DISSERTATION

ESSAYS ON ENTREPRENEURSHIP AND SOCIAL CAPITAL IN THE WAKE OF A CATASTROPHIC DISASTER

Submitted by

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ABSTRACT

ESSAYS ON ENTREPRENEURSHIP AND SOCIAL CAPITAL IN THE WAKE OF A CATASTROPHIC DISASTER

Research on the economics of disasters has seen a surge in interest in recent years following a series of high-profile events, such as the 2004 Indian Ocean Tsunami, the 2005 Atlantic hurricane season, and the 2010 Haitian Earthquake (Cavallo et al., 2011). In the United States, recent hurricanes such as Harvey, Irma, and Maria have continued to draw attention to the economic consequences associated with catastrophic natural disasters. Both global climate change and the shifting of people and economic activity towards coastal areas increase the likelihood of major climatic disasters occurring in the future (Nordhaus, 2010).

This dissertation utilizes Hurricane Katrina as a case study to investigate the various ways in which disasters impact a community, and the factors that both attenuate and exacerbate these impacts.

The first chapter describes a framework for identifying the effects of a disaster. Using the synthetic control method, originally proposed by Abadie and Gardeazabal (2003) and Abadie et al. (2010), the chapter identifies the long-term population effects of Hurricane Katrina across the eight most damaged counties. Results highlight significant variation in terms of the magnitude of out-migration across these areas. Cross-county differences in population outcomes are largely the consequence of the severity of housing damage. Pre-existing county characteristics, such as the percent of the population with hazard insurance, were only weakly correlated with population outcomes. Results suggest a near unit-elastic relationship between the severity of housing damage and out-migration. Notable outliers include Jefferson and St. Tammany Parish, who experienced disproportionate out-migration due to the disaster. The paper argues that this is likely due to the significant amount of commuters that work in Orleans but reside in these two counties.

The decision to return and rebuild one's home is dependent on whether one's neighbors plan to rebuild, if and when the government restores utilities and infrastructure, and whether surrounding businesses return. Because of the interdependent nature of these decisions, the process of disaster recovery is often characterized as a collective action problem, in which the degree of necessary coordination increases with the extent of out-migration. The second chapter seeks to test the hypothesis advanced by Storr et al. (2016) that entrepreneurs are important first movers in post-disaster environments. The chapter expands on the framework described in chapter one and applies the synthetic control method to all counties that experienced housing damages from Hurricane Katrina and/or Rita. Using these estimated effects as a dependent variable, the chapter explores the role of entrepreneurship in disaster recovery. Results indicate positive correlations between new firm formation and disaster recovery, both with respect to initial impacts, as well as throughout the recovery period.

The final chapter investigates the impacts of Hurricane Katrina on social capital in the New Orleans Metropolitan Statistical Area (MSA). Previous research has found that disasters often generate "therapeutic communities," in which altruism, trust, and charity increase following an event. However, the only empirical study to examine the impacts of Hurricane Katrina on social capital finds the opposite effect, in which the concentration of community-based organizations decreased after the disaster. Building on this work, I use the synthetic control method to identify the impacts of Hurricane Katrina on a social capital index, constructed using the concentration of community-based establishments and nonprofit organizations in the New Orleans MSA. The chapter finds that this index increased significantly after Hurricane Katrina, by approximately half a standard deviation relative to the level implied by the synthetic control. Additionally, the paper shows that this increase persists through the entire sample period, even as population levels recover in the area. Decomposing the index by its various components shows that this increase was fairly uniform across included establishment sectors and nonprofit organizations.

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Chapter 1

Identifying the Effects of a Catastrophic Disaster

1.1 Introduction

Recovery from a natural disaster is often described as the least understood phase of a disaster event (Chang, 2010; Cheng et al., 2015; Mileti, 1975). In particular, the question of why some areas recovery faster relative to others remains poorly understood. This lack of understanding partly originates from the difficulty in defining what it means for a community to be recovered.

A key problem, and the focus of this chapter, involves the definition of a threshold that must be overcome for a community to be considered *recovered*. Traditionally, this threshold has been defined as a return to pre-disaster conditions. For example, an economy may be considered recovered once GDP has returned to the level just before the disaster occurred. Past research has questioned this criterion (Chang and Rose, 2012; Cheng et al., 2015). Such a definition inadequately accounts for pre-disaster dynamics. For example, if an area is growing or contracting prior to the disaster, these dynamics will likely influence post-disaster outcomes. Additionally, post-disaster shocks (unrelated to the disaster itself) might similarly confound outcomes. For example, a large macroeconomic event, such as the 2008 recession, will influence many indicators we care about, such as migration, employment, housing, and income.

Forwarding a definition of recovery that addresses both pre-disasters dynamics and post-disaster confounding events necessitates counterfactual reasoning. Although we observe post-disaster outcomes, we do not observe what these outcomes would have been had the disaster not taken place. Estimating a counterfactual trajectory of *what would have happened* allows us to identify the effects of a disaster. This identification is needed to make comparisons across impacted areas and/or disaster events.

Previous studies have emphasized the issue of correctly identifying a counterfactual in the context of disasters analysis (e.g. Barone and Mocetti, 2014; Cavallo et al., 2013; Coffman and Noy, 2012; duPont IV and Noy, 2015). These studies have employed the synthetic control method, originally proposed by Abadie and Gardeazabal (2003), to estimate this missing counterfactual. The construction of a "synthetic control" is based on a weighted combination of unaffected areas, where weights are chosen to minimize the difference between the observed and synthetic series during the pre-disaster period. Applying these weights to the post-disaster period results in an estimate of what would have happened had the disaster not occurred. The effect of a disaster can thus be defined as the difference between observed outcomes relative to the synthetic control. Disaster recovery can be represented by the time it takes for observed trends to return to the counterfactual. If a community never returns to the synthetic series, this would suggest the disaster had a permanent impact on the area, and thus never fully recovered.

The purpose of this chapter is to employ the synthetic control method to investigate disaster recovery following Hurricanes Katrina. Hurricane Katrina was one of the most destructive natural disasters in United States history. The storm caused over 100 billion dollars in direct property damage and resulted in approximately 1,800 lost lives. Catastrophic flooding due to breeched levees led to an immense displacement of people from the area. Although there is a significant amount of literature documenting the immediate effects of the hurricane, little is known about the long-term consequences of the storm. In particular, little quantitative work has been applied to the question of why we observe differences in recovery across affected communities.

Investigating the determinants of recovery, however, requires first isolating the effects of a disaster. Using the synthetic control method, I estimate the long-term population impacts of Hurricane Katrina across eight counties that were severely impacted by the storm. These counties include four Louisiana Parishes: Jefferson, Orleans, Plaquemines, St. Bernard, and St. Tammany, and four Mississippi Counties: Hancock, Harrison, and Jackson.[1]

Migration is one of the main channels in which a natural disaster affects a local economy (Coffman and Noy, 2012; Xiao, 2011; Yun and Waldorf, 2016). Large scale out-migration implicates a variety of features of the regional economy, including rents, wages, GDP growth, and

[1]The state of Louisiana is divided into 64 parishes, which are political subdivisions equivalent to counties in other states. Throughout the analysis the terms "county" and "parish" can be viewed as interchangeable.

unemployment. Hurricane Katrina, in particular, had a significant impact on household migration across the region. For example, Groen and Polivka (2008b) estimate that 1.5 million people (aged 16 and older) left their homes because of Hurricane Katrina. Additionally, Vigdor (2008) notes that the city of New Orleans lost roughly 200,000 people due to out-migration. This represents a 20% reduction relative to the city's pre-Katrina population level. Migration was not proportional across different socioeconomic and demographic groups. Lower-income, less educated, and minority households were less likely to return to the region after evacuating (Groen and Polivka, 2010). Selective out-migration complicates indicators typically utilized in economic research. For example, in New Orleans per-capita income and the employment population ratio both dramatically increased after Hurricane Katrina. These increases are likely due to lower-income and/or unemployed households leaving the area, rather than reflecting "true" increases. It is difficult to judge whether such increases are "good" or "bad," and whether a return to a counterfactual trend is ideal. Population as an indicator does not suffer from this feature. It also tends to be relatively stable over time and is available annually for all counties in the United States. These features make it an ideal indicator for comparing recovery across communities.

This chapter identifies the population effects of Hurricane Katrina across eight highly damaged areas and tests whether these effects persist across the sample period. Results illustrate different experiences across the eight areas, both in terms of magnitude and the dynamics of recovery. The chapter additionally examines the correlation between estimated effects and damages, insurance rates, and a series of covariates. Results suggest that severe housing damage is a key driver of observed differences across the eight counties. Insurance rates were surprisingly uncorrelated with population outcomes across the sample. The following chapter expands this framework to all 122 counties damaged by Hurricanes Katrina and Rita, and further examines county characteristics relevant to disaster resilience. In particular, it explores the notion that entrepreneurship is an important factor in attenuating the negative consequences of a disaster.

The remainder of this chapter is organized as follows. Section 1.2 reviews the literature related to the economics of disasters. Section 1.3 provides background on Hurricane Katrina. Section 1.4

describes the synthetic control method and data used in the analysis. Section 1.5 presents results. Section 1.6 concludes with a summary and discussion of next steps.

1.2 Disaster Literature

There have been a number of studies that have estimated the effects of a natural disaster across various indicators and geographical scales. A common theme throughout this literature is noting that economic theory does not provide clear intuition for how a disaster should impact a local economy, and thus requires empirical investigation (Barone and Mocetti, 2014; Belasen and Polachek, 2009; Cavallo et al., 2011; Coffman and Noy, 2012; Ewing et al., 2009). For example, natural disasters can generate significant damage to physical capital and infrastructure, which will negatively impact economic activity. Disasters also attract a large influx of transfer payments in the form of assistance, charity, and insurance payouts (Coffman and Noy, 2012). The need for reconstruction, in combination with outside financing, results in a positive stimulus for an affected area. This stimulus acts as a countervailing force to the negative effects accruing from damages, resulting in ambiguity as to the overall local effect (Cochrane, 2004). Previous studies seeking to identifying these effects have found mixed results.

For example, Belasen and Polachek (2009) use a generalized-difference-in-difference approach to estimate the average impact of 19 hurricane events that took place in Florida from 1988-2005. They find that on average county employment decreased by 4.76 percent and earnings increased by 4.35 percent. These effects, however, tend to dissipate quickly after the event.

Coffman and Noy (2012) estimate the long-run impacts of Hurricane Iniki on the Hawaiian island of Kauai. The authors exploit the fact that Kauai was the only island hit by the hurricane and use the other unaffected islands to construct a synthetic control. The authors find that 18 years after the event there remains a persistent gap between observed employment, population, and income, relative to their constructed control. Additionally, the authors find that the storm had no effect on per capita income, noting that the negative consequences of the hurricane were driven primarily by out-migration from the area.

Xiao (2011) examines the economic impacts of the 1993 Midwest flood across 361 counties that sustained either commercial or industrial damage. The author uses a Mahalanobis distance matching strategy to identify a control county for each impacted area. Effects are then estimated using an autoregressive integrated moving average (ARIMA) model. The author finds in both low and high damaged areas that total employment was unaffected by the flood event. In contrast to Coffman and Noy (2012), the study finds negative and significant effects of the flood on per capita income immediately after the event. These negative effects were no longer significant in the years following the flood for high damaged counties, and were positive and significant for counties with a low level of damage.

In general, the above research reaches dissimilar conclusions. Across studies, we observe inconsistencies in whether a certain indicator was negatively or significantly affected by a disaster, as well as whether these effects were permanent or transitory. Barone and Mocetti (2014) is one of the few studies to examine *why* we observe differences across disaster events. The authors employ the synthetic control method to investigate the impacts of two earthquakes that occurred in different regions in Italy. The paper identifies divergent experiences, finding positive long-term effects following the 1976 earthquake in Friuli, and negative long-term effects following the 1980 earthquake in Irpinia.[2] The authors argue that these different experiences can be explained by contrasting institutional quality between the two regions.[3] There are likely a number of factors that govern disaster recovery. The exploration of these factors requires developing a consistent framework for comparing recovery experiences. Building on work by Barone and Mocetti (2014), this paper seeks to identify the population effects of Hurricane Katrina across eight severely damaged counties along the Gulf Coast. Given the availability of detailed housing damages across these counties, estimated effects can be compared at a finer geographic scale then examined by Barone and Mocetti (2014), utilizing a larger number of case studies.

[2]Specifically, the paper identifies the effects of the earthquakes on per capita GDP growth

[3]Barone and Mocetti (2014) capture institutional quality with the following four time-varying variables: total number of crimes related to corruption and/or fraudulent behavior, number of appointed members of parliament involved in a scandal, election turnout, and newspaper readership

1.3 Background on Hurricane Katrina

Hurricane Katrina first made landfall on Florida's coast as a Category 1 hurricane on August 25th, 2005. As the storm moved westward across the warmer waters of the Gulf of Mexico, it intensified. By August 28th, the storm strengthened to a Category 5. At the storm's peak winds reached over 170 miles per hour. The hurricane weakened to a Category 3 storm just before making landfall on the Louisiana/Mississippi border on August 29th, 2005.

Hurricane Katrina caused approximately 100 billion dollars in losses, damaged more than 300,000 homes and 150,000 businesses, displaced 1.5 million people, and claimed over 1,800 lives (Zahran et al., 2011). The storm ranks as the third deadliest hurricane since 1990, and in terms of damage, was one of the costliest in world history. Catastrophic flooding associated with breeched levees severely affected St. Bernard and Orleans Parish. Failures at the Industrial Canal, 17th Street Canal, and the London Avenue Canal led to flooding in roughly 80% of New Orleans and resulted in a near complete evacuation from the city.

The literature on the impacts of Hurricane Katrina is substantial (for a complete survey of this literature see Erikson and Peek, 2011). Previous economic studies have examined the immediate impacts of the disaster with respect to major indicators, such as population, employment and housing (Vigdor, 2008), labor market consequences for evacuees (Groen and Polivka, 2008a, 2010), and spillover effects to neighboring areas (McIntosh, 2008; Xiao and Nilawar, 2013).

The longer run impacts of Hurricane Katrina have comparatively been less examined. Deryugina et al. (2014) is one notable exception. The authors exploit tax return data and use filing addresses as a way of identifying individuals living in New Orleans prior to the hurricane. The data allows for these same individuals to be tracked in subsequent years after the storm. Results indicate that the hurricane had transitory impacts on earnings and unemployment relative to matched controls from similar cities. This suggests that at the micro scale the negative effects (in terms of the labor market indicators used in the analysis) of Hurricane Katrina are short lived.

Currently, I am unaware of any studies that have documented the long-term consequences of Hurricane Katrina at the regional scale. It is plausible that though individuals recover from an event, a city or region is permanently impacted. This chapter is interested in the capacity of a disaster to permanently relocate households in space, altering the long-run population of affected regions.

1.4 Methodology

To identify the regional population effects of Hurricane Katrina, I follow Abadie and Gardeazabal (2003) and Abadie et al. (2010) and estimate a “synthetic control" for eight severely damaged counties. Abadie and Gardeazabal (2003) an Abadie et al. (2010) describe a data-driven procedure for constructing a missing counterfactual to identify the effects of an event or policy intervention. The synthetic control method was originally applied in the context of identifying growth impacts of terrorism, and the influence of Proposition 99 on smoking consumption in California, respectively. The method consists of constructing a weighted average of control areas that were unaffected by the event or intervention of interest. Weights are chosen to minimize a cost function that depends on pre-period lags of the outcome variable and several predictor variables. If this weighted average roughly matches outcomes in the treated area prior to the event, the intuition is that it will provide an approximation of the evolution of this outcome in the treated area had the event or intervention not occurred.

The effects of Hurricane Katrina can thus be represented as the difference between observed outcomes and outcomes defined by estimated synthetic controls. Additionally, a placebo analysis is utilized to investigate the statistical significance of these estimated effects. A more detailed description of the synthetic control method is provided below.

The Synthetic Control Method

Assume there are $J + 1$ geographic areas, where the first area is treated by an event of interest (in this case Hurricane Katrina). The remaining J areas represent potential controls counties, which hence forward will be referred to as the *donor pool*. Let Y_{it} be some indicator of interest (in this case population) for area i at time t. Let T_0 be the number of periods prior to the event. Additionally, let Y_{it}^0 be what the indicator would have been absent the event. The method assumes that for $t \leq T_0$, $Y_it^1 = Y_it^0$. Intuitively, this implies that the disaster has no impact on population prior to occurring, and thus is an exogenous event. For $t > T_0$, the effect of the event will be the deviation of Y_{it} from Y_{it}^0. Given that Y_{1t} is observed, to identify the effect of a disaster, Y_{1t}^0 must be estimated. Abadie et al. (2010) suggests estimating Y_{1t}^0 by taking a weighted average across a donor pool of unaffected areas. Thus, for the treated area the effect of Hurricane Katrina, α_{1t}, can be expressed as:

$$\alpha_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \tag{1.1}$$

where w_j is a non-negative weight applied to county j. These weights are estimated by minimizing the cost function described in Eq 1.2 below. W is a $(1 \times J)$ vector encompassing these J weights. X_1 is a $(1 \times K)$ vector of predictors for the treated region, and X_0 is the corresponding $(J \times K)$ matrix of these same predictors for each potential control county. Additionally, let V be a $(K \times K)$ symmetric and positive semidefinite matrix, with the diagonal elements representing the "importance" of each predictor (Smith, 2015). County weights are thus chosen by minimizing the following cost function:

$$||X_1 - X_0W||_V = \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)} \tag{1.2}$$

such that:

$$w_j \geq 0$$

$$\sum_{j=2}^{J+1} w_j = 1$$

Abadie et al. (2010) state that the above inferential procedure is valid for any choice of V. However, the authors suggest choosing V such that the mean squared prediction error of the outcome variable is minimized for the pre-period. In context of this example, this implies minimizing the mean squared prediction error between synthetic and observed population during the years prior to Hurricane Katrina.

Data

County population data are provided annually by the Bureau of Economic Analysis (BEA). These data reflect mid-year estimates, corresponding with population levels on July 1st of each year. Given that Hurricane Katrina struck at the end of August in 2005, the disaster's impact on population does not manifest until the following year, in 2006. These data have been adjusted by dividing by a 2004 base level. This is done so that level differences in population across counties do not affect matches arrived at by the synthetic control algorithm.

Predictor variables of county population are provided by the 2000 Decennial Census and the BEA. These include population density, median home value, median rent, median income, median age, the percent of occupied housing that is owned (opposed to rented), the percent of population with a bachelor's degree, the percent of the population below the poverty rate, population growth, employment growth, and income growth. Lagged population levels for 1990, 1995, 2000, and 2005 are also included in the analysis. These predictors and their respective sources are listed in Table 1.1.

Data on housing damage, damage in terms of home ownership, and insurance rates are provide by Federal Emergency Management Agency (FEMA) and the Department of Housing and Urban Development (HUD). These data represent the count of damaged homes in terms of minor, major, and severe categories. Categories are based on direct housing inspections performed by FEMA after Katrina. Each category corresponds with one of the three available reimbursement levels, less than $5,200, $5,200, and $10,500. Importantly, reimbursements constitute a small fraction of the total damage sustained. For instance, in Orleans Parish the median verified loss for homes classified as suffering severe damage was $107,815. Since assessments were done to determine eligibility for FEMA housing assistance, any individual who did not register with FEMA is not included in these damage counts. Vacant houses and second homes were also not included. The data reports the number of homes that were owned versus rented for each damage category. For owner occupied housing, FEMA also reports whether the home owner had hazard insurance, hazard and flood insurance, or no insurance prior to Hurricane Katrina.

Table 1.1: List of included predictor variables and their respective source

Predictor Variables	Source
Population Density (pop per square mile)	2000 Decennial Census
Median Housing Value	2000 Decennial Census
Median Rent	2000 Decennial Census
Median Income	2000 Decennial Census
Median Age	2000 Decennial Census
Occupancy Rate	2000 Decennial Census
Bachelor Degree or Higher (% of pop 25 and older)	2000 Decennial Census
Average Population Growth: 1990-2004	Bureau of Economic Analysis
Average Employment Growth: 1990-2004	Bureau of Economic Analysis
Average Income Growth: 1990-2004	Bureau of Economic Analysis
Lagged Population: 1990, 1995, 2000, 2005	Bureau of Economic Analysis

Implementation

The synthetic control method is typically applied in the context of one treated area and a small pool of donors. For example, in Abadie and Gardeazabal (2003), the authors estimate the economic impact of terrorist activities in Basque Country Spain by utilizing a donor pool of the 16 remaining autonomous communities in Spain. Abadie et al. (2010) examine the effects of proposition 99 (a large-scale tobacco control initiative) on California's tobacco consumption. They construct a synthetic control for California using the remaining 38 states that had not adopted large-scale tobacco programs during their sample period.

In applying the synthetic control method at the county scale, there are over 3,000 counties (or county equivalents) which could constitute the donor pool. This results in a substantially larger donor pool relative to these previous applications. A donor pool of this size introduces the potential for interpolation bias, particularly if weighted counties are substantially different from the treated unit. Following a suggestion made in Abadie et al. (2010), and to guard against this bias, I restrict the donor pool to a smaller size of counties that are similar along the dimensions of the included predictors. First, I eliminate any county that experienced housing damages from Hurricane Katrina, Rita, or Wilma. Next, I construct a "distance" metric based on the covariates described in Table 1.1. All predictor variables are normalized by dividing by associated standard deviations to control for differences in units. Using the “distance” between treated and donor predictors (see Eq 1.3), I identify a unique set of 30 control areas with the smallest “distance” for each treated county. In the below equation, *Treated Area* is a column vector where each row i is associated with a matching variable. X_j is an identical vector for each j control county. $Distance$ is a column vector that describes the squared differences between predictor values in the treated area and each control area. The donor pool is selected by choosing thirty counties in which this difference is the smallest. Lists of included areas and corresponding weights are provided in the appendix Tables A.1 and A.2.

$$Distance = \sqrt{(Treated\ Area - X_j)'(Treated\ Area - X_j)} \tag{1.3}$$

Study Area

The above methodology is applied to the eight counties most severely impacted by Hurricane Katrina.[4] These include four Louisiana Parishes: Jefferson, Orleans, St. Bernard, and St. Tammany, and three Mississippi Counties: Hancock, Harrison, and Jackson. Table 1.2 shows the degree of housing damages experienced by the eight counties. These values depict the percent of occupied housing that suffered minor, major or severe damages. Figure 1.1 maps major and severe damages across theses counties. In each case, the majority of occupied housing was affected by some degree of damage. In Hancock Mississippi, 90% of occupied housing reported damages after Katrina. St. Bernard, Plaquemines, and Orleans endured the highest degree of severe damage, ranging from 42% in Orleans, to 55% in St. Bernard. Jefferson was the least damaged county in the study. 53% of its housing reported some level of damage, 64% of which was classified as minor. Table 1.3 summarizes differences in owner occupancy and hazard and flood insurance across the study area. Owner occupancy is defined as the percent of *total* damaged homes that were occupied by the owner, rather than a renter. The table also shows whether these owned homes had hazard and flood insurance, just hazard insurance, or no insurance. There is a fair amount of variation across

[4] *Severely impacted* in terms of housing damage

the eight counties. For example, 81% of St. Tammany's damaged housing was owner occupied, compared to Orleans, where only 50% was occupied by the home owner. Plaquemines stands out as having the highest percentage of uninsured damaged housing, at 43%. The next highest was Harrison County at 23%.

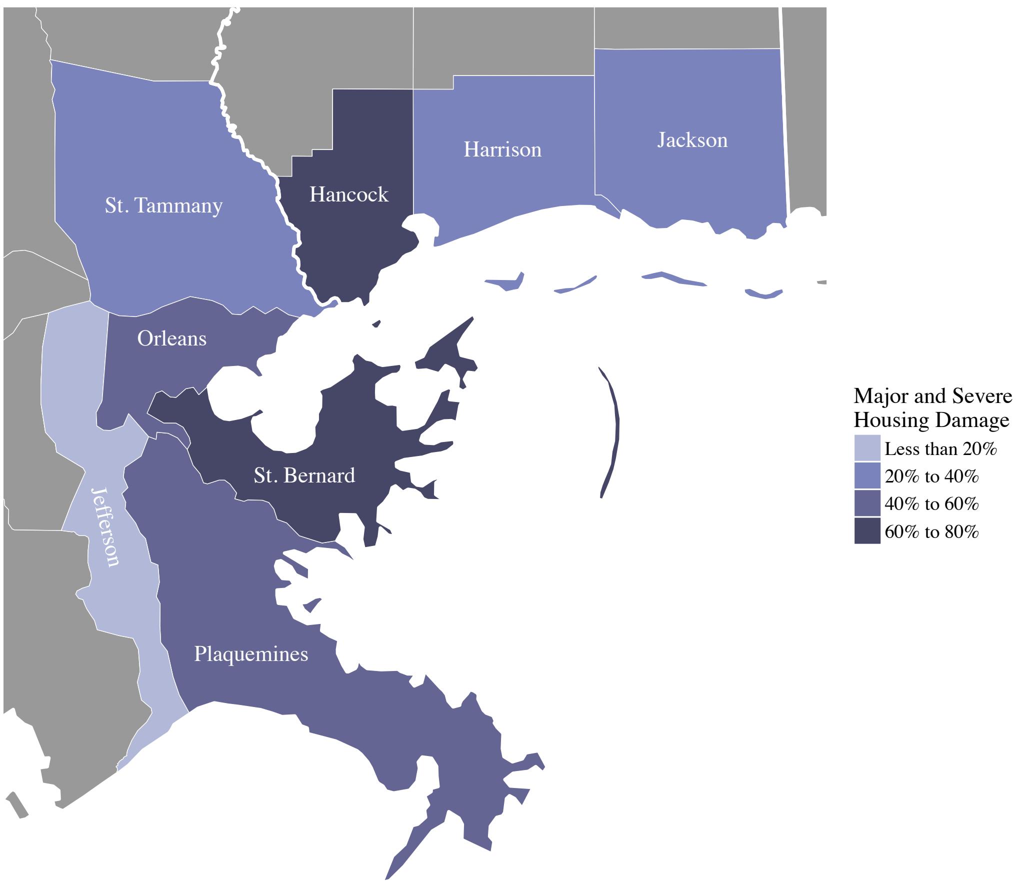

Figure 1.1: Major and severe housing damage across the study area

1.5 Results

Synthetic Control Results

Figures 1.2 and 1.3 plot results from the synthetic control analysis for each county. The black solid lines on each plot corresponds to observed population. These values have been rescaled

Table 1.2: Percent of occupied housing with minor, major and severe damages

	Minor Dam.	Major Dam.	Severe Dam.	Total Dam.
Jefferson, LA	33.8%	16.8%	2.7%	53.3%
Orleans, LA	15.5%	14%	41.9%	71.5%
Plaquemines, LA	22.5%	13.2%	44.3%	80%
St. Bernard, LA	2.2%	23.6%	54.7%	80.6%
St. Tammany, LA	45%	23%	2.4%	70.5%
Hancock, MS	20.2%	42.5%	27.3%	90%
Harrison, MS	33.8%	23.5%	10.6%	68%
Jackson, MS	29.8%	29.9%	4.3%	64%

Table 1.3: Home ownership and insurance rates across the study area

	Total Dam.	Owner Dam.	Hazard and Flood	Hazard Only	No Insurance
Jefferson, LA	53.3%	60.4%	64.1%	25.1%	10.8%
Orleans, LA	71.5%	49.5%	61%	23.3%	15.7%
Plaquemines, LA	80%	70.6%	37.3%	19.8%	42.8%
St. Bernard, LA	80.6%	69.3%	64.6%	21.8%	13.6%
St. Tammany, LA	70.5%	81%	39.3%	47.1%	13.6%
Hancock, MS	90%	72.5%	24.2%	52.6%	23.1%
Harrison, MS	68%	56.9%	14.7%	65.5%	19.8%
Jackson, MS	64%	70.9%	15.4%	66.4%	18.2%

such that they reflect *total population*, rather than a normalized series.[5] The purple dashed line corresponds to each county's synthetic control. These synthetic controls represent a weighted average of observed population data from the control counties in the donor pool. Tables A.1 and A.2 list the matched control counties for each treated area and the associated weights resulting from Eq 1.2. The dotted vertical line separates the pre- and post-Katrina periods. In the pre-Katrina period, the purple dashed line approximates observed population, indicating strong pre-period matches. To evaluate the strength of each match, I calculate the mean absolute error for each county. The average error across all eight counties was approximately 566 people, or roughly 0.49%. This implies that the synthetic control estimate during the pre-period was on average off by

[5]This normalization is done during the matching procedure described above. Values are rescaled to aid in the interpretability of results.

half a percentage. Jefferson Parish had the highest error, with a mean-percent difference of 1.5%. The lowest pre-period error was St. Tammany correspond with an error of 0.15%.

In the post-Katrina period, the divergence of the two series represents the estimated population effect of the disaster. Table 1.4 presents these estimated effects, depicting observed population, synthetic population, the difference, and percent difference (relative to synthetic) for each of the eight areas. These values have been averaged over the post-Katrina period. Estimated population losses range from 4,000 in Jackson Mississippi, to 153,000 in Orleans Parish. The most impacted area in the study was St. Bernard, which saw a 46% reduction in population. St. Tammany and Jackson saw the least amount of out-migration, at 4% and 3% respectively. The four Louisiana Parishes on average had higher levels of out-migration, losing 18% of their total population, relative to the three Mississippi Counties, which lost 7%.

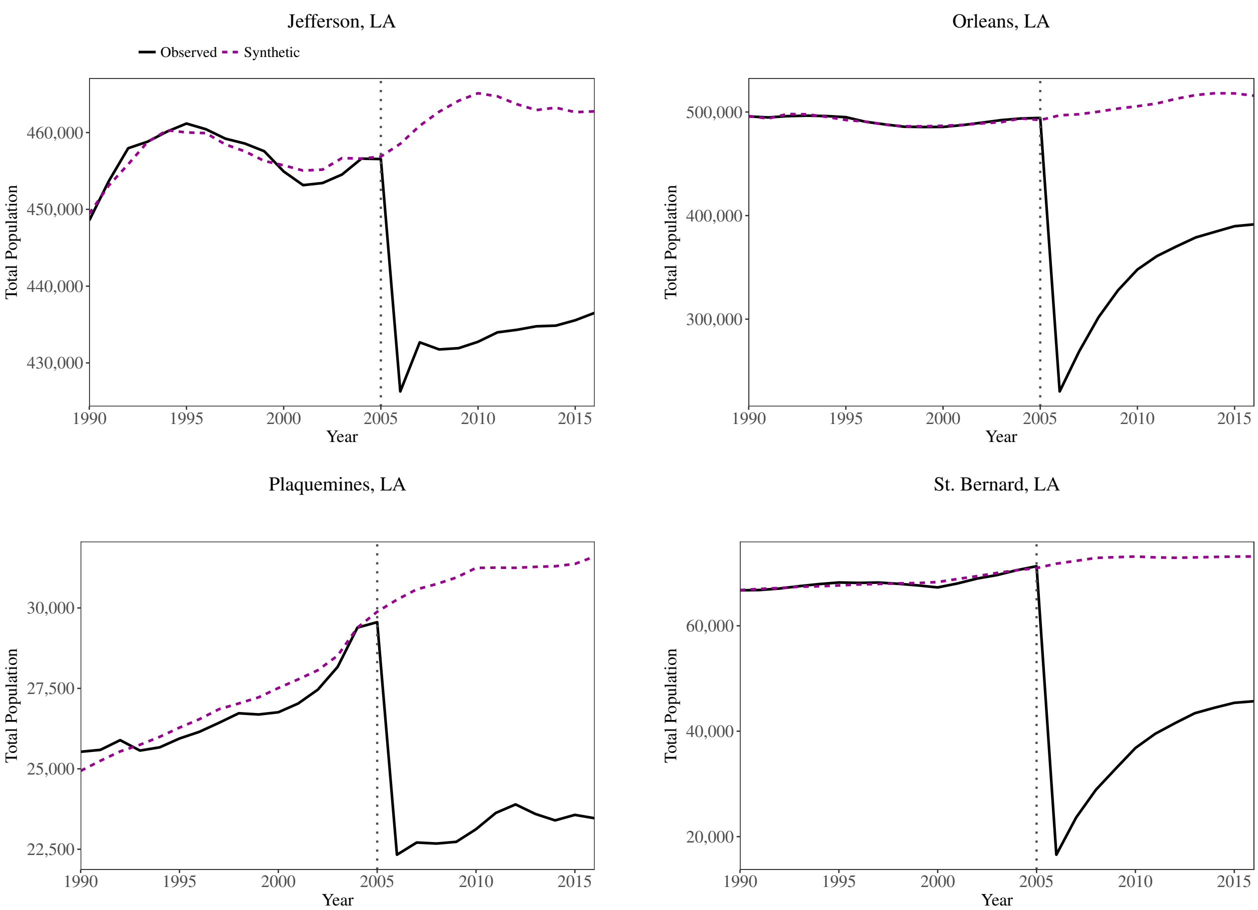

Figure 1.2: Synthetic control results for Jefferson, Orleans, Plaquemines, and St. Bernard Parish

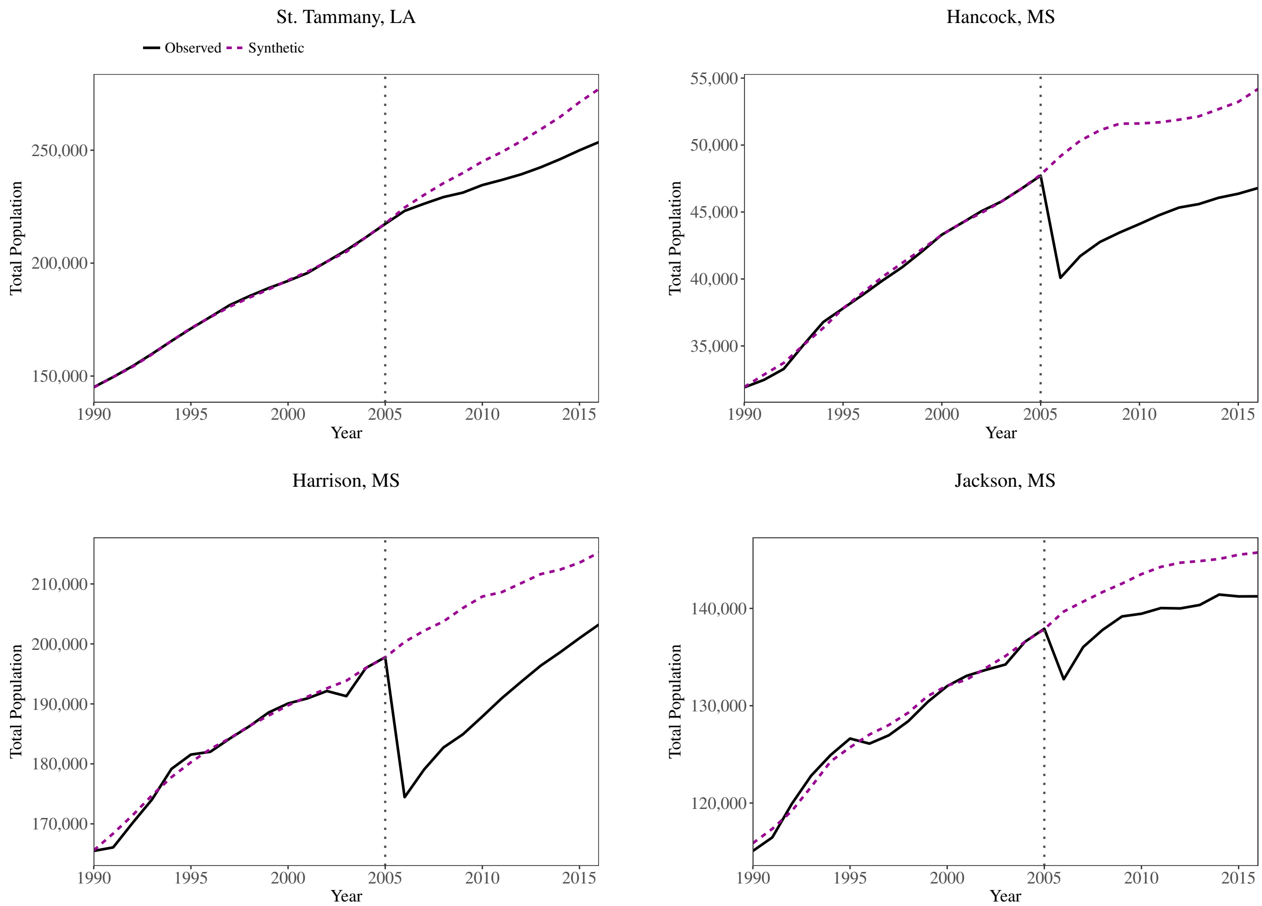

Figure 1.3: Synthetic control results for St. Tammany Parish, Hancock, Harrison, and Jackson County

Table 1.4: Results from the synthetic control analysis

Parish/County	Observed	Synthetic	Difference	Difference (%)
Jefferson, LA	435,163	462,358	-27195	-6%
Orleans, LA	353,851	507,126	-153,275	-30%
Plaquemines, LA	23,722	30,975	-7,252	-23%
St. Bernard, LA	39,167	72,690	-33,523	-46%
St. Tammany, LA	235,833	247,346	-11,512	-4%
Hancock, MS	44,562	51,450	-6,887	-13%
Harrison, MS	190,886	207,455	-16,568	-8%
Jackson, MS	138,946	143,013	-4,066	-3%

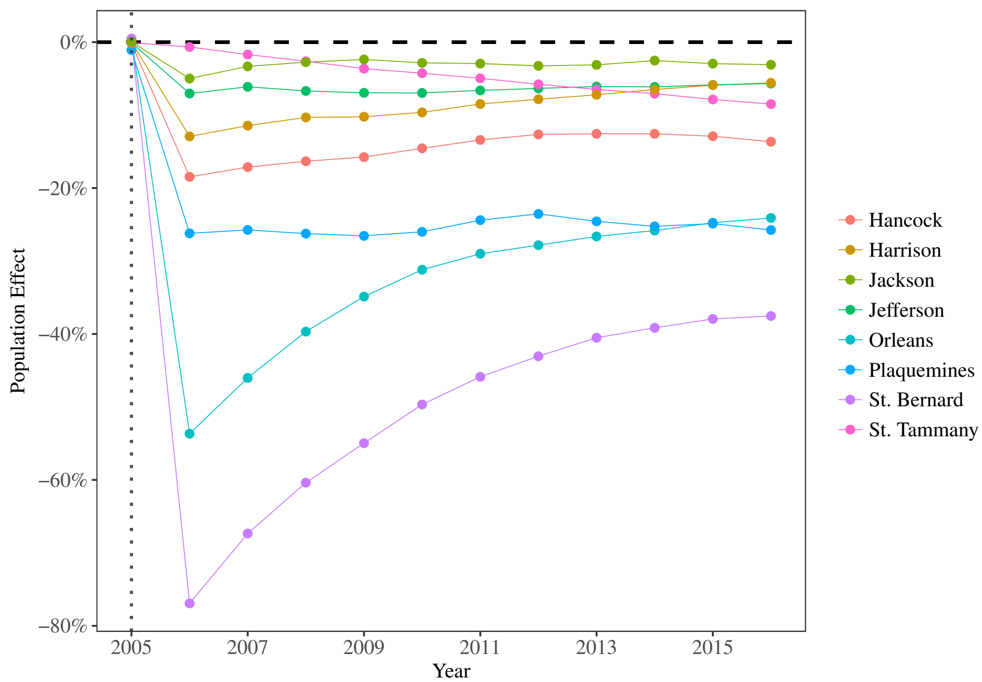

Figure 1.4: Estimated population effects over time

Figure 1.4 illustrates the dynamics of these estimated effects. The y-axis reflects the percent differences between observed and synthetic population. The figure highlights the variation in disaster experiences across the eight counties. Although there are differences in terms of magnitude and dynamics, in all eight cases there remains a gap between observed and synthetic population. This gap does not appear to be closing, suggesting that Hurricane Katrina had a permanent impact on the population trajectories of each of these counties. To test the statistically significance of these estimates, and further investigate the permanence of estimated effects, I employ a placebo analysis described below.

Placebo Analysis

The synthetic control method typically utilizes a group of "placebos" to measure the statistical significance of results (Abadie et al., 2010). This entails repeating the synthetic control procedure for a group of non-treated areas, typically the areas that constitute the donor pool. The process of repeating the synthetic control procedure for each control county results in a distribution of

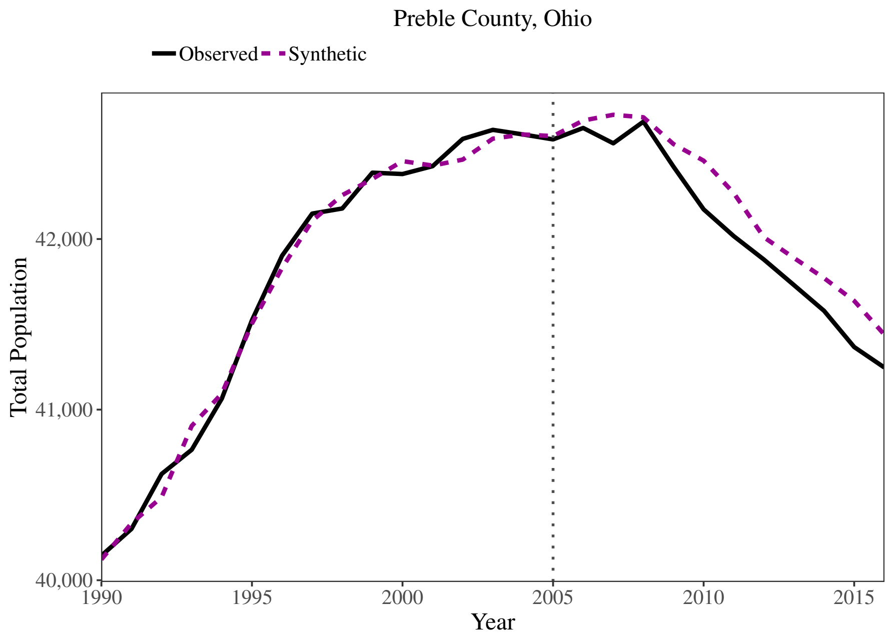

Figure 1.5: Placebo example for Preble County, Ohio

estimated effects that can then be compared relative to the treated areas. Following the synthetic control method literature, I repeat the same procedure for ever county listed in Tables A.1 and A.2, done with the same predictor variables and donor pool restrictions as outlined above. This process results in a distribution of 30 placebo effects for each treated area.

Figure 1.5 depicts an exemplary case of this process. The figure plots observed and synthetic population for Preble County, Ohio, one of the included counties in St Bernard's donor pool. Given that Preble County was not impacted by Katrina, its corresponding synthetic control should approximately match observed population in both the pre- and post-periods. We see that the synthetic control tracks the population decline during 2006-2016. Because Preble County was not damaged by Katrina, this difference reflects error with the method. In the example this error is minimal; however, not all placebo cases have such strong post-period matches. This could be the result of poor pre-period matches or could be driven by unaccounted for exogenous forces unique to the county.

To get a sense of the statistical significance of results across the eight damaged counties above, I repeat the above procedure for all 240 counties in the donor pool. This results in a distribution of

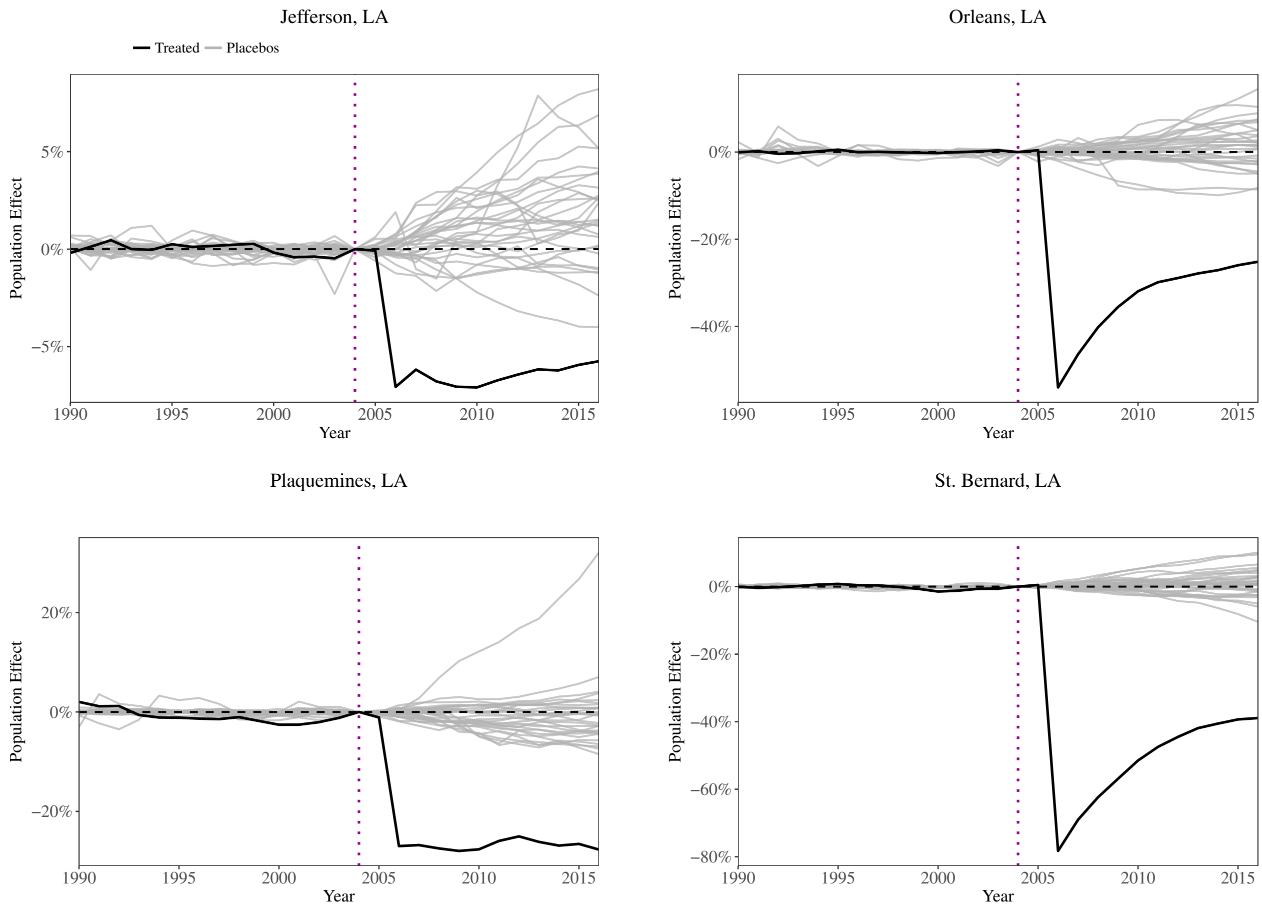

Figure 1.6: Placebo analysis for Jefferson, Orleans, Plaquemines, and St. Bernard Parish

non-treated effects, which can be compared to estimated effects across the eight treated counties. Figures 1.6 and 1.7 plots these distributions for each parish. The black lines represent the difference between observed population in each treated county relative to its synthetic control. The light gray lines correspond to this same difference for each of the thirty placebo counties in that area's donor pool. To construct something akin to a p-value, I count the number of cases in which the absolute estimated effect for the placebo counties was greater than the effect associated with each treated area. I then divide this count by the total number of placebos. For example, in 2013 three placebo counties had larger absolute differences relative to Jefferson Parish; three divided by thirty (the number of counties in the donor pool) results in a value of 0.1 or 10%. This represents the probability of committing a type one error. Table 1.5 presents estimated effects for each treated county and assigns statistical significance to each year based on this calculation.

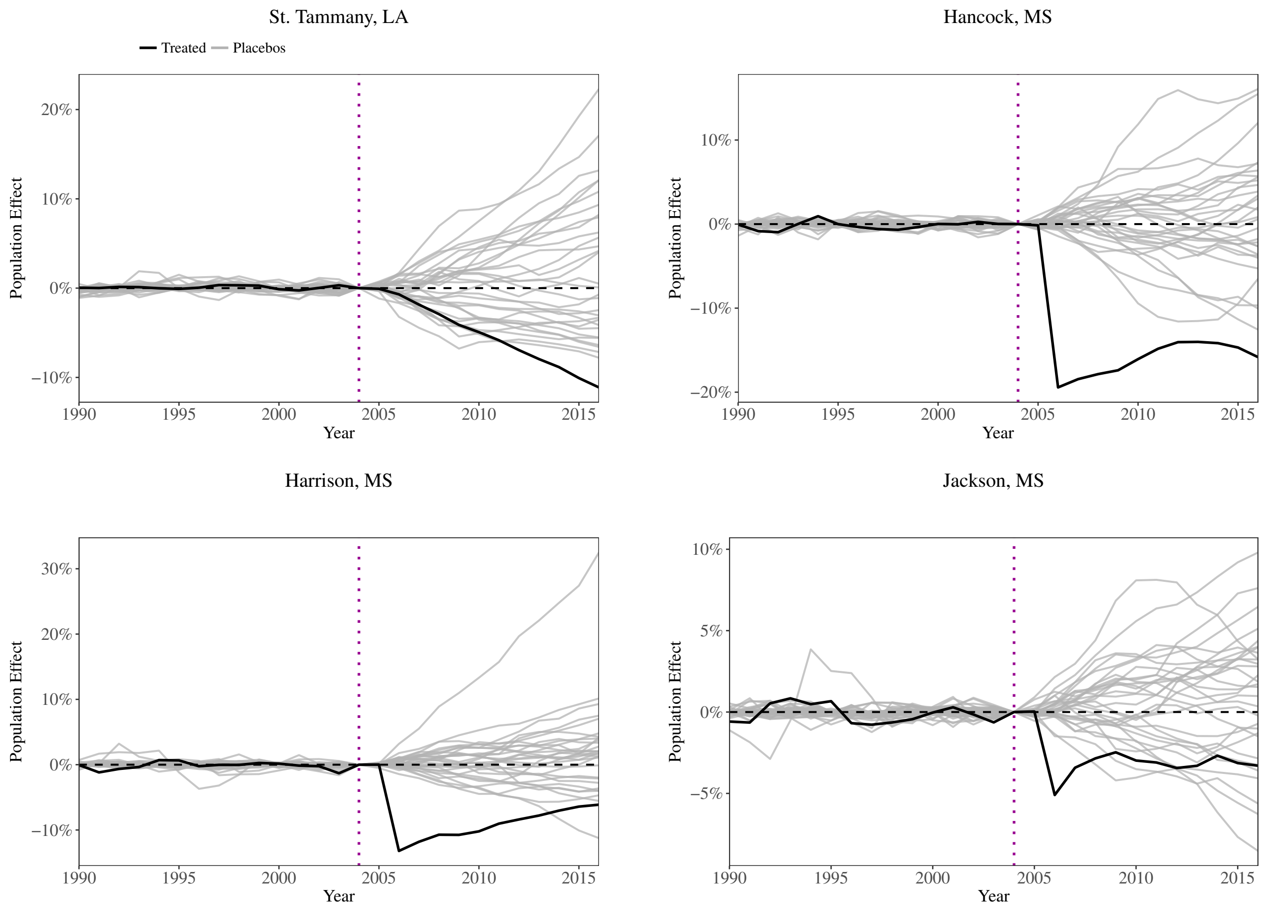

Figure 1.7: Placebo analysis for St. Tammany Parish, and Hancock, Harrison, and Jackson County

Table 1.5: Statistical significance of estimated effects

Year	Jefferson, LA	Orleans, LA	Plaquemines, LA	St. Bernard, LA	St. Tammany, LA	Hancock, MS	Harrison, MS	Jackson, MS
2006	-32,256***	-266,618***	-7,929***	-55,223***	-1,478	-9,078***	-25,882***	-6,960***
2007	-28,203***	-229,092***	-7,870***	-48,705***	-3,903	-8,619***	-23,137***	-4,670***
2008	-30,959***	-198,514***	-8,067***	-44,005***	-6,159	-8,340***	-21,014***	-3,888
2009	-32,222***	-175,502***	-8,216***	-40,136***	-8,708	-8,126***	-21,061**	-3,377
2010	-32,370***	-157,708***	-8,122***	-36,327***	-10,427	-7,507***	-20,004**	-4,069
2011	-30,736***	-147,427***	-7,625***	-33,474***	-12,345	-6,930**	-17,689**	-4,233
2012	-29,383***	-142,691***	-7,355***	-31,388***	-14,677*	-6,562**	-16,435**	-4,697
2013	-28,160*	-137,502***	-7,681***	-29,561***	-16,794*	-6,548**	-15,267**	-4,510
2014	-28,389*	-133,794***	-7,900***	-28,612***	-18,697*	-6,618**	-13,788	-3,660
2015	-27,105*	-128,219***	-7,802**	-27,745***	-21,297	-6,861**	-12,579	-4,282
2016	-26,239*	-124,271***	-8,136**	-27,457***	-23,508	-7,395**	-12,003	-4,501

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

In general, most of the eight counties sit outside the distribution of placebos throughout the entire post-Katrina series. Jefferson, Orleans, Plaquemines, St. Bernard and Hancock are all statistically significant for the entirety of their series. The estimated effects in Harrison county are only significant until 2013. Jackson was only significant in the first two years following the disaster. St. Tammany is insignificant until 2011, and then becomes significant (at the 10% level) from 2012-2014.

Variation in Recovery

Results from the synthetic control analysis suggest different experiences. Although all eight counties were highly damaged by Hurricane Katrina, some experienced large-scale out-migration, where others experienced *relatively* minimal losses. For example, Orleans and St. Bernard lost 30% and 46% of their population. In contrast, Jefferson, St. Tammany, and Jackson experienced average losses of 6%, 4%, and 3%. This next section explores how estimated population effects correlate with different damage categories, insurance rates, and other county characteristics.

First, I look at the correlation between each damage category and estimated population effects over time. Figure 1.8 plots the relationship between the population effect on the y-axis relative to each damage category: minor, major, and severe. Intuitively, we expect to see a negative relationship between damages and out-migration. This is evident in the severe damage graphic, which depicts a strong negative correlation, and an associated correlation coefficient of -0.887.

Both minor and major damage categories are positively correlated with the estimated population effect. Because in all eight counties a majority of occupied housing was damaged, areas with higher minor damages tend to have lower severe damages. The same is true with respect to major damages, though to a lesser extent.[6] In general, Figure 1.8 suggests that out-migration after the disaster was primarily driven by differences in severe damages. Minor and major damages appear less impactful.

Though there is strong relationship between severe damage and out-migration, much of the disaster literature emphasizes pre-existing conditions as influencing post-disaster outcomes. Prior research notes that lower-income and minority households tend to be disadvantaged throughout the disaster process (Fothergill and Peek, 2004). Additionally, the purpose of hazard and flood insurance is to protect individuals against the unexpected costs of a disaster, facilitating recovery. Table

[6] The correlation coefficient between minor and severe damages is -0.89 and major and severe is -0.2.

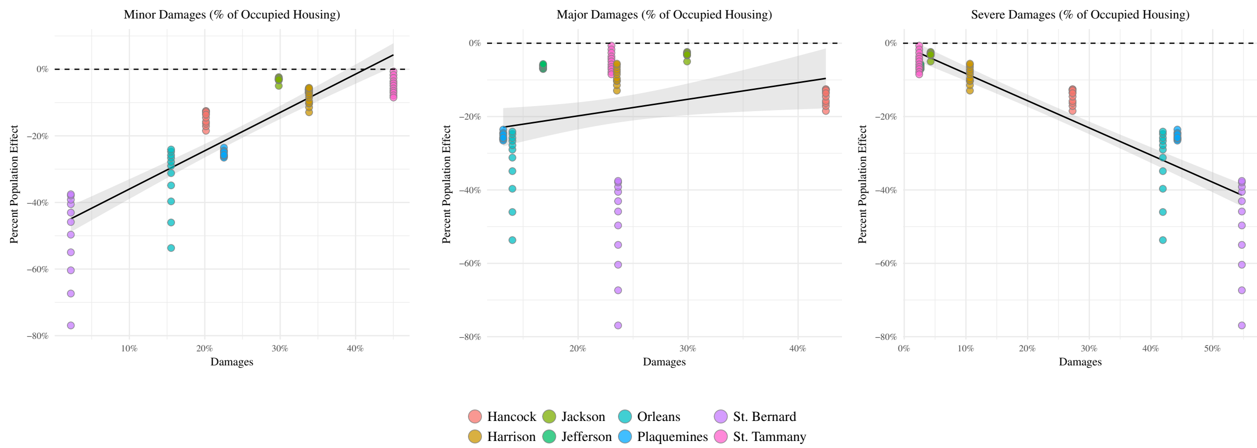

Figure 1.8: Relationship between estimated population effects and minor, major, and severe damage

1.6 shows the correlation between the estimated population effect and damages, insurance rates, and a series of covariates. The table depicts both the population effect in 2006 and an average over the post-period. Correlation coefficients largely correspond with intuition. Pre-period population growth tends to be associate with less out-migration (i.e. a positive population effect). Areas with lower median home values, higher poverty rates, and higher non-white population also tended to have more out-migration, supporting findings described in Fothergill and Peek (2004). Interestingly, insurance rates appear to have little impact on observed differences. The "No Insurance" variable, which represents the percent of households that did not have hazard or flood insurance, is near zero. Though "Hazard Only" and "Hazard and Flood" variables are correlated with both variables list in Table 1.6, Hazard and Flood is negatively correlated, and Hazard Only is positively correlated. The magnitude of these effects are almost perfectly off-setting. Given the signs on each variable, it is likely that areas with higher flood insurance experienced more severe damages, and vice versa. Thus, the correlations are likely just a reflection of differences in sustained damages across the counties. Areas with higher flood insurance rates likely experienced more flooding. Importantly, values in Table 1.6 are correlations, rather than depicting a causal relationship. Many of the variables listed in the table are correlated with one another, making interpretations somewhat confounded. However, the table supports previous studies with respect to pre-period growth and socioeconomic variables. Additionally, the table again suggests that severe damages stands out as being a key driver in observed differences, and also suggests insurance rates seem to have little impact on out-migration decisions across these eight areas.

Table 1.6: Table of correlation coefficients

Predictors	Pop. Effect 2006	Avg. Pop. Effect
Minor Dam.	0.92	0.91
Major Dam.	0.22	0.26
Severe Dam.	-0.9	-0.94
Owner Dam.	0.31	0.21
Hazard and Flood	-0.6	-0.6
Hazard Only	0.61	0.68
No Insurance	0.05	-0.09
Poverty Rate	-0.45	-0.38
Med. Home Val.	0.42	0.3
Non-White	-0.25	-0.19
Pop. Growth	0.51	0.46

As a final exercise in decomposing observed differences, I normalize estimated population effects by severe damages for each post-Katrina year. Results are depicted in Figure 1.9. The figure highlights that once differences in damage severity are accounted for, most counties responded remarkably similar to the disaster. Differences remain in the initial drop across the eight areas. In 2006, St. Tammany was only minorly impacted. Plaquemines and Hancock were less impacted relative to Harrison, Jackson, Orleans and St. Bernard. However, the dynamics across these areas and their ending values in 2016 are remarkably similar once severe damages is accounted for. Jefferson and St. Tammany stand out as two significant outliers, both in terms of post-Katrina dynamics and final ending points in 2016. Though both counties had relatively small levels of severe damages and out-migration, the ratio suggests that the extent of out-migration was higher than expected. One plausible explanation for why Jefferson and St. Tammany are dissimilar relative to the other six counties could be a product of their relationship with Orleans. The Longitudinal Employer-Household Dynamics data provides data on county commuting patterns. Using values from 2004, Jefferson had 58,000 commuters who lived in Jefferson, but worked in Orleans. St. Tammany had

16,000 commuters living in St. Tammany and working in Orleans. This represents 13% and 8% of their total population respectively. If we compare these commuting values relative to each county's total labor force, this represents 25% in Jefferson, and 18% in St. Tammany.[7] Though both Jefferson and St. Tammany experienced relatively minimal counts of severe damages, the fact that they are strongly geographically connect to Orleans likely resulted in negative spillover effects. Given high job loss in Orleans, out-migration is Jefferson and St. Tammany could have been driven by these losses, rather than direct damages.

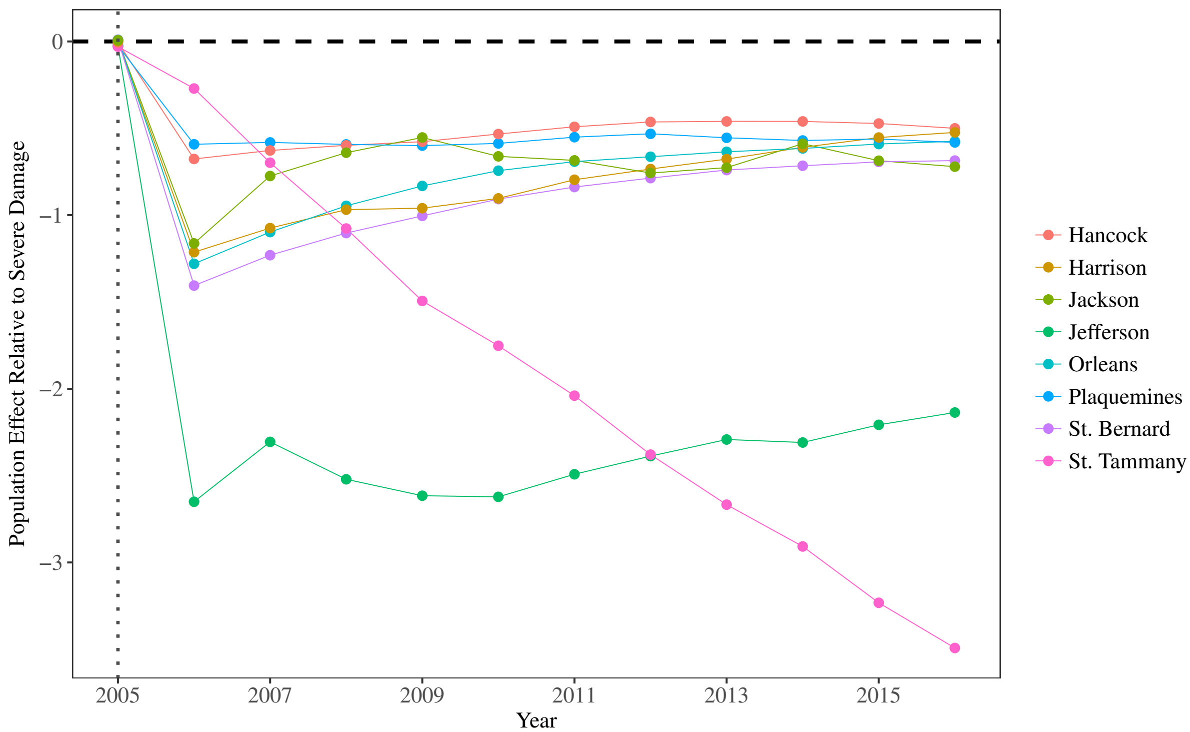

Figure 1.9: Population effects over time normalized by severe damages

1.6 Conclusions

Understanding the forces that govern disaster recovery requires a framework for consistently defining what recovery means, both within and across disaster events. Traditionally, disaster re-

[7]Total labor force estimates are from the 2000 Decennial Census.

covery is defined as the time it takes to return to pre-disaster conditions. Such a definition does not account for confounding forces. Instead, it is necessary to compare observed outcomes to where these outcomes would have been had the disaster not occurred. This requires the construction of a counterfactual.

This chapter applied the synthetic control method to the case study of Hurricane Katrina and constructed "synthetic" population estimates for eight highly damaged counties. These synthetic controls provided estimates of how each county would have evolved had the disaster not occurred. The construction of each series is based on a weighted average of population levels in unaffected similar counties. Results illustrated different experiences across the eight areas, both in terms of the magnitude of the estimated population effects, as well as population recovery in each area.

The remainder of the chapter attempted to unpack these differences. It examined the correlation between damages, insurance rates, and a series of covariates. These correlations were largely consistent with previous disaster studies, in which pre-period dynamics and socioeconomic factors were correlated with population effects. Notably, however, is how much of observed differences were driven by severe damages. Minor and major damage had little impact on out-migration.

Storr et al. (2016) and others have argued that one notable feature of disaster recovery is the necessary coordination across actors. The decision to return and rebuild your home is linked to the decisions of other households, businesses, and the local government. Additionally, the ability to begin repairs often requires public utilities to be restored and supplies from surrounding businesses. At the same time, store owners are making decisions about re-opening based on their expectations of household recovery. Likewise, there is evidence that governments also make decisions based on their expectations of future neighborhood redevelopment (Storr et al., 2016). The results from this chapter support the notion that damages have a non-linear effect in terms of out-migration. It is plausible that this non-linearity is due to coordination across actors becoming increasingly challenging in the presence of severe damages. A larger initial evacuation generates tremendous uncertainty with respect to if and when an area will recovery. The next chapter further explores this notion, and quantifies the Storr et al. (2016) hypothesis that entrepreneurship provides an important signal to households and other actors that disaster recovery is underway.

Chapter 2

Entrepreneurship and Disaster Recovery

2.1 Introduction

Research on the economics of disasters has seen a surge in interest in recent years. This is likely in reaction to a series of high-profile events, such as the 2004 Indian Ocean Tsunami, the 2005 Atlantic hurricane season, and the 2010 Haitian Earthquake (Cavallo et al., 2011). In the United States, recent hurricanes such as Harvey, Irma, and Maria have continued to draw attention to the economic consequences associated with large-scale natural disasters. These consequences are likely to continue moving forward. Both global climate change and the shifting of people and economic activity towards coastal areas increases the likelihood of major climatic disasters occurring in the future (Nordhaus, 2010). Understanding the economic burdens that result from a natural disaster, and the factors which attenuate or exacerbate these burdens is thus relevant for informing disaster mitigation and better preparing for future events.

The previous chapter employed the synthetic control method to identify the long-run population effects of Hurricanes Katrina across the eight most damaged counties and parishes in the area. The chapter showed that differences in out-migration and population recovery were strongly correlated with the severity of sustained damages. Community recovery following a disaster involves a tremendous amount of coordination from different actors in an economy. For example, the decision to return and rebuild your home is dependent on whether your neighbors plan to rebuild, if and when the government restores utilities and infrastructure, and whether surrounding businesses return. Governments and business are simultaneously making decisions based on their observations and expectations of which areas will likely recovery. This process is often characterized as a collective action problem, in which the degree of necessary coordination increases with the extent of out-migration and thus the severity of damages. Chamlee-Wright and Storr (2009b) and Storr et al. (2016) argue that an important first mover in the disaster recovery process is the entrepreneur. The re-establishment of local businesses acts as a beacon, signaling to other economic actors that a community will return. This hypothesis suggests that communities engaged in higher entrepreneurial activity are better poised to absorb the negative impacts of the event and will recovery faster compared to similarly damaged areas.

The purpose of this chapter is to quantify and test the role of entrepreneurship in accelerating disaster recovery. To do so, I expand the synthetic control methodology developed in the previous chapter to all counties damaged by Hurricanes Katrina and Rita. Using estimated population effects as a dependent variable, I quantify entrepreneurial activity and test its significance in attenuating the negative consequences of the hurricanes. Results show a strong negative correlation between out-migration and entrepreneurial activity, both when examining the extent of the initial shock, as well as a community's ability to recover. Results also show that the degree to which a county's sectors are export-oriented versus locally-oriented aids in the absorption of the initial shock of the disaster. Additionally areas with less renters also appear more resilient to out-migration immediately following an event.

The remainder of the paper is organized as follows. Section 2.2 describes a theoretic framework depicting the role of entrepreneurship in facilitating disaster recovery. Section 2.3 describes the data used in the empirical analysis, including a summary of the results obtained from the synthetic control method. Section 2.4 presents regression results, and section 2.5 concludes.

2.2 The First Mover Problem and Entrepreneurship

Storr et al. (2016) note that the decision to return and rebuild following a catastrophic disaster is costly, and the benefits of returning are "necessarily" uncertain. Following Hurricane Katrina, the city of New Orleans saw significant damages, entire neighborhoods were destroyed, and over 80% of the city was flooded. The decision to return and rebuild is based on a personal calculus, where one compares the benefits of returning to the costs. Though the costs may be known,[8] the benefits are highly uncertain. An individual may or may not know if they still have a job, if friends and neighbors also plan to return, or if their favorite local businesses will recover. Groen

[8] or at least loosely estimated

and Polivka (2010), in exploring the determinants of return migration following Hurricane Katrina, emphasize "location-specific capital" as a key determinant of migration choices. This encompasses amenities, public and private services, sense of place, and social networks. The authors argue that these characteristics "tie an individual to a place." The perceived benefits of returning home include these non-pecuniary motivations. Catastrophic disasters, however, create a high degree of uncertainty with respect to how these location specific characteristics have changed, and if they will return to their pre-disaster states.

Disaster recovery requires significant coordination between actors. For example, to repair your home you need a supply store to be open, electricity and other utilities to be back on, and likely help from various professionals/experts. For a supply store to be open the store owner has to have an expectation that there will be enough people returning who will demand his/her products. The store owner may also be waiting for the return of public utilities before opening. Simultaneously, local governments are financial constrained. The government has limited resources that need to be dispersed across a highly damaged landscape. When making decisions regarding public goods, the government is trying to do so based on their own expectations of which neighborhoods will recovery. Chamlee-Wright and Storr (2010), utilizing qualitative data gathered post-Katrina, document different individuals beliefs about the government's "intent" and "capacity." In the Ninth Ward neighborhood, households tended to view the government's "capacity" optimistically - in the sense that they believed the government had the ability to aid in disaster related assistance, however, were pessimistic of the government's "intent"- believing that government assistance would not be provided in a way that benefited them. Given the degree of uncertainty described above, opinions and expectations regarding how the government will respond post-disaster implicate decisions made by households and businesses, regardless if these expectations are correct.

Storr et al. (2016) outline a simple model that encapsulates some of the core issues described above. The authors describe a two player single shot game, in which both players make a decision to either stay in their displaced area, or return home. The key feature of their model is that both players operate under imperfect information and that communication between players is difficult.

The model provides structure to the key components of the decision to return, noting that the benefits of returning depend on the decision of the other player. Thus, the outcome of the model is largely dependent on the "perceived probability" that one assigns to the chances the other player will return. The authors go on to argue that entrepreneurs play a "crucial role" in signaling that a community will rebound. Supporting this notion, Chamlee-Wright and Storr (2009b) examine the role of "social entrepreneurship" in post-Katrina recovery. They state that one of the key roles of the social entrepreneur is to help solve collective action problems associated with "returning and rebuilding communities." They support this claim with narratives of interviewees who were asked about their "interactions with social entrepreneurs" and the "role that social entrepreneurs played in their recovery efforts."

The notion that the successes and failures of entrepreneurs provide important signals to other economic actors is not specific to natural disasters, and has been described in various applications in the economics literature (Bunten et al., 2015; Conroy et al., 2017; Weiler, 2000). For example, Weiler (2000) examines the "private strategies" of entrepreneurs in investing in decaying urban areas. The paper describes a two player no-cooperative game, in which players make decisions about entering a depressed area, with some probability p attached to the success of their venture. Different from the "returning home" model described in Storr et al. (2016) and Chamlee-Wright and Storr (2009a), this game operates in two stages, in which the first player makes an "entry" decision, and the second player is able to view the outcome of this decision. The model highlights that there are private incentives motivating entrepreneurs to invest in depressed areas. As noted in Storr et al. (2016), large disasters create various needs that the market is not able to meet. Entrepreneurs are nimble enough to recognize these profit opportunities and react. Unlike the scenarios described above, in which no one has the incentive to be a first-mover, this representation of market entry depicts monopoly profits driving the entrepreneur. "Thin markets," in which goods and services are limited in a post-disaster environment, provide the opportunities for entrepreneurs to enter the space. Second, the model suggests that first-movers reveal information about the viability of the area. This information is an important spillover benefit associated with entrepreneurship.

Bunten et al. (2015) formalize this notion and embed entrepreneurship into an endogenous growth model. Entrepreneurship has long been recognized as a driver of economic growth (Bunten et al., 2015; Conroy et al., 2017; Low et al., 2005; Mueller, 2007; Stephens and Partridge, 2011). This has been shown both in urban environments (Glaeser and Gyourko, 2005) and rural/depressed areas (Stephens and Partridge, 2011). Bunten et al. (2015), note that not only is there a direct benefit of entrepreneurship, in which new firms increase employment and economic activity, but makes explicit the indirect benefits associated with the information revealed by the successes and failures of entrepreneurial pursuits. Their results show that "highly dynamic economies," in which there is a high level of entrepreneurial churn, see faster employment growth because of the information revealed.

Expanding on the work by Chamlee-Wright and Storr (2009b) and Storr et al. (2016), this chapter investigates the role of entrepreneurship in signaling to households that disaster recovery is underway. Specifically, it quantifies entrepreneurial activity and tests whether it has an attenuating effect on the negative consequences of damages. In doing so, the paper takes a narrower perspective on what an entrepreneur *is* relative to Chamlee-Wright and Storr (2009b) and Storr et al. (2016). Due to data limitations, the chapter focuses specifically on commercial entrepreneurial activities. The final chapter explores the impacts of a large scale disaster on social capital, and touches on concepts embedded in the "social entrepreneur" described in Chamlee-Wright and Storr (2009b).

2.3 Data Description

To quantify the effects of entrepreneurship in attenuating the consequences of a disaster, I expand the synthetic control framework described in the previous chapter to all counties damaged by Hurricane Katrina and Rita. I then combine these results with county-level data on housing damages, establishment births, and a series of county-level controls. The below sections describes the process for constructing each of these variables and their respective sources.

Population Effect

The previous chapter defined the population effect of a disaster as the difference between observed population and what population would have been had the disaster not taken place. This required constructing a counterfactual series for each treated area of interest. To do so, I utilized the synthetic control method described originally in Abadie and Gardeazabal (2003) and Abadie et al. (2010). This chapter expands that framework to all counties damaged by Hurricanes Katrina and Rita, resulting in a set of identified annual population effects, covering 11 years and 122 counties. This includes counties from Texas, Louisiana, Mississippi, and Alabama.

The construction of each synthetic control is done using an identical data model as described in the previous chapter. Each treated county is matched with thirty potential control counties based on a series of covariates defined in Table 1.1. These control counties are given weights such that the difference between observed population and the weighted average of the set of controls is minimized. Weights are then applied to the post-disaster period to estimate a counterfactual time series.

Figures 2.1 and 2.2 summarize estimated population effects and compares these effects to incurred damages. Figure 2.1 depicts two maps. The top shows total housing damage across impacted counties.[9] Darker shades of purple indicate areas with a higher percentage of damage. These areas largely correspond with the paths of each hurricane, with Hurricane Rita striking near the Texas/Louisiana border, and Katrina near the Louisiana/Mississippi border. The second map depicts the percent difference between observed and synthetic population averaged over the post-period. Positive and negative values suggests in-migration and out-migration attributable to the hurricanes. The map highlights that many counties experienced minimal changes in population, with a small-subset experiencing significant out-migration. These areas (depicted in dark blue) tend to correspond to the same counties that incurred higher levels of damages. The lightest blue shade in the second map corresponds to areas that had a greater than 2% increase in population attributable to the hurricanes. Table 2.1 summarizes the distribution of population effects, both in

[9]Housing damages are defined as the percent of occupied homes that reported damages to FEMA

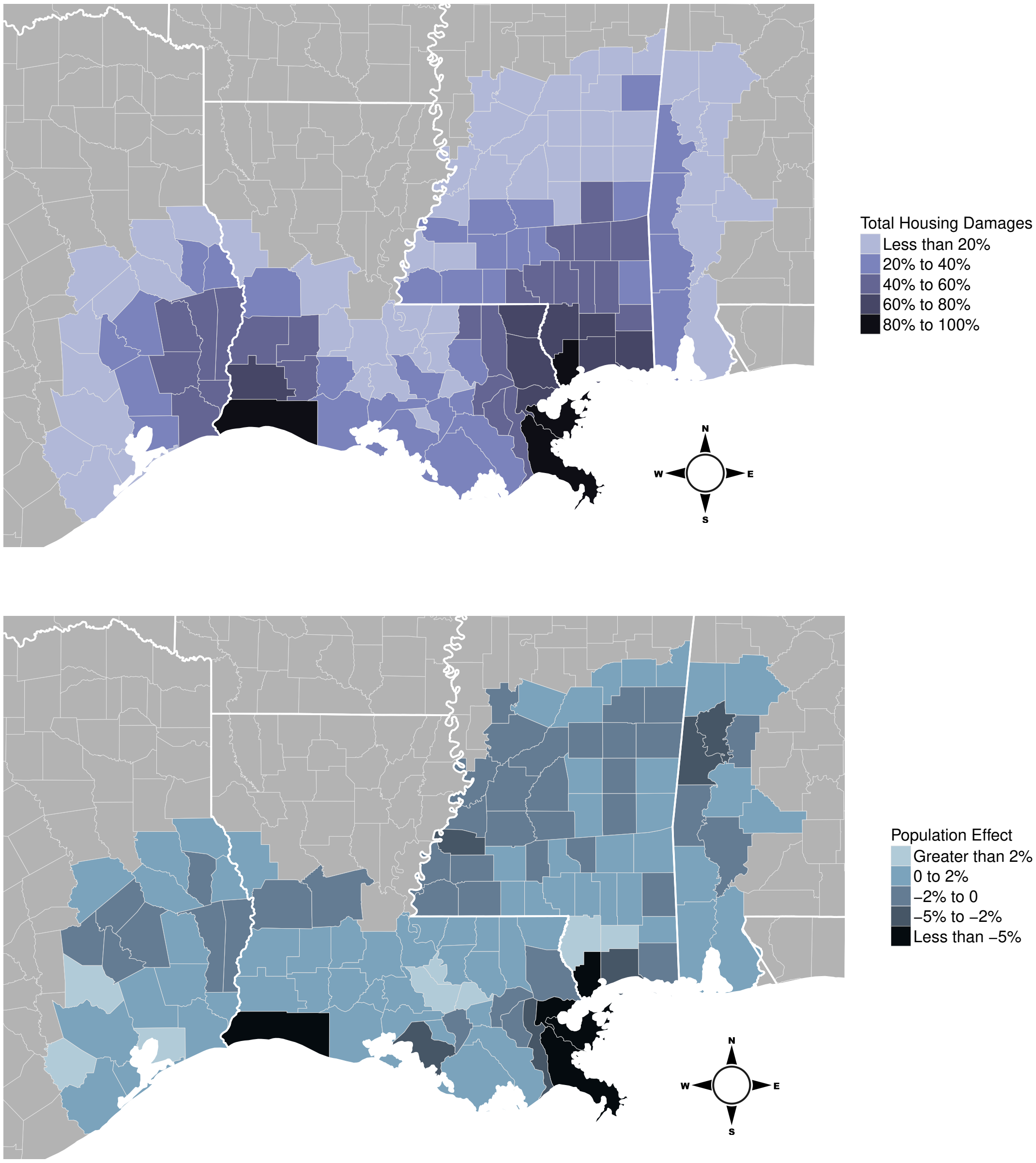

Figure 2.1: Total housing damages and population effects across the gulf

level and percentage terms. The table depicts averages over the post-disaster period. The largest out-migration occurred in Orleans Parish (the city of New Orleans), with an estimated population loss equaling 266,618. Harris County (the city of Houston) saw the largest influx of people, gaining an average of 51,831 people due to the hurricanes.

Figure 2.2 shows a scatter plot of the population effect and severe damage. The plot includes points for all 122 counties over the entire post-disaster period. A linear trend line and associated

Table 2.1: Distribution of population effects and damages

Variable	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Avg. Pop. Effect (2006-2016)	-266,618	-146	6	-278	223	121,704
Percent Effect (2006-2016)	-76.8%	-0.4%	0.01%	-0.3%	0.6%	16.9%
Minor Dam.	0.1%	10.4%	20.8%	23.2%	34.3%	59.3%
Major Dam.	0%	0.2%	0.8%	3.3%	3.1%	42.5%
Severe Dam.	0%	0.04%	0.1%	2.2%	0.4%	54.7%
Total Dam.	0.1%	10.7%	24.4%	28.6%	44.8%	90.2%

standard error is also depicted in the figure. The line demonstrates a strong negative relationship between the two variables, in which higher levels of severe damage is associated with higher levels of out-migration. The plot also highlights a bunching of counties near zero, showing that many of the included areas had both minor damage and minimal changes in population.

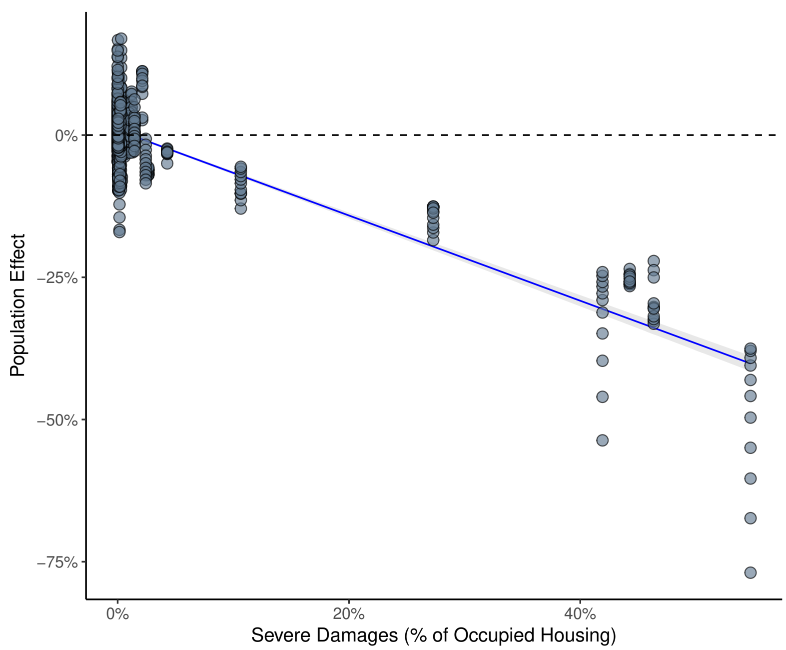

Figure 2.2: Scatter plot depicting severe damage and the population effect

Entrepreneurship

Following previous literature, I use establishment birth rates as a proxy for entrepreneurship (Bunten et al., 2015; Conroy et al., 2017; Low and Weiler, 2012). Data on establishment births are derived from the Statistics of US Businesses (SUSB) Employment Change Tables provided by the US Census Bureau. The data are provided annually at the county scale. Establishment births correspond to the count of newly formed firms over the last year. SUSB covers all establishments with paid employees. Notable exclusions are railroad transportation, non-employer businesses, agricultural production, and most government entities. Data are derived from the Census Bureau's economic census, business surveys, and quarterly and annual Federal tax records. To create a "birth rate" and to control for level differences in establishment counts across counties, I divide the count of new establishments by the total number of establishments in that county for each year. Total establishment numbers are derived from the County Business Patterns (CBP) Tables also provided by the US Census Bureau.

Controls

To control for differences in damages, I utilize data provided by the Federal Emergency Management Agency (FEMA) and the Department of Housing and Urban Development (HUD). This includes information on the number of occupied homes that experienced minor, major, or severe damage. These categories are based on direct housing inspections performed by FEMA after both Hurricanes Katrina and Rita.

To control for other factors relevant in disaster recovery, I include a measure of average population growth, export orientation, median home value, and renter occupancy.

Past disaster studies have noted that pre-disaster trends are often accelerated by a disaster. For example, Vigdor (2008) notes that growing cities tend to recovery quickly following disasters, whereas declining cities often stagnate. Chang (2010) shows that long-term patterns of population across nine constituent city wards in Kobe, Japan were accelerated by the 1995 earthquake. Chang (2010) also notes a similar pattern with respect to trends related to small businesses, in which pre-period declines appeared to accelerate following the earthquake. To control for pre-disaster population trends, I calculate average population growth for each county during the 10 years prior to Katrina and Rita. Population data is provided by the Bureau of Economic Analysis.

A second possible factor relevant in dictating disaster experiences relates to the sectoral composition of a county. Previous empirical research has found differences in sectoral effects resulting from a disaster (Belasen and Polachek, 2009; Chang, 2010; Ewing et al., 2009). There is also a lengthy literature that utilizes input-output models and computable general equilibrium (CGE) models to explore the sectoral effects of large natural disasters (Hallegatte, 2008; Okuyama, 2007; Okuyama et al., 2004; Rose and Liao, 2005; Rose et al., 1997). Chang (2010) suggests that observed sectoral differences could be driven by whether an industry services export or local markets. This is particularly relevant in circumstances in which a disaster induces large out-migration. Given a large exodus of people from an area, sectors that service the local population not only experience damages from the disaster but also a negative demand shock due to this out-migration. Export oriented sectors, though also experience damages, likely see little to no change in demand (given that they service unaffected markets). Thus, it is plausible that the degree of export versus local orientation of an area's industries is related to its general resilience against the negative consequences of damages.

To measure export orientation I apply the location quotient approach outlined in Isserman (1980) and construct a measure of the percent of county employment that is export oriented. Eq. 2.1 presents the specification of a location quotient:

$$LQ_{ir} = \frac{(E_{ir}/E_r)}{(E_{in}/E_n)} \tag{2.1}$$

where subscripts i refers to a particular sector or industry, r to a region of interest, n to the national level (or other reference level), and E to a measure of economic activity, typically represented by the employment level. A location quotient equal to one implies that an area has the same concentration of a particular industry as the nation; Greater than one implies the region has a higher concentration, less than one, a lower concentration. Utilizing Eq. 2.1, export-oriented employment X is defined by Eq. 2.2 below.

$$X_{ir} = \left(1 - \frac{1}{LQ_{ir}}\right) E_{ir} \tag{2.2}$$

Which can be rearranged to:

$$X_{ir} = \left(\frac{E_{ir}}{E_r} - \frac{E_{in}}{E_n}\right) E_{in} \tag{2.3}$$

Isserman (1980) describes E_{ir}/E_{in} as proxying for the share of output of industry i regionally, and E_r/E_n as the share of regional consumption. Thus, the parenthetical term in Eq. 2.3 is an estimate of the difference between the region's share of output and its consumption. If output is greater than consumption, the remainder is a reflection of regional exports. Utilizing Eq. 2.2, I then construct the percent of total employment that is export oriented, shown below.

$$X_r(\%) = \sum_{i=1}^{I} X_{ir}/E_r \tag{2.4}$$

To operationalize this procedure, I use data from the County Business Patterns tables (CBP) produced by Census Bureau. These data provide a detailed accounting of industry employment based on the North American Industry Classification System (NIACS). Location quotients are constructed using four-digit NAICS codes. Any suppressed employment data is estimated using the midpoint of employment ranges attached to establishment counts.

More widely discussed factors relevant to disaster recovery relate to socioeconomics characteristics of the population. Fothergill and Peek (2004) review and synthesize studies on the relationship between poverty and disasters in the US. They find that low-income households are disadvantaged at each stage of a the "disaster process." Preparation, evacuation, and recovery tend to be more challenging for low-income households. Bondonio and Greenbaum (2018) find that counties with lower pre-disaster socioeconomic conditions experience slower economic recovery in terms of employment, number of establishment, and payroll. To control for county socioeconomic differences, I include a measure of median home value from the 2000 Decennial census. Additionally, I include the percent of occupied homes that were rented versus owned. Renter occupancy is strongly correlation with the poverty rate, lower-education attainment, and higher minority populations. Renters are also less financially attached to an area, and thus less likely to return home after evacuating.

2.4 Empirical Framework and Results

The following section explores the relationship between entrepreneurship and disaster recovery. Specifically, I examine the extent that entrepreneurship contributes to both static and dynamic resilience. Bondonio and Greenbaum (2018) defines static resilience as the ability of a community to "absorb" a shock, and dynamic resilience as its ability to quickly recovery from one. Figure 2.4 depicts both notions.

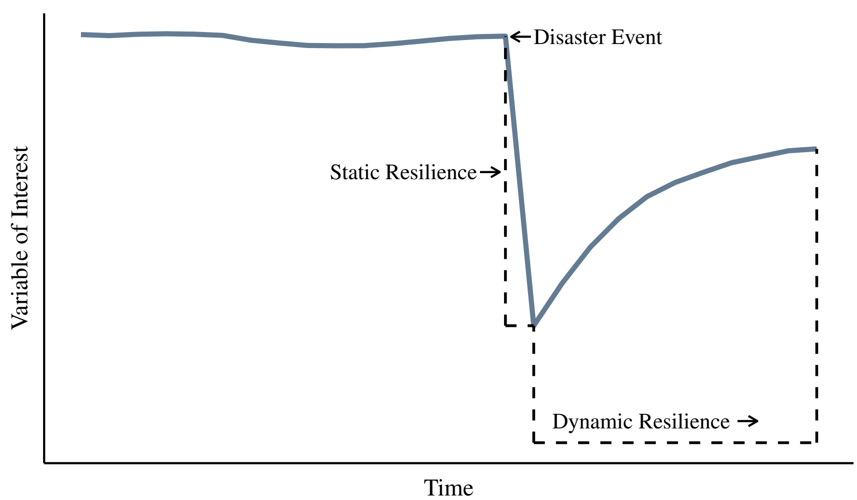

Figure 2.3: Representation of static and dynamic resilience

To examine the role of entrepreneurship and other economic factors in influencing static resilience, I run a series of cross-sectional linear models. Tables 2.2 and 2.3 present results from these regressions. The dependent variable used in these models is the estimated population effect in 2006 - the year following both Hurricanes Katrina and Rita. This estimated effect represents the percent differences between observed and synthetic population. Focusing on the first year following the disaster allows me to test whether pre-disaster characteristics help attenuate the initial consequences of an event. Later regressions will focus on the dynamics of the recovery. Model 5 in Table 2.3 is the main specification of interest. It is a simple interaction model including severe damages and establishment births. The model is described by Eq. 2.5 below. The additional models in Table 2.2 outline the process that ultimately led to the specification of Eq. 2.5. Models 6-9 explore the interaction between damages and other county characteristics.

$$
\begin{aligned}
Perc\ Pop\ Effect_{\,i,\,2006} = \\
& \beta_1 + \beta_2 * Severe\ Dam_i + \beta_3 * \ Birth\ Rate_{i,\,2004} \\
& + \beta_4 * (Birth\ Rate_{i,\,2004} \times Sev._i) + \varepsilon_i \qquad (2.5)
\end{aligned}
$$

The first two models show that severe damages is strongly correlated with out-migration. The models suggests that a 1% increase in severe damage translates into approximately 0.98% more out-migration in 2006. Minor and major damages seem to have little explanatory power in terms of accounting for variation in the dependent variable. Both are positive, statistically insignificant, and near zero in terms of magnitude. Because of which, the models that follow use severe damages exclusively.

Model 3 includes severe damages and the full set of covariates described above. Model 4 adds in additional interactions of each covariate with severe damages. To lessen the extent of multicollinearity, all variables have been centered around their mean value. Covariates are measured during the pre-disaster period. Establishment births and export orientation are based on 2004 values. Median home value and renter occupancy are from the 2000 Decennial Census. Population growth reflects the average growth rate from 1995-2005.

Table 2.2: Cross sectional models.

	(1)	(2)	(3)	(4)
Constant	-0.023^{***}	-0.013^{***}	-0.008	-0.009^{***}
	(0.006)	(0.004)	(0.006)	(0.003)
Minor Dam.	0.038			
	(0.025)			
Major Dam.	0.025			
	(0.081)			
Severe Dam.	-0.983^{***}	-0.975^{***}	-0.986^{***}	-1.033^{***}
	(0.059)	(0.042)	(0.044)	(0.025)
Birth Rate			-0.0001	-0.294
			(0.227)	(0.209)
Birth Rate $\times$ Sev.				-9.318
				(9.912)
Pop. Growth			-0.002	0.005^{*}
			(0.005)	(0.002)
Pop. Growth $\times$ Sev.				0.435^{***}
				(0.072)
Export Orient.			0.037	0.089^{***}
			(0.050)	(0.029)
Export Orient. $\times$ Sev.				5.737^{***}
				(1.126)
Home Value			0.001^{*}	0.0003^{**}
			(0.0003)	(0.0001)
Home Value $\times$ Sev.				-0.005
				(0.005)
Renter Occ.			-0.105	0.002
			(0.070)	(0.033)
Renter Occ. $\times$ Sev.				3.690^{***}
				(0.881)
Observations	122	122	122	122
R^2	0.821	0.816	0.830	0.973
Adjusted R^2	0.816	0.814	0.821	0.971
Residual Std. Error	0.040 (df = 118)	0.041 (df = 120)	0.040 (df = 115)	0.016 (df = 110)
F Statistic	180.215^{***} (df = 3; 118)	531.982^{***} (df = 1; 120)	93.635^{***} (df = 6; 115)	363.112^{***} (df = 11; 110)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$			

Results from model 3 tend to be insignificant.[10] Given that the synthetic control method matches on various county characteristics in constructing the synthetic control, the difference between observed and synthetic population should be the identified effect of the hurricane. Thus, it is not surprising that the direct influence of covariates are largely insignificant since they have already been accounted for in the construction of the dependent variable. To test specifically whether these factors attenuate or exacerbate the consequences of the disasters, it is necessary to interact each factor with damages. With the inclusion of these interactions, the marginal effect of damages will be dependent on these additional covariates. The sign and magnitude of each interaction coefficient will describe the degree in which the covariate diminishes or worsens the effect of the disaster.

Model 4 in Table 2.2 includes all covariates and their associated interaction terms. The explanatory power of the model increases substantially relative to the previous specification. The adjusted R-squared is 0.97, suggesting that almost all the cross-sectional variation in the estimated population effect can be explained by the current model. Although there are factors that likely influence disaster resiliency that have been ignored, this result suggests that there is not much room for improvement in terms of accounting for the variance in the dependent variable. However, the variance inflation factor for model 4 indicates that it suffers from severe multicollinearity.[11] Multicollinearity inflates the variances of the coefficient estimates and impacts the sign and magnitude of coefficient. Because of which, the individual coefficients are largely uninterpretable. To get a better sense of the influence of each predictor, I run a series of regressions for each covariate and an interaction term separately. These models and results are presented in Table 2.3.

Model 5 depicts the correlation between pre-disaster establishment births and the population effect in the first year following the disaster. Severe damages is still negative and highly significant. Both establishment births and the interaction term are positive and significant. The coefficient on the interaction term suggests that higher establishment birth rates in the pre-disaster period di-

[10]With the exception of severe damages, which is significant at the 1% level and median home value is significant at the 10%

[11]Common practice typically assumes a VIF score of 10 or greater indicates problematic multicollinearity. Interaction terms in model 4 range from 9.6 to 61

Table 2.3: Individual interaction models

	(5)	(6)	(7)	(8)	(9)
Constant	-0.015^{***}	-0.013^{***}	-0.013^{***}	-0.010^{**}	-0.012^{***}
	(0.003)	(0.004)	(0.002)	(0.005)	(0.003)
Severe Dam.	-1.062^{***}	-0.928^{***}	-1.026^{***}	-0.981^{***}	-0.934^{***}
	(0.034)	(0.043)	(0.026)	(0.043)	(0.036)
Birth Rate	0.362^{**}				
	(0.160)				
Birth Rate × Sev.	23.215^{***}				
	(2.566)				
Pop. Growth		0.005			
		(0.003)			
Pop. Growth × Sev.		0.200^{***}			
		(0.059)			
Export Orient.			0.034^{*}		
			(0.018)		
Export Orient. × Sev.			2.645^{***}		
			(0.191)		
Home Value				0.0002	
				(0.0002)	
Home Value × Sev.				-0.004	
				(0.003)	
Renter Occ.					-0.044
					(0.038)
Renter Occ. × Sev.					-1.890^{***}
					(0.279)
Observations	122	122	122	122	122
R^2	0.892	0.833	0.931	0.821	0.873
Adjusted R^2	0.889	0.829	0.929	0.816	0.870
Residual Std. Error (df = 118)	0.031	0.039	0.025	0.040	0.034
F Statistic (df = 3; 118)	323.730^{***}	196.256^{***}	531.197^{***}	179.972^{***}	271.081^{***}
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$				

minishes out-migration post-disaster. Model 5 supports the notion that environments attractive to entrepreneurs are also better insulated against the immediate consequences of damages. To get a sense of the magnitude of this relationship, I plot model results for three different counties that experienced different levels of severe damages. Figure **??** plots the relationship between establishment birth rates and corresponding fitted values implied by model 5. The figure utilizes damage levels experienced by Orleans Parish, Harrison County, and St. Tammany Parish. Orleans had 41% of its occupied housing severely damaged, Harrison had 11%, and St. Tammany had 2%. As noted above, establishment births and damage severity have been centered on zero by subtracting their mean value. To ease interpretation, the dotted vertical line corresponds to the mean establishment birth rate. Values to the right of the dotted line represent a higher than average birth rate, and to the left of the dotted line, a lower than average birth rate. In Orleans Parish, a 1% increase in establishment births in 2004 translates to a 9% reduction of out-migration in 2006. The plot highlights that this relationship is weaker in areas with lower levels of damage. For example, in Harrison County a 1% increase in establishment births would translate to a 2% reduction in out-migration. In St. Tammany Parish, a 1% increase in establishment births would translate to a 0.42% reduction in out-migration. In terms of levels, this implies that the addition of one new firm in 2004 in Harrison would result in 123 less people leaving the area in 2006.

Models 6-9 largely corroborate previous literature. Pre-disaster population growth is an attenuating force of damages. Counties whose sectors are more export oriented are less impacted by damages. Higher percentages of renters translates into higher levels of out-migration.

Importantly, models 5-9 depict simple correlations rather than representing causal effects. Entrepreneurship may be correlated with other omitted factors which directly influence an area's static resilience. If omitted factors are highly correlated with establishment births, this would result in biased coefficient estimates. To examine this point, I construct a correlation matrix between establishment births and included control variables. Given coefficients in models 6-9, and correlation coefficients in Figure 2.5, it is possible to sign the direction of the bias on establishment births. Figure 2.5 shows that population growth is moderately correlated with establishment

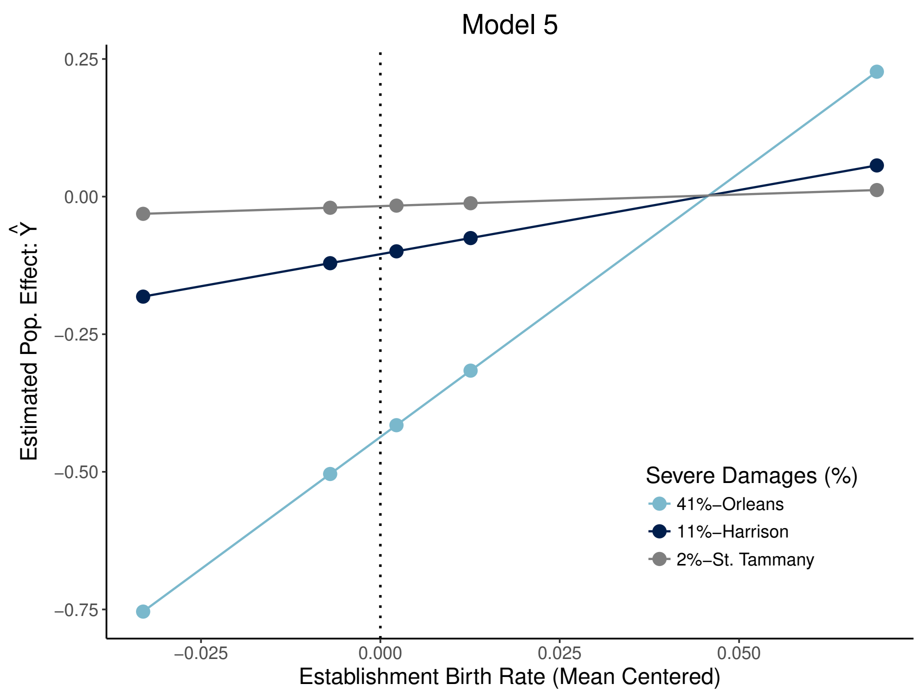

Figure 2.4: Representation of static and dynamic resilience

births. Export orientation, median home value, and renter occupancy are all weakly correlated. Because pre-period population growth is positively correlated with the dependent variable (as depicted in model 6) and positively correlated with establishment births, this suggests that model 5 over-estimates the coefficient on establishment births, and thus the coefficient on the interaction term.

To better explore the relationship between entrepreneurial activity and disaster recovery I next examine the notion of dynamic resilience. The model presented in Table 2.4 uses the difference between the population effect in 2016 and 2006 as the dependent variable. This difference represents the extent of recovery between the first and last periods of the post-disaster sample. Model 10 is estimated using ordinary least squares and the full set of covariates described above. Establishment births rates are defined by taking the average over the post-period, between 2006 and 2016. The remaining covariates reflect pre-disaster characteristics. The statistical model can be represented Eq 2.6.

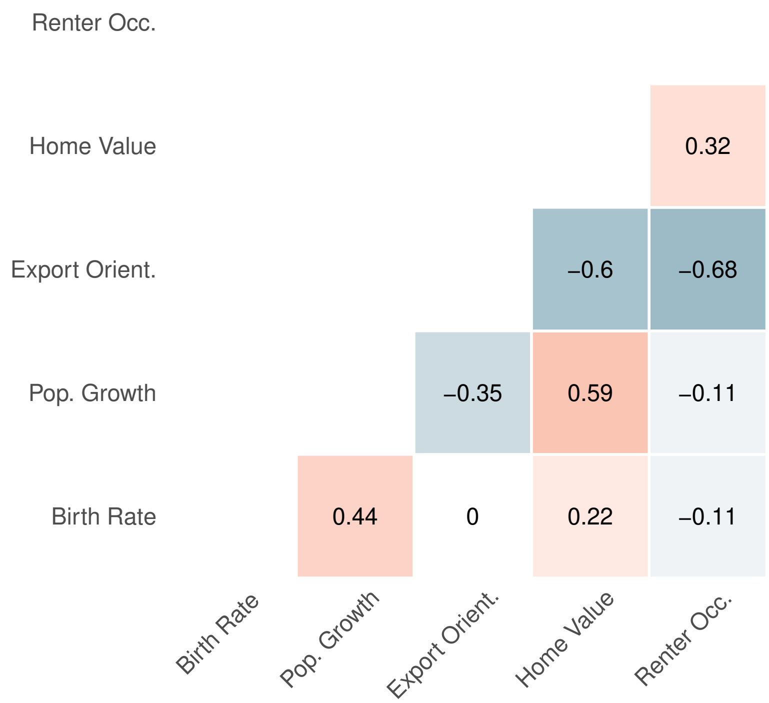

Figure 2.5: Correlation coefficients

$$\begin{aligned}(Perc\ Pop\ Effect_{i,\,2016} - Perc\ Pop\ Effect_{i,\,2006}) = \\ \beta_1 + \beta_2 * Severe\ Dam_i + \beta_2 * Avg\ Birth\ Rate_i \\ + X_i * \delta + \varepsilon_i \end{aligned} \tag{2.6}$$

Results in Table 2.4 show that severe damage has a positive and significant impact on the recovery. This is intuitive given that severe damage is so strongly correlated with initial out-migration. Areas that saw large population losses are situated to have large population gains between 2006 and 2016 (relative to their synthetic control). For example, after the mass out-migration of people from New Orleans, the city experienced high population growth in the years that followed. This growth corresponded to people returning to the area.

In model 10, establishment birth rates are positive and significant. Results suggests a 1% increase in establishment births corresponds to 1.37% higher population recovered. In Orleans, an

Table 2.4: Model of dynamic resilience

	(10)
Constant	0.005
	(0.008)
Severe Dam. (%)	0.276^{***}
	(0.070)
Birth Rate	1.374^{**}
	(0.599)
Pop. Growth	0.009
	(0.008)
Export Orient.	-0.080
	(0.072)
Home Value	-0.001
	(0.0004)
Renter Occ.	0.082
	(0.102)
Observations	122
R^2	0.319
Adjusted R^2	0.283
Residual Std. Error	0.058 (df = 115)
F Statistic	8.961^{***} (df = 6; 115)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

annual average increase of one new establishment during the post-Katrina period would translate to 207 more people returning back to the area. The remaining variables in model 10 seem to have little impact on recovery. None are significant, and their coefficients are near zero in magnitude. Similar to the above models, this result is not identified and represents a correlation. In model 10, because entrepreneurship is measured as an average taken over the post-Katrina period, it is possible that the relationship runs the other direction. Although the specification alleviates concerns of omitted variable bias by including the full set of controls, the specification introduces concerns of reverse causation between the dependent variable and average establishment births. For example, higher population recovery could result in higher entrepreneurial activity, rather than new establishment births leading to recovery. To untangle the causal influence of entrepreneurship, and more directly test the notion of whether entrepreneurs are "first-mover," the remaining models use a panel specification including lagged establishment births.

The final two models presented in Table 2.5 aim at capturing the role of entrepreneurs as first-movers in the recovery process. Both models are a panel covering the post-disaster time period, from 2006 to 2016. The dependent variable is the population effect, defined as the percent difference between observed and synthetic employment. The model includes county fixed effects, a time trend, and three years of lagged establishment birth rates. The regression model is described by Eq. 2.7 below. Again, results depict a positive correlation between establishment birth rates and population recovery. The magnitude of this correlation is larger and statistically significant in the second and third lagged periods. This result is inline with previous work on entrepreneurship, which also finds evidence of two and three year lags as mattering for new establishment births (Conroy et al., 2017). This supports the notion that entrepreneurs move first in the recovery process and send signals to households that recovery is underway. Model 12 subsets the full sample of counties to areas that experienced a high degree of damage from the disaster, defined as a county in which at least 25% of housing was damaged.[12] The exercise shows that the positive effect of entrepreneurship increases in more damaged areas. Areas with a higher degree of damage experience

[12]25% is the median value of housing damages across included counties.

a more complex coordination challenge in their recovery. This result again supports the notion that entrepreneurs provide signals to households that recovery is underway, and that these signals matter in terms of overcoming the collective action challenges associated with disaster recovery.

The final model is the closest specification to representing a "causal" relationship between entrepreneurship and disaster recovery. However, as noted in Bunten et al. (2015) there is concerns of endogeneity while examining entrepreneurship and growth. For example, if entrepreneurs have insight into which areas will recovery, they will likely choose to locate in these areas. In such a context, though entrepreneurs are still acting as "first-movers," they are not necessary sending a signal to households, and causally influencing household decisions. In such a context, areas that recovered would have recovered anyways, irrespective of the actions of entrepreneurs. In reality, recovery is an endogenous process. Entrepreneurs are both sending signals to households, but are also locating in areas they suspect will recovery. The model does not identify recovery that is specific to the "signal" sent by the entrepreneur, but rather just depicts a correlation between previous year establishment births and household population recovery.

$$
\begin{aligned}
&Perc\ Pop.\ Effect_{i,\,t} = \\
&\qquad \beta_1 + \beta_2 * Birth\ Rate_{i,\,t-1} + \beta_3 * Birth\ Rate_{i,\,t-2} \\
&\qquad +\ \beta_4 * Birth\ Rate_{i,\,t-3} + \beta_5 * Time\ Trend + \alpha_i + \varepsilon_{i,\,t} \\
&\qquad for\ t > 2005
\end{aligned}
\tag{2.7}
$$

The above results depict strong and consistent correlations between estimated populations effects and entrepreneurship. Both in context of static and dynamic resilience, the data suggests that entrepreneurial activity is an attenuating force in terms of population out-migration following a disaster. The last panel model implies that entrepreneurs play an important role as first movers in the disaster recovery process, helping overcome collective action challenges instigated by a disaster. Results provide quantitative support for the extensive qualitative research that has documented

Table 2.5: Panel results with county fixed effects

	Full Sample	High Damage
	(11)	(12)
Constant	-2.545^{***}	-4.684^{***}
	(0.607)	(1.008)
Time Trend	0.001^{***}	0.002^{***}
	(0.0003)	(0.001)
Birth Rate (1 yr. lag)	0.001	0.021
	(0.034)	(0.049)
Birth Rate (2 yr. lag)	0.060^{*}	0.099^{**}
	(0.033)	(0.046)
Birth Rate (3 yr. lag)	0.093^{***}	0.153^{***}
	(0.033)	(0.046)
County Fixed Effects	X	X
Observations	1,098	522
R^2	0.933	0.954
Adjusted R^2	0.924	0.948
Residual Std. Error	0.021 (df = 972)	0.023 (df = 460)
F Statistic	107.676^{***} (df = 125; 972)	155.506^{***} (df = 61; 460)
Note:		*p<0.1; **p<0.05; ***p<0.01

entrepreneurs as important facilitators of post-disaster recovery. However, these results should be interpreted with caution. The section also details issues in all three models, including concerns of omitted variable bias, reverse causality, and endogeneity. These results should thus be interpreted as correlations, rather than as casuals relationships.

2.5 Conclusions

This paper has argued that one of the main challenges in disaster recovery relates to a collective action problem, in which everyone is taking a “wait and see” strategy in terms of their own recovery. The decision to return to a damaged area is linked to the decision of your neighbors, local businesses, and the local government. Because entrepreneurs by definition are “agents of change,” they are well equipped to identify opportunities and move first in a post-disaster environment (Storr et al., 2016). Disasters change the economic landscape and lead to thin-markets, in which the market under provides needed goods and services related to recovery. Entrepreneurs are nimble enough to identify and respond to these opportunities. Importantly, the presence of entrepreneurs signals to other actors that an area will recover. Entrepreneurs reveal information about the post-disaster environment, which helps alleviate uncertainty created by the event.

The purpose of this chapter was to quantify and test the role of entrepreneurship in attenuating out-migration attributed to Hurricanes Katrina and Rita. Using the synthetic control method, I estimate population effects across all 122 counties with reported housing damage from the hurricanes. I then examine a series of regression models that look at both the immediate impacts of the disaster and the recovery process. To proxy for entrepreneurial activity, I follow previous research and use annual establishment births. Establishment births are consistently highly correlated with both the immediate effects of the disaster and the recovery process. This provides empirical support for qualitative work performed in previous research (Chamlee-Wright and Storr, 2009b; Storr et al., 2016). To the best of my knowledge, this is the first work that has empirically examined this relationship.

The below figure plots the establishment birth rate in the city of New Orleans. The purple line indicates the year of the disaster. The graphic shows that in years following the hurricane there was a spike in establishment births. This is fairly intuitive. Given that many establishments went out of business, this created opportunities for new ventures. This increase in entrepreneurial churn suggests that the sectoral landscape of the area could have changed. Given the amount of charitable activity associated with the recovery period, commercial entrepreneurship could have shifted towards ventures aimed at helping and/or supporting the community. These "social entrepreneurs" have been emphasized in research that largely influenced this chapter (Chamlee-Wright and Storr, 2009b; Storr et al., 2016). The next chapter continues exploring the effects of Hurricane Katrina on impacted counties, but focuses specifically on the notion of social capital. Exploiting similar data, the chapter estimates the impact of Hurricane Katrina on establishments and nonprofits that service community well-being.

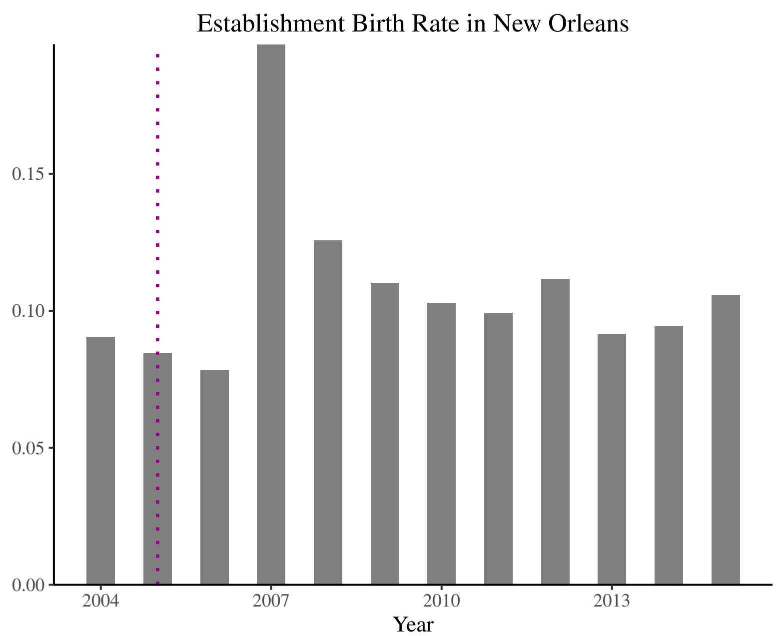

Figure 2.6: New Orleans establishment birth rate over time

Chapter 3

The Impacts of Hurricane Katrina on Social Capital

3.1 Introduction

The media coverage in the immediate aftermath of Hurricane Katrina depicted the city of New Orleans reduced to chaos and disorder, describing widespread looting, rampant murders, and "sniper fire aimed at rescuers" (Sommers et al., 2006). Though this portrayal turned out to be inaccurate and hyperbolic, the story of Hurricane Katrina includes racial discrimination, armed vigilantes, large-scale evacuation, and government failures (Horne, 2008). These narratives suggest a potential fragmenting of community following the hurricane; however, the bulk of disaster research predicts the opposite outcome. Namely, that disasters bring communities together as they work to overcome collective action challenges (Aldrich and Meyer, 2015; Chamlee-Wright and Storr, 2009b, 2011; De Alessi, 1975; Douty, 1972). It is unclear if characteristics specific to Hurricane Katrina and the city of New Orleans led to a contrasting outcome, or if in-fact the hurricane led to increased social capital in the area.

There is a significant amount of research describing the role of social capital in attenuating the consequences of natural disasters. To a lesser extent has the relationship been studied in the opposite direction, i.e. how natural disasters shape a community's social capital. Wang and Ganapati (2018) empirically investigate this notion. The paper constructs a social capital index utilizing private and nonprofit establishment data and evaluates the short-term impacts of Hurricane Katrina on this index. Results indicate that the disaster led to an initial decrease in social capital, followed by a slowdown of growth relative to pre-disaster trends. This result contrasts with previous empirical studies, which illustrate increases in various measures of social capital post-disaster (Pena et al., 2014; Toya and Skidmore, 2014; Yamamura, 2016).

The purpose of this chapter is to expand on the work by Wang and Ganapati (2018) and further examine Hurricane Katrina's influence on the area's social capital. Specifically, I apply a different methodology and a longer time horizon to test whether Hurricane Katrina increased or decreased social capital, and if these changes were permanent. In line with previous chapters, I employ the synthetic control method to estimate how social capital would have evolved had the disaster not occurred. The paper deviates from Wang and Ganapati (2018) by focusing on the New Orleans Metropolitan Statistical Area (MSA). This area encompasses some of the most damaged counties by the hurricane. This chapter makes a novel contribution by identifying the *long-term* impacts of the disaster on social capital - something rarely identified in this literature. Additionally, the paper decomposes the effect on the various components of the index, and examines whether results are being driven by any single component, or if impacts were approximately equally distributed.

Results from the analysis demonstrate that in the New Orleans MSA social capital increased significantly the year after the disaster. This increase amounts to approximately half a standard deviation relative to the level implied by the synthetic control, and persisted through the entire sample period. Decomposing the index into its two sources, County Business Patterns and National Center for Charitable Statistics, indicates that both saw similar increases relative to the overall index. A falsification exercise is undertaken to verify that these increases were specific to establishments and nonprofits aimed at servicing the community, rather than being the product of population out-migration from the area.

The remainder of the paper is organized as followed. Section 3.2 describes previous economic literature on social capital and natural disasters. Section 3.3 describes the methods and data used in the analysis. Section 3.4 presents results from the synthetic control analysis and section 3.5 concludes.

3.2 Social Capital and Disasters

Chamlee-Wright and Storr (2011) define social capital as a resource that "facilitates collective action for mutual benefit." There is a growing body of research emphasizing the importance of social capital in disaster preparedness and recovery. For example Bolin and Stanford (1998) describe how vulnerable populations after the Northridge Earthquake struggled to access federal assistance, and that this assistance (when accessed) often inadequately addressed their needs. The paper describes how community-based organizations and other non-governmental organizations were able to use federal funds and local expertise to address these unmet needs. Aldrich (2011) examines population recovery following the 1995 Kobe earthquake. Using lagged per capita counts of non-profit organizations to proxy for social capital, the paper finds that social capital expedited recovery across neighborhoods in Kobe. Chamlee-Wright and Storr (2011) argue that a community's perceived self-image influences how the area recovers from a disaster. The authors examine recovery in St. Bernard Parish, one of the most damaged areas by Hurricane Katrina. The paper finds that the shared identity of their community as "close-knit" and "self-reliant" led to the utilization of informal networks, rather than external assistance, throughout redevelopment.

More recently research has begun to explore how natural disasters shape different components of social capital, such as trust, altruism, community participation, and charitable giving. For example, Toya and Skidmore (2014) perform a cross-country analysis examining the relationship between the occurrence of natural disasters and societal trust. They find that natural disasters positively impact trust. However, when decomposing this effect by disaster type, only the "storm" category was positive and statistically significant. The authors speculate that because storms are more predictable, and tend to be "indiscriminate" in terms of the people affected, they increase the development of "bridging capital."[13]

Yamamura (2016) investigates the impacts of 1995 Kobe Earthquake on community participation, another common proxy for social capital. They find that community participation increased in 1996 relative to previous survey years. This effect was found to be spatially dependent on the distance of the interviewee from Kobe.

Pena et al. (2014) find positive increases in net assets and revenue of nonprofits organization following a disaster, suggesting increases in charitable giving after an event. The paper argues that the small magnitude of this correlation is indicative of a "downstream" effect, in which charity originally flows to nonlocal larger organizations, and slowly trickles to local organizations, who have better local knowledge and local credibility.

[13]In contrast to other types of disasters, such as floods or earthquakes.

As noted above, Wang and Ganapati (2018) study the impact of Hurricane Katrina on a county-level index of social capital. They construct their index using a number of community based establishments and nonprofit organizations derived from the County Business Patterns and National Center for Charitable Statistics. In contrast to the above literature, they find decreases in social capital following Hurricane Katrina. Additionally, the paper finds a positive correlation between government assistance and social capital, suggesting that assistance has some success in offsetting the negative consequences of a disaster.

The above research suggests a strong relationship between social capital and natural disasters. Pre-existing social capital has been identified as lessening the negative effects of a disaster event. Additionally the above literature suggests that social capital often increases following a natural disaster, with the exception of previous empirical research on Hurricane Katrina. It is possible that characteristics of Hurricane Katrina and/or the affected area are unique relative to these other cases. For example, Storr and Haeffele-Balch (2012) note that more cohesive communities tend to be viewed as more resilient to disasters. The paper depicts how a heterogeneous neighborhood in the New Orleans area was able to rally around existing organizations, which helped facilitate recovery in this particular neighborhood. Certain areas may not have the existing social infrastructure for social capital to flourish post-disaster. Relatedly, Chang (2010) notes that disasters tend to accelerate existing dynamics and trends. It is possible that communities with weak existing social capital respond differently than communities with higher pre-disaster levels. In general, the above literature suggests some ambiguity as to whether social capital increased or decreased in the New Orleans metropolitan following Hurricane Katrina. Importantly, it is unclear whether increases or decreases were transitory or continue to persist. To explore these questions, I utilize the synthetic control method to construct a counterfactual of how social capital would have evolved had the disaster not occurred.

The next section describes the manner in which I quantity social capital and describes the data model employed in the synthetic control analysis.

3.3 Methodology

To identify the impacts of Hurricane Katrina on social capital in the New Orleans MSA, I construct a counterfactual series using the synthetic control method (Abadie and Gardeazabal, 2003; Abadie et al., 2010). The paper follows a similar approach as described in the first chapter, in which I employ Mahalanobis distance matching to identify a set of controls areas that are similar to the New Orleans MSA. These matches are based on measures of social capital as well as variables that influence the evolution of social capital. The synthetic control is then constructed by taking a weighted average of these matched areas. Weights are chosen such that control areas approximate the evolution of social capital in New Orleans prior to Hurricane Katrina. These weights are then applied to the post-disaster period, providing an estimate of how New Orleans would have evolved had the hurricane not occurred. The next sections describe the data used in the implementation of this procedure.

Measuring Social Capital

There is a considerable amount of research on the importance of social capital that spans multiple disciplines, including economics, sociology, and psychology. Sobel (2002) provides an overview of two major works on social capital, including Robert Putnams' book *Bowling Alone*, and *Social Capital: A Multifaceted Perspective* published by the World Bank. The paper describes different perspectives of the concept of "social capital" and the various criticisms that have followed. Criticisms and debates about the role of social capital are often a product of the vagueness in its definition. Given that social capital is multidimensional, and its definition is somewhat nebulous, empirically measuring the concept is not straightforward.

Previous research has adopted two widely used approaches for quantifying social capital. The first uses survey questionnaires aimed at measuring societal trust. For example, Rosenfeld et al. (2001) uses questions on trust from the General Social Survey (GSS) in their construction of a social capital index while examining the relationship between homicide rates and social capital. Toya and Skidmore (2014) use survey data on societal trust to test whether natural disasters impact social capital at the country scale. Bjørnskov (2006) employs a principle component analysis on components from the World Values Survey to identify elements that comprise social capital. One of the three components identified is social trust, which the author argues drives the effects of social capital on various outcomes, such as quality of governance and life satisfaction.

However, previous research has raised skepticism regarding the appropriateness of survey data in quantifying actual trusting behavior. In a laboratory setting Glaeser et al. (2000) shows that "attitudinal" survey questions aimed at quantifying trust were not predictive of outcomes in experimental trust games.

The second commonly used approach is to proxy for membership in clubs, civic organizations, and other group activities using publicly available establishment data (Deller and Deller, 2010; Rupasingha et al., 2006; Wang and Ganapati, 2018). These past studies rely on sectoral establishment data from the County Business Patterns Tables (CBP) and nonprofit organizations data from the National Center for Charitable Statistics (NCCS). The main advantage of this approach is that it utilizes data available at the county scale, spanning a multitude of years. These data are often coupled with other indicators such as voter participation (Rupasingha et al., 2006), the county response rate to the Decennial Census (Rupasingha et al., 2006), and the concentration of religious congregations (Deller and Deller, 2010).

To build a panel dataset at the metropolitan level, I adopt this second methodology and utilize data from the CBP and the NCCS to construct an index of social capital. The CBP is an annual series that provides economic data for all US counties. This includes information on the count of employer establishments for various industries. Industry definitions are based on the 2012 North American Industry Classification System (NAICS). Following previous applications (Deller and Deller, 2010; Rupasingha et al., 2006; Wang and Ganapati, 2018), I subset these data by establishments that service their community, such as youth and family services, temporary shelters and food banks, and other civic organizations. Additionally I include establishments that capture "bohemian" characteristics and other gathering places, such as the number of independent artists and barber and beauty shops (Deller and Deller, 2010). Table 3.1 presents the different NAICS industries included in the final social capital index. Establishments counts are aggregated to the scale of the MSA and defined in per capita terms.

The NCCS provides data on the number of nonprofits who filed form 990 with the Internal Revenue Service (IRS). This data is provided annually and contains descriptive information on operating nonprofits. Using these data, I aggregate the number of nonprofit organizations operating in each included MSA and divide by total population to get a corresponding per capita quantity. Table 3.1 lists the different nonprofit classifications included in the final index.

Table 3.1: Included establishments by source

County Business Patterns (CBP)	National Center for Charity Statistics (NCCS)
Individual and Family Services	Arts, Culture, and Humanities
Community Food and Housing, and Emergency Relief	Education
Independent Artists, Writers, and Performers	Environmental Quality, Protection, and Beautification
Social Advocacy Organizations	Crime, Legal Related
Civic and Social Organizations	Recreation, Sports, Leisure, Athletics
Business, Professional, Labor, and Political Organizations	Youth Development%
Barber Shops, Beauty Salons, and Nail Salons	Human Services - Multipurpose and Other
Fitness and Recreational Sports Centers	Civil Rights, Social Action, Advocacy
	Community Improvement, Capacity Building
	Public, Society Benefit
	Religion Related

To sum across different establishment series, I employ multiple stages of z-scoring. The purpose of z-scoring is so that the units of each component are based on standard deviations, and thus will contribute equally to the final index when aggregated. This is particularly important if an industry has low establishment counts relative to the other included series. For example, in New Orleans *community food and housing* tends to have lower establishments counts relative to other included industries. It is possible that these counts are actually high relative to other cities, implying a relatively higher degree of social capital in that dimension, but this point would be washed out by the other included components. By z-scoring, units are rescaled so they are relative to the other included MSAs. To rescale each establishment series in this manner, I first calculate the mean and standard deviation across all MSAs over the sample period. Establishment series are then rescaled by subtracting the overall mean and dividing by the associated standard deviation. This is done for each series listed in Table 3.1.

After z-scoring individual series I then aggregate by each data source. I re z-score these aggregate series so that I have an index that summarizes components derived from the CBP and NCCS respectively. This ensures that both sources contribute equally to the final index and allows for a comparison of the effects of Hurricane Katrina on each data source separately. Finally, the social capital index is constructed by summing the CBP and NCCS z-scores. This final value is also z-scored so the mean over the sample period is zero and the units reflect standard deviations. The result of this procedure is a panel data set from 1998 to 2015 for 380 unique MSAs. Figure 3.1 maps the final index across all included MSAs. Lighter shades of blue indicate areas with relatively lower levels of social capital and dark shades of blue depict areas with high levels of social capital. Similar to the county level analysis in Rupasingha et al. (2006), there are higher levels of social establishments in the Midwest and Northeast. Southern cities tend to have relatively lower levels. The process of z-scoring at multiple stages represents a deviation from Wang and Ganapati (2018), which summed across per-capita establishments. If establishment counts are relatively similar across included components, the choice of z-scoring versus aggregating per-capita totals should not yield significantly different results. However, if there is high variance across the per-capita values of included components, summing across these components inadvertently weights these industries with a higher importance in the final index. Since the purpose of this paper is to not only identify the effects of Hurricane Katrina on social capital, but also decompose these effects, I instead opt for an approach that approximately applies equal weighting. [14]

[14]The process described above does not result in an exact equally weighting of each component, since NCCS has eleven components compared to the CBP which has eight. The second round of z-scoring ensures that each respective source (CBP and NCCS) contributes equally to the final index, resulting in slight differences in weighting between individual components.

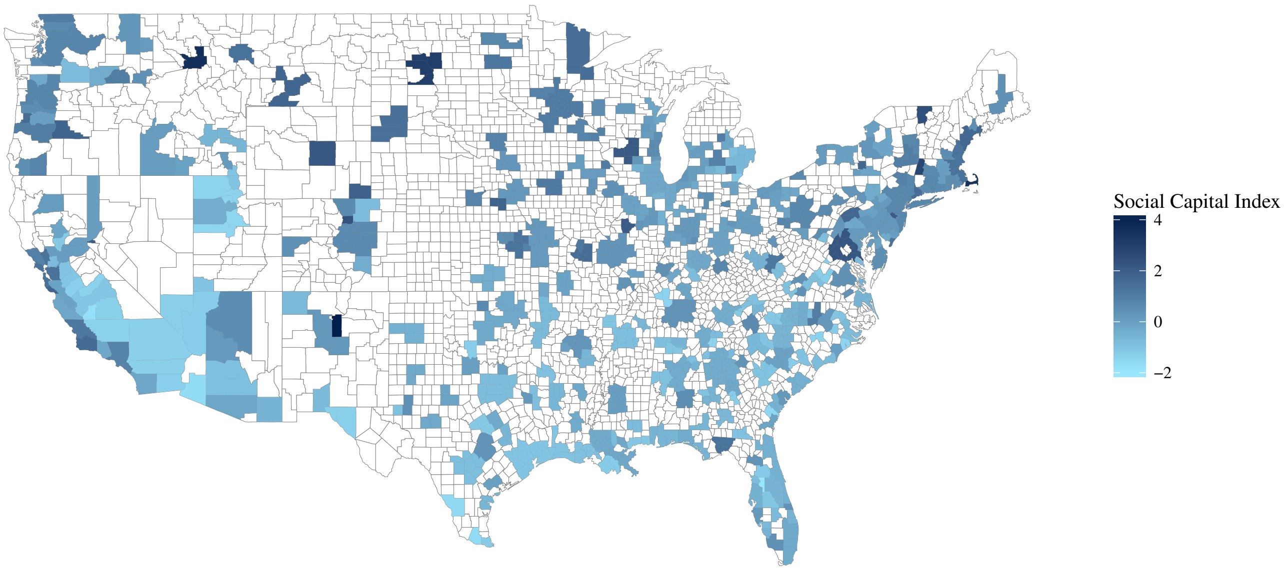

Figure 3.1: Map of Average Social Capital across US Metropolitan Statistical Areas

Donor Pool

To construct a synthetic control for the New Orleans MSA I use distance matching to identify thirty MSAs that are similar to New Orleans across various dimensions. These dimensions primarily measure differences in group fragmentation and community heterogeneity.

Previous research has emphasized community heterogeneity, such as ethnic diversity or income inequality, as negatively impacting social capital. For example, Alesina and La Ferrara (2000) finds that participation in social activities is lower in more unequal and racially diverse areas. Vigdor (2004) finds heterogeneous communities, in terms of race, age, and income are predictive of lower response rates to the Decennial Census questionnaire. Additionally, previous studies on disaster recovery has emphasized that homogenous, "tight-knit", communities are better able to solve collective action problems during redevelopment (Chamlee-Wright and Storr, 2009a, 2011; Storr and Haeffele-Balch, 2012).

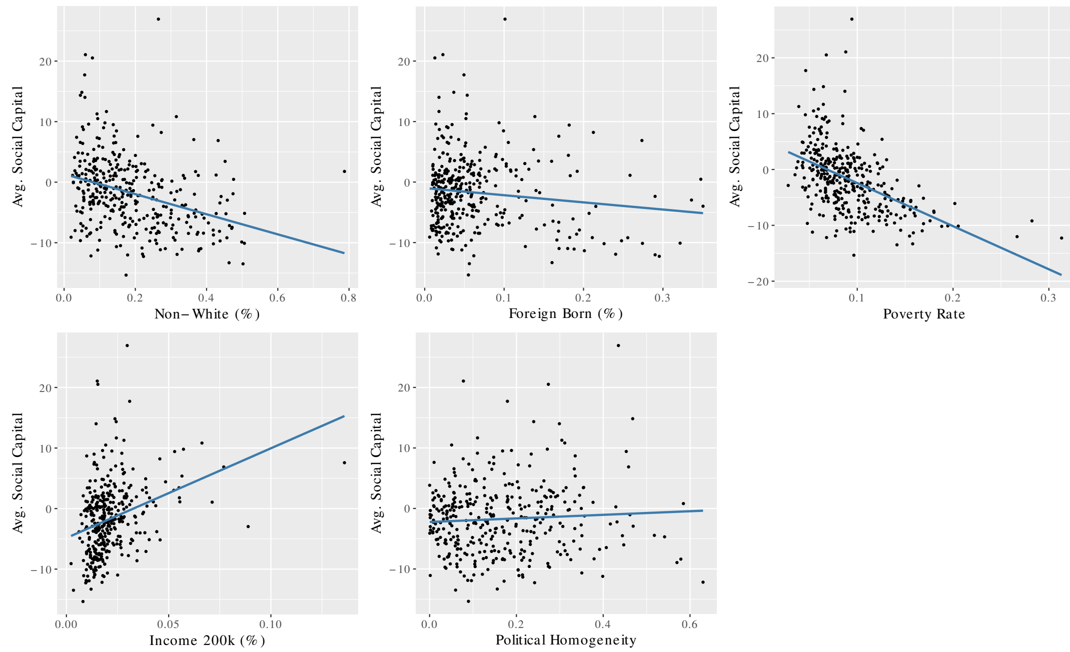

Figure 3.2: Correlations between measures of community diversity and social capital

To account for the notion that homogeneous communities behave differently relative to more diverse communities, I match on measures of racial, income, and political diversity. Specifically, I include the percent of the population that is non-white, the percent of the population that is foreign born, the family poverty rate, and the percent of families that earn 200 thousand dollars or more in annual income. These variables are all provided by the 2000 Decennial Census. Additionally I construct a measure of politically homogeneity using election result data from the 2000 Presidential election. I calculate the percent of total votes that were for Bush relative to Gore. I then rescale the data such that a zero indicates a metropolitan that was perfectly split, with 50% of votes for Bush and 50% for Gore, and a one indicates 100% went to one of the two candidates.[15] Figure 3.2 displays the correlation between average social capital during the pre-disaster period (1998-2004) relative to these different measures of diversity. A linear trend line is plotted through each graphic to display the direction of the correlation. The correlations depicted in each plot correspond with previous research. Percent non-white, Percent foreign born, and the poverty rate are negatively

[15] I ignore smaller party candidates and limit the measure to votes cast either for Bush or Gore.

correlated with the index. Political homogeneity and high income are positively correlated with the index.

Table 3.2: List of predictor variables and their respective source

Predictor Variables	Source
Population Density (pop per square mile)	2000 Decennial Census
Percent Non-White	2000 Decennial Census
Percent Foreign Born	2000 Decennial Census
Family Poverty Rate	2000 Decennial Census
Percent of Families with Income of 200K or More	2000 Decennial Census
Political Homogeneity	Federal Elections Project (American Univ.)
Average Employment Growth: 1998-2004	Bureau of Economic Analysis
Average Social Capital: 1998-2004	CBP and NCCS
Lagged Social Capital: 1998 and 2004	CBP and NCCS

Additionally, I include measures of population density, employment growth, and pre-disaster social capital when matching. Table 3.2 lists all included variables and their respective source. Following the methodology described in chapter one, variables are normalized by dividing by their standard deviation to control for differences in units. Using equation 3.1, I identify a unique set of thirty areas with the smallest "distance" relative to New Orleans. In the below equation, *New Orleans* is a column vector where each row i is associated with a matching variable. X_j is an identical vector for each j control MSAs. $Distance$ is a column vector that describes the squared difference between predictor values in New Orleans and each j control area. Table 3.3 depicts the thirty closest MSAs that result from this procedure. [16]

$$Distance = \sqrt{(New\ Orleans - X_j)'(New\ Orleans - X_j)} \tag{3.1}$$

3.4 Results

Results from the synthetic control method are presented in Figure 3.3. The black line depicts observed social capital in the New Orleans MSA. The units on the y axis are measured in standard

[16] Any MSA that experienced damages from Hurricanes Katrina and/or Rita are dropped from consideration.

deviations. The dotted vertical line separates the pre- and post-hurricane periods. The purple-dashed line is the estimated synthetic control. The difference between the synthetic control and the observed series is the estimated effect of Hurricane Katrina on social capital. The synthetic control is constructed by taking a weighted average of the included metro areas in Table 3.3. Weights are chosen to minimize a cost function based on the predictor variables listed in Table 3.2. The synthetic control series for the New Orleans MSA consists of 61% from Memphis, 10% from Columbus, 21% from Albuquerque, 6% from Anthens, and 1% from Montgomery.

Figure 3.3 shows a small initial dip in 2005 (the year of Katrina), followed by a large positive shift in the index. The gap between observed and synthetic social capital persists throughout the post-disaster period. The result suggest that the disaster increased the density of social establishments in the area by approximately 0.57 standard deviations. The average growth rate from 2008-2015, the years after the large initial spike, was significantly higher relative to the synthetic control; 25% compared to 8%. In general, these results suggest a stark contrast relative to previous findings in Wang and Ganapati (2018), which showed that social capital decreased following Hurricane Katrina and led to lower growth relative to pre-period trends.

This result is not surprising. As the previous chapters highlighted, Hurricane Katrina created a large out-migration of people from the New Orleans area. Summary statistics on total establishments and population trends show that population was more negatively impacted by Hurricane Katrina relative to business establishments. Thus, a density dependent measure of social capital based on private and nonprofit establishments should increase following the disaster. These results speak to the fact that although social networks were disrupted by out-migration, the physical entities that facilitate the development of social capital remained. The previous chapter showed a jump in establishment births during the years following Hurricane Katrina. It is likely that new firm formation during this period was not uniform across sectors. The results from Figure 3.3 suggest that even as residents filtered back to the area, community oriented establishments remained more concentrated relative to the synthetic control. Establishments geared towards servicing the community appear more successful in a post-disaster environment. This relates to the narrative

Table 3.3: Included control areas and their associated weights

MSA Name	Weight
Albany, GA	0%
Albuquerque, NM	21.2%
Anniston-Oxford-Jacksonville, AL	0%
Athens-Clarke County, GA	5.7%
Augusta-Richmond County, GA-SC	0%
Birmingham-Hoover, AL	0%
Charleston-North Charleston, SC	0%
Columbia, SC	0%
Columbus, GA-AL	10.3%
Corpus Christi, TX	0%
Florence, SC	0%
Gadsden, AL	0%
Huntsville, AL	0%
Jackson, TN	0%
Macon-Bibb County, GA	0%
Memphis, TN-MS-AR	61.3%
Monroe, LA	0%
Montgomery, AL	1.3%
Pine Bluff, AR	0%
Saginaw, MI	0%
San Antonio-New Braunfels, TX	0%
Savannah, GA	0%
Shreveport-Bossier City, LA	0%
Sumter, SC	0%
Texarkana, TX-AR	0%
Valdosta, GA	0%
Vineland-Bridgeton, NJ	0%
Virginia Beach-Norfolk-Newport News, VA-NC	0%
Waco, TX	0%
Yakima, WA	0.1%

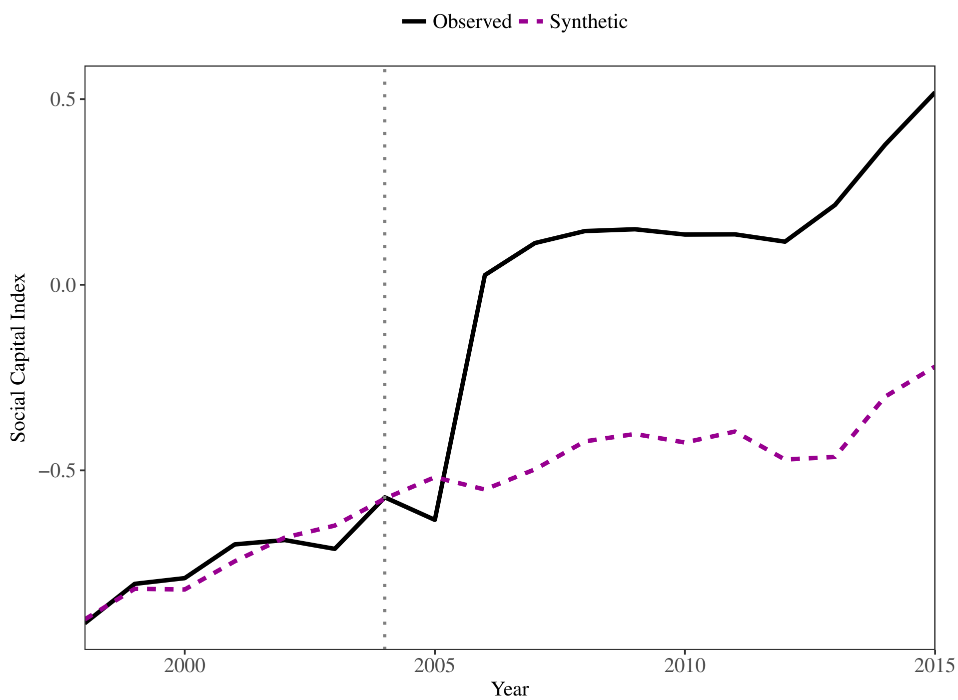

Figure 3.3: Synthetic control results for the New Orleans MSA

from the previous chapter that entrepreneurs recognize the needs created by disasters and respond to those needs.

To test the significance of this estimated effect, I use a placebo analysis originally proposed in Abadie et al. (2010). This involves repeating the above procedure for a group "placebo" areas that were unaffected by Hurricane Katrina. Given that these placebo areas were not "treated" by the event, their synthetic controls should roughly match observed trends. Any deviation can be thought of as representative of the error associated with the method. Following Abadie et al. (2010), I estimate synthetic controls for each of the thirty control areas listed in Table 3.3. This is done using the same data model described above. Repeating the synthetic control procedure for each control area results in a distribution of placebo effects. The estimated effect for the New Orleans MSA can then be compared relative to this distributions. Results of this test are presented in Figure 3.4. The black line represents the difference between the observed social capital index and the estimated synthetic control for the New Orleans MSA. The gray lines represent this same difference for each placebo area. The figure illustrates that on average the effect for the New Orleans MSA is large compared to the distribution of placebo effects. Starting in 2006, the New Orleans series sits completely outside this distribution. The only exceptions are in 2011 and 2012. In 2011, one of the 30 placebos has a higher estimated effect. In 2012, two of the thirty placebos have higher effects. For these two years, this indicates that the probability of estimating a larger effect with random permutations is 3.3% and 6.6% respectively. In general, results from the placebo exercise are highly significant, confirming that Hurricane Katrina had a large positive effect on the New Orleans MSA, and that this effect has continued to persist.

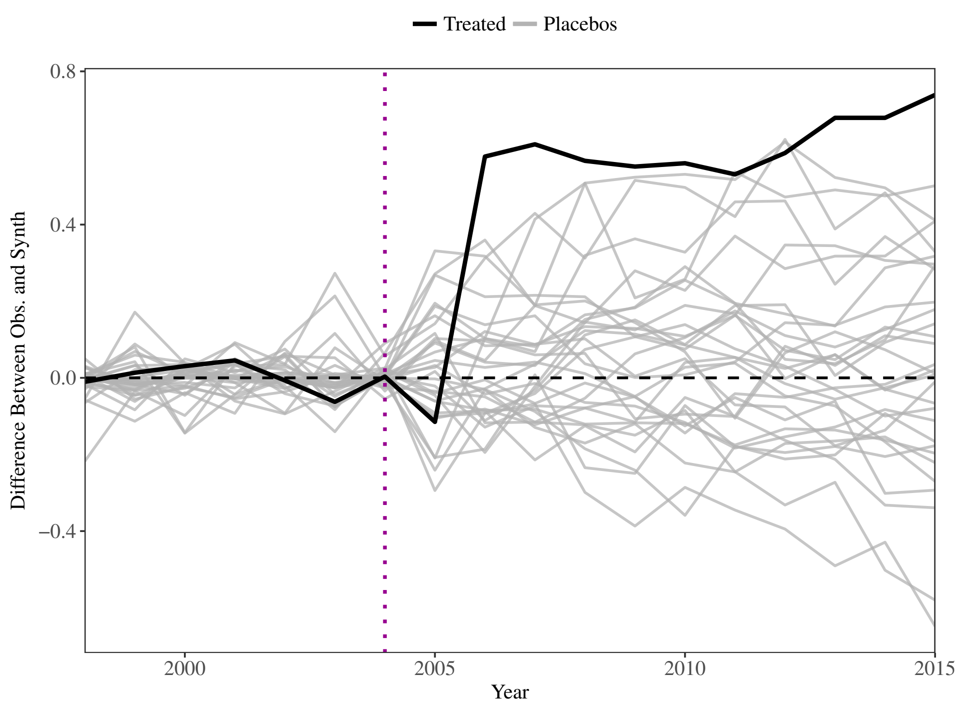

Figure 3.4: Social Capital placebo analysis

Lastly, I decompose the social capital index by its various components. This is done to explore whether increases after Hurricane Katrina were driven by a particular industry or nonprofit, or if increase were uniform across included establishments. Figures 3.5 and 3.6 examine the impacts of Hurricane Katrina on establishment counts associated with each of the data sources that constitute the index. Figure 3.5 plots the observed synthetic index for CBP and NCCS series. These synthetic controls were estimated following the same procedure as described above. The plots show that the nonprofit sector was less concentrated in the New Orleans MSA relative to included sectors from CBP at the start of the series. However, over the sample period nonprofits grew at a faster rate and end up being almost a full standard deviation higher than the CBP series by 2015. The synthetic controls suggest that both sources were similarly impacted by the event. Figure 3.6 plots the differences between the observed and synthetic series for each source. The plot shows that both series initially experienced a small dip in 2005, followed by a large increase in 2006. Additionally, the plot suggests an average increase of 0.5 standards deviations across both sources.

To decompose the index further, I plot each individual component of the social capital index over time. Figure 3.7 depicts observed z-scores for each component listed in Table 3.2. The total social capital index is also included as a benchmark. The color of each tile corresponds with the associated z-score for that year. Darker shades indicate lower values, and lighter shades, higher. The graphic has been sorted based on the difference between 2006 and 2005 values. The top series represents the sector or nonprofit organization that had the largest difference across these two years. The color of the overall plot suggests a clear break in 2006, where values to the right side of the image consistently tend to be lighter relative to the left. Across most sectors we see a jump in color from dark to light happening between 2005 and 2006. The largest difference in z-score between 2005 and 2006 occurred in human services (NCCS), food and housing, and emergency relief (CBP), and community improvement nonprofits (NCCS). All three represent sectors and organizations that relate to disaster recovery and would aid in the redevelopment of the city. The sectors with the lowest (or negative) difference relative to 2005 values include independent artists (CBP), civic organizations (CBP), social advocacy (CBP), and barber and beauty shops (CBP). In general, the table suggests that most of the included components increased following Hurricane Katrina. Increases appear larger in sectors more geared towards disaster recovery. The concentration of industries that have little to do with recovery, such as independent artists and barber and beauty shops, appear largely unaffected by the event. Importantly, the graphic shows trends over

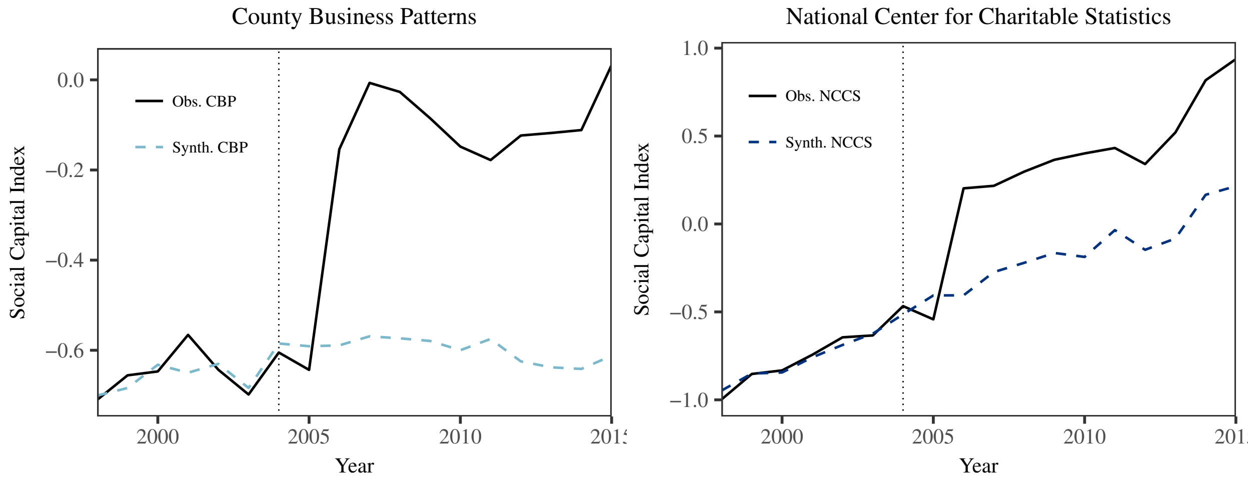

Figure 3.5: Synthetic control results for CBP and NCCS

time rather than identified effects. However, the clear break between 2005 and 2006 is suggestive of the influence of Hurricane Katrina, rather than an upward trend.

Falsification

Because this social capital index is based on *per capita* establishment and organization counts, it is possible that observed increases are the outcome of a change in the denominator, rather than reflecting an increase in the concentration of social capital. The area experienced a large out-migration of people between 2005 and 2006. If establishments were less impacted than population, this would result in increased concentration of *all* establishments, rather than establishments specific to servicing the well-being of the community. As a robustness check, I compare the evolution of two industries arguably unrelated to social capital with select series from Figure 3.7.

Shaffer et al. (2004) and Deller and Deller (2010) define social capital as referring to "social organizations such as networks, norms, and social trust" that facilitate coordination and cooperation. Proxying for social capital with businesses and nonprofits that support "community well-being" emphasizes that social capital develops through the involvement and participation in organizations that support the community (Putnam, 1995; Putnam et al., 1994). Two industries important to the New Orleans MSA, but not important to building community well-being include: 1) Mining, quarrying, and oil and gas extraction, and 2) accommodations. Both industries are export oriented in

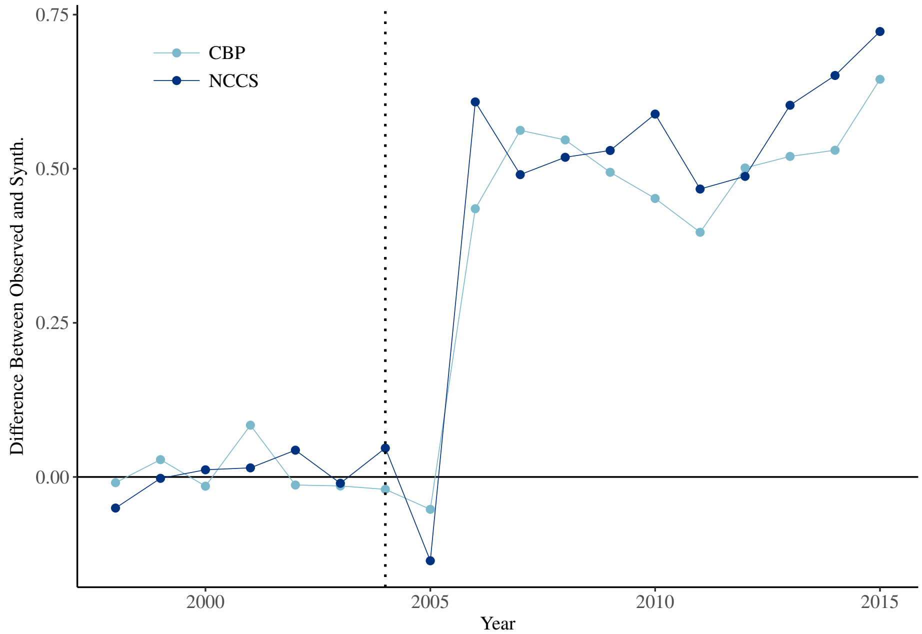

Figure 3.6: Estimated impact of Hurricane Katrina on CBP and NCCS series

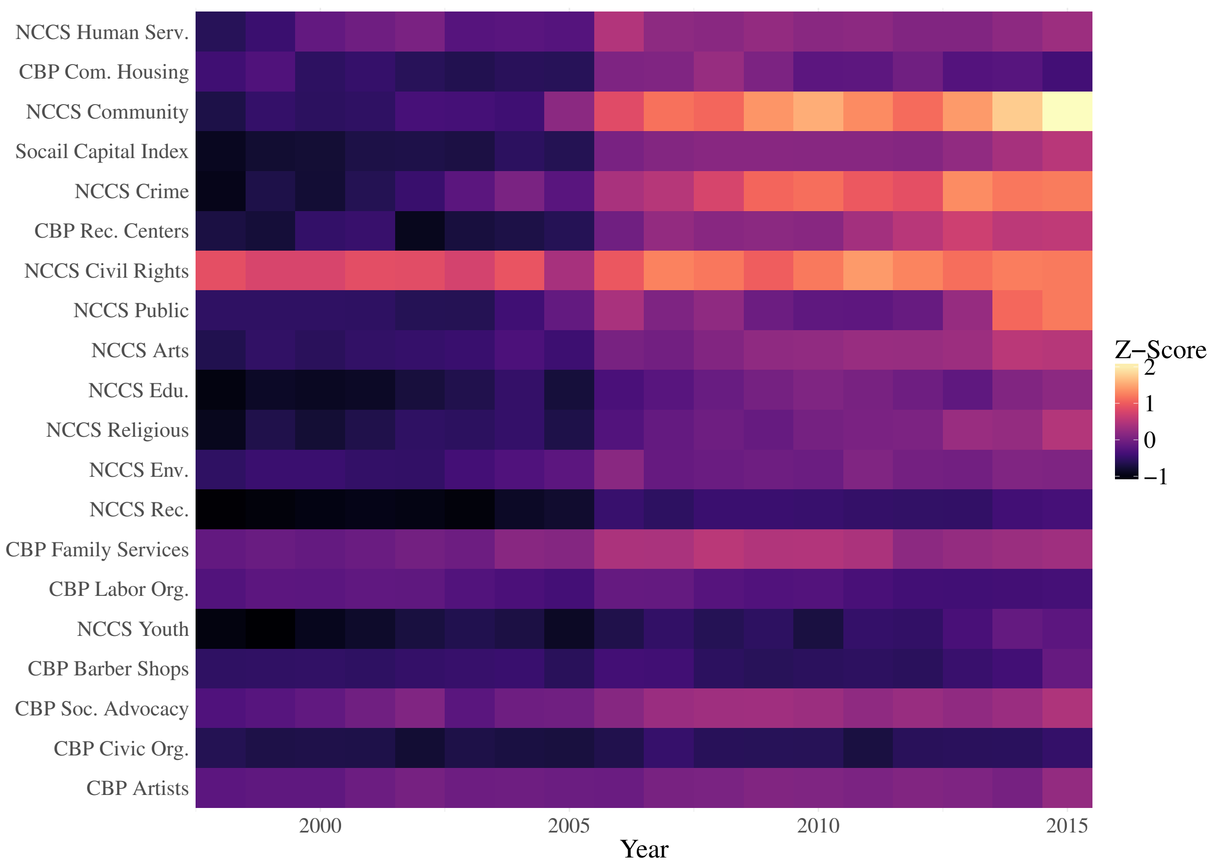

Figure 3.7: Heat map depicting each component of the Social Capital Index over time

the sense that they primarily service customers outside the local economy. In contrast, a locally oriented business, such as a coffee shop, arguably can build social capital through repeated interactions between customers. Additionally, industries that service the local population can play the role of a community gathering place, facilitating both "bonding" and "bridging" types of social capital (Aldrich and Meyer, 2015). Because hotels and oil and gas extraction service outside customers, they do not have this same feature. These industries benefit their communities by providing jobs and inflows of revenue from outside regions. Additionally, all businesses have the ability of generating relationships across co-workers, and workers and their families might form tight-knit communities based around their employment. However, mining, quarrying, and oil and gas extraction, and accommodations, arguably do not service the community in the same way that nonprofit community/social organizations do.

Figure 3.8 plots the time series of five different sectors: community improvement nonprofits (NCCS), recreation, sports, and leisure (CBP), social advocacy organizations (CBP), mining, quarrying, and oil and gas extraction (CBP), and accommodations (CBP). Because each series starts at a different level, values reflect the difference between each year's z-score relative to its 2005 value. This results in each series starting at zero in 2005. The units on the y axis can still be interpreted as standard deviations. A value of 0.5 thus represents an increase of 0.5 standard deviations relative to its 2005 value. The plot highlights that the three industries included in the index, community improvement nonprofits, recreation, and social advocacy organizations, all saw larger increases in 2006 relative to the two non-social capital industries. If the increase in the concentration of social capital was driven solely by changes in population, each industry in Figure 3.8 should experience similar changes in magnitude. However, the plot shows the opposite. Even social advocacy organizations, which Figure 3.7 depicts as having lower growth relative to other components, is consistently higher than both hotels and oil and gas extraction throughout the post-Katrina period. Importantly, hotels and oil and gas extraction do increase from 2005 to 2006, corresponding with the large out-migration of households from the area. This increase, however, represents roughly 0.15 standard deviations, which is considerably less than increases in community improvement

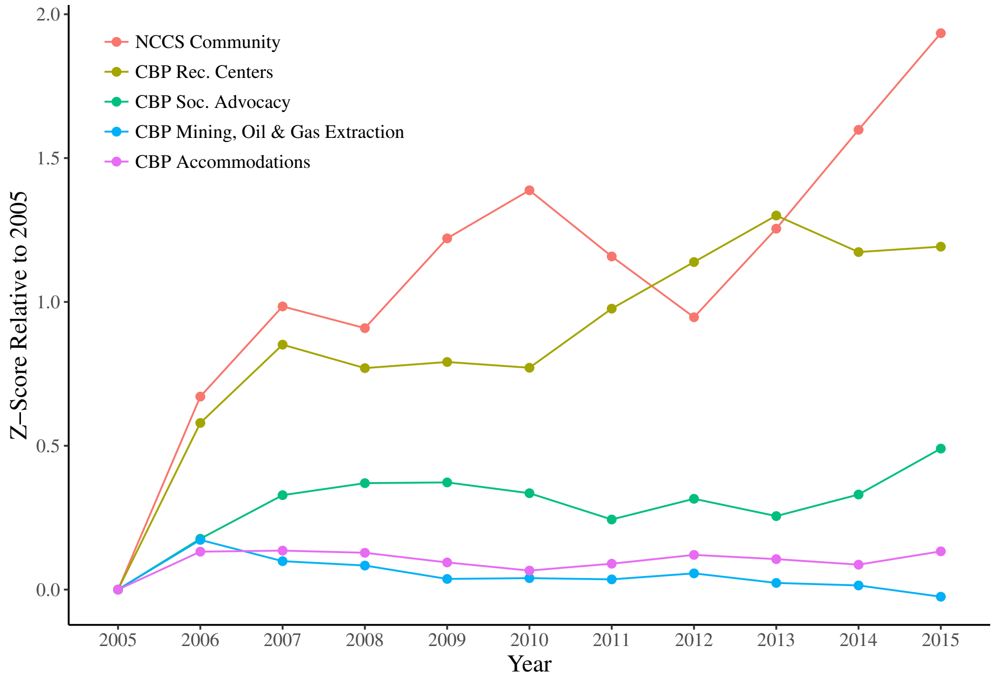

Figure 3.8: Falsification exercise

nonprofits and recreation establishments; it is also considerably less than the increase in the overall social capital index. By the end of the series, oil and gas extraction is below its 2005 value, and accommodations is just slightly above.

This section illustrated that Hurricane Katrina had a positive and significant impact on social capital in the New Orleans MSA. This impact has persisted for ten years after the hurricane. Decomposing the index across its various sources suggests that this positive increase affected private establishments and nonprofits uniformly. Decomposing the index further shows that Human Services (NCCS), Food and Housing, and Emergency Relief (CBP), and Community Improvement nonprofits (NCCS) saw the highest change between 2005 and 2006. A robustness check shows that the increase in establishment concentration was not experienced by all sectors in the economy. Mining, quarrying, and oil and gas extraction, and accommodations, both saw slight increases between 2005 and 2006, but these increases were significantly less relative to the overall social capital index.

3.5 Conclusions

Though disasters are often portrayed as generating looting, social disorganization, and "deviant" behavior, the bulk of academic research suggests the opposite (Tierney et al., 2006). Namely that disasters bring people together as they work to solve collective action challenges, both utilizing and building societal trust and social capital.

This chapter quantified and explored the impacts of Hurricane Katrina on social capital. I proxy for social capital using data on community establishments and nonprofit organizations. To estimate a counterfactual series, I first identify similar metropolitans based on a seres of covariates, including measures of community heterogeneity. Using the synthetic control method, I identify optimal weights, such that a weighted average of these matched metropolitans approximates pre-disaster trends in the New Orleans MSA. The effect of the disaster is identified by the deviation between this estimated synthetic control and observed social capital post-Katrina. Results indicate that the disaster dramatically increased social capital in the New Orleans MSA. This increase persists through the entire sample period. Additionally results show that the growth rate in observed social capital was higher relative to the growth rate defined by the synthetic control, suggesting that the gap between the two is widening over time.

Decomposing this effect by each included data source yields remarkably similar results, in which both private establishments and nonprofit organizations increased by a similar magnitude. Examination of individual components suggests that establishments most focused on servicing the community saw the largest increases immediately following the disaster. Other establishments typically included in measures of social capital, but less relevant to disaster recovery, had either minimal or negative growth in the years following the event. This result implies that establishments and organizations relevant to disaster recovery tend to flourish after events. The result also highlights path dependency, in which even ten years out from the event, these establishments continue to be highly concentrated in the area.

Natural disasters are devastating events. They result in lost lives, lost homes, and permanent displacement. However, this research suggests a silver lining. In order for a community to overcome the various obstacles generated by a disaster, the community has to work together. The social capital built during this process appears to persist long after the event.

Bibliography

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

Alberto Abadie, Alexis Diamond, and Jens Hainmueller. Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of the American statistical Association*, 105(490):493–505, 2010.

Daniel P Aldrich. The power of people: social capital's role in recovery from the 1995 kobe earthquake. *Natural hazards*, 56(3):595–611, 2011.

Daniel P Aldrich and Michelle A Meyer. Social capital and community resilience. *American Behavioral Scientist*, 59(2):254–269, 2015.

Alberto Alesina and Eliana La Ferrara. Participation in heterogeneous communities. *The quarterly journal of economics*, 115(3):847–904, 2000.

Guglielmo Barone and Sauro Mocetti. Natural disasters, growth and institutions: a tale of two earthquakes. *Journal of Urban Economics*, 84:52–66, 2014.

Ariel R Belasen and Solomon W Polachek. How disasters affect local labor markets the effects of hurricanes in florida. *Journal of Human Resources*, 44(1):251–276, 2009.

Christian Bjørnskov. The multiple facets of social capital. *European journal of political economy*, 22(1):22–40, 2006.

Robert Bolin and Lois Stanford. The northridge earthquake: community-based approaches to unmet recovery needs. *Disasters*, 22(1):21–38, 1998.

Daniele Bondonio and Robert T Greenbaum. Natural disasters and relief assistance: Empirical evidence on the resilience of us counties using dynamic propensity score matching. *Journal of Regional Science*, 2018.

Devin Bunten, Stephan Weiler, Eric Thompson, and Sammy Zahran. Entrepreneurship, information, and growth. *Journal of regional science*, 55(4):560–584, 2015.

Eduardo Cavallo, Ilan Noy, et al. Natural disasters and the economy–a survey. *International Review of Environmental and Resource Economics*, 5(1):63–102, 2011.

Eduardo Cavallo, Sebastian Galiani, Ilan Noy, and Juan Pantano. Catastrophic natural disasters and economic growth. *Review of Economics and Statistics*, 95(5):1549–1561, 2013.

Emily Chamlee-Wright and Virgil Henry Storr. Club goods and post-disaster community return. *Rationality and Society*, 21(4):429–458, 2009a.

Emily Chamlee-Wright and Virgil Henry Storr. The role of social entrepreneurship in post-katrina community recovery. *International Journal of Innovation and Regional Development*, 2(1-2): 149–164, 2009b.

Emily Chamlee-Wright and Virgil Henry Storr. Expectations of government's response to disaster. *Public choice*, 144(1-2):253–274, 2010.

Emily Chamlee-Wright and Virgil Henry Storr. Social capital as collective narratives and post-disaster community recovery. *The sociological review*, 59(2):266–282, 2011.

Stephanie E Chang. Urban disaster recovery: a measurement framework and its application to the 1995 kobe earthquake. *Disasters*, 34(2):303–327, 2010.

Stephanie E Chang and Adam Z Rose. Towards a theory of economic recovery from disasters. *International Journal of Mass Emergencies and Disasters*, 2012.

Shaoming Cheng, Emel Ganapati, and Sukumar Ganapati. Measuring disaster recovery: bouncing back or reaching the counterfactual state? *Disasters*, 39(3):427–446, 2015.

Hal Cochrane. Economic loss: myth and measurement. *Disaster Prevention and Management: An International Journal*, 13(4):290–296, 2004.

Makena Coffman and Ilan Noy. Hurricane iniki: measuring the long-term economic impact of a natural disaster using synthetic control. *Environment and Development Economics*, 17(02): 187–205, 2012.

Tessa Conroy, Sarah A Low, and Stephan Weiler. Fueling job engines: impacts of small business loans on establishment births in metropolitan and nonmetro counties. *Contemporary Economic Policy*, 35(3):578–595, 2017.

Louis De Alessi. Toward an analysis of postdisaster cooperation. *The American Economic Review*, 65(1):127–138, 1975.

Steven C Deller and Melissa A Deller. Rural crime and social capital. *Growth and Change*, 41(2): 221–275, 2010.

Tatyana Deryugina, Laura Kawano, and Steven Levitt. The economic impact of hurricane katrina on its victims: evidence from individual tax returns. Technical report, National Bureau of Economic Research, 2014.

Christopher M Douty. Disasters and charity: some aspects of cooperative economic behavior. *The American Economic Review*, 62(4):580–590, 1972.

William duPont IV and Ilan Noy. What happened to kobe? a reassessment of the impact of the 1995 earthquake in japan. *Economic Development and Cultural Change*, 63(4):777–812, 2015.

Kai Erikson and Lori Peek. Hurricane katrina research bibliography. *Brooklyn, NY: Social Science Research Council Task Force on Katrina and Rebuilding the Gulf Coast*, 2011.

Bradley T Ewing, Jamie B Kruse, and Mark A Thompson. Twister! employment responses to the 3 may 1999 oklahoma city tornado. *Applied Economics*, 41(6):691–702, 2009.

Alice Fothergill and Lori A Peek. Poverty and disasters in the united states: A review of recent sociological findings. *Natural hazards*, 32(1):89–110, 2004.

Edward L Glaeser and Joseph Gyourko. Urban decline and durable housing. *Journal of political economy*, 113(2):345–375, 2005.

Edward L Glaeser, David I Laibson, Jose A Scheinkman, and Christine L Soutter. Measuring trust. *The quarterly journal of economics*, 115(3):811–846, 2000.

Jeffrey A Groen and Anne E Polivka. The effect of hurricane katrina on the labor market outcomes of evacuees. *The American Economic Review*, 98(2):43–48, 2008a.

Jeffrey A Groen and Anne E Polivka. Hurricane katrina evacuees: who they are, where they are, and how they are faring. *Monthly Lab. Rev.*, 131:32, 2008b.

Jeffrey A Groen and Anne E Polivka. Going home after hurricane katrina: Determinants of return migration and changes in affected areas. *Demography*, 47(4):821–844, 2010.

Stéphane Hallegatte. An adaptive regional input-output model and its application to the assessment of the economic cost of katrina. *Risk Analysis: An International Journal*, 28(3):779–799, 2008.

Jed Horne. *Breach of faith: Hurricane Katrina and the near death of a great American city*. Random House Incorporated, 2008.

Andrew M Isserman. Estimating export activity in a regional economy: A theoretical and empirical analysis of alternative methods. *International Regional Science Review*, 5(2):155–184, 1980.

Sarah Low, Jason Henderson, Stephan Weiler, et al. Gauging a region's entrepreneurial potential. *Economic Review-Federal Reserve Bank of Kansas City*, 90(3):61, 2005.

Sarah A Low and Stephan Weiler. Employment risk, returns, and entrepreneurship. *Economic Development Quarterly*, 26(3):238–251, 2012.

Molly Fifer McIntosh. Measuring the labor market impacts of hurricane katrina migration: evidence from houston, texas. *American Economic Review*, 98(2):54–57, 2008.

Dennis S Mileti. Natural hazard warning systems in the unites states: a research assessment. Technical report, University of Colorado Institute of Behavioral Science, 1975.

Pamela Mueller. Exploiting entrepreneurial opportunities: The impact of entrepreneurship on growth. *Small Business Economics*, 28(4):355–362, 2007.

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

Yasuhide Okuyama. Economic modeling for disaster impact analysis: past, present, and future. *Economic Systems Research*, 19(2):115–124, 2007.

Yasuhide Okuyama, Geoffrey JD Hewings, and Michael Sonis. Measuring economic impacts of disasters: interregional input-output analysis using sequential interindustry model. In *Modeling Spatial and Economic Impacts of Disasters*, pages 77–101. Springer, 2004.

Anita A Pena, Sammy Zahran, Anthony Underwood, and Stephan Weiler. Effect of natural disasters on local nonprofit activity. *Growth and Change*, 45(4):590–610, 2014.

Robert D Putnam. Bowling alone: America's declining social capital. *Journal of Democracy*, 6: 65–78, 1995.

Robert D Putnam, Robert Leonardi, and Raffaella Y Nanetti. *Making democracy work: Civic traditions in modern Italy*. Princeton university press, 1994.

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

Adam Rose, Juan Benavides, Stephanie E Chang, Philip Szczesniak, and Dongsoon Lim. The regional economic impact of an earthquake: Direct and indirect effects of electricity lifeline disruptions. *Journal of Regional Science*, 37(3):437–458, 1997.

Richard Rosenfeld, Eric P Baumer, and Steven F Messner. Social capital and homicide. *Social Forces*, 80(1):283–310, 2001.

Anil Rupasingha, Stephan J Goetz, and David Freshwater. The production of social capital in us counties. *The journal of socio-economics*, 35(1):83–101, 2006.

Ron Shaffer, Steve Deller, Dave Marcouiller, et al. *Community economics: linking theory and practice.* Number Ed. 2. Blackwell Publishing, 2004.

Brock Smith. The resource curse exorcised: Evidence from a panel of countries. *Journal of Development Economics*, 116:57–73, 2015.

Joel Sobel. Can we trust social capital? *Journal of economic literature*, 40(1):139–154, 2002.

Samuel R Sommers, Evan P Apfelbaum, Kristin N Dukes, Negin Toosi, and Elsie J Wang. Race and media coverage of hurricane katrina: Analysis, implications, and future research questions. *Analyses of Social Issues and Public Policy*, 6(1):39–55, 2006.

Heather M Stephens and Mark D Partridge. Do entrepreneurs enhance economic growth in lagging regions? *Growth and Change*, 42(4):431–465, 2011.

Virgil Henry Storr and Stefanie Haeffele-Balch. Post-disaster community recovery in heterogeneous, loosely connected communities. *Review of Social Economy*, 70(3):295–314, 2012.

Virgil Henry Storr, Stefanie Haeffele-Balch, and Laura E Grube. *Community revival in the wake of disaster: Lessons in local entrepreneurship*. Springer, 2016.

Kathleen Tierney, Christine Bevc, and Erica Kuligowski. Metaphors matter: Disaster myths, media frames, and their consequences in hurricane katrina. *The annals of the American academy of political and social science*, 604(1):57–81, 2006.

Hideki Toya and Mark Skidmore. Do natural disasters enhance societal trust? *Kyklos*, 67(2): 255–279, 2014.

Jacob Vigdor. The economic aftermath of hurricane katrina. *The Journal of Economic Perspectives*, 22(4):135–154, 2008.

Jacob L Vigdor. Community composition and collective action: Analyzing initial mail response to the 2000 census. *Review of Economics and Statistics*, 86(1):303–312, 2004.

Lili Wang and Nazife Emel Ganapati. Disasters and social capital: Exploring the impact of hurricane katrina on gulf coast counties. *Social Science Quarterly*, 99(1):296–312, 2018.

Stephan Weiler. Pioneers and settlers in lo-do denver: Private risk and public benefits in urban redevelopment. *Urban Studies*, 37(1):167–179, 2000.

Yu Xiao. Local economic impacts of natural disasters. *Journal of Regional Science*, 51(4):804–820, 2011.

Yu Xiao and Uttara Nilawar. Winners and losers: analysing post-disaster spatial economic demand shift. *Disasters*, 37(4):646–668, 2013.

Eiji Yamamura. Natural disasters and social capital formation: The impact of the g reat h anshin-a waji earthquake. *Papers in Regional Science*, 95:S143–S164, 2016.

Seong Yun and Brigitte S Waldorf. The day after the disaster: forced migration and income loss after hurricanes katrina and rita. *Journal of Regional Science*, 56(3):420–441, 2016.

Sammy Zahran, Lori Peek, Jeffrey G Snodgrass, Stephan Weiler, and Lynn Hempel. Economics of disaster risk, social vulnerability, and mental health resilience. *Risk analysis*, 31(7):1107–1119, 2011.

Appendix A

Table A.1: Control counties and corresponding weights for Jefferson, Orleans, Plaquemines, and St. Bernard Parish

Jefferson., LA		Orleans, LA		Plaquemines, LA		St. Bernard, LA	
Controls	Weights	Controls	Weights	Controls	Weights	Controls	Weights
Jefferson, AL	52.8%	Jefferson, AL	0%	Colusa, CA	51.5%	Spalding, GA	14%
Pulaski, AR	0%	Montgomery, AL	4.1%	Glenn, CA	0%	Walker, GA	18.4%
Bibb, GA	3.1%	Bibb, GA	0%	Logan, CO	0%	Jersey, IL	0%
Muscogee, GA	0%	Dougherty, GA	0%	Baldwin, GA	0%	Kankakee, IL	7.1%
Madison, IL	0%	Muscogee, GA	0%	Floyd, GA	0%	Clark, IN	0%
Peoria, IL	0%	Richmond, GA	0%	Spalding, GA	0%	Clay, IN	0%
St. Clair, IL	5.2%	Coles, IL	0%	Troup, GA	0%	Decatur, IN	0%
Lake, IN	0%	Delaware, IN	0%	Kosciusko, IN	0%	Gibson, IN	0%
Marion, IN	0.1%	Marion, IN	17.2%	Marshall, IN	0%	Jackson, IN	0%
St. Joseph, IN	0%	Vigo, IN	0%	Ripley, IN	0%	Ripley, IN	0%
Vanderburgh, IN	0%	Lyon, KS	0%	Whitley, IN	0%	Scott, IN	0%
Black Hawk, IA	0%	Jefferson, KY	9.3%	Allegan, MI	0%	Pottawattamie, IA	0%
Dubuque, IA	0%	Caddo, LA	0%	Branch, MI	0%	Henderson, KY	0%
Scott, IA	0%	Jackson, MO	0%	Ionia, MI	0%	Simpson, KY	0%
Campbell, KY	0%	Cortland, NY	22.7%	Montcalm, MI	0%	Androscoggin, ME	35%
Jefferson, KY	0%	Lucas, OH	0%	Catawba, NC	0%	Muskegon, MI	0%
Kenton, KY	0%	Montgomery, OH	0%	Davidson, NC	0%	Perry, MO	0%
Hampden, MA	0%	Comanche, OK	0%	Nash, NC	0%	Dodge, NE	0%
Jackson, MO	0%	Custer, OK	19.5%	Vance, NC	0%	Hall, NE	0%
Livingston, NY	0.1%	Providence, RI	0%	Wayne, NC	0%	Caldwell, NC	0%
Madison, NY	22.2%	Taylor, TX	0%	Highland, OH	0%	Fayette, OH	0%
Rensselaer, NY	0%	Tom Green, TX	0%	Morrow, OH	0%	Muskingum, OH	0%
Lucas, OH	0%	Wichita, TX	0%	Umatilla, OR	0%	Preble, OH	0%
Stark, OH	0%	Newport News, VA	0%	Union, PA	0%	Ross, OH	0%
Summit, OH	0.1%	Norfolk, VA	27.2%	Anderson, SC	0%	Tuscarawas, OH	0%
Union, OR	16.5%	Portsmouth, VA	0%	Lancaster, SC	0%	Perry, PA	0%
Dauphin, PA	0%	Richmond, VA	0.1%	Spartanburg, SC	0%	Snyder, PA	25.5%
Erie, PA	0%	Roanoke, VA	0%	Hunt, TX	0%	Dyer, TN	0%
Providence, RI	0%	Cabell, WV	0%	Cowlitz, WA	0%	Monroe, WI	0%
Hamilton, TN	0%	Milwaukee, WI	0%	Chippewa, WI	48.5%	Taylor, WI	0%

Table A.2: Control counties and corresponding weights for St. Tammany Parish and Hancock, Harrison, and Jackson County.

St. Tammany, LA		Hancock, MS		Harrison, MS		Jackson, MS	
Controls	Weights	Controls	Weights	Controls	Weights	Controls	Weights
Maricopa, AZ	0%	Autauga, AL	0.4%	Craighead, AR	5.1%	Sebastian, AR	0%
Nassau, FL	0%	Elmore, AL	0%	Pueblo, CO	0%	Floyd, GA	0%
Santa Rosa, FL	0%	St. Clair, AL	0%	Duval, FL	0%	Spalding, GA	0%
Seminole, FL	0%	Montrose, CO	26.5%	Escambia, FL	0.3%	Kankakee, IL	14.6%
Columbia, GA	23.8%	Bay, FL	0.5%	Spalding, GA	0%	Clark, IN	11.3%
Ada, ID	0%	Polk, FL	6.3%	Clark, IN	0%	Elkhart, IN	15%
Boone, IN	0%	Habersham, GA	9.2%	Putnam, IN	0%	Putnam, IN	0%
Hancock, IN	0%	Morgan, GA	0%	Franklin, KS	0%	Ripley, IN	0%
Johnson, IN	0%	Oglethorpe, GA	0%	Clark, KY	0%	Pottawattamie, IA	0%
Jessamine, KY	16.7%	Bonner, ID	0.3%	Bossier, LA	0%	Franklin, KS	0%
Shelby, KY	0%	Mille Lacs, MN	0%	Lee, MS	0%	Clark, KY	0%
Cass, MO	0%	Broadwater, MT	0%	Jasper, MO	0%	Simpson, KY	0%
St. Charles, MO	0%	Flathead, MT	0%	Craven, NC	0%	Lee, MS	0%
Sarpy, NE	4.4%	Franklin, NC	0%	Rowan, NC	0%	Catawba, NC	0%
Washoe, NV	0%	Pender, NC	0%	Clinton, OH	0.4%	Craven, NC	0%
Cabarrus, NC	0%	Crook, OR	12.3%	Umatilla, OR	0%	Rowan, NC	0%
New Hanover, NC	11.1%	Jefferson, OR	1.4%	Berkeley, SC	0%	Wilson, NC	0%
Polk, OR	4.2%	Georgetown, SC	0%	Florence, SC	0%	Umatilla, OR	28%
Lexington, SC	0%	Blount, TN	0%	Pickens, SC	0%	Union, PA	12.2%
York, SC	0%	Cumberland, TN	0%	Spartanburg, SC	0%	Anderson, SC	0%
Wilson, TN	7.8%	Jefferson, TN	0%	Meade, SD	0%	Florence, SC	0%
Comal, TX	12.1%	Sevier, TN	19.3%	Pennington, SD	0%	Pickens, SC	0%
Parker, TX	0%	Austin, TX	0%	Bradley, TN	0%	Spartanburg, SC	0%
Greene, VA	0%	Blanco, TX	1.2%	Madison, TN	37.1%	Bradley, TN	0%
Chesapeake (), VA	19.9%	Henderson, TX	5.1%	Gregg, TX	0%	Madison, TN	7.8%
Benton, WA	0%	Medina, TX	17.1%	McLennan, TX	20.9%	Grayson, TX	0%
Clark, WA	0%	Franklin, VA	0%	Nueces, TX	13.7%	Nueces, TX	10.9%
Thurston, WA	0%	Louisa, VA	0%	Victoria, TX	0%	Victoria, TX	0%
Whatcom, WA	0%	Mason, WA	0.1%	Franklin, VT	0%	Franklin, VT	0.2%
St. Croix, WI	0%	Morgan, WV	0%	Spokane, WA	22.5%	Monroe, WI	0%