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An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
of Emory University in partial fulfillment
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Abstract

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This paper estimates the economic impact of natural disasters in Florida using county-level data from 1960 to 2019. Limiting the focus to the Florida counties yields estimates specific to the geographic characteristics of this state. We find that a severe disaster tends to cause an increase in crop and property damage and a decrease in the poverty growth rate. The effects of natural disasters on the growth rates of median household income, poverty rate, and housing units vary by disaster and severity.

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Introduction

In 2018, the National Wildlife Federation published a report stating that climate change influences certain natural disasters and increases risk of being affected by them. Rising global temperatures worsen the occurrence and duration of heatwaves, hurricanes, fires, droughts, and floods. As these natural disasters occur more frequently and at higher intensities, wildlife, ecosystems, and the livelihoods of individuals will continue to be affected. Similarly, the IPCC identifies climate change as an underlying factor increasing damage incurred by weather related disasters[1]. For example, the NOAA and NCEI have recorded 310 severe weather-related events since 1980, which have caused $2.155 trillion in costs[2]. Most of the events and damages occurred in the past ten years, indicating a positive relationship between the number of natural disasters and damages sustained. As global warming and climate change increase the frequency and intensity of natural disasters, economies are at risk of facing higher monetary damages.

The geographic location of a population factors into their risk exposure to natural disasters. Population growth, urbanization, and migration towards the coasts increase the vulnerability of communities located in coastal zones.[3] Close to 40% of the United State population live in coastal counties, Florida has the third highest state coastal population.[4] Seventy six percent of Florida's population is concentrated on thirty-five coastline counties. From 1851 to 2020, Florida was hit by 120 hurricanes, 37 of which were of category 3 or higher, marking Florida as the most propense state to be impacted by a hurricane.[5] Consequently, Florida has incurred $3.44 billion in property damage from natural disasters in the last five years.[6] Florida has a vulnerable population that is at a high risk for natural disasters, which have caused billions in economic damage. Estimating these impacts would benefit the decision-making process of private and public entities as they budget for capital, resources, and time spent mitigating these issues. Hence, estimating precise economic impacts of natural disasters would better inform their decisions.

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[1] The Intergovernmental Panel on Climate Change (IPCC) examines the impact of climate change on vulnerability.
[2] The National Oceanic and Atmospheric Administration (NOAA) collected information on the total costs and deaths caused by disasters. The National Centers for Environmental Information (NCEI) analyze the economic and social impact of severe events. Severity is defined as any disaster incurring at least a billion dollars in damage.
[3] Cambers (2001) defines vulnerability as the resources at risk from coastal hazards.
[4] From the National Coastal Population Report Population Trends from 1970 to 2020
[5] Statista compiled this data from NOAA
[6] From the Spatial Hazard Events and Losses Database for the United States (SHELDUS)

This paper analyzes the long and short-term effects of weather-related disaster by estimating their direct and indirect impacts in Florida using county level data from 1970 to 2019. The long term effect is seen in the growth rates of housing units, median household income, and poverty rate. The short-term, direct impacts are captured in crop damage and property damage. The indirect impacts are seen in the effects to the growth rates of median household income and poverty rate. The impact of a natural disaster on the economic outcomes is captured by the severity of a disaster and the number of different disasters. A severe disaster is statistically significant to property damage and crop damage.[7] On average, an additional severe disaster generates approximately $308.8million and $34.5million of property and crop damage, respectively. These estimates are robust to the method of determining severity.[8] The most impactful disasters to crop damage are the additional number of hail, lightning, hurricanes, and winter weather hazards. The most impactful disasters to property damage are the additional occurrence of a hurricane or lightning hazard. A severe disaster is statistically significant to property damage and crop damage, but not to the long-term outcomes, such as the growth rates of the median household income, poverty rate, or housing units (henceforth referred to as the "growth rates"). The effect of the number of certain hazards, such as floods, hail, hurricane, and winter weather, are statistically significant to the growth rates.

The cross-county panel data for the present study is compiled from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), Integrated Public Use Microdata Series for the United States of America (IPUMS USA), IPUMS National Historical Geographic Information System (IPUMS NHGIS), and the Federal Reserve Bank of St. Louis (FRED). The Ordinary Least Squares (OLS) method with fixed effects is used to estimate the parameters affecting the growth rates. The OLS standard errors are corrected with the Newey-West method to yield Heteroskedasticity- and Autocorrelation- Consistent (HAC) standard errors. The natural truncation on the crop and property damage data requires the implementation of the Tobit model. The Maximum Likelihood Estimation (MLE) method is applied to the Tobit model to obtain robust estimates to truncation.

[7] Severe disasters are defined as those above the 95th percentile in total property damage per capita
[8] See Table 2 and Table 4

This paper aims to expand the relatively small literature on the impact of natural disasters on local economies by narrowing the geographic focus to Florida counties. Botzen et al (2019) notes that there are relatively few economic studies of climate change at the regional and local level.[9] Prior studies tackle this intersection at the national and global level[10]. However, the effects of climate change are experienced differently across varying geographic regions and economic dynamics. Botzen et al suggests that "regional models are able to provide a deeper understanding of the channels for disaster impacts and the causal links between these impacts and economic outcomes." Therefore, this paper seeks to uncover such deeper understanding by focusing on the state of Florida.

Previous studies analyze the impact of natural disasters on local economic outcomes. The most similar to the present paper is that of Boustan et al (2020), it examines the effects of natural disasters on migration rates using US county level data. Boustan et al conduct a few regressions on housing and poverty outcomes, but their primary focus is migration rates. Additionally, we include analysis on the direct costs in the form of crop and property damages. Shimada (2022) examines the impact of climate-related disasters on Africa's agriculture production. It finds that severe disasters and droughts negatively affect crop production. This paper finds a similar trend to Shimada, a severe disaster significantly increases crop damage, which would decrease the crop production output. Tran et al (2020) examine the dynamic responses of local economies to natural disasters with a specific focus on personal income per capita. They find that disasters increase total and per capital personal income in the short- and long-term, a finding that is replicated for some disasters in the present study. Tran et al indicates that hurricanes increase income, but floods do not. This paper also finds that hurricanes tend to lead to a growth in income, but we find floods to have mildly significant negative impact.

Additionally, this paper takes a macroeconomic approach relying on county level data to examine the general county response to natural disasters. Some studies focus on a large, one-time event, such as Hurricane Katrina and Hurricane Andrew, to explain the causal effects that a

[9] Botzen et al (2019) reviews empirical models applied to the study of natural disasters.
[10] Narita et al (2009) forecast the global economic impacts of storms due to climate change. Dobroviþová et al (2015) estimate the impacts of floods on the world economy using country level data.

disaster has on an economy.[11] Although it is relevant to examine the immediate effects of a destructive hazard, their findings are limited to the one observed disaster and that specific hazard type. In comparison, this paper derives the short-term and long-term effects of natural disasters from a wide range of hazard observations.

Background on Natural Disasters in Florida

The US has experienced $1,143.9 billion in total direct damage induced by hazards from 1960 to 2019.[12] The cumulative property damage was $946.3 billion, and the cumulative crop damage was $197.6 billion. Florida has the third in highest losses across the United States at $131.2 billion, which makes up for 11.5% of the US total direct damage since 1960. As of 2019, the total number of recorded hazards in the US is close to 925k, the number of recorded hazards in Florida is 19k, which makes up 2% of the entire US count since 1960. The number of disasters in Florida make up a small percentage of the total US count, but account for a large amount of the total damages. In other words, the hazards impacting Florida yield higher costs.

Comparing the geographical size of Florida to Texas, Florida experiences costlier hazards even though Texas is more prone to them due to its larger land area. Texas has the second highest count of hazards at 49.5k and the highest losses at $195.6 billion. On average, a hazard in Texas incurs $3.9 billion in damage. In comparison, Florida had an average of $6.9 billion damage per hazard. This could mean that, on average, the disasters impacting Florida are more severe than those impacting Texas, even though Texas experiences them more often. Another interpretation is that Texas is more prone to disasters but has better coping mechanisms that reduce the potential damage per hazard. The present study's focus on a single state perfectly controls for state specific conditions such as differences in the quality of natural disasters and existing response infrastructure.

The SHELDUS data provides the number of recorded hazards per county per year in Florida from 1961 to 2019. The counties with the highest observed hazards were Hillsborough, Pinellas, Broward, Polk, and Miami-Dade. These five counties experienced a total of 2,862 hazards in the

[11] Deryugina et al (2014) suggests that Hurricane Katrina's victim experienced a decrease in wages in the short-term, but recover to previous levels in the medium-term. Lamb (1998) finds a decrease in the stock returns of property and firms exposed to 1992's Hurricane Andrew.

[12] Figure calculated by The Center for Emergency Management and Homeland Security in the 2019 assessment report, which summarizes the SHELDUS hazard data recorded across the United States.

past six decades, which is equivalent to experiencing an average of 572 hazards per year. There were fewer than 50 combined total incidents of other types of hazards such as wind, thunderstorm, hurricane, lightning, and flooding. The sum of other types of hazards, such as landslides, drought, heat, and fog, was less than 50 total observations, meaning that Florida is not as prone to these types of disasters.

Discussion of Theoretical Predictions

From an economic perspective, a natural disaster can be analyzed as a shock to the economy. An economic shock is defined as an unexpected event that negatively or positively disrupts the economy. Botzen et al (2019) defines a disaster as the sudden loss of production factors (such as labor and capital). It consequently creates a causal chain effect that impacts other aspects of the economy, these effects can be experienced in the short-term and long-term. Environmental economists have analyzed natural disasters through two lenses: direct and indirect costs. Botzen defines direct impacts or costs as “the damage to assets caused by a natural disaster.” Direct costs are easier to identify as they are related to tangible losses, such as the destruction of properties, and they are measured during or shortly after the natural disaster occurs. The direct costs can have longer-lasting effects and lead to indirect costs, which refer to changes in economic activity that follow the disaster. Indirect costs capture the effects of natural disaster on the changes in economic growth and direction. This paper identifies short-term direct costs through crop damage and property damage. Long-term indirect costs are identified through impacts on household income, poverty rate, and changes to housing stock.

This paper examines the impact on five economic outcomes: crop damage, property damage, the growth rate of median household income, the growth rate of poverty, and the decadal growth rate of housing units. The impacts on each of these varies by disaster and through different mechanisms, which are outlined below.

Growing crops heavily depends on weather conditions. A severe disaster would destroy crops, hence, in the short term, there would be an immediate increase in crop damage. Shimada (2022) finds that severe disasters and droughts had the largest negative impact affecting crop production in Africa.[13] To a lesser extent, floods and storms also decreased crop production. Although there

[13] Shimada (2022) defines severity as a threshold of the number of people affected or killed by the disaster.

are geographical differences across both of the studies, it can be implied that a decrease in crop production is derived from an increase in crop damage. Hence, we expect drought, floods, storms, and hurricanes be the most impactful disasters to crop damage in Florida counties.

A 2021 report on climate change catastrophe from CoreLogic finds that the largest natural catastrophe events incurred $56.21 billion in property damage in the US. CoreLogic looked at over 120 million residential structures in the US. The large disasters impacted over 14.5 million homes, which is about 1 in every 10 homes in the United States. Properties are directly impacted by the increasing frequency and severity of natural disasters. Hence, we would expect to see higher property damage when a severe disaster occurs.

The housing stock located in coastline counties is also prone to damage. The rise of global sea levels, induced by climate change, has slowly increased over time. Higher sea levels not only consume a portion of land, but also increase the likelihood and intensity of future coastal storms, such as hurricanes. The landfall of hurricanes might not directly cause property damage, but the aftermath of it, such as flooding, severe storms, and tornados, might destroy housing inventory.

Belasen and Polachek 2009 finds that a hurricane that impacted Florida counties decreased a worker' earnings by up to four percent. They observed an opposite trend on neighboring counties, where the earnings increased. Belasen and Polachek identify a long-term trend, workers in counties affected by a hurricane experienced a faster earnings and slower employment growth than in unaffected counties. These observations are explained due to the migration of individuals fleeing an affected county into an unaffected one. Policymakers and local governments aim to rebuild the affected counties by increasing wages, which serves as an incentive for individuals to stay or migrate into those counties. We expect to see that a severe disaster would increase the median household income.

Severe disasters cause large amounts of property damage, which can include the loss of residential houses and businesses. The destruction of business would lead to a direct loss of jobs if working remotely is not an option. Consequently, we would expect that an additional severe disaster, an additional hurricane, and an additional flood increases the poverty rate.

Data Sources

The dataset used in this paper compiles information for the 67 Florida counties from 1960 to 2020. The data is gathered from multiple sources. The natural disaster data is from SHELDUS, income and employment data comes from FRED, the county population is from IPUMS USA, and the housing units comes from IPUMS NHGIS. Details for each follow.

The natural disaster data was collected from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), which is annually revised and maintained by Arizona State University Center for Emergency Management and Homeland Security. SHELDUS provides county-level data on natural hazards affecting the United States from January 1960 to December 2019. The data on natural hazards covers information on thunderstorms, hurricanes, floods, wildfires, and tornados as well as perils such as flash floods, and heavy rainfall. The data is available for each individual disaster recorded. We aggregate these into yearly and decadal totals. Since damages cannot be negative and many counties have zero damage in some years, a specialized model is applied to analyze the truncated data.

The population data for the base year (1940) is collected from IPUMS USA. The total population count per county in the base year is used in the population time trend fixed effect variable, which is discussed in the methodology section. IPUMS USA provides the complete 1940 population for all 67 counties in Florida. The 1940 complete count data is a result of a collaboration with Ancestry.com.

The median household income data is collected from FRED, which compiles median household income data from the U.S Census Bureau. The data is available from 1989 to 2020. However, there is missing data for 1994 and 1996, the reason for which is unknown. The data is recorded annually and is provided in dollar units, not seasonally adjusted. The household income accounts for the income of the household and all other people 15 years and older who reside in the household, disregarding if they are related to the householder. The reported median household income supplies information on the middle part of the data. The median is based on the income distribution of all households for all possible amounts of income earned, including no income.

The data on the housing inventory per county per decade is collected from the IPUMS National Historical Geographic Information System (NHGIS). IPUMS NHGIS compiles data into summary statistics and GIS files for US censuses and nationwide surveys from 1970 onwards.

Data files are available across different geographic denotations, such as county level per state. IPUMS NHGIS compiles the full count of housing units from 1970 to 2020 on a time series table. The housing data is available per county per decade, and it was directly derived from decennial US census data.

The1940 county employment data and decadal national employment data are used to construct a proxy measure of employment to avoid potential endogeneity issues. The employment per industry and per county in Florida was gathered from IPUMS USA. The total employment per industry in the United States was downloaded from (FRED). IPUMS USA compiles and provides access to US population data from federal decennial censuses. The variables of interest were Employment Status and Industry-1950. The Industry-1950 variable records the number of people working in an industry according to the industry classification of the 1950 Census Bureau. FRED provides employment data for non-farm industries dating from January 1939 to February 2022. Total Nonfarm employment makes up 80% of the workers who contribute to GDP, and this broad category excludes several types of professions such as proprietors, private household employees, unpaid volunteers, farm employees, and the self-employed. The FRED series comes from the Current Employment Statistics (Establishment Survey) conducted by the Bureau of Labor Statistics (BLS). The data is available at the monthly and yearly frequencies, and it is seasonally adjusted.

Methodology

The econometric method applied to estimate the parameters of equation (1) was the Pooled Ordinary Least Squares (OLS), which is a special case of multiple linear regression specific to panel data. The Pooled OLS method incorporates all observations into one regression, and it estimates the unknown parameters of the independent variables. The empirical model is below:

$$Y_{it} = \mu_i + \xi_D + \beta_1 * Disasters_{it} + \beta_2 * \Delta employ_{iD} + \beta_3 * (X_i * t) + \beta_4 t + \varepsilon_{it} \qquad (1)$$

The set of dependent variables analyzed include property damage, crop damage, the growth rate of the median household income, decadal growth rate of housing units, and growth rate of poverty. The explanatory variables are on the right side of the equation, which includes control variables that account for county fixed effects, decade fixed effects, a 1940s population time trend, and a time trend.

The Disasters variable identifies a severe natural disaster recorded in a specific county i in a particular year t or decade D. The severity of a disaster is calculated as the 95th percentiles of property damage per capita incurred per natural disaster. Boustan et al (2020) and Shimada 2022 define severity as a threshold of fatalities or individuals affected by a disaster. Due to inconsistencies in fatality and injury recording in the SHELDUS data, this paper measures severity via the property damage per capita. As a robustness check, we implement a model that defines severity as the 95th percentile of fatalities.

The disaster counts are also included as explanatory variables. Hazards with a low frequency, such as landslides, drought, heat, and fog, are excluded from the analysis. Even though they could have been in the regressions, we chose to omit them because the coefficients would not be meaningful due to the lack of variation in these observations.

Economic analysis of natural disasters poses challenges with endogeneity. The outcome variables, poverty rate and median household income determine the level of employment to a certain degree. Individuals living in poverty may not be able to find a job, which decreases a county's employment. Low wages may disincentivize individuals to work if they have the alternative to earn more from government funded programs, which would decrease employment. To avoid this potential endogeneity, Bartik (1991) and Blanchard and Katz (1992) developed a formula (2) to forecast a county's employment growth that relies on the 1940's industry county-specific employment and a national growth rate (GR). Since this proxy variable is constructed based on the national growth, it is exogenous to local changes in the economic conditions in a county and free of potential endogeneity.

$$\Delta employ_{ijD} = \frac{\sum_{l=1}^{L}\left[EMPLOY_{\{i,1940,l\}} * GR_{\{t,l\}}\right]}{EMPLOY_{\{i,1940\}}} \quad (2)$$

Fixed effects μ_i and ξ_D are implemented to control for the impact of unobserved county and decade specific factors, respectively. The control variable t is calculated number of years that have passed since 1940. The last control variable is $(\boldsymbol{X}_{it} * t)$ which is the product of the 1940s (the baseline year) population per county times the time trend. The purpose of this variable is to control for trends in the dependent variable.

Two issues that arise from using pooled OLS on panel data are heteroskedasticity and autocorrelation. Due to the nature of the panel data, the error term might be serially correlated. The pooled OLS estimators of the coefficients are not affected by the serial correlation in the error term. However, the standard errors are not robust. Thus, the Newey-West method is implemented into the regression to adjust for autocorrelation and heteroscedasticity.

The Newey-West method yields robust standard errors, also known as Heteroscedasticity- and Autocorrelation- Consistent (HAC) standard errors. In pooled OLS, covariance of the error term ε_{it} for county l in year t with the error term $\varepsilon_{i(t+1)}$ is not zero. To correct for this, the variance of the estimators is adjusted by a factor that estimates the covariance of the error terms (see equation 3). The Newey-West method (equation 4) conducts this correction by imposing declining influence as the time between observations increases, with all influence truncated after some fixed number of periods m. Following standard practice, we implement this method with the truncation parameter m specified in (5), where T is the length of the panel.

$$var(\hat{\beta}_1) = \left[\frac{1}{T}\frac{\sigma^2}{(\sigma_x^2)^2}\right] \times f_T, \text{where } f_T = 1 + 2\sum_{j=1}^{T-1}\left(\frac{T-j}{T}\right)\rho_j \tag{3}$$

$$\hat{f}_T = 1 + 2\sum_{j=1}^{m-1}\left(\frac{m-j}{m}\right)\tilde{\rho}_j \tag{4}$$

$$m = 0.75T^{1/3} \tag{5}$$

The data on crop damage and property damage is left censored at zero. The distribution of these two variables is right-skewed and includes values greater than or equal to zero. The OLS estimators is biased for such data. Therefore, the Tobit model (6) is used and estimated via the Maximum Likelihood Estimation (MLE) (7) to obtain a robust estimate of the coefficients when the dependent variables are crop damage and property damage.

$$y_{it}^* = \mu_i + \xi_D + \beta_1 * Disasters_{it} + \beta_2 * \Delta employ_{iD} + \beta_3 * (X_{it} * t) + \beta_4 t + \varepsilon_{it} \tag{6}$$

$$y_{it} = \begin{cases} y_{it}^*, & if\ y_{it}^* > 0 \\ 0, & otherwise \end{cases}$$

The Tobit model (6) describes the relationship between the latent and observed values. The realized values are observed in y_t, where zero is the point at which the data is truncated. The observed values are truncated at zero, and the latent values are described by the latent variable y_t^*. Beta explains the relationship between the explanatory variables and the latent variable. The latent variable then determines the dependent variable when the latent variable is greater than zero.

$$\hat{\beta}, \hat{\sigma} = \underset{\beta,\sigma}{\arg\max}\, [\ln\mathcal{L}(\beta, \sigma] = \underset{\beta,\sigma}{\operatorname{argmax}} \left[\sum\nolimits_{y_t} \ln\left(\frac{1}{\sigma}\phi\left(\frac{y_t - x_t'\beta}{\sigma}\right)\right) + \sum\nolimits_{y_t=0}\left(1 - \Phi\left(\frac{x_t'\beta}{\sigma}\right)\right)\right] \qquad (7)$$

The MLE method estimates the parameters of the Tobit model that maximizes the probability of observing the outcome data given the explanatory data and a certain assuming that the data is generated by the Tobit model presented above.

Table 4 presents the impact of disaster severity (defined as the 95th percentile of fatalities) on the outcome variables. The second type of robustness check consists of removing one fixed effect and control variable at a time. The purpose of this is to examine the variation across the estimated parameters and to understand the impact captured by the control variables had we not included decade fixed effects, employment growth, the time trend, or a population time trend.

Results

This section discusses the estimates of the empirical models presented in the methodology. Overall, a severe disaster has a large effect on property damage and crop damage, however, it is not statistically significant when looking at growth rates of median household income, poverty rate, or housing units. The type of disasters that were impactful across most of the outcomes were the floods, hail, tornados, and hurricanes. The following section discusses the results per outcome.

One additional severe disaster increases crop damage by approximately $34.5 million. An additional flood, hail, hurricane, or winter weather hazard has a significant impact on crop damage. Winter weather has the largest estimated parameter, as it increases crop damage by $35.5 million per additional event. An unexpected outcome of the analysis is that an additional thunderstorm negatively impacts crop damage.

One additional severe disaster increases property damage by approximately $308.8 million. Hurricanes and lightning hazard have a significant impact on property damage, as each incurs $43.8 million and $31.1 million in damage per additional event. An unexpected outcome is that an additional flood or winter weather event has a significant negative impact on property damage.

An additional severe disaster decreases the poverty growth rate by 1.7 percentage points. While this is an unexpected outcome, a severe disaster may require more individuals to contribute to the restoration of a community. The government may incentivize individuals to participate in their community's recovery by paying them. As more individuals provide labor in exchange of wages, the income earned may not define them as someone living in poverty. The natural disasters listed on Table 6 that have a significant impact on the poverty growth rate are the number of floods, hail, and winter weather disasters. An additional flood and an additional winter weather hazard increase the poverty growth rate by 1.1 percentage points and 1.7 percentage points, respectively. However, an additional hail hazard decreases the poverty growth rate by 3.2 percentage points. As seen on Table3, an additional hail hazard imposes significant crop and property damage. Hence, the poverty growth rate may decrease as more people work in agriculture after a hail hazard damages the crop production.

The occurrence of a severe disaster does not have a significant impact on the growth rate of housing units from decade to decade. An additional flood, thunderstorm, and winter weather hazard are statistically significant and each lead to a decrease in the housing growth rate by 1.1, 1.1, and 6.9 percentage points, respectively. The magnitude of the impact of a winter weather hazard is larger than the magnitude of the rest of the variables. An additional hurricane and wind hazard are also statistically significant, but they increase the housing growth rate by 1.8 and 1.3 percentage points, respectively. This positive relationship is an unexpected outcome.

The occurrence of a severe disaster does not have a significant impact on the growth rate of the median household income. An additional flood and winter weather hazard have a statistically significant impact on the median household income growth rate as each decrease it by 0.3 and 1.4 percentage points. The decrease in income can be caused by the decrease in number of people working. Floods and winter weather may have a longer duration period which may worsen the working conditions for some individuals. Hence, this would put some people out work for a few days or weeks. If their wages are paid by hours worked, then the hazard would prevent them from working the normal hours they otherwise would. An additional hurricane is also significant, but it increases the median household income growth rate by 0.7 percentage points. Coupling this information with the previous analysis of the impact of a severe disaster on the poverty rate, a local government may incentivize individuals to contribute to the restoration of the community by offering jobs with higher wages than in a previous year.

Boustan et al (2019) and Shimada (2022) use a fatality threshold to define a severe disaster. Hence, we perform a robustness check to test for any variation when disaster severity is defined differently. Table 4 defines a severe disaster as the 95th percentile of fatalities, these results are compared to Table 2, which defines a severe disaster as the 95th percentile of property damage per capita. One major difference is that the poverty growth rate is not significantly impacted by the severe disaster when it is defined as a fatality threshold. In comparison, the poverty growth rate is significantly impacted by a severe disaster when it is defined as a threshold of property damage per capita. Aside from this observation, the rest of the coefficients are similar across magnitudes and significance. Looking at the estimates in Table 2 and Table 4, reveal that, in general, the severity measure does not alter the significance or magnitude of the estimators. Hence, the estimators are robust.

Robustness checks are performed on the regressions that included fixed effects. Table 6, Table 7, and Table 8 summarize the robustness for the median household income growth rate, poverty growth rate, and housing units' growth rate. The significance and magnitude of the coefficients do not change drastically unless the regressions do not control for decade fixed effects. This indicates that the changes in the growth rates are explained by variations across time. After excluding the decade fixed effects, the estimated parameters suffer from omitted variable bias. Other variables capture the effects that would have otherwise been captured by the decade fixed effects.

Discussion

The previous section identifies the dollar and percentage impact that natural disasters have on the economic outcomes. These estimates indicate large direct costs in crop and property damage.

The estimates also provide insight into the macroeconomic response of the Florida counties after experiencing a severe disaster or a specific hazard. Such response is captured by the effects on the growth rates in median household income, poverty rate, and housing units. Quantifying the estimates inform public and private entities about the impacts of natural disasters specific to the Florida counties. This type of information can help these entities make better decisions regarding the amount of capital, resources, or time they need to invest to mitigate these potential impacts.

This paper performs a retrospective analysis on the macroeconomic response to natural disasters in Florida counties, which expands the understanding of the economic impact of disasters on localized regions. Some of the findings are in par with the theoretical predictions. However, others, such as the reduction of crop damage per additional tornado and the reduction in property damage by flooding, are counterintuitive. These unexpected outcomes suggest avenues for researchers to explore in the future.

Additional data should be implemented on future studies to explore the effects of natural disasters on vulnerable demographic groups. The findings of this paper are limited to the macroeconomic impacts of disasters. A future avenue for research is to consider vulnerability indices, geographic data, and demographic data.[14] Additional data on a county's readiness to face a hazard, the average county's altitude above the sea level, demographic data, such as race, income levels, and educational attainment, may lead to estimates that better inform the public and legislations on disparities in the economic impacts across different population segments.

We acknowledge some limitations to the present study regarding the analysis performed on crop and property damage. As identified by Green (2004), it is commonly known that the MLE estimators and standard errors for the Tobit model with fixed effects are biased. Thus, leading to false conclusions of significance and coefficient magnitude. Given these limitations, we have chosen to omit the fixed effects entirely from the truncated estimation. We recognize that the omission of decade fixed effects and county fixed effects minimizes our ability to control for unobserved factors. Consequently, the estimators may be less accurate. As a future avenue for research, we suggest the implementation of an econometric model for truncated data that is able to implement fixed effects without generating biased estimators or standard errors. Additionally,

[14] The United Nations Office for Disaster Risk Reduction (UNDRR) defines vulnerability as the susceptibility of an individual or community to be affected by natural disasters given certain conditions.

it would be helpful to investigate methodologies applicable to truncated panel data in a model with fixed effects.

Appendix

Table 1: Count of Natural Disasters in Florida Counties from 1960 to 2020

Disaster Type	Count
Wind	5115
Severe Storm	4844
Tornado	2332
Lightning	2328
Hurricane	1279
Flooding	1242
Hail	607
Winter Weather	576
Coastal	536
Wildfire	142
Heat	17
Fog	10
Drought	2
Landslide	2

Table 2: Effect of Disasters on County-Level Economic Activity by Disaster and Severity

	Poverty Growth Rate	Housing Growth Rate	Median HH Income Growth Rate
	(1)	(2)	(3)
Severe disaster = 1	-0.017*	0.013	0.003
	(0.010)	(0.024)	(0.004)
Coastal	-0.001	0.000	0.001
	(0.004)	(0.003)	(0.002)
Flooding	0.011***	-0.011**	-0.003*
	(0.004)	(0.005)	(0.002)
Hail	-0.032***	0.004	0.006
	(0.011)	(0.008)	(0.005)
HurricaneTropicalStorm	0.001	0.018**	0.007**
	(0.008)	(0.007)	(0.003)
Lightning	-0.000	-0.001	-0.001
	(0.003)	(0.004)	(0.002)
SevereStormThunderStorm	0.004	-0.011**	-0.002
	(0.009)	(0.005)	(0.004)
Tornado	-0.004	0.000	-0.001
	(0.004)	(0.005)	(0.002)
Wind	-0.004	0.013**	0.001
	(0.009)	(0.006)	(0.004)
WinterWeather	0.017**	-0.069***	-0.014***
	(0.008)	(0.013)	(0.003)
Emp growth	-0.075	0.542	0.084
	(0.142)	(0.468)	(0.070)
County FE	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes
Time Trend	Yes	No	Yes
1940s poulation*time trend	Yes	Yes	Yes
Observations	1,315	335	1,192
R^2	0.139	0.758	0.100
Adjusted R^2	0.082	0.683	0.035
Residual Std. Error	0.103	0.216	0.047

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

Disaster severity defined as 95th percentile of property damage per capita

Table 3: Effect of Natural Disaster on Property Damage and Crop Damage (in 100,000s)

	Property Damage	Crop Damage
	(1)	(2)
Intercept	-1,603.480	-26.086
	(964.696)	(130.122)
Emp Growth	815.421	91.629
	(729.922)	(99.387)
Severe Disaster = 1	3,088.147***	344.907***
	(335.056)	(42.384)
Coastal	-227.475	19.163
	(197.256)	(26.504)
Flooding	-297.097	42.132*
	(155.543)	(19.492)
Hail	-213.771	184.552***
	(246.271)	(28.876)
Hurricane Tropical / Storm	437.547*	208.659***
	(204.443)	(25.578)
Lightning	311.326**	41.081**
	(117.825)	(15.485)
Severe Storm / Thunderstorm	229.036	-49.372*
	(167.394)	(20.945)
Tornado	77.901	-28.519
	(127.333)	(16.263)
Wind	-218.057	26.575
	(120.879)	(167.238)
Winter Weather	-713.634**	354.996***
	(237.581)	(26.367)
PopTimeT	0.0001	0.00004
	(0.00004)	(0.00001)
TimeT	4.420	-14.822
	(9.084)	(1.366)

Note: *p<0.05; **p<0.001; ***p<0.00
Severe Disaster defined as the 95^{th} percentile of property damage per capita

Table 4: Robustness Check on Disaster Severity

	Poverty Growth Rate	Housing Growth Rate	Median HH Income Growth Rate
	(1)	(2)	(3)
Severe disaster = 1	-0.007	-0.035	0.003
	(0.012)	(0.031)	(0.004)
Coastal	0.001	0.001	0.000
	(0.005)	(0.003)	(0.002)
Flooding	0.011***	-0.010***	-0.003*
	(0.004)	(0.004)	(0.002)
Hail	-0.032***	0.002	0.006
	(0.010)	(0.008)	(0.005)
HurricaneTropicalStorm	-0.002	0.015*	0.007***
	(0.008)	(0.008)	(0.003)
Lightning	0.000	-0.006	-0.001
	(0.003)	(0.004)	(0.002)
SevereStormThunderStorm	0.007	-0.003	-0.002
	(0.010)	(0.005)	(0.004)
Tornado	-0.004	-0.000	-0.001
	(0.004)	(0.005)	(0.002)
Wind	-0.007	0.008	0.001
	(0.010)	(0.006)	(0.004)
WinterWeather	0.018**	-0.036***	-0.014***
	(0.009)	(0.014)	(0.003)
Emp growth	-0.077	0.479	0.083
	(0.140)	(0.458)	(0.070)
County FE	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes
Time Trend	Yes	No	Yes
1940s poulation*time trend	Yes	Yes	Yes
Observations	1,315	335	1,192
R^2	0.137	0.786	0.100
Adjusted R^2	0.080	0.716	0.035
Residual Std. Error	0.103	0.204	0.047

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

Disaster severity defined as 95th percentile of fatalities

Table 5: Effect of Natural Disaster on Property Damage and Crop Damage, Robustness Check on Severity

	Property Damage	Crop Damage
	(1)	(2)
Intercept	-1,470.582	-22.988
	(960.839)	(129.985)
Emp Growth	559.107	59.675
	(727.532)	(99.315)
Severe Disaster = 1	5,422.056***	370.099***
	(551.777)	(67.398)
Coastal	-1,017.976***	-20.316
	(222.533)	(28.664)
Flooding	-197.641	46.823*
	(154.251)	(19.496)
Hail	34.327	217.035***
	(243.637)	(28.856)
Hurricane / Tropical Storm	1,013.557*	280.166***
	(189.105)	(24.087)
Lightning	39.564	8.179
	(117.794)	(15.625)
Severe Storm / Thunderstorm	302.2935	-38.847
	(167.450)	(21.091)
Tornado	95.094	-23.240
	(127.112)	(16.310)
Wind	-308.269	12.490
	(167.196)	(21.012)
Winter Weather	-594.852*	358.907***
	(235.367)	(23.398)
PopTimeT	0.0001	0.00003
	(0.00004)	(0.00001)
TimeT	13.032	-13.336
	(9.009)	(1.336)

Note: *p<0.05; **p<0.001; ***p<0.00

Severe Disaster defined as the 95^{th} percentile of fatalities

Table 6: Robustness Check for Poverty Growth Rate

	No Dec FE	No EMPL	No TimeT	No PopTimeT	Main Model
	(1)	(2)	(3)	(4)	(5)
Severe disaster = 1	-0.024**	-0.017*	-0.017*	-0.017*	-0.017*
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Coastal	0.003	-0.001	-0.001	-0.001	-0.001
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Flooding	0.005	0.011***	0.011***	0.011***	0.011***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Hail	-0.038***	-0.031***	-0.031***	-0.032***	-0.032***
	(0.011)	(0.011)	(0.011)	(0.010)	(0.011)
HurricaneTropicalStorm	0.004	0.001	0.002	0.002	0.001
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Lightning	0.002	-0.000	-0.000	-0.000	-0.000
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
SevereStormThunderStorm	-0.006	0.003	0.004	0.004	0.004
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Tornado	-0.004	-0.004	-0.004	-0.005	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Wind	-0.003	-0.004	-0.004	-0.005	-0.004
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
WinterWeather	0.030***	0.017**	0.017**	0.020**	0.017**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Emp growth	-0.169		-0.077	-0.078	-0.075
	(0.149)		(0.142)	(0.142)	(0.142)
County FE	Yes	Yes	Yes	Yes	Yes
Decade FE	No	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	No	Yes	Yes
1940s poulation*time trend	Yes	Yes	Yes	No	Yes
Observations	1,315	1,315	1,315	1,315	1,315
R^2	0.049	0.139	0.139	0.137	0.139
Adjusted R^2	-0.012	0.083	0.083	0.081	0.082
Residual Std. Error	0.108	0.103	0.103	0.103	0.103

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

Severe Disaster defined as the 95^{th} percentile of property damage per capita

Table 7: Robustness Check for Growth Rate of Housing Units

	No Dec FE	No EMPL	No PopTimeT	Main Model
	(1)	(2)	(3)	(4)
Severe disaster = 1	0.018	-0.006	-0.006	0.013
	(0.033)	(0.025)	(0.026)	(0.024)
Coastal	0.001	0.001	0.003	0.000
	(0.005)	(0.002)	(0.003)	(0.003)
Flooding	-0.031***	-0.011***	-0.006	-0.011**
	(0.007)	(0.004)	(0.004)	(0.005)
Hail	0.077***	0.003	-0.010	0.004
	(0.016)	(0.009)	(0.010)	(0.008)
HurricaneTropicalStorm	-0.000	0.017**	0.017**	0.018**
	(0.012)	(0.008)	(0.008)	(0.007)
Lightning	0.004	-0.007	-0.005	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
SevereStormThunderStorm	-0.027***	-0.002	-0.000	-0.011**
	(0.007)	(0.005)	(0.006)	(0.005)
Tornado	0.028***	-0.001	-0.005	0.000
	(0.006)	(0.005)	(0.005)	(0.005)
Wind	0.017**	0.007	0.005	0.013**
	(0.008)	(0.005)	(0.006)	(0.006)
WinterWeather	-0.011	-0.036***	-0.038***	-0.069***
	(0.016)	(0.014)	(0.014)	(0.013)
Emp growth	0.725		0.485	0.542
	(0.474)		(0.482)	(0.468)
County FE	Yes	Yes	Yes	Yes
Decade FE	No	Yes	Yes	Yes
1940s poulation*time trend	Yes	Yes	No	Yes
Observations	335	335	335	335
R^2	0.591	0.783	0.771	0.758
Adjusted R^2	0.466	0.714	0.698	0.683
Residual Std. Error	0.280	0.205	0.211	0.216

Note: *p<0.1; **p<0.05; ***p<0.01
Severe Disaster as the 95^{th} percentile of property damage per capita

Table 8: Robustness Check for the Growth Rate of Median Household Income

	No Dec FE	No EMPL	No PopTimeT	No TimeT	Main Model
	(1)	(2)	(3)	(4)	(5)
Severe disaster = 1	0.005	0.003	0.003	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Coastal	-0.000	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Flooding	-0.002	-0.003*	-0.003*	-0.004**	-0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Hail	0.007	0.005	0.005	0.005	0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
HurricaneTropicalStorm	0.008***	0.007**	0.007**	0.008***	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Lightning	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
SevereStormThunderStorm	0.002	-0.002	-0.002	-0.001	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Tornado	-0.001	-0.001	-0.001	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Wind	-0.001	0.001	0.001	-0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
WinterWeather	-0.012***	-0.014***	-0.014***	-0.010***	-0.014***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Emp growth	0.093		0.084	0.078	0.084
	(0.071)		(0.070)	(0.071)	(0.070)
County FE	Yes	Yes	Yes	Yes	Yes
Decade FE	No	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	No	Yes
1940s poulation*time trend	Yes	Yes	No	Yes	Yes
Observations	1,192	1,192	1,192	1,192	1,192
R^2	0.044	0.099	0.100	0.079	0.100
Adjusted R^2	-0.023	0.035	0.036	0.013	0.035
Residual Std. Error	0.049	0.047	0.047	0.048	0.047

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

Severe Disaster defined as the 95^{th} percentile of property damage per capita

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