ISSN 1936-5330

The Federal Reserve Bank of Kansas City
Research Working Papers

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September 2017
RWP 17-09
https://dx.doi.org/10.18651/RWP2017-09

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Abstract

I evaluate the effects of hurricanes of varying intensity on the financial condition of a typical resident in both affected and unaffected census tracts, where the degree of affect is determined by the relative location of a census tract's boundary with buffers around the tracks of hurricane eyes that occurred in the years 2000-2014. The primary question in the article is whether financial vulnerability, or, alternatively, "financial preparedness," affects post-hurricane disaster financial outcomes.

I find that hurricanes tend to lower credit scores, for the most, but outcomes are far from uniform across categories of hurricanes. I attribute these differences largely to number of disasters in each quarter of the study period, levels of disaster aid, and media coverage and political interest. In some cases I surmise that those in the 25-mile buffer may benefit from economic stimulus that follows a hurricane, but do not have damages and other economic losses to the same extent as those within a 15-mile buffer. Modeling hurricanes as "treatments" and interacting them with variables from consumer credit reports, I find that the financial vulnerability of residents in affected census tracts is associated with poorer financial outcomes. Considering lags, financial vulnerability is shown to have a considerable impact on post-hurricane personal finance outcomes.

JEL Codes: Q54, R11, I31

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Financial Vulnerability and Personal Finance Outcomes of Natural Disasters

> "Disasters are part of the universe's great unwinding, the fundamental perversity of inanimate matter's remorseless disordering. But whether those disasters are dystopias? That's for us to decide. . ." Doctorow (2017)

At its root, this article analyzes the impact of natural disasters on aggregate well-being in affected places. More specifically, I evaluate the effects of hurricanes of varying intensity on the financial condition of a typical resident in both affected and unaffected census tracts, where the degree of affect is determined by the relative location of a census tract's boundary with buffers around the tracks of hurricanes that occurred in the years 2000-2014. The primary question in the article, however, is whether financial vulnerability (discussed later in the text), or, alternatively, "financial preparedness," affects these post-hurricane disaster financial outcomes.

Data are analyzed on a quarterly basis. I find that hurricanes tend to lower credit scores, for the most, but outcomes are far from uniform across categories of hurricanes. I attribute these differences largely to number of disasters in each quarter of the study period, levels of disaster aid, and media coverage and political interest. In some cases I surmise that those in the 25-mile buffer may benefit from economic stimulus that follows a hurricane, but do not have damages and other economic losses to the same extent as those within a 15-mile buffer. Modeling hurricanes as "treatments" and interacting them with variables from consumer credit reports, I find that the financial vulnerability of residents in affected census tracts is associated with poorer financial outcomes. Considering lags, financial vulnerability is shown to have a considerable impact on post-hurricane personal finance outcomes.

The article proceeds as follows. Section 1 provides a conceptual foundation for why financial preparedness might be important in building resilience to natural disasters such as hurricanes. Section 2 examines existing literature that evaluates the economic costs of hurricanes. Section 3 looks at the limited literature focused on the impact of hurricanes on personal finances. Section 4 discusses the current state of knowledge on disaster preparedness at both the individual and community levels. Section 5 presents the empirical model, followed by a detailed discussion of the data in Section 6. Results are presented and discussed in Section 7, followed by concluding remarks in Section 8.

1. Conceptual Underpinnings

Most policy responses to natural disasters or other environmental phenomena emphasize resources and infrastructure, but largely ignore personal agency, which has been highlighted by the psycho-social literature as a "critical factor" in determining how affected individuals (or households, or communities) can respond to environmental threats (Brown and Westaway, 2011). Personal agency is a self-referent concept generally understood to mean the capacity of individuals to make their own choices. McLaughlin and Dietz (2008) defined personal agency more extensively to including the significance of playing "an independent causal role in history." Awareness of personal agency, and emphasizing personal agency in responding to disasters, "helps to overcome the view of people as powerless victims," and it recognizes that "humans are never just passive in the face of environmental threats" (McLaughlin and Dietz). The common thread in this literature, which is vast, is that substantial, sustainable recovery, especially if it is to be equitable, requires the expression of personal agency.

Personal agency is related to adaptive capacity, which describes the conditions necessary to enable adaptation to disaster events (such as hurricanes). Adaptive capacity is similar in concept to resilience. Resilient people and communities often experience remarkable recoveries after natural disasters, while vulnerable populations and communities often do not. A salient example is the aftermath of Hurricane Katrina (2005) in New Orleans. Katrina is possibly the most studied natural disaster of any that has occurred before or since. Much of this research relates citizen vulnerability to poverty, minority status, age, disability, gender and (residential) tenancy (see, e.g. Laska and Morrow, 2006).

Cannon (1994) argues that "hazards are natural" but that "disasters are not" (13). He argues that disasters should not be viewed as an inevitable outcome of a hazard's impact, which I take to include immediate impact hazards, such as hurricanes (or tornados, earthquakes, etc.).[2] He suggests that, in many cases, human activities often have created the conditions for disaster events. In this he is not referring to some direct human role in a natural hazard, such as one might claim in the case of climate change, or a clearly man-made disaster such as a terrorist attack, but rather the fact that natural hazards of whatever type generally do not need to be as disastrous as they are.

Cannon stresses the conditions of people which make it possible for a hazard to become a disaster. He notes that victims of disasters have come to realize that "their suffering is not simply the result of an Act of God" (17). Cannon's argument is largely predicated by his observation that a "conflict of economic interests is one of the most intractable barriers to the mitigation of disasters" (17). He provides an interesting analogy of a physician signing a death certificate with the cause-of-death listed as "natural causes" (17-18). The death certificate does not indicate whether the person's life may had been extended if he had lived in a different social system that allocated resources differently, or provided access to better healthcare that would have enabled

[2]This perspective is consistent with the remaining discussion in Cannon's book chapter.

an earlier diagnosis and treatment of many ‘natural’ causes of death, or relegated risks in a different way.

Cannon’s arguments dwell mostly in the larger socio-economic system in which people affected by natural hazards live and how resources are allocated within that system, but it does raise an important question that is also relevant at the community level, or even individual level: how disastrous does a natural hazard event have to be?

Enarson (2012) lists a number of factors likely to affect the vulnerability of individuals (in her case, women specifically) to natural disasters. Among these are poverty, physical challenges, racial or ethnic marginalization, insecure housing, language barriers, violence, lack of voice, or a (likely) combination of these factors. In this paper, I consider another potentially important component of vulnerability, and hence adaptation and resilience: financial preparedness.

Bandura (2000) notes that “[u]nless people believe that they can produce desired effects and forestall undesired ones by their actions, they have little incentive to act.” Thus, underlying the analysis of personal financial preparedness and post disaster personal financial outcomes in this paper is a conspicuous policy construct that suggests that, if financial preparedness leads to better post-disaster outcomes, then, as a society, we may want to consider ways in which we might be able to assist people in financial preparing for the (even unlikely) event of a natural disaster.

2. Social and Economic Outcomes

The initial, unanticipated shock of a *major* natural disaster generally causes significant disruption in economic activity in the affected area. Among the direct losses incurred are damage to or destruction of physical assets such as homes, businesses and business inventories, automobiles, and public infrastructure, as well as loss of life. Disasters also are known to significantly increase psychopathologies in affected populations, such as dazed confusion, disabling grief, and post-traumatic stress disorder (Perry and Lindell, 1978; Neria et al., 2013).

Substantial indirect losses typically follow and may include unemployment, losses in business revenue, reductions in tourism, and associated fiscal impacts, such as reduced tax revenues. Despite a significant number of studies that have explored indirect losses associated with natural disasters, no "rule of thumb" has emerged to assess indirect losses as some equivalent to the magnitude of direct losses (Cochrane, 2004, p. 37).[3]

While natural disasters often are very destructive to physical assets and economic activity in the affected area, economic activity may rise substantially during the reconstruction period. Clean-up and rebuilding provide an economic stimulus to the affected community. However, a large share of the remuneration could be transferred outside of the affected area. A study of disaster assistance to Alabama (Mobile area) that followed Hurricane Frederic in 1979 suggests that 71 percent of recovery dollars "leaked out" without having been "turned over" (or spent) once (Chang, 1984, p. 28).

Much of the work analyzing the economic impact of natural disasters has used international data, often demonstrating very substantial economic damage. Barro (2009) suggested that the welfare cost of a "rare disaster" (including natural disasters), is likely on the order of 20 percent of gross domestic product (GDP). That is, society would willingly give up 20 percent of GDP per year to eliminate rare disasters. The welfare cost associated with "usual

[3]In a study of the 2000 Po River flood in northern Italy, Carrera et al. (2015) estimated indirect costs of 7 to 22 percent of direct costs. Clean-up and rebuilding provide an economic stimulus to the affected community. However, a large share of the remuneration could be transferred outside of the affected area.

economic fluctuations," such as a moderate recession, is considerably smaller, as measured by an estimated willingness to sacrifice 1.5 percent of GDP to avoid them (p. 243). Barro specifically evaluated large macroeconomic shocks in OECD countries, such as those arising from the Great Depression and World Wars I and II, but he noted that the analysis would likely apply to "disasters not yet seen," such as "nuclear conflicts, large scale natural disasters (tsunamis hurricanes, earthquakes, asteroid collisions), and epidemics of disease" (262). Barro (2006) places a probability of 2 percent per year on large macroeconomic contractions.

On a regional level, natural disasters generally are expected to significantly disrupt the local economy and local labor markets. The general consensus of this literature is that natural disasters, particularly in areas receiving a "direct hit," reduce economic activity, typically measured by employment, in the immediate period, but may increase economic activity in later periods.

Brown et al. (2006) estimate initial job losses from Hurricane Katrina at 232,000 in Louisiana and 58,000 in Mississippi. The U.S. Bureau of Labor Statistics (BLS) (2007) estimates that the combined job loss of Hurricane Katrina for the eight most affected county-equivalents (parishes in Louisiana) in the following year was 128,000—88,000 of which occurred in Orleans Parish (New Orleans). In a study of 19 hurricanes making landfall in Florida between 1988 and 2005, Belasen and Polachek (2008) estimate that declines in employment of as much as 4.8 percent for high-intensity hurricanes (measured as category 4 or 5 on the Saffir-Simpson scale, discussed below) in counties that were directly hit. Even if employment returns to pre-disaster levels, a change in the mix of jobs may lead to a mismatch of skills and employment opportunities, resulting in significant unmet employment needs and relatively high levels of unemployment (Venn, 2012).

However, in an analysis of hurricanes Katrina and Rita (also 2005, largely Louisiana and Mississippi), Groen et al. (2015), find that while the storms reduced the earnings of affected individuals during the initial year of the storm, arising, for example, from job separations, migration to other areas, and business contractions; beginning in the third year following the storms, the quarterly earnings of the affected residents increased as a result of the storms. The authors associate this increase in relative (to control areas) earnings to reduced labor supply and increased labor demand brought on by reconstruction efforts. Employment losses from Katrina estimated by Brown et al. were judged to be "temporary in light of employment levels about one year later."

Employment effects often differ substantially across sectors. While some sectors suffer significant employment losses, others may do very well. In an analysis of the economic impact of Hurricane Hugo (1989, South Carolina) using a regional econometric model, Guimaraes et al. (1993) found neutral effects on employment and income overall, largely reflecting a redistribution across industrial sectors. Unsurprisingly, the construction sector benefitted most from reconstruction efforts with large gains in employment and income. Two years following Hugo, construction employment waned significantly however, returning to a baseline of economic activity in the sector in the absence of the hurricane. While forestry and agriculture suffered huge losses of wealth, income in those sectors increased above the baseline, which the authors attributed to a pushed-up harvesting (salvage) of felled trees. Transportation and public utilities saw a similar pattern. In all cases, rebuilding activity beyond that which would be required to return the impacted area to pre-disaster levels provided stimulus, boosted by an infusion of insurance payments and public assistance. For example, some receiving payment on homeowners claims may have expanded or otherwise improved upon their housing that existed prior to the hurricane. This response is likely generalized to the reconstruction phase following other disasters as well.

3. Disasters and Household Finances

While there is an abundance of literature on economic impacts of natural disasters, there is little that explores impact from the perspective of personal finances.

Gallagher and Hardy (2014) is most closely related to this paper and the only existing paper I am able to locate that directly examines personal financial outcomes of natural disasters, particularly credit outcomes.

Gallagher and Hardy evaluate household financial (specifically, credit) outcomes after Hurricane Katrina. Specifically, they compare financial outcomes for New Orleans residents in flooded census blocks (three categories based on degree of flooding) relative to residents in non-flooded census blocks. Their results show that flooding reduces total debt, and the reduction in debt was increasing in the degree of flooding.

The reduction in debt was driven “almost exclusively” by decreased mortgage debt (2), which they attribute largely to flood claims having been used to pay off mortgages rather than for rebuilding. Gallagher and Hardy also document a temporary increase of $700 (23 percent) in credit card debt, presumably used to smooth consumption. Finally, they found that, relative to residents in non-flooded areas, 90-day mortgage delinquency rates increased by ten percent for those in the most flooded areas for a one-year period following Katrina, and credit scores were lower for the most-flooded areas for a two-year period following Katrina.

4. Preparation for Natural Disasters

Natural disasters are purely exogenous events in that they cannot be controlled nor accurately or precisely predicted.[4] One cannot predict the exact location, intensity, or degree of damage *a priori*. This is not to say that a disaster cannot be forecasted based on current climate conditions. Hurricane paths often are forecasted for a few days. But those forecasts typically have a wide margin of error. Communities typically have only minutes of warning about expected paths of tornados.

While the exogeneity of natural disasters is undebatable (certainly personal finances certainly cannot "cause" hurricanes), at least on some level, one might assign probabilities of their occurring. Climactic, geological, and other relevant data can be used to assign probabilities of natural disaster events occurring in specified locations over a specified time horizon. Specific hazards, such as climate or geological conditions, influence the likelihood of a natural disaster occurring, and these hazards are not uniformly distributed over space. Residents at any given location are likely to have at least some sense of the relative likelihood of a natural disaster occurring there based on natural hazards and history, especially if these vulnerabilities are well-established, such as earthquake risk associated with living in proximity to a major seismic fault line or tornado risk in an area with a long history of severe tornados (often termed "tornado alleys").

As discussed below, I address this issue by restricting the analysis to the 15 states at risk of a hurricane strike or hurricane-strength remnants, based on hurricane activity pre-dating my

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[4] Regarding earthquakes, the U.S. Geological Survey has stated: "Neither the USGS nor any other scientists have ever predicted a major earthquake. They do not know how, and they do not expect to know how any time in the foreseeable future." See http://www.usgs.gov/faq/categories/9830/3278.

analysis. While for the most part the restriction of my study area eliminates any issues around differences in hurricane risk, some differences in risk remain.

Relative Risk. Some census tracts included in the data are likely to be more prone to hurricanes than others, even with the study area limited to several states. If the risk of a hurricane is substantially different in some census tracts than others, we might expect that residents in the more-prone areas might better prepare, for example, by outfitting their homes with hurricane straps. In that case, the impact of a hurricane on their finances may be less severe, all else equal and for a hurricane of given strength passing through the tract. A 2012 national FEMA survey found that 46 percent of respondents were “familiar” with local hazards, although the survey did not differentiate the sample by exposure to actual known hazards or question them about known hazards (FEMA, 2013).

One way to measure this potential is “relative risk” (RR) (Jaeschke et al., 1995) a concept typically employed in epidemiological contexts.[5] The goal of measuring RR is to see the probability of an event in an “exposed area” relative to the probability of an event occurring in an “unexposed” area. I consider exposure to a “storm event” at category 9 (severe gale force, 47-54 mph) and above (maximum is 12, “hurricane force,” ≥ 73 mph) on the Beaufort Wind Force Scale between 1970 and 1999 (see Wheeler and Wilkinson, 2004).

Consider a 2x2 table (Table 1). The first column indicates hurricane strikes on census tracts in the study area from 2000 through 2014. The first row indicates the number of storm exposures for census tracts over the period 1970-1999.

[5]An alternative is the odds ratio, which is asymptotically equal (for small probabilities). The less common (in economics) use of relative risk is an effort to derive a measure of that is most like that which would be perceived by residents. Lee (1994, 201) reports that “the odds ratio is incomprehensible. As emphasized by Savitz (1992) an epidemiological measure must not only convey the most germane information, but it must also be easy to communicate and to comprehend. As such, the odds ratio has no direct usefulness except as a numerical mimic to other effect measures such as the relative risk.”

Table 1: Relative Risk Calculation

		Hurricane Strikes +	Hurricane Strikes -
Storm Exposure	+	809	1,407
	-	4,206	11,393

The calculation of relative risk (RR) is

$$(1) \qquad RR = \frac{809}{809+1{,}407} \Bigg/ \frac{4{,}206}{4{,}206+11{,}393} = \frac{0.36507}{0.26963} = 1.35 ,$$

Indicating that tracts previously exposed to substantial storms between 1970 and 1999 were 35 percent more likely to have received a hurricane strike during the study period. The log transformation of RR, log(RR), is normally distributed, and the standard deviation (σ) is

$$(2) \qquad \sigma = \sqrt{\left[\frac{1}{809} + \frac{1}{4{,}206}\right] - \left[\frac{1}{809+1{,}407} + \frac{1}{4{,}206+11{,}373}\right]} = 0.0310 ,$$

and thus the Z-score is $\log(RR)/\sigma = 4.25$, indicating that the relative risk of a hurricane in a tract previously exposed to a significant storm is statistically significant ($p < 0.01$).

My perception of the RR analysis is that the RR is fairly small. That is, given the rarity of major land strikes from hurricanes, I expect that a 35 percent increased likelihood would not be sufficient to change preparedness significantly.

Personal Preparedness. Even when vulnerabilities to natural disasters are well-understood, at-risk residents often do not take protective action commensurate with risk. Such action may include hazard mitigation, emergency preparedness, and the purchase of insurance. There may be significant costs associated with protective action, such as those associated with a change in residence to mitigate flood risk. Indeed, for those who choose to live in flood plains, flood insurance premiums often are themselves sometimes prohibitive, and most flood losses are uninsured.[6] Moreover, protective behavior may also be influenced by concerns about feelings of anxiety and insecurity (Harries, 2012).

The Protective Action Decision Model (PADM) framework (Lindell and Perry, 1992), in simplified terms, espouses that responses to hazards work through a causal chain from hazard proximity through hazard experience and perceived personal risk, to adoption of hazard adjustments (including continued residence in that location). Research across a number of disciplines suggests that individuals are not fully rational in assessing their risk of exposure to a natural disaster, and to the extent they are aware, in taking commensurate protective action. Using an extensive database of property values, a recent report by the insurance consulting firm Karen Clark & Company (2015) documented an increasing concentration of aggregate property value in disaster-prone areas; specifically, in coastal areas exposed to significant earthquake or hurricane risk. They estimate that a 100-year hurricane event striking Miami (essentially a hurricane making landfall at category 5 intensity—described below) would result in $250 billion in *insurable property losses* (emphasis added). As highlighted above, losses beyond property damages can be very high.

An “optimism bias” literature has developed around the seminal work of Rethans (1979), which suggests that perceived risks typically undervalue actual risks. Rethans showed that an “overwhelming majority” of respondents to a random, stratified national survey reported that their fatality risk associated with traffic accidents was average or below normal. In conceptually

[6] Most flood damages are uninsured losses despite the best efforts of governmental programs to encourage participation by making insurance available at below fair market cost. Browne and Hoyt (2000) used the financial experience of the United States' National Flood Insurance Program (NFIP) from 1983 through 1993 to examine the hypothetical determinants of the flood insurance purchasing decision. Their analysis shows that income and price are influential factors in one's decision to purchase flood insurance.

similar work, Viscusi and Zeckhauser (2006) evaluated perceptions of fatality risk for tornados, hurricanes, and floods (as well as terrorism).[7] They argue that "risk beliefs have many rational components, but fall short of what one would expect with fully rational Bayesian assessments of risk" (34). The presence of hazards and personal experience influenced risk assessments in the "right direction," but the perceptions of personal risks were "insufficient."[8] The consensus view of research around perceptions of risk from natural hazards is that perceptions are "less a question of predicted physical outcomes than of values, attitudes, social influences, and cultural identity" (Wachinger, Renn, et al., 2010, 71).

In a telephone survey crossing 14 states (Behavioral Risk Factor Surveillance Survey), DeBastiani et al. discovered that 25.3 percent of respondents felt they were well-prepared. In addition to these perceptions, the respondents also self-reported the possession of five "household disaster preparedness items," which included a 3-day supply of food and water, a written evacuation plan, and a working battery-powered radio and flashlight. Just over one-third of respondents reported possessing four or more of these items. As expected, households were most likely to have a 3-day supply of food (82.9 percent) and a working flashlight (94.8 percent).

In another survey of 1,304 "older" U.S. adults (50 years or older, mean age 70) taking part in the 2010 Health and Retirement Study, only 34.3 percent reported participating in an educational program, reading material on disaster preparation, and/or being aware of disaster-related resources; 23.6 percent had an emergency evacuation plan, and 14.2 percent used medical devices that require electricity (Al-rousan et al., 2013). About one-third did not have an emergency supply of food, water, and medical supplies. On the other hand, more than 90 percent

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[7] Viscusi and Zeckhauser note the conceptually very different incidence patterns of traffic accident deaths (relatively high probability, low-cost events) and natural disasters (low probability, high-cost events) and anchor their analysis of disaster perceptions with a query on perceived risk of traffic accident mortality.

[8] See also, for example, Johnston et al. (1999) (volcanic hazards), and generally, Paton and Johnston (2001).

reported that they could perform an immediate exit in case of emergency without the help of another person, and 92.4 percent reported knowing people within 50 miles who could provide shelter and transportation in the event of a disaster.

Research suggests that previous exposure to natural disaster influences those who were affected to better prepare themselves for future disaster. Those in neighboring areas who were not directly affected also are more likely to prepare. In an analysis of the aftermath of the 2011 earthquake and subsequent tsunami in Japan, self-reported preparedness for natural disaster increased (Naoi et al., 2012). Specifically, 60 percent of respondents to a survey reported that they were better prepared at the time of the survey than they were before the disaster. Many households purchased earthquake insurance after the disaster, but this effort, along with other disaster mitigation efforts, such as seismic retrofitting of homes, were more likely among those with higher incomes. Shafran (2011) uses experimental methods to demonstrate a much higher willingness to engage in protective activity in the face of “high probability risk.” Large natural disasters are low probability, though the costs may be very high.

Community Preparedness

While preparedness at the community level is not directly addressed in this paper, it is important to note that preparedness at the community level is critical to post disaster outcomes for individuals and groups of individuals. Self-protection, social protection, and governance are all components of the vulnerability of individuals to natural disasters (Connor, 2008). The preponderance of existing research suggests that individuals are generally unprepared and underestimate their degree of preparedness (Donahue, 2014).

Community disaster preparedness has been shown to be cost-effective. Specifically, Healy and Malhotra (2009) estimate that $1 in preparedness investment is associated with a $15 reduction in measured damages. However, Healy and Malhotra suggest that rational political incentives may lead to underinvestment in community disaster mitigation efforts. Specifically "myopic" voters reward the incumbent for delivering disaster relief, but not for spending on disaster preparedness, leading to distortions in incentives. Donahue (2014) provides evidence suggesting that a "very strong majority" of people are willing to pay taxes to improve community disaster preparedness, but notes that a "substantial proportion" are not (116).

As an example, consider an evaluation of the Wilmington, NC pilot of FEMA's "Project Impact," which was designed to make communities more resistant and resilient to natural hazards. Ewing and Kruse (2002) find that the program was associated with labor market improvement, specifically, a lower natural rate of unemployment and a reduction in labor market risk. The authors suggest that a significant factor in the outcome was increased interaction between the public and private sectors.

5. Empirical Model

Basic Model

The empirical model incorporates a large number of variables and estimable parameters. The key parameters of interest are those representing hurricanes and credit standing. Credit variables—specifically the Equifax Risk Score (credit score)—are the dependent variables and represent personal financial outcomes. Credit variables also appear as regressors, interacted with binary variables representing hurricanes. Included are late/missed bill payments and bank card utilization rate (debt relative to credit limit). The credit-based interaction variables are lagged two quarters.

Data are aggregated at the census tract and cover quarters between 2000 and 2014. Tracts are indexed by $i = 1, \ldots, N$. Only tracts from the 15 states which experienced an Atlantic Basin hurricane since 1970 (including storm remnants still at hurricane strength) are included in the analysis (Figure 1). Included are Alabama, the District of Columbia, Delaware, Florida, Georgia, Louisiana, Maryland, Mississippi, New Jersey, North Carolina, Pennsylvania, South Carolina, Texas, Virginia, and West Virginia.[9] Exceptions are Hurricanes Gloria (1985) and Bob (1991), which experienced very unusual paths. Quarters are indexed by $t = 1, \ldots, T$.

The key variables of interest are a set of binary variables represented by the matrix **H**, with elements $h_{it}^{m,d,l}$. **H** contain the data used to identify hurricane strikes. In addition to tract (*i*) and quarter (*t*), hurricane strikes are characterized by intensity ($m = 1, \ldots, 4$) and a buffer distance around the hurricane eye, given in miles by ($d \in D$). The index $l = 0, 1, \ldots, 8$ represents the lag structure, as measured by quarter following the strike. Thus, **H** contains a total of 72 variable columns for *NT* row observations.[10] At time *t*, the element $h_{it}^{3,25,2}$ is unity if the eye of a category $\underline{3}$ hurricane crossed within a $\underline{25}$-mile radius of tract *i* at time $t - \underline{2}$, and zero otherwise.

A tract within a 15 mile buffer of a hurricane is not also recorded as being within the 25 mile buffer (although, in reality, it is, of course). This structure does not change the measured total effects of the hurricanes on consumer finance outcomes (the combined impact of the **H**

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[9]Hurricane Sandy (October 2012) was below hurricane strength when it struck the northeast coast of the United States, including New York, which is not a state considered in the analysis (see Drye, 2012). By the time it struck New York-New Jersey, the storm was considered a post-tropical nor'easter. That is not to downplay how destructive the storm was to New York City and other affected places. The cost is estimated to have been $71.4 billion for "Hurricane" Sandy, second only to Hurricane Katrina (2005) in total estimated tropical (or post-tropical) storm costs. Katrina's cost is estimated to have been $128 billion. See Hurricane Research Center, Atlantic Oceanographic and Meteorology Laboratory, National Oceanic and Atmospheric Administration, "The thirty costliest mainland United States tropical cyclones 1900-2013." Accessed online March 26, 2017 at http://www.aoml.noaa.gov/hrd/tcfaq/costliesttable.html.

[10]There was not a category 4 hurricane with an eighth-quarter lag in the data, so the actual dimension is 70.

variables and all of the interactions of **H** and **C**, discussed below), but would make the results considerably more difficult to interpret

Additional regressors are indicated by **X** and **C**. **X** contains *K* control variables that are not related to personal finances, such as demographics. The variables in **X** are indexed by $k = 1, \ldots, K$. **C** contains the *R* credit variables used to evaluate personal finance outcomes. The variables in **C** are indexed by $r = 1, \ldots, R$. Introducing tract and time fixed effects, represented by μ and λ, respectively, a basic fixed effects model for an outcome *y* (say, credit score) can be written as

$$(3) \qquad y_{it} = \mu_i + \lambda_t + \mathbf{H}'_{it}\mathbf{a} + \mathbf{X}'_{it}\mathbf{b} + \mathbf{C}'_{it}\boldsymbol{\delta} + u_{it}$$

where $\mathbf{H}'_{it}$, $\mathbf{X}'_{it}$, and $\mathbf{C}'_{it}$ are the relevant row vectors of **H**, **X**, and **C**, respectively; μ, λ, **a**, **b**, and **δ** are parameters to be estimated; and $u \sim \mathrm{IID}$ is an error term capturing idiosyncratic shocks and other unspecified influences on *y*, where $E(u) = 0$.

Identification of the effects of financial preparedness in this panel data framework is accomplished by interacting the "treatment" variables, which in this case are hurricane strikes and their lags, with the regressors of interest. The model specification is essentially a difference-in-differences specification. Each variable $c^r_{it} \in \mathbf{C}$ must be pre-multiplied by the corresponding row vector $\mathbf{H}'_{it} \in \mathbf{H}$. The resulting specification is

$$(4) \qquad y_{it} = \mu_i + \lambda_t + \mathbf{H}'_{it}\mathbf{A} + \mathbf{X}'_{it}\mathbf{B} + \mathbf{C}'_{it}\boldsymbol{\Gamma} + \mathbf{H}'_{it}\boldsymbol{\varphi}\left(c^1_{it} + c^2_{it} + \cdots + c^R_{it}\right) + e_{it} \quad \forall i, t$$

Where $\boldsymbol{\varphi}$ is a vector of estimable parameters of dimension $(L \cdot M \cdot D \cdot R)$ and $e_{it} \sim N(0, \sigma^2_y)$. With 4 credit variables as regressors and a full lag structure, the empirical model would contain 256 interaction terms. While the data contain over 800,000 independent observations, parsimony in the interaction terms is important to make the interpretation of these terms tractable. Two specifications of the model are estimated, each with a single credit variable as a regressor representing financial vulnerability in the tract.

Fixed Effects

The use of fixed effects in panel data models (μ_i and λ_t in equation 3) can reduce (but not eliminate) the potential for omitted variable bias in the model, and fixed effects are exceptionally common in panel specifications. Indeed, the inclusion of fixed effects in panel data models is increasingly a standard procedure, certainly within economics. But researchers often fail to adequately consider that there are costs to using fixed effects as well. Specifically, fixed effects discards between-individual variability, measuring only variability within individuals, or in my case, census tracts. By discarding this between-tract variability (by differencing or subtracting the cross-section mean), one may be less likely to get unbiased estimates, assuming there are influential but unobserved cross-section- or time-invariant variables, but one also loses a great deal of "signal" in the data. Fixed effects may absorb virtually all of the variation in the data so that identification "rests on very slim margins" (Fisher, et al., 2012, 3757). Moreover, fixed effects can actually increase the bias due to omitted variables if the time-varying omitted variables (which could be data/measurement errors) are more strongly correlated with the treatment than time-invariant omitted variables that have been removed with fixed effects (Fisher, et al., 2012, 3760). Fixed effects models also tend to have high variance, and there may be a reasonable trade-off between variance and bias in some cases.

Random-effects models can form a compromise between the fixed-effects and pooled models (Clark and Linzer, 2015). These specifications enable estimation of model parameters with lower sample-to-sample variability by partially pooling information across units. The random-effects estimator of (2) is characterized by the error structure:

(5) $\mu_i \sim N(\overline{\mu}, \sigma_\mu^2)$, $e_{it} \sim N(0, \sigma_y^2)$.

Groups with outlying unit effects will have their respective shrunk back toward the mean, μ. This brings estimates away from the less stable fixed-effects estimate and closer to the more stable (albeit potentially biased) pooled estimate. The effects of shrinkage will be greatest for units containing fewer observations, especially when estimates are close to zero.

In addition, fixed-effects in "treatment models" such as mine assume that past treatments do not directly influence current outcome, and past outcomes do not directly affect current treatment (Imai and Kim, 2016). The assumed absence of causal relationships between past outcomes and current treatment may also invalidate some applications of before-and-after and difference-in-differences designs (Imai and Kim) (this concept is considered further in section 7 under "Additional Estimation Issues").

I do not employ fixed effects in my analysis in large part for these reasons, although I conduct some tests to evaluate the implications of excluding fixed effects (end of Section 7). In my case, the loss of signal coming from the data with the use of fixed effects is potentially significant, and between-tract variability is likely very significant.

6. Data

The empirical analysis uses quarterly series of climatic, socio-economic, and demographic data for all census tracts in the United States that are in states prone to Atlantic Basin hurricanes. The period of analysis is 2000-2014.

Cavallo et al. (2013) demonstrate that only "extremely large" disasters significantly affect output across the countries they analyzed. The distribution of natural disaster impact is heavily skewed. They define a "large disaster" as the 99th, 90th, and 75th percentiles of the world distribution the number of people killed as a share of the population. A 99th percentile event kills 233 people per 1 million inhabitants, while a 75th percentile event kills 7 people per 1 million inhabitants. A number of variables are used in the analysis in an effort to differentiate disasters by their impact, such as intensity of the disaster and the time period in which the disaster occurred.

Hurricanes

"Hurricane" is the regional name for a tropical cyclone, which has a number of defining meteorological characteristics (Holland, 1993). A hurricane is a non-frontal storm system. A meteorological front is the boundary between two air masses of different density. Non-tropical weather phenomena, such as thunderstorms, typically occur along fronts. A hurricane has synoptic scale, indicating that the system covers a large area (vaguely defined as a few hundred km) and has longevity of a few days to a week. Systems of low pressure and high pressure are other examples of synoptic scale weather patterns. A hurricane also is a low-pressure system over tropical or sub-tropical waters. Subtropics are areas near but outside of the tropics, usually defined as the area bounded by the tropics and 40° poleward. Finally, a hurricane has organized convection (thunderstorm activity), definite cyclonic surface wind circulation (rotation), and sustained surface wind speeds of 74 miles per hour (mph) or more.

Hurricane intensity typically is classified using the Saffir-Simpson Hurricane Wind Scale, which is a function of wind speed.[11] Specifically, a category is assigned based on the maximum sustained surface wind speed (peak 1-minute wind at the standard meteorological observation height of 10 meters over unobstructed exposure). The scale ranges from category 1

[11] Information in this section is derived largely from The National Hurricane Center, National Oceanic and Atmospheric Administration, "Saffir-Simpson Hurricane Wind Scale," available at http://www.nhc.noaa.gov/pdf/sshws.pdf.

(sustained winds 74-95 mph; "very dangerous winds will produce some damage") to category 5 (sustained winds 157 mph or higher; "catastrophic damage will occur"). Damage from a hurricane, which depends on a large number of factors, can be expected to increase four-fold with each increase in category.[12]

Wind speeds can vary dramatically depending on a storm's intensity at landfall. For example, Hurricane Katrina (2005) was a category 5 hurricane at its peak but was category 4 when it made landfall in Louisiana. Hurricane Matthew (2016) also was a category 5 hurricane at its peak but was at category 1 strength when making landfall in the U.S. (in South Carolina). Hurricane Andrew (1992) was the most recent hurricane that made landfall in the U.S. at category 5 strength, totally destroying the town and military base at Homestead, FL, just south of Miami (Rappaport, 1993). Before Andrew, the most recent hurricane to make landfall at category 5 in the U.S. was Camille, in 1969, which made landfall in Mississippi.[13] These are very rare events, and thus the lack of a category 5 hurricane in the sample is not surprising.

Data on hurricane paths, usually termed "tracks," were extracted from the IBTrACs database maintained by the World Data Center for Meteorology, National Centers for Environmental Information, National Oceanic and Atmospheric Administration (NOAA).[14] A track reflects the path of the eye of the hurricane, a comparatively calm, circular area in the center of the storm, around which (the eyewall) the most damage generally occurs.[15] The tracks

[12]Id.
[13]There have been category 5 hurricanes that have made landfall in Mexico, Central America, and the Caribbean in intervening years, the latest in 2007 (Hurricanes Dean and Felix).
[14]IBTrACs is an acronym for "International Best Track Archive for Climate Stewardship." More information on IBTrACs and access to the data are available at https://www.ncdc.noaa.gov/ibtracs/.
[15]The eyewall is a ring of deep convection around the eye which is the area of highest surface winds in the hurricane. See Atlantic Oceanographic and Meteorological Laboratory, Hurricane Research Center, NOAA, "Subject: A11, What is the 'eye'? How is it formed and maintained? What is the 'eyewall?' What are "spiral bands?'." Available at http://www.aoml.noaa.gov/hrd/tcfaq/A11.html.

of hurricanes making landfall in the U.S. between 2000 and 2014 are shown in Figure 2, where intensities are color-coded throughout its inland path until dipping below hurricane strength.

In estimating the impact of natural disasters, economic or otherwise, the spatial boundaries of the data must be well-defined and appropriate, as these boundaries could alter results significantly (Kousky, 2014). Only areas receiving “direct hits” of a minimum magnitude are identified as disaster areas in this study. To identify affected areas, buffers were created at 15, 25, and 50 miles around the hurricane tracks (eyes) (Figure 3) (I end up using only the 15- and 25-miles buffers in the empirical analysis due to the large area covered by a 50-mile buffer). Affected tracts were those which intersected with these boundaries (Figure 4). The intensity of the storm at the time it passed through each tract also was recorded.

Temporal boundaries also are crucial. For example, clean-up and construction during the early aftermath may provide substantial economic stimulus to the affected area, and direct costs may be mitigated by insurance payouts and government assistance. This issue is addressed by the inclusion of a lag structure which allows for an instantaneous effect and lagged effects for up to eight quarters following a hurricane.

Other Natural Disasters

The analysis covers a time window and geographic scope over which there have been thousands of climatic and seismic events in the continental United States in addition to hurricanes. The losses associated with these disasters, including loss of life, injuries to persons, physical damages, economic disruption, and social disruption, vary significantly by type and intensity of the disaster, among other factors. Only very significant disasters, as measured by intensity, are used in this study. The model specifically accounts for the presence of tornados and flooding, as significant earthquakes or catastrophic wildfires are very uncommon in the U.S.

southeast, and none occurred over the period of analysis. Tornados and flooding may lead to damages similar to a hurricane and could create significant bias if excluded from the model.

Tornados enter the model as three binary variables, which are unity if a tornado of a specified intensity occurs in the county. The variables reflect tornado intensities: EF-3, EF-4, and EF-5. Tornado intensity ratings are based on damage inflicted and related to an expected peak wind speed required to cause that level of damage. The Enhanced Fujita scale typically is used to quantify tornado intensities. For example, an EF-3 tornado causes "severe damage" and is associated with 3-second wind gusts of 138-167 mph. (Wind Science and Engineering Center, 2004; Storm Prediction Center). Physical damage associated with an EF-3 tornado would likely include the lifting and throwing of heavy cars, walls torn from well-constructed homes, and debarking and uprooting of trees.[16] An EF-5 tornado causes "incredible damage" and is associated with 3-second wind gusts in excess of 200 mph. Physical damage associated with an EF-5 tornado would include the leveling and sweeping away of strong frame houses and automobile-sized missiles flying in excess of 100 meters. Less than 1 percent of tornados are classified as EF-4 or EF-5, but these tornados account for roughly two-thirds of tornado-related deaths (Ewing et al., 2009). Tornado strikes with intensities of EF-3 and greater from 2000-2014 are mapped in Figure 5.

The classification of flooding is more problematic. Some measures of floods do exist, such as water depth, but water depth can vary substantially within very short distances depending on topography and the built environment. For the analyses in this paper the severity of a flood is deemed to be relatively more severe if there is an "emergency declaration" by FEMA (binary). Again, an indicator for intensity or severity of disasters is critical because higher-intensity events

[16] These damages are associated with the standard Fujita scale (e.g., F3, F5). The EF scale is very similar, but damages are assessed along 28 damage indicators. See http://www.spc.noaa.gov/efscale/.

generate more damage and may prolong financial recovery time for affected individuals and communities. Flood data come from FEMA's Disaster Declarations Summary-open Government dataset, which contains information on all federally declared disasters by county since 1964.[17] The dataset uses categorizations for "Major Disaster Declaration" and "Emergency Declaration (special emergency)."[18] The FEMA data are shown in Figure 6.

Socio-Economic Factors

Toya and Skidmore (2007), using a panel of OECD countries, find that higher income levels are associated with significant "improvements in safety over time," as measured by deaths (24). Educational attainment is important, even when controlling for income.

In a dataset on annual deaths from natural disasters in 73 nations over 1980-2002, Kahn (2005) demonstrates that, while national income "plays little role" in the likelihood of a natural disaster, richer nations suffer fewer deaths. Specifically, in the case of earthquakes, a 10 percent increase in per capita GDP is associated with a 5.3 percent reduction in national earthquake deaths. The negative association also holds for extreme temperature events, floods, landslides, and windstorms. Kahn attributes this finding to greater investment in and enforcement of zoning and building codes, greater investment in the computer modeling of storms, greater spread of early warning systems, and better governance. Karim and Noy find supporting evidence in their

[17] The database is available at http://www.fema.gov/media-library/assets/documents/28318.

[18] Other categories include "Fire Management" and "Fire Suppression Authorization." This paper does not directly address disasters caused by fire unless treated as a major disaster or special emergency. The procedures for disaster declaration are governed by the *Stafford Act* (§401), which was updated by the *Post-Katrina Emergency Management Reform Act of 2006* (see U.S. Congress, August 3, 2006). The process begins with a request by the governor(s) of the affected state(s). Based on information in the request, including damage estimates and state and local resources expended or committed, a "major disaster" may be declared if the disaster is "of such severity and magnitude that effective response is beyond the capability of the state and local governments and that federal assistance is necessary" (42 U.S.C. 5170). See also https://www.fema.gov/declaration-process. An emergency disaster may be declared if the response involves a "federal primary responsibility" (42 U.S.C. 5191). In this paper, an emergency declaration, which is much less common than a major disaster declaration, is used to differentiate the severity of flooding.

survey of a large number of studies covering a large number of countries, mostly developing countries.

A thinner body of existing research explores the income-disaster impact nexus intranationally for the United States. Fothergill and Peak (2004), in a review of the literature to date, suggest that “the poor” in the United States are “more vulnerable to natural disasters due to such factors as place and type of residence, building construction, and social exclusion” (89). For example, one’s socio-economic position may oblige him to reside in an area affected by natural hazards, such as flood plains. More recent work by Faber (2015) and Zahran et al. (2008) shows a significant relationship between exposure to flooding and social factors such as race, poverty, and age or other measured indicators of “vulnerable populations.”

I use a number of variables to account for socio-demographic differences across census tracts. I use the share of the population that is white and the share that is Hispanic/Latino to account for minorities [racial minorities are represented by (1 - white)]. I use the share of the population that is 65 years or older to account for potential vulnerabilities of this population.

Mobility

Elliott (2014) finds that property damage from natural disasters is positively correlated with increases in residential mobility, especially among racial and ethnic minorities. Sheller (2013) suggests that post-disaster logistics limit capabilities for mobility and introduce an “islanding effect” on affected residents (185). For those who do evacuate, the preponderance of the evidence suggests that those who return generally are better off financially.

Paxson and Rouse looked at a sample of 355 low-income enrollees in two community colleges in New Orleans immediately prior to Hurricane Katrina and who evacuated after the

Hurricane and resulting flood.[19] Of these, 176 had returned within 18 months. Exposure to water damage (regardless of depth) was a critical factor in the decision to return, as those who lived in flooded areas were 32 to 37 percent less likely to have returned (depending on model specification). Among those who did not experience flooding, homeowners and those living with friends and relatives were much more likely to return.[20] While not generalizable, this finding suggests that those most exposed to natural disasters may be the most likely to evacuate permanently. Presumably, one might expect that those who had better economic opportunities in other locations would be less likely to relocate to New Orleans, but Paxson and Rouse estimate that those who experienced flooding and did not return had monthly earnings reductions $192 larger (in magnitude) than those who experienced but did not return.

Using data from the Current Population Survey, Groen and Polivka (2008) support the findings of Paxson and Rouse, finding that evacuees who did not return to their “pre-Katrina areas” fared “much worse” in the labor market than did those who did return (48). Groen and Polivka provide evidence that the poorer economic outcomes of those who did not return was largely the result of having come from areas that experienced greater housing damage from the storm, again suggesting (indirectly) that those most exposed to natural disasters are more likely to evacuate permanently. Cahoon (2006) also provides estimates showing than those who did not return were economically worse off, as measured by unemployment rate.

Vigdor’s (2007) analysis of post Katrina return of evacuees to New Orleans is consistent with much of the other work, showing that those who returned tended to return to “normalcy,” while those who did not return exhibited “large and persistent gaps,” regardless of host

[19] The evacuees in the sample were participants in an ongoing study of low-income parents in New Orleans community colleges, which offered the authors a rare opportunity to have pre-disaster data on individuals.
[20] The decision to return by those who had experienced flooding was not affected by the attributes of the evacuees or their pre-flood circumstances.

community characteristics. Vigdor suggests government transfer payments and self-employment may have "blunted" the impact of the storm on total income. Vigdor's work also supports Venn's (2012) suggestion of possible labor market spatial mismatch in the longer-term aftermath of a natural disaster.

Consumer Finances

Credit Data. Credit data come from the Federal Reserve Bank of New York Consumer Credit Panel (CCP), which consists of a five percent sample of Equifax credit reports. All identifying information is removed from the credit reports contained in the CCP. Individuals can be tracked over time through a scrambled identification number. In order to get tract level data, averages were calculated for individuals who resided in the tract in each specific quarter. In most cases, weighted averages were used.

Other Consumer Financial Data. Credit data alone are, of course, insufficient to provide a clear picture of household finances. In addition to the credit variables, I use personal income. I also account for the presence of poverty by including the share of the adult population that receives benefits from the Supplemental Nutrition Assistance Program (SNAP, formerly, food stamps) and the share of households headed by single females with minor children. Demographic data show these households to be the poorest among possible household arrangements.

7. Results

The regressions generate dozens of parameter estimates and associated statistics. These data are reported in Table 2 but are not discussed variable-by-variable. Both sets of regression results use the Equifax Risk Score as the post-storm indicator of personal financial well-being. "Specification 1" in Table 2 provides results using past due/unpaid bills (30+ days past due) as the indicator of financial vulnerability. “Specification 2” provides results using the bank card utilization rate as the indicator of financial vulnerability. “Bank cards” are bank-branded credit cards—typically VISA or MasterCard. The utilization rate is the outstanding debt on bank card(s) as a percentage of aggregate credit limit on those card(s). If an individual carries $4,500 on a credit card with a limit of $10,000, then the utilization rate on that card is 45 percent. For ease of exposition, statistically significant parameter estimates ($p < 0.1$) are shaded in gray and negative values have a red font.

The discussion of results focuses largely on the direction and magnitude of the parameter estimates rather than “statistical significance,” of the parameter estimates. Recently the American Statistical Association released a formal statement on the use (or misuse) of *p*-values in statistical applications (Wasserstein and Lazar, 2016). The statement asserted that, among other concerns, “[p]ractices that reduce data analysis or scientific inference to mechanical ‘bright-line’ rules (such as ‘$p < 0.05$’) for justifying scientific claims or conclusions can lead to erroneous beliefs and poor decision making” (131). The statement goes on to assert that “[a]ny effect, no matter how tiny, can produce a small *p*-value if the sample size or measurement precision is high enough, and large effects may produce unimpressive *p*-values if the sample size is small or measurements are imprecise. Similarly, identical estimated effects will have different *p*-values if the precision of the estimates differs” (132). And, of course, only a very small change is required to move the significance level of an estimate from 5.1 percent to 4.9 percent (Gelman and Stern, 2006). Finally, the “counter null” provides further evidence of conceptual problems around null hypothesis testing (Rosenthal et al., 2000). Nakagawa and Cuthill (2007) provide an example where the mean value of a continuous variable is 10 and the confidence interval is

$(-1, 20)$. The null hypothesis in this example cannot be rejected because zero falls within the confidence bounds. However, 20 is as close to 10 as is zero.

Hurricanes

The dependent variable in both model specifications is the average credit score (specifically, the Equifax Risk Score) among consumers in the census tract. *A priori*, we might expect that a hurricane would lead to financial activities that reduce credit scores. For example, we might expect more late or missed bill payments or increases in revolving debt. While in many cases the parameter estimates on the H variables are negative in both specifications, and in some cases quite large in magnitude, a number of the parameter values on these binary hurricane variables are positive.

In some sense, the H variables have little meaning when considered separately from the interaction variables. Consider a simplified model where credit score is given by *CS*, the hurricane variable is given by H (= 1), and I is the credit variable interacted with H. Then

(6) $$CS = \alpha H + \beta HI$$

and the contemporaneous impact of a hurricane on *CS* is:

(7) $$CS_{|H=1} = \alpha + \beta I$$

The parameters on the H variables, considered alone, represent the effects of a hurricane on credit score when all of the credit variables are zero, which has limited empirical value. Nevertheless, hurricane strikes and the value of the interaction terms (unpaid bills or credit card utilization rate) two periods previously are completely unrelated conceptually, as a hurricane is an exogenous event post-dating the interaction variable (of course, the primary conjecture in this analysis is a contemporaneous and/or post-event relationship between hurricanes and credit variables). Thus, the variables in columns (4) and (10) can reasonably be viewed as independent effects of hurricanes on the post-storm credit score. The contemporaneous, partial effect of a category 2 hurricane within 25 miles of the tract, for example, would be a 5.4-point reduction in credit score ($H^{2,25,0} = -5.425$; see Table 2).

Consideration of the interaction term yields more consistent results. Column 6 is the net effect of a hurricane strike as measured in equation 7. Specifically, each H parameter (column 4) is added to the product of the interaction parameter (column 5) and the mean value of the interaction term, which for Specification 1 is share of residents with past due bills (3.4 percent). The contemporaneous effect of a category 2 hurricane within 25 miles of the tract would therefore be $-5.425 - 112.443(0.033395) \approx -9.180$. All else equal, the hurricane strike would, on average, reduce average credit score by about 9.2 points in the quarter of the hurricane strike. When financial vulnerability is used as the measure of financial vulnerability is a very close -9.877.

The net effects for category 1 hurricanes are economically very small. In the case of tracts within 15 miles, both the hurricane and interaction parameters are largely insignificant statistically and small. Although the hurricane parameters and interaction parameters in the case of tracts within the 15-25 mile band are all statistically significant and much larger in size, they offset, with a net effect negligible in magnitude. So for category 1 hurricanes, the impact on credit score could rightly be considered a wash. That result and its interpretation are consistent with category 1 being the lowest-intensity hurricanes: “very dangerous winds will produce some damage” (see Section 6, “Hurricanes”).

For higher intensity hurricanes, the results likely reflect a number of factors. Numbers of storms likely has some influence. Unsurprisingly, tract-quarters with category 1 hurricane activity are much more common in the data than are tract-quarters with higher-intensity hurricane activity (Figure 7). Not only are storms rated category 1 more frequent (15 over the study period making landfall in the United States), but more intense storms weaken as they track inward and all are category 1 storms over at least some tract-quarters in the data. Major hurricanes over the study period include 4 at category 2, 6 at category 3, and 1-2 at category 4.[21] Results for category 4 hurricanes for the most part only represent the impact of Hurricane Charley in 2004.

Disaster aid undoubtedly affects personal finance outcomes. The amount of aid is a function of storm intensity and the geographic location of the storm track. For example, Hurricane Sandy [2012] was a category 1 hurricane at landfall, but its strike point in the New York Metropolitan Area led to extensive damage and resulted in substantial recovery aid. Similarly, Matthew (2016) (not in sample) was a category 1 hurricane at landfall (although category 5 at maximum intensity off shore) and resulted in significant costs.

In addition, the amount of disaster aid received has been shown to partly reflect media coverage and political interest (Olsen et al., 2003). The 2005 Atlantic Basin hurricane season—the most active on record— saw 4 category 3 hurricanes make landfall in the United States. The second storm, Hurricane Katrina, was the costliest in U.S. history in dollar damages and the most costly U.S. hurricane in loss-of-life since 1928 (Okeechobee Hurricane). Hurricane Katrina received very extensive media coverage world-wide. Political interest also was high. As a result, the two hurricanes that shortly followed Katrina, Rita and Wilma, also received substantial media attention. Moreover, the federal response to Katrina was largely seen as botched (Walker, 2006; Bea et al., 2006), and recovery efforts following Rita, which significantly exacerbated existing damages and suffering from Katrina, and Hurricane Wilma (Florida panhandle) likely

[21]Hurricane Charley (2004) is the only hurricane officially classified as category 4 over the period, but a in the GIS mapping for this article, a small number of tracts were exposed to Hurricane Katrina (2005) at category 4.

were influenced by problems around Katrina.[22] A relatively large amount of aid would be consistent with results for category 3 storms—two-thirds of which occurred in 2005. The net "gain" for those in the 15-25 mile band around the hurricane tracks is likely a function of significant aid. Those within 15 miles would have received as much aid or more, but damage, economic disruption, and other personal financial disruptions would be expected to be more severe. Parameters on hurricane variables representing census tracts the 15-mile band are economically very small, suggesting that aid, though significant, may have been offset by the more extensive damage and economic disruption.

For category 2 hurricanes, One possible explanation for these seemingly confounding results is also aid. Tracts within 25 miles of the eye may benefit from stimulus entering the area following the storm, but without losses as great as those in tracts within 15 miles of the hurricane's eye.

The fundamental interest in this paper is not the impact of hurricanes on personal finances, per se, but rather the role that financial vulnerability plays in affecting personal finances following a hurricane. Specifically, the primary interest is the estimates of the interaction terms $\beta \in \mathbf{B}$, where $\mathbf{B}$ is the full set of parameters on the interaction terms in equation 7. Parameter estimates are provided in Table 2 and summarized in Figures 8 and 9. In both specifications, these parameters are almost uniformly large and negative. The exception is tract-quarters that experienced a category 3 storm within the 15-25 distance band, where the estimated parameters are positive and sufficiently large that they cannot be rightly dismissed.

[22]The first category 3 hurricane to make landfall in the U.S. was Dennis, which affected mostly the Florida panhandle. Damage was significantly lower than that associated with Katrina, Rita, and Wilma. Hurricane Wilma is the most intense hurricane in recorded history in the Atlantic Basin, with sustained wind speeds of 185 miles per hour. A tornado of the same intensity would likely be classified as an EF-4. Wilma weakened considerably before making landfall but remained a significant storm.

The estimated parameters for tract-quarters within the 15-mile band are relatively small in magnitude.

An additional potential influence on the interaction (**B**) variables are alternative procedures employed by many creditors and credit reporting agencies for addressing unpaid bills and negative reports to the credit bureaus. If an affected party contacts creditors and credit reporting agencies, they typically will “work with” the individual to ensure that credit standing is not significantly diminished. This kind of assistance is mostly standard procedure among the credit reporting agencies (Equifax; Experian; TransUnion, and also Fair Isaac Corporation, which produces the FICO score) (see Consumer Financial Protection Bureau, 2016).

Because of the several lags included in the model, it is the aggregate effect of financial vulnerability and hurricane outcomes that is arguably the critical results from the analysis. Figure 10 shows the total effect on credit score including lags. I use tract-quarters in the 15-25 mile band of Hurricane Humberto, a 2007, category 1 hurricane that initially struck the Beaumont-Port Arthur area of Texas before striking Louisiana as a tropical storm. As seen in Figures10 and 11 (utilization rate), the cumulative effect of the interaction variables is significant, even for this relatively mild storm (although is significantly affected oil refining). The chart reveals that tracts with low share of the population with unpaid bills (arbitrarily set at 1 percent), the aggregate effect of Humberto on credit score was a reduction of 16.2 percent. For a tract with an especially high rate of unpaid bills (arbitrarily set a 5 percent), the effect is strikingly larger in magnitude at -81.2 points. The median (3.09 percent) yields an average reduction in credit score of 46.4 points. Thus, half of tracts affected by Hurricane Humberto saw an average reduction in credit score of more than 46.4. These cumulative effects were significantly higher than expected ex-ante. Results from Specification 2 show a very similar pattern, with credit score reductions ranging from 17.9 percent with a 10 percent credit card utilization rate to a staggering 71.2 percent for those with a 40 percent utilization rate.

While the analysis does not consider individual outcomes, it is reasonable to expect that a consumer with a credit card utilization of, say, 100 percent, would see a substantially larger drop in credit score.

As expected, significant tornados tend to reduce credit scores in tracts within the county where the tornados occurred. The exception of category EF-5

Fixed Effects and Control Variables

As noted in section 5, given the balance of good and bad associated with fixed effects, I chose not to employ fixed effects when estimating my models. I did, however, evaluate the implications of my specification against fixed effects specifications.

The analysis includes roughly 14,000 census tracts in about 950 counties. Further, the analysis covers 54 quarters from 2000:3 to 2014:4. Any test for the presence of fixed effects in a model with thousands of cross-section units would almost certainly fail to reject a null hypothesis of fixed effects being jointly zero. Thus, the typical Wald or LM tests are largely uninformative. Instead, I look at parameter estimates across models and identify any statistically significant differences.

Table 3 shows the control variables used in the model. These results are informative not only in that the parameters can be tested for statistical equality across specifications, but also because these variables have clear expected values given their use in dozens, if not hundreds of empirical studies of credit standing. Shown in the table are parameter estimates and standard errors for three specifications: one with tract fixed effects, one with county fixed effects, and the third with no fixed effects.

As indicated by the z-scores provided in the last columns of the table, the parameter values are statistically different across specifications, which suggests there may be some bias imposed by not accounting for fixed effects. It is notable, however, that parameter estimates were most different between the models with tract fixed effects and county fixed effects, with the pooled regression model results generally lying somewhere between.

One effective way to evaluate model specification is through a "sanity check" of the parameters: do they make sense based on what we would expect theoretically and empirically? In the case of the tract fixed effects model, there are some questionable results. First, SNAP (food stamps) participation is shown to be positively (partially) correlated with Risk Score, when a negative relationship between income and credit score has been well-established. Further, on average, and all else equal, Hispanics and lower-educated people tend to have lower credit scores, but the correlates are positive in the tract fixed effects model. Finally, a mortgage, assuming it is paid on time and in good standing, typically raises a credit score, all else equal. Regardless, while there could be some bias introduced by not accounting for fixed effects, the parameters for the control variables in the model without fixed effects are highly consistent with theoretical expectations and existing empirical findings.

The key parameters in this investigation are those associated with the variables representing hurricane activity. With these variables, there are few statistically significant differences in parameters between the pooled regression model and the model with county fixed effects. Table 4 shows the *p*-values for a test of differences in the parameters. The results show that parameter estimates in the two models are statistically different only for category 1 hurricanes in the 25-mile buffer.

8. Conclusion

This paper argues that resilience on the part of individuals is an important part of community recovery from a natural disaster. The paper specifically examines financial vulnerabilities, as measured by past-due bills and bank card utilization on post-disaster personal financial outcomes. I find that hurricanes tend to lower credit scores, for the most, but outcomes are far from uniform across categories of hurricanes. I attribute these differences largely to number of disasters in each quarter of the study period, levels of disaster aid, and media coverage and political interest. In some cases I surmise that those in the 25-mile buffer may benefit from economic stimulus that follows a hurricane, but do not have damages and other economic losses to the same extent as those within a 15-mile buffer.

Modeling hurricanes as “treatments” and interacting them with variables from consumer credit reports, I find that the financial vulnerability of residents in affected census tracts is associated with poorer financial outcomes. Considering lags, financial vulnerability is shown to have a considerable impact on post-hurricane personal finance outcomes.

In general, the results suggest that those who are financially better prepared for a natural disaster tend to have better financial outcomes. The cumulative effect of the interaction variables is significant, even for relatively mild storms Tracts with low share of the population with unpaid bills (arbitrarily set at 1 percent), the aggregate effect of a category 1 hurricane on credit score was a reduction of 16.2 percent. For a tract with an especially high rate of unpaid bills (arbitrarily set a 5 percent), the effect is strikingly larger in magnitude at -81.2 points. The median (3.09 percent) yields an average reduction in credit score of 46.4 points. Thus, half of tracts affected by category 1 hurricanes saw an average reduction in credit score of more than

46.4 points. This result would drop an average credit score of 700 to just over 650, which would likely significantly affect credit terms on a new loan. These cumulative effects were significantly higher than expected ex-ante. Results from Specification 2 show a very similar pattern, with credit score reductions ranging from 17.9 percent with a 10 percent credit card utilization rate to a staggering 71.2 percent for those with a 40 percent utilization rate.

While the analysis does not consider individual outcomes, it is reasonable to expect that a consumer with a credit card utilization of, say, 100 percent, would see a substantially larger drop in credit score. Specifically, the decision to purchase insurance is likely critically important, but insurance data are difficult to acquire at best. Additional credit variables and non-credit personal finance data also would help to better understand the impact of hurricanes on personal finances and the role that financial preparedness may play in the financial outcomes of natural disasters.

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Tables & Figures

Table 2: Empirical Results

Specification 1 (Any Past Due Bills)						**Specification 2 (Bank Card Utilization)**					
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Hurricane Category	Distance from Eye (miles)	Lag	Hurricane Parameter	Interaction Parameter	Net Effect at Avg. Value of Interaction Term (**0.034**)	Hurricane Category	Distance from Eye (miles)	Lag	Hurricane Parameter	Interaction Parameter	Net Effect at Avg. Value of Interaction Term (**0.250**)
1	≤ 15	0	†	†		1	≤ 15	0	†	†	†
		1	5.466	-173.440	-0.326			1	5.086	-21.989	-0.414
		2	-1.176	1.460	-1.127			2	-3.712	8.368	-1.619
		3	-1.128	1.589	-1.075			3	-2.341	3.060	-1.576
		4	-1.149	5.313	-0.971			4	-2.316	3.583	-1.420
		5	-1.298	9.908	-0.967			5	-2.413	4.047	-1.401
		6	-1.010	-12.875	-1.440			6	-2.394	2.682	-1.723
		7	-0.479	-42.321	-1.893			7	-3.129	4.862	-1.912
		8	-1.600	-17.400	-2.181			8	-3.401	4.437	-2.291
	>15 & ≤ 25	0	7.515	-214.636	0.347		>15 & ≤ 25	0	8.912	-32.870	0.690
		1	7.354	-202.118	0.604			1	9.267	-32.317	1.183
		2	7.536	-182.357	1.446			2	8.309	-25.786	1.859
		3	7.031	-174.054	1.218			3	6.436	-19.371	1.590
		4	6.691	-186.354	0.467			4	5.151	-15.949	1.161
		5	6.363	-187.560	0.099			5	4.244	-13.242	0.932
		6	6.989	-164.801	1.486			6	4.951	-11.544	2.063
		7	6.908	-147.016	1.998			7	5.584	-12.200	2.532
		8	5.917	-164.349	0.428			8	5.172	-15.916	1.191
2	≤ 15	0	8.868	-159.150	3.553	2	≤ 15	0	5.019	-9.118	2.738
		1	6.078	-121.014	2.036			1	5.330	-11.910	2.351
		2	6.859	-143.337	2.072			2	1.765	-0.803	1.565
		3	2.756	1.347	2.801			3	1.463	5.207	2.765
		4	1.370	84.193	4.181			4	3.964	-1.138	3.679
		5	3.549	-37.488	2.297			5	1.949	1.419	2.304
		6	5.460	-112.489	1.703			6	1.018	4.570	2.161
		7	2.091	-29.448	1.107			7	-0.915	9.416	1.440

Specification 1 (Any Past Due Bills)						Specification 2 (Bank Card Utilization)					
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Hurricane Category	Distance from Eye (miles)	Lag	Hurricane Parameter	Interaction Parameter	Net Effect at Avg. Value of Interaction Term (**0.034**)	Hurricane Category	Distance from Eye (miles)	Lag	Hurricane Parameter	Interaction Parameter	Net Effect at Avg. Value of Interaction Term (**0.250**)
		8	-2.761	137.081	1.817			8	-0.286	7.364	1.556
	>15 & ≤ 25	0	-5.425	-112.443	-9.180		>15 & ≤ 25	0	-7.943	-7.732	-9.877
		1	-4.346	-114.835	-8.181			1	-6.804	-8.188	-8.853
		2	-4.015	-93.843	-7.149			2	-4.677	-12.081	-7.699
		3	-5.101	-100.000	-8.441			3	-3.142	-20.686	-8.317
		4	-5.831	-108.584	-9.457			4	-6.067	-12.148	-9.106
		5	-5.030	-107.883	-8.633			5	-7.323	-4.775	-8.517
		6	-7.527	-28.055	-8.464			6	-7.416	-5.055	-8.680
		7	-3.127	-146.355	-8.015			7	-4.367	-13.831	-7.827
		8	-2.414	-207.114	-9.330			8	-5.431	-14.327	-9.015
3	≤ 15	0	-6.965	59.470	-4.979	3	≤ 15	0	2.555	-29.050	-4.712
		1	-3.696	22.072	-2.959			1	1.938	-23.265	-3.882
		2	-2.078	31.851	-1.014			2	9.107	-40.497	-1.024
		3	2.883	-147.071	-2.029			3	7.134	-38.190	-2.419
		4	1.336	-153.566	-3.792			4	4.461	-33.353	-3.882
		5	1.257	-97.034	-1.984			5	8.635	-43.011	-2.124
		6	0.909	-45.824	-0.621			6	8.867	-39.567	-1.031
		7	3.693	-114.444	-0.129			7	10.199	-44.312	-0.886
		8	7.458	-256.465	-1.107			8	5.172	-23.866	-0.798
	>15 & ≤ 25	0	4.045	83.188	6.823		>15 & ≤ 25	0	1.943	23.817	7.901
		1	3.181	83.487	5.969			1	-0.775	32.838	7.440
		2	1.494	110.922	5.198			2	-2.211	33.683	6.215
		3	1.782	141.771	6.517			3	-2.495	36.670	6.678
		4	4.142	96.091	7.351			4	0.950	25.948	7.441
		5	2.640	118.226	6.588			5	1.156	22.353	6.748
		6	5.681	27.211	6.589			6	2.979	15.484	6.852
		7	0.586	158.995	5.896			7	-1.131	27.730	5.806
		8	-0.091	181.523	5.971			8	1.798	15.498	5.675
4	≤ 15	0	4.786	-16.920	4.221	4	≤ 15	0	10.727	-28.424	3.617
		1	2.997	-23.677	2.207			1	7.236	-22.834	1.524
		2	1.968	-8.179	1.695			2	4.290	-10.672	1.621
		3	0.130	17.907	0.728			3	-1.396	8.730	0.788

Specification 1 (Any Past Due Bills)						Specification 2 (Bank Card Utilization)					
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Hurricane Category	Distance from Eye (miles)	Lag	Hurricane Parameter	Interaction Parameter	Net Effect at Avg. Value of Interaction Term (**0.034**)	Hurricane Category	Distance from Eye (miles)	Lag	Hurricane Parameter	Interaction Parameter	Net Effect at Avg. Value of Interaction Term (**0.250**)
		4	-3.096	100.874	0.273			4	1.497	-11.985	-1.501
		5	2.393	-85.747	-0.470			5	2.943	-20.211	-2.113
		6	1.566	-33.468	0.448			6	-0.300	-5.303	-1.626
		7	3.799	-90.617	0.772			7	4.168	-21.328	-1.167
		8	‡	‡				8	‡	‡	‡
	>15 & ≤ 25	0	-1.143	-224.667	-8.646		>15 & ≤ 25	0	-4.310	-18.481	-8.933
		1	-0.113	-134.630	-4.609			1	-0.019	-19.743	-4.958
		2	0.068	-89.379	-2.917			2	-0.045	-14.000	-3.547
		3	0.762	-105.990	-2.778			3	1.230	-20.687	-3.944
		4	2.179	-168.242	-3.440			4	1.124	-20.254	-3.943
		5	-0.223	-116.177	-4.102			5	2.921	-30.221	-4.639
		6	1.518	-180.157	-4.499			6	3.155	-29.409	-4.202
		7	-0.158	-127.570	-4.419			7	1.388	-25.083	-4.887
		8	‡	‡				8	‡	‡	‡
Tornados											
EF-3			-5.419						-5.404		
EF-4			-2.939						-2.927		
EF-5			2.033						2.071		

Table3: Empirical Results, Control Variables, Estimation Methods with Alternative Specifications of Fixed Effects

	Parameter Estimates			Standard Errors				Z-Scores, Difference in Means		
	Tract FE (1)	County FE (2)	No FE (3)	Tract FE (4)	County FE (5)	No FE (6)		Tract FE/ County/FE (7)	Tract FE/ No FE (8)	County/ No FE (10)
Intercept	671.059600	555.333595	579.842250	1.240300	0.804691	0.000229		78.2742	73.5446	-30.4572
Population	0.001404	0.000321	-0.000740	0.000029	0.000010	0.000000		35.3864	73.9161	108.6385
Share 65+	0.675520	0.941643	0.973587	0.005750	0.003368	0.000003		-39.9356	-51.8377	-9.4845
White	0.147636	0.762645	0.602638	0.003690	0.001510	0.000001		-154.2579	-123.3069	105.9861
Hispanic/Latino	0.042277	-0.474708	-0.199755	0.004730	0.002370	0.000002		97.7191	51.1696	-116.0158
Female Householder w/Kids	-27.365700	-185.683801	-277.743951	0.781500	0.701472	0.000685		150.7583	320.3815	131.2385
SNAP	0.571605	-0.292803	-0.749482	0.003390	0.004338	0.000004		157.0032	389.7010	105.2684
Owner-Occupied	0.111513	0.281964	0.174667	0.004260	0.001338	0.000001		-38.1729	-14.8249	80.1819
Owner Occupied with Mortgage	-0.038420	0.244492	0.626782	0.002930	0.002389	0.000002		-74.8342	-227.0314	-160.0205
No HS Diploma	0.002170	-0.006454	-0.010148	0.000108	0.000176	0.000000		41.7965	114.0514	21.0050
BA or Higher	0.000086	0.000535	0.000852	0.000011	0.000013	0.000000		-26.7337	-69.6712	-24.9992
Time Trend		0.439743	0.544822		0.001510	0.000002				-69.5781
Adjusted R^2	0.95	0.80	0.66							

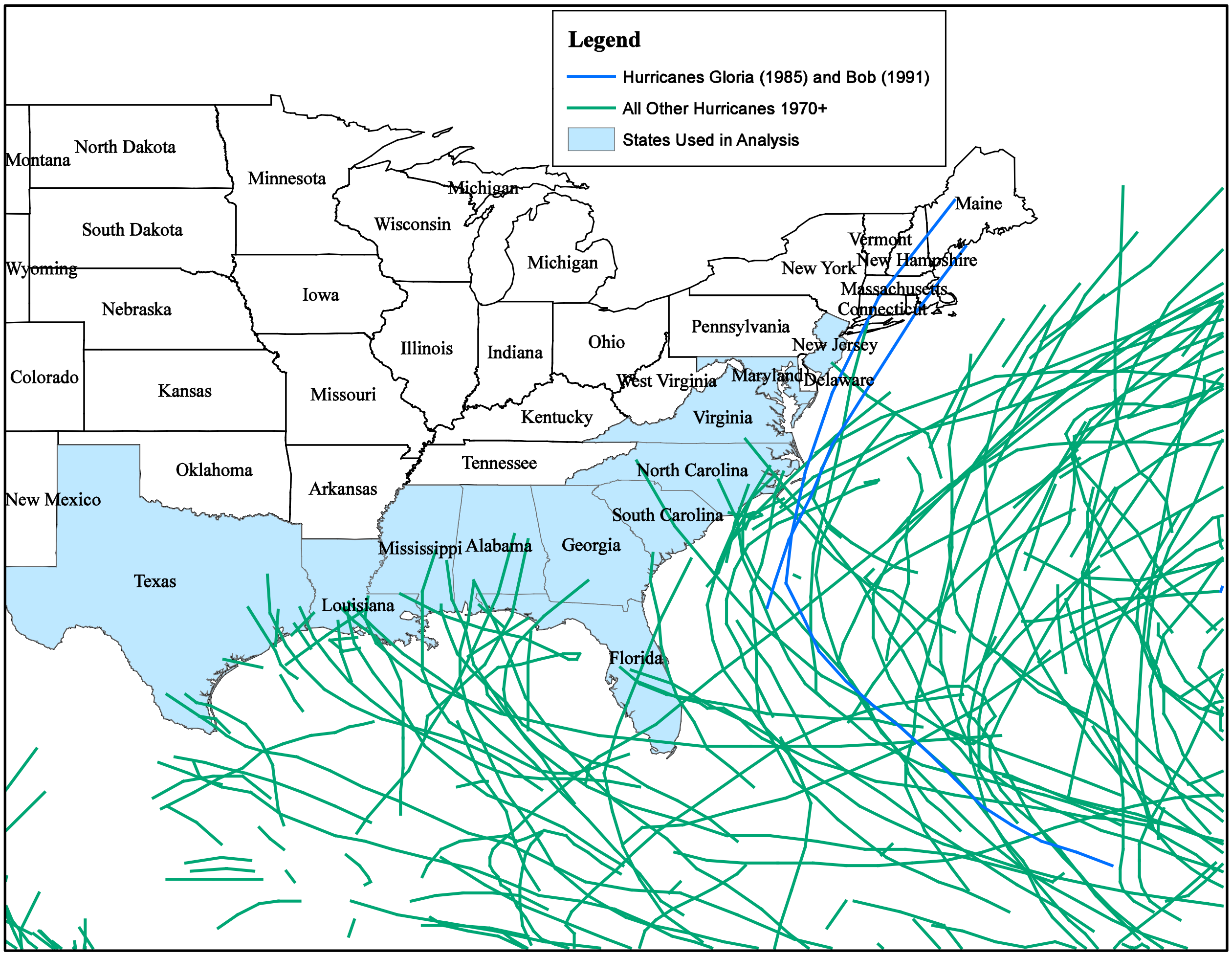
The dependent variable is the Equifax Risk Score (a credit score)
Heteroscedasticity-Consistent Standard Errors
All variables are significant at the 99 percent confidence level
All Z-scores in columns 7-9 are significant at the 99 percent confidence level.

Table 4: Difference in Parameter Values, Hurricane Variables with and without County Fixed Effects

Cat_Dist_Lag	p-value (t-dist)	Cat_Dist_Lag	p-value (t-dist)	Cat_Dist_Lag	p-value (t-dist)	Cat_Dist_Lag	p-value (t-dist)
H1_15_0	0.681	H2_15_0	0.596	H3_15_0	0.736	H4_15_0	0.774
H1_15_1	0.886	H2_15_1	0.693	H3_15_1	0.805	H4_15_1	0.843
H1_15_2	0.752	H2_15_2	0.525	H3_15_2	0.700	H4_15_2	0.908
H1_15_3	0.230	H2_15_3	0.324	H3_15_3	0.646	H4_15_3	0.973
H1_15_4	0.408	H2_15_4	0.479	H3_15_4	0.756	H4_15_4	0.959
H1_25_0	**2.7E-09**	H2_25_0	0.433	H3_25_0	0.543	H4_25_0	0.744
H1_25_1	**1.2E-07**	H2_25_1	0.587	H3_25_1	0.701	H4_25_1	0.755
H1_25_2	**4.7E-09**	H2_25_2	0.369	H3_25_2	0.486	H4_25_2	0.555
H1_25_3	**1.7E-09**	H2_25_3	0.208	H3_25_3	0.406	H4_25_3	0.684
H1_25_4	**3.6E-08**	H2_25_4	0.203	H3_25_4	0.366	H4_25_4	0.662

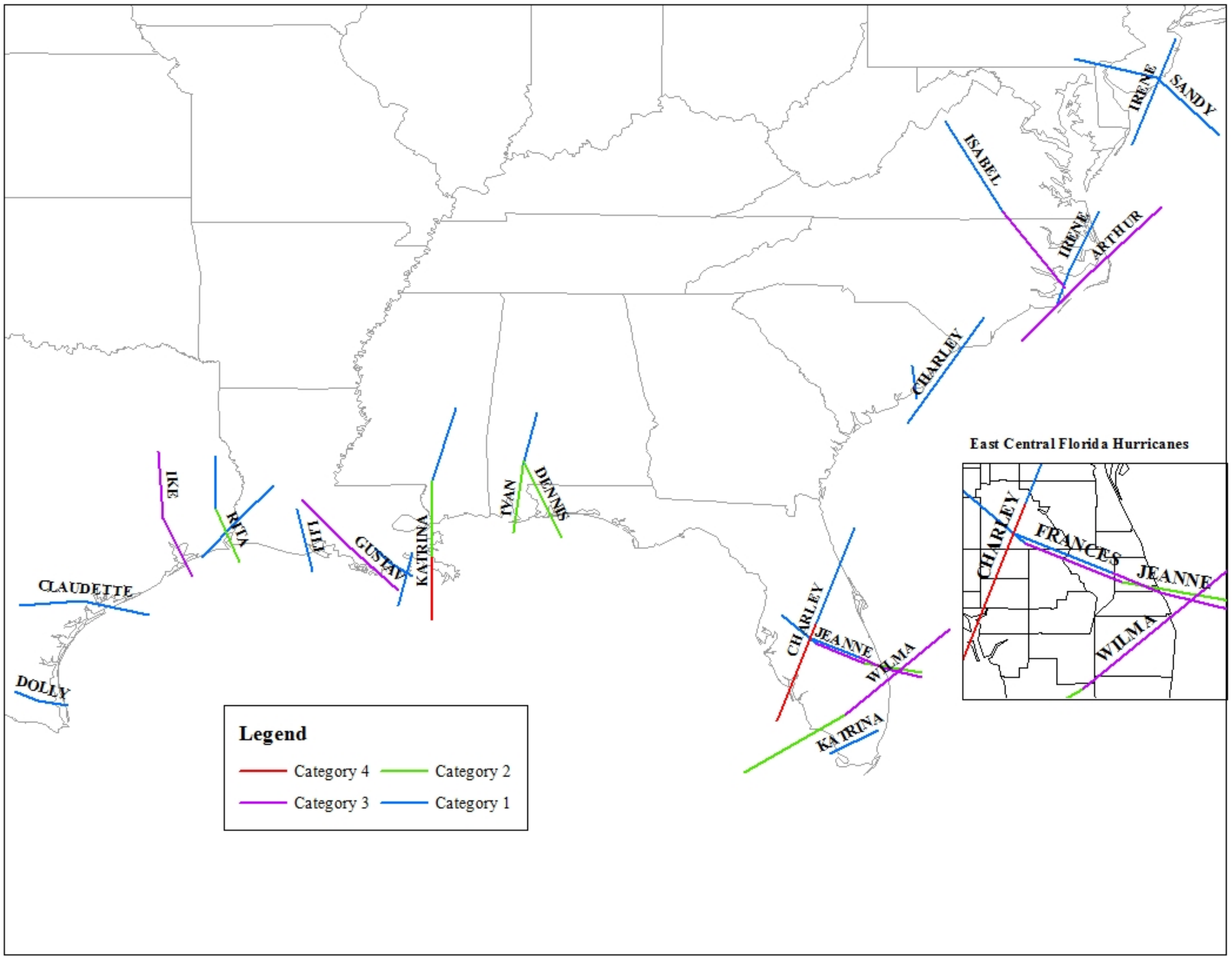
Values in bold indicate a statistically significant difference in the estimated means of the variable between the models with and without county fixed effects. In the specific case here, the probably that the H1_25 variables are different is nearly 100 percent (i.e.,, in the case of H1_25_0, the probability is 1 – 2.7E-09 ≈ 1).

Figure 1: Atlantic Basin Hurricanes, 1970 – present



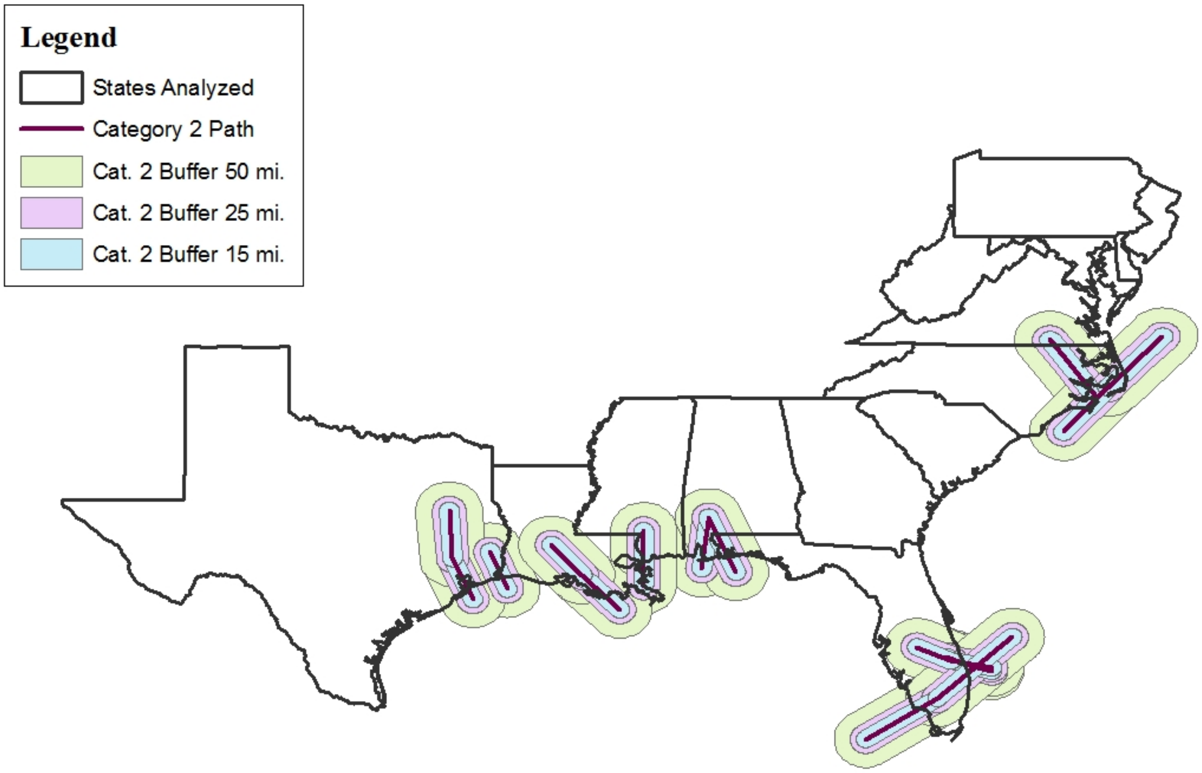
Source: IBTrACs database (maintained by the World Data Center for Meteorology, National Centers for Environmental Information, National Oceanic and Atmospheric Administration)

Figure 2: Hurricanes in the Study Period



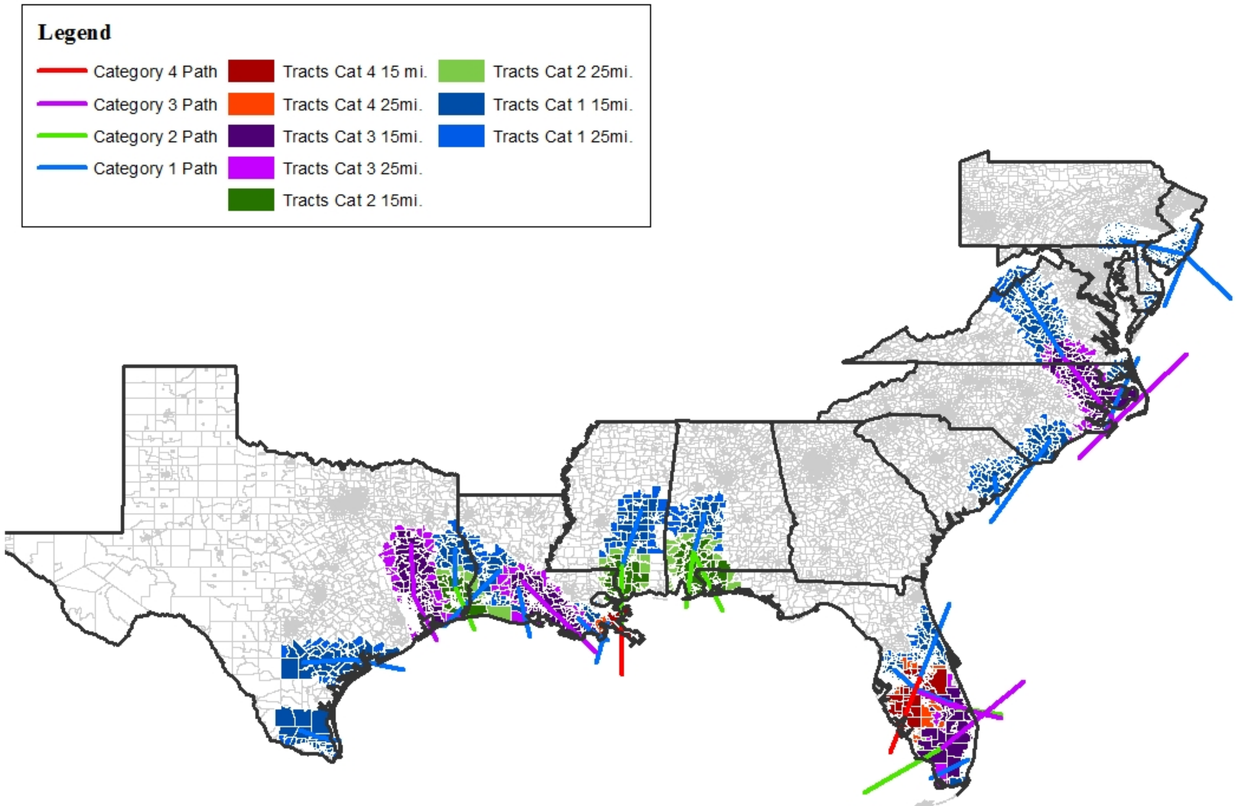
Source: IBTrACs database (maintained by the World Data Center for Meteorology, National Centers for Environmental Information, National Oceanic and Atmospheric Administration)
Note: No hurricanes were at Category 5 strength when making landfall over the period of analysis. The last Atlantic Basin hurricane to make landfall in the United States was Hurricane Andrew in 1992 (south Florida).

Figure 3: Buffers Around Hurricane Paths (Example, Category 2 Hurricanes)



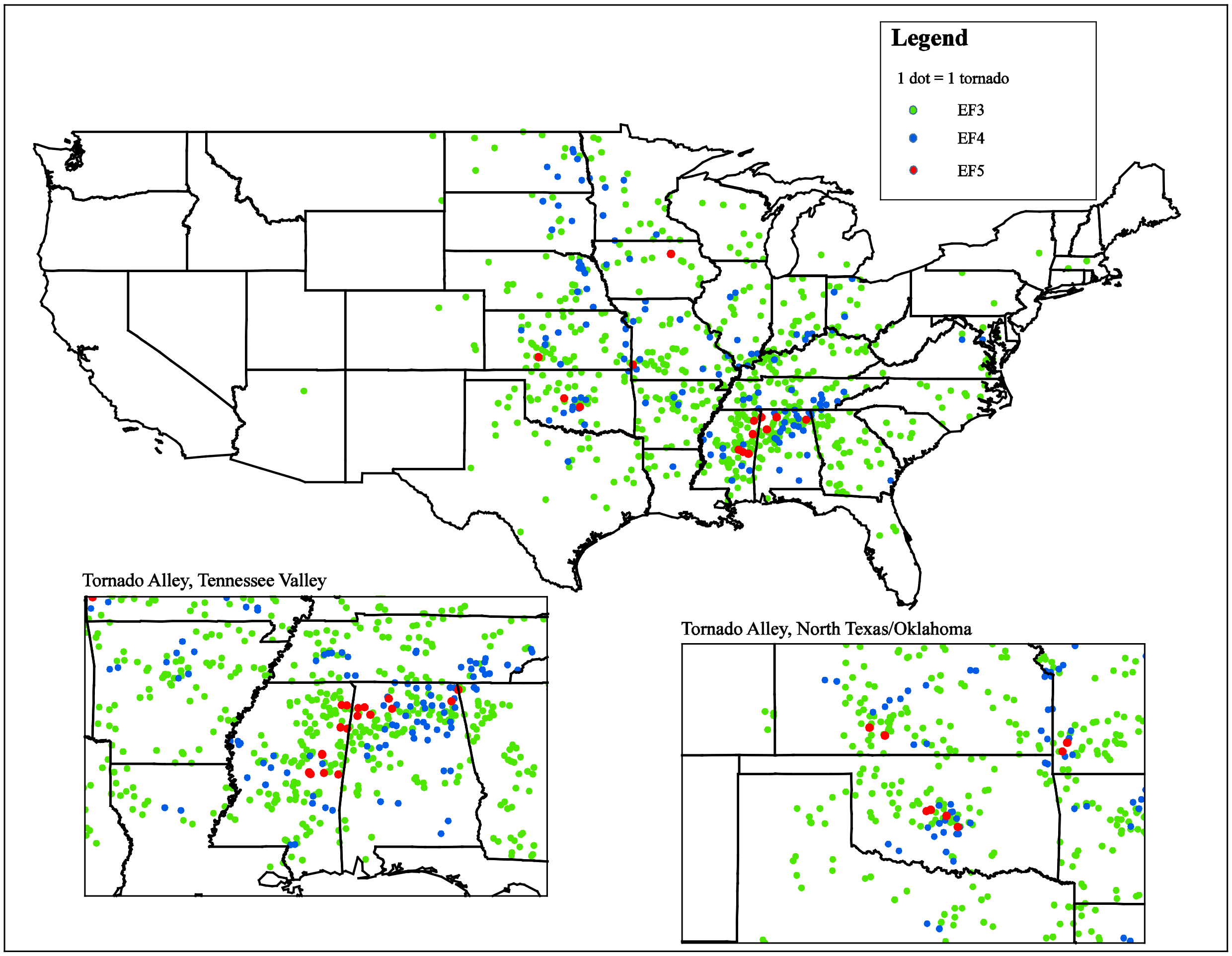
Source: Author's calculations; IBTrACs database (maintained by the World Data Center for Meteorology, National Centers for Environmental Information, National Oceanic and Atmospheric Administration)

Figure 4: Census Tracts Impacted by Hurricanes, By Strength and Distance, 2000-2014



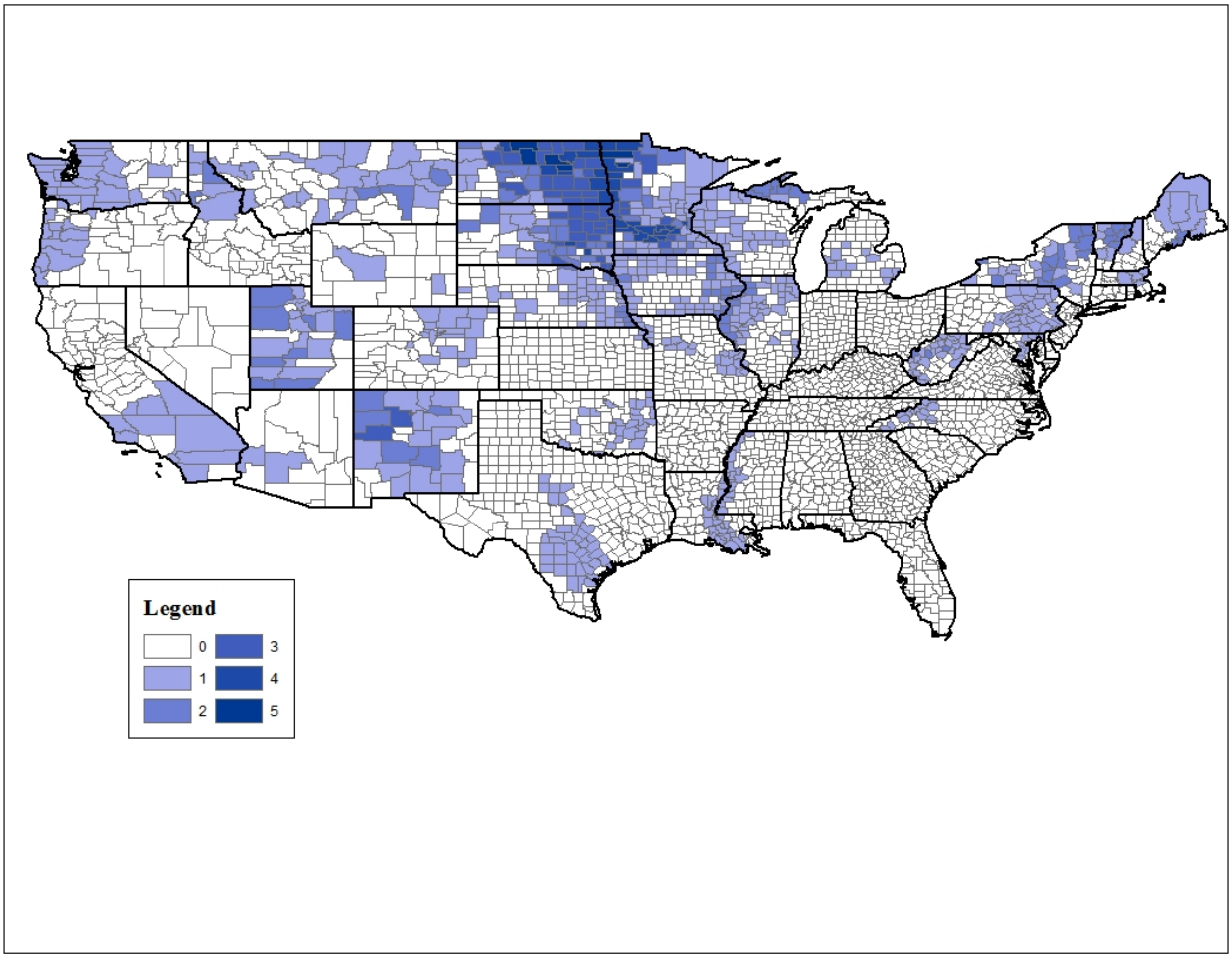
Source: Author's calculations; IBTrACs database (maintained by the World Data Center for Meteorology, National Centers for Environmental Information, National Oceanic and Atmospheric Administration)
Notes: Hurricane strength is indicated by color (blue = 1, green = 2, purple = 3, red = 4). Tracts with lighter colors are further away from the hurricane path.

Figure 5: EF-3, EF-4, and EF-5 Tornados over the Study Period



Source: Federal Emergency Management Agency

Figure 6: FEMA "Emergency" Disaster Declarations for Flooding over the Study Period (number of declarations)



Source: Federal Emergency Management Agency

Figure 7: Incidences of Hurricane Activity in Tract-Quarter

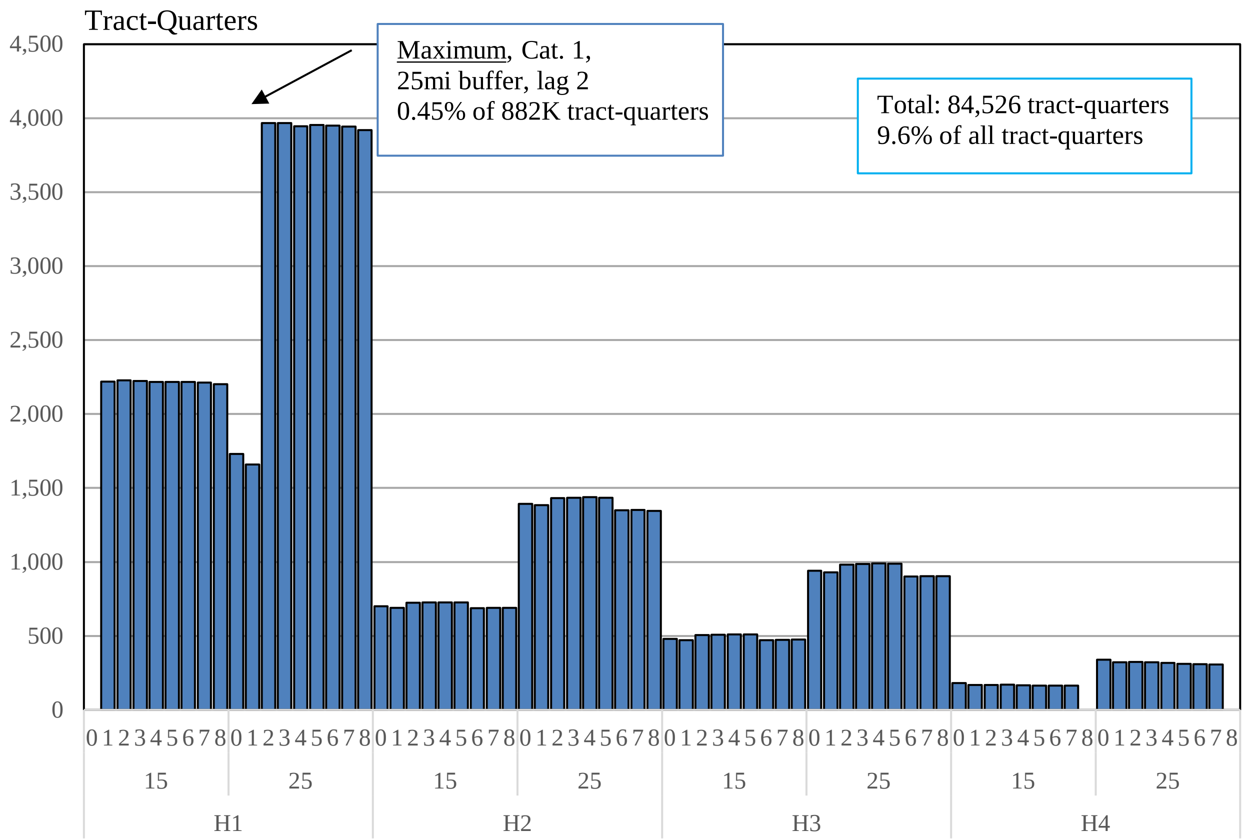
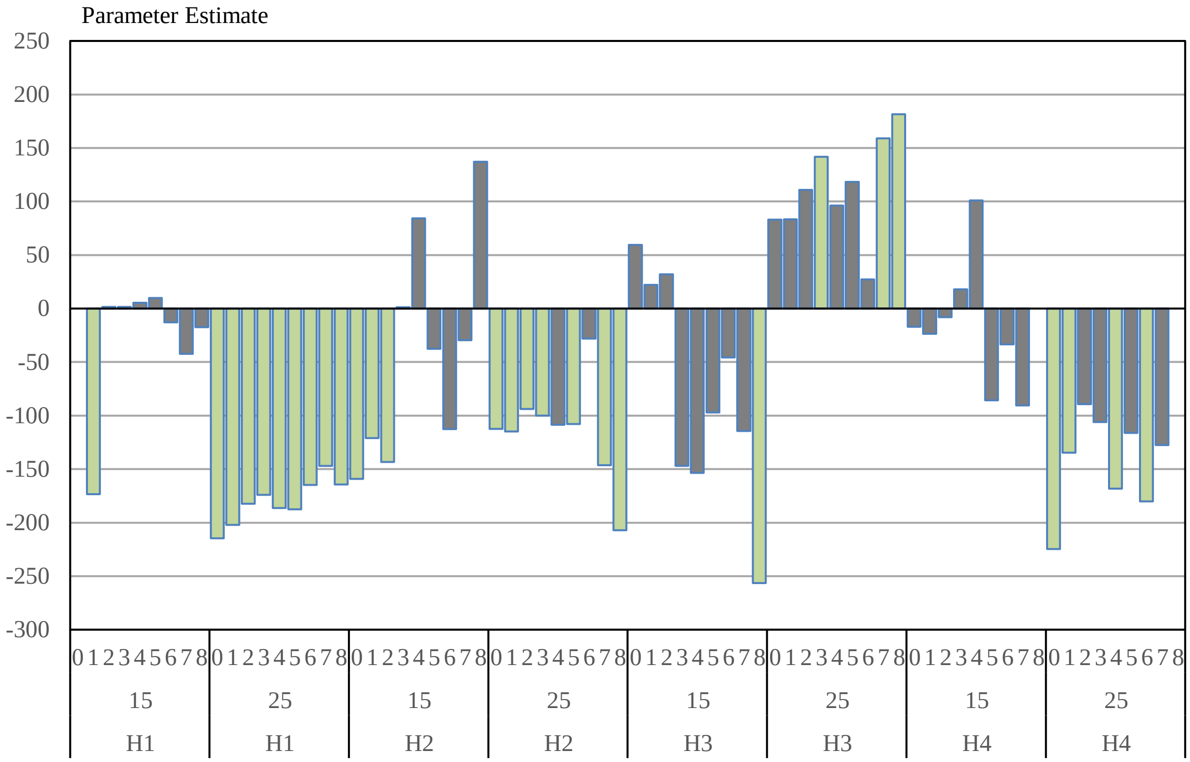
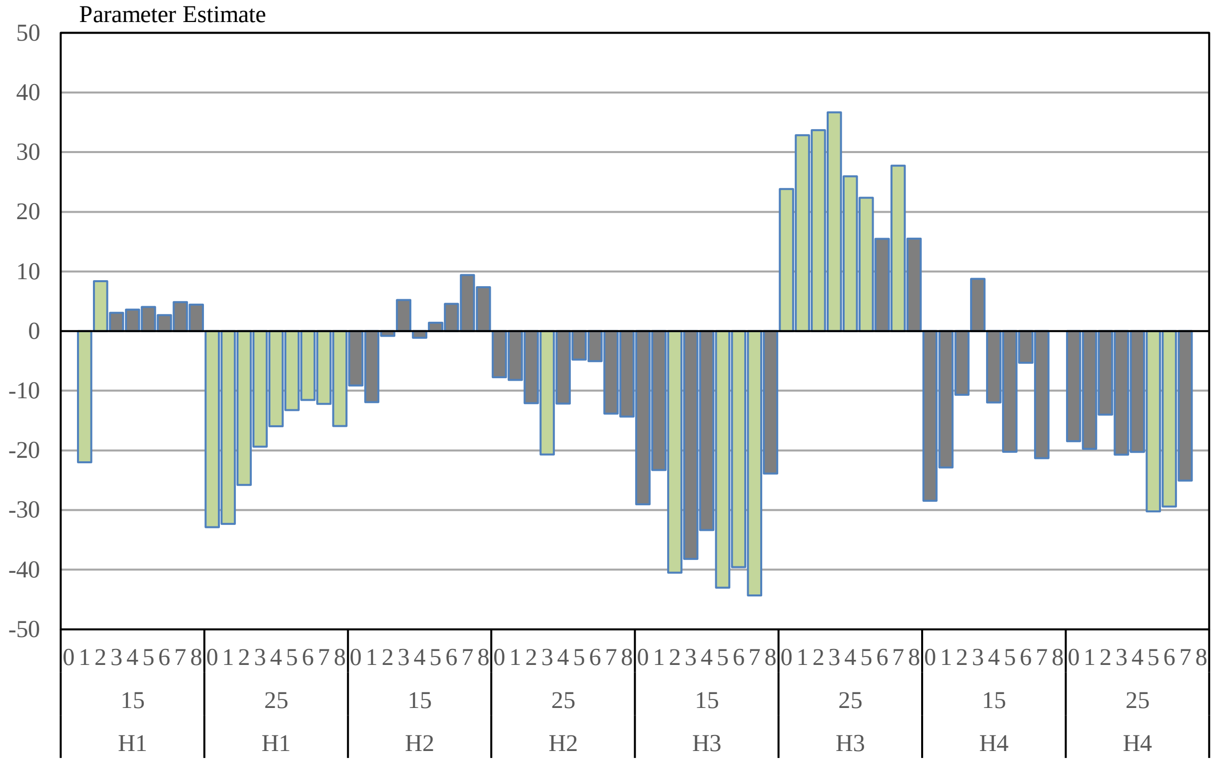


Figure 8: Effect of Pre-Storm Share of Tract Population with Past Due (30+ days) Bills on Post-Storm Equifax Risk Score



Source: Author's estimates; Risk Score, bank card balance, and bank card limit from Federal Reserve Bank of New York Consumer Credit Panel/Equifax
Note: Light gray bars are statistically significant (*p* < 0.1)

Figure 9: Effect of Pre-Storm Tract Bank Card Utilization Rate on Post-Storm Equifax Risk Score



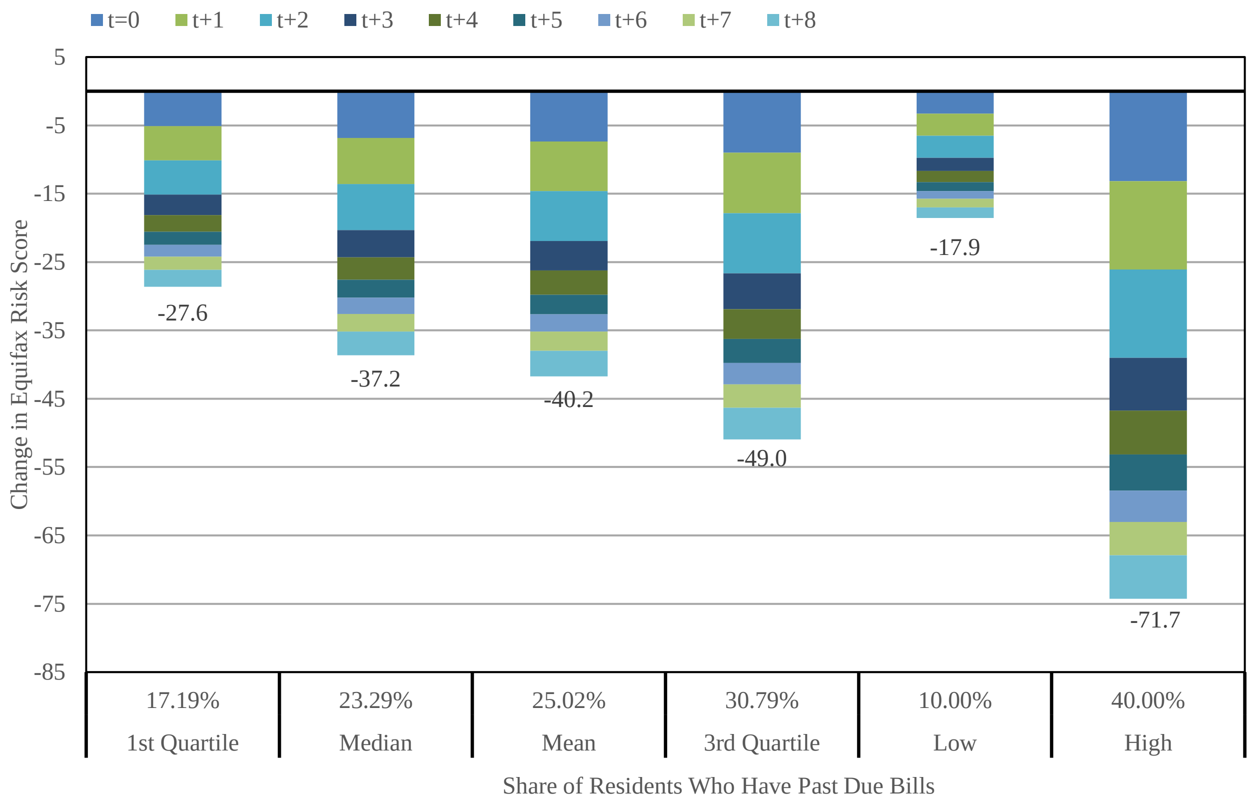
Source: Author's estimates; Risk Score, bank card balance, and bank card limit from Federal Reserve Bank of New York Consumer Credit Panel/Equifax

Note: Light gray bars are statistically significant ($p < 0.1$)

Figure 10: Total Effect of Pre-Storm Share of Tract Population with Past Due (30+ days) Bills on Post-Storm Equifax Risk Score

Source: Author's Estimates; Risk Score and Past Due Bills from Federal Reserve Bank of New York Consumer Credit Panel/Equifax

Figure 11: Total Effect of Pre-Storm Tract Bank Card Utilization Rate on Post-Storm Equifax Risk Score



Source: Author's estimates; Risk Score, bank card balance, and bank card limit from Federal Reserve Bank of New York Consumer Credit Panel/Equifax