# Surviving a Hurricane: Urban Decline and the Dynamics of Local Supply Shocks

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**Abstract**

Hurricanes are exogenous events that destroy the stock of housing in a city, allowing direct tests of theories of regional dynamics. Motivated by past research on the relation between urban decline and the elasticity of housing supply, we develop a model of a small region with durable housing, endogenous home maintenance, and disaster expectations. The model implies that declining areas (relative to growing areas) have a less well-maintained housing stock, with associated predictions on the effects of hurricanes. In order to isolate hurricane effects and test this theory, we propose a factor-based method of constructing counterfactual growth scenarios for a small region. This method greatly increases the precision with which moderate-sized hurricane effects can be estimated, increasing the power of statistical tests of the theory. Empirical results from this method support theoretical predictions, and results are notably robust to the exclusion of Hurricane Katrina in 2005.

**JEL Classifications:** R11, R31, Q54.
**Keywords:** Urban Decline, Regional Dynamics, Natural Disasters, Housing Maintenance

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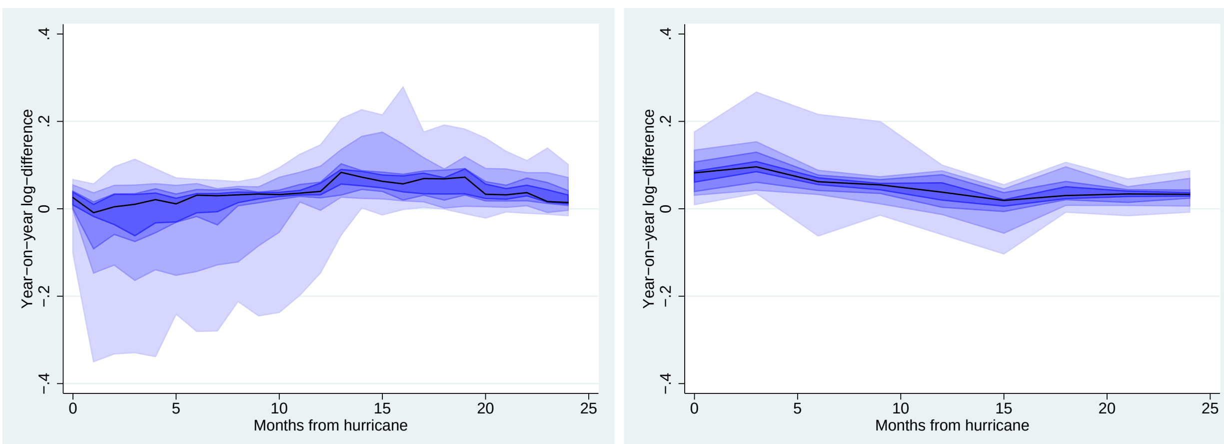
# 1 Introduction

Hurricane effects vary dramatically from storm to storm. While many destroy large quantities of housing, reduce employment, and induce significant human migration, others appear to be relatively benign. Figure 1 shows year-on-year changes in employment and weekly earnings in the months following a hurricane of Category 3 or above, with percentile bands suggesting substantial variation across events. In order to explain this variation, we develop a theoretical model of a small, open region, with durable housing, home maintenance decisions, and hurricane expectations. Our theory suggests that in addition to natural storm and local geographical factors, *economic* factors may contribute to differences in local damage and recovery.

Figure 1: Unconditional Post-Storm Dynamics, Direct Hit Category 3+ Hurricane

(a) Employment　　　(b) Weekly Earnings per Employee




These figures show year-on-year log differences in (a) monthly employment and (b) quarterly wages per worker, in the months (or quarters) that follow a hurricane strike. The lines represent the boundaries between deciles.

Unfortunately, the variation in Figure 1 is not enough to conduct empirical tests of the theory due to confounding contemporaneous economic events. This suggests a reason why, despite the potential usefulness of these relatively numerous, exogenous, localized shocks to study various important topics in the broader literature on economic growth and the geographical distribution of production, the economic research on the consequences of natural disasters remains quite limited. To overcome this measurement problem, we propose a method of isolating effects of exogenous events on a local area. This method embeds the approximate factor structure of Chamberlain and Rothschild (1983) into a dynamic autoregressive model; the factor model effectively uses information contained in the dynamic behavior of all counties to correct for the effects of aggregate shocks (of potentially different varieties) that may have heterogeneous effects on local areas.[1] By developing a "no-hurricane" counterfactual, we are able to more precisely estimate the impacts of these events.[2]

Using this empirical approach, we find that hurricane recoveries are consistent with the urban decline hypothesis (outlined below), which posits that recoveries from an exogenous, negative supply shock depend on expected returns to investment in housing structures. In the model, these returns are based on the location's economic fundamentals, which differ across areas. Declining areas are affected more by hurricanes initially, and recover less in terms of housing stock, employment, and non-worker population. These results hold regardless of whether hurricane Katrina is included in the data set, and robust to alternate explanations.

The key mechanism in the model is housing structure maintenance.[3] In an area experiencing economic decline, defined as an area where housing structure values are less than the replacement costs, there is less incentive to structurally maintain a home, making it more vulnerable to extreme wind, rain, and flooding.[4] Once destroyed, some of the housing stock in a declining area is not reconstructed, leading to permanent effects of hurricanes. On the other hand, in areas that are not declining, housing that is destroyed is rebuilt, and the hurricane has no permanent effects. These model features are consistent with Glaeser and Gyourko's (2005) "urban decline hypothesis" and findings of Gyourko and Saiz (2004), who estimate home maintenance to be up to 50% lower in declining areas.

Hurricane expectations is the other major factor affecting vulnerability to hurricanes. Areas that expect to experience a hurricane in any given season with a high probability perform maintenance on a greater share of buildings in order to mitigate hurricane risk. Such an area that is struck by an "expected" hurricane faces less damage and no change in steady-state size.[5] On the other hand, an area in which a hurricane is not expected will suffer greater losses due to lower levels of maintenance, and face a lower steady-state size following the hurricane.

[1] An example might be the housing boom, which strongly affected certain counties, but in which many counties were largely unaffected. Another example is oil shocks, which affect areas that are involved in refining and production more than other areas.

[2] This approach is similar to the synthetic control method of Abadie and Gardeazabal (2003), Abadie, Diamond, and Hainmueller (2010), and Cavallo et al. (2013).

[3] In this paper, the concept of "housing maintenance" applies only to the soundness of the structure and does not include any activities that generate amenity or consumption value.

[4] This is found by Fronstin and Holtmann (1994) to be true in the case of Hurricane Andrew in 1992. Lower valued homes had a greater probability of becoming uninhabitable or destroyed in the hurricane.

[5] See Yezer (2010) for discussion on disasters that change expectations versus those that do not. We examine the historical incidence of hurricane activity later in the paper, and use this as a measure of hurricane expectations.

In order to test these predictions, we construct a new, high-frequency dataset of county-level labor and housing market indicators, along with information on the incidence and severity of cyclone strikes, similar to Belasen and Polachek (2008, 2009), but with additional storm surge data. Our incorporation of storm surge data into the analysis is new in the literature. Previous studies such as Belasen and Polachek (2008, 2009) and Hsiang and Jina (2014) only consider wind speed. Our findings suggest that it is actually the storm surges that do much of the damage, and this damage is worse the lower the elevation of the housing stock in the county. Because wind and storm surge height are correlated, when surge information is absent from empirical specifications, parameters on wind are estimated to be too large due to omitted variable bias.

The predictions from the theoretical model are tested by estimating the effects as a function of an index of regional decline. In both growing and declining counties, large hurricanes that hit the county directly, hit a neighboring county, or induces a large storm surge, are predicted to cause substantial damage. When a storm surge is present, the fraction of households in a county below 9 feet in elevation serves as a predictor of severe damage. Absent these characteristics, a hurricane is not statistically likely to affect the outcomes under consideration. For each of these storm damage predictors, housing stock, employment, and non-worker population losses are all more severe in declining areas. Consistent with Figure 1, average earnings rise more in harder-hit areas, which is symptomatic of both fewer low-wage workers (composition effect) and higher wages and hours worked (more cleanup and reconstruction). Recoveries present a similar overall story —regions that were previously declining see less of a rebound in housing stock, measured both directly and through the issuance of housing permits. Similarly, employment and non-worker population outcomes are worse in previously declining areas versus growing ones. Critically, all of these results are robust to the exclusion of direct-hit counties during Hurricane Katrina in 2005.[6] When these counties are included in the estimates, statistical tests strengthen.

This research makes contributions in several key areas. The first is the literature on urban decline, which has existed as a theory for quite some time. Housing is easily constructed but decays only slowly, which when combined with a housing market clearing assumption implies that cities decline slowly due to the durability of the housing stock. In a declining city, the current value of many homes is less than the construction cost, attracting households who demand low price housing. This concept was first established by Thompson (1965) as

[6]St. Bernard, New Orleans, Plaquemines, and St. Tammany Parishes in Louisiana, and Hancock and Harrison Counties in Mississippi.

an "urban size ratchet," and later investigated in detail by Glaeser and Gyourko (2005). Since Glaeser and Gyourko (2005), other researchers have sought to investigate dynamics of declining cities. Most empirical models consist of subjecting an area to a demand shock and observing how prices and quantities evolve over time in growing versus declining cities, and inferring the supply response based on these observations (see Larson, 2011 and Notowidigdo, 2013). In the present paper, hurricanes present an easily identifiable natural experiment of a housing supply shock. We test many implications of the urban decline hypothesis, lending support to this concept of urban dynamics.

In addition, the findings here are interesting when viewed in light of the research on large-scale disasters and location-based fundamentals, including Cronon (1991) and Davis and Weinstein (2002). Cronon (1991) examines the effects of the great Chicago fire of 1871, which destroyed 1/3rd of the city's housing stock. Chicago has since fully rebuilt. Similarly, Davis and Weinstein (2002) show that Hiroshima and Nagasaki fully recovered from the 1945 nuclear strikes by 1955, and caught up to their pre-war trend extrapolation by 1975. In general, location-based fundamentals are known to play an important role in the recovery of regions affected by negative supply shocks. However, we know that fundamentals can change over time, and city size may not always reflect fundamentals on account of the durable nature of the housing stock. By relaxing the assumption of static location-based fundamentals, and allowing them to vary based on hurricane expectations and other factors, it is possible to expand the economic geography concepts of Henderson (1974) and Krugman (1991) to better model periods following supply shocks. We argue that natural disasters may affect area dynamics in two primary ways: 1) by destroying housing, speeding the adjustment to a smaller steady-state size previously governed by a slow decay process, and 2) altering the steady-state size itself by affecting future disaster expectations. In this regard, the durable housing model developed in this paper is perhaps generalizable to any massive shock to the housing stock, such as those associated with wars or other natural disasters, including tornadoes, earthquakes, fires and tsunamis, and can be used to explore local damage and recovery dynamics.[7]

Also related to this work is work on estimating the impact of climate change through its effect on hurricanes. Nordhaus (2010) and Hsiang and Jina (2014) find that hurricanes have substantial impacts on economic activity. Our paper provides evidence on the effects

[7]There is also a multidisciplinary literature on disaster "resilience," in the sense that regions can be more or less prepared for a disaster, and have or lack characteristics that enable recovery. For example, see Rose and Liao (2005) for a CGE model of water service interruptions, and Simmie and Martin (2010) for a useful taxonomy of disaster recovery types.

of hurricanes in the short and medium term, and additional insight into why some areas are affected differently from others.

Finally, this paper helps to bring together many of the numerous event-studies of hurricanes and their effects into a unifying, general framework. For instance, a series of excellent *Monthly Labor Review* articles, including Garber et al. (2006) and Brown et al. (2006), examine the labor market effects of Hurricane Katrina and document the extreme damage caused by the storm. Similarly, West and Lenze (1994) present Hurricane Andrew as an application of a regional spatial model. Basker and Miranda (2014) study the effects of Hurricane Katrina on businesses using establishment-level data, and find that small businesses and those facing credit constraints failed to rebuild as fully in the wake of the hurricane. Other event studies exist for virtually every hurricane with substantial damage. We view our work as complimenting these studies which are typically based on only one hurricane, but often at a finer geographical detail.

The remainder of the paper is presented as follows. In Section 2, we describe the storm data and present several new stylized facts which motivate the remainder of the paper. Next, in Section 3, we develop a model of hurricane damage and recovery. Section 4 describes the empirical models used to test the predictions in Section 3. Section 5 presents the results of these tests and Section 6 concludes.

# 2 Background on Tropical Cyclones

A tropical cyclone is a large, spiraling storm that is characterized by having a low-pressure center, strong winds and rain, and usually forms over warm ocean water. Each cyclone in the North Atlantic basin is given a name unique to the year in which it occurs, and is assigned an ordinal classification based on the Saffir-Simpson hurricane wind scale. A cyclone with a 1-minute sustained wind speed at or above 74 miles per hour is called a hurricane. The National Oceanic and Atmospheric Administration's (NOAA) International Best Track Archive for Climate Stewardship (IBTrACS) dataset contains wind, air pressure, and latitude and longitude measurements at the center of each known tropical cyclone in the world since 1848. Table 1 shows the frequency of each storm classifications between 1990 and 2012 in the Atlantic basin.[8] There were 386 large cyclones in the period, 157 of which were hurricanes, for an average of 12.0 cyclones (4.9 hurricanes) per year.

Table 1: Saffir-Simpson Cyclone Classifications

| Cyclone Classification | Wind Speed (mph) | Frequency (1990-2012) |
|---|---|---|
| Tropical Depression | 0 to 38 | 53 |
| Tropical Storm | 39 to 73 | 176 |
| Hurricane, Category 1 | 74 to 95 | 45 |
| Hurricane, Category 2 | 96 to 110 | 35 |
| Hurricane, Category 3 | 111 to 129 | 29 |
| Hurricane, Category 4 | 130 to 156 | 38 |
| Hurricane, Category 5 | 157 + | 10 |
| Total | | 386 |

Each hurricane making landfall may affect many counties. Figure 5 shows the Category 5 hurricane "Andrew" from August 16th-August 28th of that year.[9] The line in the figure gives the track of the center of the hurricane, with adjacent layers of counties given different color designations. Hurricane Andrew began over the Bahamas, made its way over the southern tip of Florida as a Category 4 hurricane, picked up wind speed in the Gulf of Mexico, made landfall again in Louisiana, then made its way inland before dissipating. Table 2 shows that from 1990-2012, there were 386 storms directly hitting counties for a total of 2,569 county-months (these counties are classified as A0 counties), but also affecting 4,259 A1 counties, defined as adjacent to the center path counties, 4,280 A2 counties that were adjacent to A1 counties, and 4,255 A3 counties that are adjacent to A2 counties. Counties are assigned to a particular storm type based on the wind speed at the A0 county.[10]

[8]In this table, and for the remainder of the analysis, 1-minute sustained wind speeds will be used according to the conversion factor $W_{1min} = W_{10min}/0.88$. According to the IBTrACS data description, different weather services measure wind speed sustained over 1, 2, and 10 minutes, depending on the agency. To construct a globally consistent dataset, all winds reported are over 10 minutes. This necessitated NOAA adjusting all of the North American basin wind speeds, which were measured over 1 minute, to 10 minute speeds using the following conversion factor: $W_{10min} = 0.88 \times W_{1min}$. Conversion back to $W_{1min}$ is therefore trivial and can be done without error.

[9]This figure mimics the map of hurricane tracks in Czajkowski, Simmons, and Sutter (2011), who examine the effects of hurricanes on fatalities.

[10]Values of A0-A3 add up to 1, meaning that counties are first assigned to A0 if directly hit in a month, then A1 if not directly hit, and then A2 if not A0 nor A1, and so on.

## 2.1 Storm Surges

A storm surge is a rise in water level associated with a particular storm, and is caused by two main factors: 1) the relatively low pressure of the storm pulling the water up, and 2) the wind pushing water away from the center of the storm. While the wind speed defines the hurricane classification, storm surges associated with hurricanes are potentially far more damaging. Storm surge data are from Western Carolina University's National Storm Surge Database and Louisiana State University's SurgeDat database. We identify 73 storm surge-county-months since 1990 that are in the direct path of a tropical cyclone, 30 of which are 9 feet or greater. Similarly, there are 189 storm surge surge-county-months one county away from the storm, 264 two counties away, and 307 three counties away.

The effects of storm surges vary based on geological features. Coastal counties with low elevation have been observed to be particularly vulnerable to storm surges. Therefore, we construct a variable measuring the fraction of households in a county who live less than 9 feet above sea level.[11]

One complication is that storm surge data are subject to censoring. Historically, only the severest storm surges were measured, reducing the probability of measurement for small surges. Based on this issue, we create a variable to represent a "big surge," or a storm surge 9 feet or greater. This eliminates the censoring issue and also is the same altitude as the housing unit elevation measure.

## 2.2 Stylized Facts

Stylized facts about tropical cyclones begin with Belasen and Polachek (2008, 2009), who are the first to construct a county-level dataset of employment, earnings, and hurricane strikes, and generalize the result that high hurricane winds are associated with housing destruction, population displacement, reduction in employment, and an increase in earnings per worker. Additionally, counties adjacent to the storm are also affected, and while bearing some damage, adjacent counties often benefit by contributing to cleanup and reconstruction efforts in the hardest-hit areas.

We reconstruct and update Belasen and Polachek's (2008, 2009) county-level storm database using NOAA and QCEW data, extend it to all areas in the United States, and

[11] A list of coastal counties identified by NOAA is used to determine if a county is coastal or not. Then, a population density map is spatially merged with an elevation shapefile in order to determine the number of households less than 9 feet above sea level.

uncover several additional stylized facts.[12] The first is, while wind speed certainly contributes to hurricane damage, there is vast unexplained variation in the dynamics of areas in response to hurricanes. The second fact is that while winds are correlated with damage, so are storm surges. Surges are important to consider because different areas exhibit different levels of vulnerability to storm surges depending on the elevation at which housing in an area is constructed.

Figure 7 shows four panels. The first three echo the results in Belasen and Polachek (2008, 2009), and the fourth shows that storm surges are also associated with severe hurricane damage. These figures suggest that the effects of storm attributes are highly nonlinear. The effects of winds up to about 110 miles per hour (below Category 3) appear to be small compared to the effects of winds above 110 mph (Category 3 and above). The average employment loss from a Category 3 hurricane is 5%, unconditional on any other variables. The recovery appears to begin in earnest around month 7, accelerating through month 14, and tapering off over the next year. Earnings effects are more pronounced than employment effects. While hurricanes below Category 3 appear to affect employment very little, a hurricane of any strength (Categories 1, 2, or 3+) positively affects earnings per worker. Most of the damage is in center-path counties. However, adjacent counties also suffer substantial damage. By the time a county is two away from the center path, damage appears to be minimal. The storm surge panel suggests minimal effects of small storm surges, but large and nonlinear effects of large ones. 12 feet appears to be the point of inflection, below which surges have low expected damage, and above which risks are substantially higher. Figure 7, along with Figure 1 in the Introduction, demonstrates the rich variability in hurricane damage and recovery, which we employ to test theories of hurricane damage and recovery in later sections.

[12]The source for labor market data is the Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages (QCEW), which provides monthly employment and quarterly wage and establishment figures by county from 1990-2012. The QCEW employment counts are from a quarterly establishment-level census. Unfortunately, this measure double-counts people who hold multiple jobs and omits self-employed, agricultural workers on small farms, members of the armed forces, and some other smaller categories. While employment is an imperfect measure of storm damage, as employment changes can be due to business interruption (see Burrus et al., 2002), structural damage to businesses, or loss to labor supply, we estimate initial employment and non-worker population effects of hurricanes to be similar in Section 5, suggesting that employment losses from hurricanes reflect supply shocks.

# 3 Model

The purpose of this section is to develop a model able to explain some sources of variation described in the prior section and shown in Figures 1 and 7. The model adapts Glaeser and Gyourko's (2005) model of urban decline, incorporating three new features: (1) endogenous dwelling maintenance performed by an infinitely lived, risk neutral lot owner, (2) hurricane damage that is a function of a particular structure's level of maintenance, and (3) the effects of hurricane expectations on maintenance decisions.[13] We will initially assume that all hurricanes are unanticipated, but will later relax the assumption. This model yields rich predictions of employment, wage, and construction dynamics when different types of areas are struck by an equivalent hurricane.

### Housing Demand

Following the regional equilibrium literature beginning with Rosen (1979) and Roback (1982), Glaeser and Gyourko (2005) assume that households can costlessly change locations and receive an interregional reservation utility $\bar{U}$, consisting of area-specific wages ($W_i$) and amenities ($A_i$), and a lot-specific disamenity of $d_{ij}$ with a rental price of $r_{ij}$. On each lot, one house is constructed with a fixed flow of housing services. The lot-specific disamenity reflects the lot's "ranking" compared with other lots, and embodies the implicit assumption that all renters agree on which lots are preferred to others.[14] Initially, we assume that all individuals that reside in a location are workers and therefore earn both the area-specific amenity and wage, and implying that population, housing, and employment are equivalent. This gives rise to the equilibrium condition

$$\bar{U} = A_i + W_i - d_{ij} - r_{ij}. \tag{1}$$

Normalizing utility to zero and defining $\theta_i \equiv A_i + W_i$ gives the rental price of every house-lot bundle, and thus the housing demand schedule, as

$$r_{ij} = \theta_i - d_{ij}. \tag{2}$$

[13] The following discussion refers to an area as a "city" but the concept is generalizable to any area, including rural areas.

[14] The lot-specific disamenity can represent distance from a central business district in the monocentric standard urban model of Alonso (1964), Mills (1967), and Muth (1969), or some other representation such as disaster risk (Frame, 1998) or proximity to a consumption amenity as in Brueckner, Thisse, and Zenou (1999).

Lot quality is uniformly distributed above $d = 0$ with density $N$.[15]

### Housing Supply

We assume housing producers are infinitely lived and risk neutral with a discount rate $\beta$. For now, assume that there are no shocks. Timing within a period is as follows: Each lot begins the period as either vacant or with a structure that is *unmaintained*. A maintenance decision is made, which can upgrade the unit to *maintained* for the period, at a cost of $m$. Then, each unmaintained home has a probability $\delta$ of collapse. Maintenance serves only to affect the durability of the unit and does not alter the flow of housing services the unit provides. At this point, new houses may be built on vacant lots (or lots in which the home has recently collapsed) at a cost of $c$. Finally, a dweller receives flow utility from the unit and pays rent.[16]

An owner will develop a lot if the present discounted flow of rents is greater than the cost of the structure. With discount rate $\beta$, the flow cost associated with the construction cost is $c(1-\beta)$. The flow cost of maintenance is $\beta m$ (maintenance is not required in the initial period). Thus, as long as the owner plans on continuously maintaining the unit, the last unit constructed is with rent $\overline{r}$

$$r > \overline{r} \equiv c(1-\beta) + m\beta \tag{3}$$

Note that $\overline{r}$ depends only on parameters of the model ($c$, $\beta$, $m$, and $\delta$) and not on the location-specific amenity $\theta_i$. This quantity summarizes the supply of housing, which at this point is constant across locations both within and across areas.

Because in reality, structural maintenance occurs in every city[17], we initially assume that $m < \delta c$ with a strict inequality, such that unmaintained buildings will not exist in cities that have reached a steady-state level of housing. Later on we will relax this assumption, such that some maintenance will occur every city but owners will not maintain all structures in any city.

[15] We assume shocks to $\theta_i$ are unanticipated.

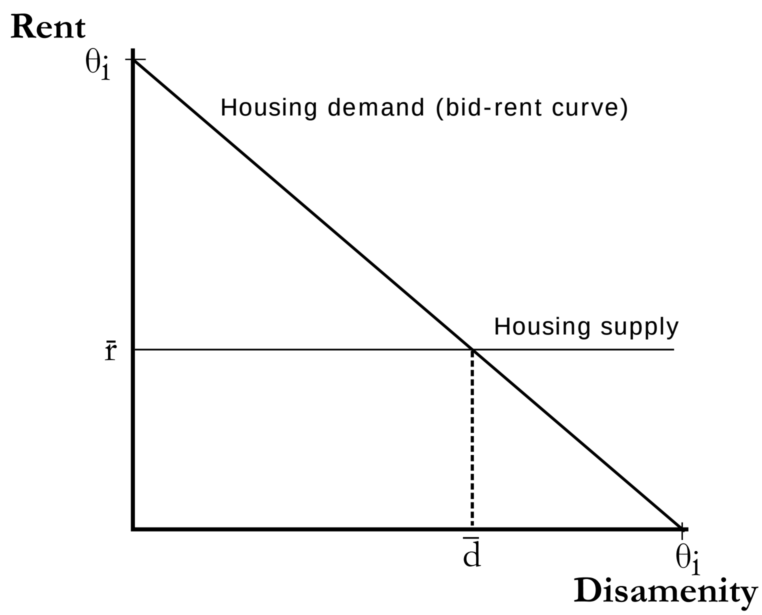
[16] This set-up is equivalent to Glaeser and Gyourko (2005), but with a maintenance mechanism as opposed to exogenous collapse as in the case of their paper.

[17] This can include roof and window repair, beam maintenance, submersible pump installation, and numerous other recurring expenditures.

**Equilibrium city size**

We define the location-specific housing market equilibrium quantities $\overline{d}_i = \theta_i - \overline{r}$ to represent maximal lot-specific disamenities under which construction (with maintenance) would occur. Figure 2 shows $\overline{d}_i$, the intersection of the supply curve and the demand curve (equations 2 and 3). All units are maintained and construction will occur on all lots with disamenity below $\overline{d}_i$.

Figure 2: Housing market equilibrium




In a steady-state city, the number of housing units $P_i$, is determined by $\overline{d}_i$. The number of houses built is given by the density of housing at each lot disamenity level, $N$, multiplied by the range of disamenities of lots on which housing is built, with city size increasing in amenities and wages and decreasing in construction and maintenance costs.

$$P_i = N\overline{d}_i = N\left[\theta_i - (c(1-\beta) + m\beta)\right]. \tag{4}$$

## 3.1 Growing Area

Now suppose there is an unanticipated shock to $\theta$ equal to $\Delta > 0$, so now housing demand is given by $r_{i,j} = \theta - d_{i,j} + \Delta$. Lot owners adjust their optimal maintenance and construction plans accordingly. Housing is constructed on all lots with disamenity less than $\theta + \Delta$, which is greater than the previous highest disamenity level. New construction is treated as being maintained, so there will be no unmaintained structures. City size rises by $\Delta N$.

### 3.2 Declining Area

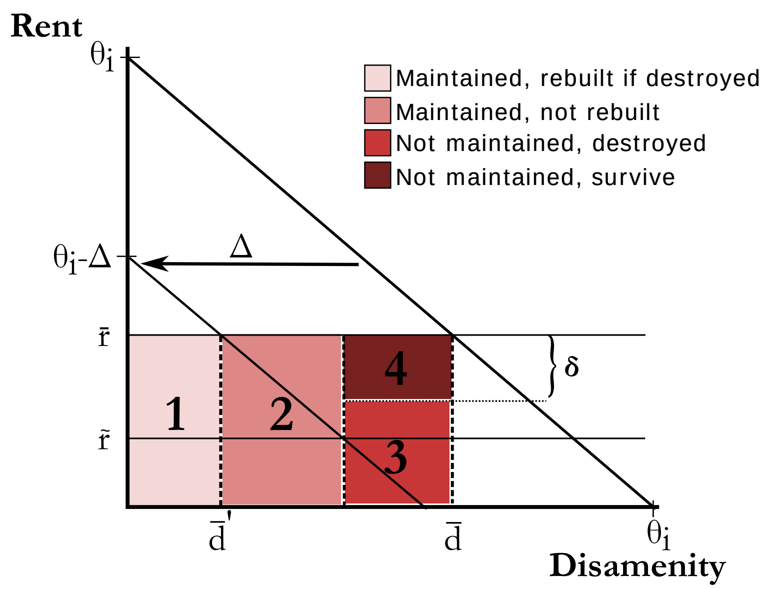
Instead, suppose $\Delta < 0$. Houses on lots having disamenity levels between $\overline{d}_i - \Delta \equiv \overline{d}_i'$ and $\overline{d}_i$ would no longer be rebuilt were they to be destroyed. However, some lots in this range will still be maintained, since the building cost $c$ is sunk. The cutoff for maintaining is given by

$$\widetilde{r} \equiv \frac{m(1-\beta(1-\delta))}{\beta\delta}. \tag{5}$$

It can be shown that $\widetilde{r} < \overline{r}$ for normal parameter values. We define $\widetilde{d}_i \equiv \widetilde{r} - (\theta_i - \Delta)$ (the point at which the new housing demand curve crosses $\widetilde{r}$). For lot disamenities between $\overline{d}_i'$ and $\widetilde{d}_i$, structures are maintained but not rebuilt if destroyed. For lot disamenities between $\widetilde{d}_i$ and $\overline{d}_i$, structures are not maintained. Thus, in the period of the shock, $\left(\overline{d}_i - \widetilde{d}_i\right) N\delta$ will be destroyed due to lack of maintenance. The population falls by the number of homes that are destroyed.[18] In this simple version of our model, unmaintained dwellings are found only in declining areas. This is consistent with the empirical findings of Gyourko and Saiz (2004), who show that home maintenance is perhaps 50% lower in declining cities. The dynamics of housing supply in the declining city would play out as the destruction of a proportion $\delta$ of (a decreasing number of) unmaintained dwellings with disamenities between $\widetilde{d}_i$ and $\overline{d}_i$ until a new steady-state city size is reached in the long run. This new steady-state city size is larger than the size of a "new" city with $\theta = \theta_i - \Delta$, as there are some lots that would not have been built at the new local amenity level, but are maintained because the building cost is sunk. Figure 3 shows the first period of decline after a change in $\theta$ of $\Delta$.

[18] Note that a growing city's employment changes by $\Delta N$. This gives the asymmetric employment response to a demand shock identified by many in the urban decline literature, including Glaeser and Gyourko (2005).

Figure 3: Decay in a Declining Area




## 3.3 Hurricane Strike

Suppose then, that a hurricane strikes each area at the end of the period, after initial housing maintenance and construction decisions. We assume that the hurricane strike is unanticipated. The hurricane destroys maintained units at a rate $\phi$ and unmaintained units at a rate $\hat{\lambda}\phi$, where $\hat{\lambda}(1-\delta) > 1$.[19] This reflects the notion that dwellings that are not properly maintained are structurally less resilient to wind, rain, and flooding. In a growing area, $\Delta\phi$ units are destroyed and then rebuilt, with no permanent effects. To simplify notation, we define $\lambda = \hat{\lambda}(1-\delta)$.

In a declining area, the inner fraction of units that are maintained suffers destruction at a rate of $\phi$ and is rebuilt for lots with $d_{ij} < \overline{d}_i'$. A proportion $\phi$ of lots for which $\overline{d}_i' < d_{ij} < \widetilde{d}_i$ is destroyed, and not rebuilt. In the unmaintained range, $d_{ij} > \widetilde{d}_i$, housing is destroyed at a rate $\lambda\phi$. These homes are not rebuilt. In the declining case, the hurricane causes a permanent drop in the stock of housing among unmaintained and low-rent maintained units, and a temporary drop in maintained units.

[19]The $(1-\delta)$ term reflects the fact that $\delta$ unmaintained units would have been destroyed in the absence of the hurricane.

### Implications

This model gives rise to several empirically testable predictions. These cover a range of concepts, which include the initial damage to the housing stock, the ensuing recovery (or lack thereof), and the changing skill and wage distributions in the area as a result of the hurricane.

The first prediction considers the relative damage in a growing versus a declining area.

**Prediction 1.** *Destruction of the housing stock, employment, and population is more severe in a declining area than in a growing area.*

By "more severe," we mean that the total proportion of housing destroyed is greater when comparing two cities of initially equal sizes. In a steady-state or growing city, there are no unmaintained housing units. This means that a hurricane destroys a fraction of housing units equal to $\phi$. On the other hand, we have defined a declining city as one that has experienced a reduction in $\theta_i$ equal to $\Delta$. Recall that as a fraction of housing units, $\phi$ maintained and $\lambda\phi$ unmaintained units are destroyed as a result of the hurricane. In a declining city, we see some unmaintained units, which are more vulnerable.

**Prediction 2.** *A declining area rebuilds less housing relative to a growing area, with associated lower recoveries in employment and population*

This prediction arises because in a growing city, all houses are rebuilt. However, in a declining city, unmaintained and some maintained houses that end up destroyed are not rebuilt, as they have disamenities that are above the maximal disamenity. Because housing, population, and employment are all equivalent, housing drives differential recoveries in both housing and employment as well.

At this point, we introduce two separate generalizations of the model as it has been presented up to now. These generalizations are not needed to generate the predictions discussed in this section (and they do not reverse them, either), but they are needed to produce other predictions that are important to the overall story we tell about the effects of hurricanes. The first generalization introduces stochastic maintenance requirements, while the second introduces heterogeneous worker skill. The first allows us to discuss the impact of hurricane expectations on maintenance decisions, while the second allows us to explore the effects of hurricanes on wages.

## 3.4 Effects of Hurricane Expectations

Up to now, we have assumed that the cost of maintenance is fixed at each point in time. This is sufficient to generate a number of predictions regarding the effects of hurricane strikes in growing and declining areas. However, this assumption allows maintenance to vary only along the extensive margin (certain houses' amenity levels in declining areas are maintained, and changes to costs and benefits change the levels of disamenity at which maintenance occurs). We feel that such a case is too rigid for exploring the effect that hurricane expectations have on maintenance decisions. In order to do so, we first assume that maintenance requirements are no longer constant, but arrive at random to each unit in each time period.[20] For maintenance requirements above a certain threshold, it is optimal to not maintain a unit, even in a growing area. This threshold is affected by hurricane expectations, thus generating an incentive for greater maintenance when hurricanes are expected due to the greater probability of an adverse event. However, this increased maintenance and probability of structure destruction is costly, shifting up the area housing supply curve and reducing equilibrium size.

### Stochastic maintenance requirements

Maintenance costs arrive according to an *iid* process, $M_{ijkt} \sim F_M(m)$, where $ijkt$ indexes the specific housing unit $k \in [0,1]$ located at $d_{ij}$ at time $t$. For convenience, we suppose that $M$ is distributed according to an exponential distribution with parameter $\eta$, having support $[0,\infty)$. Its CDF is denoted $F_M(m) = \exp\{-\eta m\}$. At the time at which a unit is built, nothing is known about future maintenance needs except the distribution.

We write the value function of the property owner as

$$V = r + \beta \max\left[V - m, V - \delta c, V(1-\delta)\right] \tag{6}$$

In the case of a degenerate $M$ distribution and $V \geq c$, we get $r = V(1-\beta) + \beta\delta c$ or $r = V(1-\beta) + \beta m$ (i.e., one builds if and only if $c \leq V$). If the distribution of $M$ is nondegenerate, the problem splits into two cases, $V \geq c$, in which case the $\beta(V - \delta c)$ term dominates, and $V < c$, in which case the $\beta V(1-\delta)$ term dominates. The former of these cases represents rent levels for which new housing would be constructed were there room

[20]For example, sometimes a home needs only to have a broken window fixed in a year. In others, the roof needs to be replaced. Both render the house vulnerable to hurricanes, but have much different costs of restoration.

to do so; the latter represent areas in which new housing is not constructed but in which housing currently exists—a situation only occurring in declining areas.

### Growing or stable areas

We start by assuming that $V \geq c$, which is the case in the entirety of a steady-state area, and in the inner region of a declining area. Then the decision to maintain depends on the size of $M$ relative to $\delta c$, and from here on out, $V$ will represent $\mathbb{E}V$, its *ex ante* expectation before the current draw of $M$. $V$ can be expressed as

$$V = r + \beta \mathbb{E}\left[V - M \,|M < \delta c\right] + \beta \mathbb{E}\left[V - \delta c \,|M \geq \delta c\right]. \tag{7}$$

It is relatively straightforward to derive $V$,

$$V = \frac{r - (\beta/\eta)F_M(\delta c)}{1-\beta}. \tag{8}$$

Let $V(r)$ express the asset value of a home as a function of the rent, $r$. This equation states that the asset value of a home that rents at $r$ depends on $r$ and the expected level of maintenance required—but maintenance is capped at $\delta c$. In this case, there will be a single $r$ for which $V(r)$=c (the point at which developers are indifferent). As before, we can derive the highest disamenity lot on which a new home would be built in a city with local amenity $\theta$,

$$\overline{d}_i(c,\theta) = \theta - c(1-\beta) - \frac{\beta}{\eta}F_M(\delta c). \tag{9}$$

As before, any changes in $\theta$ induce one-for-one changes in $\overline{d}_i$.

### Declining areas

Suppose a downward shift $\theta_i \rightarrow \theta_i' = \theta_i - \Delta$, as previously considered. This causes $V < c$ in a portion of the area, initiating a decay process. Instead of Equation 8, we get

$$V = r + \beta \mathbb{E}\left[V - M \,|M < \delta V\right] + \beta \mathbb{E}\left[V(1-\delta) \,|M \geq \delta V\right] \tag{10}$$

It can be shown that each value of $r$ admits a unique value of $V$, which we denote $V(r)$, and that $\partial V(r)/\partial r > 0$. Intuitively, below the $V = c$ cutoff point (that is, for values of $d_{ij}$ above $\overline{d}_i$), houses that are destroyed by lack of maintenance are not rebuilt. This makes it so that the maintenance decision depends not on whether $M > \delta c$ but whether $M > \delta V(r)$.

If $r > r'$, then a unit renting at $r$ is more likely to be maintained than one renting at $r'$.

Any houses built on lots with disamenities above $\overline{d}_i$ will not be rebuilt if destroyed. In each period, a fraction of them are destroyed equal to $\delta(1 - F_M(\delta V(r)))$. For values $d_{ij} \in \left(\overline{d}_i(c, \theta_i - \Delta), \overline{d}_i(c, \theta_i)\right]$, $N\left(1 - \delta(1 - F_M(\delta V(r)))\right)^t$ units remain after $t$ time periods from the shift in $\theta$. Of these, a fraction $F_M(\delta V(r))$ are maintained. The amount of maintenance in these areas depends positively on the rent, the number of structures in these areas declines geometrically, and lower-rent areas experience faster rates of decline.

### Hurricane Expectations

We also relax the assumption of zero hurricane expectations. We assume hurricanes only destroy housing and have no other effects, implying that hurricanes only affect the decision surrounding home construction and maintenance. A higher chance of a hurricane affecting a location increases the discounted costs associated with owning a home in that location, and thus reduce housing supply. Because hurricanes are more likely to destroy unmaintained units, the maintenance decision will therefore also change with hurricane expectations, with a higher proportion maintained units.

Suppose that a hurricane strikes a location with probability $q$, destroying a unit with probability $\phi$ and an unmaintained unit with probability $\lambda\phi$ where $\lambda > 1$. Then if we define $p = q\phi$, we have the following analog to Equation 7:

$$V = r - \beta pc + \beta \max\left\{V - m, V - c(\delta + (\lambda - 1)p)c\right\}. \tag{11}$$

The analog to Equation 8 is similarly

$$V = \frac{r - \beta pc - \frac{\beta}{\eta} F_M((\delta + (\lambda - 1)p)c)}{1 - \beta} \tag{12}$$

**Prediction 3.** *An increase in hurricane expectations reduces the steady-state area size*

We know this because $\lambda > 1$ and $\partial F_M(m)/\partial m > 0$. Increasing the probability of a hurricane affecting a city thus causes an upward shift in the housing supply curve. This increases equilibrium rents and decreases equilibrium city size.

In addition, we derive the following prediction:

**Prediction 4.** *An increase hurricane expectations increases average maintenance levels, reducing hurricane damage*

This prediction follows from the fact that the maintenance cutoff increases with $p$, or equivalently, $(\delta - (\lambda - 1)\, p)\, c > \delta c$.

### 3.5 Effects on Skill Mix

The final model generalization considers the introduction of a second income group. This generates predictions regarding skill mix changes following hurricane strikes as well as the concentration of workers versus non-workers in an area. Following Glaeser and Gyourko (2005), suppose low human capital workers receive wage $W$, but high human capital workers receive wages equal to $(1+\gamma)W$, $\gamma > 0$. Additionally, both area- and lot-specific amenities and earnings are complements such that the utility received from amenities is $(1+\gamma)(A-d)$ for high human capital workers and $A - d$ for low human capital workers. High human capital workers receive a reservation utility $\overline{U}$ versus the normalized reservation utility for low human capital workers of zero.

Then, low human capital workers are willing to pay $W + A - d$ and high human capital workers are willing to pay $(1+\gamma)(W + A - d) - \overline{U}$. This creates an equilibrium where high human capital workers outbid low human capital workers for high-rent units (or perhaps for all units, if construction costs are sufficient). In equilibrium, high-ability workers will suffer at most a disamenity level of

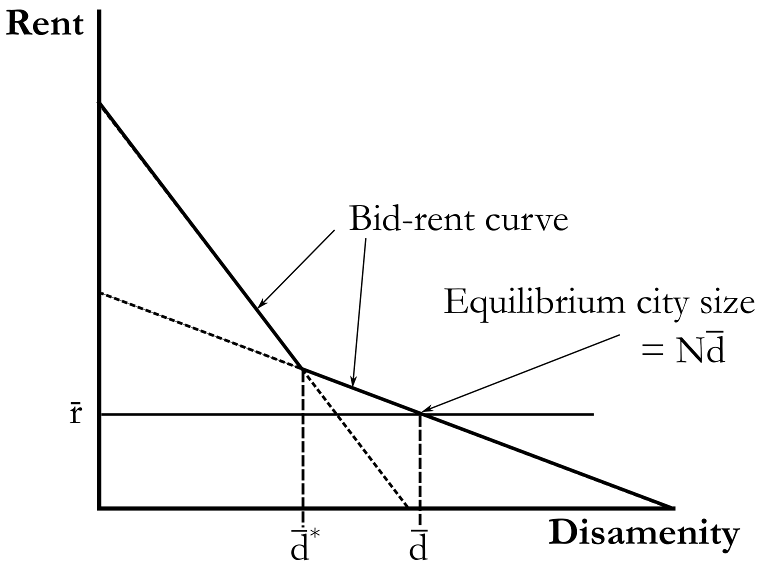
$$\overline{d}_i^{m,h} = \theta_i - \frac{m\beta + c(1-\beta) + \overline{U}}{1-\gamma} \tag{13}$$

whereas low-ability workers will suffer at most a disamenity of

$$\overline{d}_i^{m,l} = \theta_i - \left[m\beta + c(1-\beta)\right]. \tag{14}$$

Figure 4 shows the two bid-rent curves meeting at $d_i^* = \theta_i - \overline{U}/\gamma$. Thus, both types of workers will be present only if both $d_i^{m,h} > d_i^*$ and $\overline{d}_i^{m,h} > d_i^*$, in which case we will see $\overline{d}_i^{m,l} > \overline{d}_i^{m,h}$.

Figure 4: Variation in Amenity Preference




These additions to the model yields two additional predictions.

**Prediction 5.** *A hurricane increases the average skill level in a declining area, increasing the average wage rate.*

To see this, we start by assuming that both skill types are present. A negative shock to $\theta_i$ will cause the bid-rent curves of both types of shift equally to the left. All housing in the declining region will be consumed only by low-skilled workers, since the new $d_i^*$ has shifted to the left by $\theta_i$ and so low-skilled workers out-bid high-skilled workers for units with rents below replacement cost. Since unmaintained units are destroyed in larger proportion than maintained units, and are occupied solely by low-skilled workers, hurricanes increase the average skill level in declining cities.[21]

**Prediction 6.** *A hurricane increases the employment-population ratio.*

If one instead characterizes the two groups as employed and non-employed, then a hurricane will reduce the number of non-employed households in the area while not reducing the number of employed households.

[21] This is important to distinguish from a change in the price level of labor. Instead, the model instead suggests that wages will rise due to the human capital composition of households.

# 4 Methods

This section designs tests of each of the six predictions from Section 3. The most straightforward way to test these predictions is to first estimate hurricane effects as the difference between actual outcomes following hurricanes and no-hurricane counterfactuals. These hurricane effects can then be modeled as a function of natural and economic factors, including hypothesized determinants in the preceding section.

## 4.1 Estimating Hurricane Counterfactuals

In an OLS regression, the counterfactual is implied by controlling for any non-hurricane variation using additional explanatory variables. However, because of the orthogonality of hurricanes with respect to other potential explanatory variables, it is relatively straightforward to capture the residuals from an auxiliary regression, and use these as unbiased hurricane effect estimates. These hurricane effect estimates are then usable in a variety of applications.

Our approach is influenced by the literature on synthetic controls developed by Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010), and used to in the context of large natural disasters by Cavallo et al. (2013). However, their approach is mainly applied to single or small numbers of isolated, rare treatments with long pre-periods, whereas hurricanes occur frequently and with varying magnitudes. The method provides little guidance for hypothesis testing when pooling the effects of these disasters and comparing them across classes of locations. This method also requires solving a two-level nested non-linear programming problem for each disaster in question, which with thousands of hurricane hits would prove to be computationally prohibitive. For these reasons, rather than adopting the particular synthetic controls approach of Abadie and Gardeazabal (2003), we use the approximate factor structure (Chamberlain and Rothschild, 1983) to model the effects of shocks and trends common across areas in the absence of a hurricane.

For an arbitrary scalar $Y_{it}$, the standard linear factor model is of the form

$$Y_{it} = D_i' F_t + e_{it}. \tag{15}$$

Here, $Y_{it}$ is some variable of interest, $F_t$ is an $r \times 1$ vector of "common factors," and $D_i$ is a vector of "factor loadings." The factors capture the sources of pervasive covariation in the panel, including macroeconomic events (recessions and expansions), lags and leads in these events, and region or industry specific factors (coastal areas, oil producing, automobile manufacturing, etc.). The loadings $D_i$ represent the responsiveness of the cross-section to the factors, thus permitting cross-sectionally heterogeneous effects of aggregate shocks.[22] Factors are unobserved, but can be estimated using principal components analysis following Bai (2003) and Greenaway-McGrevy, Han, and Sul (2012).

A standard panel model is complicated by two attributes of the problem at hand. First, we would like to allow dynamics to be different across areas, rather than pooling across areas. Second, because the purpose of the analysis is to estimate a hurricane counterfactual, observations affected by hurricanes must be removed from estimation. This necessitates the creation of a highly unbalanced panel. Guided by Greenaway-McGrevy, Han, and Sul (2012), we estimate a large panel, projecting the dependent and independent variables onto the factor loadings estimated from a principal components analysis procedure. This procedure is applied only to the $H = 0$ sample. We then estimate the following regression, where $i$, $t$, and $k$ indicate the area, time period, and factor, respectively:

$$Y_{it} = C_i(L)Y_{it} + \sum_{k=1}^{r} F_{kt}D_{ik} + e_{it} \tag{16}$$

In this case, $C_i(L)$ and the $F_{kt}$ are treated as parameters. This method allows different dynamic behavior in response to aggregate and local shocks, as suggested by Greenaway-McGrevy and Hood (2014).[23]

Once the parameters from this model are estimated using the $H = 0$ sample, they can be applied to periods of hurricane strikes and recovery to produce counterfactual values of $Y$ as if no hurricane occurred, $Y^*_{it,H=0} = \hat{Y}_{it,H=0}$. Substituting into Equation 16 and rearranging gives the estimate for $H_{it}$

$$H_{it} = Y_{it} - Y^*_{it} + e_{it} \tag{17}$$

Rather than identifying $H$, this approach identifies $\hat{H} = Y_{it} - Y^*_{it}$. In this specification, $H$ is measured with error that is distributed the same as the model for $Y$ in the estimation sample. Figures 8a-8c shows hurricane damage and recovery in employment and earnings in the same manner as Davis and Weinstein's (2002) depiction of the population recovery of Japanese cities following World War II. The horizontal axis is the measurement of H one

[22] This approach encompasses a "common time effect" specification, as well as many others.

[23] There is an information constraint that is imposed on C(L) based on the number of time periods between an observation and the needed counterfactual. For instance, for a 1-period counterfactual (i.e. hurricane damage), C(L) may begin with the first lag. However, using monthly data, a 13 month counterfactual (i.e. the recovery after a hurricane) prohibits the use of any lag less than 13.

month after a "large" hurricane, and the vertical axis is the 13-month value of H which corresponds to the 12-month recovery after the initial shock. This figure depicts a negative relationship between the initial damage and ensuing recovery in both employment and wages. In the employment figure, the slope of the line is -0.71, suggesting that the recovery is 71% complete, on average, 1 year after the hurricane, though there is clearly large variation in recoveries. Interestingly, there seems to be no relationship between the initial non-worker population shock and subsequent growth, suggesting that this population leaves and never returns.

## 4.2 Initial Hurricane Damage

Having identified $H$, it is now possible to estimate the effects of storm and area characteristics on $Y$. The two most important storm characteristics are the wind speed and the size of the storm surge generated. Area characteristics serve to mitigate or exacerbate storm damage, as hypothesized in Predictions 1 and 4, which suggest that area decline and cyclone strike probability, respectively, are two key determinants of storm damage. Additionally, areas of low elevation have historically suffered more from hurricanes, so an elevation variable is interacted with the storm surge variable. These attributes give rise to the following stochastic specification.

$$\begin{aligned} H_{it} = \gamma_1 + \gamma_2 wind_{it} + \gamma_3 wind_{it} \times decline_i + \gamma_4 wind_{it} \times past\ hurricanes_i + \\ + \gamma_5 surge_{it} + \gamma_6 surge_{it} \times decline_i + \gamma_7 surge_{it} \times past\ hurricanes_i + \\ + \gamma_8 surge_{it} \times elevation_i + v_{it} \end{aligned} \tag{18}$$

The variable *wind* is then defined as equal to 1 if the hurricane is category 3+, and zero otherwise. Similarly, the variable *surge* is defined as 1 if the storm surge is greater than 9 feet, and zero otherwise, and *elevation* is defined as the fraction of households in a county with an elevation of 9 feet or below. Under these variable definitions, the hypotheses, $\gamma_3 < 0$, $\gamma_6 < 0$, and the joint hypothesis $\gamma_3 + \gamma_6 < 0$ each serve as tests of Proposition 1. Similarly the hypotheses, $\gamma_4 > 0$, $\gamma_7 > 0$, and the joint hypothesis $\gamma_4 + \gamma_7 > 0$ each serve as tests of Prediction 4

## 4.3 Hurricane Recovery

A model of hurricane recovery can be estimated structurally, as in Equation 18, or reduced-form by taking hurricane damage as given, and modeling the recovery as a function of the initial damage following Davis and Weinstein (2002). The reduced-form model can be expressed as follows, where time is normalized such that $t = 0$ corresponds to the time of the hurricane and $t + h$ as the h period recovery.

$$H_{it+h} = \delta_1 + \delta_2 decline_i + \delta_3 H_{it} + \delta_4 H_{it} \times decline_i + \varepsilon_{it+h} \tag{19}$$

An estimate of $\delta_3 = -1$ corresponds to a complete recovery after 1 year– the damage from $H_{it}$ affects growth by an equal and opposite amount. By similar logic, if decline mutes recoveries, then $\delta_4 > 0$, a hypothesis which serves as a test of Prediction 2.

## 4.4 Measuring Decline

The ideal decline measure is presented in Glaeser and Gyourko (2005) as the fraction of housing units in a city with values less than replacement costs. However, this measure is calculated using micro data available only in large cities. What is needed at present is a county-level of measure, so we instead apply the decline index of Larson (2011), which proxies for Glaeser and Gyourko's (2005) measure using change in the total value of the housing stock over a period of time. This acts as a measure of decline on the basis that increases in demand for housing manifest themselves through housing construction, house price increases, or both, and that value increases captures both of these effects. The persistence of decline is key to identification, as lagged decline is both unrelated to current shocks, yet is highly correlated to current decline.

Given the high correlation with Glaeser and Gyourko's measure, and the persistence of decline, the change-in-value approach is used here.[24] The decline index presented in this paper is the log-difference in the value of the housing stock from the 1970 to the 1990 Decennial Census. This is standardized such that the decline index is mean 0 and variance 1, and positive values represent greater decline. This index has the additional benefit of being a continuous measure, as submarkets within a city can exist in different states of decline.[25]

[24]Other measures are also correlated with decline, including population changes. However, population measures are inaccurate measures of decline if the area is housing supply constrained, for instance through topographic constraints or housing and land use regulations (Saiz, 2010).

[25]See Guerrieri, Hartley, and Hurst, 2012, for more discussion on decline within submarkets.

Figure 9 shows a map of the decline index by county for the United States. This map shows that growth between 1970 and 1990 is primarily in coastal counties and in the southwest. Decline is mostly in the midwest and Great Plains. Suburban counties appear to have experienced greater demand increases than center-city counties, especially the suburbs surrounding Minneapolis-St. Paul, Chicago, and Dallas.

# 5 Results

In general, results support general intuition and the theoretical predictions in Section 3. Natural forces explain some of the variance in storm damage, as do the predicted economic determinants, decline and disaster expectations. Modeling recoveries is more difficult due to the need for multi-period counterfactuals (counterfactuals in this case must be based on information that comes from further in the past). Despite this fact, there is evidence that recovery is less complete in declining areas. These estimates are robust to different areas of effect (direct hit versus one county away), exclusion of particular hurricanes, including Katrina in 2005, different decline proxies, and "big" storm surge cutoffs.

## 5.1 Hurricane Damage

*Ex ante*, one would expect hurricane damage to be highest in areas struck by high wind speeds and/or storm surges.[26] Because estimated hurricane effects include the counterfactual error, we limit the sample of observations in the damage regressions to areas either directly hit by or adjacent to hurricane-class wind speeds or a storm surge with a height of 9+ feet.

Table 3 presents condensed estimates of Equation 18. The specification also includes strikes one-county-away and weaker hurricanes. Full results are available in the appendix. It is important to pool observations of various storm strength because in many cases, a county is some distance away from the center of a storm, yet is hit by a surge. In this specification, the "baseline" result is an adjacent county affected by a weak hurricane and no storm surge.

A direct strike by a Category 3+ hurricane is estimated to reduce employment by 9.2% in the period after the strike, non-worker population by 1.4%, increase earnings of those remaining by 6.0%, and reduce the housing stock by 3.7%. An area with double the prior number of strikes experiences about half of these damage impacts. Wind speed appears to affect growing and declining areas similarly, though wind and storm surges are correlated. A

[26] Were this able to explain the entirety of the damage caused by a hurricane, the hurricane attributes themselves could be used as a supply shock.

large storm surge when 100% of an area is beneath the height of the surge (such as is nearly the case in many Louisiana counties) results in a further employment loss of approximately 18%. Over all, county decline appears to affect the hurricane response of the non-worker population more than it affects the response of employment, but in general it amplifies the effect of a hurricane strike.

Viewed together, these estimates provide a substantial degree of evidence for the model. Consistent with Belasen and Polachek (2008, 2009), hurricanes reduce employment and increase earnings in direct-hit counties. Positive hurricane expectations, measured using an area's history of hurricanes, affect resilience to hurricanes and storm surges, and area decline exacerbates storm impacts. What is also remarkable about this series of estimates is that these are not simply statistically significant estimates; they are also economically extremely large and meaningful. They suggest that while hurricanes have highly variable effects, several factors can predict a wide range of outcomes. For example, suppose a Category 3 hurricane with a 15 foot storm surge strikes an area, and that area has no history of hurricanes, is 100% below 10 feet, and has a decline index value of 1. Then that hurricane would be expected to reduce employment by about 32%. Now, consider if that same hurricane had struck an area with 3 hurricanes in the last 100 years (the log of which is approximately 1), was growing (a decline index of -1), and was at high elevation (0% below 10 feet). Then the same hurricane that caused a 1/3 drop in employment in the first area would cause almost no damage in the second.

## 5.2 Hurricane Recovery

Having established some key determinants of hurricane damage, the question now turns to the determinants of recovery. Recovery is inherently more difficult to model for two reasons. The first is the difficulty of establishing a reliable counterfactual. A reliable no-hurricane counterfactual is relatively difficult to establish because it involves developing a multi-period conditional forecast of an area's economy, whereas estimating initial damage requires only a one-period-ahead conditional forecast. This additional forecast error has the potential to introduce random noise and thus attenuate any recovery estimates. The second is the complicated milieu of expectations, incentives, and constraints facing areas as they rebuild: while damage is a relatively simple reaction to a large, exogenous event, recovery takes into expectations of the future, changes in those expectations, policy constraints, and returns to investment of different types. Despite these issues, we provide some evidence of differential recoveries in growing versus declining areas that are largely consistent with our theory.

The noisiness of the counterfactual necessitates restricting the estimation sample of the recovery models. In order to maintain a useful signal-to-noise ratio, we employ two different specifications. Our preferred estimator involves weighting observations by the severity of the initial damage under the belief that the signal-to-noise ratio of the observation is higher, making the observation more reliable. We also perform a robustness exercise which includes unweighted observations, but with a more censored sample in order to eliminate observations with very small effects and comparatively large counterfactual errors.

Table 4 presents results from Equation 19. This table shows the one-year recovery from a hurricane strike.[27] The parameter on the initial effect of the hurricane is -0.59, suggesting that about 59% of the initial employment loss is restored one year after the hurricane. The interacted coefficient is +0.17, indicating that a declining area faces a slower recovery; an area with a decline index of 1 only recovers 45% of its loss in employment growth.

At first glance, the earnings estimates appear to run counter to the theory presented in the paper. The interacted coefficient is negative, suggesting declining areas experience *faster* adjustment than growing areas. We postulate that this discrepancy is due to the treatment of labor demand as exogenous in our theory. The empirical result, rather, suggests a fall in labor demand, as both earnings and employment fall in a declining area. This evidence is consistent with the notion that some amount of local employment is endogenous, with higher population increasing demand for locally-produced goods. Substantial relocation of the non-worker population and a slow recovery in employment may cause local demand for basic goods and services to relocate as well. It follows that once the population leaves in a declining area after a hurricane, labor demand eventually falls as well, causing wages to return to pre-hurricane levels despite the lower labor supply. We leave further expansion of our theoretical model to incorporate endogenous labor demand as an area for future research.

Interestingly, non-worker population growth continues to fall by 32.4% of the initial hurricane shock amount. There is also modest evidence that this persistence in the effect of the shock is actually higher in growing areas as opposed to declining ones, as indicated by the negative parameter estimate on the interacted variable. This makes sense when one considers that growth rates in declining areas are already near zero, but growth rates in growing areas often begin quite high and are still large even following the hurricane. We cautiously interpret this non-worker population result as a change in disaster expectations on the basis of Prediction 4, which states that non-working populations are more reactive to

[27]The dependent variable is a growth rate, meaning that estimates should be interpreted as changes in growth rates, not changes in levels. This is important because the model considers the question of whether an area returns to its pre-hurricane *trend*.

natural disasters. The high growth rates in growing cities suggest higher amenity levels, a fall in which is consistent with a change in disaster expectations.

There are two pieces of evidence in favor of Prediction 5, which states that low-income households are more likely to leave in the event of a hurricane. First, an employment recovery in absence of a non-worker population recovery implies it is low-income households that do not return. Second, the earnings persistence result combined with the relatively faster employment recovery suggests that high earnings households are more likely to return than low earning households. These are both consistent with the proposition that marginal housing is destroyed but not rebuilt in the case of a hurricane, and the low-(or no-)income households that reside in these units are unlikely to return. Also, whereas Cutter and Emrich (2006) argue that social vulnerability plays a role in hurricane damage, we present a more benign explanation, that it is due to the low returns from rebuilding that they do not return.

**Hurricane Recovery and Housing Permits**

When looking at the effect of hurricanes on the subsequent issuance of housing permits, we must use a somewhat different approach to the recovery regressions above. Because permits themselves represent a planned change in the housing stock, rather than a level, and because in some areas housing permits can be quite small or quite volatile, it is difficult to observe a pattern in percent changes in the permitting variable. In addition, permits do not have to be used once issued, and builders must apply for them in advance. This means that hurricanes do not appear to have a substantial effect on the issuance of permits in the year of the strike.

We take note of the fact that hurricane strikes reduce the housing stock, and to rebuild, permits, which are measured with the same units as houses, must be issued. Thus, we look at permit issuance as a response to housing stock destruction. We regress the log of the change in permits in the year following a hurricane on the log of the negative of the change in housing stock (if the change is less than -100 units). Implicitly, we are restricting our analysis to hurricanes which destroyed housing, and for which some permitting increased the following year.

Results are shown in table 5. For a county that is neither growing nor declining, approximately one new permit is issued for each housing unit destroyed. Declining counties issue fewer permits per destroyed unit, while growing counties issue more. These results present additional evidence that recoveries are stronger in growing areas, and that housing loss is an important channel through which hurricanes affect the labor market.

**Hurricane Recovery and Fiscal Assistance**

One consideration for any analysis of natural disasters is the policy response. In the United States, for example, the Federal Emergency Management Agency (FEMA) is responsible for the first wave of post-disaster reconstruction funding. When a tropical cyclone damages an area, a governor or tribal leader can request a federal disaster declaration. In most cases, a preliminary damage assessment is then undertaken to determine if the disaster is severe enough to warrant federal funding. Then, the President may declare the area a "disaster area," which makes it eligible for disaster funding. Funding is then based on a number of factors, including the type and severity of damage, the unique capabilities of the federal government, the frequency of disasters in the area, levels of assistance from other sources, and other factors (FEMA, 2013).

Unfortunately, measuring the effect of the FEMA response is problematic. If FEMA funding goes only to areas struck by hurricanes that are having difficulty recovering in an unobservable way, it could even appear that FEMA worsens recoveries. Data are quite sparse–to the knowledge of the authors, county-level FEMA funding data are available only beginning in 1998. More than half the funding goes to the top ten counties-month observations, of which seven are Katrina-related. This calls into question the generalizability of any estimates.[28] Therefore, we leave the exploration of the effects of fiscal assistance on hurricane recoveries to further research.

## 5.3 Damage and Recovery to Housing Submarkets within a City

Another interesting question to consider is if different housing submarkets within an area are affected differently in terms of damage and recovery. We approach this question using the average earnings in NAICS industry sectors, excluding those directly related to hurricanes, as a proxy for housing structure quality and interpret changes in high versus low wage industry employment as differential effects on homes.[29] The logic behind this proxy strategy in terms of our theory is that low wage workers have lower housing expenditures, and thus occupy lower amenity lots. It therefore follows that differential hurricane-related changes

[28]In a prior version of the paper, we estimated a model similar to those reported in Table 4, showing that results were robust, and that FEMA spending slightly improved recoveries. However, while robustness of other estimates to inclusion of FEMA in the regression models still holds, we did not feel comfortable reporting the FEMA coefficients themselves. Thus, in this version, we simply note that inclusion of FEMA spending in the above equations does not substantially change in the results.

[29]These include NAICS codes 23, 52, and 56, or Construction, Finance and Insurance, and Waste Management and Remediation, respectively.

to employment of workers in high versus low wage sectors may be interpreted as evidence that different housing submarkets within an area are affected differently by a hurricane. In concrete terms, the model asserts that the average wage effects observed in Table 3 is due to a composition effect as opposed to an increase to the wage rate; that is, hurricanes cause average wage rates to rise in part due to a higher share of high wage workers, and not necessarily due to supply-induced wage increases.

As in the recovery models above, employment data contain substantial noise not related to hurricane strikes. To minimize the impact of this noise, we look only at counties that have been struck by hurricanes and experience overall employment losses of at least 0.5%, relative to a no-hurricane counterfactual. Thus, we consider whether the patterns in industry-level employment losses are predictable as a function of industry wages, in counties struck by hurricanes that lost at least 0.5% of their employment. We are interested in the coefficient on industry employment of lagged earnings per worker interacted with overall employment growth, the latter proxying for the magnitude of the effect of the hurricane. The model includes year and area fixed effects.

Results confirm model predictions. First, consider the first two columns which present models of employment changes in the period directly following a hurricane. The positive parameter on the lagged industry wage suggests higher earnings are associated with higher employment growth. To control for larger employment change dispersion in hurricanes with greater damage, the average area damage is interacted with the earnings variable. This interaction coefficient suggests that high-wage industries are associated with smaller employment impacts relative to the average.

The third and fourth columns present models of employment recovery. These both suggest greater employment growth for low-wage industries in periods following a hurricane. One comparison that is useful to consider is the first vs the third columns. The wage and constant term parameters in the damage regression is greater in magnitude and opposite in sign to the one in the recovery regression, suggesting that the recovery in low wage industries is less complete than in high wage industries.

# 6 Conclusions

In this paper, we derive and empirically test a model of hurricane destruction and recovery. This is important for two main reasons. First, the determinants of hurricane damage are useful and interesting in their own right; second, in order to treat hurricanes as exogenous supply shocks, it is necessary to understand how hurricane attributes translate to damage. Natural factors such as storm wind speed, storm surge height, and the elevation of an affected county each help to predict the damage done by a hurricane. Perhaps more interestingly, we also predict and then demonstrate that there are economic factors that determine an area's vulnerability to hurricane strikes. Areas with expectations of hurricane strikes invest in home maintenance and hurricane mitigation strategies that limit damage. On the other hand, in declining areas, where home values are less than the replacement costs of the units, low levels of structural maintenance result in greater damage from hurricane strikes. We find empirical support for each of these predictions, and show results to be robust to the exclusion of counties struck by Hurricane Katrina in 2005, and much stronger when all Katrina counties are included.

Regions also recover differently from one another. In the model that we develop, a declining area will rebuild less than a growing one because some fraction of the destroyed housing stock was of lower value before the hurricane than the cost of rebuilding. Similarly, regions facing unanticipated hurricane strikes will adjust their hurricane expectations upwards, increasing maintenance preferences and costs, and reducing equilibrium city size. Growing regions appear to recover employment faster than declining ones. This suggests that non-employed and low-skilled workers leave areas and do not return, which supports a model of segmented housing markets where there simultaneously exists growing and declining markets within an area–declining housing is destroyed but not rebuilt, whereas destroyed housing in growing segments is rebuilt. Our model is not quite rich enough to explain the earnings corrections observed in the data, which suggest endogenous local demand for labor in declining areas, whereas we assume exogenous local demand. Nevertheless, we leave relaxing this particular simplification for future research.

This paper presents a direct test of the urban decline hypothesis, that areas with housing that is priced below replacement cost have a lower elasticity of housing supply. Identification of supply shocks is direct because hurricanes are exogenous with respect to local economic activity. This is in contrast to much of the literature on urban dynamics which infers supply responses using time series or shift-share identification of demand shocks.

Our results can also be used to weigh in on the jobs versus workers debate. Just as Partridge and Rickman (2003), we find evidence both that workers follow jobs and that jobs follow workers depending on the location. In growing cities, a more complete recovery suggests that the economic fundamentals are driving availability of jobs in the location, and that workers are following jobs to these places. On the other hand, rapid population loss and rapid loss of the temporary wage gains seen in declining areas suggest that jobs may follow workers, as well.

The model in this paper, despite its specific structure, has many general implications. It can be applied to any sort of housing supply shock, including large-scale fires, earthquakes, tornadoes, or other disasters. The model also encompasses much of the prior research on hurricanes, and can potentially be used to predict the effects of future ones. Some extensions may include the estimation of effects of hurricanes on local area GDP, and the development of a regional economy hurricane simulation model.

Finally, the model suggests that a failure to recover following a hurricane may be efficient and not due to any market failure, calling into question the necessity of fiscal assistance to damaged areas. Due to data limitations, this theory cannot be directly tested empirically, but is instead inferred by our model.

# References


Abadie, A., A. Diamond, and J. Hainmueller (2010). Synthetic control methods for comparative case studies: Estimating the effect of californias tobacco control program. *Journal of the American Statistical Association 105*(490), 493–505.

Abadie, A. and J. Gardeazabal (2003). The economic costs of conflict: A case study of the basque country. *American Economic Review 93*(1), 113–132.

Alonso, W. (1964). *Location and land use: toward a general theory of land rent.* Harvard University Press.

Bai, J. (2003). Inferential theory for factor models of large dimensions. *Econometrica 71*(1), 135–171.

Basker, E. and J. Miranda (2014, March). Taken by Storm: Business Financing, Survival, and Contagion in the Aftermath of Hurricane Katrina. Working Papers 1406, Department of Economics, University of Missouri.

Belasen, A. R. and S. W. Polachek (2008). How hurricanes affect wages and employment in local labor markets. *The American Economic Review, Papers and Proceedings 98*(2), 49–53.

Belasen, A. R. and S. W. Polachek (2009). How disasters affect local labor markets: The effects of hurricanes in Florida. *Journal of Human Resources 44*(1), 251–276.

Brown, S., S. Mason, and R. Tiller (2006). The effect of hurricane katrina on employment and unemployment. *Monthly Labor Review 129*, 52–69.

Brueckner, J. K., J.-F. Thisse, and Y. Zenou (1999). Why is central Paris rich and downtown Detroit poor?: An amenity-based theory. *European Economic Review 43*(1), 91 – 107.

Burrus, R., C. Dumas, C. Farrell, and W. Hall (2002). Impact of low-intensity hurricanes on regional economic activity. *Natural Hazards Review 3*(3), 118–125.

Cavallo, E., S. Galiani, I. Noy, and J. Pantano (2013, December). Catastrophic Natural Disasters and Economic Growth. *The Review of Economics and Statistics 95*(5), 1549–1561.

Chamberlain, G. and M. Rothschild (1983). Arbitrage, factor structure, and mean-variance analysis on large asset markets. *Econometrica 51*(5), pp. 1281–1304.

Cronon, W. (1991). *Nature's metropolis: Chicago and the Great West.* WW Norton & Company.

Cutter, S. L. and C. T. Emrich (2006). Moral hazard, social catastrophe: The changing face of vulnerability along the hurricane coasts. *The Annals of the American Academy of Political and Social Science 604*(1), 102–112.

Czajkowski, J., K. Simmons, and D. Sutter (2011). An analysis of coastal and inland fatalities in landfalling US hurricanes. *Natural Hazards 59*(3), 1513–1531.

Davis, D. R. and D. E. Weinstein (2002). Bones, bombs, and break points: The geography of economic activity. *American Economic Review 92*(5), 1269–1289.

Federal Emergency Management Agency (2013). Declaration process fact sheet. Technical report, URL Accessed 12/5/2013: http://www.fema.gov/declaration-process-fact-sheet.

Frame, D. E. (1998). Housing, natural hazards, and insurance. *Journal of Urban Economics 44*(1), 93 – 109.

Fronstin, P. and A. G. Holtmann (1994). The determinants of residential property damage caused by hurricane andrew. *Southern Economic Journal*, 387–397.

Garber, M., L. Unger, J. White, and L. Wohlford (2006). Hurricane katrina's effect on industry employment and wages. *Monthly Labor Review 129*, 22–39.

Glaeser, E. L. and J. Gyourko (2005). Urban decline and durable housing. *Journal of Political Economy 113*(2), 345–374.

Greenaway-McGrevy, R., C. Han, and D. Sul (2012). Asymptotic distribution of factor augmented estimators for panel regression. *Journal of Econometrics 169*(1), 48 – 53. Recent Advances in Panel Data, Nonlinear and Nonparametric Models: A Festschrift in Honor of Peter C.B. Phillips.

Greenaway-McGrevy, R. and K. K. Hood (2014). Do workers move to jobs or do jobs move to workers? controlling for serial dependence in measures of worker and firm mobility. Working paper.

Guerrieri, V., D. Hartley, and E. Hurst (2012). Within-city variation in urban decline: The case of detroit. *American Economic Review 102*(3), 120–26.

Gyourko, J. and A. Saiz (2004). Reinvestment in the housing stock: the role of construction costs and the supply side. *Journal of Urban Economics 55*(2), 238–256.

Henderson, J. V. (1974). The sizes and types of cities. *The American Economic Review 64*(4), 640–656.

Hsiang, S. M. and A. S. Jina (2014, July). The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones. Working Paper 20352, National Bureau of Economic Research.

Krugman, P. (1991). Increasing returns and economic geography. *Journal of Political Economy 99*(3), 483.

Larson, W. D. (2011). Housing and labor markets in growing versus declining cities. Dissertation, George Washington University.

Mills, E. S. (1967). An aggregative model of resource allocation in a metropolitan area. *The American Economic Review 57*(2), 197 –210.

Muth, R. (1969). *Location and land use: toward a general theory of land rent*. University of Chicago Press.

Nordhaus, W. D. (2010). The economics of hurricanes and implications of global warming. *Climate Change Economics 01*(01), 1–20.

Notowidigdo, M. J. (2013). The incidence of local labor demand shocks. Working paper, University of Chicago.

Partridge, M. D. and D. S. Rickman (2003). The waxing and waning of regional economies: the chicken-egg question of jobs versus people. *Journal of Urban Economics 53*(1), 76 – 97.

Roback, J. (1982). Wages, rents, and the quality of life. *The Journal of Political Economy 90*(6), 1257–1278.

Rose, A. and S.-Y. Liao (2005). Modeling regional economic resilience to disasters: A computable general equilibrium analysis of water service disruptions*. *Journal of Regional Science 45*(1), 75–112.

Rosen, S. (1979). Wages-based indexes of urban quality of life. In P. Meiszkowski and M. Straszheim (Eds.), *Current Issues in Urban Economics*. Baltimore: Johns Hopkins University Press.

Saiz, A. (2010). The geographic determinants of housing supply. *The Quarterly Journal of Economics 125*(3), 1253–1296.

Simmie, J. and R. Martin (2010). The economic resilience of regions: towards an evolutionary approach. *Cambridge journal of regions, economy and society 3*(1), 27–43.

Thompson, W. R. (1965). *A preface to urban economics*. Johns Hopkins University Press.

West, C. T. and D. G. Lenze (1994). Modeling the regional impact of natural disaster and recovery: A general framework and an application to hurricane andrew. *International Regional Science Review 17*(2), 121–150.

Yezer, A. (2010). Expectations and unexpected consequences of public policy toward natural and man-made disasters. In W. Kern (Ed.), *The Economics of Natural and Man-Made Disasters*, pp. 39–64. Kalamazoo, Michigan: W. E. Upjohn Institute.

Figure 5: Counties Affected by Hurricane Andrew (1992)

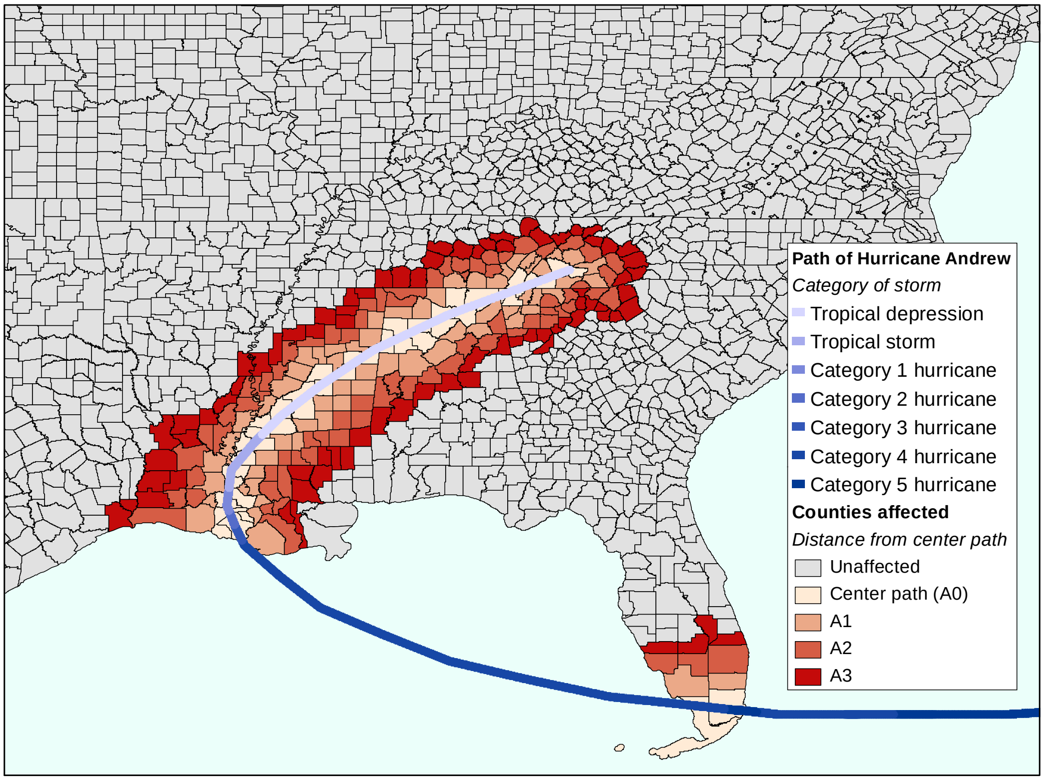


Figure 6: Direct Category 1+ Hurricane Strikes, 1900-1990

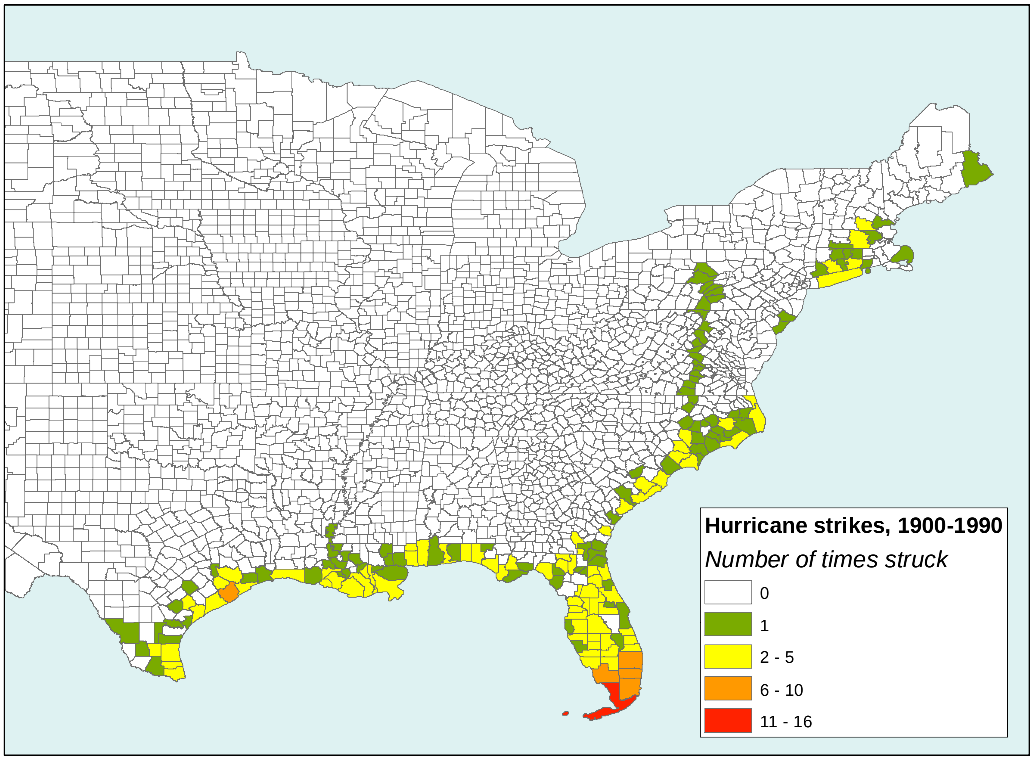
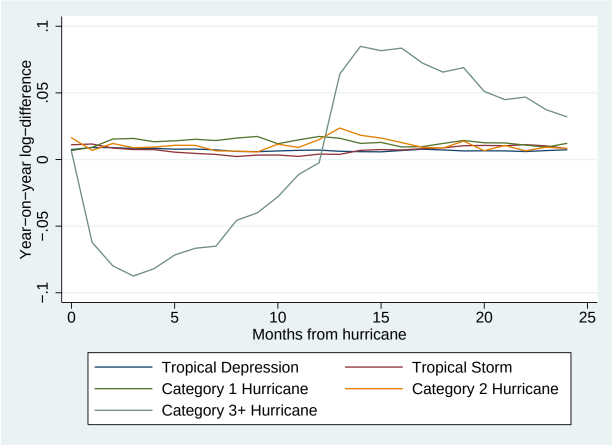
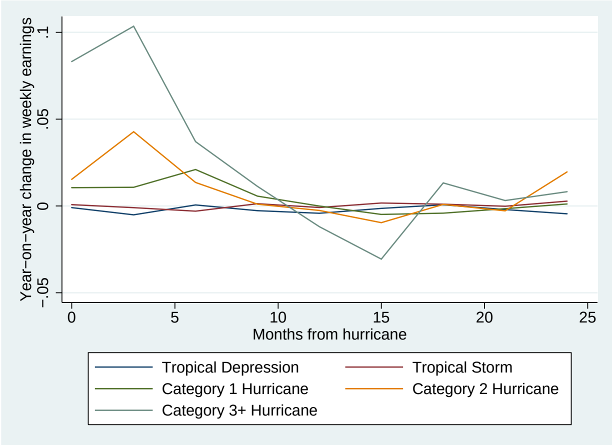


Figure 7: Employment and Earnings by Hurricane Dimension

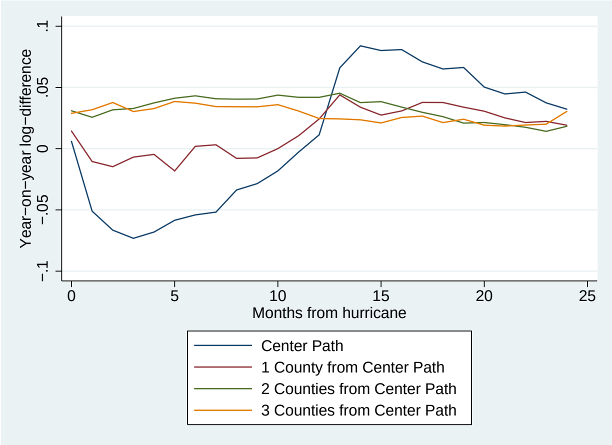
(a) Employment by Hurricane Class




(b) Earnings/Employee by Hurricane Class




(c) Employment by Proximity, Category 3+




(d) Employment by Storm Surge Height

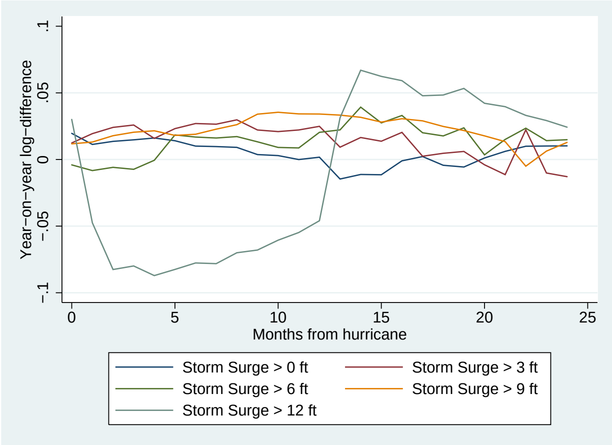
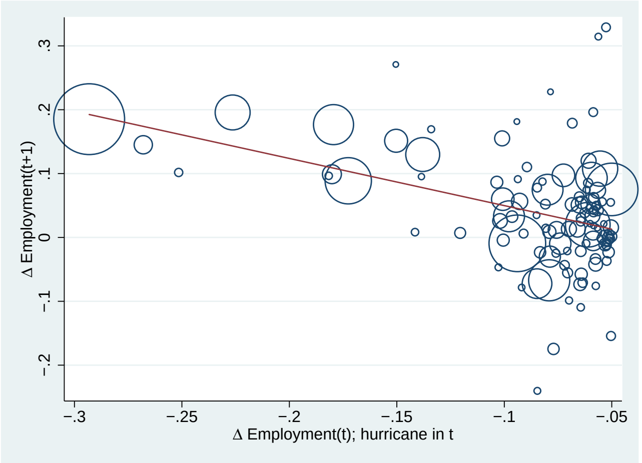
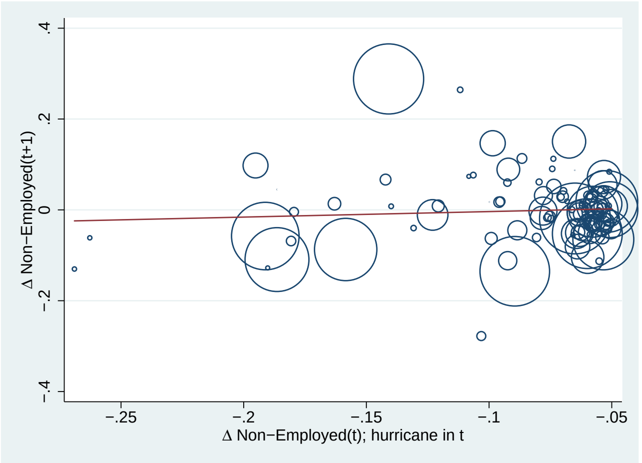


Figure 8: Damage and Recovery, All Storms 1990-2012

(a) Employment




(b) Non-Worker Population




(c) Weekly Earnings per Employee

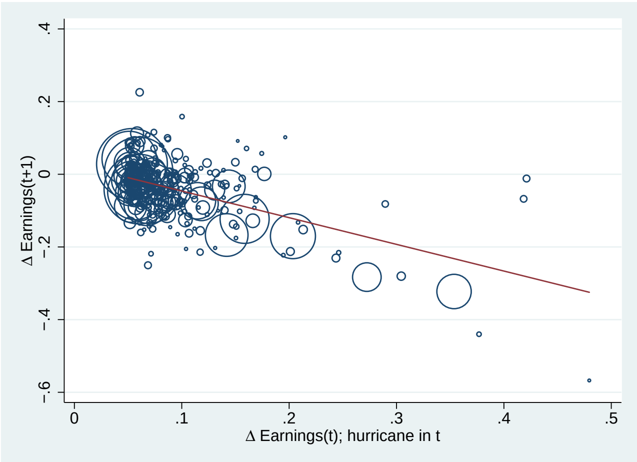


Figure 9: County Decline Index

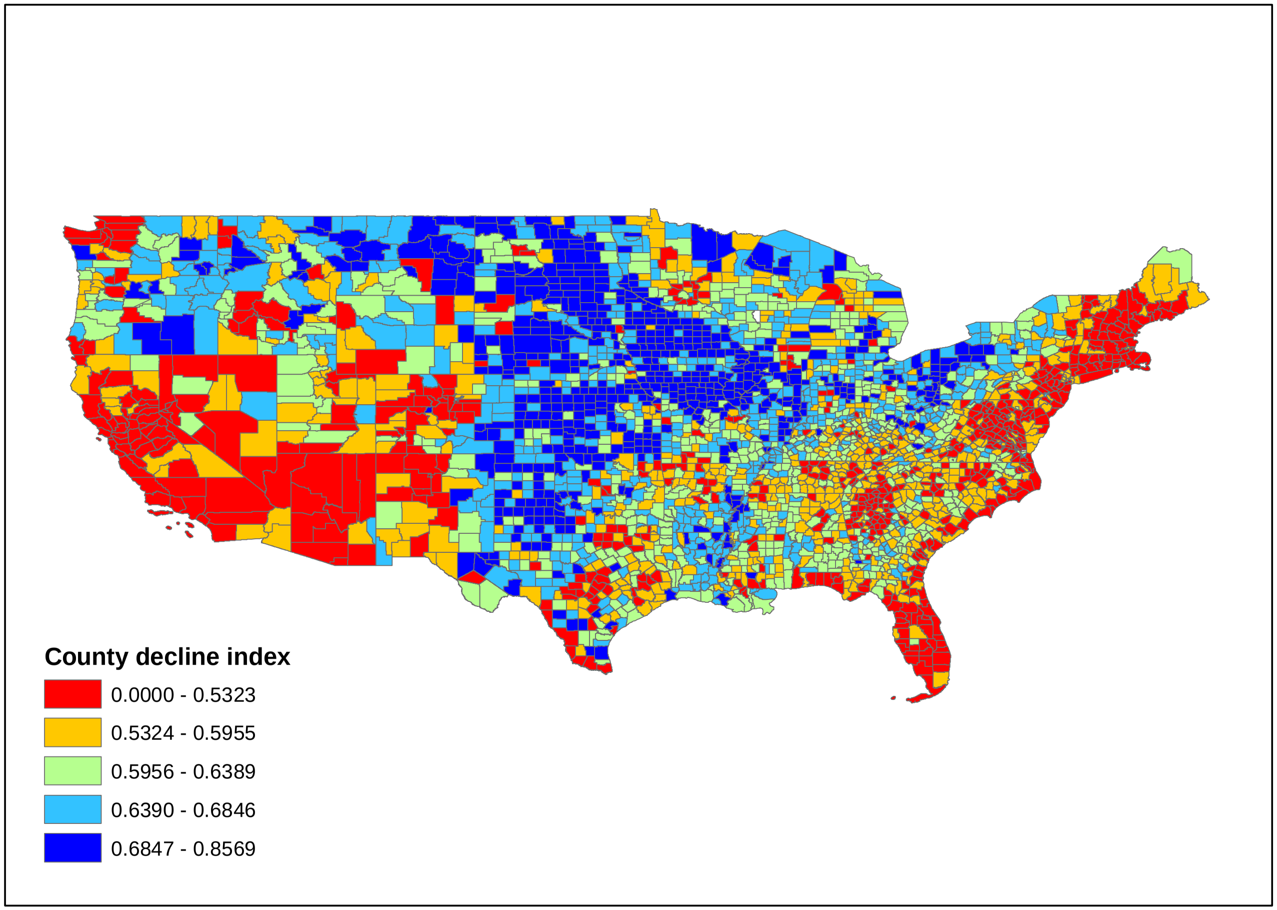


Table 2: Number of Counties Affected

| Cyclone Type | Total | County-Months | | | | |
|---|---|---|---|---|---|---|
| | | | A0 (Direct Hit) | A1 (Adjacent to A0) | A2 (Adjacent to A1) | A3 (Adjacent to A2) |
| Tropical Depression | 53 | 9,594 | 1,541 | 2,557 | 2,706 | 2,790 |
| Tropical Storm | 176 | 4,766 | 860 | 1,381 | 1,293 | 1,232 |
| Category 1 Hurricane | 45 | 489 | 84 | 143 | 127 | 135 |
| Category 2 Hurricane | 35 | 185 | 25 | 47 | 56 | 57 |
| Category 3 Hurricane | 29 | 108 | 15 | 31 | 31 | 31 |
| Category 4 Hurricane | 38 | 13 | 4 | 6 | 3 | 0 |
| Category 5 Hurricane | 10 | 10 | 1 | 2 | 3 | 4 |
| Total | 386 | 15,165 | 2,530 | 4,167 | 4,219 | 4,249 |

Note: Table presents the number of counties affected by a tropical cyclone in a particular month in the sample. Each county can be assigned to one of A0-A3 in a given month. County-month cyclone types are classified based on the wind speed at the time of impact. Counties are assigned A0-A3 values by first assigning counties as A0, then if not A0 in a given month, A1, then if not A1 in a given month, A2, etc. This is to ensure that a county is not assigned as peripherally affected if in fact it was in the direct path, regardless of the cyclone wind speed.

Table 3: Initial Hurricane Effects

| Variable | Dependent variable: year on year change in orthogonalized variable | | | |
|---|---|---|---|---|
| | Employment (monthly) | Weekly Earnings (quarterly) | Non-Worker Pop. (annual) | Housing Stock (annual) |
| Category 3+ Hurricane | -0.0920*** | 0.0598*** | -0.0144 | -0.0374** |
| | (0.0128) | (0.0142) | (0.0137) | (0.0135) |
| Category 3+ × County Decline | 0.00276 | -0.00596 | 0.00483 | -0.00846** |
| | (0.00945) | (0.00640) | (0.00566) | (0.00342) |
| Category 3+ × Past Strikes | 0.0506*** | -0.0261** | 0.00498 | -0.0101 |
| | (0.0128) | (0.0117) | (0.0181) | (0.0167) |
| Big Storm Surge [> 9 Feet] | -0.0309 | 0.0394* | -0.0237 | -0.0450 |
| | (0.0192) | (0.0191) | (0.0266) | (0.0305) |
| Big Surge × County Decline | -0.0136** | 0.0188** | -0.0291** | -0.0341* |
| | (0.00565) | (0.00854) | (0.0135) | (0.0168) |
| Big Surge × Past Strikes | 0.0327** | -0.0210 | 0.0184* | 0.0189 |
| | (0.0124) | (0.0124) | (0.0101) | (0.0120) |
| Big Surge × Low Elevation | -0.179*** | 0.0790** | -0.125** | -0.153*** |
| | (0.0170) | (0.0343) | (0.0468) | (0.0254) |
| Observations | 331 | 312 | 271 | 160 |
| R-squared | 0.367 | 0.145 | 0.109 | 0.451 |

Notes: Clustered standard errors (by year) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables are hurricane effects, estimated as the counterfactual value minus the actual. The sample excludes St. Bernard and New Orleans Parishes due to their highly idiosyncratic attributes. For sake of brevity, table omits results for category 1 hurricanes, category 2 hurricanes, and estimates for adjacent counties. For the full table of estimates and robustness exercises, see the Appendix.

Table 4: Hurricane Recovery

| | Dependent variable: year on year change in orthogonalized variable | | | |
|---|---|---|---|---|
| Variable | Employment (monthly) | Weekly Earnings (quarterly) | Non-Worker Pop. (annual) | Housing Stock (annual) |
| Initial Effect of Hurricane | -0.590*** | -0.684*** | 0.324* | -0.165*** |
| | (0.0175) | (0.179) | (0.180) | (0.00952) |
| Initial Effect × County Decline | 0.172*** | -0.241** | 0.542*** | 0.116*** |
| | (0.0274) | (0.0900) | (0.114) | (0.0158) |
| County Decline | -0.000193 | 0.0105* | 0.0238*** | 0.00196 |
| | (0.00402) | (0.00552) | (0.00409) | (0.00262) |
| Constant | -0.0110** | 0.0179* | 0.0199** | 0.00461* |
| | (0.00455) | (0.00890) | (0.00787) | (0.00248) |
| Observations | 2,049 | 2,705 | 2,017 | 572 |
| R-squared | 0.503 | 0.386 | 0.174 | 0.794 |

Notes: Clustered standard errors (by year) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables are hurricane effects, estimated as the counterfactual value minus the actual. The sample includes all recoveries where the initial hurricane effect is 0.5% or greater. The sample excludes St. Bernard and New Orleans Parishes due to their highly idiosyncratic attributes. Observations with larger initial hurricane effects are given greater weight due to higher signal-noise ratio in the estimated effect. For tables of robustness exercises, see the Appendix.

Table 5: Hurricane Recovery-Housing Permits

| | Dependent variable: log $\Delta$ housing permits | | |
|---|---|---|---|
| Sample | All Counties | No Outliers | No Katrina |
| Initial Effect on Housing Stock | 0.899*** | 1.048*** | 1.118*** |
| | (0.199) | (0.127) | (0.105) |
| Initial Effect $\times$ County Decline | -0.0786*** | -0.0747*** | -0.0788*** |
| | (0.0183) | (0.0178) | (0.0167) |
| Fixed Effects by Year | yes | yes | yes |
| Observations | 183 | 181 | 178 |
| R-squared | 0.333 | 0.362 | 0.355 |

Notes: Clustered standard errors (by year) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample includes all recoveries where the prior housing stock change is lower than -100 homes in the time of the hurricane. The "All Counties" sample includes all counties experiencing a direct or adjacent strike of wind speed category 1+ or a measured storm surge. The "No Outliers" sample excludes St. Bernard and New Orleans Parishes due to their highly idiosyncratic attributes. The "No Katrina" sample omits all counties directly hit by hurricane Katrina.

Table 6: Industry-Employment Results

| Variable | Dependent variable: year on year change in industry employment | | | |
|---|---|---|---|---|
| | Damage Models | | Recovery Models | |
| Earnings per worker (lag) | 0.326*** | -0.0129* | -0.179*** | -0.0239* |
| | (0.0677) | (0.00727) | (0.0516) | (0.0126) |
| Area Employment growth $\times$ Earnings per worker (lag) | | -1.633*** | | |
| | | (0.216) | | |
| Constant | -0.264*** | -0.0444*** | 0.179*** | 0.0509*** |
| | (0.00124) | (0.000245) | (0.000917) | (0.000493) |
| Observation Weighting | Yes | No | Yes | No |
| Fixed Effects by Year | Yes | Yes | Yes | Yes |
| Fixed Effects by Area | Yes | Yes | Yes | Yes |
| Observations | 1,002 | 1,002 | 939 | 939 |
| R-squared | 0.657 | 0.621 | 0.286 | 0.305 |

Notes: Clustered standard errors (by year $\times$ area) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variable is year-on-year log-difference in 2-digit NAICS employment, excluding industries that often benefit from hurricane recovery (NAICS 23, 52, and 56; Construction, Finance and Insurance, and Waste Management and Remediation, respectively), estimated as the counterfactual value minus the actual. The sample includes all recoveries where the initial hurricane effect is 0.5% or greater. The sample excludes St. Bernard and New Orleans Parishes due to their highly idiosyncratic attributes. In weighted models, observations with larger initial hurricane effects are given greater weight due to higher signal-noise ratio in the estimated effect. Earnings are normalized within each year/area combination. The squared term is omitted from recovery model with no weights because it model-encompasses the model with a squared term.

# A-1 Appendix

Table A-1: Initial Hurricane Effects–Employment

| Sample | All Counties | No Outliers | No Katrina |
|---|---|---|---|
| *Direct Hit Counties* | | | |
| Category 3+ Hurricane | -0.189*** | -0.0920*** | -0.0178 |
| | (0.0400) | (0.0128) | (0.0269) |
| Category 3+ × County Decline | -0.0118 | 0.00276 | 0.00104 |
| | (0.0225) | (0.00945) | (0.00771) |
| Category 3+ × Past Strikes | 0.0846*** | 0.0506*** | 0.0102 |
| | (0.0222) | (0.0128) | (0.0203) |
| Big Storm Surge [> 9 Feet] | -0.0686** | -0.0309 | -0.0195 |
| | (0.0273) | (0.0192) | (0.0142) |
| Big Surge × County Decline | -0.0528*** | -0.0136** | -0.0149 |
| | (0.00799) | (0.00565) | (0.00940) |
| Big Surge × Past Strikes | 0.0699*** | 0.0327** | 0.0266** |
| | (0.0175) | (0.0124) | (0.0109) |
| Big Surge × Low Elevation | -0.375*** | -0.179*** | -0.162*** |
| | (0.0265) | (0.0170) | (0.0384) |
| *Adjacent Counties* | | | |
| Category 3+ Hurricane | -0.0589* | -0.0372* | -0.0278* |
| | (0.0282) | (0.0181) | (0.0139) |
| Category 3+ × County Decline | -0.0312 | -0.0173 | -0.0132 |
| | (0.0232) | (0.0148) | (0.0120) |
| Category 3+ × Past Strikes | -0.00151 | 0.00118 | 0.00176 |
| | (0.0290) | (0.0202) | (0.0169) |
| Big Storm Surge [> 9 Feet] | -0.00672 | -0.00780 | -0.00550 |
| | (0.00841) | (0.00857) | (0.00840) |
| Big Surge × County Decline | -0.00298 | -9.53e-05 | 0.00146 |
| | (0.00613) | (0.00596) | (0.00523) |
| Big Surge × Past Strikes | 0.0158 | 0.0118 | 0.0142 |
| | (0.0121) | (0.00950) | (0.00863) |
| Big Surge × Low Elevation | -0.164*** | -0.104*** | -0.110*** |
| | (0.0235) | (0.0122) | (0.0125) |
| Constant | 0.00420 | 0.00242 | 0.00124 |
| | (0.00294) | (0.00265) | (0.00257) |
| Observations | 335 | 331 | 324 |
| R-squared | 0.522 | 0.367 | 0.270 |

Notes: Clustered standard errors (by year) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables are hurricane effects, estimated as the counterfactual value minus the actual. The "All Counties" sample includes all counties experiencing a direct or adjacent strike of wind speed category 3+ or a 9 foot+ storm surge. The "No Outliers" sample excludes St. Bernard and New Orleans Parishes due to their highly idiosyncratic attributes. The "No Katrina" sample omits all counties directly hit by hurricane Katrina.

Table A-2: Initial Hurricane Effects–Earnings

| Sample | All Counties | No Outliers | No Katrina |
|---|---|---|---|
| *Direct Hit Counties* | | | |
| Category 3+ Hurricane | 0.0802*** | 0.0598*** | 0.0411** |
| | (0.0179) | (0.0142) | (0.0156) |
| Category 3+ × County Decline | -0.00289 | -0.00596 | -0.00755 |
| | (0.0101) | (0.00640) | (0.00434) |
| Category 3+ × Past Strikes | -0.0333** | -0.0261** | -0.0190 |
| | (0.0118) | (0.0117) | (0.0113) |
| Big Storm Surge [> 9 Feet] | 0.0472** | 0.0394* | 0.0353* |
| | (0.0203) | (0.0191) | (0.0197) |
| Big Surge × County Decline | 0.0270** | 0.0188** | 0.0165* |
| | (0.00919) | (0.00854) | (0.00907) |
| Big Surge × Past Strikes | -0.0286** | -0.0210 | -0.0209 |
| | (0.0122) | (0.0124) | (0.0133) |
| Big Surge × Low Elevation | 0.120*** | 0.0790** | 0.0745 |
| | (0.0316) | (0.0343) | (0.0443) |
| *Adjacent Counties* | | | |
| Category 3+ Hurricane | 0.0255*** | 0.0202** | 0.0162** |
| | (0.00773) | (0.00703) | (0.00674) |
| Category 3+ × County Decline | 0.0151* | 0.0116* | 0.00971* |
| | (0.00724) | (0.00565) | (0.00501) |
| Category 3+ × Past Strikes | 0.00917 | 0.00847 | 0.00815 |
| | (0.0107) | (0.00903) | (0.00779) |
| Big Storm Surge [> 9 Feet] | 0.0159** | 0.0161* | 0.0152* |
| | (0.00707) | (0.00764) | (0.00736) |
| Big Surge × County Decline | 0.00915*** | 0.00865*** | 0.00781*** |
| | (0.00203) | (0.00234) | (0.00200) |
| Big Surge × Past Strikes | -0.00744* | -0.00644** | -0.00756*** |
| | (0.00349) | (0.00291) | (0.00217) |
| Big Surge × Low Elevation | 0.0630*** | 0.0486** | 0.0512*** |
| | (0.0131) | (0.0186) | (0.0167) |
| Constant | 0.00647 | 0.00692* | 0.00727* |
| | (0.00370) | (0.00389) | (0.00407) |
| Observations | 316 | 312 | 305 |
| R-squared | 0.257 | 0.145 | 0.092 |

Notes: Clustered standard errors (by year) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables are hurricane effects, estimated as the counterfactual value minus the actual. The "All Counties" sample includes all counties experiencing a direct or adjacent strike of wind speed category 3+ or a 9 foot+ storm surge. The "No Outliers" sample excludes St. Bernard and New Orleans Parishes due to their highly idiosyncratic attributes. The "No Katrina" sample omits all counties directly hit by hurricane Katrina.

Table A-3: Initial Hurricane Effects–Non-worker Population

| Sample | All Counties | No Outliers | No Katrina |
|---|---|---|---|
| *Direct Hit Counties* | | | |
| Category 3+ Hurricane | -0.190*** | -0.0144 | -0.00431 |
| | (0.0592) | (0.0137) | (0.0213) |
| Category 3+ × County Decline | -0.0374 | 0.00483 | 0.00779 |
| | (0.0583) | (0.00566) | (0.00612) |
| Category 3+ × Past Strikes | 0.0394 | 0.00498 | 0.00382 |
| | (0.0729) | (0.0181) | (0.0195) |
| Big Storm Surge [> 9 Feet] | -0.127** | -0.0237 | -0.0248 |
| | (0.0441) | (0.0266) | (0.0289) |
| Big Surge × County Decline | -0.127*** | -0.0291** | -0.0280** |
| | (0.0364) | (0.0135) | (0.0107) |
| Big Surge × Past Strikes | 0.113*** | 0.0184* | 0.0219 |
| | (0.0224) | (0.0101) | (0.0134) |
| Big Surge × Low Elevation | -0.613*** | -0.125** | -0.129** |
| | (0.0565) | (0.0468) | (0.0490) |
| *Adjacent Counties* | | | |
| Category 3+ Hurricane | -0.0491** | 0.00682 | 0.00969 |
| | (0.0225) | (0.0107) | (0.0129) |
| Category 3+ × County Decline | -0.0433* | -0.00684 | -0.00537 |
| | (0.0227) | (0.00468) | (0.00628) |
| Category 3+ × Past Strikes | -0.0182 | -0.0129** | -0.0126** |
| | (0.0262) | (0.00509) | (0.00470) |
| Big Storm Surge [> 9 Feet] | 0.00766 | 0.00552 | 0.00659 |
| | (0.0162) | (0.00414) | (0.00419) |
| Big Surge × County Decline | 0.00182 | 0.00536** | 0.00574** |
| | (0.00723) | (0.00244) | (0.00238) |
| Big Surge × Past Strikes | 0.0222*** | 0.00407*** | 0.00477** |
| | (0.00692) | (0.00134) | (0.00160) |
| Big Surge × Low Elevation | -0.199*** | -0.00549 | -0.00724 |
| | (0.0531) | (0.00413) | (0.00605) |
| Constant | 0.00630 | -0.000153 | -0.000489 |
| | (0.00444) | (0.00317) | (0.00327) |
| Observations | 275 | 271 | 266 |
| R-squared | 0.437 | 0.109 | 0.112 |

Notes: Clustered standard errors (by year) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables are hurricane effects, estimated as the counterfactual value minus the actual. The "All Counties" sample includes all counties experiencing a direct or adjacent strike of wind speed category 3+ or a 9 foot+ storm surge. The "No Outliers" sample excludes St. Bernard and New Orleans Parishes due to their highly idiosyncratic attributes. The "No Katrina" sample omits all counties directly hit by hurricane Katrina.

Table A-4: Initial Hurricane Effects–Housing Stock

| Sample | All Counties | No Outliers | No Katrina |
|---|---|---|---|
| *Direct Hit Counties* | | | |
| Category 3+ Hurricane | -0.0727** | -0.0374** | 0.0379*** |
| | (0.0253) | (0.0135) | (0.00792) |
| Category 3+ × County Decline | -0.0189* | -0.00846** | 0.00348 |
| | (0.00862) | (0.00342) | (0.00900) |
| Category 3+ × Past Strikes | -0.00450 | -0.0101 | -0.0339** |
| | (0.0208) | (0.0167) | (0.0113) |
| Big Storm Surge [> 9 Feet] | -0.0661 | -0.0450 | -0.0160 |
| | (0.0398) | (0.0305) | (0.0157) |
| Big Surge × County Decline | -0.0535** | -0.0341* | -0.0296* |
| | (0.0205) | (0.0168) | (0.0144) |
| Big Surge × Past Strikes | 0.0278 | 0.0189 | 0.00995 |
| | (0.0144) | (0.0120) | (0.0123) |
| Big Surge × Low Elevation | -0.198*** | -0.153*** | -0.128*** |
| | (0.0496) | (0.0254) | (0.0264) |
| *Adjacent Counties* | | | |
| Category 3+ Hurricane | -0.000272 | 0.00796 | 0.0178 |
| | (0.00335) | (0.00471) | (0.0102) |
| Category 3+ × County Decline | -0.0194 | -0.00988 | 0.000265 |
| | (0.0108) | (0.00596) | (0.00298) |
| Category 3+ × Past Strikes | -0.0301 | -0.0239 | -0.0154** |
| | (0.0181) | (0.0146) | (0.00596) |
| Big Storm Surge [> 9 Feet] | -0.00104 | -0.00350 | 0.00287 |
| | (0.00836) | (0.00439) | (0.00661) |
| Big Surge × County Decline | -0.00526 | -0.00521 | -0.00253 |
| | (0.00458) | (0.00342) | (0.00227) |
| Big Surge × Past Strikes | 0.000343 | 7.12e-05 | 0.00593 |
| | (0.0101) | (0.00863) | (0.00323) |
| Big Surge × Low Elevation | -0.0553*** | -0.0255*** | -0.0391* |
| | (0.00996) | (0.00595) | (0.0177) |
| Constant | 0.00525** | 0.00400** | 0.00156 |
| | (0.00196) | (0.00156) | (0.00163) |
| Observations | 162 | 160 | 156 |
| R-squared | 0.625 | 0.451 | 0.348 |

Notes: Clustered standard errors (by year) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables are hurricane effects, estimated as the counterfactual value minus the actual. The "All Counties" sample includes all counties experiencing a direct or adjacent strike of wind speed category 3+ or a 9 foot+ storm surge. The "No Outliers" sample excludes St. Bernard and New Orleans Parishes due to their highly idiosyncratic attributes. The "No Katrina" sample omits all counties directly hit by hurricane Katrina.

Table A-5: Hurricane Recovery–Employment

| | Dependent variable: year on year change in orthogonalized variable | | | | | |
|---|---|---|---|---|---|---|
| Sample | All Counties | | No Outliers | | No Katrina | |
| Initial Effect of Hurricane | -0.431*** | -0.416*** | -0.590*** | -0.592*** | -0.591*** | -0.573*** |
| | (0.0146) | (0.0274) | (0.0175) | (0.103) | (0.0261) | (0.133) |
| Initial Effect × County Decline | 0.375*** | 0.279*** | 0.172*** | 0.152** | 0.183*** | 0.144** |
| | (0.0407) | (0.0497) | (0.0274) | (0.0555) | (0.0263) | (0.0623) |
| County Decline | 0.0154*** | 0.00654 | -0.000193 | -0.000198 | 0.000923 | -0.000587 |
| | (0.00469) | (0.00536) | (0.00402) | (0.00573) | (0.00382) | (0.00581) |
| Constant | -0.00141 | -0.00247 | -0.0110** | -0.0113* | -0.0117** | -0.0105 |
| | (0.00483) | (0.00434) | (0.00455) | (0.00595) | (0.00417) | (0.00690) |
| Observation Weighting | yes | no | yes | no | yes | no |
| Observations | 2,056 | 319 | 2,049 | 317 | 2,042 | 313 |
| R-squared | 0.880 | 0.179 | 0.503 | 0.144 | 0.426 | 0.108 |

Notes: Clustered standard errors (by year) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables are hurricane effects, estimated as the counterfactual value minus the actual. The sample includes all recoveries where the initial hurricane effect is 0.5% or greater. The "All Counties" sample includes all counties experiencing a direct or adjacent strike of wind speed category 3+ or a 9 foot+ storm surge. The "No Outliers" sample excludes St. Bernard and New Orleans Parishes due to their highly idiosyncratic attributes. The "No Katrina" sample omits all counties directly hit by hurricane Katrina. Observations with weights are weighted by initial hurricane effects due to higher signal-noise ratio in the estimated effect. Observations without weights are restricted to those with larger initial effects to eliminate noisy observations.

Table A-6: Hurricane Recovery–Earnings per Worker

| | Dependent variable: year on year change in orthogonalized variable | | | | | |
|---|---|---|---|---|---|---|
| Sample | All Counties | | No Outliers | | No Katrina | |
| Initial Effect of Hurricane | -0.635*** | -0.664*** | -0.684*** | -0.727*** | -0.684*** | -0.727*** |
| | (0.179) | (0.198) | (0.179) | (0.202) | (0.180) | (0.204) |
| Initial Effect × County Decline | -0.218** | -0.217* | -0.241** | -0.249** | -0.243** | -0.252** |
| | (0.0934) | (0.109) | (0.0900) | (0.104) | (0.0897) | (0.103) |
| County Decline | 0.00963 | 0.0180 | 0.0105* | 0.0204* | 0.0106* | 0.0206* |
| | (0.00564) | (0.0106) | (0.00552) | (0.0104) | (0.00551) | (0.0104) |
| Constant | 0.0159* | 0.0254 | 0.0179* | 0.0304 | 0.0179* | 0.0301 |
| | (0.00862) | (0.0173) | (0.00890) | (0.0189) | (0.00887) | (0.0188) |
| Observation Weighting | yes | no | yes | no | yes | no |
| Observations | 2,713 | 303 | 2,705 | 301 | 2,693 | 297 |
| R-squared | 0.354 | 0.223 | 0.386 | 0.250 | 0.387 | 0.249 |

Notes: Clustered standard errors (by year) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables are hurricane effects, estimated as the counterfactual value minus the actual. The sample includes all recoveries where the initial hurricane effect is 0.5% or greater. The "All Counties" sample includes all counties experiencing a direct or adjacent strike of wind speed category 3+ or a 9 foot+ storm surge. The "No Outliers" sample excludes St. Bernard and New Orleans Parishes due to their highly idiosyncratic attributes. The "No Katrina" sample omits all counties directly hit by hurricane Katrina. Observations with weights are weighted by initial hurricane effects due to higher signal-noise ratio in the estimated effect. Observations without weights are restricted to those with larger initial effects to eliminate noisy observations.

Table A-7: Hurricane Recovery–Non-worker Population

| | Dependent variable: year on year change in orthogonalized variable | | | | | |
|---|---|---|---|---|---|---|
| Sample | All Counties | | No Outliers | | No Katrina | |
| Initial Effect of Hurricane | -0.401*** | -0.269*** | 0.324* | 0.129 | 0.308* | 0.114 |
| | (0.00340) | (0.0423) | (0.180) | (0.214) | (0.176) | (0.211) |
| Initial Effect × County Decline | 0.278*** | 0.0779 | 0.542*** | 0.347 | 0.608*** | 0.414* |
| | (0.0162) | (0.0849) | (0.114) | (0.214) | (0.120) | (0.233) |
| County Decline | 0.00581 | 0.00691 | 0.0238*** | 0.0210* | 0.0259*** | 0.0241** |
| | (0.00602) | (0.00500) | (0.00409) | (0.0101) | (0.00423) | (0.0108) |
| Constant | -0.0300** | -0.00893** | 0.0199** | 0.0122 | 0.0197** | 0.0120 |
| | (0.0112) | (0.00358) | (0.00787) | (0.0117) | (0.00813) | (0.0119) |
| Observation Weighting | yes | no | yes | no | yes | no |
| Observations | 2,019 | 266 | 2,017 | 264 | 2,012 | 261 |
| R-squared | 0.968 | 0.220 | 0.174 | 0.021 | 0.196 | 0.026 |

Notes: Clustered standard errors (by year) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables are hurricane effects, estimated as the counterfactual value minus the actual. The sample includes all recoveries where the initial hurricane effect is 0.5% or greater. The "All Counties" sample includes all counties experiencing a direct or adjacent strike of wind speed category 3+ or a 9 foot+ storm surge. The "No Outliers" sample excludes St. Bernard and New Orleans Parishes due to their highly idiosyncratic attributes. The "No Katrina" sample omits all counties directly hit by hurricane Katrina. Observations with weights are weighted by initial hurricane effects due to higher signal-noise ratio in the estimated effect. Observations without weights are restricted to those with larger initial effects to eliminate noisy observations.

Table A-8: Hurricane Recovery–Housing Stock

Dependent variable: year on year change in orthogonalized variable

| Sample | All Counties | | No Outliers | | No Katrina | |
|---|---|---|---|---|---|---|
| Initial Effect of Hurricane | -0.543*** | -0.410*** | -0.165*** | -0.168*** | -0.0122 | -0.148*** |
| | (0.00573) | (0.0128) | (0.00952) | (0.00440) | (0.0180) | (0.0147) |
| Initial Effect × County Decline | -0.197*** | 0.0351 | 0.116*** | 0.198*** | 0.281*** | 0.255*** |
| | (0.0225) | (0.0363) | (0.0158) | (0.0374) | (0.0221) | (0.0440) |
| County Decline | -0.0246*** | 0.00252 | 0.00196 | 0.00750* | 0.00917*** | 0.00930** |
| | (0.00463) | (0.00368) | (0.00262) | (0.00338) | (0.00217) | (0.00336) |
| Constant | -0.0363*** | -0.00249 | 0.00461* | 0.00457* | 0.00914*** | 0.00492** |
| | (0.000670) | (0.00226) | (0.00248) | (0.00193) | (0.00274) | (0.00177) |
| Observation Weighting | yes | no | yes | no | yes | no |
| Observations | 574 | 170 | 572 | 168 | 569 | 165 |
| R-squared | 0.918 | 0.664 | 0.794 | 0.503 | 0.718 | 0.431 |

Notes: Clustered standard errors (by year) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables are hurricane effects, estimated as the counterfactual value minus the actual. The sample includes all recoveries where the initial hurricane effect is 0.5% or greater. The "All Counties" sample includes all counties experiencing a direct or adjacent strike of wind speed category 3+ or a 9 foot+ storm surge. The "No Outliers" sample excludes St. Bernard and New Orleans Parishes due to their highly idiosyncratic attributes. The "No Katrina" sample omits all counties directly hit by hurricane Katrina. Observations with weights are weighted by initial hurricane effects due to higher signal-noise ratio in the estimated effect. Observations without weights are restricted to those with larger initial effects to eliminate noisy observations.

Table A-9: Robustness exercise–Damage regressions with other cross-sectional covariates

| | Dependent variable: year on year change in orthogonalized employment | | | | | |
|---|---|---|---|---|---|---|
| Additional covariate: | None | % Vacant units | % Single-family units | % Mobile homes | % Poverty | % over 65 |
| *Direct Hit Counties* | | | | | | |
| Category 3+ Hurricane | -0.0888*** | -0.0555** | 0.103 | -0.0994*** | -0.0172 | -0.0627*** |
| | (0.0132) | (0.0235) | (0.0625) | (0.0325) | (0.123) | (0.0138) |
| Category 3+ × Past Strikes | 0.0487*** | 0.0476** | 0.00740 | 0.0495*** | 0.0452*** | 0.0706*** |
| | (0.0137) | (0.0170) | (0.0213) | (0.0155) | (0.0131) | (0.0226) |
| Big Surge × Past Strikes | 0.0339** | 0.0335*** | 0.0353** | 0.0389** | 0.0290** | 0.0367* |
| | (0.0123) | (0.0105) | (0.0140) | (0.0158) | (0.0130) | (0.0175) |
| Big Surge × Low Elevation | -0.180*** | -0.171*** | -0.181*** | -0.196*** | -0.173*** | -0.202*** |
| | (0.0174) | (0.0176) | (0.0189) | (0.0311) | (0.0146) | (0.0334) |
| Big Storm Surge [> 9 Feet] | -0.0304 | -0.0212 | 0.0244 | -0.0387 | 0.0132 | -0.0113 |
| | (0.0179) | (0.0137) | (0.0225) | (0.0294) | (0.0424) | (0.0180) |
| Category 3+ × County Decline | 0.00436 | -0.00484 | 0.00411 | 0.00388 | 0.0165 | -0.00752 |
| | (0.00849) | (0.00677) | (0.00718) | (0.00913) | (0.0279) | (0.0111) |
| Big Surge × County Decline | -0.0144** | -0.0229*** | -0.0104 | -0.0121** | -0.00805 | -0.0178* |
| | (0.00526) | (0.00475) | (0.00695) | (0.00478) | (0.00929) | (0.00861) |
| Category 3+ × Covariate | | -0.216 | -0.238** | 0.0496 | -0.305 | -0.412* |
| | | (0.155) | (0.0796) | (0.122) | (0.590) | (0.196) |
| Big Surge × Covariate | | -0.0966 | -0.0931 | 0.0547 | -0.222 | -0.188 |
| | | (0.116) | (0.0596) | (0.0912) | (0.277) | (0.284) |
| Constant | 0.000751 | 0.000608 | 0.00111 | 0.000669 | 0.000505 | 0.00103 |
| | (0.00346) | (0.00349) | (0.00344) | (0.00351) | (0.00348) | (0.00346) |
| Observations | 130 | 130 | 130 | 130 | 130 | 130 |
| R-squared | 0.423 | 0.454 | 0.450 | 0.428 | 0.435 | 0.450 |

Notes: Clustered standard errors (by year) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variable is hurricane effect on county-level employment, estimated as the counterfactual value minus the actual. The sample excludes St. Bernard and New Orleans Parishes due to their highly idiosyncratic attributes. The sample includes all counties directly hit by a Category 3+ hurricane or ¿9 foot high storm surge.

Table A-10: Robustness exercise–Recovery regressions with other cross-sectional covariates

Dependent variable: year on year change in orthogonalized employment

| Additional covariate: | None | % Vacant units | % Single-family units | % Mobile homes | % Poverty | % over 65 |
|---|---|---|---|---|---|---|
| Initial Effect of Hurricane | -0.590*** | -0.809*** | -0.929* | -0.732*** | -0.787*** | -0.728*** |
| | (0.0175) | (0.114) | (0.505) | (0.0336) | (0.0845) | (0.115) |
| Initial Effect × County Decline | 0.172*** | 0.320*** | 0.162*** | 0.172*** | 0.158*** | 0.196*** |
| | (0.0274) | (0.0461) | (0.0187) | (0.0196) | (0.0179) | (0.0340) |
| County Decline | -0.000193 | 0.00923** | -0.00239 | 0.000292 | -0.00223 | 0.00139 |
| | (0.00402) | (0.00426) | (0.00339) | (0.00331) | (0.00386) | (0.00356) |
| Initial Effect × Covariate | | 1.267* | 0.501 | 1.174*** | 1.108* | 1.140 |
| | | (0.680) | (0.790) | (0.333) | (0.581) | (1.153) |
| Covariate | | 0.0935* | 0.0868 | 0.0597 | 0.0980 | 0.125 |
| | | (0.0525) | (0.0964) | (0.0459) | (0.0595) | (0.0983) |
| Constant | -0.0110** | -0.0256*** | -0.0708 | -0.0168 | -0.0301** | -0.0276 |
| | (0.00455) | (0.00769) | (0.0671) | (0.00990) | (0.0138) | (0.0174) |
| Observations | 2,049 | 2,049 | 2,049 | 2,049 | 2,049 | 2,049 |
| R-squared | 0.503 | 0.525 | 0.506 | 0.525 | 0.507 | 0.504 |

Notes: Clustered standard errors (by year) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables are hurricane employment effects, estimated as the counterfactual value minus the actual. The sample includes all recoveries where the initial hurricane effect is 0.5% or greater. The sample excludes St. Bernard and New Orleans Parishes due to their highly idiosyncratic attributes. Observations with larger initial hurricane effects are given greater weight due to higher signal-noise ratio in the estimated effect.