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Damages Done: The Longitudinal Impacts of Natural Hazards on Wealth Inequality in the United States

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ABSTRACT

This study investigates a largely ignored contributor to wealth inequality in the United States: damages from natural hazards, which are expected to increase substantially in coming years. Instead of targeting a specific large-scale disaster and assessing how different subpopulations recover, we begin with a nationally representative sample of respondents from the restricted, geocoded Panel Study of Income Dynamics. We follow them through time (1999–2013) as hazard damages of varying scales accrue in the counties where they live. This design synthesizes the longitudinal, population-centered approach common in stratification research with a broad hazard-centered focus that extends beyond disasters to integrate ongoing environmental dynamics more centrally into the production of social inequality. Results indicate that as local hazard damages increase, so does wealth inequality, especially along lines of race, education, and homeownership. At any given level of local damage, the more aid an area receives from the Federal Emergency Management Agency, the more this inequality grows. These findings suggest that two defining social problems of our day – wealth inequality and rising natural hazard damages – are dynamically linked, requiring new lines of research and policy making in the future.

KEYWORDS: wealth inequality; social inequality; natural hazards; disasters; FEMA aid.

Social movements such as Occupy Wall Street, presidential candidates such as Bernie Sanders, and popular books such as Thomas Piketty's *Capital* have all called attention to rising wealth inequality in the United States. This type of inequality, it is argued, constitutes a more fundamental social problem than its close affiliate – income polarization – because the assets that comprise one's wealth are more tightly tied to long-term stability, family well-being, and inter-generational transmission of inequality (Shapiro 2017). To explain today's wealth inequality, researchers commonly highlight not only rising income disparities and differential returns on investments but also changes in federal policies that regulate how incomes, investments, inheritances, and interest rates contribute to the differential accumulation of assets (Alvaredo et al. 2013; Charles and Hurst 2002; Keister 2014; Volscho and Kelly 2012). In the present study, we acknowledge these factors but highlight and investigate another important but largely ignored contributor: damages from natural hazards.

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There are a number of reasons why scholars, policy makers, and the public should care about damages from natural hazards and their effects on social inequality. The first involves their scale, scope, and trajectory. In 2015 alone (the latest year of complete data) U.S. insurance companies and the Federal Emergency Management Agency (FEMA) distributed 30 *billion* dollars in recovery funds to areas damaged by adverse weather and geological events. And, with recent Hurricanes Harvey, Irma, and Maria, 2017 became the most costly hurricane season on record in the United States, with these three storms causing more than 260 billion dollars in direct damages (NOAA 2018). These and other major disasters have attracted a good deal of attention. However, we contend that to focus strictly on extreme events can be misleading, because damages from natural hazards are far more chronic and geographically pervasive than most of us realize. Data from federally funded sources (described below) indicate that since 2000, 99.7 percent of all U.S. counties have experienced notable property damage from natural hazards (Hazards and Vulnerability Research Index [HVRI] 2016).[1] They also show that over the past half-century, the average U.S. county has experienced damages from five events *per year* totaling millions of dollars annually (HVRI 2016), with researchers forecasting even higher costs in the future. Even under the most optimistic scenario – where the frequency and intensity of natural hazards remain unchanged from past decades – studies predict that direct damages to property will double to quadruple current levels by 2050, net of inflation and despite new warning systems, improved building codes, and other mitigation efforts implemented to slow otherwise rising costs (Preston 2013; see also Pielke et al. 2008).

This chronic, pervasive, and increasingly expensive reality of natural hazards makes them an important social problem in their own right. When they interact with social inequality, the problem only compounds. Sociological research on disasters has long documented how less-privileged residents often suffer losses in economic as well as social and cultural resources after hazards hit, while more-privileged residents, by contrast, tend to recover more quickly and may even benefit financially (Brunsma, Overfelt, and Picou 2010; Elliott and Pais 2006; Fussell and Harris 2014; Pais and Elliott 2008). Prior research also points out how these inequalities are not simply a function of physical damages incurred but also of how recovery resources are designed and distributed in ways that ripple forth unequally throughout affected areas (Dahlhamer 1994; Dash, Peacock, and Morrow 1997; Gotham and Greenberg 2014; Tierney 2005).

These dynamics bring us to another reason why we should care about the ongoing and often hidden effects of natural hazard damages on wealth inequality. Namely, if a fundamental conclusion of recent disaster studies is that damages alone are not the issue but rather their intersection with existing social inequalities, then the problem is much more pervasive and ongoing than either stratification or disaster research currently acknowledges. The reason lies in the dual ubiquity of natural hazard damages and social inequalities. This dual ubiquity, we think, calls for a new, complementary way of investigating the intersection of social stratification and natural hazards throughout the United States. Instead of targeting a specific event and investigating how different subpopulations recover, we begin with a nationally representative sample of individuals. We then follow these individuals through time as natural hazards inflict varying amounts of property damage to the counties where they live. This design synthesizes the longitudinal, population-centered approach common in studies of wealth inequality with the hazard-centered focus of disaster research in a way that integrates the two more deeply and directly than in prior research.

To proceed, we first review current explanations for wealth inequality, examining how hazard damages and related policies might contribute. We then empirically evaluate these contributions using longitudinal, individual-level data from the geocoded, restricted-access version of the Panel Study of Income of Dynamics (PSID) for the period 1999–2013. To these data we link county-level data on

1 Assessments of natural hazard impacts sometimes distinguish between "damages" and "losses." "Damages" refers to the destruction of physical assets, most notably property; "losses" refers to the reduction of flows of benefits, most notably income (Brusentsev and Vroman 2016). The empirical focus in this study is on damages, though the two tend to overlap.

natural hazard damages from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), as well as census data at the tract and county level to control for key background factors. Thereafter, we add information on local FEMA aid to assess the unintended consequences of varying levels of assistance. Results from longitudinal models indicate that as local hazard damages increase, so too does wealth inequality, especially along the lines of race, education, and homeownership. Results also indicate that the more funds areas receive from FEMA, the more this wealth inequality increases. We conclude with implications for future research and policy.

WEALTH INEQUALITY

U.S. wealth inequality is substantial, has been increasing over recent decades, and has detrimental effects on other forms of social stratification, such as educational attainment, physical health, and emotional well-being (Hansen 2014; Keister 2014; Shapiro 2017). Commonly defined as the value of assets minus liabilities, wealth is primarily accumulated through three means: wages and other forms of income that accrue over the short term; returns on investments that accrue over the longer term; and, intergenerational transfers that accrue across life times (Alvaredo et al. 2013; Charles and Hurst 2002; Fox 2016; Keister 2014; Oliver and Shapiro [1995] 2006; Volscho and Kelly 2012). With respect to income, research shows that contemporary boards of public companies determine the salaries of their top executives based on short-term changes in corporate stock prices and based on the wages of executives at comparator companies (Keister 2014; Volscho and Kelly 2012). This combination has driven the compensation of top earners upward as businesses continue to outsource lower skill jobs and labor unions continue to decline in both number and influence. The result has been stagnant and even declining incomes – and thus wealth potential – for many middle- and low-wage workers in ways that extend beyond the top 1 percent to affect all workers and families in increasingly unequal ways (Keister 2014; Kristal 2010; Volscho and Kelly 2012).

Similar changes are also polarizing investment returns. Research shows that individuals with substantial capital to purchase high-end stocks are profiting at disproportionate rates relative to those without such capital to invest (Volscho and Kelly 2012). Additionally, the appreciation of real estate markets continues to be highly inequitable, bringing divergent returns to more and less advantaged areas and residents in ways that accumulate over time. In this way, inequalities of the past not only play forward to influence those of the present and future, they also link with historical inequalities of race that concentrate in space as well as time (Fox 2016; Gotham 2014; Shapiro 2017). These unequal returns on housing investments not only contribute to wealth inequality, they also dovetail with increasingly unequal intergenerational transfers of assets (Alvaredo et al 2013; Charles and Hurst 2002; Fox 2016). Research shows that such transfers from parents to children are now growing steadily and unequally not just after parents' deaths but throughout their lives (Hansen 2014). These transfers, like differential investments and returns, do not just benefit many middle- and upper-class families, they also leave many less-privileged members of society vulnerable to schemes and strategies that reduce what little wealth they have or hope to have (Charles and Hurst 2002; Fox 2016; Oliver and Shapiro [1995] 2006). This brings us to the liability side of wealth inequality: debt.

Recent studies emphasize how interest rates on loans have become more unequal over time, further contributing to wealth inequality. Take, for example, subprime mortgages disproportionately granted to low-income and minority home-buyers (Fisher 2009; Rugh, Albright, and Massey 2015). Higher rates associated with these loans make them more difficult to pay off, and the problem compounds dramatically when payments are missed. This type of financial strain became widely evident with the housing crash and widespread foreclosures of the late 2000s, further eroding what little wealth many less-privileged Americans possessed. This sort of inequality in liability interest rates continues daily in many marginalized communities, where formal banks are absent and payday loan establishments thrive by charging less-affluent borrowers considerably higher rates than those available to other Americans in more privileged areas (Graves 2003).

The overarching point is that wealth inequality is occurring at both the top and bottom segments of U.S. society in highly divergent ways. It is also extending into the realm of politics and government, where recent changes in tax policies, financial regulations, and redistributive programs have contributed to, and in many ways institutionalized, the ongoing bifurcation of wealth (Alvaredo et al. 2013; Keister 2014; Kristal 2010; Volscho and Kelly 2012). The most obvious of these ways involve policies directly linked to income and wealth, but our contention is that they also encompass how U.S. society deals with the high and rising cost of natural hazard damage.

NATURAL HAZARDS AND WEALTH INEQUALITY

The types of natural hazards we highlight in this study are those that damage property, or material assets. Some of these assets are public, such as roads, schools, levees, and other infrastructures built and maintained with taxpayer dollars. And some of these assets are private, such as residences, businesses, and other physical possessions. Until the mid-1700s, political leaders historically responded to such damages by declaring them to be acts of God and thus outside the realm of government control and responsibility. With the rise of the modern state, however, things began to change, as Dynes (1997) explains in his study of the 1755 Lisbon Earthquake, which was the first to evoke a coordinated state emergency response and comprehensive plan for reconstruction. Since that time, governments have expanded and institutionalized these responses, not simply because they now seem the right thing to do, but also because it helps to maintain and expand their own institutional legitimacy.

In the United States, these efforts date back to at least 1803 when Congress voted to waive duties and tariffs on imported goods in Portsmouth, New Hampshire, to help property owners and the commercial elite recover from massive fires (Davies 2014). Not long after, in 1811 and 1812, Congress donated free public lands to property-holding residents displaced by a series of powerful earthquakes in New Madrid, Missouri; and in 1827, it allocated taxpayer funds for immediate relief and long-term recovery of private residences and businesses in Alexandria, Virginia, following fires there. According to Dauber (2005), these public interventions established a *de facto* policy of federal disaster assistance as early as the 1830s, which then set the precedent for massive government outlays following the 1906 San Francisco earthquake and great Mississippi floods of 1927 and 1937. It was not until 1950, however, that Congress codified such assistance into law with the federal Disaster Relief Act. Today, assistance under this act includes not just helping with temporary housing and other forms of immediate relief but also administration of hazard insurance programs, rebuilding damaged infrastructure, and providing low-interest loans to private property holders and business owners, nearly all of which are aimed at restoring (and often expanding) local property and wealth-generation capacities in affected areas.[2]

In these efforts, FEMA now redistributes billions of dollars of taxpayer money annually to hazard-stricken communities, and the National Flood Insurance Program (NFIP) has grown to become the single, largest hazard insurer in United States, with more than five million policyholders claiming more than a trillion dollars in coverage on properties that would otherwise go mostly uninsured. In addition, there is also the private insurance market, which reflects the market decisions and profit motives of large publicly traded companies. These companies now insure more than $13 trillion in exposed residential and commercial properties along the Atlantic and Gulf coasts alone, where hazard damages have been historically high and continue to rise (AIR Worldwide 2016). As we consider what these dynamics mean for wealth inequality, it is important to consider broadly how public and private hazard assistance work.

2 As part of federal disaster assistance, the Small Business Administration (SBA) extends loans through its Home Disaster Loan Program. These loans fall into two broad categories: personal property loans and real property loans. The former can cover items such as personal cars, clothes, and furniture and is currently capped at $40,000 per family; the latter provides up to a fixed amount (currently $200,000) to an eligible homeowner to repair his or her primary residence to pre-disaster condition (Brusentsev and Vroman 2016). The SBA describes both types of loans as low interest, but interest rates can vary by applicants' income, and payback periods can be relatively short.

Both forms of assistance are designed primarily to restore property, or wealth, which is presumed to help re-establish individual, family, and community well-being in both direct and indirect fashion. This approach means that those with more property as well as more income with which to insure it are likely to experience significantly different recoveries than those with less property and income. For example, more privileged residents and property owners may gain access to new resources and opportunities that include new business prospects supported by federal recovery investments; low-interest loans; significant payouts from public and private insurance policies; and, opportunities to transfer wealth to adult children through sharing of financial windfalls or property restoration and investment (Gotham 2014). By contrast, for less privileged residents and non-property owners, local damages are more likely to trigger financial liabilities as a result of experiencing an increased likelihood of losing one's job (Elliott and Pais 2006); having to move (Elliott and Howell 2017); paying higher rents due to reduced housing stock (Vigdor 2008); and, dipping into already meager savings to compensate for such expenses. In some cases, government recovery programs have even suspended legal protections for low-wage workers to speed up recovery and get local economies "going again."

After Hurricane Katrina, for example, the federal government directed billions of dollars of aid to the Gulf Coast as it simultaneously suspended wage regulations, worker safety laws, and affirmative action considerations for businesses receiving federal contracts. The polarizing effects of these initiatives were compounded by federally funded contracts that paid good money to businesses that then sub-contracted the actual work to companies that paid comparatively lower wages, often to undocumented migrants who were sometimes victims of wage theft, or lack of payment for their labor (Fussell 2009; Fussell 2011). Although not all local workers may experience such mistreatment first-hand, the indirect effects can nonetheless ripple forth to suppress earnings and opportunities for workers throughout the affected area. In these ways, natural hazards can trigger public and private assistance programs that can become either resources or liabilities, depending on the social status of those involved, as well as the scale of local damage and assistance. The research design below outlines how we will go about investigating these dynamics from a population-centered approach.

RESEARCH DESIGN

Most research on natural hazards' interface with social stratification uses a case study approach to analyze patterns and processes of inequality after an extreme event. By contrast, we develop and apply a longitudinal, population-centered approach. This novel design links data from a large, nationally representative sample of adults to information on local damages attributed directly to natural hazards. With these linked data, we test the hypothesis that, over time, such damages influence wealth trajectories differently for different segments of the population, net of a wide array of other individual, family, household, and contextual factors. Statistically, this approach means looking for moderating, or interaction, effects of local hazard damage on individual wealth trajectories by existing dimensions of socioeconomic inequality. We focus on three such dimensions emphasized in prior research: race, education, and homeownership.

We also investigate two ideas related to the above discussion. First, we test the hypothesis that unequal trajectories in wealth remain noteworthy even after controlling for the amount of money that individuals invest in private insurance. In this way, we assess the extent to such inequity implicates not just unequal insurance investments but more general systems of recovery. Second, we test the hypothesis that the amount of federal assistance given to an area by FEMA, net of actual damage incurred, also influences local wealth trajectories in an unequal fashion. If confirmed, this finding would imply that the way that federal hazard assistance is structured and distributed is not neutral, but in fact, contributes to wealth inequality in unexpected and largely hidden ways.

DATA

The primary data for our analyses come from the restricted-access, geocoded Panel Study of Income Dynamics (PSID), which began tracking a representative sample of U.S. families in 1968. Through time, the survey has continued to follow those families as well as families these original ones have spun off (e.g., through divorce, remarriage, and aging children). In 1999, the survey added a subsample of new families to account for the influx of new immigrant groups over recent decades. We start with this year, 1999, in order to include robust numbers of Latinos, Asians, and other race individuals alongside whites and blacks. We use the restricted-access, geocoded version of the survey in order to link respondents to their neighborhood and county locations over time, thereby offering greater statistical control for confounding contextual factors. All respondents were interviewed at two-year intervals, from 1999 to 2013, the last year of data currently available.

To these PSID respondents we link information from three other databases. For hazard damages, we utilize the Spatial Hazard Events and Losses Database for the United States, Version 15.2 (SHELDUS, HVRI 2016). SHELDUS is a government-funded database maintained by the Hazards and Vulnerability Research Institute, which assembles data on fatalities and property damages associated with eighteen types of natural hazards, including hurricanes (the most costly), floods (the most common), severe storms, tornadoes and wildfires. SHELDUS provides this information for every county in the United States back to 1960, drawing data principally from the National Climatic Data Center, the National Geophysical Data Center, and the Storm Prediction Center. The database includes information on all loss-causing events from 1996 to the present (Gall, Borden, and Cutter 2009). SHELDUS also includes start and end dates for each event, which we use to align data to each respondent at the county level for each wave of the PSID.

For contextual data at the tract- and county-level, we use the 2000 U.S. Decennial Census Long Form as well as the 2006–2010 and the 2011–2015 American Community Survey 5-year Summary Files (ACS-5) (U.S. Census Bureau 2001; 2011; 2016). From these datasets we linearly impute information on the socioeconomic status of respondents' residential tracts at that start of the respective interview interval, as well as information about the total population and relative urban/rural status of the counties in which they reside (described below). For these imputations, we assign the 2006–2010 ACS data to the year 2008 and the 2011–2015 ACS data to the year 2013.

For county-level FEMA data on federal recovery expenditures (discussed below) we draw from the FEMA Public Assistance Funded Projects Summary - Open Government Initiative (FEMA 2016).

MEASUREMENT

Wealth Trajectories

Consistent with prior research, we measure wealth using the PSID's wealth variable, which sums, at the immediate family level, reported values of all checking and saving accounts, real estate holdings (including equity), vehicles, farms, businesses, stocks, annuities/IRAs, and other savings; it then subtracts the sum of all reported debts. This is done for each interview year. We adjust all years to 2012 dollars to control for inflation. Means are displayed alongside descriptive statistics for other variables in Table 1; they range from $172,000 in 2001 to $329,000 in 2009, just before the housing crash.[3] Statistically, these means are inflated by the very wealthy. Median values over the same period range from just $21,000 to $30,000. To adjust for this rightward skew in our statistical models (described below), we investigated various numeric transformations and selected the one that provided the closest approximation to a normal distribution. This transformation adjusts all values of wealth upward by the global minimum to ensure no negative values (resulting from debt); it then takes the square root of that value. For all examples and graphical displays, we convert results back to un-transformed dollars for ease of interpretation.

3 To ensure the housing crash is not responsible for our findings, we ran supplemental analyses that incorporated a dummy variable denoting the pre- versus post-crash year of 2008. This variable was not statistically significant in any models, nor did it meaningfully change results presented. The supplemental results are available upon request.

Table 1. Descriptive Statistics for Respondents by Last Year of Respective Two-Year Interview Interval

	2001	2003	2005	2007	2009	2011	2013
Wealth							
Total ($000s)	172.46	188.19	213.44	286.49	328.68	273.31	276.03
Hazard Damage and Federal Aid							
Direct Hazard Damage in Residential County ($millions)	26.30	26.45	47.55	111.43	19.69	17.90	61.16
FEMA Aid to Residential County ($millions)	5.12	7.52	5.82	29.16	10.73	2.07	26.29
Individual-Level Factors							
Race							
White	0.59	0.59	0.59	0.59	0.59	0.59	0.59
Black	0.31	0.31	0.31	0.31	0.31	0.31	0.31
Latino	0.06	0.06	0.06	0.06	0.06	0.06	0.06
Other	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Foreign Born	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Education (years)	13.08	13.08	13.08	13.08	13.08	13.08	13.08
Age (years)	45.21	47.22	49.17	51.21	53.20	55.22	57.20
Family-Level Factors							
Married	0.69	0.68	0.67	0.66	0.64	0.62	0.60
Number of Children at Home	1.09	1.00	0.91	0.80	0.69	0.56	0.47
Household-Level Factors							
Renter	0.27	0.25	0.24	0.25	0.24	0.26	0.26
Moved	0.20	0.23	0.21	0.22	0.19	0.18	0.17
Wealth in 1999 ($000s)	145.23	145.23	145.23	145.23	145.23	145.23	145.23
Neighborhood-Level Factors							
Tract Socioeconomic Status	−0.06	−0.06	−0.06	−0.05	−0.05	−0.05	−0.06
County-Level Factors (other than Hazard Damage)							
Total Population (000s)	878.11	888.78	913.95	918.26	914.64	927.59	926.91
Urban/Rural Scale (1=most urban; 9=most rural)	2.34	2.34	2.33	2.34	2.34	2.35	2.35
Property Insurance							
Yearly Insurance Premiums ($000s)	1.43	1.72	1.73	1.55	1.46	1.48	1.56
N				3,408			

Note: For example, for 2001 wealth corresponds to reported wealth in 2001, but direct hazard damage, FEMA aid, and information about residential moves reference to the period 1999-2001.

Natural Hazard Damages

Property damages from natural hazards are measured at the county level using SHELDUS's variable for direct damages to (non-crop) property. These values do not include more general disruptions to commerce or production, nor do they include fire assistance grants for mobilizing equipment and personnel. Thus, they provide a conservative measure of direct, local damages to property (Gall, Borden, and Cutter 2009). To align this variable temporally with longitudinal data in the PSID, which begins its interviews in March of each odd year, we define the hazard period as extending from March 1st of the previous interview year to February 28th of the respective interview year. In this way, local hazard damages during the two-year interval are matched to reported values of other variables, including wealth, at the end of that interval. Due to the variable's extended range and rightward skew, we use its natural log in all models after standardizing all values to 2012 dollars.

Other Key Variables

To assess wealth inequality over time, we focus on three main dimensions of social stratification. One is *race*, which is measured based on self-reports that are coded into four mutually exclusive categories: white, black, Latino (or Hispanic), and other (primarily Asian). Another dimension is *education*, which is measured as the total years of school completed by the time of the respective interview. And, the third dimension is *homeowner status*, which is measured according to whether one rents or owns their primary residence (1= rent; 0= own).

To assess the mediating influence of *private insurance investments*, we compute a continuous variable that sums all premiums paid for home and automobile coverage during the interview year, adjusted to 2012 dollars. This variable offers a proxy for the amount of private recovery capital a household *might* access to cover various costs and to restore lost property or wealth. Measuring actual insurance payouts, rather than premiums, would require information about the amount and type of coverage retained, required deductibles, and the types of natural hazards (not) covered by respective policies – information not currently available in the PSID.[4]

To assess *federal assistance*, we total the amount of funding provided to each county directly through FEMA during each interview interval, not including fire assistance grants for mobilizing equipment and personnel. This type of (non-fire) aid typically becomes available only if local hazard damages for a specific event financially exceed local and state government capacities. Once federal assistance is requested and approved, the president declares a major disaster, and FEMA drafts a State Agreement that indicates the period of the disaster, areas eligible for assistance, cost-sharing provisions with the state, and types of assistance (FEMA 2010). Immediate Needs Funding (INF), for example, is earmarked for the most urgent work required immediately after an event. Individual and Household Program (IHP) funding targets longer term needs, including local housing vouchers, temporary units, and financial grants to alleviate damage-related needs and expenses not covered by other assistance programs or private insurance. These grants can include financial assistance for housing repairs and replacement of personal property as well as certain uninsured personal needs (e.g., medical or funeral or other personal expenses). For cases where natural hazards damaged property but did not result in FEMA aid, we set the value of this continuous variable to zero.

Control Variables

In our statistical models (described below), we measure and include a number of additional individual, family, household, tract, and county level controls. At the individual level, we measure *age* in years, with the expectation that it correlates positively with wealth.[5] We also measure *foreign birth* as a simple categorical variable (1= foreign born; 0= U.S. native), to control for differences in wealth trajectories by nativity. At the family level, we measure and include two variables. One is *marital status*, which in the PSID also includes permanently co-habiting couples (1= married or permanently cohabiting; 0= otherwise). The other is *number of children* under the age of 18 living in the household. At the household level, in addition to homeowner status, we also measure whether a respondent moved during the two-year period preceding the interview (1= yes; 0= no).

At the tract level, we measure the *socioeconomic status* of a respondent's (primary) residential neighborhood at each interview as a multi-item index. This index is computed as a scalar variable that includes three measures at the level of the census tract: median income; proportion of adults with at least a bachelor's degree; and, the portion of adults currently employed. These values are linearly interpolated from the census data described above, which means that values can change from wave to

4 A reviewer noted that premiums are often higher for the same insurance in marginalized neighborhoods, despite providing the same or worse coverage. This tendency would most likely render estimated effects of this variable statistically conservative because it would not account for this or other types of heterogeneity in the ratio of premiums to payouts.

5 The relationship between wealth and age is not curvilinear as it is for income, because wealth can accumulate via investments even in retirement. Hence, a quadratic age term is not significant in our models and thus is not included.

wave, even for non-movers, due to changes in the socioeconomic status of their neighborhood over time.

At the county level, we measure and include a variable for *total population* to control for the overall size and development of a respondent's county of residence. We also measure the relative level of local development using an index of *rural-urban* status codified in the 2013 U.S. Department of Agriculture Rural-Urban Continuum codes. These codes comprise a 9-point ordinal scale that distinguishes counties by metropolitan status, total population, degree of urbanization, and adjacency to nearby metropolitan areas. Higher values indicate more rural, or marginal, status within the U.S. settlement system; lower values indicate more urban, or central, status. Both county-level variables help to control for broad variation in the number of people and amount of property at risk of damage from local hazards.

SAMPLING AND MODELING

Unlike most surveys, the PSID collects data for every member of sampled households, which means that researchers can choose who they include in their analyses. This choice is important for the present study because wealth is measured at the family level (within households), which means that including everyone risks analyzing non-independent cases. Historically, researchers have solved this problem by selecting the "head" of household. Yet in the PSID, heads of household are designated to be an adult male, if one is present. This convention means that when researchers select only "heads" of households, they effectively mix their samples to include all men – single, married and cohabiting – but only single women and those in same-sex households, thereby biasing results.

Thus, we choose to estimate all models separately for men and women – one per household. However, given similarities in results across genders (available upon request), we choose to display and discuss only those derived from the female sample. This sample includes all adult females (one per household) present in the PSID at the beginning and end of the study period (1999 and 2013, respectively) and who participated in at least four of the seven interview waves.

To assess the impacts of natural hazard damages and FEMA assistance on wealth inequality, we use panel regression models to estimate changes and correlations over respective waves of data comprising the 1999–2013 period. In these models, hazard damages and FEMA aid are each allowed to accumulate over time, as is wealth. Supplemental analyses with non-cumulative measures of local damage and aid from one (two-year) interval to the next yield substantively similar results to those reported below. To control for the fact that wealth (and debt) tend to compound, each model includes the respondent's starting value of wealth in 1999 as a control, as well as a continuous measure for the respective survey year, ranging from 1 in 1999 to 14 in 2013. For all other variables, we standardize values around a global mean of zero for the entire period in order to render results more consistent across models.

For estimation purposes, we use random effects specification, which reduces omitted variable bias while also allowing for inclusion of time-invariant factors, such as race. These are the models we report below. To test their sensitivity to alternative specifications, we re-estimated all models using a hybrid approach to apply fixed effects for time-variant factors of interest – local hazard damage and FEMA aid – and random effects for all other factors. Results confirm that the bulk of the reported effects for hazard damage and FEMA aid occur for given individuals over time, rather than across individuals, thereby lending further support to findings and inferences presented below.

RESULTS

Earlier we reported that since 2000 nearly all U.S. counties have experienced property damage from natural hazards. Table 1 now shifts analysis to the individual level, using respondents in the nationally representative PSID. Results show that the average county-level damage for respondents ranged from \$237 million during the first interview interval, 1999–2001, to \$1.15 billion during 2005–07. Over the entire study period, 1999–2013, some individuals reached even higher cumulative values, which occurred not just because of major disasters such as Hurricane Katrina in 2005 but also because of repeated damages over time. Residents of Linn County, Iowa, for example, experienced major flooding in 2008, followed by recurrent flooding thereafter, which eventually resulted in approximately $10 billion in cumulative damages by 2013.

Natural Hazard Damages and Wealth Inequality

Turning to multivariate analyses, Table 2 reports models predicting wealth in 2013 controlling for wealth in 1999, rendering results effectively models of change. Model 1 offers a baseline assessment with only hazard damage used as a predictor. Here, results reveal a strong, positive correlation (3.47; $p < 0.05$), indicating that as local hazard damages increase, average wealth does too. Model 2 confirms this general correlation (2.86; $p < .05$) even after controlling for a wide array of background factors.

Next we examine racial inequality by interacting race with hazard damage, net of other background factors. Results in Model 3 show that the positive correlation found in Model 2 holds only for whites, not for respondents of color. Specific calculations, for example, indicate that whites who lived in counties with very little hazard damage ($100,000) over the 1999–2013 period gained, on average, $26,000 in wealth. By comparison, similar whites living in counties that experienced $10 billion in hazard damage gained nearly five times that much, or $126,000. For blacks, results cut the other way. Those who lived in counties with just $100,000 in hazard damage gained an estimated $19,000 on average; whereas those living in counties with $10 billion in hazard damage *lost* an estimated $27,000. For Latinos, these numbers are $72,000 versus *negative* $29,000. And, for other race (mostly Asian) individuals, the numbers are $21,000 versus *negative* $10,000. Again, these differences within and between racial groups are statistically significant even after controlling for a wide array of background factors including respondents' age, education, nativity, family status, homeownership, residential mobility, neighborhood status, as well as their county's population and urbanity. To display these results graphically, Panel A of Figure 1 uses results from Model 3 to plot estimated wealth in 2013 by local hazard damages, holding all other variables constant at their sample means, including starting wealth in 1999.

Next, we test for the moderating influence of education. As with race, results in Model 4 show that on average and all else being equal, the relationship between local hazard damages and individual wealth diverges significantly along educational lines, as evidenced by the interaction coefficient for years of schooling completed (5.98, $p < 0.05$). Panel B of Figure 1 displays this divergence for three common values of this variable – 10 years, 12 years, and 16 years – all else being equal. Here, we see that compared with college-educated counterparts who lived in areas with little natural hazard damage, those who lived in counties with higher levels of damage accumulated more wealth by 2013. Conversely, as hazard damages increased, high school dropouts accumulated less wealth.

Finally, we test for the moderating influence of homeownership. Results in Model 5 show that, all else being equal, homeowners' wealth increases with local hazard damages; whereas the opposite is true for renters. These results are reflected in the negative interaction coefficient for renters (-7.86, $p < .05$) and are displayed in Panel C of Figure 1, all else being equal.

Overall, these findings support the hypothesis that natural hazard damages are contributing to wealth inequality. Additionally, supplemental analyses (available upon request) indicate that while inequality is occurring along other lines (i.e., neighborhood SES) the most notable inequity is along the lines of race, education, and homeownership. To assess the effects of these inequalities simultaneously, Model 6 includes all three in the same model. Results indicate that each remains statistically significant even after controlling for the other two, implying their polarizing effects are cumulative. To illustrate, Figure 2 graphs results of Model 6 for two types of individuals: a white, college-educated homeowner; and a black, 10^{th} grade-educated renter. All other factors in the model are held constant, including starting wealth in 1999. Here it becomes even clearer that the bifurcating effect of local hazard damage is operating at both ends of the socioeconomic spectrum in highly unequal ways.

Table 2. Coefficients from Longitudinal Random Effects Models Predicting Wealth, Interval to Interval, 1999-2013

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*	*Model 7*
Hazard Damage, Logged	3.57 (1.27)*	2.86 (1.26)*	8.61 (1.61)*	3.04 (1.26)*	6.14 (1.42)*	8.56 (1.67)*	8.45 (1.59)*
Individual-Level Factors							
Race							
Black		−19.43 (5.09)*	−18.89 (5.09)*	−19.33 (5.09)*	−19.33 (5.09)*	−18.99 (5.10)*	−17.95 (4.84)*
Latino		−5.11 (9.32)	−3.54 (9.38)	−4.22 (9.33)	−5.50 (9.32)	−4.43 (9.38)	−4.70 (8.93)
Other		−14.14 (10.37)	−14.30 (10.37)	−15.14 (10.37)	−14.14 (10.37)	−15.02 (10.37)	−16.21 (9.86)
Foreign Born		−2.63 (23.85)	−3.34 (23.86)	−0.65 (23.85)	−2.92 (23.85)	−1.82 (23.87)	0.80 (22.76)
Education		13.45 (2.30)*	13.45 (2.30)*	13.49 (2.30)*	13.24 (2.30)*	13.36 (2.30)*	11.97 (2.19)*
Age		12.09 (2.28)*	11.78 (2.28)*	12.02 (2.28)*	12.10 (2.28)*	11.85 (2.28)*	10.20 (2.17)*
Family-Level Factors							
Married		20.08 (3.35)*	20.03 (3.35)*	20.02 (3.35)*	20.17 (3.35)*	20.03 (3.34)*	15.06 (3.21)*
Children at Home		2.25 (1.29)	1.63 (1.29)	1.96 (1.29)	2.13 (1.30)	1.58 (1.29)	1.55 (1.23)
Household-Level Factors							
Renter		−7.06 (3.46)*	−7.26 (3.46)*	−6.52 (3.46)	−7.01 (3.46)	−6.71 (3.46)	−2.43 (3.36)
Moved		4.00 (2.64)	4.25 (2.64)	4.16 (2.64)	4.57 (2.65)	4.60 (2.65)	2.71 (2.51)
Wealth in 1999		141.59 (2.38)*	141.49 (2.38)*	141.50 (2.38)*	141.59 (2.38)*	141.47 (2.38)*	139.50 (2.26)*
Neighborhood-Level Factors							
Socioeconomic Status		8.15 (1.75)*	8.05 (1.75)*	8.08 (1.75)*	8.18 (1.75)*	8.02 (1.75)*	8.18 (1.66)*
County-Level Factors							
Total Population		1.94 (2.41)	1.82 (2.41)	1.89 (2.41)	1.65 (2.41)	1.65 (2.41)	1.15 (2.29)
Urban/Rural Scale		0.14 (1.19)	0.30 (1.19)	0.09 (1.19)	0.14 (1.19)	0.21 (1.19)	0.54 (1.13)

(continued)

Table 2. Coefficients from Longitudinal Random Effects Models Predicting Wealth, Interval to Interval, 1999-2013 (continued)

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*	*Model 7*
Property Insurance							
Yearly Premiums Paid							7.90 (1.11)*
Year (Interview Year - 1998)	3.92 (0.50)*	2.87 (0.61)*	2.72 (0.61)*	2.87 (0.61)*	2.81 (0.61)*	2.74 (0.61)*	3.01 (0.58)*
Interaction Terms							
Hazard*Black			−12.62 (2.34)*			−8.04 (2.52)*	−8.79 (2.37)*
Hazard*Latino			−12.32 (4.34)*			−4.58 (4.59)	−6.02 (4.46)
Hazard*Other			−9.65 (4.34)*			−7.46 (4.37)	−7.86 (4.21)
Hazard*Education				5.98 (1.05)*		4.53 (1.12)*	3.78 (1.06)*
Hazard*Renter					−11.40 (2.28)*	−7.04 (2.43)*	−6.23 (2.28)*
Constant	1747.14 (3.32)	1747.62 (4.64)	1748.75 (4.64)	1747.63 (4.64)	1747.82 (4.64)	1748.49 (4.64)	1748.84 (4.42)
N of Individuals	3,408	3,408	3,408	3,408	3,408	3,408	3,408

*p $<$ .05; two-tailed test.

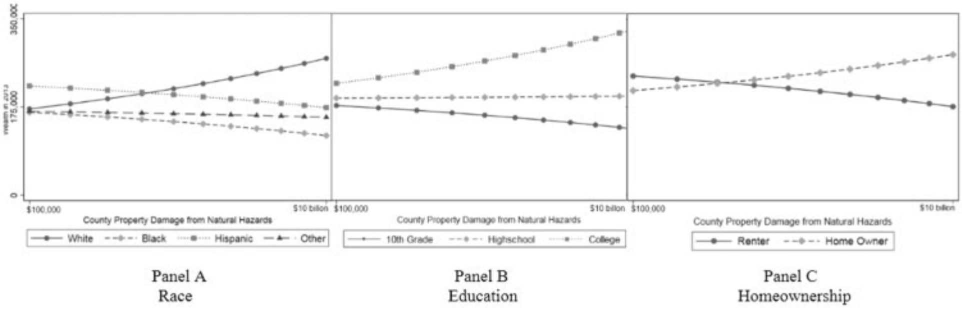

Figure 1. Predicted Wealth by Local Hazard Damage Interacted with Race, Education and Ownership Independently, All Else Equal

Source: Respective interaction models in Table 2 (Model 3 for Panel A; Model 4 for Panel B; and, Model 5 for Panel C). All other covariates in the respective model are held constant at their sample means.

Note: The x-axis is on a log-linear scale; labeled ranges are reported in actual, non-logged dollars to facilitate interpretation.

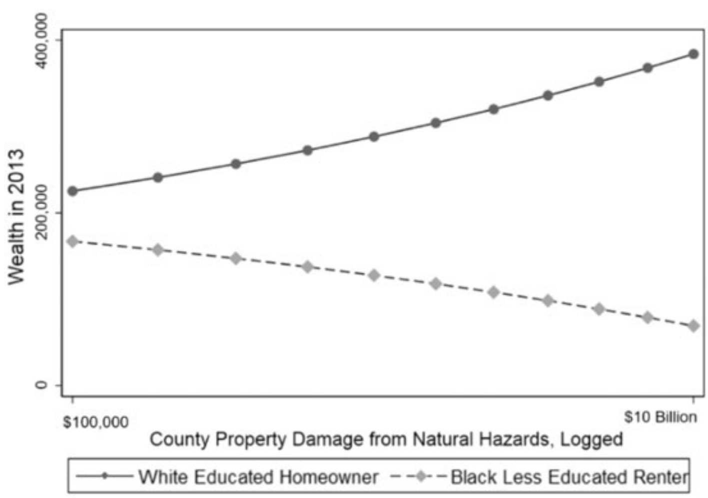

Figure 2. Estimated Wealth by Local Hazard Damage for a White, Educated Homeowner Compared with a Black, Less Educated Renter, All Else Equal

Source: Model 6 of Table 2. All other covariates in the model are held constant at their sample means.

Note: The x-axis is on a log-linear scale; labeled ranges are reported in actual, non-logged dollars to facilitate interpretation.

In the final analyses of Table 2, Model 7 tests whether this inequality remains evident even after controlling for private insurance payments. The logic is that people who invest more in home and auto coverage are better positioned to receive larger payouts and thus grow their wealth when local hazard damages increase. Results support this hypothesis: Insurance payments and wealth trajectories correlate positively and significantly. However, results also show that after controlling for this correlation, the polarizing effects of race, education, and homeownership barely change. In other words, observed patterns in Figure 2 are not explained by differential investments in privately held insurance. Something more systemic is also operating.

Table 3. Coefficients from Longitudinal Random Effects Models Predicting FEMA Aid to County, Interval to Interval, 1999-2013

	County FEMA Aid
County-Level Factors	
Hazard Damage, Logged	0.25 (0.01)*
Total Population	0.07 (0.01)*
Rural/Urban Scale	−0.04 (0.01)*
Year (*Year-1998*)	0.19 (0.00)*
Constant	−0.51 (0.01)
Within-county R^2	0.44
Between-county R^2	0.17
Overall R^2	0.33
N of Individuals	3,408

*p < .05; two-tailed test.

FEMA Aid and Wealth Inequality

Next, we examine whether the amount of county-level FEMA assistance, net of local hazard damage incurred, also bifurcates wealth trajectories. As background, we first examine the correlation between hazard damages and FEMA aid at the county-level over the full 1999–2013 period. Results appear in Table 3 and confirm that as local hazard damages increase, so too does local FEMA aid. However, this correlation is only 0.25 after controlling for a county's total population and relative urban status, thereby reducing concern about multicollinearity. Background analyses also indicate that local FEMA aid, like local natural hazard damage, is much more pervasive than often realized. During the 14-year study period, every respondent in the PSID lived in a county that received at least some FEMA aid. The amount, however, ranged dramatically from under $1,000 to over $7.5 billion. To assess how this variation corresponds to wealth inequality, we re-estimate the full models from Table 2 but now add FEMA aid alongside local hazard damage and private insurance premiums. To test for inequality, we interact FEMA aid with race, education, and homeownership in a manner similar to that above. Results appear in Models 1–3 of Table 4.

Again, results show evidence of inequity along each of the three dimensions of social stratification. That is, the more FEMA aid a county receives, the more unequal wealth becomes between more and less advantaged residents, holding all else constant, including local hazard damages. For example, results in Model 1 indicate that, all else being equal, whites living in counties that received $900 million in FEMA aid during 1999–2013 accumulated $55,000 *more* wealth than otherwise similar whites living in counties that received only $1,000 in FEMA aid. Conversely, blacks living in counties that received $900 million in FEMA aid accumulated $82,000 *less* wealth than otherwise similar blacks living in counties that received only $1,000 in FEMA aid. Similarly, Latinos accumulated $65,000 *less*, and other races (mostly Asians) accumulated $51,000 *less*. Models 2 and 3 show the same general patterns along educational and homeownership lines.

To probe these findings further, we examined interaction terms between FEMA aid and other control variables in Table 4. Results (available upon request) also indicate strong moderating effects for marital and neighborhood status, as well as initial wealth (in 1999). We show results for the latter, initial wealth, in Model 4. These findings indicate that the more wealth one has, the more one benefits from living in a county that receives more FEMA aid, all else being equal, including local damages incurred.

Next, in Model 5, we examine the various moderating influences simultaneously. Results indicate that, net of hazard damage, FEMA aid polarizes wealth along racial, educational, and initial wealth

Table 4. Coefficients from Longitudinal Random Effects Models Predicting Wealth and Considering FEMA Aid, Interval to Interval, 1999-2013

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*
FEMA Aid, Logged	4.29 (1.52)*	0.13 (1.28)	2.28 (1.42)	−0.07 (1.28)	3.70 (1.59)*
Hazard Damage, Logged	2.68 (1.24)*	2.43 (1.23)*	2.55 (1.23)*	2.42 (1.23)	2.59 (1.23)*
Individual-Level Factors					
Race					
Black	−17.10 (4.86)*	−17.87 (4.85)*	−18.38 (4.85)*	−18.14 (4.85)*	−16.95 (4.86)*
Latino	−6.35 (8.89)	−7.39 (8.89)	−5.97 (8.88)	−5.74 (8.88)	−7.33 (8.89)
Other	−15.59 (9.85)	−15.53 (9.86)	−15.37 (9.86)	−15.43 (9.86)	−15.57 (9.85)
Foreign Born	−2.34 (22.77)	−2.23 (22.76)	0.17 (22.75)	−0.68 (22.75)	−2.95 (22.78)
Education	12.08 (2.19)*	12.47 (2.19)*	11.99 (2.19)*	12.07 (2.19)*	12.31 (2.19)*
Age	10.10 (2.17)*	10.41 (2.17)*	10.40 (2.17)*	10.47 (2.17)*	10.16 (2.17)*
Family-Level Factors					
Married	14.95 (3.21)*	14.85 (3.21)*	14.97 (3.21)*	15.10 (3.21)*	14.90 (3.21)*
Children at Home	1.56 (1.24)	2.01 (1.23)	2.10 (1.23)	2.19 (1.23)	1.53 (1.24)
Household-Level Factors					
Renter	−2.83 (3.36)	−2.38 (3.36)	−2.86 (3.36)	−2.80 (3.36)	−2.93 (3.36)
Moved	2.51 (2.51)	2.41 (2.51)	2.57 (2.51)	2.15 (2.51)	2.69 (2.51)
Wealth in 1999	139.52 (2.26)*	139.51 (2.26)*	139.62 (2.26)*	138.38 (2.27)*	138.51 (2.27)*
Neighborhood-Level Factors					
Socioeconomic Status	8.18 (1.66)*	8.32 (1.66)*	8.13 (1.66)*	8.35 (1.66)*	8.24 (1.66)*
County-Level Factors					
Total Population	1.36 (2.29)	1.27 (2.29)	1.25 (2.29)	1.31 (2.29)	1.19 (2.29)
Rural/Urban Scale	0.52 (1.14)	0.38 (1.14)	0.42 (1.14)	0.41 (1.13)	0.44 (1.13)

(*continued*)

Table 4. Coefficients from Longitudinal Random Effects Models Predicting Wealth and Considering FEMA Aid, Interval to Interval, 1999-2013 (continued)

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*
Property Insurance					
Yearly Insurance Cost	8.12 (1.11)*	8.04 (1.11)*	7.98 (1.11)*	8.12 (1.11)*	7.89 (1.11)*
Year	3.08 (0.63)*	3.14 (0.63)*	3.13 (0.62)*	3.18 (0.63)*	3.10 (0.63)*
Interaction Terms					
FEMA*Black	−11.35 (2.30)*				−7.64 (2.45)*
FEMA*Latino	−9.62 (3.70)*				−3.61 (3.93)
FEMA*Other	−8.79 (4.54)				−8.10 (4.55)
FEMA*Education		4.42 (0.98)*			3.07 (1.06)*
FEMA*Own			−8.04 (2.14)*		−3.14 (2.29)
FEMA*Wealth in 1999				5.89 (0.90)*	5.19 (0.91)*
Constant	1748.91 (4.48)	1748.04 (4.48)	1748.27 (4.48)	1747.84 (4.48)	1748.69 (4.48)
N of Individuals	3,408	3,408	3,408	3,408	3,408

*p $< .05$; two-tailed test.

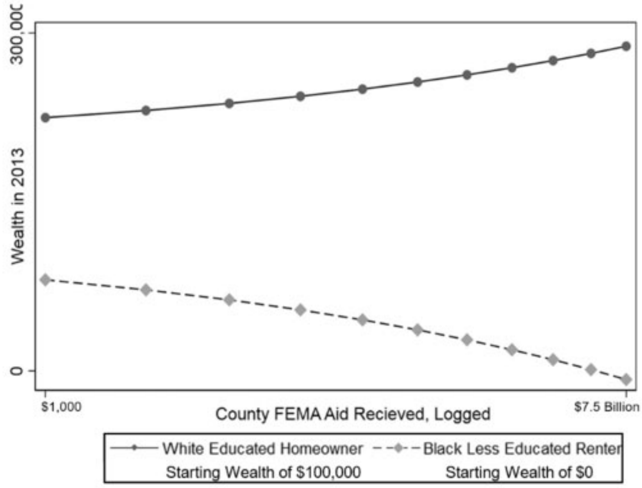

Figure 3. Estimated Wealth by Local FEMA Aid for a White, Educated, Homeowner with Starting Wealth of $100,000 Compared with a Black, Less Educated Renter with Starting Wealth of Zero, All Else Equal

Source: Model 4 of Table 5. All other covariates in the model are held constant at their sample means.

Note: The x-axis is on a log-linear scale; labeled ranges are reported in actual, non-logged dollars to facilitate interpretation.

lines, as evidenced by the statistically significant interaction coefficients. To illustrate, Figure 3 graphs results from Model 5 in a manner similar to that in Figure 2; that is, for two different types of individuals, all else being equal, including this time local hazard damages. Here again we see divergent trajectories. For the black, less-educated renter with zero household wealth in 1999, as local FEMA aid increases, predicted wealth in 2013 steadily declines; whereas, the opposite is true for the white, more-educated homeowner with $100,000 in household wealth in 1999. These results show how, even when controlling for local hazard damage, the more FEMA aid areas receive, the more polarized wealth becomes across already unequal individuals.

CONCLUSION

Wealth inequality in the United States is historically high and rising. Academic research shows that this development is eroding the well-being of the average American (Hansen 2014; Keister 2014). Public opinion polls report that most Americans consider this trend to be unfair (Gallup 2015). And, some politicians have declared it *the* moral issue of our time (Sanders 2017). In studying this social problem, scholars have highlighted market forces, government regulations, and tax policies linked directly to income, investment returns, inheritance, and high-liability interest rates (Alvaredo et al. 2013; Keister 2014; Kristal 2010; Volscho and Kelly 2012). We agree that these factors are important. However, findings from the present study indicate that natural hazard damages also play an important, growing, and largely hidden role, especially along the lines of race, education, and homeownership. These findings are disconcerting because such damages are widespread; they are projected to increase dramatically over coming years; and, FEMA aid – as currently administered – appears to exacerbate the problem.

The broader implication is that two major social problems of our day –wealth inequality and rising costs of natural hazards – are connected in ways that involve not just how we develop and administer policies related to incomes and finance but also environmental hazards.

So what are we to do? As scholars, we must continue to research these connections to confirm findings reported here and to better determine the pathways through which natural hazard damages and FEMA aid polarize wealth trajectories along already established lines of inequality. This work can proceed along a number of different methodological and epistemological lines, but a useful heuristic in all of these approaches is likely to involve the twin realization that natural hazards do not just bring damages, they also bring resources; and, equal aid is not equitable aid, especially when it is systemically designed to restore property rather than communities.

Developing this line of work also requires moving away from the view that social and environmental dynamics are distinct and disconnected. It requires understanding that in most instances, areas hit by natural hazards are not monolithic wholes, with all residents equally affected. It is better instead to view such areas, like U.S. society as a whole, as being already highly unequal. Stallings' (2002) reinterpretation of Moore's classic, *Tornadoes over Texas*, offers a useful example. Whereas Moore's original account highlights the collective resilience of all involved, Stallings shows how socially marginalized residents became worse off during respective recoveries, while more privileged residents benefitted. In this way, hazard recovery is understood not as a unified act of resilience but as a struggle by privileged residents to restore the local social order, as well as opportunities it presents. The corollary now widely accepted in disaster studies is that socially marginalized residents are vulnerable not just to damages from natural hazards but also to subsequent recovery efforts (Gotham 2014). In an ideal world, FEMA aid would help to mitigate this problem. But, results of the present study indicate that wealth inequality actually increases at a steeper rate in counties that receive more FEMA aid, even when the scale of local hazard damage is the same.

This assessment is not to suggest that FEMA aid is unnecessary, unfounded, or unwanted – quite the opposite. Natural hazards can have devastating impacts that are both immediate and long lasting, as well as indirect. For centuries, governments have committed themselves to offering assistance in the wake of such events, partly to help those in need and partly to maintain institutional legitimacy. The broader point is that now is a good time to rethink how such assistance happens and what role social science can play in such thinking. To start, we have pointed out that the current system is one built largely around the restoration of private property, and, thus, wealth. This approach is not inherently bad, but it is incomplete and inequitable. It is incomplete because it ignores other dimensions of recovery related to individual and social well-being; it is inequitable because it uses broadly collected tax and insurance dollars to do so. The end result is a segmented system of recoveries that drives and divides what comes next. We do not claim to have a solution to this ongoing challenge, but we do hope that we have helped to bring its growing scale, scope and trajectory to light.

REFERENCES

AIR Worldwide. 2016. *The Coastline at Risk: 2016 Update to the Estimated Insured Value of U.S. Coastal Properties*. Boston, MA: AIR Worldwide Corporation.

Alvaredo, Facundo, Anthony B. Atkinson, Thomas Piketty, and Emmanuel Saez. 2013. "The Top 1 Percent in International and Historical Perspective." *Journal of Economic Perspectives* 27(3):3–20.

Brunsentsev, Vera and Wayne Vroman. 2016. *Disasters in the United States: Frequency, Costs, and Compensation*. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Brunsma, David L., David Overfelt, and J. Steven Picou. 2010. *The Sociology of Katrina: Perspectives on a Modern Catastrophe*. New York: Rowman & Littlefield.

Charles, Kerwin Kofi, and Erik Hurst. 2002. "The Transition to Home Ownership and the Black–White Wealth Gap." *Review of Economics and Statistics* 84(2):281–97.

Dahlhamer, James M. 1994. *Loan Request Outcomes in the U.S. Small Business Administration Business Disaster Loan Program*. Newark, DE: Disaster Research Center.

Dash, Nicole, Walter G. Peacock, and Betty H. Morrow. 1997. "And the Poor Get Poorer: A Neglected Black Community." Pp. 206–225 *in Hurricane Andrew: Ethnicity, Gender, and the Sociology of Disasters*, edited by W. G. Peacock, B. H. Morrow, and H. Gladwin. New York: Routledge.

Dauber, Michelle L. 2005. "The Sympathetic State." *Law and History Review* 23(2):387–442.

Davies, Gareth. 2014. "The Emergence of a National Politics of Disaster, 1865–1900." *Journal of Policy History* 26(3):305–326.

Elliott, James R., and Junia Howell. 2017. "Beyond Disasters: A Longitudinal Analysis of Natural Hazards' Unequal Impacts on Residential Instability." *Social Forces* 95(3):1181–1207.

Elliott, James R., and Jeremy Pais. 2006. "Race, Class, and Hurricane Katrina: Social Differences in Human Responses to Disaster." *Social Science Research* 35(2):295–321.

Federal Emergency Management Agency. 2010. *A Citizen's Guide to Disaster Assistance*. Seattle, WA: CreateSpace Independent Publishing Platform.

Federal Emergency Management Agency. 2016. *FEMA Public Assistance Funded Projects Summary - Open Government Initiative.* Retrieved July 28, 2016 (https://www.fema.gov/media-library/assets/documents/28344).

Fisher, Linda E. 2009. "Target Marketing of Subprime Loans: Racialized Consumer Fraud & Reverse Redlining." *Journal of Law and Policy* 18(1):121–155.

Fox, Liana E. 2016. "Parental Wealth and the Black-White Mobility Gap in the U.S." *Review of Income and Wealth* 62(4):706–723.

Fussell, Elizabeth. 2009. "Hurricane Chasers in New Orleans: Latino Immigrants as *a Source of a Rapid Response Labor Force." Hispanic Journal of Behavioral Sciences* 31(3):375–394.

Fussell, Elizabeth. 2011. "The Deportation Threat Dynamic and Victimization of Latino Migrants: Wage Theft and Street Robbery." *The Sociological Quarterly* 52(4):593–615.

Fussell, Elizabeth, and Elizabeth Harris. 2014. "Homeownership and Housing Displacement after Hurricane Katrina among Low-Income African-American Mothers in New Orleans." *Social Science Quarterly* 95(4):1086–1110.

Gall, Melanie, Kevin A. Borden, and Susan L. Cutter. 2009. "When Do Losses Count? Six Fallacies of Natural Hazards Loss Data." *Bulletin of the American Meteorological Society* 90(6):799–809.

Gallup. 2015. "Americans Continue to Say U.S. Wealth Distribution Is Unfair." Washington, DC: Gallup World Headquarters. Retrieved April 15, 2017 (http://www.gallup.com/poll/182987/americans-continue-say-wealth-distribution-unfair.aspx).

Gotham, Kevin Fox. 2014. "Racialization and Rescaling: Post-Katrina Rebuilding and the Louisiana Road Home Program." *International Journal of Urban and Regional Research* 38(3):773–790.

Gotham, Kevin Fox, and Miriam Greenberg. 2014. *Crisis Cities: Disaster and Redevelopment in New York and New Orleans*. New York: Oxford.

Graves, Steven M. 2003. "Landscapes of Predation, Landscapes of Neglect: A Location Analysis of Payday Lenders and Banks." *The Professional Geographer* 55(3):303–317.

Hansen, Marianne Nordli. 2014. "Self-Made Wealth or Family Wealth? Changes in Intergenerational Wealth Mobility." *Social Forces* 93(2):457–481.

Hazards and Vulnerability Research Index (HVRI). 2016. *Spatial Hazard Events and Losses Database for the United States, Version 15.2*. [Online Database]. Columbia, SC: Hazards and Vulnerability Research Institute, University of South Carolina. Retrieved July 2, 2016 (https://cemhs.asu.edu/sheldus).

Keister, Lisa A. 2014. "The One Percent." *Annual Review of Sociology* 40:347–367.

Kristal, Tali. 2010. "Good Times, Bad Times: Postwar Labor's Share of National Income in Capitalist Democracies." *American Sociological Review* 75(5):729–63.

NOAA. 2018. "State of the Climate: Hurricanes and Tropical Storms for Annual 2017." *National Centers for Environmental Information*. Retrieved May 21, 2018 (https://www.ncdc.noaa.gov/sotc/tropical-cyclones/201713)

Oliver, Melvin L., and Thomas M. Shapiro. [1995] *2006. Black Wealth/White Wealth*. New York: Routledge.

Pais, Jeremy, and James R. Elliott. 2008. "Places as Recovery Machines: Vulnerability and Neighborhood Change after Major Hurricanes." *Social Forces* 86(4):1415–1453.

Panel Study of Income Dynamics (restricted use dataset). 2016. Produced and distributed by the Survey Research Center, Institute for Social Research. Ann Arbor, MI: University of Michigan.

Pielke, Roger A., Jr., J. Gratz, C. Landsea, D. Collins, M. Saunders, and R. Musulin. 2008. "Normalized Hurricane Damage in the United States: 1900–2005." *Natural Hazards Review* 9(1):29–42.

Preston, Benjamin L. 2013. "Local Path Dependence of U.S. Socioeconomic Exposure to Climate Extremes and the Vulnerability Commitment." *Global Environmental Change* 23(4):719–732.

Rugh, Jacob S., Len Albright, and Douglas S. Massey. 2015. "Race, Space, and Cumulative Disadvantage: A Case Study of the Subprime Lending Collapse." *Social Problems* 62(2): 186–218.

Sanders, Bernie. 2017. "Income and Wealth Inequality." *Bernie*. Retrieved April 15, 2017 (https://berniesanders.com/issues/income-and-wealth-inequality/).

Shapiro, Thomas M. 2017. *Toxic Inequality: How America's Wealth Gap Destroys Mobility, Deepens the Racial Divide, and Threatens Our Future*. New York: Basic Books.

Stallings, Robert A. 2002. "Weberian Political Sociology and Sociological Disaster Studies." *Sociological Forum* 17(2):281–305.

Tierney, Kathleen J. 2005. "Social Inequality, Hazards, and Disasters." Pp. 109–128 *in On Risk and Disaster: Lessons from Hurricane Katrina*, edited by R. J. Daniels, D. F. Kettl, and H. Kunreuther Philadelphia, PA: University of Pennsylvania Press.

U.S. Census Bureau. 2001. "2000 Census Summary File 3, FactFinder." Retrieved February 18, 2014 (http://factfinder2.census.gov).

U.S. Census Bureau. 2011. "American Community Survey, 2006-2010." *American Community Survey 5-Year Estimates, FactFinder*. Retrieved January 24, 2017 (http://factfinder2.census.gov).

U.S. Census Bureau. 2016. "American Community Survey, 2011-2015." *American Community Survey 5-Year Estimates, FactFinder*. Retrieved January 24, 2017 (http://factfinder2.census.gov).

Vigdor, Jacob. 2008. "The Economic Aftermath of Hurricane Katrina." *Journal of Economic Perspectives* 22(4):134–145.

Volscho, Thomas W., and Nathan J. Kelly. 2012. "The Rise of the Super-Rich Power Resources, Taxes, Financial Markets, and the Dynamics of the Top 1 Percent, 1949 to 2008." *American Sociological Review* 77(5):679–99.