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The Socioeconomic Impact and Allocative Discrepancies of FEMA Disaster Declarations and Aid

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Abstract: In my thesis I examine the impact of natural disaster declarations on socioeconomic outcomes. I use counties that requested, but did not receive, a natural disaster declaration as controls for treatment counties that received the requested declaration. I construct a county-by-year panel dataset covering 2005 to 2016. I estimate a difference-in-differences model to estimate socioeconomic outcomes resulting from the disaster declaration decision. I find that receiving a declaration was associated with a 0.8 percentage point poverty reduction in 2010, but no other years or changes in socioeconomic outcomes were causally and significantly established by my model.

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I. Introduction

The U.S. Federal Emergency Management Agency (FEMA) was formally created in 1979 under President Carter to combine multiple agencies involved in emergency management and civil defense under one umbrella organization. FEMA was founded as an organization to provide federal aid to states, territories, and tribal lands to mitigate disasters, prepare for them, and recover.[1] Since the conception of FEMA as an agency, however, they have taken on an increasingly crucial role in supporting U.S. communities on the individual, infrastructural, and public levels. For its first 10 years, FEMA declared on average around 27 disasters per year.[2] The number of disasters and emergencies FEMA manages has since increased to an average of 135 disasters per year.[3] The increase in FEMA declared disasters is suggestive of both an uptick in U.S. natural disaster events, and an increasing local dependence on federal financial aid. FEMA has given out over 36 billion USD since 2005 in public assistance disaster grants alone. The agency is clearly an essential pillar and enormous safety net for communities at risk of natural disaster damages. However, with that power comes the potential to increase existing inequities and harm communities if they are not thoughtful about the allocation of declarations and aid.

There are innumerable costs associated with natural disasters from short term, immediate costs such as property damage and medical expenses to longer term costs that can compound over time like lower educational attainment during the time of the disaster. When examining the natural disaster recovery process, it is important to consider on whom

[1] < https://www.fema.gov/about/history> Accessed January 22, 2021.
[2] <https://www.fema.gov/disasters/historic> Accessed February 5, 2021.
[3] *2007-2017 average, <https://www.fema.gov/disasters/historic> Accessed February 5, 2021.

these costs are primarily falling and how recovery may vary across communities depending on factors like income. Not only should we care about the long-term distributional impacts of natural disasters for basic equity reasons, but they may also have a bearing on the ability for a community to recover from and respond to future disaster events. At a time where the annual disaster count is on a strong upward trend and with so much essential aid at stake; it is important to examine how these relief funds are distributed through individuals, state governments, and local governments.

My paper seeks to expand on past disaster literature by joining analysis on the impacts of disaster aid with the factors contributing to the allocation of aid. I utilize data on all FEMA disaster declarations as well as all requested disaster declarations which FEMA did not declare between 2005 and 2016. I use this quasi-natural experiment and a difference-in-differences framework to analyze socioeconomic outcomes in the presence of federal aid. First, I provide background information and a brief literature review on the means of FEMA declaration, natural disaster frequency, and environmental justice. I review past literature on U.S. natural disaster recovery and the impacts and motivations of FEMA aid. I will then provide summary statistics for the declaration versus no declaration conditioned groups as well as difference of means tests on all covariates of interest. I then proceed to a probit analysis of the factors which increase or decrease the likelihood of receiving a declaration, and find that electoral value, race, and disaster type all significantly influence whether a county's declaration request is approved. Finally, I outline my primary model and DID analysis results and interpretations, along with discussion of my event study validation results.

II. Background and Relevant Literature

The process of FEMA disaster evaluation and declaration was in large part written by the Robert T. Stafford Disaster Relief and Emergency Assistance Act (Public Law 93-288). The Stafford Act adjusted not only the parameters of disaster classification, but where the budgetary power lies for emergency response. The Stafford Act gave the President the power to declare a national emergency, and once an emergency is declared FEMA has the power to provide aid primarily from the "President's Disaster Relief Fund". Under this current model only the President has the power to declare a national emergency in response to localized disasters. Therefore, the President wields a staggering amount of unilateral power over whether or not state and local governments overwhelmed by a natural disaster will get federal assistance. The actions and level of FEMA assistance and intervention are overseen by a congressional committee. However, without a disaster declaration the federal government bears no obligation to assist.

Natural disasters globally are getting more frequent and costlier. The global costs of weather-related disasters have increased from $8.9 billion USD annually (1977-1986) to $45.1 billion a year (1997-2006) and continues to rise (Bouwer et al. 2007). Hallegatte (2014) summarizes the expected trends in natural disasters and analyzes their costs under the various climate change scenarios used by the Intergovernmental Panel on Climate Change. Generally speaking, climate models can predict increasing likelihoods of disasters, but there is still uncertainty around the way it will manifest in different regions. This means that certain regions may be severely under equipped to mitigate future hazards associated with a changing climate. The challenge of mitigation and increase in losses will serve to make disaster recovery efforts more essential in the future, and thus the economic impacts of disaster relief and emergency management agencies like FEMA will only become more pronounced over time.

Past research has looked at data on severity of natural disaster events and the subsequent FEMA decision to declare a disaster in the period over 1991 to 1999 (Garrett & Sobel 2003). Garrett and Sobel (2003) run a Poisson model on the number of FEMA declarations at the state level, controlling for severity of disaster as well as demographic, electoral value, and election year variables. By interpreting the marginal effects of their analysis, they are able to estimate the factors that contribute most heavily to the likelihood of receipt of a FEMA declaration and disaster aid. The researchers find that only about half of disaster aid can be explained by the severity of a given disaster, and much of the determination of whether or not a state receives FEMA disaster declaration has to do with their electoral value and if it is an election year (Garrett & Sobel 2003).

Both the short- and long-term economic consequences of natural disasters have been a heavily researched subject for decades. Research has long supported a narrative of disaster resilience in the United States. Case studies and empirical research have most commonly examined these impacts in the wake of hurricanes, while I expand natural disaster analysis to include all eight FEMA disaster classifications: severe storm, severe ice storm, hurricane, typhoon, earthquake, tornado, flood, and fire. Deryugina (2007) uses an event study to estimate the impact hurricanes have on government transfers, wages, and unemployment on the aggregated county level post natural disaster and finds no significant drop in earnings or employment. By analyzing counties impacted by hurricanes in both the short term (0-4 years) and the long term (5-10), she finds that government transfers are likely able to offset a significant amount of the damages and wage loss resulting from natural disasters. Likewise, Pleninger (2020) finds that in the year of a disaster, counties have on average similar distributional characteristics in spite of a decrease in income across the population. She examines FEMA declared disasters between 1996 and 2017 through a panel fixed-effects regression model to determine drivers of inequality and changes within income groups. Pleninger (2020) suggests that adverse socioeconomic consequences are most concentrated in the middle class, and thus inequality and poverty rates remain fairly stable through natural disasters and recovery. This narrative of the strength of our socioeconomic system's ability to stand up to natural disasters has been perpetuated by analysis of several major disasters. Notably, Shaughnessy et al. study a pre and post Hurricane Katrina New Orleans to find that the local Gini coefficient actually decreased after the disaster (Shaughnessy 2010). These bodies of research suggest great confidence in our disaster safety nets including direct disaster aid, unemployment insurance, income maintenance payments, and public medical assistance. There is still uncertainty behind these results, however, because in the large-scale disasters studied, the most economically disadvantaged populations may be unable to return to the area and therefore be uncounted in later time series data.

Schulz and Elliott (2013) conducted an analysis which diverges from the previous narrative of community-level economic rebound success from disasters. They analyze what they identify as a "recovery machine": the way in which conferrals of private and public aid seem to "boost rather than discourage uneven growth and development in affected areas over the long run" (Schulz & Elliott 2013). Those in middle- and upper-income groups are able to receive financial windfalls through both government assistance and private insurance claims. Particularly those in high-value areas with more assets often see a net benefit from disasters while individuals below or near the poverty line are net negatively impacted (Schulz & Elliott 2013). The researchers find that in disaster-stricken areas there is greater socioeconomic inequality and income polarity than before the disaster. Even more troubling, these impacts appear to be amplified for non-white populations. Schulz & Elliott (2013) analyzed the percent change in family income and percent change in poverty populations for a multitude of variables and found that non-white groups saw a decrease in household income and increase in poverty percentage, both significant at the one percent level. Not only is it clear that the interplay between private and public disaster relief has the potential to create an equity issue, but it is an environmental justice concern as well.

Schulz and Elliot only focus on demographic shifts in disaster-stricken areas which did receive a FEMA disaster declaration. In my paper I hope to examine this "recovery machine" further by analyzing differences in socioeconomic outcomes between counties impacted by a natural disaster which received FEMA aid versus those that requested FEMA aid, but did not receive it. As FEMA is far and away the largest provider of public assistance in the wake of disasters, I will be able to isolate the federal response impacts on inequality and economic outcomes from the solely private, state, and local disaster response. This analysis can help understand whether this recovery machine is truly propelled by FEMA; or primarily driven by state, local, and private mechanisms. By looking at socioeconomic changes on a county level I will be able to determine whether FEMA support is a driver of the inequality associated with the recovery machine or a savior for lower income populations whose recovery would otherwise be outpaced by aid from the private sector.

Racial disparities in environmental vulnerability and safety are a growing literature which focuses on the intersection of race and disaster impact. This literature has grown particularly since Hurricane Katrina in 2004 where the damages from a catastrophic disaster disproportionately impacted the Black population in the geographics affected. Not only was Hurricane Katrina a harsh reminder of the greater environmental vulnerability of the Black population in the U.S., but the government response with little to no immediate relief left New Orleans residents with a difficult road ahead for disaster recovery (Bolin & Kurtz 2018).

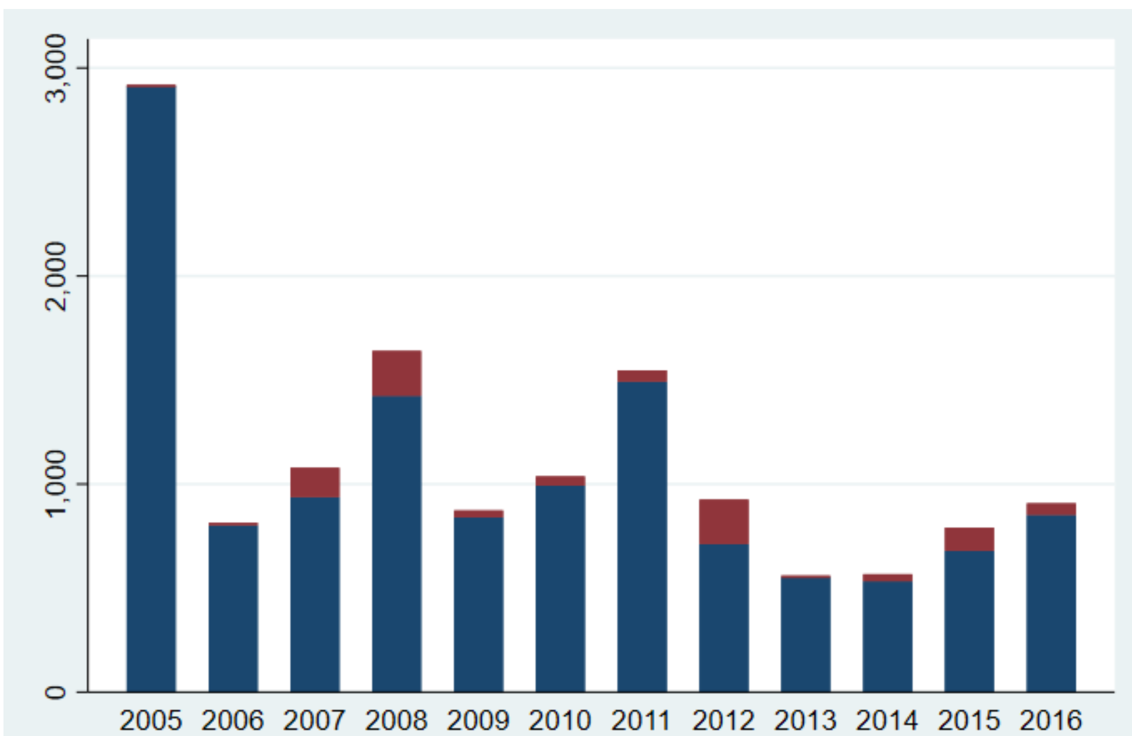
Another example given by Bolin and Kurtz (2018) is that of flooding in El Paso, Texas. Most high-income individuals in El Paso live up on a hillside for many reasons including less pollution, less congestion, and aesthetics. When El Paso was hit with a series of floods in 2006, the wealthier individuals at higher elevation were protected from home damage and personal injury, whereas the predominantly Mexican and Latino inhabited low-income *colonias* were severely inundated and damaged during the floods (Bolin & Kurtz 2018). These *colonias* acted as informal settlements for thousands of low-income Hispanic individuals, a large majority of whom lack U.S. documentation. While the rich hillside homes that were inherently less exposed to the floods were able to fall back on flood insurance and FEMA payments if they were damaged, people in the *colonias* found themselves unable to take advantage of either. Flood insurance is a private good that many low-income individuals cannot afford. Additionally, because many impacted people were undocumented, they were ineligible for aid from FEMA (Bolin & Kurtz 2018). Not only were undocumented people excluded from FEMA aid, but until fairly recently FEMA only provided flood insurance information in English (Bolin & Kurtz 2018). Therefore, non-

English speakers found themselves unable to take advantage of essential FEMA aid payments. This implies that even in the cases where a county receives a FEMA declaration and subsequent aid, there very well may be unequal receipt of benefits within the county. Natural disasters can be devastating to any community affected, but there is an inherently greater vulnerability for lower income communities. There is typically a risk premium associated with living in an area with known disaster risk, thereby lowering home prices and making them more attractive to low-income individuals. In the United States, this clustering of low-income individuals in more vulnerable and hazardous areas is intrinsically linked to race.

III. Data and Descriptive Analysis

I implement a difference-in-differences research design that compares counties that received a requested disaster declaration to counties that had their request turned down before and after a disaster event. I use this to isolate the short-term impact of a FEMA disaster declaration on economic outcomes and inequality. The counties struck by a disaster severe enough to request FEMA assistance, but who ultimately did not receive a disaster declaration, will act as a control group, and the counties that were granted a disaster declaration and thus FEMA assistance are the treatment group. Between 2005 and 2016, 43 out of 50 states experienced both a disaster declaration and a disaster turndown. The other seven states had significantly fewer disasters in general, and never had a request turned down by FEMA. Between 2005 and 2016 there were 19,693 FEMA declared disasters, and 1,929 instances of a disaster declaration request and subsequent federal turndown. Figure 3.1 shows variation in the number of declared disasters and turndowns during my sample period. There are four stand-out years with more disaster declaration turndowns than others: 2007, 2008, 2012, and 2015. Another clear outlier is 2005, where there are many more disasters than usual and of them, few turndowns. This is likely driven primarily by Hurricane Katrina and subsequent flooding disasters, which hit in 2005 and impacted thousands of households across Mississippi, Alabama, and Louisiana (Braine 2006).

Figure 3.1. Disasters from 2005-2016 broken down into FEMA declared disasters (blue) and disaster declaration requests turned down by FEMA (red)



The first clear challenge with this analysis is that the assignment of an emergency declaration by the federal government is nonrandom. We can expect that some events may have their request turned down because the event was not severe enough to warrant federal aid. The FEMA website breaks down the disaster request process, the primary component of which is an application filled out either by a state governor or tribal council executive.[4] The application does not request quantifiable accounts of the severity of the disaster, but rather asks for descriptive statements about the nature of the disaster, the allocation of state and local resources to the disaster, and a list of reasons the state, local, or tribal government cannot supply the necessary aid and resources. As these requests are made before accurate disaster cost estimates are available, it's unclear to what extent the severity of the disaster impacts the declaration decision.

In my primary analysis I focus on four outcome variables, each of which measures socioeconomic conditions on the county level: poverty rates, unemployment percent, SNAP benefit enrollment, and inequality. Data on poverty rates is an annual county-level average obtained from the U.S. Census American Community Survey poverty and income inequality dataset from 2000 to 2019. Unemployment rate by county is taken from the St. Louis Federal Reserve Bank's FRED database from 2000 to 2019. As a proxy for dependence on public assistance I use data from the USDA Food and Nutrition Service on SNAP benefit enrollment by household, specifically the fraction of enrolled households in a county. Lastly, I obtained data on income distribution by county from the American Community Survey. Due to changes in content and granularity of the ACS, this data was only publicly available for the years between 2010 and 2019. I use ACS data on estimates

[4] <https://www.fema.gov/disasters/how-declared> Accessed April 14, 2021.

of the percent of households in different income brackets in the county to construct a top-to-bottom ratio in every year for each county as a measure of income inequality. The top-to-bottom ratio is the percent of households with an income of $100,000 and above divided by the percent of households in the annual income bracket of $25,000 and under.

I include additional variates in my model to control for county demographics and disaster type. I create indicator variables for all disaster groups recognized by FEMA: hurricane, storm, flood, snow, ice storm, earthquake, coastal storm, tornado, fire, and an "other" category. For county- and year-specific demographic covariates I include median income, percent Black, percent white, percent Hispanic, percent of the population under 19 years old, percent of the population over 65 years old, total population, and percent female. I also create an indicator variable to denote swing states based on the criteria of electoral attention and spending by presidential candidates in the elections of 2004, 2008, 2012, and 2016 (Center for Presidential History 2020). On average across the elections around my sample, the states that received the most campaign funds and attention relative to their population were: Arizona, Florida, Iowa, Michigan, Minnesota, Nevada, New Hampshire, New Mexico, Ohio, Pennsylvania, and Wisconsin. Below I include summary statistics on the outcomes and covariates of interest in my dataset as well as the results of difference-of-means tests comparing treatment and control counties.

Table 3.1. Summary statistics for treatment and control groups including disaster and demographic data at the county level used in my primary analysis between 2005 and 2016

	Received Declaration (Treatment)		Request Turned Down (Control)		
Variable	Mean	S.E.	Mean	S.E.	**Difference-of-Means**[5]
Median Income	44,275	11,168	44,275	11,183	1,663***
Poverty Percent	16.24	0.057	16.49	0.201	0.251
Unemployment Rate	6.38	0.023	6.40	0.089	0.022
SNAP Ratio	0.189	0.002	0.200	0.005	0.013**
Polarity[1]	0.822	0.002	0.819	0.041	-0.0028
Percent Black	8.59	0.140	13.04	0.550	4.45***
Percent Hispanic	8.15	0.133	6.21	0.271	-1.94***
Percent White	86.31	0.156	82.12	0.582	-4.20***
Percent Pop.< 19 Yrs.	25.96	0.003	26.51	0.010	0.54***
Percent Pop.> 65 Yrs.	16.67	0.004	15.95	0.015	-0.72***
Swing State	0.127	0.003	0.047	0.211	-0.080***
Hurricane	0.236	0.004	0.0054	0.073	-0.231***
Storm	0.380	0.004	0.402	0.016	0.023*
Flood	0.069	0.002	0.043	0.203	-0.009***
Tornado	0.004	0.001	0.156	0.012	0.153***
Snow	0.031	0.002	0.014	0.004	-0.0165***
Fire	0.070	0.002	0.117	0.322	0.051***
Other	0.0002	0.001	0.176	0.013	0.176***

[5] Significant at 10%*, 5%**, and 1%***

Summary statistics on disaster types can be interpreted as the percentage of the control or treatment group each type of disaster accounts for. Severe storms play a large role in both the declared and turned down samples, making up 38% and 40% respectively. Other disasters that account heavily for turndown observations in my sample are fires, tornadoes, and "other" disasters. Hurricane disasters appear to be very rarely turned down and make up a significant portion of the declared disaster category, about 23% more than the control county significant at the 1% level (Table 3.1). Floods and snow declarations are also significantly more representative of declarations than turn downs, but do not make up as much of the treatment sample as hurricanes and storms. Because hurricanes and storms represent such a large proportion of the disasters in my sample, my results are most likely primarily driven by the way counties impacted by hurricanes and storms react to the disaster declaration treatment.

Initial summary statistics suggest that there are significant differences between the control and treatment groups in my analysis. Most notable of my demographic variables are white, Hispanic, and Black percentages as well as the swing state indicator. Percent Black in a county has the largest difference of means result of all other explanatory demographic factors, suggesting that counties which received turndowns on average have a Black population 4.45 percentage points greater than those that receive declarations, a difference that is significant at the 1% level (Table 3.1). On the other hand, the counties that receive declarations are 4.2 percentage points whiter on average than those that receive turndowns; this difference is significant at the 1% level (Table 3.1). Hispanic population is also 1.94 percentage points greater in the declared group than the turndown group which the t-test suggests is significant at the 1% level (Table 3.1).

The swing state designation is also significantly different between the treatment and control groups. Declared counties are in a swing state 12.7% of the time in my analysis, while counties that experience a turndown any given year are in a swing state only 4.7% of the time. The difference of means test suggests that federal turndowns occur 8% more in counties that are not in swing states compared with those that are, significant at the 1% level (Table 3.1). This result is aligned with the prevailing theory that presidents may be incentivized to favor providing aid for the states that they feel will be most valuable in their election or reelection effort (Garrett & Sobel 2003). To explore how swing state status may be related to race I simply calculated the average county-level Black and Hispanic percentages for swing states versus the average Black and Hispanic percentages for counties in non-swing states. I found that the average Black population percentage for the counties in the swing state group was only 3.9%, which is nearly 7% less than the non-swing state county average of 10.4% Black. There is also a difference in mean percent between swing and non-swing states for Hispanic percentages, but it is less pronounced: in swing-state county mean Hispanic population is 7.5% whereas the non-swing state Hispanic population is 8.7% on average.

This presidential inclination towards aiding swing states with the most electoral value over others is not only harmful in that non-swing states may get disasters declared less frequently. It may also be operating more nefariously through channels of systemic racism, which could leave predominantly Black communities aided less frequently than white communities. The disparity here is even worse when considering that counties with

Black percentages over the mean experience more natural disasters overall. I divide my sample counties into counties above and below the mean Black population percentage to analyze event counts through a discrete variable. The average number of events by county in the majority Black counties during my sample period was 7.3 disasters, while the average number of disasters for counties below the mean Black percentage was 6.7 disasters in my sample. A t-test suggests that this difference is statistically significant at the 1% level. This result is in line with other environmental justice research that suggests that communities of color are and will increasingly become more vulnerable to natural disasters compared to whiter communities (Bolin & Kurtz 2018).

Prior to conducting my primary regression analysis, I examine factors that explain variation in the declaration decision in the spirit of Garrett and Sobel (2003). While the difference-of-means results are quite striking, it is important to control for any other explanatory variable like disaster type before claiming demographic causality on the declaration decision. To do this, I estimate a probit model where the dependent variable takes the value of one if there was at least one disaster declaration in the county-year and zero if there was a turndown.

Table 3.2. Probit Analysis. Probit model results on likelihood of receiving a declaration including year fixed effects and clustered errors around FIPS code. The declaration decision is defined as a binary variable which takes on a value of 1 when declared and 0 when turned down.[6]

Variable	**B**	**Robust S.E.**	**P > |z|**
Percent Black	-0.00077***	0.00019	0.000
Percent Hispanic	0.00019	0.00028	0.495
Percent Pop. < 19 yr.	-0.00217**	0.00102	0.034
Percent Pop. < 65 yr.	-0.0007	0.00081	0.382
Swing State	0.0553***	0.00849	0.000
Storm	-0.09565***	0.01179	0.000
Hurricane	0.0732***	0.02099	0.001
Tornado	-0.7512***	0.01618	0.002
Fire	-0.13313***	0.01427	0.000
Snow	-0.05712***	0.01801	0.000
Coastal Storm	-0.3883***	0.04124	0.000
Ice Storm	-0.10978***	0.01438	0.000
Flood	-0.06765***	0.01404	0.000
Other Disaster	-0.5152***	0.03283	0.000

*disaster specific coefficients relative to omitted earthquakes

[6] Significant at 10%*, 5%**, and 1%***

A probit analysis allows me to interpret marginal effects as likelihood estimates which predict the probability of receiving a declaration resulting from a marginal change in one of my model covariates. Percent Hispanic and percent of the population over 65 years old do not appear to interact significantly with the probability of receiving a declaration. The other three included covariates, however, do suggest that they are significant factors in estimating the likelihood of receiving a declaration. Per Table 3.2, percent Black in a county is significant at the 1% level, suggesting that a 1 percentage point increase in Black population is associated with a 0.07 percentage point decrease in the likelihood of receiving a declaration. Although this change may seem small, it is significant evidence that even when controlling for things like disaster type, year, swing states, and median income, racial composition still has a significant association with FEMA declaration status. It is important here that I control for the swing state variable, because I determine a very large gap in receipt of declaration on average for more Black communities, and those counties are more likely to be in a non-swing state than in a swing state. Perhaps the relatively small size of the percent Black coefficient results because I control for the swing state designation in the probit analysis. This analysis also suggests that historically, holding all else fixed, Black communities have had rejections to disaster declaration requests significantly more than predominantly white communities, and therefore the consequences of being denied a declaration I find in my primary analysis are impactful not only to those counties, but to equity considerations on the federal level.

Percent of the population in a county under the age of 19 also has a significant association with the probability of receiving a disaster declaration from FEMA. My probit model suggests that a 1 percentage point increase in percent of the population under 19 years old is associated with a decreased probability of receiving a declaration by 0.22 percentage points, holding all else equal and significant at the 5% level (Table 3.2). This is also a significant demographic factor as percent under 19 being greater means that the population is more heavily demographically weighted toward children.

Swing state analysis in the probit model as with the difference of means summary statistics demonstrates continued support of the hypothesis that electoral value may sway the FEMA declaration decision made by the President per Garrett & Sobel (2003). Holding all else equal, if a county is in a swing state, they are 5.5 percentage points more likely to receive a disaster declaration than counties that are not in swing states (Table 3.2). This result seriously calls the mechanisms by which disasters are declared into question. Counties in non-swing states may be going through the disaster recovery process without federal aid more frequently than those in swing states partially because they are of less electoral value.

The results of the probit analysis related to disaster type are interpreted relative to the omitted disaster type, earthquake. All of the estimated marginal effects for these variables are significantly different from zero at the 1% level. Notably, hurricanes are the only disaster type more likely to receive a federal disaster declaration than earthquakes (7.3 percentage points more likely). Disasters in the “other” category are much less likely, 51.5 percentage points, to receive a declaration than an earthquake. This result is unsurprising as requests made for a disaster type of “other” are outside of the typical scope or categories of disasters that FEMA deals with which could be a basis for rejection. Interestingly, tornado disaster requests for declaration are 75.1 percentage points less likely to be declared than earthquakes, which is even more severe than disasters in the “other” group.

Clearly the type of disaster is a very significant determinant as to whether or not a declaration will be received, which is why I include disaster type indicator variables in my primary analysis which I discuss in the following section.

IV. Main Empirical Strategy

Here I discuss my primary empirical analysis. I exploit a quasi-experimental event study where all counties (*i*) in year *t* that are impacted by a natural disaster request a federal disaster declaration. Upon request some counties receive a declaration and some do not, creating a treatment and control group. My empirical model follows a difference-in-differences framework which for each year in my sample period separately estimates the change in socioeconomic outcomes from the year prior to the year after the disaster:

$$Y_{i,t} = \beta_0 \text{int} + \beta_1 \text{Post}_{i,t} + \beta_2 \mu + \beta_3 \delta + \beta_4 \text{Declaration}_{i,t} + \beta_5 \text{Declaration}_{i,t} \times \text{Post}_{i,t} + \beta_6 \text{Year} + \varepsilon_{i,t}$$

$Y_{i,t}$ denotes the outcome variable for my model, which I run separately for all four outcomes of interest: poverty rate, unemployment rate, SNAP ratio, and income top-to-bottom ratio. In my model I include a post dummy variable, which indicates the next year after the disaster declaration or turndown year. I also include a declaration indicator variable that takes on the value of 0 if the disaster declaration request is turned down, and 1 if the disaster declaration request is approved. Finally, I include an interaction term between the post and treatment indicator variables. This term shows the impact of having a disaster declared versus turned down, comparing the year before and after the disaster between control and treatment counties. The coefficient of the interaction term will estimate the predicted change in a socioeconomic outcome variable given that a county is in the post period and that the county was "treated" by receiving a declaration.

As this is a panel fixed effects model, my analysis will naturally control for county level fixed effects, but it is important to add other controls which may impact the declaration decision and subsequent community outcome response. I include both disaster-specific controls in my model as well as time varying demographic data. The set of indicator variables I generated to specify disaster type is included in my model as δ. The demographic data included in my analysis denoted as μ is a vector of county specific characteristics in the year of the disaster. These characteristics include population, racial composition percentages: white, Black, Hispanic; median income, age distribution: above 65 and below 19; and percent female. I also include a Year indicator variable to account for year fixed effects in my model.

V. Results

In order to interpret the results of the difference-in-differences models as estimates of the causal impact of a disaster declaration, the so-called parallel trends assumption must be satisfied. In this context, the assumption requires no trend differences between the treatment and control groups for the outcome variables in the years leading up to treatment. To explore this, I estimate event study models. The parallel trends assumption is used to confirm that the counties that requested a disaster declaration and were turned down are a valid counterfactual for those counties that did receive a disaster declaration. If there are statistically different trends between treatment and control groups in the outcome variables estimated by the difference-in-differences model in the years leading up to the disaster year, then the resulting estimates cannot be interpreted as causal. To estimate the event studies, I limit my primary analysis to the years 2010 to 2015. Because my disaster specific and county level demographic data is only available starting in 2006, I require at least four years of approximated lag year trends to certify whether the parallel trend assumption holds.

I construct my event analysis using the methods laid out by Clarke and Schythe (2020) in "Implementing the Panel Event Study". Because the event of a natural disaster and corresponding aid acts as a treatment that takes place in different counties at different times, I include lag variables in my analysis denoted as *j*, and lead variables indicated by *k*. These act as binary variables to distinguish how many periods away the other variables of interest are from the event, denoted as Event_i. This will set up the panel with an event in county *i* and in year *t* with four binary variables on either side: Lag 4, Lag 3… Lead 0, Lead 1 (Clarke & Schythe 2020).

$$Y_{i,t} = \beta_0\text{int} + \beta_1\text{Treatment}_{i,t} + \beta_2\mu + \beta_3\delta + \beta_4\text{Year} + \lambda_4(\text{Lag }4) + \lambda_3(\text{Lag }3) + \ldots + \gamma_0(\text{Event}_{i,t}) + \gamma_1(\text{Lead }1) + \varepsilon_{i,t}$$

I create a graph with data points for average outcome variables I observe for each year. The points on the graphs demonstrate the difference in outcome between my treatment and control counties in the four years leading up to the disaster event and one year after with a 95% confidence interval (Figure 4.1 - 4.4). I find from this analysis that the control and treatment group I designated are unfortunately fairly poor counterfactuals for one another. This may be due to the fundamental differences I discover between the counties that receive a declaration and do not in my Descriptive Analysis section above. The counties that do not receive a declaration from FEMA seem to trend in fairly different ways in the four years leading up to their natural disaster than those that do receive a declaration. Although I control for all time-varying factors included in my Descriptive Analysis, swing state excluded, this result suggests that there are factors at play other than just the FEMA declarations that might motivate significant movement and differences in socioeconomic outcomes between the two groups. It appears from my primary DID regression analysis that there are numerous correlations between outcome variates and the post×treatment interaction term significant at the 1% level, however, I cannot assign a causal interpretation to most of my results. In fact, the only years and outcome variables that I can potentially interpret as causal are Poverty Percentage in 2010, 2014, and 2015; Unemployment Rates in 2015, and the Top-to-Bottom income ratio in 2014. The SNAP ratio never upheld parallel trends for any of my sample years, and therefore although my results support a possible positive and significant correlation between SNAP ratio and the post×treatment interaction term, I will not interpret any of these results as causal because the SNAP ratio trends are significantly different between the declaration and turndown groups (Figure 4.3).

Below I include the results from my difference-in-differences model on all four outcome variables. My results display how the interaction term between my post and treatment variable impacts outcomes for all years 2010 to 2015. Due to data limitations from changes in the ACS granularity and survey format, I only had the necessary data to construct a top-to-bottom ratio with adequate lag data to analyze parallel trends beginning in 2014 and ending in 2015. Additionally, any counties that had multiple observations in one year (declare or turndown) are eliminated from these results to avoid interference between two treatments or the magnification of one treatment. In my results tables I include the coefficient of the interaction term, the term's standard error in parentheses below, and an indication of whether the interaction was found significant at the 1% (***), 5% (**), or 10% (*) level.

Table 5.1. Estimates of the coefficient of the interaction term between the post natural disaster and declaration indicator variable for county level poverty percentage, unemployment rate, SNAP benefit enrollment fraction, and top-to-bottom ratio of income.

Outcome Measures:	Poverty Percentage	Unemployment Rate	SNAP Ratio	Polarity
2010	-0.8194*** (0.2736)	-0.68823*** (0.2552)	-0.0033575 (0.00911)	-
2011	0.15517 (0.25479)	-0.69496*** (0.186605)	0.05106*** (0.00695)	-
2012	0.168194 (0.12978)	0.655444*** (0.080534)	-0.02453 (0.00654)	-
2013	1.2892*** (0.41486)	6.71997*** (0.19843)	0.055166*** (0.01963)	-
2014	-0.36813 (0.368347)	0.0218 (0.30208)	0.053559*** (0.01994)	-0.005078 (0.00458)
2015	-0.21482 (0.19993)	0.43158*** (0.16156)	0.02395*** (0.00453)	0.038184*** (0.00971)
Observations	81,930	81,930	61,070	19,929

Having used the event study to limit my results to include only those that fit the parallel trends, I can now interpret my primary results in earnest. I find that once I filter for counties that are fairly stable counterfactuals for one another and uphold the parallel trends assumption, there is only one significant interaction term left to interpret. Poverty percentage in 2010 has parallel trends between declare and turndown counties leading up to the disaster year. The interaction term in 2010 suggests that receiving a declaration is associated with a 0.819 percentage point decrease in poverty in the following year relative to counties that did not receive a declaration, significant at the 1% level (Table 5.1). The other two years the poverty percentage variable upholds parallel trends (2014 & 2015) also have a negative coefficient but are not statistically significant, and therefore it is difficult to draw any finite conclusions based on what appears to be a fairly inconsistent relationship.

VI. Discussion

To discuss the findings in my thesis I will start by going over the probit analysis and difference-of-means findings from my Descriptive Analysis section. This analysis helps to contextualize the results from my primary difference-in-differences and event study analyses by illuminating the patterns and influencers of FEMA disaster declarations. My primary analysis goes on to break down the short-term economic consequences, if any, of receiving a disaster declaration or not. The results found in my primary analysis are relevant to the Descriptive Analysis because I find an either a positive or neutral effect of receiving a declaration. My probit analysis and summary statistics on the factors which lead to a FEMA declaration versus a turndown show that there are significant factors potentially outside of disaster severity which influence the response to county disaster declaration requests. Finally, I will discuss the shortcomings of my analysis and how they influence the implications of my results.

I find that the greater population percentage Black a county is the less likely they are to receive a disaster declaration. There is also evidence in my descriptive statistics that this relationship between communities of color and having disaster declarations turned down more frequently could be manifesting through the channel of electoral value. The that swing states in my sample have a significantly smaller average Black population than non-swing states, and therefore the swing stage influence likely has racial consequences. Additionally, I find through my difference of means test and probit model that swing states are significantly more likely to receive a disaster declaration than non-swing states, holding all else equal. This reinforces the results from Garrett & Sobel (2003) that the disaster declaration decision may be in large part motivated by electoral opportunism and attempts to remain in the favor of residents of the states that will decide an election or reelection for the individual or the political party. Garrett and Sobel examined this pattern between 1991 and 1999, and the analysis I perform of the time period between 2005 and 2016 suggests that this trend is alive and well.

A recent, salient example of the politicization of natural disaster aid was the response of the Trump administration to the five severe California wildfires in 2020. Former President Trump initially refused to grant a disaster declaration to the impacted counties in California when Governor Newsom submitted a formal request. The California fires of 2020 were reported to have destroyed 340,000 acres and caused over 25,000 people to flee their homes, but the Trump Administration refused to grant a disaster declaration, arguing that the submission was "not supported by the relevant data" (Wilson & Elfrink 2020). The sheer magnitude of the damage caused by these fires along with previous threats to withhold federal disaster aid in response to California's alleged "liberal irresponsibility" make it seem that political alignment plays a larger role in federal disaster aid decision making than it ought to (Wilson & Elfrink 2020).

Ultimately, the Creek Fire and others received a disaster declaration after additional pressure and scrutiny was applied to the federal government. The disaster was extremely devastating, and it was fairly obvious that a disaster declaration and aid was deserved and necessary. It does beg the question, however, for smaller disasters on the severity margins where they may warrant a declaration or may not; whether these decisions will always be made fairly. Under the current system, the President faces electoral incentives constantly and unilaterally makes the decision whether or not to grant natural disaster aid. Given two identical counties impacted by a disaster with one in a swing state and one not, based on my analysis and the way the disaster declaration decision operates, I would expect the county in the swing state to be favored for federal aid over the other.

My primary analysis does not find particularly significant patterns or a consistent causal association between receiving a disaster declaration and socioeconomic outcomes in the following year. It is very possible that disaster declaration may be too heavily related to the damages caused by a given disaster and is therefore influencing the comparison of outcomes between the two groups. Even if disaster recovery with respect to the socioeconomic indicators I use in my analysis is much stronger in the presence of a FEMA declaration, the larger-scale disasters which receive declarations more frequently could dwarf the impact of the declaration. The disaster itself may be depressing the outcome variables I analyze more severely in cases with a declaration than those without. Schulz and Elliott (2013) suggest that counties may shift in the direction of greater inequality in the wake of a natural disaster due to a confluence of private and public aid payments, what they call the "recovery machine". In the year 2010, my model suggests that receiving a declaration led to a poverty reduction in the counties that received a declaration in the year after the disaster compared with the counties that did not receive a declaration. Even if natural disaster recovery in the U.S. operates in a way that reduces equality after a disaster, my results suggest that lower income individuals might be better off in the presence of FEMA aid rather than without federal assistance. Ultimately my findings were more aligned with the research done by Deryugina (2007) and Pleigner (2020), both of whom suggested that the social safety nets and disaster recovery strategies in the U.S. are highly effective at mitigating the adverse economic effects of natural disasters. The one year with significant findings suggested that receiving a disaster declaration significantly reduced poverty rate by 0.8 percentage points, and the other years and outcomes turned out to be insignificant between declared and not declared counties. If the argument made by Schulz and Elliott (2013) is true and disaster aid allocation is working to harm those at the poorer end of the economic spectrum and aid those at the wealthiest, it is likely that the pattern is encouraged more by private and state/local aid rather than FEMA aid as my results on income inequality did not suggest a significant causal relationship.

One shortcoming of my analysis is that I only observe the difference between the year before a disaster and the year after for declared and non-declared counties. It is possible that the effects of receiving a disaster or not may become significant and identifiable further into the future. The challenge with isolating the longer-term impact is that there is no clear pre-treatment and post-treatment period when it comes to natural disaster declaration. Some counties that receive a declaration in one year may have another disaster the next and receive a turndown. This is why I only estimated my model for one year post and prior and I did it separately for every year. The more years one adds to the analysis, the more challenging it would become to isolate the effects of one disaster from another if they overlapped in the timeframe.

VII. Conclusion

My findings are a double-edged sword when it comes to understanding the impacts and motivations behind U.S. natural disaster relief. On one hand, my difference-in-differences model largely suggests that FEMA declarations do not cause socioeconomic harm or inequality when compared with counties that did not receive a declaration. In fact, if anything federal disaster aid is a poverty reduction tool which will leave counties better off after a disaster if they receive a disaster declaration. However, by analyzing a group largely excluded from past literature, counties that request a disaster declaration and are rejected, I expose potential significant biases in the U.S. disaster recovery model. There appear to be factors outside of the natural disaster itself that influence whether or not federal aid is made available to help counties recover. From a policy perspective, it seems that there will continue to be an increasing need for disaster support with climate change hazards predicted to worsen in coming decades. This trend along with increasing political polarization may lead to a need for the reevaluation of who allocates federal funds for natural disaster relief. Perhaps future evaluation will find that it has become a conflict of interest for the President to have full decision-making power, because it may have adverse equity impacts on disaster recovery.

Potential future analysis related to FEMA aid allocations could study the hazard mitigation funding program run through FEMA. My thesis focused only on the disaster declaration itself and the socioeconomic impacts which could be causally linked to receiving aid in the post-disaster period. Disaster assistance grants account for a large portion of the FEMA budget, however they are not the only tool employed by FEMA to help the U.S. cope with natural disasters. FEMA has a large hazard mitigation budget which goes to projects that will increase community resilience to future disasters. This can involve activities from retrofitting buildings in high-risk earthquake areas to building floodwalls. Past literature has examined the cost-benefit analysis of these mitigation programs and found that they are an extremely effective and beneficial investment in communities at risk for natural disasters (Rose et al. 2007). Rose et al. (2007) estimate that the average cost benefit ratio of a FEMA disaster mitigation program is 4:1, making it an attractive strategy for reducing the economic impact of natural disasters in the U.S. Future research could implement a similar methodology as I do when estimating a likelihood function to determine factors that lead to a declaration, but instead analyze how hazard mitigation funding is granted. This could be a way to test whether the apparent allocative bias I determine within FEMA disaster aid is a result of the declaration structure (Presidential power), or a product of FEMA itself.

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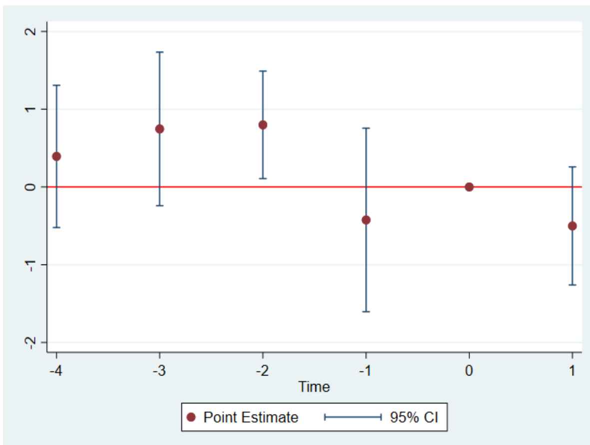
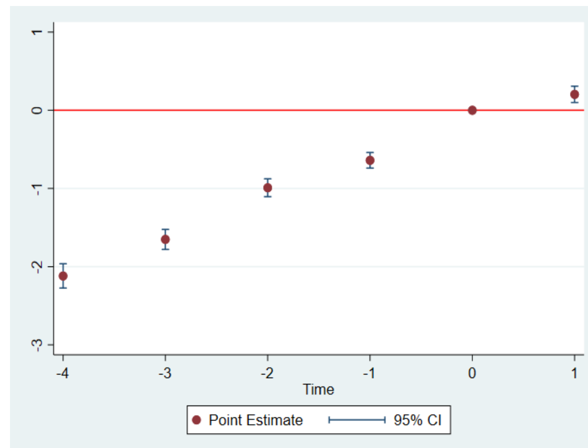
IX. Appendix

Figure 4.1. Poverty Event Study Graphs (2010-2015). Lags and lead years with 95% confidence intervals for difference from the disaster year (t = 0)

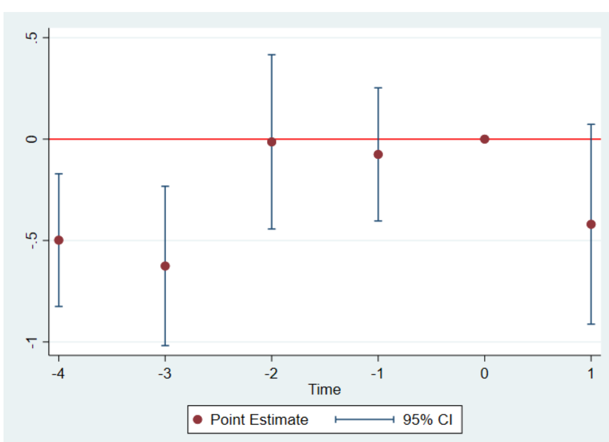
2010



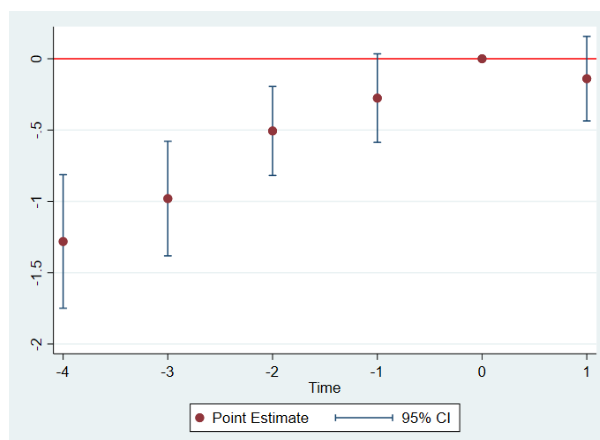
2011



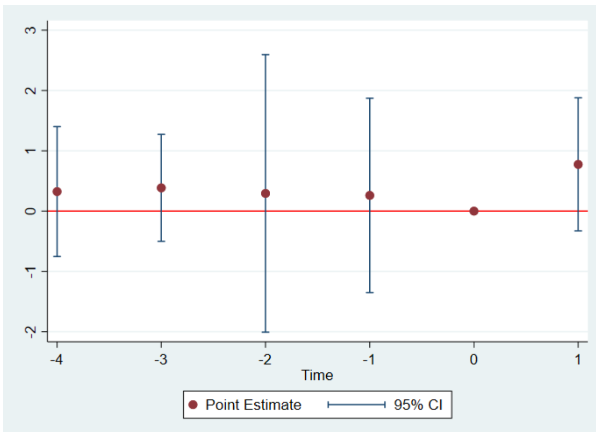
2012



2013

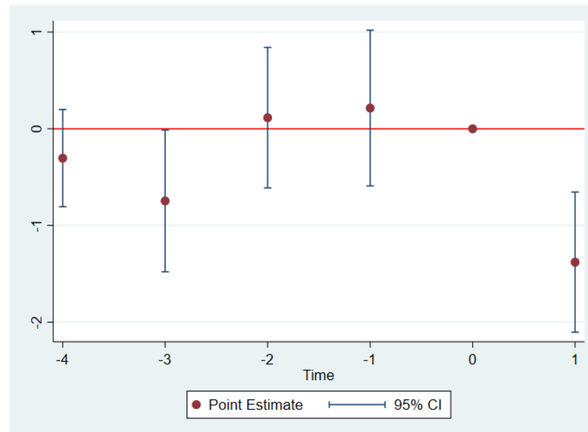


2014



3
2
1
0
-1
-2
-4
-3
-2
-1
0
1
Time
Point Estimate
95% CI

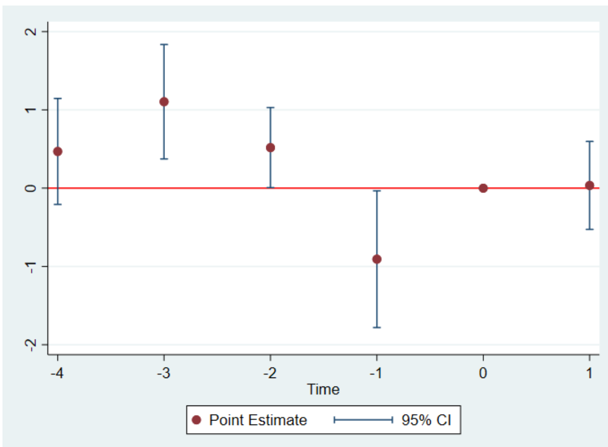
2015



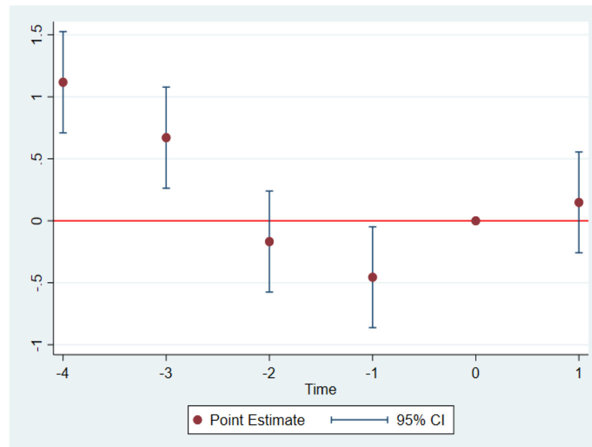
1
0
-1
-2
-4
-3
-2
-1
0
1
Time
Point Estimate
95% CI

Figure 4.2. Unemployment Rate Event Study Graphs (2010-2015). Lag and lead years with 95% confidence intervals for difference from the disaster year (t = 0)

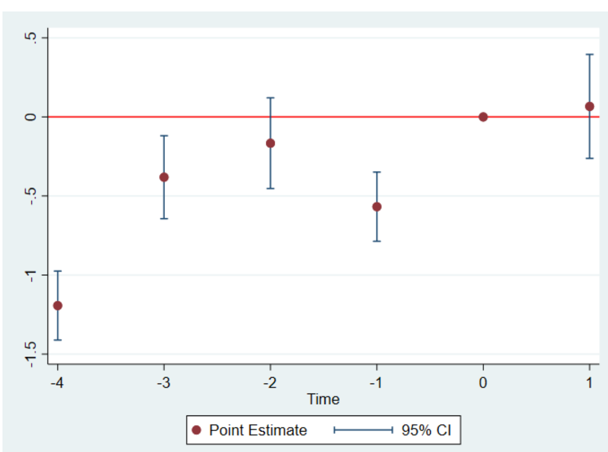
2010



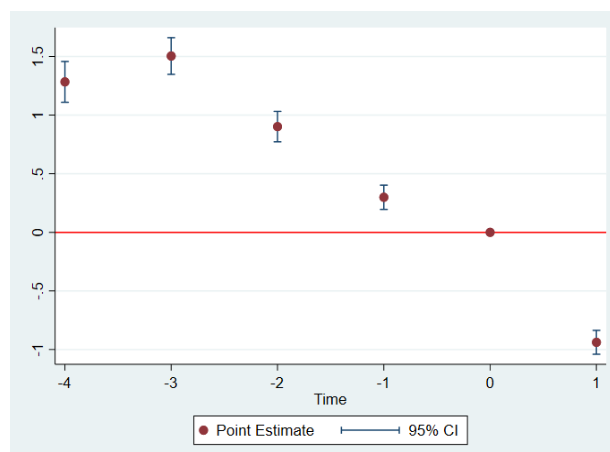
2011



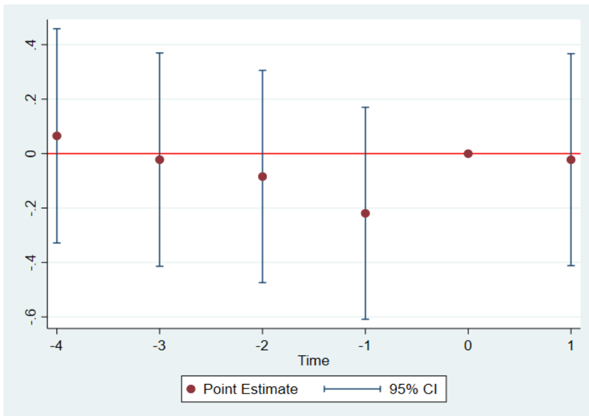
2012



2013



2014



2015

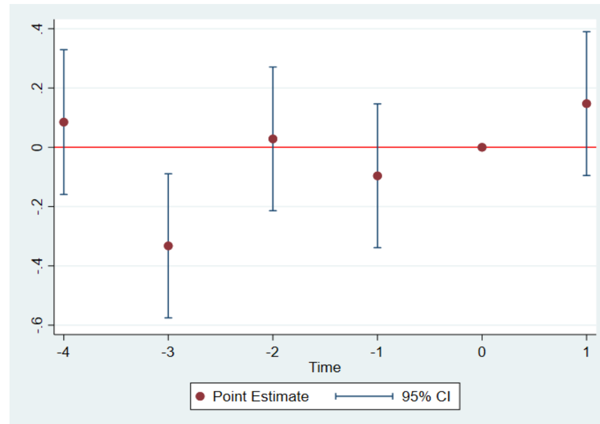
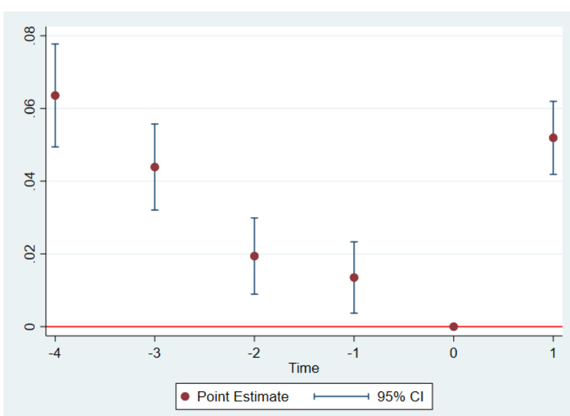
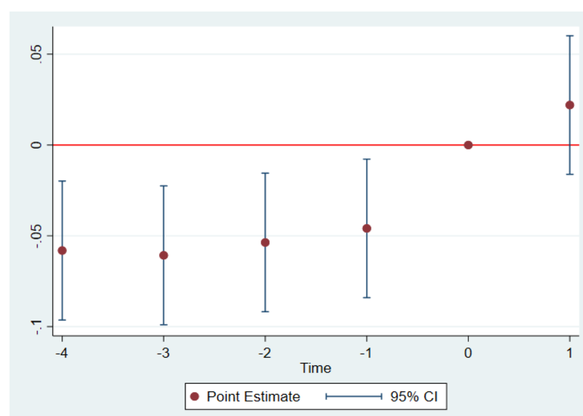


Figure 4.3. SNAP Benefit Ratio Event Study Graphs (2006-2015). Lag and lead years with 95% confidence intervals for difference from the disaster year (t = 0)

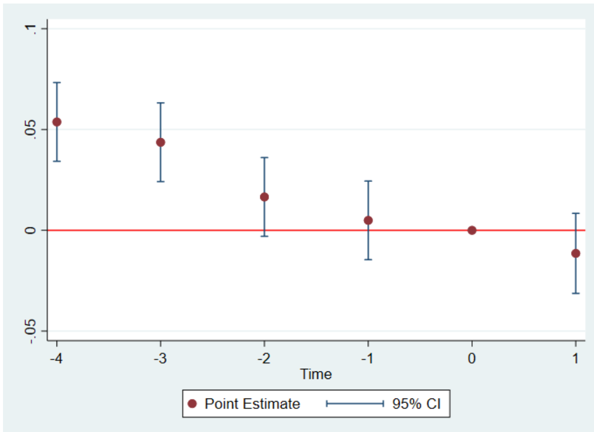
2010



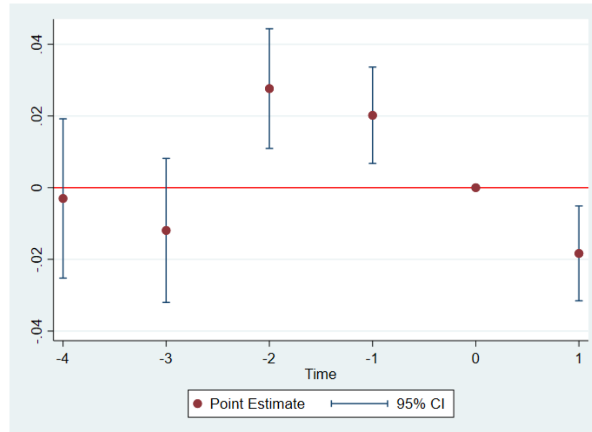
2011



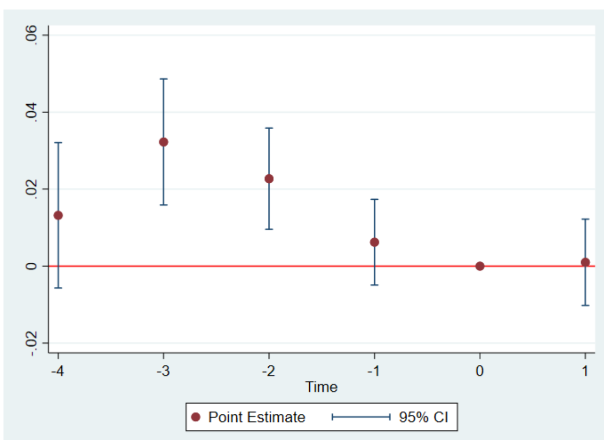
2012



2013



2014



2015

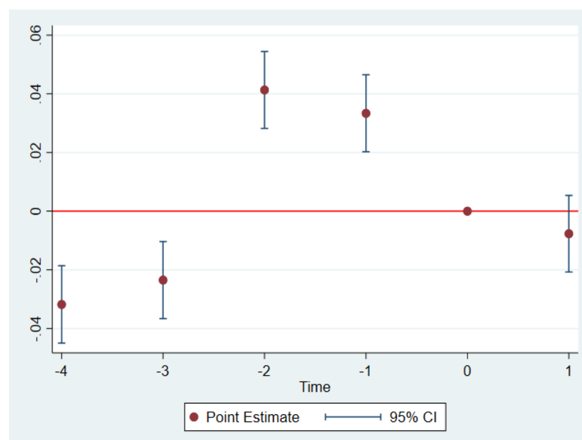
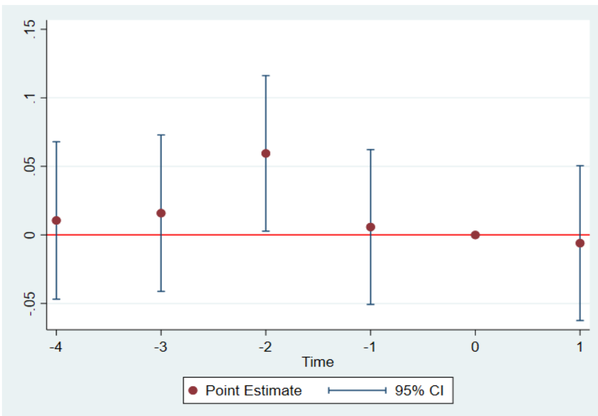


Figure 4.4. Income Top to Bottom Ratio Event Study Graphs (2014-2015). Lag and lead years with 95% confidence intervals for difference from the disaster year (t = 0)

2014



2015