widespread (appendix tables D.8–D.10). For example, there is a significant rise in the likelihood of having debt in collections (any and utility) across the three credit score groups (poor, fair, and good). However, we do not find evidence that the amounts of debt in collection rises for people with a good credit score before the disaster.

Figure 6
Financial Hardship Increases Over Time in Communities Hit by Medium-Sized Disasters
Change in the likelihood and amount of total and utility debt in collections by year(s) after disaster



Source: Urban Institute calculations based on credit bureau, ACS, and FEMA data.

Notes: Values represent estimates of average differences in each outcome between people affected by medium-sized disasters and matched people from unaffected areas. Effects are estimated separately for each of the four years following the disaster. *p < 0.1, **p < 0.05, ***p < 0.01

Turning to effects on declarations of bankruptcy, the results show that the share of people with a recent bankruptcy declaration is higher by about 1 percentage point in each post-disaster year (figure 7). While this effect is small in absolute terms, the overall rate of bankruptcy in the comparison group is itself only about 1 percent. That is, people affected by disasters declare bankruptcy at a rate roughly double that of unaffected people.

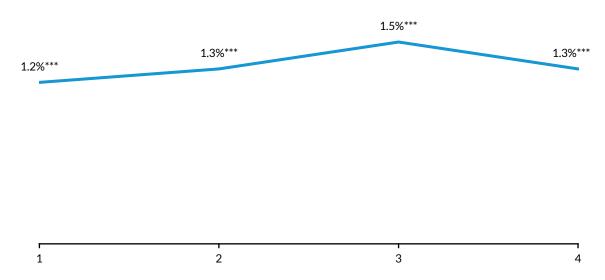
These effects on bankruptcy appear to be driven by people with lower credit scores before the disaster. There is some evidence that effects on bankruptcy and debt in collections may be stronger for younger and working age people than for older people. The effects are similar in low- and higher-income neighborhoods (appendix table D.10).

For Sandy, as other large disasters, we do not observe strong effects on bankruptcy or debt in collections, though, at least for collection measures, the results are broadly and qualitatively consistent (appendix table D.7).

FIGURE 7

Residents Hit by Medium-Sized Disasters Are More Likely to Declare Bankruptcy

Change in the share of people with bankruptcy in the past two years and year(s) after disaster



Source: Urban Institute calculations based on credit bureau, ACS, and FEMA data.

Notes: Values represent estimates of average differences in the share of people with bankruptcies on their public records between individuals affected by medium-sized disasters and matched individuals from unaffected areas. Effects are estimated separately for each of the four years following the disaster.

p < 0.1, p < 0.05, p < 0.01

How Do Natural Disasters Affect Credit Card Access and Debt?

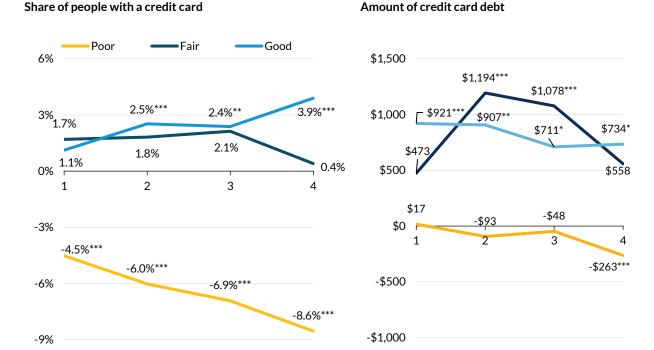
Credit cards can serve as an important source of liquidity for people during and after a natural disaster, though accumulating credit card debt can reflect financial challenges. We look at the effect of disasters both on whether people have a credit card, which we interpret as indicative of access to credit, and the amount of credit card debt, which we interpret to reflect a gap between cash resources and needs. Note that rising levels of credit card debt can also lead to other financial challenges, both directly, as people need to stay current on at least minimum payments and interest charges that accumulate, as well as indirectly, as rising balances can cause credit scores to decline if people utilize more than 30 percent of their available credit (Elliott and Lowitz 2018).

The effect of natural disasters on *credit card access and debt differs depending on people's pre-disaster financial health.* We see this most clearly among those affected by medium-sized disasters, as shown below in figure 8.

FIGURE 8

Credit Card Access Declines for Struggling Residents, and Credit Card Debt Increases for Better-Off
Residents, Hit by Medium-Sized Disasters

Change by pre-disaster credit score group and year(s) after disaster



Source: Urban Institute calculations based on credit bureau, ACS, and FEMA data.

Notes: Values represent estimates of average differences in each outcome between people affected by medium-sized disasters and matched people from unaffected areas. Effects are estimated separately for each of the four years following the disaster. The VantageScore credit scores used here range from 300 to 850. Poor scores range from 300 to 649, fair from 650 to 699, and good from 700 to 850.

p < 0.1, p < 0.05, p < 0.01.

For those with poor credit before the disaster, the likelihood of having a credit card falls by 4.5 to 8.6 percentage points, while the amount of credit card debt trickles downward over time, on average. By the fourth year after the disaster, this poor credit group has less credit card debt on average than comparable people not hit by a disaster. In contrast, for those with good credit before the disaster, the likelihood of having a credit card rises, by 2.4 to 3.9 percentage points in years two through four, and the amount of credit card debt they carry is higher by about \$900 in the first two years following the

disaster and higher by about \$700 in years three and four. These smaller and only marginally significant effects in years three and four are consistent with some degree of recovery for this group.

For the middle group—those with fair credit before the disaster—we see an intermediate pattern. There is a positive but insignificant effect on the likelihood of having a credit card in the years following a disaster, and positive effects on the level of credit card debt, which are large and statistically significant in the second and third years after the disaster.

We interpret this pattern of results as consistent with more at-risk borrowers losing access to credit cards following disasters (possibly due to other disaster-induced deteriorations in their capacity to borrow, consistent with, for example, the reductions we see in credit scores for this group), while higher credit-score borrowers use credit cards as a source of liquidity following disasters.

Looking across subgroups for medium-sized disasters, the most noteworthy differences emerge by age (appendix table D.13). The likelihood of having a credit card actually falls for age groups younger than 65; for those 65 and older, it increases by 4 to 6 percentage points in years two through four. Also, by neighborhood, the reduced likelihood of having a credit card appears larger for people living in communities of color (appendix table D.14).

For Hurricane Sandy, effects on credit card debt are generally less pronounced and often not statistically significant. In particular, the clear pattern across pre-disaster credit score groups that emerges for medium-sized disasters is not evident for people affected by Sandy (appendix table D.12).

How Do Natural Disasters Affect Mortgage Delinquency and Foreclosures?

Homeowners can suffer particular financial impacts following natural disasters, having to manage mortgage payments along with necessary repairs, and in addition, when their residence is rendered uninhabitable by the disaster, any costs associated with temporary housing. Falling behind on mortgage payments, as indicated by mortgage delinquency, can be an early marker of financial distress for mortgage holders. Experiencing a foreclosure, which typically results from an accumulation of difficulties in staying current, can be an indication of deeper financial distress. And as with many of our other measures, negative effects on these outcomes not only reflect but can amplify the consequences of disasters for financial health. People with credit files reflecting delinquent mortgage payments or foreclosures will find other sources of credit to be more expensive or difficult to obtain.

We find *increases in mortgage delinquency and foreclosure* in the years after a natural disaster that are stronger and more persistent for those affected by Hurricane Sandy than for those affected by medium-sized disasters, as shown in figure 9, below.

FIGURE 9
Mortgage Delinquency and Foreclosures Increased Following Hurricane Sandy
By year(s) after disaster

Hurricane Sandy — Medium-sized disasters 1.2% 1.1%*** 1%* 1%*** 0.9% 0.6%* 0.5%*** 0.6% 0.5%** 0.4%*** 0.3% 0.3%*** 0.3% 0.4%* 0.2% 0.0% 0.0% 0.0% 2 3 3 4 -0.1% -0.2% -0.3% -0.3%

Share of people with foreclosures

Source: Urban Institute calculations based on credit bureau, ACS, and FEMA data

Notes: Values represent estimates of average differences in each outcome between individuals affected by the indicated disaster (or set of disasters) and matched individuals from unaffected areas. Effects are estimated separately for each of the four years following the disaster.

Share of people with delinquent mortgages

For those affected by Sandy, we see sustained increases in both mortgage delinquency (60 days past due) and foreclosures. These effects are relatively large: in years two through four the mortgage delinquency rates are higher by roughly one percentage point, over a comparison group mean that is in the range of 2 to 3 percent over that same period. The foreclosure rates for people affected by Sandy emerge with a slight lag, becoming positive and significant in year two; this is both consistent with the negative financial effects of the disaster taking time to lead people into foreclosure, in general, and with the relatively long foreclosure timelines observed in New York and New Jersey, in particular. These effects are also large: in years two through four the rate of foreclosure for people affected by Hurricane

Sandy is in the range of 0.3 to 0.5 percentage points higher than for comparison people, for whom the mean rate is around 0.5 percent.

Looking at effects across groups, we see foreclosure and delinquency effects that are stronger and more consistently negative for people with poor credit pre-Sandy, but not isolated there. Delinquencies rise significantly, if by less, for even the highest credit score group.

By age, the effects are strongest for those ages 35 to 49 and 50 to 64, which is consistent with the age ranges where we expect people to hold larger amounts of mortgage debt (appendix table D.17). Interestingly, the effects on foreclosures are not that different for people affected by Sandy in majority-white communities and communities of color (appendix table D.18).

For medium-sized disasters, we see increases in delinquency in years one and two of about half a percentage point that fade by year three. We do not see effects on foreclosure rates for this group. Note, here, that because foreclosure processes are determined by state policy, and can differ substantially across states, for this set of outcomes in particular, the difference in effects between Sandy and the medium-sized disasters may be due to differences in the geography of where these disasters occurred rather than differences having to do with their magnitude. Additionally, the range of disaster-related loss mitigation options for government-insured or -guaranteed loans may not be available after a midsized disaster.

How Do Natural Disasters Affect Auto Debt?

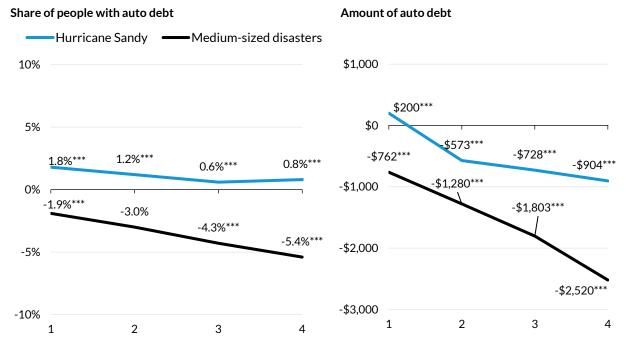
Auto debt represents an additional liability for people and comes with associated servicing costs. Natural disasters might have conflicting effects on people's level of auto debt. Auto debt might increase among people affected by natural disasters if their cars are damaged or destroyed and their automotive insurance does not fully cover the costs of replacement. If cars are largely moved out of the path of disasters such as hurricanes, or not severely damaged, there may not be substantial effects on auto debt. Reported auto debt might even fall if people respond to losses by holding off on purchases or replacing damaged cars with cheaper models.

Contrary to our expectation, we find *decreases in auto debt* following disasters, on average. People in areas affected by Hurricane Sandy have, by year four, about \$900 less in auto debt than other similar people in unaffected areas (figure 10). For those affected by medium-sized disasters, auto debt is about \$2,500 lower in year four. This is accompanied, for Sandy, by an increase of roughly 1 to 2 percentage points in the likelihood of having any auto debt relative to similar people not hit by a disaster. By

contrast, for medium-sized disasters, the fraction of people with any auto debt is 2 to 5 percentage points lower than for comparable people not hit by a disaster.

These reductions in overall auto debt appear to be driven, in part, for both Sandy and medium-sized disasters, by reductions in the likelihood of having any auto loans among people with poor credit before the disaster. Among people with poor credit before the disaster, for those in areas affected by Hurricane Sandy, the share with any auto debt is 1 to 4 percentage points lower in the years following the hurricane; for people affected by medium-sized disasters, the corresponding decline is 2 to 6 percentage points (appendix table D.20). Conversely, for Sandy in particular, the share with any auto debt is higher for people with good credit (before the disaster).

FIGURE 10
Auto Debt Declines Following the Disasters Examined
By year(s) after disaster



Source: Urban Institute calculations based on credit bureau, ACS, and FEMA data.

Notes: Values represent estimates of average differences in each outcome between individuals affected by the indicated disaster (or set of disasters) and matched individuals from unaffected areas. Effects are estimated separately for each of the four years following the disaster.

p < 0.1, p < 0.05, p < 0.01.

Particularly for disaster victims with poor credit scores, a decline in auto debt could result from a decline in access to traditional forms of credit. With limited access to traditional credit, people could respond by turning to alternative financing sources, such as "buy here, pay here" auto dealers, that are generally more expensive and likely do not report to credit bureaus and so would not show up in our data on auto debt. Additionally, people may purchase cars with insurance payouts (from the disaster), hold on longer to the cars they have, or reduce the number of cars they own.

Taken all together, the full pattern of results supports the conclusion that, in general, disasters lead to broad declines in financial health. For many outcomes, the estimated effects are substantial, and, as noted above, these are average treatment effects of residing in areas affected by a natural disaster; those residents who are directly affected are likely to suffer larger impacts. Returning to our motivating framework, we conclude that, in general, existing disaster relief programs and other forms of assistance, along with private sources of insurance and support, do not fully protect those affected by natural disaster from their financial consequences.

The overall pattern of results is also broadly suggestive that disasters may be not only harmful for affected residents on average, but may also have the effect of widening already existing inequalities. Both individuals and communities that appear more vulnerable before disasters appear to suffer more negative impacts after they strike.

Implications of Findings for Disaster Preparation and Recovery Strategies

Our findings provide insight into strategies to promote resilience and recovery for multiple actors—regulators and government (local, state, and federal), philanthropy, and nonprofit leaders focused on financial health. Some of these strategies link to our overarching findings (e.g., disaster severity, persistent negative effects, and subpopulations most impacted), while others are more directly targeted at specific financial health outcomes (e.g., credit score, delinquent utility debt). These strategies are informed by a set of interviews that we conducted with experts in the field in January and February 2019.²¹ Below we present strategies that fall into each of these groups, followed by some additional considerations raised in our conversations with field experts and direct-service providers.

We have identified four strategies that link to our overarching findings.

Post-disaster programs and resources should consider long-term needs, in addition to more immediate needs. We find that the negative effects of disasters persist, and even grow, over time. This suggests that residents in these communities need ongoing, longer-term assistance. At the federal level, one option is to extend the period of temporary assistance (e.g., more frequent extensions of temporary shelter assistance or providing D-SNAP for more than 30 days). Additionally, federal agencies should consider relaxing or extending application deadlines (e.g., allowing people more than the current 30 days to apply for disaster unemployment assistance) to accommodate the needs of households that have just experienced the trauma of disaster and are confused by their assistance and rebuilding options. Our findings also speak to the need for additional focus from state and local governments, as well as philanthropy, to fund ongoing programs aimed at stabilizing and improving residents' financial health. Generating the support for long-term assistance could be more difficult over time, as the US is hit by more disasters, and "disaster fatigue" sets in, as one interviewee put it. Focusing on longer-term needs does not suggest that strategies to address short-term needs should be curtailed or that they are not critical. Response, relief, and rebuilding should always be a focus of governmental resources. Yet, financial well-being is very much a foundation for individual households' ability to access those services. In fact, our findings suggest that the short-term hit to people's finances leads to greater deterioration of financial health over time and reinforces the need for immediate intervention.

A larger share of recovery resources should be aimed at communities struggling before the disaster hit. Physical property retrofits, hazard property insurance and health insurance, and other preventative measures have been proven strategies for reducing costs to all parties after a disaster (Multihazard Mitigation Council 2018). Financial "mitigation" activities should be encouraged and supported. This recommendation especially links to our finding that people living in low-income communities and communities of color are often the hardest hit by disasters. We find that declines in credit scores are larger and emerge earlier for people in both low-income communities and communities of color (than for people in higher-income and predominantly white communities). This finding implies a widening gap between the haves and have-nots, and thus increases in economic inequality after natural disasters hit, unless there is a concerted effort to provide a greater share of resources to more vulnerable communities.

Given the complexity of the paperwork and filing for assistance, the federal government could make it easier for people in these communities to apply and qualify for assistance. Local nonprofits and mortgage holders (e.g., Fannie Mae) often step in to help navigate this process but leave a patchwork support network. Given the possibility of barriers around education, language, and accessibility, simplification of the process could have an outsized benefit for these vulnerable communities. In addition, efforts focused on residents and vulnerable communities would ideally address residents' needs before disasters hit and could, for example, include efforts to help vulnerable residents obtain adequate amounts of insurance. Moreover, after a disaster strikes, it is essential to ensure that reasonable loss mitigation options are available to homeowners who may have been delinquent before the disaster but who can qualify for hardship assistance.

Expand the post-disaster resources available to communities and people hit by less-severe disasters. As currently designed, there is significantly less disaster relief provided to residents hit by less-severe disasters than those hit by large disasters. Because of the limited resources available to communities and residents in the aftermath of less-severe disasters, we hypothesize that people hit by medium-sized (versus large) disasters suffer greater declines in financial health. Our results are consistent with this hypothesis. ²² This suggests that government (from federal to local) and philanthropy should reevaluate and expand resources made available to residents affected by less-severe disasters to improve both their short-term and long-term financial health and stability. Stability and consistency—accompanied by clear and transparent triggers for aid launch and program eligibility requirements—across the various aid programs can minimize confusion among local providers and households, as well as reduce redundancies that

can make precious disaster assistance funds go further. In some cases, for example with CDBG-DR funding, permanent statutory authority is needed to ensure that communities and their residents can plan appropriately.

A corollary to this suggestion is the expansion of conduits for informing affected households of their options and aid eligibility—for example, through their private lenders or creditors and through credit reporting agencies. These organizations are financial "first responders" for households and should be tapped as communication channels since they also directly benefit from households' increased assistance receipt and other supports.

State and local resilience and disaster recovery plans should be more common and incorporate financial health. The traditional model of disaster management focuses first on relief and response, followed by property rebuilding. Links to long-term community planning and household financial health are needed. Communities should have better knowledge about housing and household conditions before a disaster to more quickly and appropriately recover after. The federal government has recently encouraged local governments to anticipate recovery needs, but there are still many more lessons to be learned. A survey by the National Association of Counties finds that only 44 percent of reporting counties have a disaster recovery plan (National Association of Counties 2019), and it is unlikely that financial health is a priority area. At a basic level, local leaders should think about how to integrate financial health into existing platforms. In terms of resiliency, for example, local non-profits could incorporate family budgeting and disaster planning (e.g., discussions about insurance needs) in local workforce development programs. In our conversations with experts in the field, we heard of local efforts to increase residents' savings so they will be more resilient after the next natural disaster. We also heard about the importance of communicating with residents about having backups of important documents, such as tax records, marriage certificates, and a secure title to one's home. This action is a common emergency preparedness tip, but one that directly supports financial resilience. In the aftermath of disasters, programs designed to address residents' immediate basic needs could incorporate elements to address their longer-term financial health needs (e.g., steps to improve credit scores).

These plans should also consider how data can aid in disaster preparation and recovery. For example, understanding where the most vulnerable residents are is helpful in targeting resources to those communities in the aftermath of a disaster. Also, we heard from one of the experts we spoke with that in order to get businesses and philanthropy to invest in an area after a disaster, facts about local conditions are needed even if they are not perfect.

In addition, we have identified three strategies that link to specific outcomes we examined—credit scores, utility debt, and mortgage delinquencies and foreclosures.

Consider rules and guidance around how natural disasters and subsequent delinquencies are identified on consumers' credit reports and incorporated into credit scores. A recently released Consumer Financial Protection Bureau (CFPB) report (Banko-Ferran and Ricks 2018) shows that a natural disaster indicator stays on a consumers' credit report for an average of only two months. Our findings suggest that two months is not long enough and that consumers could benefit from having these indicators on their report for well over a year. ²³ The CFPB report also finds that many consumers never receive a natural disaster indicator, and if they do, it is often only associated with some elements of the credit report (e.g., mortgage, but not credit cards). Coordination of data between FEMA, the credit bureaus, and credit scoring companies (Vantage and FICO) and federal regulatory agency rules around how natural disaster related hardships (e.g., credit utilization rates, delinquencies) are identified on consumers' credit reports and incorporated into credit scores could help stem the tide of increasing and persistent declines in credit scores after disasters hit.

At the same time, federal, state, and local governments could *limit the ability of employers to examine credit reports in the hiring process*. Residents whose employment is disrupted as a result of a natural disaster could be doubly harmed by having potential employers check their credit report. Restricting employers' ability to check credit reports in the hiring process—as recently done in New York City²⁴—could improve the long-term prospects of natural disaster victims.

• States and municipalities should take steps to provide consumers with utility-related protections after a disaster hits. Our empirical analyses suggest that there are early increases in delinquent utility debt (within the first year) and that these increase over time. While these later increases could indicate general levels of financial distress, these early delinquencies can have cascading effects. Beyond increases in delinquent utility debt, our qualitative interviews suggest that some disaster victims have their utilities disconnected due to nonpayment of bills, even where the home may not be receiving utility service because of the disaster. To help protect disaster victims, states could pass laws that require state-regulated private utilities to better address consumer needs; local leaders should consider similar laws related to municipal utilities (often water and sewer). States and localities could take steps to revise billing procedures, ensure that all customers can negotiate payment plans and they are treated equally (e.g., consumers with earlier delinquencies are not held to a higher standard), and put into place strong rules around the disconnection of utilities (National Consumer Law Center 2018). The National Consumer

Law Center (2018) provides a number of additional strategies around utility consumer protections.

In addition to consumer protections, states should be aware that *federal LIHEAP program funds* can be used flexibly after disaster. While states have flexibility, they do not receive additional LIHEAP funds. Thus, additional federal LIHEAP funds administered to states after a natural disaster would help to protect low-income and vulnerable consumers.

Mortgage lenders and government sponsored enterprises should update existing mortgage delinquency and foreclosure policies to account for long-term financial burdens following disasters. Current policies provide short-term foreclosure moratoria, forbearance plans, and loan modifications following disasters. After Hurricane Sandy, mortgage delinquency and foreclosure increased significantly in the second, third, and fourth years following a disaster, suggesting that homeowners affected by disasters need assistance for many years. Homeowners may not risk mortgage delinquency until they have already drawn down existing savings. One option is to extend existing moratoria and forbearance periods, as well the availability of disaster-related loss loan modifications. Such extensions must be accompanied by oversight to ensure compliance with governing rules. Another option is better assistance navigating the disaster aid application process. In 2018, Fannie Mae began offering disaster case management to help affected homeowners with Fannie Mae-owned mortgages navigate the process of applying for assistance. Funding this sort of program to all homeowners should be considered. Some state and local governments have hosted post-disaster "info fairs" to connect consumers to relevant mortgage company representatives to provide information on the process for receiving relief (which varies by owner of the debt), but these programs tend to be short-lived and mechanisms should be considered to provide this assistance three and four years after a disaster.

Also, homeowners face a much higher risk of delinquency and foreclosure if their homes are under-insured. Increased education and regulation should be considered. This is particularly important with regards to the National Flood Insurance Program (NFIP). Homeowners need to understand what is and isn't covered under traditional homeowner's insurance and what is and isn't covered under their NFIP insurance plan. Homeowners also need strong consumer protections to allow them to access available homeowner's insurance coverage. Mortgage companies should be required to clearly communicate insurance payout requirements, and regulators should ensure compliance with existing standards.

Much of the work associated with operationalizing these recommendations lies in the hands of the federal program administrators, starting with the Individual Assistance program managers and applicant reviewers in each FEMA region. Federal officials play a critical role in allotting recovery funds that eventually reach the disaster-affected households, and therefore play a critical role in incentivizing state and local jurisdictions to monitor the financial conditions of residents before disasters as much as their financial needs after. However, those same state and local entities can independently reduce siloes between economic development, long-term planning, and financial safety net activities that they conduct as part of routine business into disaster planning to ensure that all needs are anticipated more robustly and that aid is delivered directly at timely points along a household's recovery. Rethinking and realigning the disaster safety net requires thoughtful coordination between these agencies but, ultimately, requires legislation to change the statutory authorities and assistance program rules. Further, consistency and timeliness in appropriations across disaster types can keep households from falling off the financial cliff after the short-term financial aid and credit relief dries up after less severe disasters, or from falling between the cracks of that temporary aid and potential long-term assistance delivered years later.

Private-sector lenders, creditors, banks and affiliated financial institutions such as mortgage underwriters and credit-reporting agencies also have a role in providing information to public officials for planning and response functions. Developing consistent and transparent rules about what they can provide in different disaster scenarios can mitigate some of the chaos that occurs for households. They can also serve as conduits of information about public and private assistance resources since they are often the first lines of communication to borrowers and consumers; it is in these institutions' best interest to ensure that their customers understand their options and get back on solid financial standing quickly and sustainably.

Beyond the seven strategies above, the field experts and direct service providers that we spoke with underlined several strategies aimed at ensuring vulnerable individuals and communities are not left behind in rebuilding efforts—for example, ensuring that damaged or destroyed affordable rental units be replaced on a one-to-one basis, and in areas with low risk of being affected by a future disaster. ²⁵ Echoing this theme, one respondent described communities using the disaster rebuilding process as an opportunity to increase the equity and vibrancy of the community—for example, by replacing damaged or destroyed housing in ways that create more mixed-income communities.

As we highlight in this section, there are a number of strategies that hold promise for increasing resilience and improving residents' financial health following a natural disaster. These strategies range from considerations for disaster preparedness and resiliency planning to improvements to approaches

to recovery and rebuilding. Together they highlight the importance of involvement of many actors—from individuals and families to state and local governments and community organizations to national nonprofits and philanthropy to private sector organization to federal policy and agencies. Changes across these levels would strengthen recovery and resilience efforts, and thereby lessen the negative effects of natural disasters on residents' financial health that we find in this study.

Appendix A. Major Public-Sector Assistance Programs

This appendix describes the major public-sector assistance programs for individuals affected by disasters.

Relief for Immediate Needs

Mass Care/Emergency Assistance is provided by FEMA to all residents in an affected region in the immediate aftermath of a disaster. It coordinates with the American Red Cross to provide evacuee support and the delivery of shelter, food, emergency supplies—costs that might otherwise be borne by individual households. The Mass Care program also provides coordination and technical assistance for federal, state, and local agencies engaged in response and recovery. ²⁶

Transitional Shelter Assistance (TSA) is funded by FEMA and available to individuals who are unable to return to their residence after a disaster and after temporary shelter closures. Under TSA, disaster survivors with severely damaged homes are eligible to stay in participating hotels and motels, thereby eliminating the interim housing costs that some of the affected households might face. TSA is a component of FEMA IA, and is therefore available only if a state requests it and FEMA inspections confirm housing damage as part of the governor's declaration request to the president. Depending on the severity of the disaster damage, TSA is available for as few as five days or up to six months. ²⁷

Low Income Home Energy Assistance Program (LIHEAP) Emergency Contingency Funds are distributed at the discretion of the Department of Health and Human Services (HHS) to states to supplement annual formula grants. States can divert LIHEAP funds to pay for temporary shelter, clothes, and blankets, and for utility replacement or reconnection for households that cannot afford to pay electric, gas, or other energy utility bills after a disaster (Perl 2018).

Relief for Home Repair and Replacement of Personal Property

FEMA Individuals and Households Program (IHP—a component of, and also referred to as, Individual
Assistance or IA) provides various financial assistance channels to individuals affected by disasters with

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unmet needs—that is, needs not covered after insurance claims—for temporary housing, repair, replacement, and reconstruction and for other needs such as disaster-related medical costs, funeral expenses, or personal property loss. The maximum duration of any IHP assistance is 18 months. There are no eligibility requirements beyond US residency, evidence from FEMA-verified disaster loss, and proof of ownership and insurance claim gaps, but the maximum value individual assistance is capped annually at a value determined by Congress. The affected state or states can request IHP assistance as part of their request for a Presidential disaster declaration.²⁸

Disaster Loan Assistance (SBA loans) is a program from the US Small Business Association (SBA) that provides low-interest loans to eligible homeowners and businesses. Individuals may borrow up to \$40,000 to repair or replace items damaged in the disaster, and homeowners may apply for up to \$200,000 to repair or replace their damaged residence. ²⁹ SBA considers households' creditworthiness in their loan reviews, thereby limiting the pool of eligible homeowners.

Community Development Block Grant Disaster Recovery (CDBG-DR) provides additional funding for unmet housing needs, targeted especially for low- and moderate-income households with remaining uninsured needs in the most severely affected regions. CDBG-DR funds are a congressionally appropriated backstop, and are not available for every declared disaster or in every year. Congress appropriates the funds to HUD, which then allocates and distributes them to states or entitlement county and city jurisdictions. ³⁰ HUD regulations stipulate household eligibility terms, but the receiving community decides the manner and focus of household-level distribution. As the second largest source for disaster recovery assistance after FEMA's IA, CDBG-DR's application is critical when IHP eligibility runs out 18 months after a disaster event.

Relief for ECONOMIC HARDSHIP

Disaster Unemployment Assistance (DUA) is also funded by FEMA under its Stafford Act authorities but is overseen by the Department of Labor. The DUA program provides funds to state, local, tribal, and territorial governments to provide unemployment benefits and reemployment services to people who have become unemployed because of a disaster but are not eligible for traditional unemployment insurance.³¹

Disaster Supplemental Nutrition Assistance Program (D-SNAP) is an extension of the SNAP program that gives food assistance to low-income households following a natural disaster. States seek approval

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from US Department of Agriculture Food and Nutrition service to operate D-SNAP. D-SNAP is only available to states in which FEMA IA programs are authorized.³²

Disaster Housing Assistance Program (DHAP) was a housing assistance program that provided a rental subsidy with case management that contracted over time for households that remained without housing after Hurricanes Katrina and Rita, Hurricanes Gustav and Ike, and Superstorm Sandy.³³

Disaster Tax Relief is often provided by the Internal Revenue Service in the form of delayed payment or filing deadlines.³⁴ With supporting legislation, this relief can extend to temporary alterations to tax terms for individual households, such as calculations of casualty losses or charitable contributions and tax credits.³⁵

Additional human services programs provided by FEMA in the aftermath of a disaster include Crisis Counseling Assistance and Training Program, Disaster Legal Services, and Disaster Case Management—all services whose costs would be borne by individual households or otherwise forgone.³⁶

Relief for homeowners with mortgages

Federal Housing Administration (FHA) provides a foreclosure moratorium on FHA-insured mortgages and instructs lenders to allow forbearance plans and loan modifications to all affected borrowers within a declaration region for 90 days. At their discretion, lenders may also waive late fees or allow other modification for individual borrowers.³⁷ Veteran Affairs home loans, which are a small share of the mortgage market, are occasionally modified after large disasters just like FHA-insured loans.

Fannie Mae provides a Disaster Response Network providing credit counseling, assistance filing FEMA, insurance, and SBA claims, along with credit reporting moratoria, forbearance plans, loan modifications and relaxed regulations for homeowners with Fannie Mae–owned mortgages.³⁸

Freddie Mac provides forbearance programs, modifications, credit reporting moratoria, and the waiving of late charges for homeowners with Freddie Mac-owned mortgages.³⁹

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Appendix B. Methods

We estimate the effects of natural disasters on financial health by comparing financial outcomes of residents in affected areas to financial outcomes of otherwise similar individuals in comparison communities that were not affected by natural disasters.

To do this, we first identify, for each disaster, a set of comparison communities following the approach of Deryugina, Kawano, and Levitt (2018) and Groen, Kutzbach, and Polivka (2017). We use propensity score matching to identify the five nearest neighbor zip codes for each zip code affected by a disaster (where affected zip codes are identified, as above, as those where 20 percent or more of residents applied for FEMA Individual Assistance following the disaster). The comparison set of zip codes is drawn from the universe of zip codes in our data that have not been affected by a natural disaster in any year in our data (years 2010 to 2017). We predict propensity scores based on a set of zip-level credit and demographic characteristics. ⁴⁰

To estimate the effects of natural disasters on financial health of individuals, we then compare financial outcomes, such as credit scores, of individuals residing in affected areas in the year of the disaster with those of otherwise similar individuals in comparison areas. ⁴¹ Because we cannot identify which residents in affected areas suffered direct financial (or other) losses due to the disaster, this analysis compares all individuals in affected areas to (matched) individuals in unaffected areas. As a result, these estimates show the effects of living in affected areas, averaged over directly affected individuals and other individuals. This likely leads our estimates to understate the effects of a disaster on those directly affected. On the other hand, natural disasters are intrinsically spatial events in ways that are likely to generate substantial spillovers from directly affected individuals; even individuals not suffering property damage, personal injury, or other direct effects might still suffer financially if their local communities and economies are negatively affected by the disaster.

We estimate these effects using a propensity score matching model using nearest-neighbor matching. For estimates of the effects of single disasters, such as Hurricane Sandy, the pool of comparison individuals is everyone in the comparison set of zip codes for Hurricane Sandy, identified as described above. For estimates of effects pooled across multiple disasters (our set of other large and medium-sized disasters), the pool of comparison individuals is everyone in the pooled set of comparison zip codes. We predict propensity scores using an individual's age, age squared, and the pre-disaster values of the credit bureau outcome for which we are estimating treatment effects (e.g., when

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estimating the effects of disasters on credit scores we match on individual credit scores in the year before the disaster). Standard errors account for the fact that propensity scores are estimated.

We employ propensity score matching at the individual level for estimating the effects of natural disasters on individuals living in affected areas in order to compare affected individuals to similar unaffected individuals. For many outcomes, linear regressions with controls for the matching variables produce qualitatively similar results; however, because the distributions of many of our outcomes (e.g., levels of credit card debt) are highly skewed some estimates are difficult to interpret (or require log transformations). For ease of presentation and interpretation for this brief, we prefer and present the propensity score estimates. Note that one tradeoff associated with the propensity score model is that while it does take advantage of the time dimension of our data it does not exploit its panel structure; estimates for each year following a disaster are from separate models. We can also estimate these effects in a fixed-effect regression framework, which we have done for some of these disasters and outcomes, and which generally indicate negative (but typically weaker) effects of disasters on financial health outcomes. One robustness check we can perform with the propensity score estimates is to restrict estimation in each post-disaster year to a common sample; these results are qualitatively similar to those we report in the brief (which do not impose this restriction).

We examine effects separately by disaster group for a period of four years following the disaster and for a set of subgroups defined by individual-level and community-level characteristics:

Disaster magnitude: We look at the effects of disasters separately for three groups of disasters: (a) Hurricane Sandy, by far the largest disaster in our analysis; (b) other disasters causing over \$200 million in damage (which we label "large" disasters); and (c) disasters with less than \$200 million in damage but large enough to trigger FEMA individual assistance (labeled "medium-sized" disasters).

Effects over time: Our analyses focus on disasters that hit from 2011 through the summer of 2014, allowing us to observe people's financial health the year before the disaster hit and for four years afterwards (up to 2017).

Subgroups: We look separately at effects by age and pre-disaster financial health (as captured by their credit score in the year before the disaster). We also estimate separate effects by whether individuals live in communities of color or low-income neighborhoods.

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Appendix C. Interview Methods

The study team conducted two rounds of interviews to inform this work. An initial round of interviews with service providers built understanding of the processes linking natural disasters and financial health and helped refine the study analysis plan. A second round of interviews with field experts provided information needed to interpret study results and link study findings to disaster preparation and recovery strategies. In this appendix we describe interview methods in greater detail.

Initial Service Provider Interviews

In the initial round of interviews (conducted June 2018), we spoke to five service provider organizations. The goal of these interviews was to provide insight into the needs and responses of communities after a disaster, to assist in our identification of strategies communities use to build resilience, and to validate and provide feedback on our methodology for the quantitative analysis. Organizations were selected based on their size, scope of services, and natural disaster experience. Two of the respondent organizations provide direct financial services, including financial coaching, and the remaining three provide support and technical assistance to smaller direct service organizations. The respondent organizations work in areas affected by California wildfires and Hurricanes Harvey, Irma, and Sandy.

Follow-Up Field Expert Interviews

The project team conducted a second round of interviews in early 2019, as findings from the quantitative analyses were beginning to solidify. This second round of interviews had two goals. The first was to solicit feedback and help interpreting results of the quantitative analysis. The second goal was to inform our recommendations for stakeholders (e.g., government, philanthropy, financial service providers, national regulators) to help residents build resilience before a disaster hits and better cope afterward. With these goals in mind, we spoke to several types of organizations: national organizations with expertise in regulation or working with local governments; organizations involved in planning for and executing community-level responses to natural disasters; and local organizations in areas recently affected by natural disasters with experience collecting and harnessing local-level data to assist in recovery. We spoke with seven organizations in this second round of interviews.

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Interview Procedures

Respondents were recruited through Urban Institute and JPMorgan Chase networks. Interviews were conducted via one-hour phone calls. Senior members of the research team led the interviews, and junior members took detailed notes. Each interviewed organization had one to three staff members of various roles available for the calls. Interviews were semi-structured. The project team followed an interview guide but asked additional questions as they arose. Interview notes were reviewed and coded to identify key themes.

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Appendix D. Detailed Results Tables

TABLE D.1

Effect of Natural Disasters on Credit Score

| | Hurrica | ne Sandy | | Large D | isasters | Medium-Sized Disasters | | |
|-------------------------|--------------------|-------------------|-----|--------------------|------------------|------------------------|------------------|-----|
| Years after disaster | Comparison mean | Estimated effect | d | Comparison mean | Estimated effect | Comparison mean | Estima effec | |
| 1 | 679 | -6.85 * (0.81) | *** | 654 | -1.93 (2.29) | 622 | -9.15 (1.46) | *** |
| 2 | 686 | -8.19 * (0.86) | *** | 659 | -2.78 (2.47) | 631 | -11.53 (1.57) | *** |
| 3 | 692 | -9.55 * (0.90) | *** | 663 | -2.84 (2.51) | 639 | -19.20 (1.66) | *** |
| 4 | 698 | -10.11 * (0.95) | *** | 668 | -3.19 (2.73) | 647 | -21.72 (1.79) | *** |

Source: Urban Institute calculations based on credit bureau, FEMA, and ACS data.

Notes: The estimated effects are average differences in credit score between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. Standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01

TABLE D.2

Effect of Natural Disasters on Credit Score by Pre-Disaster Credit Score Groups

| Years | | Hurricane Sand | у | Medium-Sized Disasters | | | | |
|-------------------|-------------|----------------|-------------|------------------------|-------------|-------------|--|--|
| after disaster | Poor Credit | Fair Credit | Good Credit | Poor Credit | Fair Credit | Good Credit | | |
| 1 | -2.04 | -4.89 ** | -2.46 *** | -12.51 *** | -15.37 *** | -4.02 * | | |
| | (1.52) | (2.27) | (0.71) | (1.62) | (4.11) | (2.27) | | |
| 2 | -6.55 *** | -6.82 *** | -4.05 *** | -15.67 *** | -15.85 *** | -0.87 | | |
| | (1.69) | (2.51) | (0.81) | (1.76) | (4.80) | (2.54) | | |
| 3 | -5.79 *** | -10.28 *** | -4.95 *** | -26.42 *** | -19.76 *** | -4.68 * | | |
| | (1.76) | (2.66) | (0.87) | (1.98) | (5.01) | (2.81) | | |
| 4 | -7.94 *** | -6.83 ** | -6.82 *** | -28.92 *** | -17.43 *** | -8.44 *** | | |
| | (1.92) | (2.84) | (0.91) | (2.08) | (5.28) | (3.08) | | |

 $\textbf{Source:} \ \textbf{Urban Institute calculations based on credit bureau, FEMA, and ACS data.}$

Notes: The estimated effects are average differences in credit score between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. We use VantageScore credit scores which range from 300 to 850. "Poor" scores range from 300 to 649, "fair" from 650 to 699, and "good" from 700 to 850. Standard errors in parentheses. *p < 0.1, ***p < 0.05, ****p < 0.01

Effect of Natural Disasters on Credit Score by Age Groups

| Years | | Hurricane Sandy | | | | | | Medium-Sized Disasters | | | | | | | | |
|-------------------|---------------|-----------------|---------------|-----|---------------|-----|----------------|------------------------|----------------|-----|----------------|-----|----------------|-----|---------------|-----|
| after disaster | 24-3 | 34 | 35-4 | 19 | 50- | 64 | 65 a old | | 24-3 | 34 | 35-4 | 9 | 50-6 | 64 | 65 a old | |
| 1 | -4.3 (2.0) | ** | -2.9 (1.4) | ** | -3.3 (1.2) | *** | -7.9 (1.9) | *** | -15.2 (2.8) | *** | -11.7 (2.4) | *** | -3.8 (2.5) | | -9.1 (3.5) | *** |
| 2 | -7.8 (2.1) | *** | -5.5 (1.6) | *** | -5.1 (1.4) | *** | -10.3 (2.1) | *** | -16.8 (3.1) | *** | -17.5 (2.7) | *** | -10.3 (2.8) | *** | 4.3 (3.7) | |
| 3 | -7.1 (2.3) | *** | -7.4 (1.7) | *** | -6.3 (1.5) | *** | -10.6 (2.0) | *** | -29.6 (3.4) | *** | -23.9 (3.0) | *** | -19.4 (3.2) | *** | -0.1 (4.4) | |
| 4 | -9.5 (2.4) | *** | -9.6 (1.8) | *** | -6.7 (1.5) | *** | -11.7 (2.1) | *** | -34.2 (3.7) | *** | -24.1 (3.2) | *** | -20.9 (3.4) | *** | -0.0 (4.4) | |

Notes: The estimated effects are average differences in credit score between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

TABLE D.4
Effect of Natural Disasters on Credit Score by Zip Code Income Level

| | Hurrica | ne Sandy | Medium-Size | ed Disasters |
|----------------------|----------------------|-------------------------|----------------------|-------------------------|
| Years after disaster | Low-income zip codes | Higher-income zip codes | Low-income zip codes | Higher-income zip codes |
| 1 | 2.32 | -7.41 *** | -3.77 ** | 0.07 |
| | (6.03) | (0.82) | (1.90) | (2.93) |
| 2 | -8.19 | -8.84 *** | -10.86 *** | -3.79 |
| | (5.21) | (0.88) | (1.98) | (2.98) |
| 3 | -4.15 | -10.00 *** | -18.67 *** | -10.10 *** |
| | (6.32) | (0.91) | (2.08) | (3.22) |
| 4 | -6.29 | -10.68 *** | -21.68 *** | -9.36 *** |
| | (7.29) | (0.96) | (2.28) | (3.45) |

Notes: The estimated effects are average differences in credit score between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. Low-income zip codes are those in which at least 50 percent of households have incomes below 200 percent of the federal poverty level; all others defined as higher-income zip codes. Standard errors in parentheses.

TABLE D.5

Effect of Natural Disasters on Credit Score by Zip Code Racial and Ethnic Composition

| | Hurrica | ne Sandy | Medium-Sized Disasters | | | |
|-------------------------|--------------------------------|-------------------------|--------------------------------|----------------------------|--|--|
| Years after disaster | Areas majority people of color | Areas majority white | Areas majority people of color | Areas majority white | | |
| 1 | 0.52 | -8.79 *** | -10.37 *** | 1.98 | | |
| | (1.90) | (0.96) | (1.61) | (3.19) | | |
| 2 | -5.86 *** | -9.44 *** | -14.61 *** | 3.02 | | |
| | (1.97) | (1.03) | (1.75) | (3.77) | | |
| 3 | -7.93 *** | -9.39 *** | -25.71 *** | -4.53 | | |
| | (2.14) | (1.05) | (1.87) | (4.15) | | |
| 4 | -9.72 *** | -10.7 *** | -30.87 *** | -4.17 | | |
| | (2.30) | (1.10) | (2.01) | (4.12) | | |

Source: Urban Institute calculations based on credit bureau, FEMA, and ACS data.

Notes: The estimated effects are average differences in credit score between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. Standard errors in parentheses.

^{*} p < 0.1, ** p < 0.05, *** p < 0.01

^{*} p < 0.1, ** p < 0.05, *** p < 0.01

TABLE D.6
Effect of Natural Disasters on Debt in Collections

| | Hurrica | ne Sandy | | Large D | isasters | Medium-Siz | Medium-Sized Disasters | | | | | | | |
|-------------------------|--|------------------|---------|--------------------|-------------------|--------------------|------------------------|-----|--|--|--|--|--|--|
| Years after disaster | Comparison mean | Estimated effect | | Comparison mean | Estimated effect | Comparison mean | Estimat effect | | | | | | | |
| | Share of people with any debt in collections (%) | | | | | | | | | | | | | |
| 1 | 29.73 | -0.05 (0.30) | | 39.85 | -0.69 (0.75) | 50.82 | 4.98 (0.52) | *** | | | | | | |
| 2 | 28.61 | 0.36 (0.34) | | 39.29 | 0.50 (0.83) | 48.09 | 6.07 (0.59) | *** | | | | | | |
| 3 | 27.01 | 0.65 (0.37) | * | 38.45 | 0.24 (0.91) | 45.02 | 6.75 (0.64) | *** | | | | | | |
| 4 | 25.07 | 0.29 (0.38) | | 37.12 | 0.34 (0.96) | 42.51 | 10.00 (0.68) | *** | | | | | | |
| | | | Т | otal amount of de | ebt in collection | ns (\$) | | | | | | | | |
| 1 | 2467 | 188 (128) | | 2747 | -414 (366) | 3152 | 1420 (269) | *** | | | | | | |
| 2 | 2260 | 81 (139) | | 2786 | -441 (334) | 2834 | 1745 (268) | *** | | | | | | |
| 3 | 2027 | 22 (137) | | 2686 | -691 ** (352) | 2635 | 1701 (399) | *** | | | | | | |
| 4 | 1804 | 67 (140) | | 2494 | -467 (331) | 2715 | 2014 (453) | *** | | | | | | |
| | | | Share o | f people with uti | | ections (%) | | | | | | | | |
| 1 | 9.62 | -0.51 (0.23) | ** | 14.71 | -1.06 (0.79) | 20.39 | 2.38 (0.59) | *** | | | | | | |
| 2 | 9.44 | 0.78 (0.26) | *** | 15.02 | -0.28 (0.83) | 20.04 | 3.66 (0.63) | *** | | | | | | |
| 3 | 9.15 | 0.23 (0.27) | | 14.74 | 0.85 (0.86) | 20.30 | 7.64 (0.67) | *** | | | | | | |
| 4 | 9.25 | 0.50 (0.28) | * | 14.89 | 0.65 (0.88) | 18.86 | 10.10 (0.71) | *** | | | | | | |
| | | • | Aı | mount of utility d | ebt in collectio | ns (\$) | • | | | | | | | |
| 1 | 63 | 15 (4) | *** | 100 | -6 (11) | 134 | 32 (11) | *** | | | | | | |
| 2 | 62 | 21 (4) | *** | 106 | 8 (13) | 139 | 51 (11) | *** | | | | | | |
| 3 | 62 | 23 (5) | *** | 114 | 14 (13) | 157 | 100 (13) | *** | | | | | | |
| 4 | 69 | 27 (5) | *** | 119 | 5 (14) | 157 | 158 (14) | *** | | | | | | |

Notes: The estimated effects are average differences for each outcome between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. Standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01

TABLE D.7
Effect of Natural Disasters on Bankruptcy

| | Hurrica | ne Sandy | Large D | Disasters | Medium-Sized Disasters | | |
|-------------------------|--------------------|---------------------|--------------------|--------------------|------------------------|--------------------|--|
| Years after disaster | Comparison mean | Estimated effect | Comparison mean | Estimated effect | Comparison mean | Estimated effect | |
| | | ith a bankruptcy | (%) | | | | |
| 1 | 1.13 | -0.36 *** (0.10) | 1.03 | -0.06 (0.75) | 1.08 | 1.19 *** (0.22) | |
| 2 | 0.93 | -0.12 (0.10) | 1.00 | -0.48 ** (0.83) | 0.90 | 1.33 *** (0.21) | |
| 3 | 0.82 | -0.10 (0.09) | 0.83 | -0.22 (0.91) | 0.73 | 1.48 *** (0.21) | |
| 4 | 0.69 | -0.23 *** (0.07) | 0.69 | 0.20 (0.96) | 0.69 | 1.26 *** (0.21) | |

 $\textbf{Source:} \ \textbf{Urban Institute calculations based on credit bureau, FEMA, and ACS data.}$

Notes: The estimated effects are average differences for each outcome between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. Standard errors in parentheses.

* p < 0.1, ** p < 0.05, *** p < 0.01

TABLE D.8

Effect of Natural Disasters on Debt in Collections and Bankruptcy by Pre-Disaster Credit Score Groups

| | Medium-Sized Disasters | | | | | | | | |
|-------------------------|------------------------|-----|--------------------------|----------------|----------|-----|--|--|--|
| Years after disaster | Poor Cred | it | Fair Cred | it | Good Cre | dit | | | |
| | |) | | | | | | | |
| 1 | 4.10 | *** | 5.66 | *** | 2.77 | *** | | | |
| | (0.60) | | (2.02) | | (1.02) | | | | |
| 2 | 5.06 | *** | 8.20 | *** | 2.51 | ** | | | |
| | (0.68) | | (2.23) | | (1.09) | | | | |
| 3 | 6.00 | *** | 5.55 | ** | 2.42 | ** | | | |
| | (0.76) | | (2.34) | | (1.13) | | | | |
| 4 | 10.00 | *** | 7.55 | *** | 3.56 | *** | | | |
| | (0.80) | | (2.44) | | (1.18) | | | | |
| | | | Amount of debt in co | llections (\$) | | | | | |
| 1 | 2,042 | *** | 673 | | 84 | | | | |
| | (378) | | (958) | | (277) | | | | |
| 2 | 1,789 | *** | 1,436 | * | 115 | | | | |
| | (535) | | (769) | | (269) | | | | |
| 3 | 2,075 | *** | 1,246 | ** | 23 | | | | |
| | (532) | | (612) | | (191) | | | | |
| 4 | 2,132 | *** | 1,201 | * | 157 | | | | |
| | (606) | | (673) | | (225) | | | | |
| | | | Share of people with a k | pankruptcy (%) | | | | | |
| 1 | 1.15 | *** | 0.40 | | 0.35 | | | | |
| | (0.30) | | (0.50) | | (0.24) | | | | |
| 2 | 1.42 | *** | 0.72 | | 0.26 | | | | |
| | (0.29) | | (0.55) | | (0.25) | | | | |
| 3 | 1.73 | *** | 1.05 | * | -0.11 | | | | |
| | (0.29) | | (0.60) | | (0.17) | | | | |
| 4 | 1.32 | *** | 1.59 | ** | 0.14 | | | | |
| | (0.27) | | (0.74) | | (0.20) | | | | |

Notes: The estimated effects are average differences for each outcome between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. We use VantageScore credit scores which range from 300 to 850. "Poor" scores range from 300 to 649, "fair" from 650 to 699, and "good" from 700 to 850. Standard errors in parentheses.

^{*} p < 0.1, ** p < 0.05, *** p < 0.01

TABLE D.9

Effect of Natural Disasters on Debt in Collections and Bankruptcy by Age Groups

| Years after | Medium-Sized Disasters | | | | | | | | | | | |
|-------------|--|-----|----------|------------|----------------------|-----|-----------|-----|--|--|--|--|
| disaster | 24-3 | 4 | 35-4 | 9 | 50-64 | 1 | 65 and ol | der | | | | |
| | Share of people with debt in collections (%) | | | | | | | | | | | |
| 1 | 5.95 | *** | 6.07 | *** | 5.00 | *** | 2.04 | | | | | |
| | (1.09) | | (0.94) | | (1.07) | | (1.43) | | | | | |
| 2 | 7.27 | *** | 6.60 | *** | 6.52 | *** | 1.16 | | | | | |
| | (1.27) | | (1.07) | | (1.22) | | (1.60) | | | | | |
| 3 | 9.59 | *** | 7.99 | *** | 5.59 | *** | 1.32 | | | | | |
| | (1.41) | | (1.18) | | (1.32) | | (1.79) | | | | | |
| 4 | 13.20 | *** | 11.90 | *** | 8.71 | *** | 3.90 | ** | | | | |
| | (1.44) | | (1.25) | | (1.42) | | (1.93) | | | | | |
| | | | Amou | nt of debi | t in collections (\$ | 5) | | | | | | |
| 1 | 1,721 | *** | 2,250 | *** | 570 | • | 512 | | | | | |
| | (609) | | (742) | | (444) | | (446) | | | | | |
| 2 | 1,373 | ** | 3,416 | *** | -436 | | -600 | | | | | |
| | (594) | | (681) | | (1205) | | (640) | | | | | |
| 3 | 1,834 | *** | 4,322 | *** | 1,005 | *** | -1,144 | | | | | |
| | (535) | | (694) | | (389) | | (713) | | | | | |
| 4 | 2,205 | *** | 4,587 | *** | 387 | | -149 | | | | | |
| | (699) | | (727) | | (488) | | (381) | | | | | |
| | | | Share of | people wi | ith a bankruptcy | (%) | | | | | | |
| 1 | 1.79 | *** | 1.90 | *** | 0.79 | * | 0.48 | | | | | |
| | (0.54) | | (0.51) | | (0.42) | | (0.39) | | | | | |
| 2 | 1.76 | *** | 1.24 | *** | 1.39 | *** | 0.99 | ** | | | | |
| | (0.53) | | (0.44) | | (0.43) | | (0.47) | | | | | |
| 3 | 1.25 | *** | 1.53 | *** | 1.40 | *** | 1.33 | *** | | | | |
| | (0.47) | | (0.42) | | (0.43) | | (0.50) | | | | | |
| 4 | 1.19 | *** | 1.48 | *** | 1.03 | ** | 0.66 | | | | | |
| | (0.48) | | (0.41) | | (0.41) | | (0.40) | | | | | |

Notes: The estimated effects are average differences for each outcome between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. Standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01

TABLE D.10
Effect of Natural Disasters on Debt in Collections and Bankruptcy by Zip Code Income Level

| | Medium-Sized Disasters | | | | | | | |
|----------------------|------------------------|----------|-----------------------------|-----|--|--|--|--|
| Years after disaster | Low-income codes | e zip | Higher-inco zip codes | | | | | |
| | Share of people w | ith debt | in collections (%) | | | | | |
| 1 | 4.06 (0.64) | *** | 3.63 (0.98) | *** | | | | |
| 2 | 4.88 (0.72) | *** | 4.73 (1.11) | *** | | | | |
| 3 | 5.61 (0.80) | *** | 4.38 (1.19) | ** | | | | |
| 4 | 8.53 (0.86) | *** | 7.94 (1.29) | *** | | | | |
| | | Amount | of debt in collections (\$) | | | | | |
| 1 | 524 (714) | | 968 (594) | | | | | |
| 2 | 1,730 (352) | *** | 1,819 (543) | *** | | | | |
| 3 | 2,198 (319) | *** | 1,496 (488) | *** | | | | |
| 4 | 2,023 (347) | *** | 1,425 (517) | *** | | | | |
| | Sh | | eople with a bankruptcy (%) | | | | | |
| 1 | 1.16 (0.25) | *** | 1.66 (0.48) | *** | | | | |
| 2 | 1.36 (0.25) | *** | 1.29 (0.43) | *** | | | | |
| 3 | 1.28 (0.25) | *** | 1.93 (0.46) | *** | | | | |
| 4 | 1.17 (0.24) | *** | 1.45 (0.43) | *** | | | | |

Notes: The estimated effects are average differences for each outcome between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. Low-income zip codes are those in which at least 50 percent of households have incomes below 200 percent of the federal poverty level; all others defined as higher-income zip codes. Standard errors in parentheses.

^{*} p < 0.1, ** p < 0.05, *** p < 0.01

TABLE D.11 **Effect of Natural Disasters on Credit Card Debt**

| | Hurrica | ne Sandy | Large [| Disasters | Medium-Sized Disasters | | |
|-------------------------|---------------------|------------------|---------------------|--------------------|------------------------|--------------------|----|
| Years after disaster | Compariso n mean | Estimated effect | Compariso n mean | Estimated effect | Compariso n mean | Estimate effect | d |
| | | | Share of people v | with a credit car | d (%) | | |
| 1 | 68.20 | 0.18 | 55.58 | -0.22 | 48.16 | -3.91 | ** |
| | | (0.27) | | (0.71) | | (0.50) | |
| 2 | 71.24 | 0.07 | 57.96 | 0.02 | 53.46 | -4.7 | ** |
| | | 0.30 | | (0.80) | | (0.58) | |
| 3 | 74.14 | -0.27 | 60.82 | 0.05 | 58.41 | -5.35 | ** |
| | | (0.32) | | (0.87) | | (0.63) | |
| 4 | 76.61 | 0.39 | 63.89 | -0.0892 | 62.27 | -6.45 | ** |
| | | (0.33) | | (0.91) | | (86.0) | |
| | | | Amount of cr | edit card debt (\$ | 5) | | |
| 1 | 4130 | -4 | 2854 | -120 | 1995 | 206 | ** |
| | | (120) | | (179) | 2770 | (74) | |
| 2 | 4456 | 89 | 3095 | 242 | 2311 | 257 | ** |
| | | (125) | | (173) | | (88) | |
| 3 | 4748 | 66 | 3298 | 12 | 2608 | 263 | ** |
| | | (132) | | (212) | | (90) | |
| 4 | 4909 | 351 * | 257/ | 240 | 3109 | 23 | |
| | | (143) | | (222) | | (114) | |

Notes: The estimated effects are average differences for each outcome between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. Standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01

TABLE D.12
Effect of Natural Disasters on Credit Card Debt by Pre-Disaster Credit Score Groups

| Years | | Hurricane Sand | ly | Medi | Medium-Sized Disasters | | | | | | | |
|-------------------|--|----------------|-------------|-------------------------|------------------------|-------------|--|--|--|--|--|--|
| after disaster | Poor Credit | Fair Credit | Good Credit | Poor Credit | Fair Credit | Good Credit | | | | | | |
| | Share of people with a credit card (%) | | | | | | | | | | | |
| 1 | 1.16 * | -0.31 | 0.33 | -4.52 *** | 1.70 | 1.12 | | | | | | |
| | (0.63) | (0.75) | (0.21) | (0.64) | (1.62) | (0.72) | | | | | | |
| 2 | 0.79 | -0.22 | 0.48 ** | -6.03 *** | 1.82 | 2.53 *** | | | | | | |
| | (0.70) | (0.83) | (0.23) | (0.74) | (1.89) | (0.83) | | | | | | |
| 3 | 0.32 | 0.55 | -0.03 | -6.93 *** | 2.13 | 2.38 ** | | | | | | |
| | (0.74) | (0.90) | (0.27) | (0.81) | (1.88) | (0.93) | | | | | | |
| 4 | 1.29 * | 1.05 | 0.37 | -8.55 *** | 0.40 | 3.90 *** | | | | | | |
| | (0.77) | (0.89) | (0.29) | (0.88) | (2.09) | (1.01) | | | | | | |
| | | | Amount of | f credit card debt (\$) | | | | | | | | |
| 1 | -161 | -182 | -2 | 17 | 474 | 921 *** | | | | | | |
| | (176) | (518) | (156) | (62) | (532) | (298) | | | | | | |
| 2 | 239 | -374 | -60 | -93 | 1194 *** | 907 ** | | | | | | |
| | (184) | (472) | (170) | (70) | (460) | (359) | | | | | | |
| 3 | -6 | -836 | 168 | -48 | 1078 ** | 711 * | | | | | | |
| | (197) | (615) | (175) | (89) | (507) | (376) | | | | | | |
| 4 | 435 ** | -665 | 347 * | -263 *** | 558 | 734 * | | | | | | |
| | (215) | (526) | (190) | (94) | (552) | (427) | | | | | | |

Notes: The estimated effects are average differences for each outcome between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. We use VantageScore credit scores which range from 300 to 850. "Poor" scores range from 300 to 649, "fair" from 650 to 699, and "good" from 700 to 850. Standard errors in parentheses. *p < 0.1, ***p < 0.05, ****p < 0.01

TABLE D.13
Effect of Natural Disasters on Credit Card Debt by Age Groups

| Years after | Medium-Sized Disasters | | | | | | | | | |
|-------------|--|-----|--------|-------------|-------------------|-----|--------------|-----|--|--|
| disaster | 24-34 | | 35-49 | 35-49 50-64 | | | 65 and older | | | |
| | Share of people with a credit card (%) | | | | | | | | | |
| 1 | -6.58 | *** | -4.05 | *** | -1.28 | | 1.18 | | | |
| | (1.14) | | (0.96) | | (0.97) | | (1.15) | | | |
| 2 | -6.88 | *** | -5.02 | *** | -3.27 | *** | 2.96 | ** | | |
| | (1.33) | | (1.11) | | (1.11) | | (1.38) | | | |
| 3 | -8.84 | *** | -5.71 | *** | -1.99 | * | 3.45 | ** | | |
| | (1.45) | | (1.19) | | (1.20) | | (1.52) | | | |
| 4 | -13.00 | *** | -6.46 | *** | -2.29 | * | 4.66 | *** | | |
| | (1.59) | | (1.26) | | (1.29) | | (1.71) | | | |
| | | | Amo | unt of cred | dit card debt (\$ |) | | | | |
| 1 | -192 | | -49 | | -103 | | 509 | * | | |
| | (117) | | (136) | | (169) | | (282) | | | |
| 2 | -132 | | -96 | | 19 | | 672 | ** | | |
| | (148) | | (164) | | (200) | | (334) | | | |
| 3 | -220 | | 30 | | 430 | ** | 930 | *** | | |
| | (200) | | (194) | | (211) | | (361) | | | |
| 4 | -44 | | -63 | | 14 | | 647 | | | |
| | (191) | | (224) | | (230) | | (463) | | | |

Notes: The estimated effects are average differences for each outcome between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. Standard errors in parentheses.

* p < 0.1, ** p < 0.05, *** p < 0.01

TABLE D.14

Effect of Natural Disasters on Credit Card Debt by Zip Code Racial and Ethnic Composition

| | | Medium-Sized Disasters | | | | | | | |
|-------------|----------|--|-------------|------------------------|---|--|--|--|--|
| Years after | disaster | Areas majority of color | | Areas majorit white | у | | | | |
| | | Share of people with a credit card (%) | | | | | | | |
| 1 | | -4.53 | *** | -1.93 * | | | | | |
| | | (0.56) | | (1.15) | | | | | |
| 2 | | -5.57 | *** | -1.78 | | | | | |
| | | (0.66) | | (1.29) | | | | | |
| 3 | | -6.61 | *** | -0.54 | | | | | |
| | | (0.71) | | (1.37) | | | | | |
| 4 | | -7.87 | *** | -0.39 | | | | | |
| | | (0.78) | | (1.47) | | | | | |
| | | | Amount of c | redit card debt (\$) | | | | | |
| 1 | | 243 | *** | 4 | | | | | |
| | | (67) | | (269) | | | | | |
| 2 | | 221 | *** | 260 | | | | | |
| | | (81) | | (307) | | | | | |
| 3 | | 124 | | 463 | | | | | |
| | | (86) | | (297) | | | | | |
| 4 | | 109 | | 3 | | | | | |
| | | (99) | | (344) | | | | | |

Notes: The estimated effects are average differences for each outcome between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. Standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01

TABLE D.15
Effect of Natural Disasters on Mortgage Delinquencies and Foreclosures

| | Hurrica | ne Sandy | | Large D | isasters | | Medium-Sized Disasters | | | | | |
|-------------------------|---|------------------|-------------|--------------------|--------------------|---------|------------------------|--------------------|----|--|--|--|
| Years after disaster | Comparison mean | Estimated effect | | Comparison mean | Estimate effect | | Comparison mean | Estimate effect | ed | | | |
| | Share of people with delinquent mortgages (%) | | | | | | | | | | | |
| 1 | 3.69 | 0.38 * | * * | 3.32 | 0.04 | | 2.83 | 0.63 | ** | | | |
| | | (0.16) | | | (0.40) | | | (0.26) | | | | |
| 2 | 3.11 | 0.96 * | k** | 3.06 | -0.06 | | 2.23 | 0.52 | ** | | | |
| | | (0.17) | | | (0.39) | | | (0.24) | | | | |
| 3 | 2.48 | 1.10 * | *** | 2.69 | 0.80 | * | 1.81 | 0.32 | | | | |
| | | (0.17) | | | (0.43) | | | (0.22) | | | | |
| 4 | 2.06 | 0.99 * | *** | 2.41 | 1.04 | ** | 1.82 | -0.28 | | | | |
| | | (0.16) | | | (0.43) | | | (0.21) | | | | |
| | | | Sha | are of people wit | th foreclo | sures (| %) | | | | | |
| 1 | 0.88 | -0.12 | | 0.83 | -0.18 | | 0.52 | 0.17 | ** | | | |
| | | (0.09) | | | (0.20) | | | (0.13) | | | | |
| 2 | 0.62 | 0.28 * | *** | 0.66 | 0.00 | | 0.45 | -0.15 | ** | | | |
| | | (0.09) | | | (0.20) | | | (0.09) | | | | |
| 3 | 0.44 | 0.51 * | ** * | 0.54 | 0.23 | | 0.33 | 0.00 | | | | |
| | | (0.10) | | | (0.20) | | | (0.09) | | | | |
| 4 | 0.33 | 0.39 * | *** | 0.46 | 0.09 | | 0.24 | 0.01 | | | | |
| | | (0.08) | | | (0.18) | | | (80.0) | | | | |

 $\textbf{Source:} \ \textbf{Urban Institute calculations based on credit bureau, FEMA, and ACS data.}$

Notes: The estimated effects are average differences for each outcome between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. Standard errors in parentheses.

* p < 0.1, ** p < 0.05, *** p < 0.01

TABLE D.16

Effect of Natural Disasters on Mortgage Delinquencies and Foreclosures by Pre-Disaster Credit Score Groups

| Years after disaster | Hurricane Sandy | | | | | | | | |
|----------------------|---|-----|--------------------|--------------|-------------|-----|--|--|--|
| Tears after disaster | Poor Cree | dit | Fair Credi | it | Good Credit | | | | |
| | Share of people with delinquent mortgages (%) | | | | | | | | |
| 1 | 0.75 | ** | -0.1 | | -0.05 | | | | |
| | (0.36) | | (0.49) | | (0.13) | | | | |
| 2 | 1.84 | *** | 0.27 | | 0.3 | ** | | | |
| | (0.39) | | (0.53) | | (0.15) | | | | |
| 3 | 1.90 | *** | 0.74 | | 0.5 | *** | | | |
| | (0.38) | | (0.55) | | (0.15) | | | | |
| 4 | 1.92 | *** | 0.87 | | 0.27 | ** | | | |
| | (0.38) | | (0.54) | | (0.13) | | | | |
| | | Sha | are of people with | foreclosures | (%) | | | | |
| 1 | -0.13 | | -0.05 | | -0.19 | *** | | | |
| | (0.23) | | (0.21) | | (0.04) | | | | |
| 2 | 0.66 | *** | 0.37 | | -0.05 | | | | |
| | (0.23) | | (0.25) | | (0.06) | | | | |
| 3 | 1.08 | *** | 0.66 | ** | 0.07 | | | | |
| | (0.23) | | (0.29) | | (0.07) | | | | |
| 4 | 0.78 | *** | 0.45 | * | 0.10 | | | | |
| | (0.20) | | (0.26) | | (0.06) | | | | |

Notes: The estimated effects are average differences for each outcome between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. We use VantageScore credit scores which range from 300 to 850. "Poor" scores range from 300 to 649, "fair" from 650 to 699, and "good" from 700 to 850. Standard errors in parentheses.

* p < 0.1, ** p < 0.05, *** p < 0.01

TABLE D.17
Effect of Natural Disasters on Mortgage Delinquencies and Foreclosures by Age Groups

| Years after | Hurricane Sandy | | | | | | | | | |
|-------------|-----------------|---------------|-----------|---------------|-----------|--------|-----|--|--|--|
| disaster | 24-34 | 35-49 | 50-64 | | 65 and ol | der | | | | |
| | | Share of peop | le with d | elinquent m | ortgages | s (%) | | | | |
| 1 | -0.07 | 0.97 | ** | 0.46 | | 0.06 | | | | |
| | (0.33) | (0.39) | | (0.34) | | (0.28) | | | | |
| 2 | 0.34 | 1.94 | *** | 0.95 | *** | 0.67 | ** | | | |
| | (0.37) | (0.42) | | (0.35) | | (0.32) | | | | |
| 3 | 0.30 | 2.35 | *** | 1.10 | *** | 0.64 | ** | | | |
| | (0.36) | (0.42) | | (0.34) | | (0.33) | | | | |
| 4 | 0.34 | 1.93 | *** | 0.97 | *** | 0.87 | *** | | | |
| | (0.36) | (0.40) | | (0.30) | | (0.34) | | | | |
| | | Share of p | oeople w | ith foreclosu | ıres (%) | | | | | |
| 1 | -0.30 | -0.10 | | 0.01 | | -0.26 | * | | | |
| | (0.21) | (0.21) | | (0.19) | | (0.15) | | | | |
| 2 | 0.07 | 0.40 | * | 0.47 | ** | 0.20 | | | | |
| | (0.19) | (0.22) | | (0.20) | | (0.16) | | | | |
| 3 | -0.05 | 0.80 | *** | 0.89 | *** | 0.33 | * | | | |
| | (0.18) | (0.22) | | (0.21) | | (0.18) | | | | |
| 4 | 0.03 | 0.60 | *** | 0.53 | *** | 0.46 | ** | | | |
| | (0.16) | (0.19) | | (0.17) | | (0.19) | | | | |

Notes: The estimated effects are average differences for each outcome between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. Standard errors in parentheses.

^{*} p < 0.1, ** p < 0.05, *** p < 0.01

TABLE D.18

Effect of Natural Disasters on Mortgage Delinquencies and Foreclosures by Zip Code Racial and Ethnic Composition

| | Hurricane Sandy | | | | | | | | |
|-------------------------|---|------------------|-------------------------|-----|--|--|--|--|--|
| Years after disaster | Areas ma people o | | Areas majority white | | | | | | |
| | Share of people with delinquent mortgages (%) | | | | | | | | |
| 1 | 0.88 | ** | 0.25 | | | | | | |
| | (0.36) | | (0.18) | | | | | | |
| 2 | 2.04 | *** | 0.62 | *** | | | | | |
| | (0.40) | | (0.19) | | | | | | |
| 3 | 2.09 | *** | 0.77 | *** | | | | | |
| | (0.39) | | (0.19) | | | | | | |
| 4 | 2.41 | *** | 0.52 | *** | | | | | |
| | (0.39) | | (0.18) | | | | | | |
| | S | hare of people v | with foreclosures (%) | | | | | | |
| 1 | -0.05 | | -0.10 | | | | | | |
| | (0.21) | | (0.10) | | | | | | |
| 2 | 0.43 | ** | 0.24 | ** | | | | | |
| | (0.22) | | (0.10) | | | | | | |
| 3 | 0.65 | *** | 0.47 | *** | | | | | |
| | (0.21) | | (0.11) | | | | | | |
| 4 | 0.49 | *** | 0.36 | *** | | | | | |
| | (0.19) | | (0.09) | | | | | | |

Source: Urban Institute calculations based on credit bureau, FEMA, and ACS data.

Notes: The estimated effects are average differences for each outcome between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

TABLE D.19
Effect of Natural Disasters on Auto Debt

| Hurrica | ne Sandy | | Large D | isasters | Medium-Sized Disasters | | | | | |
|------------------------------------|--|---|---|---|---|--|---|--|--|--|
| Comparison mean | Estimated effect | | Comparison mean | Estimated effect | Comparison mean | Estimated effect | | | | |
| Share of people with auto debt (%) | | | | | | | | | | |
| 25.93 | 1.84 | *** | 25.09 | 0.56 | 21.01 | -1.90 | *** | | | |
| | (0.37) | | | (0.92) | | (0.51) | | | | |
| 28.35 | 1.18 | *** | 27.70 | -0.01 | 24.62 | -3 | *** | | | |
| | (0.41) | | | (1.01) | | (0.58) | | | | |
| 30.63 | 0.59 | | 29.63 | 0.56 | 28.57 | -4.25 | *** | | | |
| | (0.43) | | | (1.07) | | (0.64) | | | | |
| 32.82 | 0.81 | * | 31.94 | 0.63 | 31.40 | -5.44 | *** | | | |
| | (0.45) | | | (1.12) | | (0.69) | | | | |
| | | | Amount of a | auto debt (\$) | | | | | | |
| 4377 | 200 | * | 4342 | 197 | 3559 | -762 | *** | | | |
| | (104) | | | (304) | | (119) | | | | |
| 4960 | -573 | *** | 5002 | 282 | 4443 | -1280 | *** | | | |
| | (118) | | | (329) | | (139) | | | | |
| 5544 | -728 | *** | 5673 | 316 | 5372 | -1803 | *** | | | |
| | (130) | | | (379) | | (155) | | | | |
| 6114 | -904 | *** | 6336 | 527 | 5980 | -2520 | *** | | | |
| | (134) | | | (394) | | (168) | | | | |
| | 25.93 28.35 30.63 32.82 4377 4960 5544 | mean effect 25.93 1.84 (0.37) 28.35 1.18 (0.41) 30.63 0.59 (0.43) 32.82 0.81 (0.45) (104) 4960 -573 (118) 5544 -728 (130) 6114 -904 | Comparison mean Estimated effect 25.93 1.84 *** (0.37) 28.35 1.18 *** (0.41) 30.63 0.59 (0.43) 32.82 0.81 * (0.45) 4377 200 * (104) 4960 -573 *** (118) 5544 -728 *** (130) 6114 -904 *** | Comparison mean Estimated effect Comparison mean 25.93 1.84 *** 25.09 (0.37) 28.35 1.18 *** 27.70 (0.41) 30.63 0.59 29.63 (0.43) 32.82 0.81 * 31.94 (0.45) Amount of a 4377 200 * 4342 (104) 4960 -573 *** 5002 (118) 5544 -728 *** 5673 (130) 6114 -904 *** 6336 | Comparison mean Estimated effect Comparison mean Estimated effect Share of people with auto debt (\$90.37) 25.93 1.84 **** 25.09 0.56 (0.37) (0.92) (0.92) 28.35 1.18 **** 27.70 -0.01 (0.41) (1.01) (1.01) 30.63 0.59 29.63 0.56 (0.43) (1.07) (1.07) 32.82 0.81 * 31.94 0.63 (0.45) (1.12) (1.12) Amount of auto debt (\$) 4377 200 * 4342 197 (104) (304) (304) 4960 -573 *** 5002 282 (118) (329) 5544 -728 *** 5673 316 (130) (379) 6114 -904 *** 6336 527 | Comparison mean Estimated effect Comparison mean Estimated effect Comparison mean Share of people with auto debt (%) 25.93 1.84 *** 25.09 0.56 21.01 (0.92) 28.35 1.18 *** 27.70 -0.01 24.62 (0.41) (1.01) 30.63 0.59 29.63 0.56 28.57 (0.43) (1.07) 32.82 0.81 * 31.94 0.63 31.40 (0.45) (1.12) Amount of auto debt (\$) 4377 200 * 4342 197 3559 (104) (304) 4960 -573 *** 5002 282 4443 (118) (329) 5544 -728 *** 5673 316 5372 (130) (379) 6114 -904 *** 6336 527 5980 | Comparison mean Estimated effect Comparison mean Estimated effect Comparison mean Estimated effect Share of people with auto debt (%) 25.93 1.84 **** 25.09 0.56 21.01 -1.90 (0.37) (0.92) (0.51) 28.35 1.18 **** 27.70 -0.01 24.62 -3 (0.41) (1.01) (0.58) 30.63 0.59 29.63 0.56 28.57 -4.25 (0.43) (1.07) (0.64) 32.82 0.81 * 31.94 0.63 31.40 -5.44 (0.45) (1.12) (0.69) Amount of auto debt (\$) 4377 200 * 4342 197 3559 -762 (104) (304) (119) 4960 -573 **** 5002 282 4443 -1280 (118) (329) (139) 5544 -728 *** 5673 316 5372 -1803 (130) | | | |

Notes: The estimated effects are average differences for each outcome between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. Standard errors in parentheses.

* p < 0.1, ** p < 0.05, *** p < 0.01

TABLE D.20
Effect of Natural Disasters on Auto Debt by Pre-Disaster Credit Score Groups

| Years after | | F | lurricane S | Sandy | / | Medium-Sized Disasters | | | | | | |
|-------------|--------------------------|-----|-------------|-------|-------------|------------------------|---------------|-------------|--------|------|-------------|-----|
| disaster | Poor Credit | | Fair Credit | | Good Credit | | Poor Cr | Poor Credit | | edit | Good Credit | |
| | Share with Auto Debt (%) | | | | | | | | | | | |
| 1 | -1.17 | ** | -0.39 | | 4.64 | *** | -1.97 | *** | 2.07 | | 2.12 | * |
| | (0.57) | | (1.10) | | (0.52) | | (0.58) | | (1.73) | | (1.27) | |
| 2 | -2.72 | *** | -0.82 | | 4.62 | *** | -2.65 | *** | -2.9 | | 1.69 | |
| | (0.64) | | (1.22) | | (0.57) | | (0.69) | | (1.92) | | (1.41) | |
| 3 | -3.77 | *** | -0.75 | | 4.13 | *** | -4.13 | *** | -3.4 | | 0.945 | |
| | (0.70) | | (1.29) | | (0.60) | | (0.75) | | (2.07) | | (1.49) | |
| 4 | -3.94 | *** | -0.16 | | 4.39 | *** | -5.74 | *** | -4.96 | ** | 0.75 | |
| | (0.75) | | (1.35) | | (0.62) | | (0.83) | | (2.26) | | (1.59) | |
| | | | | | Am | ount of A | uto Debt (\$) |) | | | | |
| 1 | -270 | * | -745 | ** | 624 | *** | -587 | *** | -212 | | -294 | |
| | (143) | | (370) | | (153) | | (123) | | (455) | | (317) | |
| 2 | -992 | *** | -515 | | -61 | | -1105 | *** | -1669 | *** | -1028 | *** |
| | (174) | | (371) | | (171) | | (160) | | (464) | | (383) | |
| 3 | -947 | *** | -1590 | *** | -308 | * | -1756 | *** | -1724 | *** | -827 | ** |
| | (235) | | (415) | | (168) | | (177) | | (573) | | (380) | |
| 4 | -1331 | *** | -1285 | *** | -416 | ** | -2361 | *** | -2172 | *** | -1284 | *** |
| | (242) | | (452) | | (169) | | (190) | | (547) | | (373) | |

Notes: The estimated effects are average differences for each outcome between people affected by the indicated disaster (or set of disasters) and matched people from unaffected areas, as described in the methods section. Effects are estimated separately for each disaster for each of the four years following the disaster. We use VantageScore credit scores which range from 300 to 850. "Poor" scores range from 300 to 649, "fair" from 650 to 699, and "good" from 700 to 850. Standard errors in parentheses.

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes

- ¹ To understand more about residents' financial needs after a natural disaster, our research team spoke to several organizations with direct-service experience in areas affected by recent natural disasters. The links described here between natural disasters and financial health emerged from these conversations. See Appendix C for a description of these conversations.
- ² "Fact Sheet for Homeowners and Renters," US Small Business Administration, accessed February 7, 2019, https://disasterloan.sba.gov/ela/Information/FactSheetHomeownersRenters.
- ³ "2016 CDBG-DR Webinar Series Training Materials," US Department of Housing and Urban Development, accessed February 6, 2019, https://www.hudexchange.info/news/2016-cdbg-dr-webinar-series/.
- ⁴ Karan Kaul and Laurie Goodman, "The Mortgage Industry Needs a Modernized Disaster Recovery Toolkit," *Urban Wire* (blog), Urban Institute, September 22, 2017, https://www.urban.org/urban-wire/mortgage-industry-needs-modernized-disaster-recovery-toolkit.
- ⁵ Carlos Martín, "Five Ways Households Are Left Behind in the Disaster Recovery and Data Supply Chain," *Urban Wire* (blog), Urban Institute, September 11, 2018, https://www.urban.org/urban-wire/five-ways-households-are-left-behind-disaster-recovery-and-data-supply-chain.
- Mark H. Levin, "Legislation Provides Temporary Tax Relief to Victims of Federally Declared Disasters," The CPA Journal, March 2018, https://www.cpajournal.com/2018/03/19/legislation-provides-temporary-tax-relief-victims-federally-declared-disasters/.
- See, for example, "California Wildfires Immediate Assistance Program," Red Cross, accessed February 11, 2019, https://www.redcross.org/about-us/our-work/disaster-relief/wildfire-relief/2018-california-wildfires-relief-information/immediate-assistance-program.html.
- See Groen, Kutzback, and Polivka (2017) for a brief review and Howell and Elliott (2018) for recent contributions.
- ⁹ Earlier explorations of the employment effects from disasters include Guimaraes, Hefner, and Woodward (1993) after Hugo in 1989; Brown et al. (2006) after Katrina; and Venn (2012) in an international context. These studies suggest that employment losses are short-lived (e.g., are reduced after one to two years) but may result in changes in the mix of jobs with a resulting mismatch in skills demand.
- ¹⁰ See appendix C for a description of study team conversations with service provider organizations aimed at informing our analyses.
- ¹¹ Data are available for download here: https://www.fema.gov/media-library/assets/documents/34758.
- ¹² The sample of disasters, then, invariably includes those for which FEMA's IA programs were triggered and offered.
- ¹³ Estimates of the number of households in each zip code come from the American Community Survey.
- ¹⁴ This represents a 2 percent random probability sample from the credit bureau.
- ¹⁵ One caveat is that because we only observe people in August of each year, we need to make an assumption about where people are living when a disaster hits, for those disasters that do not hit in August (which are most disasters). We identify people's location based on where they lived in the August before the disaster hit. For example, if a hurricane hit 50 zip codes in October 2012, we assume that the people living in those zip codes in October 2012 are the same people who were living there in August 2012.
- ¹⁶ Zip-level credit characteristics used in our propensity score calculations include mean credit card debt, mean credit score, and the shares of residents with subprime credit scores (300–600), with a delinquent mortgage,

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- with auto debt, with utility debt in collections, and with a tax lien on their public records. Demographic characteristics include population, and shares of residents that are nonwhite and residents that are low-income (families with income below 200 percent of the federal poverty level).
- ¹⁷ We predict propensity scores using an individual's age, age squared, and the pre-disaster values of the credit bureau outcome for which we are estimating treatment effects (e.g., when estimating the effects of disasters on credit scores we match on individual credit scores in the year before the disaster). Standard errors account for the fact that propensity scores are estimated.
- ¹⁸ See "What Is a Good Credit Score?," Experian, accessed February 7, 2019, https://www.experian.com/blogs/ask-experian/credit-education/score-basics/what-is-a-good-credit-score/.
- ¹⁹ Results by income level are presented in appendix table D2.
- ²⁰ The share of people in the comparison group with any debt in collections in year four is 42.5 percent.
- This round of interviews gathered perspectives from national organizations with expertise in regulation or working with local governments; organizations involved in planning for and executing community-level responses to natural disasters; and local organizations in areas recently affected by natural disasters with experience collecting and harnessing local-level data to assist in recovery. See Appendix C for additional details on interview methods.
- ²² Most of the people affected by medium-sized disasters in our analysis were affected by a 2014 storm that hit urban areas in and around Detroit, making it difficult to conclusively attribute the differences we see across disasters of differing magnitudes to that factor alone.
- For more detail, see "Letter Urging Credit Bureaus to Provide Credit Reporting Relief to Consumers Affected by Natural Disasters," National Consumer Law Center, accessed February 12, 2019, https://www.nclc.org/images/pdf/credit_reports/ltr-credit-reporting-natural-disaster.pdf.
- ²⁴ "Credit Check Law: Frequently Asked Questions," NYC Human Rights, accessed February 28, 2019, https://www1.nyc.gov/site/cchr/media/credit-check-law-frequently-asked-questions.page.
- For additional detail, see "Top Priorities for Any Disaster Recovery Package," National Low Income Housing Coalition, accessed February 12, 2019, https://nlihc.org/sites/default/files/DHRC-Priorities_Disaster-Recovery-Package.pdf.
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- ⁴¹ We estimate these effects using a propensity score matching model using nearest-neighbor matching. We predict propensity scores using an individual's age, age squared, and the pre-disaster values of the credit bureau outcome for which we are estimating treatment effects (e.g., when estimating the effects of disasters on credit scores we match on individual credit scores in the year before the disaster). Standard errors account for the fact that propensity scores are estimated.

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The Urban Institute's Collaboration with JPMorgan Chase

The Urban Institute is collaborating with JPMorgan Chase over five years to inform and assess JPMorgan Chase's philanthropic investments in key initiatives. One of these is financial capability, a multipronged effort to improve household and community financial health by identifying, supporting, and scaling innovative solutions that help low- and moderate-income families increase savings, improve credit, and build assets. The goals of the collaboration include using data and evidence to inform JPMorgan Chase's philanthropic investments, assessing whether its programs are achieving desired outcomes, and informing the larger fields of policy, philanthropy, and practice. In service of these goals, this suite of products strengthens the evidence base for understanding how natural disasters impact residents' financial health.

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