Race, Government Assistance, and Recovery from Natural Disasters

PRELIMINARY AND INCOMPLETE

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Abstract

I use nighttime light luminosity data to estimate the effect of race on the recovery economic activity following a natural disaster. Within counties where a major disaster is declared by the Federal Emergency Management Agency, census tracts with higher proportions of Hispanic and black residents grow significantly more slowly in the immediate aftermath of the natural disaster. The result is robust to the inclusion of a variety of tract-level demographic and economic controls. Using a method similar to a "triple differences" approach, I find that census tracts with a high proportion of minority residents in counties declared disaster areas do not recover more quickly than similar tracts that are not eligible for disaster aid, while tracts with a high proportion of white residents are substantially better off. These results are consistent with a model of disaster recovery where the racial bias policymakers partially determines the allocation of scarce government resources.

1 Introduction

Allegations of racial bias in relief efforts seemingly follow every major natural disaster in the United States. The devastating hurricane season of 2017 renewed this debate, in particular with respect to the federal government's response to various disasters. Compared to the response to Hurricane Harvey which struck the mainland US earlier in the year, the federal response to Hurricane Maria in Puerto Rico was substantially slower and less well-funded (Vinik, 2017), an outcome that many attributed to the racial bias of government officials, and in particular President Trump. But such allegations are not unique to the most recent American regime. In a high profile television appearance following Hurricane Katrina in 2005, musician Kanye West addressed the perceived lack of government response to the unfolding disaster in New Orleans by pronouncing: "it's been five days because most of the people are black [...] America is set up to help the poor, black people, the less well-off, as slow as possible [*sic*]," before famously concluding that "[President] George Bush doesn't care about black people."

Surveys and other case studies have provided some evidence in support of this hyperbole. A survey conducted by the Kaiser Family Foundation in the aftermath of Hurricane Harvey found that black and Hispanic people affected by the storm had higher income loss and recovered more slowly than whites after controlling for income and demographics (Hamel et al., 2017), and an investigation by the Center for Southern Studies found that minority applications for federal aid were significantly less likely to be approved than white applications (Sturgis, 2018). One year after the storm, the New York Times reported that minority residents of the areas affected by Harvey remained substantially worse off than white residents (Fernandez, 2018).

But despite this anecdotal evidence, no systematic study of the effects of race on the recovery from natural disasters exists. I fill this gap by analyzing the month over month growth following natural disasters at the census tract level from 2012 to 2018. My sample covers all wide-scale natural disasters in the United States over this time period. Using census data, I correlate the racial composition of each census tract that experiences a natural disaster with the subsequent growth rate.

I measure the recovery from natural disaster as the change in monthly economic activity as measured by nighttime light luminosity. The luminosity data is available monthly at a 500m^2 resolution everywhere in the United States. Nighttime light luminosity is a useful proxy for income economic output (Henderson, Storeygard, and Weil, 2012), and has been used in a variety of settings to measure local economic conditions (Donaldson and Storeygard, 2016).

In a preview of the main results, I find that census tracts with relatively high populations of Hispanic and black residents recover more slowly from natural disasters than other tracts within similarly affected counties. The result is robust to the inclusion various specifications and demographic controls, and appears to be primarily driven by the recovery from hurricanes specifically. To address possible issues of endogeneity, I compare census tracts on the border of counties that are designated disaster areas (and are therefore eligible for federal aid) with tracts just outside those counties. The results are similar in this "border discontinuity" design.

This paper is organized as follows. In section 2 I describe the institution background of disaster declarations and the allocation of resources following a natural disaster. In section 3 I present a simple model of recovery from natural disaster where policymaker preference and bias can affect the recovery of an area. Section 5 presents the main empirical results, with the implications and policy recommendations presented in section 6.

2 Background

The Federal Emergency Management Agency (FEMA) was created by executive order in 1979 and been a part of the Department of Homeland Security since 2003. Natural disaster assistance occurs through three main channels: Pre-disaster preparedness and preparations, the coordination of various public and private organizations in the aftermath of disaster, and cash assistance. Disaster relief efforts (coordination and direct assistance) are conditional on a executive declaration of a "major disaster," typically defined at the county level. While the President has direct authority to declare a major disaster, it is more typical for state governors to request federal assistance before being approved by the executive. The availability of FEMA resources is therefore jointly determined by the political economy both state and federal entities in addition to the magnitude of the disaster itself.

Once a county has been declared a major disaster area, FEMA assumes bureaucratic control of state, federal, and sometimes private relief efforts. In addition, state and local organizations (public and private) may then apply directly for cash grants from the federal government. State and local authorities retain control over these funds once granted, and the actual usage and allocation of these funds is determined without any additional oversight from the federal government. Therefore the effects of state, federal, and private preferences and actions on inter-regional differences in recovery cannot be separately identified in the data.

In addition to these channels, however, a major disaster declaration allows private citizens to apply directly for federal assistance through FEMA's housing assistance program, which allows both renters and home owners apply directly for cash assistance. Buildings and rental units must be inspected by FEMA personnel, and grants may be awarded if damage is found during inspection. FEMA collects data at the zip-code level on applications, inspections, and grants. While this program is limited in scope, these data can provide preliminary insight into the demographic determinants of recovery efforts.

Matching FEMA's zip-code level data (*Federal Emergency Management Agency* 2019) with 2010 census data (*U.S. Census Bureau* 2019), I regress the number of housing assistance applications on the demographics of the zip code. Column 1 of table 1 indicates that race—in particular the proportion of black and Hispanic residents of a zip code—has no significant effect on the number of housing grant applications. However, race appears to be positively correlated with whether a FEMA inspector finds damage at a property conditional on an application being submitted (column 2), particularly for Hispanic zip codes. This correlation might indicate that zip codes with higher minority populations experience more damage from natural disasters.

Despite being no more likely to apply for disaster assistance and being more likely to have reported damage, Hispanic zip codes are substantially less likely to receive a grant. Conditional on a FEMA inspector observing disaster-related damage, a property owner in an entirely Hispanic zip code is approximately 28% less likely to receive a cash grant than a homeowner in a zip code without any Hispanic residents, despite being 7% more likely to have reported damage.

FEMA does not collect data on individual demographics and the inspector reports are not publicly available, therefore precluding a more robust causal analysis of the effects of race. Because of this, the estimates reported in table 1 should should only be considered correlational. But while inconclusive, the results of these simple regressions in table 1 suggest that race plays in important role in disaster management and recovery.

3 A Model of Disaster Recovery

Regions affected by natural disasters are provided government assistance in the form of capital investment. Normalizing the date that the disaster occurs to $t = 0$, the amount of

Table 1: Zip-code Level Correlates of FEMA Housing Assistance Grants

	Dependent variable:		
	Inspected	Damage reported	Grant received
	(1)	(2)	(3)
%Hispanic/100	0.013	0.069*	−0.279***
	(0.029)	(0.040)	(0.097)
%Black/100	0.011	0.055	−0.021
	(0.020)	(0.065)	(0.099)
%Female-headed households/100	0.219**	0.325**	−0.858
	(0.087)	(0.165)	(0.785)
%Rental/100	−0.008	−0.085***	0.032
	(0.009)	(0.021)	(0.029)
Median age	−0.00004	0.001	−0.003
	(0.0005)	(0.001)	(0.004)
%Male/100	0.188***	0.417**	−0.662
	(0.054)	(0.210)	(0.916)
Observations	22,998	22,998	14,956
R^2	0.207	0.212	0.233
Note:			*p<0.1; **p<0.05; ***p<0.01

All regressions include disaster fixed effects. Standard errors are clustered at the disaster level.

government investment in an affected area t periods after the disaster is:

$$G(t) = \Gamma(K(t) - K(-1), x), \tag{1}$$

where $K(t) - K(-1)$ captures the level of destruction of the capital stock to the pre-disaster level of capital $K(-1)$. The vector x contains all other factors which may influence government aid, such as policymaker preference or logistics. Given x, government aid is assumed to only be made available in areas that have experienced capital destruction as a result of the disaster and is monotonically increasing in the level of destruction:

$$\Gamma(0, x) = 0 \tag{2}$$

$$\frac{\partial}{\partial K(t)}\Gamma(K(t) - K(-1), x) < 0 \tag{3}$$

Aggregate investment each period after a natural disaster is therefore

$$I(t) = I^P(t) + G(t), \tag{4}$$

where $I^P(t)$ is private investment. Following a disaster, the capital stock evolves according to

$$\dot{K} = I(t) + G(t) - \delta K(t), \tag{5}$$

where δ is the depreciation rate.

The above equation is equivalent to the traditional law of motion from the neoclassical growth model with the addition of the government aid term $G(t)$. With a neoclassical production function and a constant gross savings rate, the capital law of motion can be linearized as,

$$\frac{\dot{Y}}{Y(t)} = -(\phi - \gamma' x)(\ln Y(t) - \ln Y^*) \tag{6}$$

where $Y(t)$ is output, ϕ is a constant equal to the labor share of income divided by the depreciation rate, and $\gamma' x$ is the linearization of $G_{K(t)}(0, x)$:

$$\begin{align}
\frac{\partial}{\partial K(t)} \Gamma(K(t) - K(-1), x) &\approx \gamma_1 x_1 + \gamma_2 + x_2 + \cdots + \gamma_n x_n \tag{7} \\
&= \gamma' x \tag{8}
\end{align}$$

The rate of convergence to the pre-disaster level of output is $\lambda = (\phi - \gamma' x)$, with $\dfrac{\partial \lambda}{\partial x_i} = -\gamma_i$. A positive coefficient $gamma_i$ means that the variable x_i is negatively correlated with the rate of convergence. Note that the coefficients in γ are the (linear approximation of the) cross-partial derivatives of the government aid function $\Gamma(\cdot)$—that is, the rate of government responsiveness to a decrease in the capital stock due to a natural disaster. A positive γ_i means that the government invests less in disaster-stricken areas with high x_i than similar areas with low x_i.

Solving for $\ln \dfrac{Y(t)}{Y(0)}$ yields the usual growth equation

$$\ln Y(t) - \ln Y(0) = \left(1 - e^{-\lambda t}\right) (\ln Y(-1) - \ln Y(0)) \tag{9}$$

$$= C - e^{-\phi t} e^{\gamma' x t} (\ln Y(-1) - \ln Y(0)) \tag{10}$$

where $C = \ln Y(-1) - \ln Y(0)$ is the (negative of the) reduction in output experienced because of a natural disaster.

Equation 9 is similar to the canonical "Barro regression" equation. Historically, empirical analysis of equations such as this have been primarily focused on the identification of the determinants of the parameter C, which is related to the steady-state growth level for a region or economy.[1] In the current setting, the analog to the steady state level of output is the pre-disaster ouptut $Y(-1)$, which is observed (see section 5). Instead, the parameters of interest are the γs, which determine the rate of convergence λ.

The primary empirical implication of the model is that the growth rate in output following a natural disaster is a function of the magnitude of destruction $y(t) - y(0)$ as well as the local characteristics defined by x. In particular, any x_i that lowers the amount of government investment $G(t)$ will lower the growth rate. Verification of this latter result is the primary purpose of the empirical results reported in section 5.

4 Data

The primary unit of observation in the analysis to follow is the census tract. The tracts are semi-permanent geographic areas defined by US Census Bureau, designed to contain an average of 4,000 residents. The geographic boundaries are provided by the Census bureau's TIGER/Line shapefile products, and the demographic data for each census tract from the

[1]See for instance Barro (1991) and Sala-i-Martin (1997).

Table 2: Summary Statistics

Statistic	Mean	St. Dev.	Min	Max
Proportion Black	0.14	0.22	0.00	1.00
Proportion Hispanic	0.14	0.20	0.00	1.00
Population	4,310.61	1,994.48	102	37,452
Male population	2,119.45	1,001.27	3	26,093
Median age	38.97	7.18	12.70	82.90
Proportion under 18	0.23	0.06	0.00	0.91
Proportion over 65	0.14	0.07	0.00	0.89
Proportion female headed households	0.13	0.08	0.00	1.00
Proportion rental properties	0.34	0.22	0.00	1.00
Population density (per square km)	1,637.56	3,694.24	0.01	196,409.20
Log luminosity	107.19	23.85	9.41	201.03

Note: Census tracts with population less than 100 are excluded.

2010 census is obtained from the Census bureau's American Fact Finder (*U.S. Census Bureau* 2019). The result is a 2010 cross-section of demographic data for all census tracts in the United States along with the geospatial characteristics of each tract.

Next, the nighttime-light luminosity is calculated for each census tract shape. The luminosity data is collected by the Visible Infrared Imaging Radiometer Suite (VIIRS) onboard the Suomi National Polar-Orbiting Partnership spacecraft. The day/night panchromatic band measures nighttime light luminosity at a 500m^2 resolution, capturing most of the planet's surface once per day. In this analysis, I utilize mosaics of the monthly averages of this luminosity measure. For each census tract, I extract the aggregate luminosity for each month within the tract boundaries using the TIGER/Line shapefiles. The result is a panel of monthly observations from April, 2012 to May, 2018 ($T = 64$). This panel is then merged with the (cross-sectional) demographic data from the 2010 census. Summary statistics are provided in table 2.

FEMA declares major disasters at the county level. Because the unit of observation (the census tract) is smaller than declared disaster area, I select a subset of natural disasters (storms, earthquakes, and flooding) that are ex ante likely to indiscriminately affect large geographic areas within a county. Between April, 2012 and May, 2018 major disasters of this type were designated 4,957 times in 2,499 counties. 74.8% of counties have had at least one major disaster of this type declared, with an average of 1.98 disasters per county (conditional on having at least one declared disaster).

The disaster declarations are matched to the tract-level data. A tract is coded as a disaster area if it is within a county designated as a major disaster area by FEMA in the month during which the disaster was declared.

5 Results

In this section I estimate the relationship between census-tract demographics and rate of recovery from natural disasters. As in the model presented in section 3, the growth rate of production following a disaster at time $t = 0$ is of primary interest. Since production is not directly observable, I use tract-level luminosity as a proxy and assume the functional relationship

$$y_i(t) = a_i + \ell_i(t) + \eta_i(t), \tag{11}$$

where $\ell_i(t)$ is the log luminosity of tract i in the t months following a natural disaster, $y_i(t) = \log(Y_i(t))$ is the log of production, and $\eta_i(t)$ is a tract-specific, normally distributed mean zero disturbance. Subtracting the equivalent expression for $y_i(0)$ from both sides of equation 11 yields

$$\ell_i(t) - \ell_i(0) = y_i(t) - y_i(0) + \tilde{\eta}_i(t), \tag{12}$$

where $\tilde{\eta}_i(t)$ is normally distributed with mean zero. Equation 12 implies that the growth of luminosity can be used in place of the growth in productivity as a dependent variable in a linear regression, as any differences between the two ($\tilde{\eta}$) will be captured in the OLS error term and will not bias point estimates. I therefore use the expressions $y(t) - y(0)$ and $\ell(t) - \ell(0)$ interchangeably for the remainder of the paper.

Because FEMA and the states do not in general collect fine-grained data on the target locations of disaster aid efforts, it is impossible to directly test for the presence of racial bias in government assistance efforts. It is therefore possible that any systematic differences in recovery explained by demographics may be due to unobservable characteristics correlated with race and recovery but that are unrelated to the preferences and actions of policymakers. Some theoretical possibilities for these unobserved characteristics are systematic differences in savings rates by race, capital heterogeneity, or differences in production technologies.

I use two main strategies to address this shortcoming. First in section 5.1, I will proxy for these unobservables using other economic and demographic information, including the percentage of rental units, population density, gender, age, and the percentage of female-headed households at the census tract level. In these specifications, the identification assumption is that differences in recovery by race conditional on the other observable characteristics of the tracts is due to differences in government assistance.

In section 5.2, I consider the recovery of only those tracts that lie on the border of a county that is declared a major disaster area. Here the identification assumption is that the unobservable characteristics of the bordering census tracts are uncorrelated with the disaster declaration. Differences in recovery across border tracts can therefore be attributed to the aid efforts of the various government entities, and any differences in recovery by race across these two groups of tracts (disaster versus non-disaster) is attributable to the availability and effectiveness of government efforts as a function of race.

5.1 Within-County Estimates

I begin by estimating the difference in recovery across census tracts within counties where FEMA has declared a disaster area. The month of each disaster declaration is coded as $t = 0$, allowing for each tract to appear more than once in the data if more than one disaster is declared in that county during the sample period. The resulting data consists of 121,655 tract-disaster observations. The estimating equation is

$$y_{id}(t) - y_{id}(0) = \beta_1(Hispanic_i/pop_i) + \beta_2(black_i/pop_i) + \delta[y_{id}(0) - y_{id}(-1)] + \\ + \theta' X_i + \mu_{cd} + \varepsilon_{cd} \tag{13}$$

The left-hand-side variable is the growth rate in luminosity (output) in the t months following natural disaster d in tract i. $Hispanic_i$ and $black_i$ are the Hispanic and black populations of tract i, and pop_i is the tract's total population. The coefficients β_1 and β_2 therefore measure the marginal effect of the respective proportion of Hispanics or blacks on disaster recovery. Negative coefficient estimates on the βs therefore signify that a higher nonwhite population is associated with slower recovery.

The expression $y_{id}(0) - y_{id}(-1)$ is the difference in luminosity in the month of the natural disaster compared to the month immediately before. This captures the effect of the disaster on economic activity. According to standard growth theory and empirics, this deviation from the pre-existing trend or steady-state has a causal effect on the subsequent growth rate.

The remaining variables in equation 13 are X_i, which is a vector of tract-level demographic controls, and the county by disaster fixed effects μ_{cd} which account for any secular differences in growth rates or measurement error in the light/output relationship that varies by county (such as cloud cover). This fixed effect also accounts for seasonality in production or nighttime light activity. The mean zero error term ε_{cd} is similarly clustered at the county-disaster level.

Estimation results for the three month, six month, and one year growth rates are reported in table 3. In the three months following a natural disaster (column 1), tracts with 100% Hispanic populations grow and estimated 14 percentage points more slowly than tracts with no Hispanic population. A one standard-deviation increase in Hispanic population is associated with a 2.8 percentage point decrease. Similarly, a one standard-deviation increase in the proportion of black residents in a census tract decreases the subsequent growth rate by 0.88 percentage points.

The sign and statistical significance of these estimates is unaffected by the inclusion of additional tract-level controls (column 2). Conditional on the observed economic and demographic data, the magnitude of both estimates increases. Short-term recovery from natural disaster appears to be substantially related to the racial makeup of a census tract, even when controlling for observable characteristics that might determine the amount of aid received by government agencies.

The effects of race on long-term recovery is more ambiguous. The six-month growth rate following a disaster (columns 3 and 4) does not appear to vary with race, and the one year growth rate is positively associated with the Hispanic population (though negatively associated with the black population).

The heterogeneity of growth rates over time is further investigated in table 4. Equation 13 is modified to estimate the three month growth rate starting at various intervals following the disaster that occurred at $t = 0$:

$$y_{id}(t+3) - y_{id}(t) = \beta_1(Hispanic_i/pop_i) + \beta_2(black_i/pop_i) + \delta[y_{id}(t) - y_{id}(-1)] + \\ + \theta' X_i + \mu_{cd} + \varepsilon_{cd} \tag{14}$$

Results are reported in table 4. From three to six months following a disaster (column

Table 3: The Effect of Race on Luminosity Following Natural Disasters

	Dependent variable:					
	$y(3) - y(0)$	$y(3) - y(0)$	$y(6) - y(0)$	$y(6) - y(0)$	$y(12) - y(0)$	$y(12) - y(0)$
	(1)	(2)	(3)	(4)	(5)	(6)
Proportion Hispanic	-0.140^{***}	-0.224^{***}	-0.036^{***}	-0.017	-0.004	0.030^{***}
	(0.027)	(0.033)	(0.013)	(0.017)	(0.009)	(0.011)
Proportion Black	-0.042^{***}	-0.120^{***}	0.005	0.026	-0.032^{***}	-0.036^{***}
	(0.016)	(0.023)	(0.011)	(0.025)	(0.007)	(0.012)
$y(0) - y(-1)$	-0.638^{***}	-0.641^{***}	-0.723^{***}	-0.726^{***}	-0.630^{***}	-0.638^{***}
	(0.056)	(0.057)	(0.052)	(0.053)	(0.051)	(0.051)
Population (log)		0.009^{***}		0.002		0.003
		(0.004)		(0.003)		(0.002)
(Male pop)/pop		0.139^{**}		-0.065		-0.067^{**}
		(0.063)		(0.042)		(0.027)
Median age		-0.002^{**}		0.001^{**}		0.001^{***}
		(0.001)		(0.001)		(0.0004)
Proportion under 18		0.196^{***}		0.072^{*}		-0.108^{***}
		(0.059)		(0.040)		(0.040)
Proportion over 65		0.127^{*}		-0.082		-0.130^{***}
		(0.066)		(0.054)		(0.033)
(Female headed hh)/hh		0.139^{**}		-0.078		0.079^{**}
		(0.066)		(0.055)		(0.036)
Proportion rentals		0.069^{***}		0.021^{*}		0.032^{***}
		(0.016)		(0.012)		(0.008)
Population density (log)		-0.003		-0.005^{**}		-0.014^{***}
		(0.004)		(0.002)		(0.002)
Observations	91,015	90,891	88,641	88,519	86,184	86,069
R^2	0.635	0.636	0.702	0.702	0.742	0.745

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

County level cluster robust standard errors in parentheses. All regressions include county by disaster fixed effects. Disaster dates are normalized to $t = 0$. The variable $y(t)$ corresponds to log luminosity in time t, observed at the census tract level.

Table 4: Time-Heterogeneity in Recovery

	Dependent variable:			
	$y(3) - y(0)$	$y(6) - y(3)$	$y(9) - y(6)$	$y(12) - y(9)$
	(1)	(2)	(3)	(4)
Proportion Hispanic	-0.224^{***}	0.007	0.025	0.038^{***}
	(0.033)	(0.020)	(0.018)	(0.013)
Proportion Black	-0.120^{***}	0.047^{*}	-0.018	-0.003
	(0.023)	(0.027)	(0.021)	(0.011)
Observations	90,891	81,897	61,623	67,551
R^2	0.636	0.747	0.813	0.837

Note: *p<0.1; **p<0.05; ***p<0.01

County level cluster robust standard errors in parentheses. All regressions include county by disaster fixed effects. Disaster dates are normalized to $t = 0$. The variable $y(t)$ corresponds to log luminosity in time t, observed at the census tract level. All regressions include the complete set of controls from table 3. Column 1 reproduces the estimates reported in column 2 of table 3.

2), both the relatively Hispanic and black tracts show higher growth rates (though not significant for Hispanic tracts). These results suggest that tracts with relatively high nonwhite populations have delayed recovery relative to white tracts.

Taken together, the estimation results in tables 3 and 4 suggest that the primary cause of differential recovery by race is due to timing. While long-run growth rates are indistinguishable, tracts with minority populations recover slowly. There are many possible explanations for this observation. The initial government response may favor areas with lower minority populations, but aid may eventually find its way to minority areas after some time. Alternatively, it may be the case that disaster recovery occurs rapidly in the presence of government assistance, causing low minority areas return to pre-disaster levels of output within a few months. If convergence in the absence of aid would occur within the six to 12 month time frame, it would be impossible to observe the effects of differential aid over this these time frames. In other words, tracts with large minority populations may experience a slower rate of convergence λ, which cannot be detected with the linear specifications of equations 13 and 14. Future versions of this paper will address this hypothesis directly via nonlinear estimation of the parameters in equation 9.

Table 5: Disaster Recovery by Disaster Type

	Dependent variable:				
	Hurricanes	Severe Storms	Floods	Snow	Ice Storms
	(1)	(2)	(3)	(4)	(5)
Proportion Hispanic	-0.343^{***}	0.018	-0.031	-0.059	0.667^{**}
	(0.038)	(0.030)	(0.035)	(0.049)	(0.315)
Proportion Black	-0.196^{***}	-0.023	0.002	0.117^{***}	0.061
	(0.030)	(0.024)	(0.025)	(0.024)	(0.318)
Observations	39,901	24,422	17,012	4,532	4,951
R^2	0.386	0.754	0.651	0.861	0.551

Note: *p<0.1; **p<0.05; ***p<0.01

County level cluster robust standard errors in parentheses. The dependent variable in all regressions is the three month luminosity growth rate $y(3) - y(0)$. All regressions include county by disaster fixed effects. Disaster dates are normalized to $t = 0$. The variable $y(t)$ corresponds to log luminosity in time t, observed at the census tract level. All regressions include the complete set of controls from table 3.

Table 5 shows the results of the estimation of equation 13 on data partitioned by disaster type. The largest (in magnitude) negative estimates of β_1 and β_2 correspond to counties affected by hurricanes (column 1). In contrast, the estimated coefficients for non-hurricane severe storms and floods (columns 2 and 3) are statistically indistinguishable from zero. The characteristics that separate hurricanes from other storms and flooding are scale and magnitude. By definition, storms severe enough to be classified as hurricanes affect broader areas and cause more extensive damage than other types of storms. Because of the amount of damage, it is likely that hurricanes impose the greatest strain on state and federal assistance, forcing policymakers and aid workers to prioritize certain groups for relief efforts. In other words, the faster recovery of white tracts following hurricanes may be due to the marginal preferences of aid officials that only become apparent when resources are scarce.

Alternatively, the pattern of racial disparities that emerges in table 5 may be a function of geography. Columns 4 and 5 indicate that black and Hispanic tracts more quickly from damage caused by snow and ice storms, respectively. These types of storms are more likely to occur in northern climates in places that tend to have more liberal policies, while hurricanes disproportionately occur in southern areas with primarily conservative officials. The racial disparities in recovery observed across disaster types may therefore be caused by the political preferences of local policymakers and aid workers. Future versions of this paper will consider this hypothesis directly.

5.2 Border Tracts

The specifications in section 5.1 identify the causal effect of race on within-county characteristics. The unbiasedness of the estimates depends on the covariates capturing 100% of the variability in factors that correlate with disaster recovery. Unobserved tract-level variables that correlate with both race and recovery, such as systematic differences in structural parameters across racial groups, create an untestable identification threat.

In this section I overcome this problem by restricting the sample to only those census tracts that lie on the border of a declared disaster area. Major disaster declarations occur at the county level, so the comparison of tracts that are in a county declared a disaster with neighboring tracts in counties that are not declared a disaster allows for more robust estimation of the causal effects of government assistance and race. If two neighboring tracts are identical on average—conditional on observables—then robust causal estimates can be obtained.

Formally, I estimate the following equation:

$$
\begin{aligned}
y_{id}(t) - y_{id}(0) = \beta_1(Hispanic_i/pop_i) + \beta_2(black_i/pop_i) + \\
+ \beta_3 D_i^F + \beta_4 D_i^F(Hispanic_i/pop_i) + \beta_5 D_i^F(black_i/pop_i) + \\
+ \delta[y_{id}(0) - y_{id}(-1)] + \theta' X_i + \rho' D_F X_i + \mu_{cd} + \varepsilon_{cd} \qquad (15)
\end{aligned}
$$

The primary difference between equation 15 and the previous estimating equation 13 is the presence of the dummy variable D_i^F, which is equal to one if a tract is located in a county where a major disaster is declared and zero otherwise. The coefficient β_3 captures the marginal effect of a tract being in a FEMA-declared disaster county compared to a tract just outside a FEMA county. β_1 and β_2 capture the difference in growth for Hispanic and black tracts that border disaster areas, while β_4 and β_5 are the marginal effects of the disaster declaration conditional on the Hispanic and black population. Finally, the control variables in X_i are interacted with the FEMA treatment variable D_i^F to account for heterogeneity in the average treatment effect of being in a disaster county (Lin et al., 2013; Gibbons, Serrato, and Urbancic, 2018).

Estimation results are in table 6. In all specifications, the estimates for β_4 and β_5 are negative and statistically significant. For census tracts in counties that have been declared part of disaster area, higher proportions of Hispanic and black residents decreases the growth rate following the disaster. In the preferred specifications with the full set of controls (columns 2, 4, and 6), the estimates for β_1 and β_2 are positive and significant. In border tracts that are not declared disaster areas, higher proportions of Hispanic and black residents is associated with an increase in growth rates following the disaster.

The primary identification threat for the estimates in section 5.1 were the unobservable characteristics of Hispanic and black tracts that were negatively associated with disaster recovery. The results in table 6 are highly suggestive that this is relatively unimportant. If

Table 6: The Effect of Race on Disaster Recovery for Disaster Area Border Tracts

	Dependent variable:					
	y(3) - y(0)		y(6) - y(0)		y(12) - y(0)	
	(1)	(2)	(3)	(4)	(5)	(6)
Proportion Hispanic	0.350^{***}	0.358^{***}	0.505^{***}	0.492^{***}	0.321^{***}	0.398^{***}
	(0.007)	(0.008)	(0.002)	(0.003)	(0.003)	(0.004)
Proportion Black	-0.056^{***}	0.063^{**}	0.061^{***}	0.363^{***}	0.016^{***}	0.313^{***}
	(0.015)	(0.025)	(0.010)	(0.004)	(0.006)	(0.004)
FEMA tract (D_i^F)	0.321	0.595	0.059	0.635^{**}	-0.026	0.519^{***}
	(0.418)	(0.632)	(0.055)	(0.255)	(0.118)	(0.188)
$D_i^F\times$(Proportion Hispanic)	-0.244^{***}	-0.284^{**}	-0.508^{***}	-0.512^{***}	-0.386^{***}	-0.426^{***}
	(0.093)	(0.129)	(0.071)	(0.081)	(0.078)	(0.090)
$D_i^F\times$(Proportion Black)	-0.025	-0.085	-0.193^{**}	-0.395^{***}	-0.119^{***}	-0.375^{***}
	(0.090)	(0.124)	(0.087)	(0.081)	(0.029)	(0.067)
Controls	No	Yes	No	Yes	No	Yes
Observations	16,530	16,518	16,194	16,183	18,231	18,217
R^2	0.297	0.300	0.420	0.434	0.451	0.467

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Disaster level cluster robust standard errors in parentheses. All regressions include disaster fixed effects. Disaster dates are normalized to $t = 0$. The variable $y(t)$ corresponds to log luminosity in time t, observed at the census tract level. The control variables (when applicable) are the same as those from table 3.

these unobservables exist, then they should exist in border tracts that are just outside the disaster area at similar rates to their occurrence within disaster areas. In other words identification assumption for equation 15 is that the expected recovery from a disaster for border tracts outside of declared disaster counties is the same as neighboring tracts inside disaster counties—assignment to a disaster county D_i^F is orthogonal to the unobserved characteristics of those tracts. In this sense, the specification in equation refeq:border is similar to a triple-difference estimation, where the primary interest is the heterogeneity in the "treatment" variable D_i^F.

In the preferred specifications, a tract being in a disaster declaration county is positively associated with recovery from natural disaster (though not significantly related with the three-month growth rate, the point estimate is similar in magnitude to the six and twelve-month estimates). In the year following the disaster (column 6), tracts in disaster-declared counties have grown 51.91% faster than neighboring tracts, on average. However, the majority of this benefit accrues to tracts with low Hispanic and black populations. For all Hispanic and black tracts, the marginal effect of being in a disaster declaration county ($\beta_3 + \beta_4$ and $\beta_3 + \beta_5$) is statistically indistinguishable from zero ($p = 0.57$ and $p = 0.52$, respectively). In other words, tracts that are primarily Hispanic or black receive no benefit to being in a county declared a natural disaster area, while tracts with low Hispanic and black populations receive a large benefit in the short and long run.

6 Discussion

Conditional on being in a county that is declared a major disaster area by the federal government, census tracts with high Hispanic and black populations recover from natural disasters more slowly than census tracts with low Hispanic and black populations. This result holds true when comparing census tracts within counties that are declared disaster areas and when comparing census tracts that lie on the border of disaster areas.

These empirical results are consistent with a model of government aid where discriminating aid workers and government officials funnel scarce resources toward areas with low minority populations, causing them to return to pre-disaster levels of output more quickly than minority areas. However, the source of the racial bias cannot be identified at present. While FEMA and the federal government are ultimately responsible for declaring natural disasters, a large portion of disaster relief efforts fall to local governments and organizations. The relative importance of these different actors to the recovery process and the relative biases of each cannot be separately identified at this time. But this lack precise identification highlights a key policy implication of this analysis: the need for increased oversight and transparency regarding relief efforts. These results suggest that a thorough investigation of the fundamental causes of these systematic racial disparities should be a priority for both federal and state aid agencies and private organizations.

It is important to note that direct discrimination need not be the prevailing cause of the systematic racial disparities in disaster recovery. Ultimately the only empirical fact established in the preceding analysis is that Hispanic and black areas affected by natural disasters tend to recover more slowly than white areas despite the availability of federal disaster aid. Cultural and language barriers may exist—well intentioned government actors may overlook or underserve minority communities because of informational asymmetries or other similar frictions.

But despite the ultimate cause of the observed disparities, the policy recommendations remain the same. Minority neighborhoods that disproportionately suffer following a natural disaster should be specifically targeted by aid workers, and information and additional funds should be provided to residents of these areas. Additionally, more oversight into how funds and workers are dispersed so as to uncover the fundamental causes of racial disparities in disaster recovery is needed.

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