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What Happened to Louisiana? A Case Study on the Economic Growth Effects of Hurricane Katrina

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Abstract: This paper investigates the short-run and long-run effects of Hurricane Katrina on state-level economic growth in Louisiana. To provide explanatory value for any findings, the paper additionally includes an analysis of Katrina's effects on possible transmission channels to economic growth, including residential population, labour, and physical capital. Using the Synthetic Control Method, first developed by Abadie and Gardeazabal (2003), we conduct analyses by constructing a synthetic counterfactual to Louisiana which is then compared to the real state. In contrast to most other previous studies on the effects of natural disasters on economic growth, the results show that the short-run effects of Hurricane Katrina on state-level economic growth are significant and positive. The results also show that the long-run effects on economic growth are insignificantly different from the counterfactual outcome, indicating that Louisiana's economic growth in the long term is neither higher nor lower in comparison to absent the hurricane. In addition, compared to absent Katrina, the paper finds that the effects on the transmission channels to economic growth are a sustained decline in residential population, a decline in the unemployment rate during the years after Katrina, an unchanged employment-population ratio, and a capital accumulation in the years following the hurricane. These results provide explanatory value for Katrina's effects on economic growth as well as for what groups of people migrated: mostly those unemployed and those outside the civilian noninstitutional population.

Keywords: Hurricane Katrina, Natural disasters, Economic growth, Transmission channels, Labour

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Concepts and Definitions

DiD	=	Difference-in-Difference
SCM	=	Synthetic Control Method
MSPE	=	Mean Square Prediction Error
RMSPE	=	Root Mean Square Prediction Error
LA	=	Louisiana
SLA	=	Synthetic Louisiana
GDP	=	Gross Domestic Product
DPI	=	Disposable Personal Income
PCE	=	Personal Consumption Expenditures
TFP	=	Total Factor Productivity
mph	=	Miles Per Hour (1 mph $\approx$ 1.609 km/h)

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1 Introduction

"I am speaking to you from the city of New Orleans – nearly empty, still partly underwater, and waiting for life and hope to return. Eastward from Lake Pontchartrain, across the Mississippi coast, to Alabama and into Florida, millions of lives were changed in a day by a cruel and wasteful storm." (George W. Bush 2005)

Hurricane Katrina reached the United States on August 25, 2005, and subsequently came to be the largest natural disaster to hit the U.S. since the 1920s. Striking multiple states along the southeastern coast of the U.S., where the largest damages occurred in and around the city of New Orleans in Louisiana, Katrina killed more than 1800 people and left many regions nearly empty through out-migration.

The direct destruction attributed to Katrina was widely discussed by the media, governments, and the general public long after the immediate aftermath of the disaster, indicating that the destruction translated into substantial direct economic damages for the affected areas. Observing a declining economic growth in Louisiana following Katrina also give indications of support for the economy being adversely affected. *Figure 1* displays this trend of negative economic growth – a trend which exhibits its first two-year consecutive growth one decade after the disaster. Simply considering the real GDP per capita is, however, not enough to assess a potential causal effect of Katrina on economic growth, since it does not reveal what would have occurred in the absence of Katrina. Would there, for instance, have been a similar decline in economic growth? Has Katrina caused a long-term negative effect on economic growth that had not otherwise happened? Although these questions regarding the effects of Katrina are of interest to answer for policy applications in future instances of hurricane disasters, none of them have been pursued in previous research.

In this paper, we study the short-run and long-run effects of Hurricane Katrina on state-level economic growth in Louisiana. To potentially be able to derive explanatory value for any findings and get a better understanding of the observed effects, we additionally include an analysis of Katrina's effect on possible transmission channels to economic growth, including residential population, labour, and physical capital. Our paper hence aims to both gain better understanding of the short-run and long-run effects on growth following Hurricane Katrina and to contribute to the broader field of research on the economic impacts of natural disasters.

In contrast to most other previous studies on the effects of natural disasters on economic growth, we find no negative effect on short-run economic growth. Instead, our study shows a significant and positive short-run effect on economic growth. Furthermore, we find that the long-run effects are insignificantly different from the counterfactual outcome, indicating that Louisiana's economic growth in the long term is neither higher nor lower in comparison to absent the hurricane. Regarding the effect of Katrina on the transmission channels to economic growth, we, among others, find a substantial decline in the total population as a direct consequence of Hurricane Katrina that continue to be lower than the counterfactual state, had Katrina not occurred, throughout our sample period. Furthermore, our results show an increase in the unemployment rate the year of the disasters, followed by years with a lower unemployment rate than in the absence of Katrina. The employment-population ratio, however, stays as it would in the absence of Katrina. These results provide explanatory value for Katrina's effects on economic growth as well as for what groups of people migrated: mostly those unemployment and those outside the civilian noninstitutional population. Moreover, our study shows – however more ambiguous – a physical capital accumulation per capita during the aftermath of the disaster, and a return to the pre-disaster level in the long-run.

1.1 Research Purpose

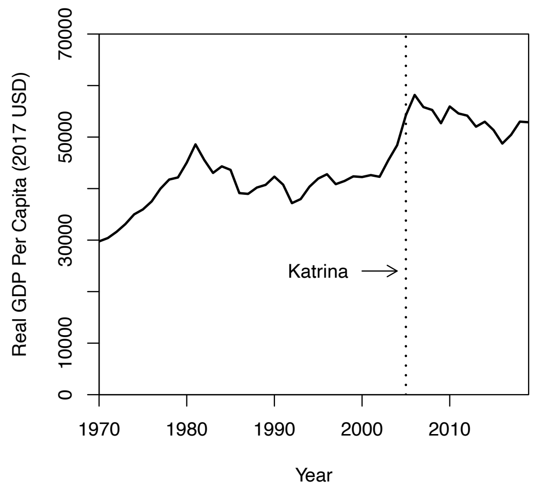


Figure 1: Real GDP Per Capita in Louisiana 1970-2019
Source: U.S. Bureau of Economic Analysis (2020)

The domain of research studying the effects of natural disasters on macroeconomic growth is a growing field in the economic literature, nevertheless, no study has Hurricane Katrina as the case setting. The present studies on other powerful natural disasters indicate a direct negative short-run effect on economic growth, which is generally attributed to destruction of capital (see, for instance, Noy 2009; Felbermayr and Gröschl 2014). However, ambiguity prevails about the long-run effects – the time extending beyond the immediate years following the disaster-year. While traditional neoclassical growth models predict that economies will return to their steady-state in the long run after a systemic shock, some endogenous growth models predict a long-run negative effects and others a long-run positive effects, where the latter one is predicted by Schumpeter's creative destruction process (Schumpeter 1942). Empirically, the current literature provides competing evidence that suggest that natural disasters on economic growth give negative long-run effects (see, e.g., Best and Burke 2019) positive long-run effects (see, for instance, Skidmore and Toya 2002; Berlemann and Wentzel 2016), and recovery to pre-disaster path (see, for example, Klomp and Valckx 2014; Cavallo and Noy 2013).

Given the prevailing ambiguity of long-term effects of natural disasters, the most recent review of the literature in the field, performed by Botzen, Deschenes and Sanders (2019), suggests more research on the effect on economic growth of natural disasters. More specifically, the authors recommend, firstly, more research to examine the long-run effects and, secondly, more research to conduct empirical case studies to better understand the causal mechanisms of transmission channels through which natural disasters affect economies. A more comprehensive understanding of economic impacts of natural disasters is of significance to better implement effective policy responses and institutional arrangements to mitigate damages, support communities and cope with destruction in aftermaths (Loayza et al. 2012; Kousky 2019; Kellenberg and Mushfiq Mobarak 2011). Furthermore, since climate models predict that natural disasters may increase both in frequency and intensity with climate change (see, for instance, Rummukainen 2012; Herring et al. 2018; Nordhaus 2010), understanding the economic consequences is topical.[1]

Following these suggestions, as well as interest in the case of Katrina, our paper sets out to study the short-run and long-run effects of Hurricane Katrina on state-level economic growth in Louisiana – a major natural disaster that has yet not been examined in a macroeconomic context.[2] Additionally, as further suggested, we perform analyses of potential transmission channels to economic growth, as to give explanatory value of any effects found, including residential population, labour, and physical capital. The aim of our study is hence to gain a better understanding of the short-run and long-run economic growth effects of the specific case of Hurricane Katrina, as well as to contribute to the broader understanding of long-term effects of catastrophic natural disasters. Since the short-run effect has a more extensive evidence in previous literature, our study on the short-run effect is primary studied due to it being linked to the long-run effect as well as understanding if we also in the context of Katrina can support the results of previous studies.

For our study, we take advantage of the relatively new statistical model for deriving causal effects in comparative case studies: the Synthetic Control Method (SCM) (Abadie and Gardeazabal 2003; Abadie, Diamond and Hainmueller 2010, 2015). The SCM provides an approach to find potential causal effects of Katrina on economic growth, answering the question of what would have occurred with the state-level economic output in the absence of Katrina. By utilising U.S. state-level panel data, the idea of SCM in our study is to artificially construct an appropriate counterfactual state of Louisiana using one or several other unaffected states such that a synthetic Louisiana is created exhibiting no effects of Hurricane Katrina. The counterfactual state hence represents a synthetic Louisiana consisting of a weighted combination of U.S. states not affected by Katrina, but that prior to the disaster resembles Louisiana both in path and levels on a set of key predictors to GDP per capita. By comparing the path in GDP per capita in Louisiana with its synthetic counterpart, we are able to assess the effect on economic growth in the post-disaster period.

The remained of this paper is organised as follows. Section 2 provide a background overview of Hurricane Katrina and historical economic growth in Louisiana. Section 3 then provide a review of current findings concerning the relationship between natural disasters and economic growth. Section 4 outlays our research question, hypotheses and contributions to previous literature. Section 5 presents the empirical methodology that we utilise, including model assumptions for SCM. Section 6 presents the data that we use and some of its limitations. Section 7 displays our results divided into four parts: (i) the result of constructing the synthetic Louisiana, (ii) the effects on real GDP per capita in Louisiana, (iii) the effects on transmission channels, and (iv) placebo-tests and robustness-tests. Section 8 then discusses the results by comparing our findings to previous findings as well as discusses implications. Finally, Section 9 provides concluding remarks.

[1] Review Appendix A for a short review of the relationship between climate change and natural disasters.

[2] Independently for our study, Yun and Kim (2021) conduced a similar investigation on Hurricane Katrina and its effect on the economy of Louisiana, using the same model and examining the same economic growth variable. This study was published on March 16 – one and a half following the literature conducted for this study, and half a month following this study's results were concluded. The authors of this paper found the study by Yum and Kim (2021) in May. Given the independence of this study and the study of Yun and Kim (2021), the latter is not included in our study.

2 Background

To examine the economic impacts of Hurricane Katrina, it is first necessary to have an understanding both the hurricane itself and the state we study, Louisiana. Thereby, we first present a background on the Hurricane Katrina and, second, an overview of the economic growth of Louisiana.

2.1 Hurricane Katrina and the 2005 Atlantic Hurricane Season

Between June and November each year, the Atlantic Hurricane Season take place – a period during which hurricanes often form over the Atlantic Ocean. During 2005, 28 storms developed, making it the Atlantic Hurricane Season with the highest number of storms in history, second only to that of 2020.[3] Of the storms that formed, Hurricane Katrina was the twelfth tropical cyclone, the fifth hurricane and the third major hurricane of the 2005 hurricane season.[4] At the time, Katrina became the costliest storm to ever struck the U.S., as well as the deadliest natural disaster in the country since 1928 with an official death toll of 1,833 people.

Katrina first formed as a tropical depression on August 23. The following day, the tropical depression had intensified and reached tropical storm status. On August 25, the storm reached Category 1 hurricane status – the first of five categories for hurricanes – less than two hours after its centre had made landfall on the southeast coast of Florida, resulting in a few fatalities. [5] As it moved over the Florida peninsula, Katrina weakened to a tropical storm before quickly gaining wind speed as it reached the Gulf of Mexico. Katrina then went through two rapid intensification periods and reached Category 5 hurricane status on August 28. While approaching Louisiana, Katrina lost wind speed quickly and struck Louisiana and Mississippi as a Category 3 and Category 1 respectively, before losing its hurricane status and continued as a tropical storm in over Tennessee.[6]

The most severely affected region was the state of Louisiana, and especially the city of New Orleans. Given New Orleans being situated largely below sea level and a breach in the levees would cause massive flooding, the residents in the city had long known that a direct hit on the city could cause catastrophic results. Three days before the storm reached the city, officials of Louisiana declared a state of emergency. The next morning, New Orleans' first ever mandatory evacuating order was declared, however, nearly 100,000 residents stayed in the city. Subsequent to Katrina hitting New Orleans as a Category 3, 80% of the city was under water and major physical damage had occurred. The storm caused a large fraction of buildings and other infrastructure to become complete destroyed, causing in total $161 billion (2017 USD) in direct damages. Furthermore, hundreds of thousands of residents were displaced, many times permanently (Knabb, Rhome, and Brown 2011). The year following the event, the number of residents in Louisiana had decreased by

[3]Hurricanes are the name to the North Atlantic versions of the storms known as "tropical cyclones". Tropical cyclones with maximum sustained winds of less than 39 miles per hour (mps) are called tropical depressions, and those with maximum sustained winds of 39 mps or higher are called tropical storms. When a storms maximum sustain winds reach 74 mps, it is called a hurricane.

[4]Basic facts about Katrina, if not other cited, are through publications of the National Oceanic and Atmospheric Administration (Knabb, Rhome, and Brown 2011; NOAA National Hurricane Center; NOAA National Centers for Environemntal Information).

[5]Storms are categorised by U.S. 1-minute average maximum sustained wind speed. For Tropical Cyclones, Tropical Depressions (38 mph) cause almost no damages, and Tropical Storms (39-73 mph) cause minor damages. Hurricane winds follow the Saffir-Simpson Hurricane Wind Scale, where Category 1 (74-95 mph) cause some damages, Category 2 (96-110 mph) causes extensive damages, Category 3 (111-129 mph) causes devastating damages, Category 4 (130-156 mph) causes catastrophic damages, and Category 5 (>156 mph) causes catastrophic damages.

[6]View Appendix B for the best track position of Hurricane Katrina.

nearly 274 thousand people, equivalent to a fall of almost 6% of the total state population, who migrated to mostly nearby lying states, including Texas, Arkansas, Tennessee, and Alabama (U.S. Census Bureau 2007) The aid would be larger if including the areas outside New Orleans and of Hurricane Katrina (Hoople 2013).

The aid responses to Katrina were massive. Previous research estimate that there were roughly $50 billion USD in infrastructure reconstruction aids and insurance payments directed to New Orleans – roughly $100,000 USD per capita in pre-disaster residential population numbers (Deryugina, Kawano, and Levitt 2018).[7]

The hurricane season then continued with Hurricane Rita and Hurricane Wilma – both at their peak Category 5 hurricanes – that, like Katrina, made landfalls as Category 3 hurricanes, but caused less extensive storm surges. Rita made landfall on the southwesternmost coast of Louisiana (Knabb, Brown, and Rhome 2011), meanwhile hurricane Wilma struck southern Florida and became the most costly hurricane in recent history second only to Katrina (Pasch et al. 2014).

2.2 Historical Overview of GDP per capita in Louisiana

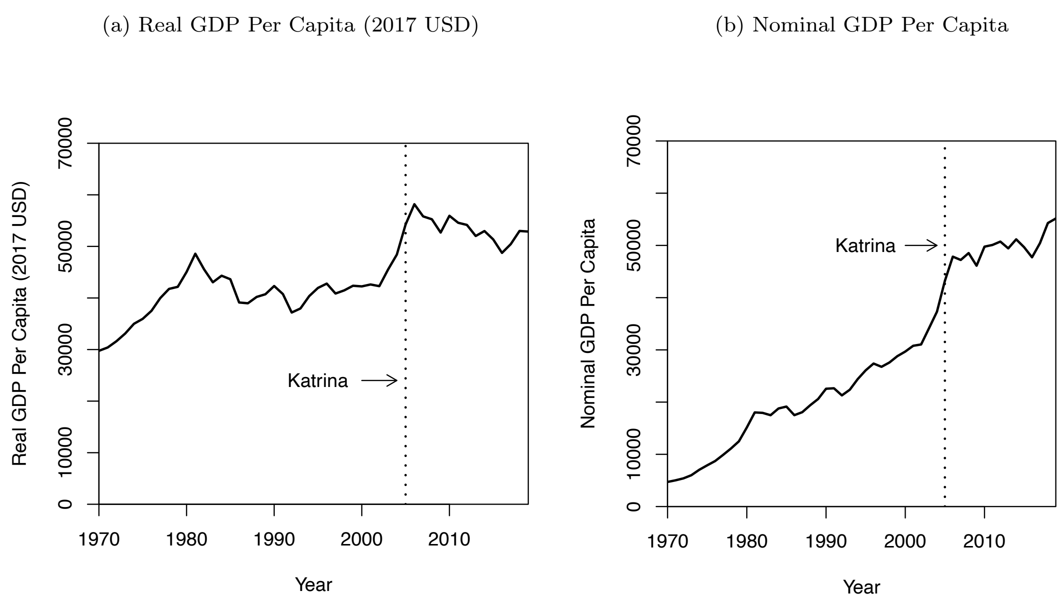


Figure 2: Real and Nominal GDP Per Capita in Louisiana 1970-2019
Source: U.S. Bureau of Economic Analysis (2020)

The case setting for our study on the effect on economic growth of Katrina is Louisiana. Therefore, we proceed with some remarks of the historical development of economic growth in the state, using real GDP per capita as a measurement for economic growth.[8]

[7] The aid would be larger if including the areas outside New Orleans, and aid towards the other hurricanes of the season 2005 (Hoople 2013).

[8] Since GDP per capita is the most used one-variable measure that can catch the potential macroeconomic effect of

Historically, Louisiana's economy has been highly dependent on the oil industry, including the oil and gas extraction industry as well as the petroleum manufacturing and refining industry. Between 1963 and 2019, the industry annually constituted a share of between 13%-39% of the state's total GDP (U.S. Bureau of Economic Analysis 2020), which has caused Louisiana's economic growth to be contingent on the crude oil prices. The uncommon negative growth trend of real GDP per capita that is visible between roughly 1982 and 1992 in Louisiana is a result of the highly variable price shocks that the oil industry is subject to (Jacks, O'Rouke, and Williamson 2011). By viewing the real WTI crude oil price trend during 1963-2019, similarities in growth trends can be observed in that of real GDP per capita.

GDP in Louisiana is also affected adversely following the financial crisis of 2008, which is visible in a negative growth in GDP during 2009 (U.S. Bureau of Economic Analysis 2020). During 2010, Louisiana's economy had more than recovered in GDP terms from the decline in the prior year. Compared to other U.S. states, the trend in output in Louisiana, however, is not uncommon during this same period, indicating that the financial crisis likely did not have an unusual impact on Louisiana compared to other states (U.S. Bureau of Economic Analysis 2020).

3 Literature Review

Natural disasters, such as Hurricane Katrina, are powerful events likely to give rise to economic consequences in affected regions. The phenomena of natural disasters have drawn a great deal of interest and researchers have been conducting various studies on the macroeconomic effects of natural disasters. In this section, we present the relevant literature on the economic aspect of natural disasters, intending to investigate the potential gap in the current state of knowledge.

There are two major strands of empirical literature when it comes to the economic aspects of natural disasters.

The first strand analyses the factors mitigating the effect of natural disasters. These studies attempt to identify individual or aggregate factors and actions that can mitigate the detrimental effects of natural disasters, both pre-disasters (such as insurance, public defensive investments, investments into infrastructure, and public information) and post-disaster (such as direct disaster relief aid and public information). Some papers in this field analyse which economy suffer less or more of natural disasters by running cross-country regressions. Noy (2009) finds that countries with higher literacy rates, better institutions, and a higher degree of trade openness suffer less from natural disaster losses. Similarly, Kahn (2005) shows that higher-income countries experience lower fatalities and smaller economic growth impact. Hoeppe (2016), however, adds by showing how these countries suffer from higher direct property losses. Furthermore, to mitigate the effects of natural disasters, governments should, for instance, have higher institutional quality (Kellenberg and Mushfiq Mobarak 2011) and invest in upgraded technology (Hallegatte 2009).

The second strand of the empirical evidence – more related to our study – investigates the economic effects of natural disasters. These studies tend to differ between the direct- and indirect effects of natural disasters, or between the short-run and long-run effects, or a combination of both distinctions. We proceed with the distinction of short-run and long-run in the literature review, but consider both direct and indirect effects. The early papers in the field many used cross-country regressions (see, for instance, Skidmore and Toya 2002), however, more recent literature also includes

a natural disaster and allow for comparison with other affected and non-affected regions, it is of interest to understand the most influential factors affecting Louisiana's.

specific case studies (see, for example, DuPont and Noy 2015; Best and Burke 2019).

As the purpose of our study is to investigate the economic impact of natural disasters, we mainly consider the second strand of literature. However, to understand our result in a wider context and to give possible remarks on policy implications, the first strand of literature is also important to recognise.

This section proceeds as follows. First, we elaborate on two basic growth models. Second, we summarise the findings from previous case studies on the economic effects of natural disasters. Third and fourth, we provide more general studies on natural disasters effects on economic growth and presenting the current state of knowledge. Fifth, we further elaborate on studies on transmission channels to economic growth. Last, we summarise previous studies on the effects of Hurricane Katrina on different aspects of the economy and society.

3.1 Two Economic Growth Models

Economists have, in some sense, always known that economic growth is important. A basic definition of economic growth is the growth in standard of living that occurs over substantial periods of times (Jones 2018). To understand how natural disasters affect economic growth, we start by introducing two basic growth models used in this paper. First, the Cobb-Douglas production function provides an analytical useful overview of routes to increased and decreased economic growth. Second, the Solow-Swan Model incorporates a greater focus on capital accumulation.

3.1.1 Cobb-Douglas Production Function

The Cobb-Douglas production function is a basic exogenous growth model indicating different routes to economic growth. Consider the Cobb-Douglas production function

$$Y = F(K, L) = \overline{A}K^{\sigma}L^{1-\sigma},$$

where Y denotes the total output, L the input of labour, K the input of capital, and $\overline{A}$ the Total Factor Productivity (TFP), defined as the efficiency with which inputs are transformed into output (Jones 2018).[9] σ is the capital input contribution to L, and thus the $1-\sigma$ the input contribution to labour. To make comparisons across time and units more plausible, the model can be transformed to show output per capita as

$$y = \frac{Y}{L} = \frac{\overline{A}K^{\sigma}L^{1-\sigma}}{L}.$$

Although simplified, the Cobb-Douglas production function yields three routes to increased or decreased economic growth. Similarly, the model suggests that it is through these routes the economy is affected after a natural disaster. Firstly, a negative effect on employment in the post-disaster period translates into a lower economic growth. Secondly, while the destruction of capital would translate into a lower growth rate, investments in capital in the post-disaster period increases economic growth. The effect on economic growth from capital therefore depends on the net effect of destruction and investments in capital. Thirdly, increasing productivity measured by TFP also yield a higher growth. For example, if the natural disaster destroys technology used in production, negatively affects education, or cause the state to invest less in research and development post the disaster, the GDP growth would decline.

[9]For example, differences in human capital, technology, institutions, and misallocations all affect the TFP (Jones 2018).

3.1.2 The Solow-Swan Model

The Solow-Swan model builds on the Cobb-Douglas function but adds one element: a theory of capital accumulation. The idea is that instead of the capital being given at some exogenous level, agents can accumulate tools, machines, computers, buildings, and similar, over time, thus making the accumulation of capital endogenised in the model. This makes it possible to see the accumulation of capital as a source of economic growth. The Solow-Model can be summarised as

$$Y_t = \overline{A} K_t^{\frac{1}{3}} L_t^{\frac{2}{3}},$$

and in per capita terms as

$$y_t = \frac{Y_t}{L_t} = \frac{\overline{A} K_t^{\frac{1}{3}} L_t^{\frac{2}{3}}}{L_t},$$

where t indicates that the model is dynamic.[10] It should be noted that the Solow-Swan Model do not recognise long-run economic growth. Instead, in the long-term, the model assumes the economy will settle at a steady state as the amount of investment in capital in any given period will become equal to the amount of capital that depreciates in that same period.[11]

3.2 Case Studies on Economic Growth

In previous literature, there are a handful of case studies on the effect on both short-run and long-run growth after natural disasters. Before presenting more general findings and the current aggregated state of knowledge, we start by introducing a selection of these studies.

DuPont and Noy (2015) revisit a study of the economic effect of the Kobe earthquake in Japan. Using a Synthetic Control Method and data on prefecture-level, they aim to estimate the long-run effect on economic growth in the prefecture where Kobe is situated.[12] In the short run, they find that the GDP per capita rose above that of the counterfactual region immediately after the disaster. They remark that the positive effect could be due to population movements as well as fiscal stimulus for reconstruction. In the long run, they find a negative impact with a reduction in GDP per capita of 12%. Furthermore, DuPont and Noy (2015) study the outcome of population, local government expenditures, and migration both out and into the prefecture. They observe a large out-migration after the disaster and a decline in the in-migration, but find that the population recovers to trend within five years. They also find that although the fiscal stimulus to the prefecture of Kobe was large, it did not necessarily that it helped the region back to its pre-disaster potential.

In another similar study, Best and Burke (2019) use the Synthetic Control Method to estimate the macroeconomic losses from the 2010 earthquake in Haiti. Averaging the effect between 2010

[10] As in the Cobb-Douglas production function, Y denotes the total output, L the input of labour, K the input of capital, and $\overline{A}$ the Total Factor Productivity (TFP).

[11] In an instance of a shock that, ceteris paribus, destroys capital or increases the number of workers, each worker will be able to work with less capital – the capital-worker ratio decreases – leading to a lower output. Due to less capital depreciating, investments will exceed depreciating capital, whereby capital-worker ratio will grow until pre-disaster levels are reached and output returns to its steady state. If TFP increases, each worker will be able to utilise the same amount of capital better and will hence produce a higher output. If there is an increase (decrease) in population growth rate, technology growth rate, or capital depreciation rate, the steady state will move such that output decreases (increases), ceteris paribus. Contrarily, an increase (decrease) in savings rate will cause the steady state to move such that output increases (decreases), ceteris paribus.

[12] Japan consists of 47 prefectures, where Kobe is the capital city of Hyōgo prefecture.

and 2015, they find macroeconomic losses in GDP of 12%. More specifically, they observe that the output losses from the earthquake continue to accumulate over time. The authors also study the effect on various sectors. Their result shows large contractions in investment and service sector and large negative effect on the road transport. They also find a temporal increase in aggregate consumption, which they discuss being due to large imports and foreign aid.

Barone and Mocetti (2014) examine the impact of two large-scale earthquakes in Italian regions from 1976 to 1980. To find the causal effect, they use a Difference-in-Difference method. Unlike the findings of DuPont and Noy (2015), as well as Best and Burke (2019), they find a negligible short-term effect, which however becomes negative if GDP is simulated in the absence of financial aid. In the long run, their study shows a positive effect for one of the disasters and a negative for the other.

Lastly, Coffman and Noy (2012) use the Synthetic Control Method to estimate the long-term impacts of the 1992 Hurricane Iniki on the Hawaiian Island Kauai. Instead of studying the effects on GDP per capita, they have income per capita as their main variable of interest. Also, they examine the effect on total private sector employment, residential population, personal income, transfer of payments, and number of hotel accommodations. By constructing a synthetic counterpart to Kauai, consisting of other Hawaiian Islands, they observe a decline in total sector employment, population, and personal income – all taking a long time to recover. More specifically, the population and employment took 6 and 13 years, respectively, to recover to the pre-disaster trend. Furthermore, they do not estimate any significant effect on real per capita income.

The case studies presented here provides different results on both the short-run and long-run effects of natural disaster on economic growth. While the study of DuPont and Noy (2015) find a positive short-run effect on economic growth, Best and Burke (2019) find a negative effect, and Barone and Mocetti (2014) a similar negative effect when controlling for aid. In the long run, the two first studies both show a negative effect larger than 10% of GDP per capita, while Barone and Mocetti (2014) cannot find any significant results. Coffman and Noy (2012) do not study GDP per capita but find interesting implications for other macroeconomic measurements.

3.3 Short-Run Effects on Economic Growth

Case studies, such as those presented in the previous section, are situational and, therefore, generally have a lower external validity and generalisability than for other studies (Bryman 2014). As the setting of Katrina and Louisiana is different from the natural disasters presented in the case studies, we continue with a broader search of the economic effects of natural disasters, also including cross-country studies that normally have higher level of external validity. We proceed by presenting studies on the short-run effect of natural disasters on economic growth before presenting the studies on the long-run effect.

In a comprehensive analysis of the short-run effects of natural disasters, Felbermayr and Gröschl (2014) use a sample of natural disasters between 1979 and 2010 in over 100 countries. The authors find that the immediate effect on GDP per capita is negative and robust. Since their empirical finding is in line with their theoretical prediction – that the destruction of capital caused the production function to shift inward, thus leading to a lower output per capita – Felbermayr and Gröschl (2014) conclude that the effect on short-run economic growth is "naturally negative". Similarly, Noy (2009) finds a significant negative impact on GDP per capita in his influential paper, when examining the short-run impact of 507 disasters between 1970 and 2003.

Noy (2009) also concludes that the significance of effects differ between countries based on their level of development and size. On average, the larger and the more developed the country is, the less significant the effect is. Previous literature also shows that the effect on economic growth varies between different disaster types. Raddatz (2009) finds that the economic significance of the negative effect on short-run economic growth is largest for droughts, with cumulative losses of 1% of GDP per capita in the short-run. For windstorms, including hurricanes, Raddatz (2009) estimates a significant negative effect for small states but not for large states. Both the studies of Noy (2009) and Raddatz (2009) therefore observe larger effects for smaller states. An explanation is, as argued by Horwich (2000), that natural disasters are almost always localised events, and may therefore only affect a limited part of the whole economy.

To summarise, the previous literature presented here on the short-run effect on economic growth suggests a negative direct effect on short-run growth, however, that the significance of the effects differ between regions and natural disaster types.

3.4 Long-Run Effects on Economic Growth

The effects of natural disasters on the economic growth in the period following the short-run time scope – that is, the long-run effects – is an inconclusive but growing area of research, both theoretically and empirically (Botzen, Deschenes, and Sanders 2019; Noy and DuPont 2016).[13] Skidmore and Toya (2002) published one of the first comprehensive study on the long-run effects, writing: "because the disaster risk differs substantially from country to country, it is reasonable to question whether there exists some relationship between disasters and long-run macroeconomic activity". Since then, the different papers support five hypotheses on the long-run effects of natural disasters on economic growth, visualised in *Figure 3*. So far, none of the five competing hypotheses have been rejected, making all hypotheses plausible for the case of Hurricane Katrina. Some discuss the reason for the different exisiting hypothesis to be that the long-run effect is situational and therefore varies time to time (Skidmore and Toya 2002), others remark the difficulty with the identification of the economic impact to be the reason (Noy 2009). The literature further makes use of various methods in attempts to identify the economic impact. Earlier papers mainly used large-scale regressions studies. In these papers, developing countries were overall overrepresented, and factors affecting growth – such as institutions and level of development – was not controlled for. The most recent papers also uses various regressions – however, often with better controls for additional factors that might influence – or take the form as comparative case studies, utilising for example DiD or SCM.

We present these five hypotheses as well as their theoretical and empirical support, mainly focusing on presenting literature studying natural disaster with similar settings to Hurricane Katrina in Louisiana. The hypotheses are listed by amount of support.

[13] Most papers refer to the long-run after the time following the short-run time scope. However, when running empirical tests, the papers tend to study the long-run as the whole post-disaster period.

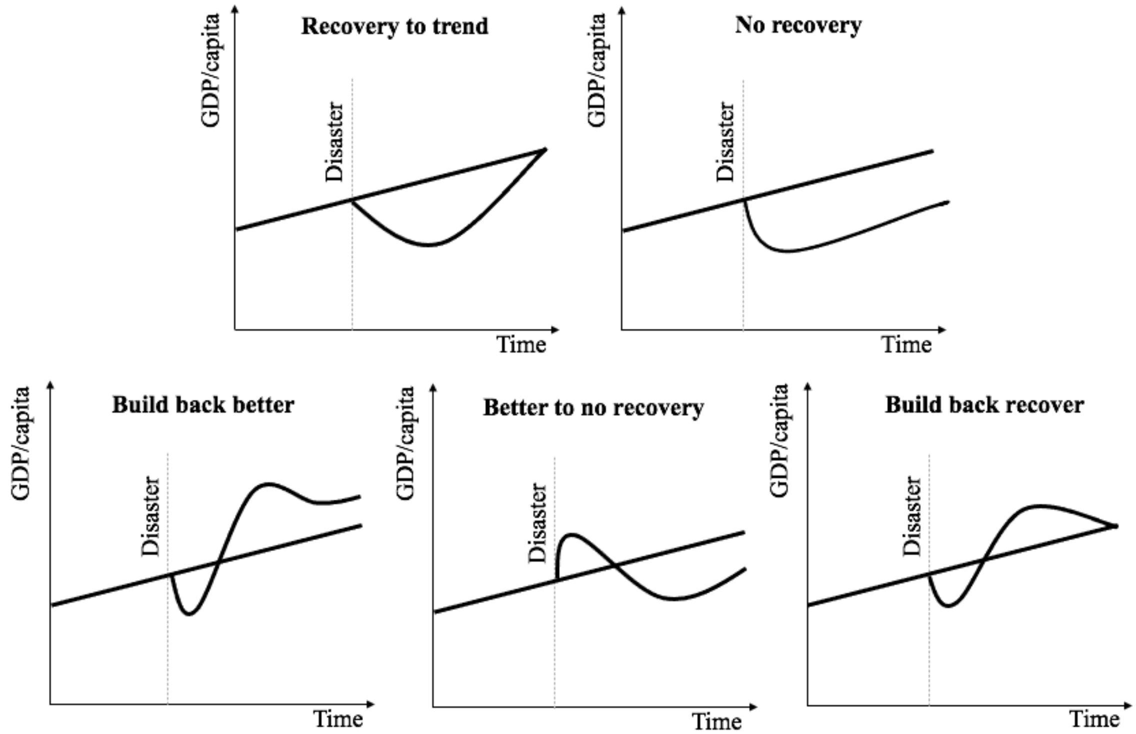


Figure 3: Five Hypotheses from Previous Literature on the Long-Run Economic Growth Effect of Natural Disasters
Source: Compiled by the authors

A: Recovery to Trend hypothesis suggests that the effects on economic growth of natural disasters are temporal and not sustained: after a negative short-run effect, the economy recovers to its long-run growth path (Hsiang and Jina 2014). The Solow-Swan model indicate support for this hypothesis if, for instance, ceteris paribus, there is a decrease in the capital-worker ratio – where, e.g., there is a substantial reduction in capital and a small reduction in population. This would temporarily reduce the output but make the economy recover to its steady state in the long run. In the empirical literature, the "recovery to trend" hypothesis has strong support. Klomp and Valckx (2014) conducts a meta-analysis on 25 primary studies on the indirect economic effects of natural disasters and conclude that economies return to their original growth path in the long-run, after a short-run direct negative impact. Furthermore, Cavallo and Noy (2013) use an aggregated model using SCM to study large natural disasters, finding no long-run effect on economic growth.

B: No Recovery Hypothesis argues that economies do not recover after the short-run negative effect on economic growth. This leaves the economy in a permanent and lower level of output, compared to the pre-disaster level. The Cobb-Douglas production function supports the hypothesis of no recovery if the recovery mechanisms of capital, labour and productivity fail to outweigh the direct destruction. As the number of case studies addressing the long-term effect of natural disasters are increasing, the support for the hypothesis has also increased. One explanation is that larger cross-country studies tend to face upward bias, given their main focus on developed countries and the selection bias of events. The studies presented earlier by Best and Burke (2019) and Barone and Mocetti (2014) both support the hypothesis of no recovery.

C: Build Back Better Hypothesis suggests that a short-run decline in growth is followed by a temporal stimulation of growth, leading to a new higher level of sustained growth. The hypothesis is closely related to the idea of Creative Destruction by Schumpeter (1942); a theory that the productivity increases in the post-disaster period of arrangements since it frees up resources and energy that can be deployed for more innovation. We find two empirical studies supporting the hypothesis of "build back better". First, Skidmore and Toya (2002) find a higher post-disaster growth arguing to be driven by upgraded capital. Second, Berlemann, and Wentzel (2016) find drought has a positive long-term effect on growth in high-income countries. High income countries have better infrastructure than low-income countries and, therefore, all else equal, face less damages. Furthermore, high-income countries have more possibilities for investments after disasters.

D: Better No Recovery Hypothesis propose that a short-term positive growth effect is followed by a long-run trend with no recovery, leaving the economy on a lower output level. The Solow-Swan model support this hypothesis if, ceteris paribus, there is a substantial increase in the capital-worker ratio, and either a lower savings rate, higher capital depreciation rate, higher technology growth rate, or a higher population growth rate – or a combination. The substantial increase in capital-worker ratio would initially increase output, but, e.g., a lower savings rate would cause the steady state to move towards a lower output. In our literature review, only one study supports this hypothesis, which is the case study by DuPont and Noy (2015).

E: Build Back Recover Hypothesis propose a negative short-run effect is followed by temporal higher growth levels than in the absence of a natural disaster, before both the output level and the growth level returns to pre-disaster levels. Hsiang and Jina (2014) hypothesise that aid following disasters leads to a temporary stimulation of growth before the economy falls back to its initial growth path as aid inflows stop. The Solow-Swan model support this hypothesis if, ceteris paribus, there is a direct decrease in capital-worker ratio in an economy immediately after a disaster, and if large investments from outside sources – such as aid – are made shortly after that cause a positive shock in capita-worker ratio. Along with the following "better to no recovery" hypothesis, the evidence for this hypothesis is weakest.

To summarise, there are competing hypothesis for the long-run effect of natural disasters on economic growth. Regarding the case of Hurricane Katrina, it is not obvious which of these hypotheses that would best explain the macroeconomic effects.

3.5 Transmission Channels

One might think of a multitude of relevant channels through which natural disasters affect economic growth, however, not many previous studies on economic growth has examined transmission channels as a part of their study (Botzen, Deschenes, and Sanders 2019). According to our knowledge, one of the only papers considering effects on transmission channels to economic growth after natural disasters are by Berlemann and Wentzel (2018). In this section, we present theoretical and empirical findings on how potential routes to economic growth are affected by natural disasters. We start with the channels from the Cobb-Douglas production function, but also consider the population variable from Berlemann and Wentzel (2018).

Labour: The effect of hurricanes on labour markets is not obvious (Belasen and Polachek 2008). Most of the present literature on the effects of disasters on labour markets support a negative effect on unemployment rate (see, e.g., Belasen and Polacheck 2008), a negative effect on employment (see, for example, Belasen and Polachek 2008; Lee 2020) as well as a negative effect on labour force participation rate (Lee 2020). However, there are some studies that stand out, such as that conducted by Kirchberger (2017) who does not find any significant effect on the unemployment rate.

Physical Capital: Destruction of physical capital is commonly associated with impacts of natural disasters (see, e.g., Crespo Cuaresma, Hlouskova, and Obersteiner 2008; Pelli and Tschopp 2017). Recovery of the physical capital depends on how developed the country is as well as how much they invest in research and development.

Total Factor Productivity (TFP): Empirically, it has been shown that negative shocks to an economy – that cause reduction in economic output – are associated with increases in TFP, either immediately following a shock or in the medium term (Mayer, Rüth, and Scharler 2016). The only exceptions to this is reductions in government spending and adverse technology shocks that lower TFP (Mayer, Rüth, and Scharler 2016). Skidmore and Toya (2002) additionally finds that climatic disasters are positively correlated with growth in TFP, while geological disasters are negatively correlated with growth in TFP. Furthermore, negative shocks to the economy potentially only cause transitory effects on TFP, while positive shocks have more permanent effects (Arbex, Caetano, and Souza 2018).

Population: The observed effects of shocks on population are several. Meanwhile Berlemann and Wenzel (2018) find that disasters have significant negative effects on net fertility in developed countries and stable or slightly increasing fertility rate in developing countries, Nobles, Frankenberg and Thomas (2015), as well as Skidmore and Toya (2002), find an increase in fertility following natural disasters. Another phenomenon is population movement following disasters. DuPont and Noy (2015) find that population decline due to out-migration is the main reason for effects on GDP per capita. Berlemann and Wenzel (2018) adds that the decreasing population in regional disaster-affected areas following hurricanes might explain slightly positive growth effects in highly developed countries.

3.6 Case Studies on Hurricane Katrina

To date, there is no study analysing in more detail the impact on economic growth caused by Hurricane Katrina. Some existing studies, however, examine the direct and indirect effect of the hurricane on delimited aspects of the regional economies in disaster-affected areas or near disaster-affected areas. Here we present the existing literature on the effects on labour markets, as well as studies on population change of natural disasters. There are also several studies on the physiological impact of the residents in the affected areas as well as the impacts on corporate finances and household finances, which we both exclude from the review since they are outside our scope.[14]

In a comprehensive analysis of Hurricane Katrina's long-term economic impact on its victims, Deryugina, Kawano, and Levitt (2018) use a panel of tax return data and find that the hurricane has a significant effect on the labour market outcome in New Orleans. More specifically, they find that the unemployment rate increased first in the short-term before starting to recover quickly afterwards. During 2006 and 2007, the victims of Katrina were 4.2 and 2.1 percentage points more likely to have no labour income than the ones in the control groups, respectively. In 2009, the difference

[14]For example, Gallagher and Hartler (2017) investigate the impact of Katrina on household finance. Their main finding is that Katrina led to a larger and immediate reduction in debt for the residents living in the most flooded blocks, as well as that people on average increased their short-term debt and received worse credit scores. The paper thus highlights the role of capital investment. Another example of a study is Massa and Zhang (2020) who show that Katrina induced firms to shift from bond financing to bank-based borrowing and to shorten the debt maturity.

is insignificant. Similarly, Vigdor (2008) examines the effect on labour market measurements, including labour force participation rate, unemployment rate, employment per sector, as well as population. The study shows a short-run increase in New Orleans' unemployment rate, but no significant effects in other cities affected. Furthermore, the author finds that the largest proportional reduction in employment occurred in service-related industries (Vigdor 2008). On a similar topic, McIntosh (2008) finds that Katrina has an adverse effect on wages and employment in Houston – a city where a large portion of Katrina evacuees in-migrated – indicating that labour markets soften in regions where many evacuees move (McIntosh 2008).

Changes in the labour market are partly affected by changes in population. The next strand of literature on Katrina studies the effect on the population, as well as who returns to the affected areas after the disaster. Groen and Polivka (2008) uses data from a population survey and find that Katrina is associated with an increase in the percentage of older residents, a decrease in the percentage of residents with low income and education, and an increase in the percentage of residents with high income and education. Furthermore, their result shows that an evacuee's age, family, income, and amount of asset damage are all important determinants of whether an evacuee returns the first year after the storm. These results, therefore, indicate that those moving away from New Orleans in the long run are the ones with a worse standard of livings before the hurricane. In another study, Paxson and Rouse (2008) study who returns after Katrina. The authors make concluding remarks that flood exposure is the single most important factor in determining who returns, however, it is not significant.

To conclude, these studies overall observe direct negative effects on especially income and employment directly after the destruction of regional societies by Katrina. In the long run, they see tendencies for recovery, even in New Orleans. The demographic profile of the population also changes – for example, to a higher ratio of pre-disaster high-income residents and a lower ratio of pre-disaster low-income residents.

4 Reserch Design

The previous literature, presented in the previous section, investigates the relationship between natural disasters and economic growth. However, there are still several gaps in the literature for research to fill. One such gap is that no study previously has studied the effects on economic growth of Hurricane Katrina, neither in the short-run nor long-run, despite Katrina being one of the largest natural disasters in the last few decades.[15] In this section, we define more clearly the research gap that this study aims at filling as well as the effects of natural disasters aim to study. Last, we present our research question and our hypotheses.

4.1 Short-Run

Most previous studies show a significant negative short-run impact on the economic growth of natural disasters. To our knowledge, only one study in the literature finds a positive effect on economic growth of a natural disaster, namely the study by DuPont and Noy (2015) who studied the effects of an earthquake in a Japanese region and showed that it led to a short-run positive GDP per capita. Moreover, no study has investigated the short-run effect on economic growth in

[15] We continue to distinguish between the short-run and long-run as in the Literature Review. First, there is no clear definition of how to draw a line between the direct and indirect. Second, the data in this study does not distinguish between the direct and indirect effects of natural disasters, instead, it estimates the overall effect.

Katrina-affected regions, even though Katrina is one of the largest natural disasters during the last decades. Combining the interest in Katrina with the fact that a relatively similar case study to ours – also in a relatively developed country, however, an earthquake instead of a hurricane – it is of interest to investigate if the setting of Katrina follows the general negative short-run effects found or, as DuPont and Noy (2015) find, a positive short-run growth effect. This is where our thesis contributes: our study provides additional empirical evidence of the short-run economic impacts on growth caused by Katrina in the state of Louisiana and how the economic growth would have developed in the absence of Katrina. Following the previous literature, we define the short-run period as the time directly following the disaster. In our case, it is the year of the disaster and the subsequent year. Additionally, to measure the effect such that it can be compared to studies on other natural disasters, we use change in GDP per capita as a measurement of economic growth.[16]

4.2 Long-Run

The long-run economic growth effects of natural disasters is neither obvious in macroeconomic theory nor in previous empirical literature. Five hypotheses exist, however, with different amounts of empirical support. This indicates more studies are needed to investigate the long-run effects, which is also recommended by the most recent literature review in the field (Botzen, Deschenes, and Sanders 2019). More specifically, the authors (2019) recommend more case studies to be conducted that could validate cross-country studies that already exist. As previously mentioned, no macroeconomic study on the long-run effects on economic growth of Katrina has been performed, which is where our study provide additional value to the field. The contributions of this paper on the long-run effects are twofold: first, we help to support findings in previous literature and thus contribute to the general field of the macroeconomic effects of natural disasters, and second, we contribute to the specific studies on the case of Katrina.[17]

We consider the long-run as the time following the short-run direct impact of the disaster. In our case, we define it as the time from 2007 to the end of the sample period.

4.3 Transmission Channels

Although there are gaps in the literature regarding both the short-run and long-run effects of natural disasters on economic growth, the number of papers investigating possible transmission channels to economic growth are even fewer. Some studies examine the impacts of disasters on variables we view as transmission channels, however, they do not connect it to economic growth. According to our knowledge, only one study analyses the transmission channels to economic growth (view Berlemann and Wenzel 2018). Due to this, Botzen, Deschenes, and Sanders (2019) also recommend more research on potential transmission channels. By including an analysis of transmission channels, possible reasons for any short-run and long-run effects of natural disasters may be derived that might function as explanatory value.

Our study adds by studying the effect of natural disasters on potential transmission channels through which economic growth might be affected. The effect on the transmission channels may help to get a better understanding of the aggregate measure of economic growth in GDP per capita.

[16]The limitations of using changes in GDP per capita as a measurement of economic growth are discussed in Section 6.2.

[17]Note, however, that the external validity of a case study generally is low, and we are therefore cautious to generalise our findings.

We do not, however, empirically study how the effects in the transmission studies transfer into an effect in economic growth, since this is an empirical estimation outside our scope.

Based on the theoretical implications from the Cobb-Douglas Production function, we study labour, physical capital, and Total Factor Productivity (TFP) as possible transmission channels to economic growth. Given the previous literature indicating that different population groups were affected differently by Katrina, we choose to study various labour measurements to be able to better understand the changes in the labour market: unemployment rate, labour force participation rate, and employment-population ratio. In addition to the three transmission channels that are intricate parts of the Cobb-Douglas production function, we also examine the effects on residential population. This is done first since population is directly connected to the per capita measurement used for studying any economic growth effects, and second since population is closely related to labour force. As such, residential population is therefore a factor included in this study to better be able to interpret the effects on GDP per capita of the natural disaster.

4.4 Contribution, Research Question and Hypotheses

Our study, as presented in previous sections, contributes to the existing gaps in the literature on both the short-run and long-run impacts on the economic growth of natural disasters. In addition, we add to the literature by including potential transmission channels to economic growth that may further provide explanatory value of any findings on economic growth effects of natural disasters. We also contribute by advancing the knowledge on the specific macroeconomic impacts of Hurricane Katrina.

Furthermore, we provide two more general contributions through our study. First, by examining both the effects on long-run economic growth and the effects on various potential transmission channels, we are able to contribute with better explanatory value of how any observed long-run effects occur. This is especially important since GDP is an aggregated measurements, and by studying the transmission channels more closely, we can potentially provide empirical explanatory value on the long-run effects on economic growth. Second, it is of interest to study the specific case of Hurricane Katrina that is still a rather unstudied case in the macroeconomic literature. Following Katrina, the U.S. government decided to invest in mitigating ex-ante disaster management to reduce the potential effects of future disasters – a number indicated to increase according to the climate-change research. The allocation of investments in ex-ante mitigating management would, however, potentially have been better conducted if the government had more understanding of the economic effects of previous large natural disasters in the U.S. setting. A wider contribution of our study is hence a better understanding of previous disasters, which might provide insightful information for policy makers to mitigate effects in future instances of natural disasters – especially in the U.S., but also possibly in other developed countries.

This leaves us with our main research questions that our study aims to answer:

What are the short-run and long-run effects of Hurricane Katrina on the state-level economic growth in Louisiana, and what are the effects of Katrina on potential transmission channels to the state-level economic growth in Louisiana?

Given previous literature, our hypothesis is that the short-run effect on GDP per capita is expected to be significantly negative, and therefore, leading to a short-run negative effect on economic growth. In addition, we expect the long-run effect to follow the hypothesis of recovery to trend – the thesis with most empirical support. Furthermore, as we are studying state-level data, we are capturing the economic growth effects in the entire state of Louisiana and not only the most affected regions – such as the city of New Orleans. Thereby, we hypothesise more confidently that a recovery to trend is likely to occur since less affected regions reasonable recover fast and offset negatively affected areas. For the transmission channels, we first expect the unemployment rate to increase but then recover to pre-trend. The labour force participation rate and the employment-population ratio are also both expected to decline and recover fast, with support from previous literature. Furthermore, we hypothesise that there will be a short-term decline in capital, however, followed by a capital accumulation. Lastly, supported by previous literature, we hypothesise that TFP will exhibit a short-term transitory positive affected that will return to pre-disaster trend in the long-run.

5 Empirical Methodology

This section motivates and present the methodology selected to estimate the potential effect of Hurricane Katrina on economic growth in Louisiana. We first give a motivation for the chosen econometric model Synthetic Control Method, followed by a definition of the model and then, an extension of the model. Thereafter, we describe how we use the model for transmission channels, before the section ends with presenting some limitations.

5.1 Using Synthetic Control Method for Comparative Case Studies

To identify a causal effect, this paper uses the Synthetic Control Method (SCM), which is a modified extension of the more common Difference-in-Difference estimation framework (DiD) (Abadie, Diamond, and Hainmueller 2010). The reason why DiD is appealing is for its ability to eliminate the effects of unobserved covariates predicting the outcome variable – that is, factors influencing the outcome variable other than the disaster (Abadie, Diamond, and Hainmueller 2010). This, however, requires two assumptions. First, that the effects on the outcome variable are constant over time. Second, that any time effects, for example a financial shock or a supply shock, are existent in both the unit affected by a disaster and the control group not affected by the disaster. These two assumptions constitute the common trends assumption, which states that absent the disaster, changes should have been the same in both the affected unit and the control group. A complication with the DiD, however, is that it can be hard to verify the common trends assumption, and if it does not hold the estimator could be biased. The SCM instead allows for the effect of unobserved variables on the outcome variable to vary with time, which relaxes the common trends assumption and hence makes the SCM attractive for a comparative case study (Abadie, Diamond, and Hainmueller 2010). The SCM achieves this by generating a weighted synthetic control group of regions that, prior to the disaster, has similar trends and levels in the outcome variable as the affected unit as well as resembles the affected unit on a set of key predictors to the outcome variable (Abadie and Gardeazabal 2003).

Moreover, the DiD would limit the number of covariates that could be used since many variables themselves are likely to be affected by the natural disaster and hence be regarded as bad controls. Examples of such covariates could in this study for instance be unemployment rate and physical capital. The SCM, on the other hand, uses these covariates as predictors to build a compelling pre-disaster counterfactual such that the confounding effect of these covariates are not present in the post-disaster period (Abadie, Diamond and Hainmueller 2010). Furthermore, the selection of units as part of the control group in the DiD are susceptible to subjectivity, which may cause additional issues. The SCM, however, overcomes this problem by allowing for a data-driven method to choose units from a donor pool based on what weighted combination of the units that best resembles the affected unit in the outcome variable (Abadie and Gardeazabal 2003). To summarise, the SCM is appealing as an identification strategy to find causal effects and, therefore, the chosen main method of this study.

5.2 The Synthetic Control Method

We now turn to define the Synthetic Control Method (SCM), drawn on Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010, 2015) in order to assess the impact of Hurricane Katrina on Louisiana's economic growth. The approach aims at generating a synthetic Louisiana (SLA) with resembling financial and economic characteristics of that of real Louisiana (LA) for the years prior to the hurricane disaster. This is done by estimating a weighted composite of other U.S. states in a donor pool that will represent SLA without the hurricane effect.[18] SLA is then used as a simulated counterfactual state had LA not been affected by the disaster, making it possible to compare LA and SLA to estimate the effect of the hurricane on LA's economic growth. The required assumption that has to hold for the model to be utilised is that the economic growth variable being studied need both similar trends and levels for every period in both LA and SLA prior to the "treatment" – where the treatment in our case is Hurricane Katrina.[19] This assumption is known as the identification assumption. In addition, Abadie and Gardeazabal (2003) suggest choosing weights of control states for SLA such that SLA best resembles LA on pre-disaster values of a set of key predictors to economic growth. If SLA is able to track the outcome variable during the pre-disaster period as well as reproduce the values of the key predictors, it lends credibility to the identification assumption.

Following Abadie and Gardeazabal (2003) and Abadie, Diamond and Hainmueller (2010, 2015), let $J + 1$ represent the number of observed states, where the first state is affected by the natural disaster and the remaining J states are the potential control states in the donor pool. Let T be the number of observed years and T_0 be the number of years prior to the disaster, where $1 \leq T_0 < T$. Let Y_{it}^N be the per capita GDP observed for state i and at time t in the absence of the hurricane, where $i = 1, ..., J+1$ at year $t = 1, ..., T$. Let Y_{it}^I be the per capita GDP observed for state i and at time t if state i is exposed to the disaster, where $i = 1, ..., J+1$ and $t = T_0+1, ..., T$. By definition, to the degree a large hurricane is unanticipated or unpredictable it has no effect on the outcome prior to its occurrence, hence $Y_{it}^I = Y_{it}^N$ for $t \in (1, ..., T_0)$ and all $i \in (1, ..., N)$. The impact of the hurricane will then be

$$\alpha_{it} = Y_{it}^I - Y_{it}^N$$

for state i at time $t > T_0$. Let a variable D_{it} take on a value of 1 if state i is exposed to the disaster at time t, and a value of 0 otherwise. Then, the observed per capita GDP of state i at time t is

$$Y_{it} = Y_{it}^N + \alpha_{it} D_{it}.$$

Since the first observed state, $i = 1$, is the only state exposed to the hurricane, and is additionally

[18] We use the R-package Synth (Abadie, Hainmueller, and Diamond 2011).

[19] Note, however, that we do not refer to treatment frequency, as natural disasters are natural phenomenons. Instead of referring to a treatment-effect, we more precisely refer to a "disaster-effect".

only exposed following year T_0, where $1 \leq T_0 < T$, the variable D_{it} takes on a value of

$$D_{it} = \begin{cases} 1, & if\ i = 1\ and\ t > T_0, \\ 0, & otherwise. \end{cases}$$

Hence, the objective is to estimate the parameters

$$\alpha_{1t} = Y_{1t}^I - Y_{1t}^N = Y_{1t} - Y_{1t}^N,$$

for which $t > T_0$. Since the value of Y_{1t}^I is empirically measured, α_{1t} will be estimated by means of estimating Y_{1t}^N. To do this, let $\boldsymbol{W}= (w_2, ..., w_{J+1})'$ be a $(J \times 1)$ vector of weights such that $\sum_{j=2}^{J+1} w_j = 1$ and that $w_j \geq 0$ for $j = 2, ..., J+1$. Each unique value of $\boldsymbol{W}$ will thus constitute a different potential SLA, each synthetic version representing a different weighted average of control states in the donor pool. Given a specific combination of weights $\boldsymbol{W}$, the estimator Y_{1t}^N for the synthetic control is

$$\widehat{Y}_{1t}^N = \sum_{j=2}^{J+1} w_j Y_{jt},$$

where $\sum_{j=2}^{J+1} w_j = 1$ and $w_j \geq 0$ for $j = 2, ..., J+1$. Hence, the estimator for α_{1t} is

$$\widehat{\alpha}_{1t} = Y_{1t} - \widehat{Y}_{1t}^N.$$

We now turn to choosing weights, $w_2, ..., w_{J+1}$, for the control states. To do this, let $\boldsymbol{X_1}$ be a $(K \times 1)$ vector of pre-hurricane values of $\boldsymbol{K}$ economic growth predictors for Louisiana. Let $\boldsymbol{X_0}=[\boldsymbol{X_2}...\boldsymbol{X_{J+1}}]$ be a $(K \times J)$ matrix containing values of the same economic growth predictor variables for the J possible control states. Let $\boldsymbol{V}$ be a $(K \times K)$ diagonal matrix consisting of positive constants, $v_1, ..., v_k$, that reflect the importance of each of the $\boldsymbol{K}$ individual economic growth predictors for the affected state before the disaster event, along the values of $X_{11}, ..., X_{K1}$. When choosing the synthetic control $\boldsymbol{W^*}= (w_2^*, ..., w_{J+1}^*)'$, we hence pick one such that it minimises

$$||\boldsymbol{X_1} - \boldsymbol{X_0 W}|| = ((\boldsymbol{X_1} - \boldsymbol{X_0 W})'\boldsymbol{V}(\boldsymbol{X_1} - \boldsymbol{X_0 W}))^{\frac{1}{2}} =$$
$$= \left(\sum_{h=1}^{K} v_h (X_{h1} - w_2 X_{h2} - ... - w_{J+1} X_{hJ+1})^2\right)^{\frac{1}{2}}.$$

Intuitively, this means that the best combination of weights is the combination which minimises some gap between $\boldsymbol{X_1}$, the pre-disaster values of the $\boldsymbol{K}$ predictors of per capita GDP for LA, and $\boldsymbol{X_0 W^*}$, the pre-disaster weighted values of the $\boldsymbol{K}$ predictors of per capita GDP for SLA, such that they are as close to each other as possible. The choice of $\boldsymbol{V}$ is picked such that the synthetic control $\boldsymbol{W}(\boldsymbol{V}) = (w_2(\boldsymbol{V}), ..., w_{J+1}(\boldsymbol{V}))'$ minimises the Mean Square Prediction Error (MSPE) of this synthetic control with regards to Y_{1t}^N

$$\sum_{t \in \tau_0} (Y_{1t} - w_2(\boldsymbol{V}) Y_{2t} - ... - w_{J+1}(\boldsymbol{V}) Y_{J+1t})^2,$$

for pre-disaster periods $\tau_0 \subseteq \{1, ..., T_0\}$. In any given period, the root of the MSPE – abbreviated RMSPE – is interpreted as the actual difference in U.S. dollars (USD) between LA and SLA's per capita GDP.[20] Considering all this, the estimator for the disaster effect, α_{1t}, is

[20] In our case, it is in 2017 USD.

$$\widehat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt},$$

for $t \in \{T_0 + 1, ..., T\}$.

If the identification assumption holds, the disaster effect on GDP per capita – in any given year during the post-disaster period – is the difference between that of LA and that of SLA. The effect on economic growth – in any given year during the post-disaster period – is thus the change in GDP per capita gap from one period to another.

5.3 Selecting Predictors

The selection of the K predictors is a fundamental part of the estimation task since they determine which weights are given to states in the donor pool to construct the synthetic state that minimises the RMSPE. Indicated by the literature review, there are many possible predictors to GDP per capita, however, previous literature using SCM (see, among others, Abadie and Gardeazabal 2003; Abadie, Diamond, and Hainmueller 2010; Cavallo et al. 2013) do not explicitly explain the methodology used to choose among the possible predictors.[21] We, therefore, aim to extend the methodology to explicitly include a data-driven procedure of selecting the predictors. With the intention of finding a set of predictors that minimises the RMSPE, we compare different combinations of predictors in a two-step process. We here present this methodology concisely. Appendix D contains technical details.

In the first step, we choose a sample of predictors used by Abadie, Diamond, and Hainmueller (2015) and create an initial base set of predictors that minimise the RMSPE. In the second step, we introduce additional covariates from the growth-literature and theoretical models. The aim with the second step is to further improve the base set of predictors. Using the selected set of predictors from the first step as a fixed base, we add combinations of these additional covariates and iterate 101 tests of sets to find combinations of predictors that minimises the RMSPE. From these 101 combinations, we study the five sets with the lowest RMSPE more closely. By further studying the fit between the five synthetic units and the real Louisiana's specific predictors, as well as the different weights on states and predictors, the purpose is to select one synthetic version that most credibly make the identification assumption hold. Based on several considerations, described in the Appendix D, we select the set of predictors used to construct the Synthetic Louisiana.

5.4 Using Synthetic Control Method for Transmission Channels

For the analysis of the effects on different transmission channels to economic growth, the methodology of utilising SCM differs slightly and the identification assumption changes. We present how we construct the synthetic counterparts for the transmission channels following the method by Andersson (2018).

Constructing the SLA is done based on the main outcome variable – in our case, GDP per capita. If the SLA is constructed on predictors with good explanatory value, other variables that are correlated to GDP per capita are expected to follow a similar trend pre-disaster. Therefore, we

[21] Abadie (2003) motivates the choice of predictors by referring to variables that are "[. . .] typically associated with growth potential [. . .]". Abadie (2015) writes "For the pre-reunification characteristics in X1 and X2, we rely on a standard set of economic growth predictors [. . .]". Cavallo et al. (2013) writes: "Following a voluminous empirical growth literature (see, among others, Barro and Sala-i-Martin 2004; Mankiw, Romer, and Weil 1992) and attempting to maximize the pre-event fit of the models, the GDP predictors [. . .]".

take the weights of control states in the donor pool – from constructing the SLA on the GDP per capita measure – to construct synthetic counterparts for each transmission channel variable.

Due to this methodology, the level of each transmission channel variable for LA and SLA, respectively, will not follow each like in the main economic growth outcome variable for which the SLA were generated to be similar to LA. As such, the identification assumption changes so that the synthetic composite of each transmission channel variable only needs to follow the same transmission channel variable in trend, but not level, for each pre-disaster period. This is important to consider when interpreting the results of the transmission channels. The change makes the identification strategy more similar to that of DiD, requiring similar paths but not levels prior to treatment. Thereby, the disaster effect on the transmission channels – in any given year during the post-disaster period – is the difference between the estimated gap between LA and SLA for a year in the post-disaster period and the average difference between LA and SLA during a selected range of years immediately prior to the disaster. As the range of years prior to the disaster from which we calculate the average difference between LA and SLA, we use 1995-2004, the 10 years prior to Hurricane Katrina.

5.5 Model Assumptions and Limitations

When using the SCM, there are some important assumptions and limitations to consider, besides the identification assumption already presented. Firstly, it is important to ensure that states affected by the disaster or similar events are excluded from the donor pool. By including such states, we would risk biasing the results since there is a possibility that they are similar to Louisiana prior to the disaster and hence would receive a positive weight different from zero in the model that would consequently lead to the outcome variable becoming skewed for the synthetic control. Also, states in the donor pool experiencing large idiosyncratic shocks to the outcome variable during the study period should also carefully be excluded if they would have had no effect on the affected state absent the disaster. Moreover, to avoid risking interpolation bias, the donor pool should be restricted to only include states that have similar characteristics to the affected state. The reason to limit the size of the donor pool to states with similar characteristics to that of the affected state is also because overfitting could become a problem. This issue of overfitting would emerge if characteristics of the affected state would be artificially matched through synthesising idiosyncratic variations in a sizable sample of unaffected states (Abadie, Diamond, and Hainmueller 2015). In other words, instead of using a limited sample with state characteristics similar to the affected state, the usage of a large sample with high variations in state characteristics would risk generating a synthetic version that would correspond too closely to the real state in per capita GDP levels and paths during the pre-disaster period. This would cause problems in utilising the synthetic state as a counterfactual since post-disaster paths and levels would become less reliable.

To account for these limitations to the model and reduce the risk of bias, we firstly exclude all U.S. states that directly and indirectly are affected by Hurricane Katrina, Rita or Wilma from the donor pool, as well as states indirectly affected that experienced large in-migrations of hurricane evacuees. Section 6.1 describes which states that we omit. Since we are studying state-level data – and not country-level data, as previously commonly used for SCM – the states are very similar in terms of factors, such as regulations, economic freedom, and institutions, since being part of the same nation. Thereby, we do not exclude any specific state for potential interpolation bias reasons since all state already share many important characteristics that make them similar as regions (Abadie, Diamond, and Hainmueller 2015).

In addition, the possibility of causing overfitting motivates our choice of performing a data-driven approach, choosing weights for the states in the donor pool by minimising the RMSPE. We also consider idiosyncratic shocks, such as other major natural disasters, and exclude all states exhibiting such during the study period – right before the disaster – as well as in the immediate periods after the disaster.[22] The financial crisis of 2008, however, is a covariant shock that affected the entire U.S. and as such is not needed to be accounted for in selection of control states.

Moreover, the validity of the SCM is dependent on an extensive pre-disaster period with data since its reliability is based on the fact that the path and level of the synthetic control most resemble that of the affected region over a longer period of time prior to the disaster (Abadie, Diamond, and Hainmueller 2015). If the pre-disaster period is short or if the pre-disaster fit is poor, the SCM hence should not be used. We are not restricted by this limitation since we use an extensive panel data between the years 1963 and 2019, with a pre-disaster period of 42 years for the model to study and find an appropriate synthetic control. In addition, if effects of the disaster arise gradually or changes over time, a longer post-disaster period would also be necessary (Abadie, Diamond, and Hainmueller 2015). Since one aim of our study is to examine potential differences in long-run effects of Katrina and since we use a post-disaster period of 14 years, we account for changes over time.

6 Data

To empirically analyse the economic impacts of Hurricane Katrina, three types of panel data for the 50 U.S. states are collected.[23] First, data on the main outcome variable. Second, data on transmission channels to economic growth. Third, pre-disaster data on potential predictors to GDP per capita. All variables are rescaled to control for differences in state size, either by using per capita measures or percentage.[24] The data is summarised in Appendix C.

Furthermore, the data are divided into pre-disaster data and post-disaster data. The pre-disaster period starts in 1963,[25] the first year of the main output variable, and ends in 2004, the year before the disaster. The post-disaster period then starts in 2005, the disaster year, and ends in 2019, the last year of the sample.[26]

Main Outcome Variable: The main outcome variable that we use to measure economic growth is real GDP per capita in 2017 U.S. dollars, calculated using nominal GDP obtained from U.S. Bureau of Economic Analysis (BEA), CPI for the entire U.S. obtained from U.S. Bureau of Labour

[22] The study period right before the disaster and the immediate period after the disaster are most important when considering idiosyncratic shocks as these potentially can affect the interpretation of causality. If large events different from the treatment effect – Hurricane Katrina – would occur many years before the treatment or many years after the treatment, the SCM would most likely not include them in the synthetic counterfactual version of the treated state. Furthermore, excluding states that experience any type of large event in any year during the pre-disaster period would limit the size of the donor pool such that the estimates from the model become unpredictable on other parameters.

[23] All U.S. states, not including District of Colombia (D.C.). We start following the availability of data by state, and end in 2019.

[24] Abadie (2020) points out that, considering a synthetic control with weights such that the synthetic control is only warranted if data for the variables are rescaled to control for differences in state size, e.g., per capita capital, or if correction is not necessary because of variable data not changing with state size, e.g., prices. Hence, all variables that we use are converted to account for this.

[25] Note, all models in this paper – with data availle to do so – are optimised from 1963, however, most plots start at 1970.

[26] Note that 2005 is included in the post-disaster period rather than pre-disaster, even though Katrina occurs in August of 2005. We expand this limitation in Section 6.2.

Statistics (BLS), and state residential population number obtained from U.S. Census Bureau. We follow, e.g., Feenstra, Inklaar, and Timmer (2015) and use the expenditure approach for the GDP measure, as well as use real values instead of nominal values to examine economic growth over time.

Transmission Channels: We use both pre-disaster and post-disaster data for the transmission channels: residential population, labour, capital stock, and Total Factor Productivity (TFP). First, we use and obtain the same data on state residential population from U.S. Census Bureau as used in calculation of the main outcome variable. Regarding labour, we employ data for labour participation rate, unemployment rate, and employment-population ratio, all obtained from U.S. Bureau of Labour Statistics (BLS). Since physical capital data does not exist on the state level, we follow previous literature on state-level economic growth in the U.S. (see, for instance, Benos, Mylonidis, and Zotou 2017; Cardarelli and Lusinyan 2015; Sharma, Sylwester, and Margono 2007) and use data estimates for physical capital stock obtained from Yamarick (2018).[27] Lastly, due to R&D expenditure data obtained from U.S. National Science Foundation (NSF), used as a proxy for TFP, is not available on an annual basis in the post-disaster period, we exclude the transmission channel analysis of TFP.[28]

Predictors to GDP per capita: For our data-driven methodology of selecting predictors to GDP per capita, as described in Section 5.3, we start with a base set of predictors used by Abadie, Diamond, and Hainmueller (2015): GDP lags, the industry share, and schooling.[29] As GDP lags, we use lagged variables based on our data for GDP per capita. For the industry share, we follow the definition of industry rate by the World Bank (2021) and use obtained data from BEA for the total share of manufacturing, utilities, and construction of all industry total state GDP. Regarding schooling, we include data on both the percentage of the state population with a bachelor's degree or more, and the percentage of the state population with a completed high school education. We will use the bachelor's degree data as the schooling variable, due to the U.S. being a highly developed country.

For additional predictors to GDP per capita, we firstly include two proxies for investment rate since we cannot obtain state-level investment rate: (i) personal savings rate – calculated as the difference between Disposable Personal Income (DPI) and Personal Consumtion Expenditures (PCE), divided by DPI – which is based on the intuitive theoretical framework that all savings are used for investments[30], and (ii) consumption rate of GDP — since noting that investment rate is a part of the expenditure approach, we instead use the consumption rate that is also part of the expenditure

[27]The estimate for state-level physical capital is produced by using the U.S. national capital stock estimates allocated to each individual state on the basis of the two-digit SIC or NAICS industry-level earnings (Yamarick 2019).

[28]Historical state-level data on TFP is not available. Acknowledging that TFP is driven by, for example, level of human capital, technology, institutions and misallocations (Jones 2018), we use R&D expenditures from NSF as a proxy for TFP. The reason for selecting R&D is because other variables are captured by already included variables in our test.

[29]Abadie, Diamond, and Hainmueller (2015) also include trade openness and inflation rate. Trade openness data is not available at the state-level, and we assume all states have the same inflation rate. Furthermore, they include investment rate, which we also will but as additional predictors instead of base predictors since we use proxies and not the true investment rate.

[30]For instance, consider a simple economy with a national income of Y, a total consumption expenditure of C, and a total savings of S. In this economy, the national income Y will be divided between the consumption expenditures C and the savings S, such that Y=C+S. On the production output PO side of the economy, only consumption goods C and investment goods I are produced. Hence, by definition, since output equals income received, national income Y must equal production output PO in the economy. This means C+S=Y=PO=C+I, from which S=I can be derived. Furthermore, Keynes highlights savings=investment if the economy is in equilibria in his book "General Theory of Employment, Interest and Money".

approach. When optimising the choice of predictors, following the method in Section 5.3, we will test both alternatives to investment rate. Second, we include the transmission channel variables, drawn from the theoretical framework of Cobb-Douglas, as predictors: labour, TFP, capital stock, and residential population. For labour we as a predictor use the employment-population ratio. Third, we include a predictor for oil dependency due to Louisiana's GDP historically being dependent on the oil industry, using oil production per capita, measured as barrels per thousand people, obtained from U.S. Energy Information Administration (EIA), as a proxy. Last, we follow Cavallo et al. (2013) and take inspiration from the growth literature to firstly include a predictor for population density (see, e.g., Abadie and Gardeazabal 2003), calculated using data obtained from the U.S. Census Bureau, and secondly include a predictor for institutions, which is a determinant for economic performance (see, among others, Acemogulu et al. 2005; North 1970, 1979, 1991). For the proxy for institutions, we carefully choose to employ the NOMINATE government ideology measurement obtained by Berry, et al. (2010), previously used in studies (see, for example Enns and Koch 2013). We refer to it as government proxy.[31]

6.1 Donor Pool

To ensure that the SLA does not catch any effect of the hurricane, we exclude states directly or indirectly affected from our initial sample of 50 states. The states directly affected are defined as states meteorologically hit by Katrina when categorised as having windspeeds of a hurricane, including Florida, Louisiana, and Mississippi. States not directly affected by the hurricane but likely to have exhibited economic effects due to their position or relation to Louisiana, we define as indirectly affected, which include Texas, Arkansas, Alabama, and Tennessee. As previous literature shows, due to their proximity to Louisiana, Texas and Arkansas are both neighbouring states to Louisiana and experienced economic activity following Katrina due to the in-migration of Louisiana residents. Furthermore, Alabama both experienced some storm surge damages in coastal regions due to Katrina and experienced some economic activity due to in-migration of residents from Louisiana and bordering states. Lastly, we define Tennessee as being indirectly affected due to being hit by Katrina as a tropical storm as well as being located close to affected states.[32] We exclude these states since an inclusion in the donor pool might distort any examined effects of Hurricane Katrina.

In addition to the states affected by Katrina, we consider states affected by large idiosyncratic shocks during the study period right before the disaster and the immediate period after, as motivated in Section 5.5. First, Hurricane Katrina was one of four major hurricanes during 2005, whereby we additionally omit Georgia that was directly affected by Hurricane Denis.[33] Second, we omit Indiana from our sample since it was adversely affected by the idiosyncratic shock of the Evansville

[31] The measurements by Berry et al. (1998, 2010), of U.S. state citizen and government ideology, rely on unadjusted interest-group rating for a state's members of Congress to infer information about (1) the ideological orientation of the electorates that selected them or (2) state legislators and the govern from the same state. To appropriately estimate the real political views of political candidates, it is important to distinguish between a legislator's public portrayals, voter's perception of such portrayals, as well as the legislator's true policy preferences. The NOMINATE measure is not created to measure voter's perception of a legislator's ideal point, but to measure the real views of the representatives themselves, and as such the measure account for the actual impact legislator's have on, among others, the economy rather than the perceived effects of the electorate (Berry et al. 2010).

[32] Tropical storms cause minor economic damage and have wind speeds of 39-73 mph, compared to hurricane wind speeds that are over 73 mph.

[33] Hurricane Denis, Rita and Wilma also impacted Florida (Denis, Rita and Wilma), Alabama (Denis), Mississippi (Denis), and Louisiana (Denis, and Rita). However, these states are already excluded due to being affected by Katrina.

Tornado outbreak in November 2005.[34]

6.2 Limitations of Data

The data we use are subject to limitations. First, the data for GDP per capita is not available on city-level, only on state-level. Since natural disasters are locally destructive (Horwich 2000), using data at lower aggregated regional levels is preferrable as it allows for more detailed insights in the effects of the natural disasters. In using state-level data, we hence risk that a negative effect in one region outweighs a positive effect in another region, making conclusions of effects more obscure. We, however, improve on national-level data used in cross-country studies of the effects of natural disasters by observing state-level data.

Second, the data we use is annualised. This limitation in time intervals between data points risk our study to especially miss a potential effect of Hurricane Katrina during Q4 2005 – the immediate aftermath of the disaster – that may potentially be offset by economic growth during the first three quarters that same year. Since no large events with possible effects on Louisiana's GDP per capita occurred during the pre-disaster period of 2005, we proceed by including 2005 as the first year of the short-run effect to catch possible effects despite potentially being offset by economic growth in previous quarters. We, however, interpret any potential results in this first year with caution.

Third, GDP per capita exhibits limitations as a measure of the impact on the economy in disaster-affected regions. For example, GDP per capita fails to account for income changes to different groups in affected societies. As such, a natural disaster may affect some people to a higher degree than others, as well as affect people differently on a scale from positively to negatively – an effect that is not cached in GDP. Moreover, GDP per capita exclude non-market productive activities, such as household work or childcare, as well as non-market transactions, such as unrecorded transactions for tax evasion. These activities cannot be cached by GDP but may increase or decrease in the aftermath of shocks and affect the society. Furthermore, money transfers, such as social security payments and gifts, as well as financial transactions, for instance investment in or sell-off of financial instruments, are also omitted from the GDP measure. These activities may in addition change due to a natural disaster and affect the economy.

Fourth, due to the R&D data that we use as a proxy for TFP does not exist on an annual basis, we are unable to include an analysis of effects of Katrina on TFP during the post-disaster period. Therefore, we cannot study the effect of TFP as a transmission channels to economic growth. However, we can still employ it as a transmission channel – the time intervals between data points, does not limit our ability to utilise the data as a predictor to GDP per capita in the pre-disaster period to construct a synthetic control.

Fifth, the estimated physical capital data obtained from Yamarik (2002, 2018) is sensitive to shocks in industry-specific earnings. The estimation methodology by Yamarik (2019) has been modified to better account for earning shocks in capital intensive mining industries, that includes the oil and gas industry, which especially are subject to substantial and frequent price shocks (Jacks, O'Rouke and Williamson 2011), however the method still faces challenges (Yamarik 2019). This potentially complicates the use of the physical capital data when analysing the effects of Katrina since Louisiana is highly dependent on the oil industry and thus affected by oil price shocks. The estimates thereby may not appropriately reveal actual changes to the physical capital stock in the state but be influenced by crude oil prices.

[34] Note, however, that the results are shown to be identical if including Indiana or not, as it obtain zero weight in the SCM.

Last, proxies of institutions exhibit some limitations, partly derived from two reasons. First, there are multiple definitions of institutions exhibiting in parallel which differ in aspects such as weight put on formal and informal institutions and the view of institutions as a constraint or as a resource.[35] Second, institutions exist on various levels of aggregations, ranging from family-level to national-level, making it difficult to find an appropriately proxy. In our study, we employ a proxy for the institutions at the governance-level, see description of the variable used in Section 6. Although previously used in literature, the measurements have some limitations, such as:(i) being limited to the governance-level, and thus, being more narrow than the common view of institutions; (ii) only including formal institutions but not informal institutions. Thereby, the proxy is not optimal, however, it still helps to capture some different in governance across states which may help predict the GDP per capita.

7 Results

This section presents the empirical results obtained from our study. First, we present the result from constructing the Synthetic Louisiana. Second, we provide the result on the economic growth both in the short run and in the long run through studying the impacts on GDP per capita. Third, we provide the results on the effects of Hurricane Katrina on the transmission channels to economic growth. Last, the placebo-tests as well as the robustness-tests for our main result on economic growth are presented.

7.1 Constructing the Synthetic Louisiana

Using the techniques presented in the methodology section, we now construct a synthetic Louisiana with weights chosen so that the resulting synthetic Louisiana best reproduces the values of the predictors of the GDP per capita in the pre-disaster period.[36] We also consider that the identification assumption holds, allowing us to proceed with the result on the effect on growth.

7.1.1 Selecting Predictors

First, we follow Section 5.3. and select which predictors in our dataset to use, by a data-driven approach. In Appendix D we describe the steps we go through in more detail. The results from the selection process indicate that the best set of predictors of Louisiana's GDP per capita are the base predictors real GDP per capita with 10 years lags, completed Bachelor's degree share and industry share of GDP, as well as the additional predictors of savings rate, TFP proxy and government proxy. The RSMPE for this combination is 799 – on average, the difference between LA and SLA in the pre-disaster period is thus $799 USD.[37]

[35] The most cited definition is from North (1991): "humanly devised constraints that shape human interaction", indicating that institutions are constraints and not resources. To support economic growth, it is fruitful to see institutions as also resources – something that helps e.g. societies to develop and improve. Definitions also range from including formal institutions (e.g. laws) and informal institutions (e.g. norms).

[36] Included as a part of the results, as it is the outcome of the selection process of predictors and running our SCM. Before interpreting the effects on growth, we must assess whether SLA is sufficiently good as a synthetic counterpart to interpret the results.

[37] Recall, all values are in 2017 USD.

7.1.2 Louisiana versus Synthetic Louisiana

If synthetic Louisiana tracks the real GDP per capita in Louisiana in the pre-disaster period and reproduces the values of the key predictors, it lends credibility to the identification assumption that the synthetic control unit provides the path of real GDP per capita between 2005-2019 in the absence of Katrina.

Figure 4 indicates that, prior to Katrina, the GDP per capita in LA and SLA track each other closely. On average in the pre-disaster period, the difference is $799 USD. In two time periods, the difference between LA and SLA is considerably larger. In 1992-1993, the difference in absolute values is on average $1,975 USD. Similarly, in 2004, the difference is $1,578 USD, which is larger than the mean. It is not encouraging to have such a large difference the year before the disaster occurs, however, similar results were obtained for the other set of predictors in our extension. Despite the increased gap in 2004, LA and SLA track each other closely the prior years, making us conclude that SLA follow LA in both trend and level pre-disaster.[38]

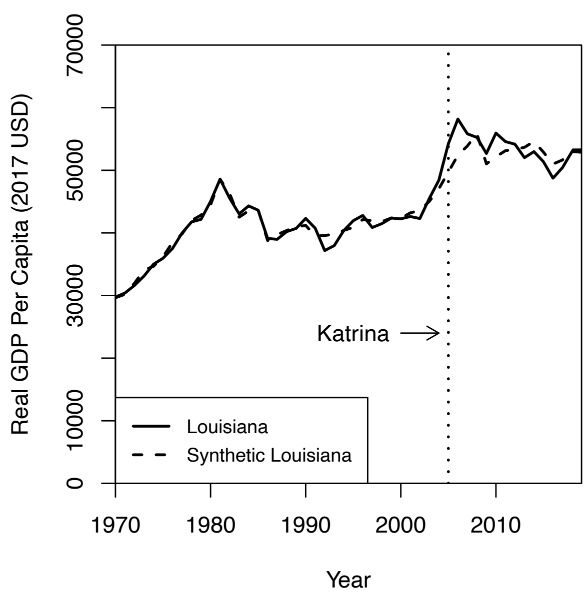


Figure 4: Path Plot of GDP Per Capita 1970-2019: Louisiana versus Synthetic Louisiana

Furthermore, *Table 1* compares the values of the key predictors for LA, SLA, and a mean of the 41 states in the donor pool. For all predictors, except the government proxy, SLA is a considerably better fit compared to the sample mean. The differences between LA and SLA are the smallest for the GDP per capita lags and the savings rate. A good fit on GDP per capita lags

[38]Dividing the pre-disaster period in different time priods, the average gap between LA and SLA in 1963-1972, 1982-1992, 1993-1998, 1999-2004 – the two latter shorter to be able to assess the differences in the year closest to the disaster – in absolute USD is $568, $559, $1,087, $1,081, and $938.

is encouraging, given that previous literature indicates that the GDP per capita lags are the most efficient predictors to the present GDP per capita. SLA also reproduces LA's bachelor's degree relatively well, especially when comparing to the sample mean. SLA's industry share and TFP proxy are not reproducing LA's values as good as the previous mentioned variables, especially true for the TFP proxy. However, by comparing SLA's value to the sample means' proves that the fit is good given the sample. For the government proxy, SLA does not reproduce a such close value to the government predictor of LA – the sample mean is a closer fit to LA than SLA is. However, if removing the government proxy, the RMSPE increases, indicating it is better to include the government proxy as a predictor than to not do it.[39]

The predictors are weighted (the V matrix) as follows: GDP per capita lag 1994 (76.3%); saving rate (13.6%); GDP per capita lag 1984 (5.3%); TFP proxy (3.2%); GDP per capita lag 2004 (1.0%); industry share (0.6%); bachelor's degree share (<0.1%); government (<0.1%). We first notice that the GDP lags receive large weights (together 82.6%). It is encouraging that the historical GDP per capita get a relatively large weight, however, we do not want it to be too close to 100%, as discussed in Appendix D. Thereby, compared to the alternative set of predictors we had, the 82.7% is reasonable. Specifically, the lagged values from 1984 and 1994 receive large weights. This can be connected to Louisiana's oil industry dependency where their real GDP per capita is contingent on crude oil prices; Louisiana experienced a downward trend in its real GDP per capita between 1982 and 1992, a period where the oil prices decreased. A decline in the real GDP per capita between these years is not an overall trend in the sample and, therefore, in combination with the lags being good predictors of the present GDP, this explains the large weights on the 1984 and 1994 lags. The smaller weight on GDP per capita in 2004, are likely to be due to the gap increases in 2004.

Last, the states with positive weights W, reported in *Table 2*, show that Louisiana is best reproduced by a combination of Oklahoma, Kentucky, Wyoming, Iowa, Alaska, South Carolina, and Wisconsin. Oklahoma has the largest weight of 44.1%, which could be explained by Oklahoma and Louisiana having a similar real GDP per capita in trends and levels between 1963-2004. This could partly be explained by the two states having similar trends and levels in crude oil production, measured both in total barrels and in barrels per capita, between 1981-2004 – a similarity cached in the real GDP through crude oil prices. Also, recall that the oil price production itself was a potential predictor that did not receive any weight. In addition, both Alaska and Wyoming are large crude oil producer states – much larger than Louisiana in per capita terms – causing crude oil prices to have a large impact on their respective GDP, and in turn, something that causes similarities in real GDP per capita trends compared to Louisiana. Furthermore, both Kentucky and Iowa have similar levels of real GDP per capita as Louisiana during 1963-2004, but not similar trends. Kentucky is in addition similar to Louisiana on many demographic metrics as well as in several social and political aspects. Also, Iowa has a similar savings rate as Louisiana. We, therefore, consider the selected states in the donor pool as reasonable.

The fit between the SLA and LA, on both real GDP per capita and its key predictors, lends credibility to our identification assumption. Therefore, we proceed with presenting the results on the effect on economic growth following Katrina.

[39]Note, however, that the government variable receives a small weight, meaning it does not affect the selection of states in the SLA to a considering degree.

Table 1: Real GDP Per Capita Predictor Means Before Katrina

Predictors	LA	SLA	Sample mean	SLA/LA
GDP per capita 1984	44,315	43,519	38,999	0.98
GDP per capita 1994	40,367	40,397	43,765	1.00
GDP per capita 2004	48,417	47,050	52,882	0.97
Bachelor's degree (%)	18.7	20.2	24.6	1.08
Industry share (%)	24.3	21.5	20.3	0.88
Savings rate (%)	11.2	11.0	8.2	0.98
TFP Proxy (%)	0.6	0.9	2.3	1.4
Government proxy	48.5	44.6	46.2	0.92

Note: Bachelor's degree is for year 2000. Industry share and Savings rate are averaged from 1997 to 2004. TFP proxy is averaged 2002 to 2004. Government proxy is averaged for 1995 to 2004. The SLA/LA compares the SLA to LA.
Source: View Appendix C

Table 2: State Weights in Synthetic Louisiana

State	Weight
Oklahoma	0.441
Kentucky	0.246
Wyoming	0.115
Iowa	0.106
Alaska	0.083
South Carolina	0.004
Wisconsin	0.001

Note: All states with weights >0.001.

7.2 Effects on Economic Growth

The post-disaster distance between LA and SLA measures the effect of real GDP per capita after the disaster, visualised in *Figure 4*. Accompanying *Figure 4* is the gap plot in *Figure 5*, showing the difference between LA and SLA in all periods of the sample. Studying the impacts on GDP per capita both in the long-run and short-run give implications for the results on economic growth.

Our results indicate a short-run positive effect on state-level economic growth in Louisiana. After Katrina, the GDP per capita in Louisiana rises so that, in 2006, the GDP per capita is 11.5% or \$5,996 USD higher than it would be in the absence of Katrina. However, in the long run, the effect on economic growth is not following a clear trend. Whether these results are significant or not are first concluded in Section 7.4 with the placebo results. We now present these respective findings in detail, starting with the short-run effect.

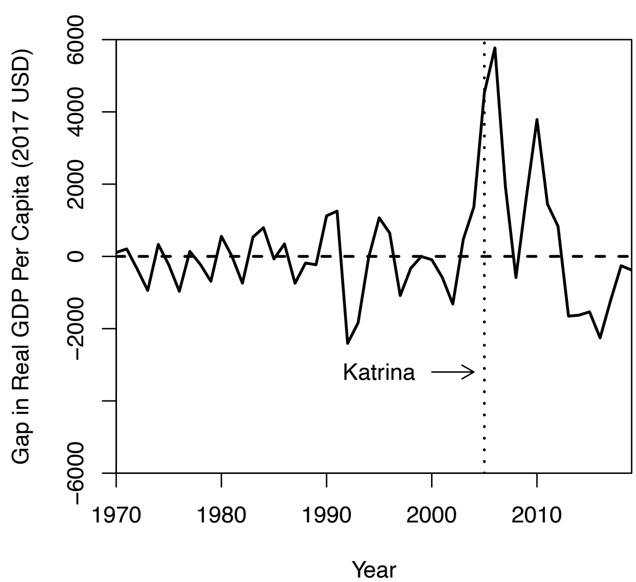


Figure 5: Gap Plot of GDP Per Capita 1970-2019: Louisiana versus Synthetic Louisiana

7.2.1 Short-Run Effect

Indicated by our result, the short-run effect of Hurricane Katrina on state-level economic growth in Louisiana is positive, derived from an estimated rise in GDP per capita. The gap between LA and SLA increases from \$1,578 USD in 2004 to \$4,746 USD in 2005, view *Table 3* and *Figure 5*. Our results show that the real GDP per capita in Louisiana is 9.6% higher in 2005 compared to what it would have been in its absence. In 2006, the disaster-effect GDP per capita increases from previous year, indicating a continued effect on economic growth that would not have occurred in the absence of Katrina. In 2006, the real GDP in Louisiana is 11.5% higher than what it would have been in the absence of Karina. Therefore, there is no support for this paper's hypothesis of a negative short-run effect on economic growth.

Table 3: Disaster Effect on GDP per capita

Year	Disaster effect ($USD)	Disaster effect (%)
2005	4,746	9.6
2006	5,996	11.5
2007	2,163	4.0
2008	-359	-0.7
2009	1,879	3.7
2010	4,010	7.7
2011	1,670	3.2
2012	1,058	2.0
2013	-1,329	-2.7
2014	-1,396	-2.6
2015	-1,300	-2.5
2016	-2,022	-4.0
2017	-982	-2.0
2018	-15.6	-0.03
2019	-133.2	-0.3

Note: The average gap in the pre-disaster period is $799 USD.
The disaster effect in percentage is the disaster effect as a fraction of the GDP per capita for LSA, any given year.

7.2.2 Long-Run Effect

The long-run effect on economic growth is not following a clear trend. *Figure 4* shows that LA shift between having higher and lower GDP per capita compared to SLA. Furthermore, *Figure 5* shows how the gap between LA and SLA shifts in both magnitude and signs.

First, as seen in *Figure 4*, the positive short-run effect on economic growth is followed by a period of stagnating economic growth, but during which the output per capita is higher than pre-disaster. While the GDP per capita continues to rise in SLA, LA's GDP per capita starts to decline, indicating a decreased gap between LA and SLA, and a stagnation in growth that would not have occurred in the absence of Katrina. At the end of 2007, the real GDP per capita is $2,163 USD or 4.0% higher than compared to in the absence of Katrina, view *Table 3*.[40] Viewed by the decline in the gap in *Figure 5*, the economic growth continues to decline until 2008. In 2008, the GDP per capita is $358 USD or 0.65% lower than it would have been in the absence of Katrina.

Second, with the exception for 2008, LA has a higher output than its synthetic counterpart during the financial crisis and the years after, until 2012.[41] The largest difference these years are in

[40]We also notice that the gaps in GDP per capita are still larger than pre-disasters, during this first period of the long-run effect. This leads us to suppose the effect is significant, however, this is decided first when the placebo-tests are presented.

[41]The GDP in the U.S. declined with 2.3% the first quarter of 2008 and continued to decline until Q2 2009 , affecting the path of GDP in both LA and SLA. By using the method of SCM, and being carefully about the donor pool and the predictors of GDP, we have done our best to isolate away this effect. Therefore, we proceed with interpreting our results.

2010, during which the GDP per capita is $4,010 USD or 7.7% higher than its synthetic counterpart. The growth these years, indicated by the changes in the gap between LA and SLA, are positive from 2008 to 2010, then negative 2010 until 2013.

Third, during the last seven years of the sample – 2013 to 2019 – the GDP per capita is lower for LA than SLA. In 2016, we find the largest negative gap in GDP per capita of $2,022 or 4.0%. The last two years of the sample, the GDP per capita in LA is relatively close to SLA – $15 USD respective $133 USD lower. The effect on economic growth these year differ: between 2012 and 2013 it is negative, 2013 to 2015 positive, 2015 to 2016 negative, 2016 to 2018 positive, and 2018 to 2019 negative again, view how the gap changes in *Table 3* or in *Figire 5*

The volatility in the size and magnitude of the gaps between LA and SLA lead us to not find any clear long-run effect on economic growth. Furthermore, we also view that the gaps in the last years of the sample are lower than the average pre-disaster gaps. This indicates that the effect on long-run economic growth is likely to be insignificant and that we need to interpret the results more carefully. Thereby, our hypothesis of no recovery, as plotted in *Figure 3*, does not find support in our result.

7.3 Transmission Channels

We now turn to present our results on the effect of Katrina on the possible transmission channels to the effect in economic growth: population, labour, and physical capital. As mention in Section 5.4, the disaster effect on the transmission channel is the difference between LA and SLA the studied year post-disaster and the average difference between LA and SLA pre-disaster.

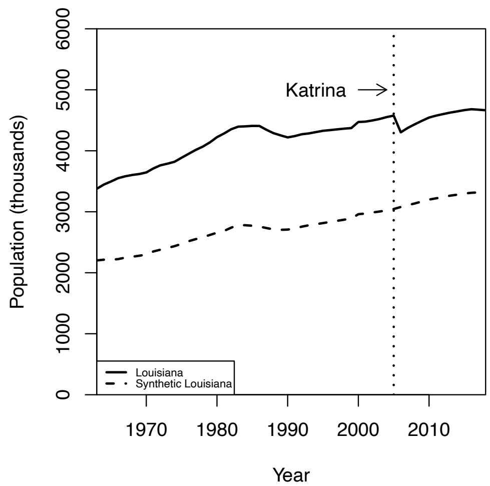
7.3.1 Population

In *Figure 6*, the population in LA and SLA are presented in *Panel 6a* and the gaps between the units in *Panel 6b*. Before Katrina, LA and SLA follow a similar path in population, seen in *Panel 6a*. This lends credibility to SCM's identification assumption for transmission channels. In 2005, the year Katrina strikes LA, there is no visible effect on the population; the gap between the units is at similar levels to prior years. However, in 2006, the gap suddenly decreases, driven by a continued increase in population in SLA while the population decline in LA. In 2006, the population in Louisiana is 282.5 thousand or 6.2% lower than compared to in the absence of Katrina.[42]

Figure 6 further indicate that the population in Louisiana stays at a lower level post Katrina. Our results, therefore, show a sustained negative effect on the population number during the years following the hurricane. Between 2006 and 2016, we find that the population stays at a lower level than compared to in the absence of Katrina, however, that the population starts to recover. The gap between LA and SLA reduces, and in 2016, the population in Louisiana is 151 thousand or 3.14% lower than compared to in the absence of Katrina. Between 2016 and 2019 the gap again increases. In 2019, our estimate show that the population is 184 thousand or 3.8% lower than compared to in the absence of Katrina.

[42] As the population is the denominator in real GDP per capita, these results can be directly related to the real GDP to understand the effect on population on GDP per capita. This is further developed in Appendix E, *Figure 17*. Our results graphically that the real GDP also falls post Katrina, however, when not taking GDP per capita the identification assumption of similar path pre-disaster does not hold. Therefore, we are not able to assess the degree on the effect on GDP per capita that comes from changes in population versus changes in real GDP.

(a) Path Plot of Population



(b) Gap Plot of Population

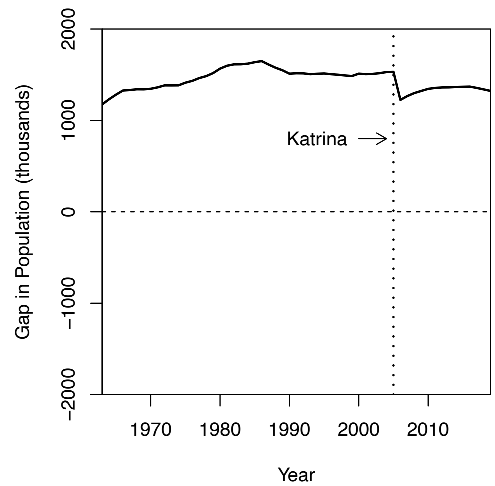


Figure 6: Path and Gap Plot of Population 1970-2019: Louisiana versus Synthetic Louisiana

7.3.2 Labour

Furthermore, we present our result on the effect on three labour measurements, starting with the unemployment rate.

Unemployment Rate
Figure 7 shows the unemployment rate in LA and SLA in *Panel 7a*, and the gaps between the units in *Panel 7b*. Furthermore, in the Appendix E, the nominator and denominator of unemployment are visualised: the unemployment numbers and the labour force size.

Prior to Katrina, the unemployment rate for LA and SLA follow relatively similar trends, view *Figure 7*, *Panel 7a*. An exception is the period between 1980 and 1990, in which the gap increases as the unemployment rate is increasing more in LA compared to SLA. Otherwise, the trends are similar, and especially the years before the disaster, which lends credibility to the identification assumption of similar trends.

The unemployment rate increases from 5.9% 2004 to 7.2% in 2005. Compared to in the absence of Katrina, the unemployment rate in 2005 is 0.93 percentage points higher. In 2006, the unemployment rate falls to 4.5% in LA and falls in SLA from 4.9% to 4.5%, leading the gap to increase. For both LA and SLA, the unemployment rate then stays at a constant level until 2008. During 2006-2008, the unemployment rate is 1.37 percentage points lower, 1.46 percentage points lower and 1.06 percentage points lower, respectively, than compared to in the absence of Katrina.

In 2009, the unemployment rate rises in both LA and SLA, to 6.8% respectively 7.45%, and then slowly reduces in both until 2019. In 2019, the unemployment rate is 4.8% respectively 3.7%. The overall trend is that the unemployment rate stays at a lower level than in the absence of Katrina, except for 2015 where it is the reverse. However, we also find that the effect over time diminishes. In both 2018 and 2019, the unemployment rate is 0.3 percentage points lower compared to in the absence of Katrina.

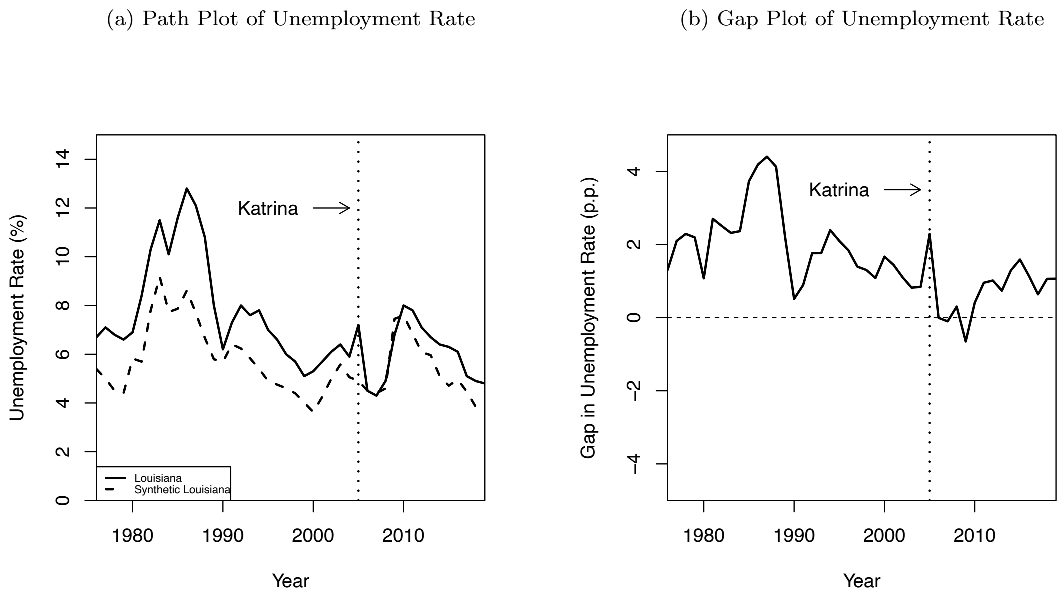


Figure 7: Path and Gap Plot of Unemployment Rate 1976-2019: Louisiana versus Synthetic Louisiana

Furthermore, we study the sources of unemployment rate, review Appendix E for visual plots of the unemployment number and the total labour force size.[43]. In 2005, the gap in unemployment increases due to an increase in the unemployment in LA but not SLA, however, the gap again reduces in 2006 to a level lower than seen in the pre-disaster period.[44] For the labour force size, the gap stays at a similar level as pre-disaster in 2005 but decreases in 2006. However, we are not able to say that the effect on labour force size is causal since the drop in labour force size is not substantially different from changes in the pre-disaster period. In the long run, the gap between LA and SLA goes back to pre-disaster levels for the unemployment number.

Employment-Population Ratio

Furthermore, *Figure 8* shows the employment-population ratio in LA and SLA in *Panel 8a*, and the gaps between the two in *Panel 8b*. LA and SLA follow a similar path in the pre-disaster period and, thus, the identification assumption holds. Post Katrina, we find no effect on the employment-population ratio. Rather, the gap stays at a similar level as pre-disaster. By further studying the number of employed and the civilian noninstitutional population – the numerator and denominator of the employment-population ratio, we find that the number employed declines, however, not

[43] *Figure 18* and *Figure 19*.

[44] The identification assumption holds for the unemployment number.

(a) Path Plot of Employment-Population Ratio

(b) Gap Plot of Employment-Population Ratio

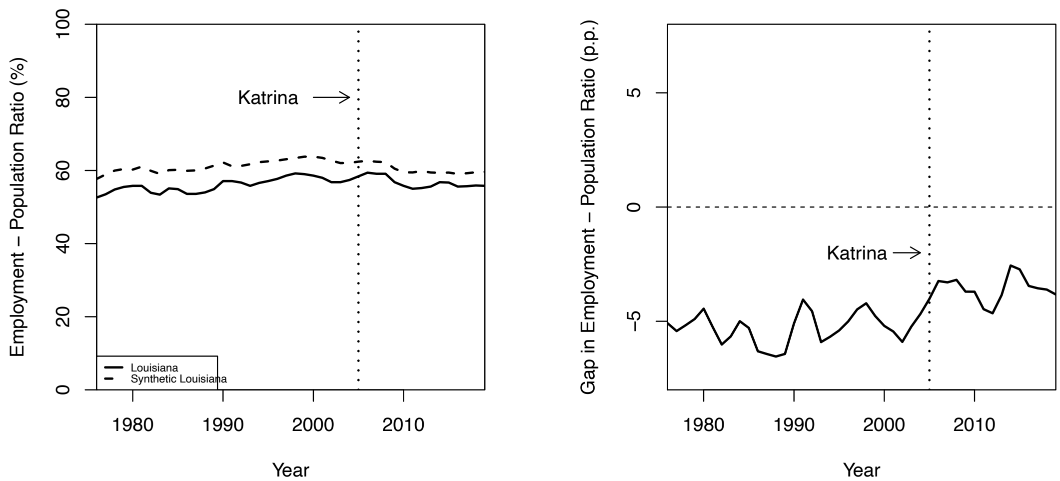


Figure 8: Path and Gap Plot of Employment-Population Ratio 1976-2019: Louisiana versus Synthetic Louisiana

substantially given the volatility in the gaps seen in the pre-disaster period.[45] Furthermore, we find a negative effect on the civil noninstitutional population: in 2005 and 2006, respectively, the noninstitutional population is 2.24% and 5.75% lower than compared to in the absence of Katrina. The effect then reduces, however, we see a reduced amount during the whole sample-period.

Civil Labour Force Participation Rate
Lastly, for the labour measurements, we study the effect on civil labour force participation rate. We see that the pre-trends between LA and SLA differ given the higher volatility in the rate for LA, view Appendix E.[46] Therefore, the identification assumption does not hold, whereby we do not continue to interpret the effect on the civil labour force participation rate.

Conclusion for Labour
To conclude, the results show that the unemployment rate the year of disaster increases compared to in the absence of Katrina, and then stays at a lower level during the whole sample period with exception for one year. In the long-run, the effect on unemployment rate is diminishing over time. Furthermore, we do not find any effect of Katrina on the employment-population ratio. For the labour force participation rate, we are unable to make any conclusions due to lacking support for the identification assumption.

[45] *Figure 20* and *Figure 21*.
[46] Appendix E, *Figure 22*.

7.3.3 Physical Capital

Figure 9 plots physical capital per capita for LA and SLA respectively, as well as the gaps between the two. The trend between the units differ between 1973 and 1987, however, during the subsequent 18 years in the pre-disaster period up until 2005, the gaps in every period are at more similar levels. A long pre-period of the same trend lends credibility to the identification assumption, however, the immediate years leading up to the disaster-year are the most important for the assumption. Even if a longer period would lead to even more credibility that the gaps between the units had stayed similar after 2005 in the absence of Katrina, we consider the 18 years as enough to assess the identification assumption to hold. However, we treat the results more carefully and do not consider exact differences, as a consequence of Katrina, in capital per capita between Louisiana and the counterfactual Louisiana.

The physical capital per capita in LA increases from 2005 until 2011, while it stays roughly at a constant level in SLA until 2011 after which point it starts to decline. As a consequence, the gap between the LA and SLA during this period reduces, which indicates a capital accumulation in LA following Katrina up until 2011. After 2011, the gap starts to increase again, which indicates a decrease capital per capita in Louisiana.

(a) Path Plot of Physical Capital

(b) Gap Plot of Physical Capital

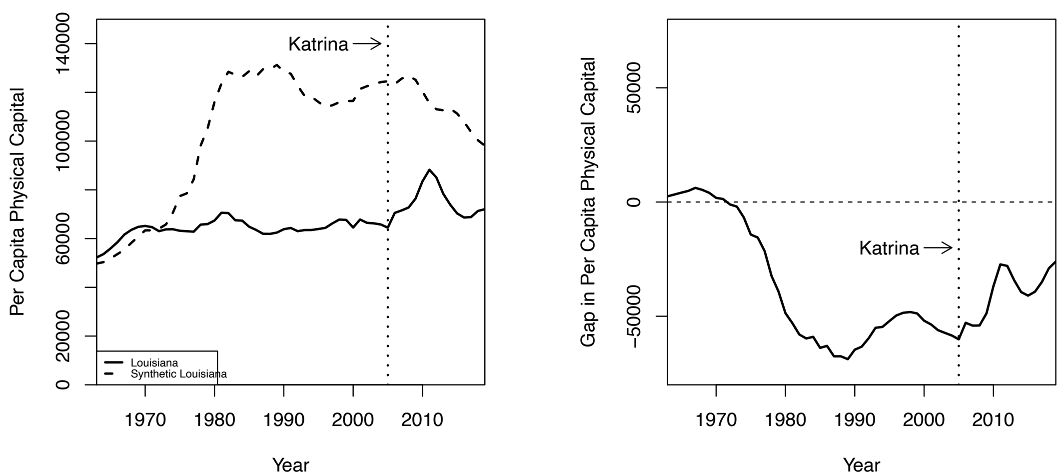


Figure 9: Path and Gap Plot of Physical Capital Per Capita 1970-2019, Louisiana versus Synthetic Louisiana

7.4 Placebo-Tests and Robustness-Tests

To assess the validity of the results in Section 7.2, we conduct a wide array of placebo studies and robustness tests following Abadie, Diamond, and Hainmueller (2015). This alternative model of inference is based on the premise that the confidence in the estimates would be undermined if we would obtain similar effects in cases where the natural disaster did not take place. The set of tests performed are (i) in-time placebo, (ii) in-space placebo, (iii) leave-one-out robustness test, and (iv) full sample robustness test. By these tests, the significance level of our results – both the short-run and long-run – are also calculated.

7.4.1 In-Time Placebo

First, the in-time test is performed by doing a falsification rerun of the model, artificially setting the disaster event at an earlier date than the actual. In our test, we shift the year of the disaster to 1992, 1995, and 2000.[47] We want to find that the placebo disaster does not result in a post-placebo disaster divergence in Louisiana and its synthetic control, since a large placebo effect casts doubt on the causality of the effect seen in *Figure 4* and *Figure 5*. The in-time tests in *Figure 10* shows the placebo effects for 1992, 1995, and 2000, and, encouragingly, no such divergence is found. Based on the first placebo tests we do not cast a doubt on the causality in our main results.

(a) 1992 (b) 1995 (c) 2000

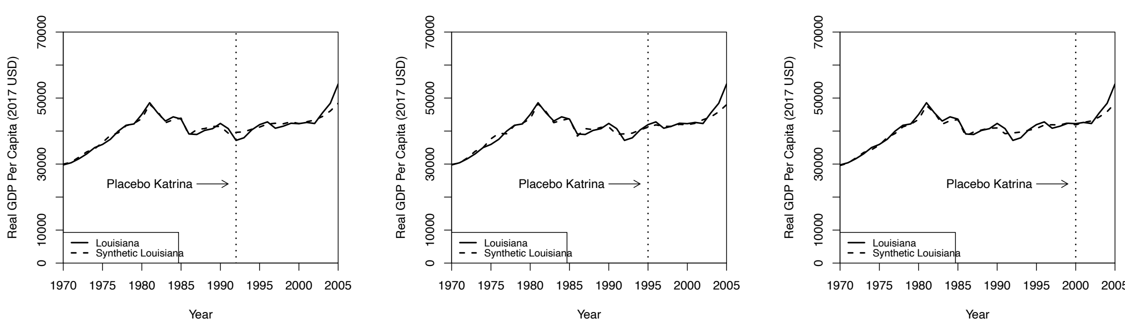


Figure 10: Placebo In-Time Tests

7.4.2 In-Space Placebo

Second, in contrast to the in-time placebo test that reassigns the disaster event to an earlier time, the in-space placebo is conducted by allocating the disaster to another unit in the donor pool. We replicate this for every region included in the donor pool, using the same methodology of constructing a synthetic counterfactual and estimating the difference in the outcome variable.[48] If

[47]Note that some of the data on predictors starts later than required for running the tests in 1992 and 1995. Prior 1992, the predictors would be even more limited. We start with 1992 and not earlier since it allows us to use relatively similar predictors as in our main tests, but still run a in-time-placebo test early in time.

[48]We run all tests at the same time, however, we omit Wisconsin and Wyoming due to unsolved problems in R. When including the two tests in both the in-space placebo test and when calculating the post-MSPE/pre-MSPE

(a) With All States (b) Excluding States

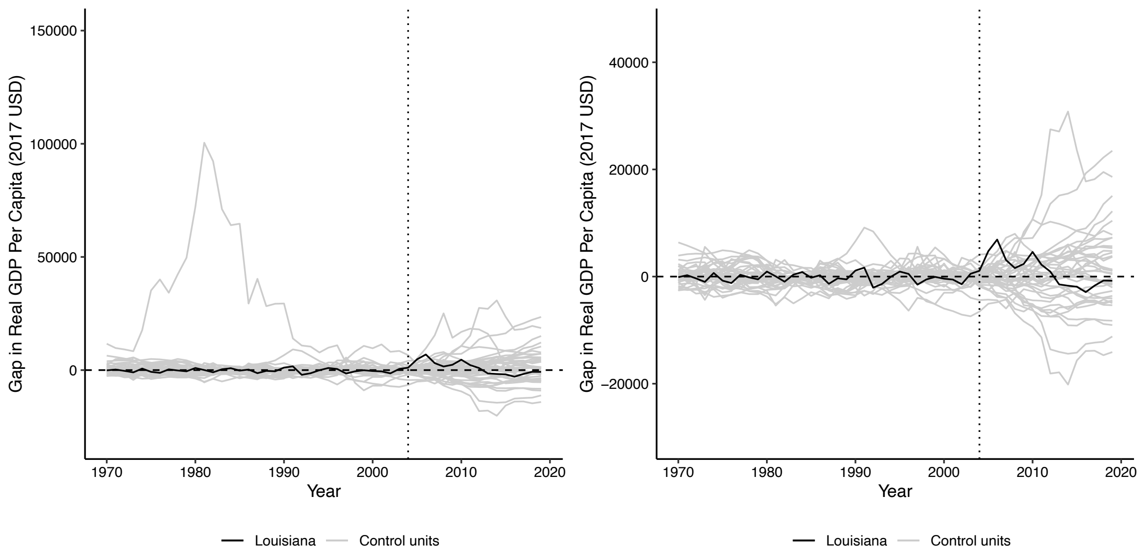


Figure 11: In-Space Placebo Tests: Real GDP Per Capita in Louisiana and Placebo Gaps for the Control States

similar or larger estimates to that in Louisiana appear in units not directly exposed to the disaster, our confidence that the synthetic control estimate reflects the effect of Katrina would be reduced. By comparing the result from Louisiana with the placebo result from each state also allows for inference and construction of a p-value, measuring the fraction of placebos with results equal or larger than the one estimated for the disaster state (Abadie, Diamond, and Hainmueller 2015).

Visualised in *Figure 11* are the results of the in-space placebo tests. The volatility in the pre-disaster path for some states, observed in *Panel 11a* showing the results for all states in the donor pool, indicate that the method is not able to find a combination for all states that replicates the path of real GDP per capita. Therefore, *Panel 11b* visualises the exclusion of the states with a pre-disaster MSPE value that is at least 20 times larger than that of Louisiana, following Abadie, Diamond, and Hainmueller (2015).

In the short run, the short-run gap in Louisiana is the largest in the sample. This can be

ratio, error codes occur. To find the root of the problem, we have tried several alternatives: (i) limiting the time – we then find that no error codes occur when excluding the years 2013-2019; (ii) scanned the data closely several times, both for missing values and wrong signs; (iii) tested replacing all the values on all variables for Wisconsin and Wyoming with values on respective variable for other states; (iv) expand the datafile to only include all 50 states instead of the 42 from limiting the donor pool. Despite these rigorous tests, the problem still persists. Therefore, we exclude the two states from our in-space placebo tests. This causes some implications, however, not significantly large ones. For both the in-placebo tests and the post-MSPE/pre-MSPE ratio tests, Wisconsin and Wyoming are not receiving any weights in any synthetic state, for any state. However, given the size of the donor pool, the donor pool still consists of 39 states (42 states in the donor pool, excluding the "treated unit" and the two excluded states). For Louisiana, which normally include Wisconsin and Wyoming in its donor pool, the path plot is identical despite the exclusion. Therefore, we assume it does not create significant changes in the in-space placebo tests or in the significance levels calculated.

viewed in *Figure 11*, *Panel 11b* – or in Appendix E in which *Panel 23b* zooms in on the short-run. Therefore, in the short-run, the p-value is estimated to range between around 0.225 in 2005 and <0.01 in 2006.[49] This indicates that the short-run effect on state-level economic growth in Louisiana is significant.

In the long-run – more specifically, the last year of our sample – there are around 5 states with a smaller gap, in absolute values, than Louisiana, and therefore around 34 states with a larger gap than Louisiana. This leads to a p-value close to 0.85.[50] The p-value also increases the longer the term is that we study – by comparing the difference years we define as the long-run – as the gap becomes closer to zero in the long run. The high p-values lead us to conclude that the long-run results are not significant.

(a) Short-Run

(b) Long-Run

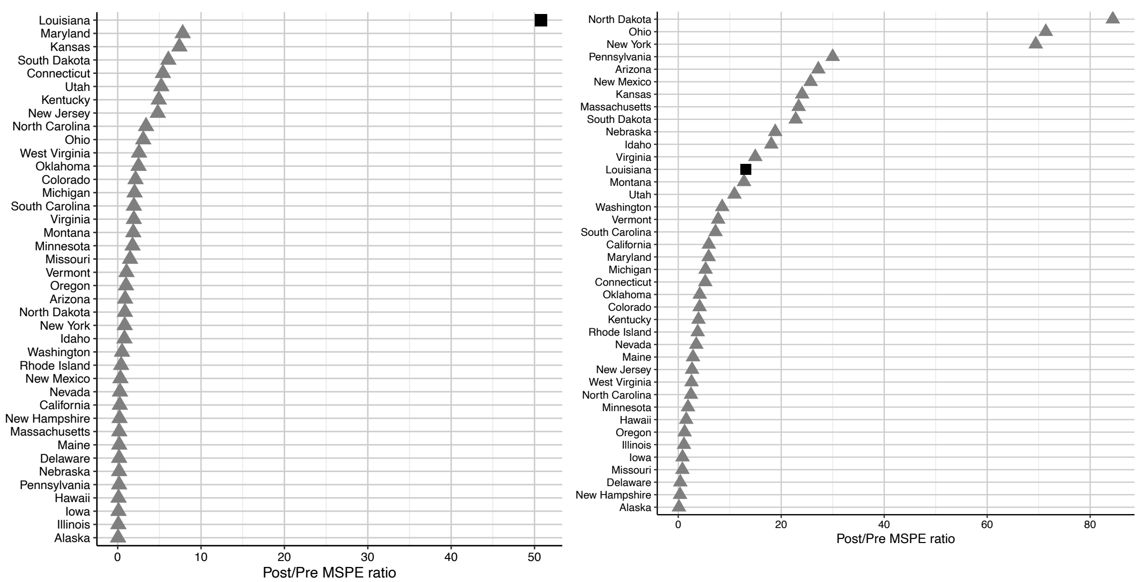


Figure 12: Post/Pre MSPE Ratio: Louisiana and Control States

However, through the in-space test above we discard states based on an arbitrarily chosen cut-off rule affecting the p-value. Another inference method is to look at the ratio of post-disaster MSPE values to pre-disaster MSPE values for all states in the donor pool and Louisiana (Abadie, Diamond, and Hainmueller 2015). A higher ratio indicates a true causal effect of the disaster, as it means a small pre-disaster prediction error and a high post-disaster MSPE value. *Figure 12* shows the ratio for the short-run period and 15 the long-run period, in *Panel 12a* and *Panel 12b*, respectively. In the short-run period, the post-MSPE/pre-MSPE ratio of Louisiana is the highest, leading to a

[49]Note that obtaining the p-values is a visual exercise – by visually studying which control states, in absolute values, that have a larger gap. In 2005, we visually estimate there to be 9 states with larger gap than Louisiana. The p-value is therefore approx. 9/40=0.225. In 2006, we visually estimate there to be no states with larger gap than Louisiana. The p-value is therefore approx. 0/40=0, which we refer to as <0.01.

[50]Note, again, that estimating the p-value is a visual exercise. We therefore refer to close to 0.85 (34/40=0.85) rather than exactly 0.85.

p-value of <0.01.[51][52] In the long-run period, there are 12 states with a higher ratio than Louisiana, leading to a p-value of 0.3.[53] The p-value obtained from the second method of inference is lower than the first, obtained from *Figure 11.* As this takes the whole post-period into account and not only 2019, we believe that this p-value better represents the significance level in our test. These results indicate that there is a significant short-run positive effect on state-level economic growth, at the lowest significance-level (<0.01), and no significant effect on the long-run economic growth.

7.4.3 Leave-One-Out Robustness Test

Third, a leave-one-out robustness test is implemented (Abadie, Diamond, and Hainmueller 2015), to examine if the main results are driven by one or a few influential controls.[54] We iteratively eliminate one state with positive weights. *Figure 13*, *Panel 13a* shows that, when leaving one state out at a time, the main results are overall robust to the elimination of one state in the donor pool at a time. However, when removing Alaska, the leave-one-out line (the line with the highest short-run spike) is above the real Louisiana both in the short-run and long-run, leading the short-run effect on economic growth to seem not as positive and the long-run effect more negative.

(a) Leave-one-out (b) Full-sample (c) Sample-variations

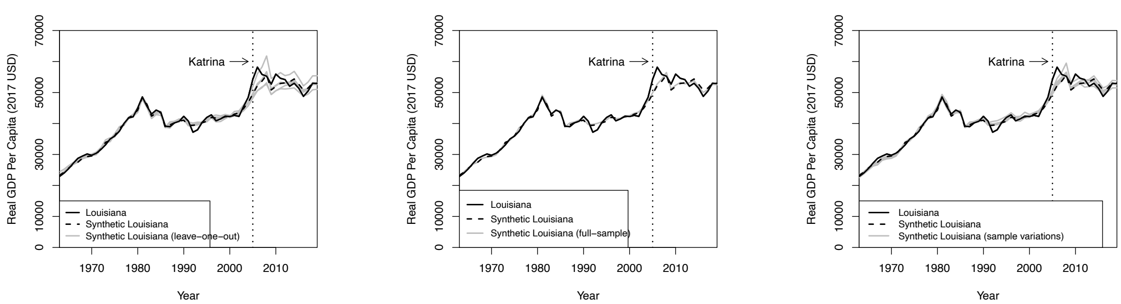


Figure 13: Path and Gap Plot of GDP Per Capita: Main Result versus Leave-one-out and Full-sample

7.4.4 Full-Sample Robustness Test

Last, the full sample test is performed by using all 49 control regions from the U.S. donor pool to construct the synthetic control state. We also run four additional tests: first omitting the states directly affected only, second the states indirectly affected, third the states omitted by other reasons,

[51] To obtain the p-value, we take 0/40=0, which we refer to as <0.01.

[52] Additionally, due to the data-limitations described in an earlier footnote, we test the post-MSPE/pre-MSPE ratio for Wisconsin and Wyoming separately. The post-MSPE/pre-MSPE ratio is 0.66 for Wisconsin and 3.41 for Wyoming – both lower than the ratio for Louisiana. Therefore, the p-value can also be calculated as 0/42, which still leads to a p-value <0.01.

[53] To obtain the p-value, we take 12/40=0.3

[54] As our choice of predictors was selected through a data-driven approach, this robustness test is of extra importance to also check that we have not overfitted our model to specific control states as a consequence.

and fourth the states both indirectly affected and omitted by other reasons.[55] *Figure 13* visualises the results for the full sample in *Panel 13b* and results, including other sample variations in *Figure 13c*. When including the full sample or the other sample variations, the results are nearly identical to Synthetic Louisiana. The weights, however, change, especially for the full sample. In the full sample, the new synthetic counterpart consists of Oklahoma (0.319), Arkansas (0.23), Wyoming (0.159), Indiana (0.147), Alaska (0.094), West Virginia (0.045), North Dakota (0.002) and Iowa (0.001). The previously excluded states, Arkansas and Indiana, now receive significant weights, and both South Carolina and Wyoming drop out. Despite these changes, the results of the estimation of the disaster effect are almost identical, both in the short-run and in the long-run. The main criteria for dropping states is to remove states also directly or indirectly affected by Katrina, to be able to isolate the effect on Louisiana. Therefore, we prefer the main result over the full sample result.

Overall, our placebo-tests show that the short-run economic growth effect is significant, while the long-run economic growth effect is insignificant. Furthermore, our robustness tests show that the main results are neither driven by any specific states nor that the exclusion of states from the donor pool noticeably impact the estimated effects on economic growth, neither in the short-run nor the long-run.

8 Discussion

This section provides a discussion of this study's results. We begin by discussing our findings, interpretations and implications – both for the short-run effect, long-run effects, and the effects on the potential transmission channels to economic growth. As a final discussion, we turn to more general points and implications of our study.

8.1 Result Discussion

8.1.1 Short-Run Effect

In contrast to most other studies on the impact of natural disasters on economic growth (see, for instance, Felbermayr and Gröschl 2014; Strobl 2012; Noy 2009; Raddatz 2009), our study does not show any negative effect on short-run economic growth in Louisiana – referred to by Felbemayr and Gröschl (2014) as "naturally negative". We do not find support for our hypothesis of a negative short-run economic growth effect. Instead, we find a positive short-run effect on economic growth that is significant at p-value <0.01, and robust.

Our results for the short-run effect on economic growth is similar to that obtained by DuPont and Noy (2015) who study the effects of the Kobe earthquake on regional economic growth in Japan and find an estimated 4.1% higher GDP per capita during the year following the disaster than absent the earthquake. Our results, however, show an even larger positive effect on economic growth derived from the rise in growth to 11.5% higher GDP per capita during the year after the disaster than in the absence of Katrina. One plausible explanation for the similarity of a positive short-run effect on economic growth in our study and that of DuPont and Noy (2015) can be drawn from previous literature on mitigating factors of natural disasters, view the beginning of Section 3. Noy

[55]Furthermore, we test the effect on Katrina on other states affected directly by Katrina, that is, Florida and Mississippi. This partly help us to understand the level of biasness of including these states in the donor pool. We find no clear effect on these states, view Appendix F.

(2009) finds that countries with better institutions, higher literacy rates, and higher trade openness, experience a reduced effect on GDP per capita from natural disasters than countries without such characteristics. Furthermore, Kahn (2005) shows that higher-income countries experience lower fatalities and smaller economic growth impact. The U.S – being a high-income and developed country with high literacy rate, ranked high in most measurements of institutional quality (see, for instance, World Governance Index by The World Bank (Kaufmann, Kraay, and Mastruzzi 2010)), and a federation with generally high trade-openness across state borders – is therefore expected to have factors mitigating natural disasters compared to countries with the reverse characteristics. These factors could, hence, be important elements helping to mitigate the potential negative impacts of Katrina on Louisiana's GDP per capita. However, no previous study, to our knowledge, provide an explanation for whether factors like these could lead to a positive short-run effect on growth and not only reduce the negative-short run effect.

8.1.2 Long-Run Effect

Our results for the long-run effect on economic growth in Louisiana are insignificantly different from that of synthetic Louisiana, indicating that Louisiana's economic growth in the long-run is neither higher nor lower as a consequence of Katrina compared to absent the hurricane. This result is robust since it is not driven by any particular state or the exclusion of states from the donor pool. Furthermore, although the long-term trend caused by Katrina is somewhat similar to the trend in the "better to recovery" hypothesis of the five main hypotheses from previous literature, the volatility observed in the effect on economic growth during the post-disaster period makes us treat our result as not supporting any of the hypotheses.

Using the Synthetic Control Method we are able to capture the effect of what would have occurred in the absence of Katrina. Still, we do not find any support for either previous hypotheses in the literature nor any significant long-run effect. The combination of the insignificant results and the multiple hypothesis in the literature raises the question if there even are any systematic long-run effects of natural disaster. This question has been raised earlier, both by Skidmore and Toya (2002) writing "because the disaster risk differs substantially from country to country, it is reasonable to question whether there exists some relationship between disasters and long-run macroeconomic activity", and by Noy (2009) when discussing that the identification strategy is hard for the long-run effects. Although case studies, like ours, generally get lower external validity, it provides further empirical support for the question if there even is any systematic long-run effects of natural disasters.

8.1.3 Transmission Channels

Our study on Katrina's effect on potential transmission channels to economic growth – with the purpose to get a better understanding of how the effects on economic growth occurs – give rise to some findings and implications.

First, as noted in the background section as well as shown in previous literature (see, for instance, Groen and Polivka 2008; Paxson and Rouse 2008), Louisiana has a large out-migration following Katrina. The literature also shows how similar trends in out-migration occurred in other instances of natural disaster, such as the Kobe earthquake. Our study thus adds to the literature by finding that the population in Louisiana is 6.2% lower in 2006 than compared to in the absence of Katrina, whereafter the population stays at a lower level during the entire sample period compared to absent Katrina. Due to this population decline, however, effects on GDP per capita – and economic growth

– becomes more difficult to interpret. It is, for example, ambiguous whether the short-run effect on economic growth is mainly driven by a decline in population or an increase in real GDP — or both. Similarly, it is complicated to determine whether the long-run changes in economic growth are driven by changes in population or real GDP — or both. It is evident that the population decline in the short-run contributes to the effect on economic growth, however, we do not measure the effect of this effect, due to two reasons. First, it is outside the scope of this paper to study exactly how effects on the transmission channel variables transfer into the effect on economic growth. Rather, we study Katrina's effects on the transmission channel variables to get a better understanding of how the effects on economic growth occur. Second, the synthetic control for the real GDP does not entirely fulfil the identification assumption: in real GDP trends, the synthetic Louisiana does not appropriately follow Louisiana during the pre-disaster period.

Second, our study shows a direct loss of jobs among Louisiana residents as a consequence of Katrina during the year of the disaster. In 2005, the unemployment rate is 0.92 percentage points higher than absent Katrina. The increased unemployment rate directly after the disaster is in line with previous literature on Katrina (see, for example, Deryugina, Kawano, and Levitt 2018; Vigdor 2008), however, our results differ by not showing any substantial effect on neither the labour-force participation rate nor the employment-population ratio – the first due to the identification assumption not holding and the latter as our results do not show a change in ratio post Katrina. Moreover, our study differs from the findings in previous literature on the effects on the unemployment rate in the year that follow 2005. Neither Deryugina, Kawano, and Levitt (2018) nor Vigdor (2008) show any significant effects on the unemployment rate in the long run, rather they find that the unemployment rate starts to recover after the short-run negative effect. Our study, however, finds that the unemployment rate falls to a lower level than pre-disaster and that the unemployment rate the year following Katrina is 1.36 percentage points lower, compared to absent Katrina. This trend of a lower unemployment rate compared to in the absence of Katrina then continues until 2008.

The observed effect on the unemployment rate could be explained by a disproportionate out-migration of people in Louisiana that either were not part of the civilian noninstitutional population or were already unemployed. This is supported by our findings in two ways. First, the estimated decline in the civilian noninstitutional population directly after Katrina is smaller than in the entire residential population – the aforementioned is estimated to be 5.8% lower and the latter 6.2% lower the year after the disaster, both compared to in the absence of Katrina. This indicates that a portion of those who moved from Louisiana were those below 16 years, those in active duty of the Armed Forces, or inmates of institutions, such as penal, mental facilities, and homes for the aged – or a combination of these groups. Second, the total number of employed people stayed at a constant level post-Katrina while the unemployment rate increased, indicating that the people that moved were mostly those already unemployed before Katrina. Taking these two findings together, our results thus suggest that the major out-migration occurred by young people and those unemployed — inmates of institutions reasonably face more difficulty to move. These findings are in line with the study by Groen and Polivka (2008), who find that Katrina is associated with a decrease in share of the population with low income and low education – for example unemployed – and an increase in the share of the population with high income and low education.

Third, our study shows indication of a capital accumulation per capita in Louisiana during the years following the disaster that would not have occurred in the absence of Katrina. Although the identification assumption holds and thus lends credibility to the finding, we treat this result a bit more carefully, partly due to the shorter period of a similar trend in the pre-disaster period, partly due to the limits of the measurement we use for physical capital, as described in Section 6.

To conclude, our study shows how all three investigated transmission channels to economic growth were effected by Hurricane Katrina. Although not empirically studied, these results provide explanatory value for the effects on economic growth.

8.2 General Discussion

We now turn to more general discussions of our results.

First, the findings of who moved have implications for the economy of Louisiana and the short-run and long-run effect on economic growth. In the short-run, the economic growth in GDP per capita is reasonably more positively affected than if people being unemployed had stayed in the state. Movement across U.S. state borders and settling in other U.S. states is generally subject to few restrictions compared to movement across many country borders. This might be one explanation for why a positive effect on growth in the short-run following Katrina is observed at the regional level in the U.S., but not in similar country-studies. The residents in Louisiana, compared to residents in countries, are not generally stuck to keep living in the affected state but can move easily to unaffected regions, which may be especially true for the young population and the unemployed. In the long-run, our results indicate that the setup in population changes – the demographic profile – which is also shown in the study by Groen and Polivka (2008) when they examine what groups of people return in the aftermath of the disaster.

Reasonably, there are also consequences that arise due to natural disasters in that people move to new locations. Our results on the transmission channels of labour indicate that a large portion of those who move are young and unemployed. Previous literature on Katrina (see, e.g., Groen and Polivka 2008) similarly indicates that the people more likely to return after Katrina are those who had higher income during the pre-disaster period, and the people less likely to return in the aftermath are those who had lower income. By moving, people can potentially find new job opportunities and education alternatives elsewhere, giving rise to possible changes in socioeconomic statuses. This opens up for interesting questions regarding the welfare effects of disasters. The analysis of this is outside the scope of our paper, but we urge future research to investigate this seemingly unstudied area.

Although our results suggest a positive short-run effect on economic growth and no long-run effect of Hurricane Katrina on Louisiana's economic growth, we do not argue that the impact of hurricanes is per se good for the economy. Rather, we first claim that the real GDP per capita measure is limited and does not capture the full effect of Hurricane Katrina on the regional society. As mentioned, GDP per capita does not measure changes in income or non-market transactions. Neither does if capture, for instance, the impact on wildlife and natural habitats. Given our focus on GDP per capita, these additional factors are outside the scope of this paper, however, we believe that effects on the economy are likely to be either underestimated or missed – or both – due to the limitations of the variable used. Second, it is important to recognise that we are studying the state-level economic growth, and not at a lower aggregated level of the economy. Given previous literature indicating that natural disasters are locally destructive (Horwich 2000), it would be interesting to also investigate the effects in, for example, only New Orleans.

9 Conclusion

Hurricane Katrina was one of the largest natural disasters to occur during the last few decades. To better be able to institute mitigating factors and better implement policies in future instances of natural disaster, it is important to have a more robust understanding of their empirical short-run and long-run consequences on economic growth. The objective of this study has been to examine the short-run and long-run effects of Hurricane Katrina on the state level economic growth in Louisiana. The identification strategy adopted was a Synthetic Control Method – to construct a control state for Louisiana that was not affected by Katrina or any other large events during the period leading up to 2005, but that had a similar level end trajectory in GDP per capita during the pre-disaster period. The synthetic Louisiana was able to reproduce the values for Louisiana on a number of key predictors to GDP per capita during 42 years prior to the disaster. We also expanded the model to include a data-driven methodology in the selection of predictors to economic growth to remove the subjectivity that may alter the conditions to find the most appropriate synthetic control.

Recall the research question: *What are the short-run and long-run effects of Hurricane Katrina on the state-level economic growth in Louisiana, and what are the effects of Katrina on potential transmission channels to the state-level economic growth in Louisiana?*

Our results suggest a short-run significant positive effects of Katrina on state-level economic growth in Louisiana. In 2005 and 2006, respectively, the GDP per capita is 9.6% and 11.5% higher compared to in the absence of Katrina – leading to a short-run positive effect on economic growth. The short-run effect on economic growth is further significant on a <0.1 significance level.[56] Furthermore, our results are robust in that they are neither driven by any specific state nor by any exclusion of states from the donor pool.

Moreover, in the long-run, we find that Katrina's effects on state-level economic growth in Louisiana are insignificant. The p-value ranges from 0.3 to 0.85, depening on method in the placebo-tests.[57] The insignificant results indicate that Louisiana's economic growth in the long-run is neither higher nor lower as a consequence of Katrina in comparison to absent the hurricane. Although not significant, the long-run result is robust to changes in the sample like for the short-run effect.

Our study further show that Hurricane Katrina has effect on resident population, labour, and physical capital – refereed to as potential transmission channels to the effect in economic growth. The population in Louisiana declines following Katrina – the year after the disaster, the population is 6.2% lower than compared to in the absence of Katrina. The population then stays at a lower level during the whole sample period. Furthermore, we find that the unemployment rate the year of the disaster increases in compared to in the absence of Katrina, however, the following years the unemployment rate is lower than in the absence of Katrina. However, we do not find any effect the employment-population ratio of Katrina. Combining the results on resident population and labour, we find a substantial reduction in residents population from an out-migration of people due to Katrina, where the people who left Louisiana were either unemployed or not in the labour force. Last, however interpreted more carefully, our study show that Katrina was followed by a capital accumulation. With that, we conclude our answer of this paper's research question.

Due to the low external validity of case studies, we argue that these results may be limited to the case of Katrina. However, lessons can be learnt – especially by those who ex-ante tries to reduce the consequences of future natural disasters - how Louisiana, despite the destruction and the large

[56] The p-value for 2006.

[57] The first p-value being more reliable, since measuring the p-value for the whole post-period and not only the last year in the sample.

number of fatalities, still managed to not face larger effects on economic growth.

Last, we have four recommendations for further research. The first recommendation is to use a similar methodology as ours to study other natural disaster in the U.S. setting, or other settings similar to Louisiana and Katrina. This to evaluate the external validity – but on similar settings – of our study by running similar tests on similar settings. Second, we suggest studies using quarterly data rather than annual data, for the case of Katrina. This is especially to better being able to derive the effect the first year of the disaster, where using annual data limit the understanding of the immediate effect. Third, we call for more studies on the topic of the transmission channels through which natural disasters might be affected. In our study, we investigate in the effect of natural disasters on the potential transmission channels to economic growth, however, we do not empirically study how the effect on the transmission channels then affect the economic growth. This is a highly relevant area for further studies to better understand why the effect on economic growth occur. Finally, we encourage more studies on the welfare effects of natural disasters, which – according to our knowledge – not have been an area for previous studies.

Altogether, we hope that this research paper inspires more research into the yet inconclusive field of natural disasters, as well as more case studies on Hurricane Katrina. Given the potential increase of natural disasters with climate change, this is a topical area for more research.

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Appendices

Appendix A: Climate Change and Natural Disasters

In this Appendix, we include a review of the relationship between climate change and natural disasters. One reason why this study is conducted on natural disasters, is due to recent prognoses on climate related research indicating that climate change may cause an increase in the frequency and intensity of some types of natural disasters. The studying of natural disasters and their impacts on society is, as such, of relevance. We therefore start with an overview of the relationship between climate change and natural disasters.

Earth has ever since its formation been subject to climate change, however, there is a growing proposition that the change in climate during the last years is extraordinary and not exclusive a natural process (Keller and DeVecchio 2012). Furthermore, as the changes in mean temperature tend to go along with changes in temperature variability and temperature extremes, there is a hypothesis that climate change might increase the frequency and intensity of natural disasters (Rummukainen 2012). The most used database of natural disasters (Emergency Events Databse, EM-DAT) indicates a steady increase of total number of natural disasters. More specifically, the hydrological and meteorological disasters have increased while the number of geophysical and climatological disasters have remained rather steady.

Although it is possible that the increased frequency of natural disasters is due to improved reporting (Cavallo and Noy 2011) and larger settlement along coastal areas most exposed to natural disasters such as storms and flooding (Neumann et al. 2015), there is a growing number of papers in climate research showing causal links between climate change and natural disasters. The is supported by meta-studies, two presented here. First, in a recent meta-study by the American Meteorological society, they find that approximately 65% identified a role of climate change while 35% did not find an appreciable effect (Herring et al. 2018). Second, a meta study in Nature find similar results. By analysing 170 papers on extreme weather events published between 2004 and 2018, they find that two-thirds of the events had a correlation to climate change (Shiermeier 2018).

For the U.S. setting, Nordhaus (2010) conducts a study on the economic impacts of U.S. hurricanes and its correlation to the climate change. Among others, the author find that greenhouse warming may lead to stronger hurricanes. He also finds that, with global warming, the number of storms that cost more than 0.1% of GDP (which he refers to 12.4 bn USD in 2005 GDP) would increase from 15 to 27. Moreover, he estimates that the average annual U.S. hurricane damages will increase with 10 billion USD in 2005 incomes due to global warming. That is, 0.8 percent of GDP.

In short, the literature suggests that natural disasters are becoming more frequent and intense, both when studying cross-country and when study the U.S. setting.

Appendix B: Hurricane Katrina Details

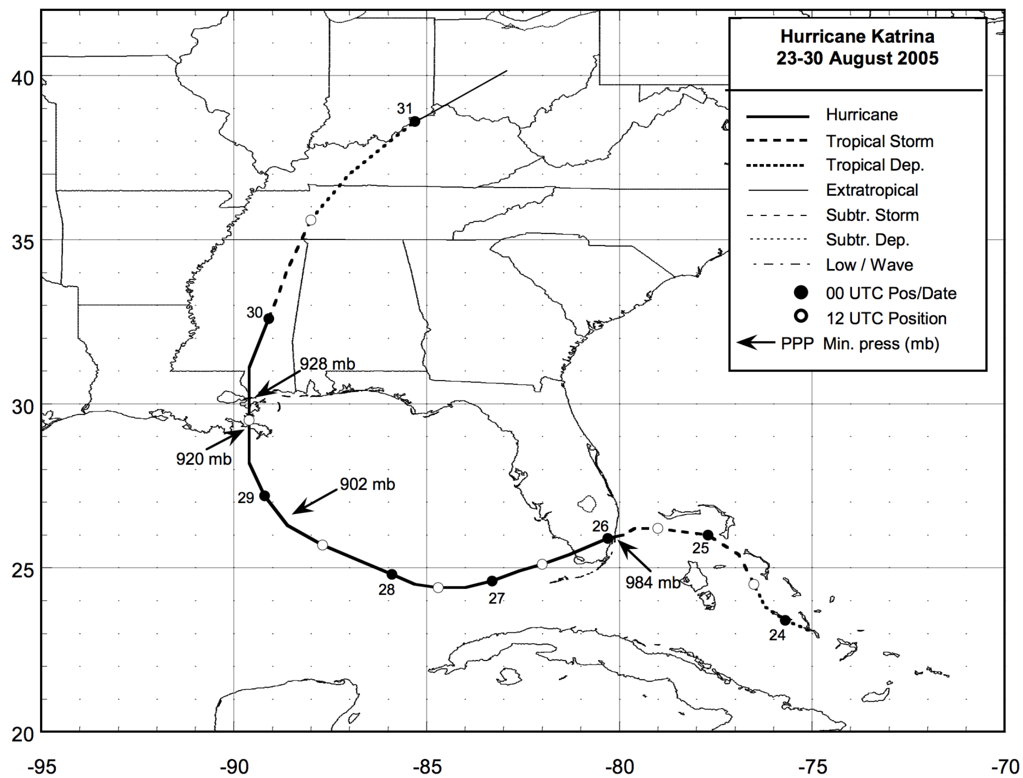


Figure 14: Best Track Position for Centre of Hurricane Katrina, 23-30 August 2005
Note: Hurricane Katrina striking southern Florida, southeastern Louisiana, and southern Mississippi
Source: Knabb, Rhome, and Brown 2011

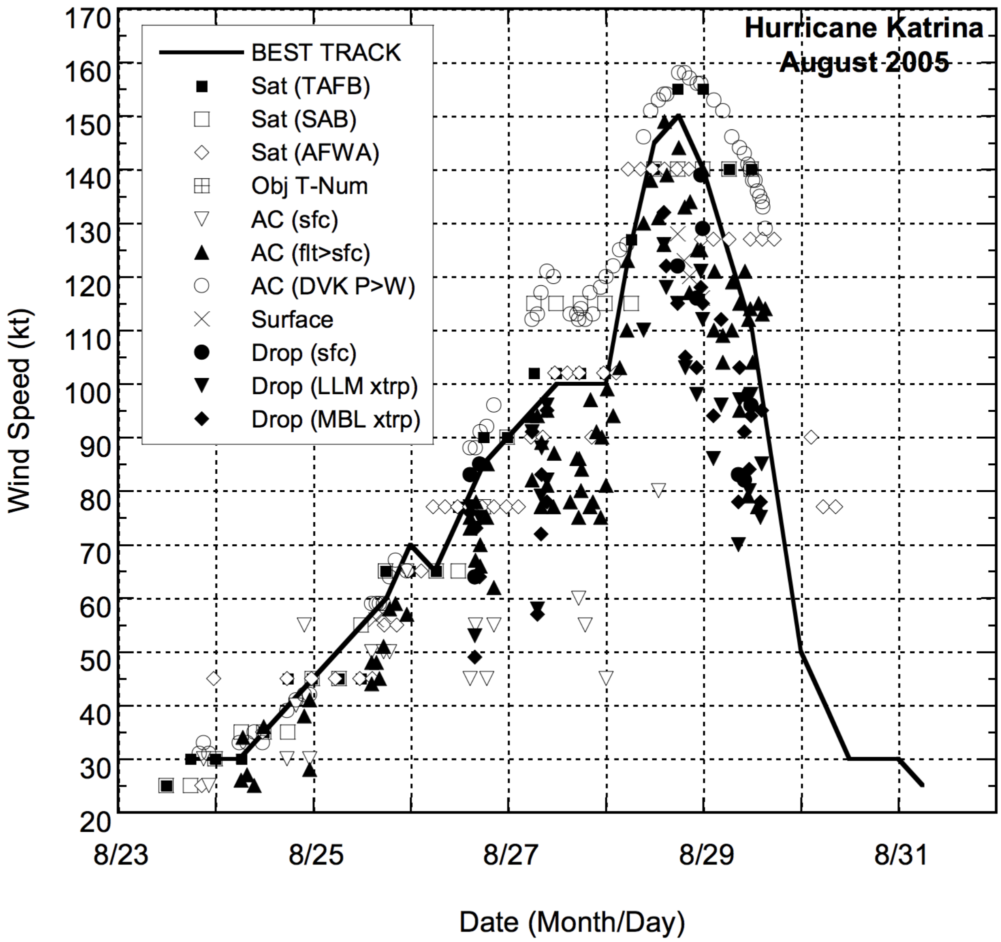


Figure 15: Best Track Position for Centre of Hurricane Katrina, 23-30 August 2005
Note: Hurricane Katrina striking southern Florida, southeastern Louisiana, and southern Mississippi
Source: Knabb, Rhome, and Brown 2011

Appendix C: Data Sources

Table 4: Annual U.S. State-Level Data

	Description	Data Period
Real GDP	Real GDP in Millions of 2017 USD	1963-2019
Real GDP per capita	Real GDP per capita in Millions of 2017 USD	1963-2019
Physical Capital per capita	Real Physical Capital per capita in Millions of 2017 USD	1963-2019
Industry Share (%)	Sum of Industry Earnings in Utilities, Construction, & Manufacturing, Divided by GDP	1996-2019
Crude Oil Production	Crude Oil Production in Barrels Per 1,000 People in Residential Population	1981-2019
Savings Rate (%)	Total DPI and Total PCE Difference, Divided by Total DPI	1997-2019
Consumption Rate (%)	Total PCE, Divided by GDP	1997-2019
TFP-Proxy (%)	Total R&D Expenditures by State, Divided by GDP	1991;1993;1995; 1997-2000;2002-2017
Population Density	Residential Population Divided by Total State Area	1963-2019
Labour Force Participation Rate (%)	Total Labour Force, Divided by Noninstitutional Civilian Population	1976-2019
Employment-Population Ratio (%)	Total Employed, Divided by Total Labour Force	1976-2019
Unemployment Rate (%)	Total Unemployed, Divided by Total Labour Force	1976-2019
Bachelor's Degree (%)	People with Bachelor's Degree or Higher Education	1990;2000;2009
Government Proxy	State Government Ideology	1963-2017

Table 5: Annual U.S. State-Level Data Sources

	Source	Data Period
Real GDP	U.S. Bureau of Economic Analysis	1963-2019
Real GDP per capita	U.S. Bureau of Economic Analysis& U.S. Bureau of Labor Statistics & U.S. Census Bureau	1963-2019
Physical Capital per capita	Garofalo and Yamarik (2002) & El-Shagi and Yamarik (2018)	1963-2019
Industry Share (%)	U.S. Bureau of Economic Analysis	1996-2019
Crude Oil Production	U.S. Energy Information Administration	1963-2019
Savings Rate (%)	U.S. Bureau of Economic Analysis	1997-2019
Consumption Rate (%)	U.S. Bureau of Economic Analysis	1997-2019
TFP-Proxy (%)	U.S. National Science Foundation	1991;1993;1995; 1997-2000;2002-2017
Population Density	U.S. Census Bureau	1963-2019
Labour Force Participation Rate (%)	U.S. Bureau of Labor Statistics	1976-2019
Employment-Population Ratio (%)	U.S. Bureau of Labor Statistics	1976-2019
Unemployment Rate (%)	U.S. Bureau of Labor Statistics	1976-2019
Bachelor's Degree (%)	U.S. Census Bureau	1990;2000;2009
Government Proxy	Berry et al. (2010)	1963-2017

Appendix D: Selecting Predictors

The selection of predictors is a fundamental part of the estimation task since they determine which weights are given to the synthetic state to minimise the RMSPE (Root Mean Square Predictor Error). Recall that the RMSPE is the squared root of the MSPE (Mean Square Predictor Error). We refer to RMSPE as it is more easy to interpret – it can for GDP per capita be directly interpreted in USD. Thereby, as motivated in Section 5.3, we incorporate an additional step by explicitly including a data driven procedure of selecting the predictors. We do this in a two-step process, to find a set of predictors that lends credibility to the identification assumption. Here we, first, describe in detail how this is done and, second, the results from applying the method on our data.

Method

The method is developed with the intention to find a set of predictors that lends credibility to the identification assumption. We therefore both aim for a set of predictors that minimise the difference between LA and SLA in the pre-disaster period, as well as finds considerable good fit on specific predictors. We do this in two steps.

Step 1. In the first step, we create a base-set of predictors that minimise MSPE and similarly RMSPE. The variables from which we minimise the RMSPE are based on Abadie, Diamond, and Hainmueller (2015) – a paper by the developers of SCM that also uses GDP per capita as outcome variable. The variables included are thus lagged GDP per capita, industry share and Bachelor's degree share. In previous literature, authors have treated lagged GDP different. Some use specific lags with 10 years in between, others specific lags with 5 years in between, and others an average of different lags. We therefore test for both 5 years between lags (1994, 1999, 2004), 10 years between lags (1984, 1994, 2004) and an average of the 10 years before the disasters (1995-2004). By testing all possible combinations of the three set of lags as well as the three other predictors, we get 12 combinations. The selected set of base predictors are the set with lowest RMSPE.

Step 2A. In the first part of the second step, we introduce additional variables to improve the fit from the final outcome of the first step. The variables are motivated in Section 6 are:

- Two proxies for investment rate: savings rate and consumption rate
- Physical capital per capita
- Employment (employment-population ratio)
- TFP Proxy
- Government proxy
- Population density
- Oil dependency proxy

By using the base set of predictors, the outcome from the first step, we then add different combinations of the additional predictors. We are not able to test all possible combinations (in total: 8191), but we aim to iterate the test for over 100 combinations. For all combinations, we note the RMSPE.

Step 2B. We could simply take the set of predictors in Step 2A as our final set of predictors. However, we notice that some predictors historically are more frequent in literature. For example, we want a large weight on the lagged GDP variables as they have been shown to be the best predictors to the GDP per capita. Furthermore, it could be the case that the best set of predictors according to the RMSPE is significant different to the other set of predictors with low RMSPE. If there are more set of predictors with relatively similar and low RMSPE, we also want to make sure that the selected set of predictors are relatively like the other possible set of predictors.

Therefore, we select the five set of predictors from Step 2A with the lowest RMSPE. Along those, we consider (i) the values on specific predictors to see if there are any predictors that have large differences from Louisiana, (ii) the weights on the predictors, (iii) the weights on the states in the synthetic state. We then choose the set of predictors that fulfil these three steps best.

Result
We here present the detailed results from the selection process of the predictors, by using the method in the first part of this Appendix.

Step 1. Table 6 shows the 12 set of predictors tested as potential base-set of predictors. More specifically, it specifies which variables are included in each set of predictors as well as the MSPE and RMSPE outcome. As seen, alternative E has the lowest RMSPE of 847. That means, on average when using this set of base predictors, the difference between LA and SLA are $847 U.S. dollar in the pre-disaster period. The median RMSPE of the alternatives of base sets are 1,159. Alternative E is significant smaller. Therefore, the base set of predictor consists of GDP lags 10 years, Bachelor's degree share and industry share.

Table 6: Step 1 – Base Predictors

Predictors	GDP_cap mean	GDP_cap lag 10yrs	GDP_cap lag 5yrs	BSc degree	Industry share	MSPE	RMSPE
Time	1995-2004	1984;1994;2004	1994;1999;2004	2000	1997-2004	1963-2004	1963-2004
A	X			X	X	26 331 111	5131
B	X				X	35 375 709	5948
C	X			X		22 697 818	4764
D	X					27 361 185	5231
E		X		X	X	717 523	847
F		X			X	830 562	911
G		X		X		1 188 980	1090
H		X				1 364 520	1168
I			X	X	X	1 063 366	1031
J			X		X	1 072 502	1036
K			X	X		1 324 509	1151
L			X			1 865 145	1366

Step 2A. Table 7 shows the 101 set of predictors tested as potential set of predictors. Furthermore, Figure 16 plots the distribution of RMSPE. The RMSPE varies between 795 for Alternative BL and 1,579 for the Alternative CT. The median of the combinations is 869 indicating that the base predictors themselves are better than the median of when adding additional predictors. Furthermore, it is encoring to see that we are able to improve the RMSPE from the base set of predictors.

Table 7: Step 2 – Iteration of 101 Predictor Combinations

	Base Predictors	**Additional Predictors**								**Outcome**	
Period	*Base Predictors*	Savings	Consumption	Phys. Capital	Employment	TFP	Government	Pop. Density	Oil	MSPE	RMSPE
		1997-2004	1997-2004	1995-2004	1995-2004	2002-2004	1995-2004	1995-2004	1995-2004	1963-2004	1963-2004
A	X	X	X	X	X	X	X	X	X	657 970	811
B	X	X								685 190	828
C	X		X							805 511	898
D	X			X						706 897	841
E	X				X					821 434	906
F	X					X				633 102	796
G	X						X			714 228	845
H	X							X		716 342	846
I	X								X	661 620	813
J	X	X	X							685 417	828
K	X	X		X						759 840	872
L	X	X			X					821 434	906
M	X	X				X				716 240	846
N	X	X					X			649 286	806
O	X	X						X		691 162	831
P	X	X							X	674 133	821
Q	X		X	X						660 833	813
R	X		X		X					937 815	968
S	X		X			X				937 145	968
T	X		X				X			717 167	847
U	X		X					X		717 167	847
V	X		X						X	668 466	818
W	X			X	X					1 291 718	1 137
X	X			X		X				677 723	823
Y	X			X			X			927 243	963
Z	X			X				X		708 834	842
AA	X			X					X	875 164	936
AB	X				X	X				1 234 043	1 111
AC	X				X		X			1 187 859	1 090
AD	X				X			X		718 011	847
AE	X				X				X	1 651 207	1 285
AF	X					X	X			717 167	847
AG	X					X		X		663 931	815
AH	X					X			X	639 495	800
AI	X						X	X		918 706	958
AJ	X						X		X	1 316 926	1 148
AK	X							X	X	1 248 791	1 117
AL	X		X	X	X	X	X	X	X	683 427	827
AM	X	X		X	X	X	X	X	X	711 820	844
AN	X	X	X		X	X	X	X	x	910 845	954
AO	X	X	X	X		X	X	X	X	1 063 745	1 031
AP	X	X	X	X	X		X	X	X	737 876	859
AQ	X	X	X	X	X	X		X	X	849 609	922
AR	X	X	X	X	X	X	X		X	687 818	829
AS	X	X	X	X	X	X	X	X		666 315	816
AT	X	X	X	X						711 509	844
AU	X	X	X		X					829 847	911
AV	X	X	X			X				867 670	931
AW	X	X	X				X			780 415	883
AX	X	X	X					X		663 931	815
AY	X	X	X						X	1 034 461	1 017
AZ	X	X		X	X					818 124	905
BA	X	X		X		X				684 502	827
BB	X	X		X			X			643 491	802
BC	X	X		X				X		640 803	801
BD	X	X		X					X	639 727	800
BE	X	X			X	X				667 679	817
BF	X	X			X		X			739 149	860
BG	X	X			X			X		759 734	872
BH	X	X			X				X	1 313 841	1 146
BI	X	X				X	X			638 110	799
BJ	X	X				X		X		669 435	818
BK	X	X				X			X	663 074	814
BL	X	X					X	X		631 435	795
BM	X	X					X		X	735 650	858
BN	X	X						X	X	889 710	943
BO	X		X	X	X					968 212	984
BP	X		X	X		X				654 277	809
BQ	X		X	X			X			769 015	877
BR	X		X	X				X		849 280	922
BS	X		X	X					X	1 613 665	1 270

BT	X	X		X	X				699 492	836
BU	X	X		X		X			957 736	979
BV	X	X		X			X		1 066 470	1 033
BW	X	X		X				X	1 266 199	1 125
BX	X	X			X	X			756 903	870
BY	X	X			X		X		867 506	931
BZ	X	X			X			X	939 439	969
CA	X	X				X	X		639 013	799
CB	X	X				X		X	658 769	812
CC	X	X					X	X	682 855	826
CD	X		X	X	X				1 283 007	1 133
CE	X		X	X		X			920 766	960
CF	X		X	X			X		803 830	897
CG	X		X	X				X	684 919	828
CH	X		X		X	X			695 271	834
CI	X		X		X		X		862 100	928
CJ	X		X		X			X	673 268	821
CK	X		X			X	X		900 896	949
CL	X		X			X		X	966 249	983
CM	X		X				X	X	638 454	799
CN	X			X	X	X			642 513	802
CO	X			X	X		X		1 093 957	1 046
CP	X			X	X			X	1 400 259	1 183
CQ	X			X		X	X		1 156 978	1 076
CS	X			X		X		X	1 267 244	1 126
CT	X			X			X	X	2 492 275	1 579
CU	X				X	X	X		657 863	811
CV	X				X	X		X	662 619	814
CW	X				X		X	X	1 164 034	1 079
CX	X					X	X	X	1 244 340	1 115

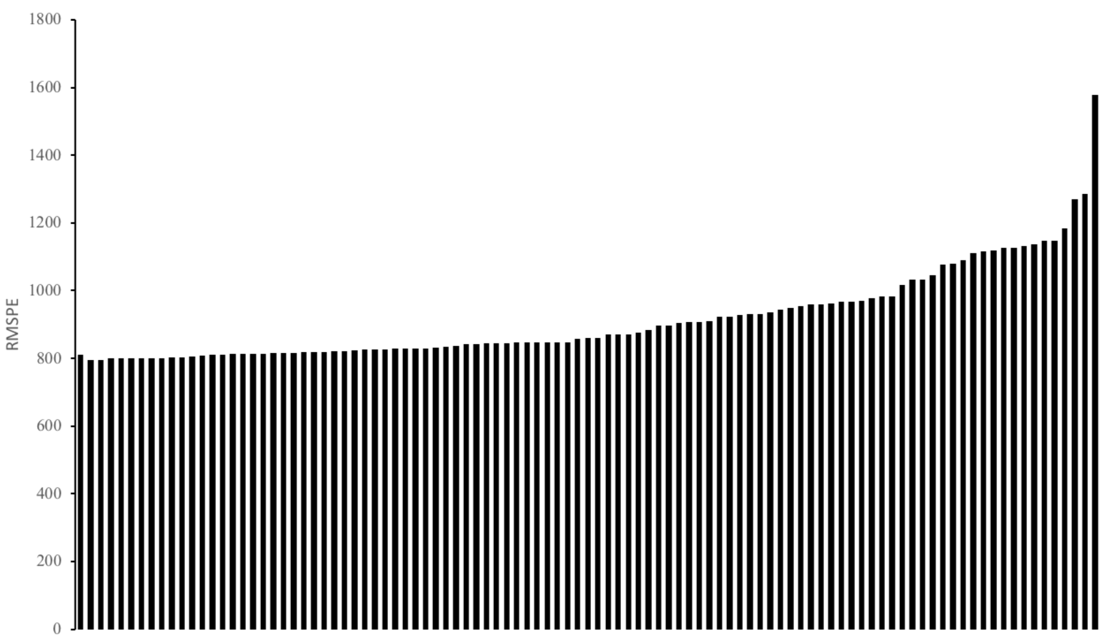


Figure 16: RMSPE Distribution
Note: The distribution of RMSPE along the 101 set of predictors.

Step 2B. Along the 101 combinations in Step 2A, we select the five with lowest RMSPE and study their output more closely. That is, both values on the specific predictors and the weights on the predictors, and on the states in the synthetic state. The RMSPE range from 795 and 799.

First, we study their values on the specific predictors to see if there are any predictors that have large difference from Louisiana, view Table 8. We note that the GDP per capita lags and the savings rate are similar across all synthetic units, as well as the real Louisiana, which lends credibility for the predictors. The bachelor's degree, consumption rates, TFP proxy and government proxy differ slightly, however, all synthetic units have very similar values which are better than the whole sample mean for both variables. Both the oil dependency proxy and the physical capital predictors stand out by not being able to reproduce a close value to the real Louisiana. Therefore, we direct omit the synthetic units including those: CM and CA. Finally, the population density differs between both the synthetic units and Louisiana, however, it is considerable better than the sample mean for both units.

Table 8: Step 2 – Predictor Values for Louisiana & Combinations with Lowest RMSPE

Variables	Louisiana	Synthetic Louisiana (1, BL)	Synthetic Louisiana (2, F)	Synthetic Louisiana (3, BI)	Synthetic Louisiana (4, CM)	Synthetic Louisiana (5, CA)
GDP per capita 1984	44,315	43,489	43,488	43,519	43,509	43,499
GDP per capita 1994	40,367	40,396	40,378	40,397	40,407	40,412
GDP per capita 2004	48,417	47,251	47,252	47,050	47,406	47,340
Physical Capital per capita	66,085	-	-	-	118,140	-
Industry Share (%)	24.3	21.1	21.4	21.5	21.2	21.4
Crude Oil Production	25,378	-	-	-	77,717	19,672
Savings Rate (%)	11.1	11.0	-	11.0	-	-
Consumption Rate (%)	64.6	-	-	-	-	68.1
TFP-Proxy (%)	0.6	-	0.9	0.9	-	-
Population Density	32.6	26.2	-	-	20.3	-
Employment-Population Ratio (%)	57.9	-	-	-	-	-
Bachelor's Degree (%)	18.7	20.3	20.3	20.1	20.4	20.4
Government Proxy	48.5	44.9	-	44.6	-	44.3

Second, we consider the weights of predictors, view Table 10. We start with the base predictors. Recall that we do not consider CM or CA as potential set of predictors given their values on oil and physical capital, therefore, they are not a part of the argument. In this part, we do not want to see that for example a specific GDP lag get an unproportionally large weights. Although the lags of the output variables in previous literature have been shown to be the most efficient predictors, by having a larger variation of predictors it is more likely that other variables as transmission channels to GDP follow a similar trend. Based on the lags, we consider alternative BI as most attractive. The alternative has a spread in weights for the lags. Furthermore, we consider alternative F as less attractive, given its large weighs (>90%) on GDP lag 1994.

Furthermore, we consider the weights on the additional predictors. We want the selected set of predictors in the end to follow similar trends in the predictors as other combinations that have shown to be good set of predictors. Along the three set of predictors left, we note that two positive weights (>0) have savings rate, two TFP proxy, two government proxy and one population density. Alternative BI includes all the three variables which are similar across two units. Furthermore, alternative BI do not includes no predictor that are not a part of any of the other four set of predictors, that is, no outlier.

Third, we consider the weights on states in the donor pool along BL, F and BI, view Table 9. The alternatives alternatives have positive weights for similar states.

Based on this reasoning, we select alternative BI as our synthetic Louisiana. It does not have inappropriate large weights on any specific predictor, includes predictors similar to the other attractive alternatives of set of predictors and, lastly, have similar states in the donor pool. Compared to alternative BL, it both has predictors more similar across the other units. Compared to alternative F, it has lower weights on GDP lags. Henceforth, we therefore refer to alternative BI as our synthetic Louisiana.

Table 9: Step 2 – State Weights for the Five Combinations with Lowest RMSPE

Predictor Combinations	BL	F	BI	CM	CA
Country					
Alaska	0.08	0.08	0.08	0.08	0.08
Arizona	-	-	-	0.00	-
Cal	-	-	-	0.00	-
Iowa	0.11	0.14	0.11	0.13	0.15
Kentucky	0.20	0.21	0.25	0.19	0.20
Maine	-	-	-	0.00	-
Missouri	-	-	-	0.00	-
New York	-	-	-	0.00	-
Nevada	-	-	-	0.00	-
North D	-	-	-	0.00	0.00
North Kar	-	-	-	-	0.00
Pennyslavania	-	-	-	0.00	-
Ohio	0.00	-	-	0.00	-
Oklahoma	0.42	0.46	0.44	0.46	0.45
Rhode I	0.03	-	-	0.00	-
South Dakota	-	-	-	0.00	-
South K	-	-	0.00	-	-
States	-	-	-	-	-
West V	0.03	-	-	0.01	-
Wisconsin	-	-	0.00	-	-
Wyoming	0.12	0.12	0.12	0.12	0.11

Table 10: Step 2 – Five Predictor Combinations with Lowest RMSPE

Predictors	Period	BL	F	BI	CM	CA
Base Predictors						
GDP per capita 1984	1984	0.03	0.01	0.05	0.09	0.04
GDP per capita 1994	1994	0.84	0.97	0.76	0.87	0.92
GDP per capita 2004	2004	0.02	0.01	0.01	0.03	0.03
Bachelor's Degree (%)	2000	0.01	0.00	0.00	0.01	0.01
Industry Share (%)	1997-2004	0.00	0.00	0.01	0.00	0.00
Additional Predictors						
Savings Rate (%)	1997-2004	0.08	-	0.14	-	-
Consumption Rate (%)	1997-2004	-	-	-	-	0.00
Physical Capital per capita	1995-2004	-	-	-	0.00	-
Employment-Population Ratio (%)	1995-2004	-	-	-	-	-
TFP-Proxy (%)	2002-2004	-	0.01	0.03	-	-
Government Proxy	1995-2004	0.00	-	0.00	-	0.00
Population Density	1995-2004	0.02	-	-	0.00	0.00
Crude Oil Production	1995-2004	-	-	-	0.01	-
MSPE	1963-2004	631,435	633,102	638,110	638,454	639,013
RMSPE	1963-2004	795	796	799	799	799

Note: The base predictors include GDP lags 10 years lags, Bachelor's degree share, and industry rate. All set of predictors include the base predictors.

Appendix E: Main Results Appendix

Real GDP

(a) Path Plot (b) Gap Plot

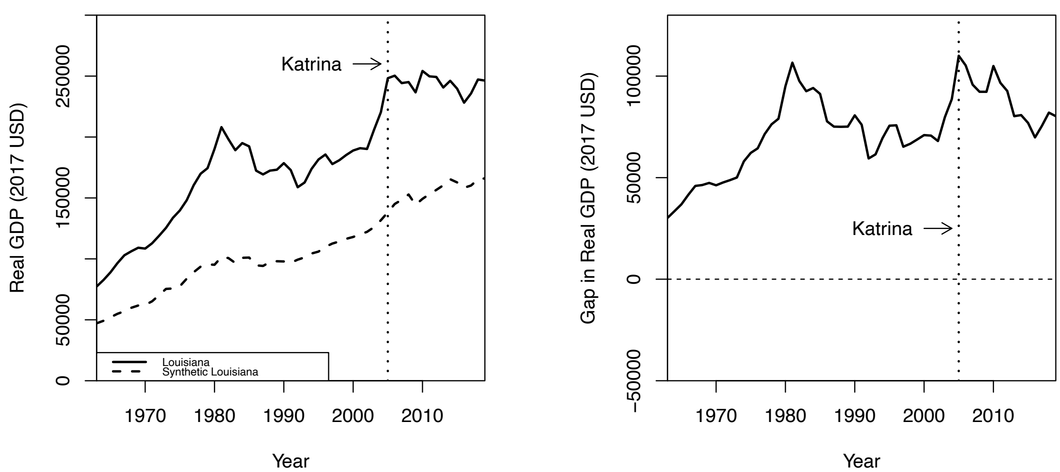


Figure 17: Path and Gap Plot of Real GDP (2017 USD) 1970-2019: Louisiana versus Synthetic Louisiana

Unemployment Number

(a) Path Plot (b) Gap Plot

Figure 18: Path and Gap Plot of Unemployment Number GDP 1976-2019: Louisiana versus Synthetic Louisiana

Labour Force Size

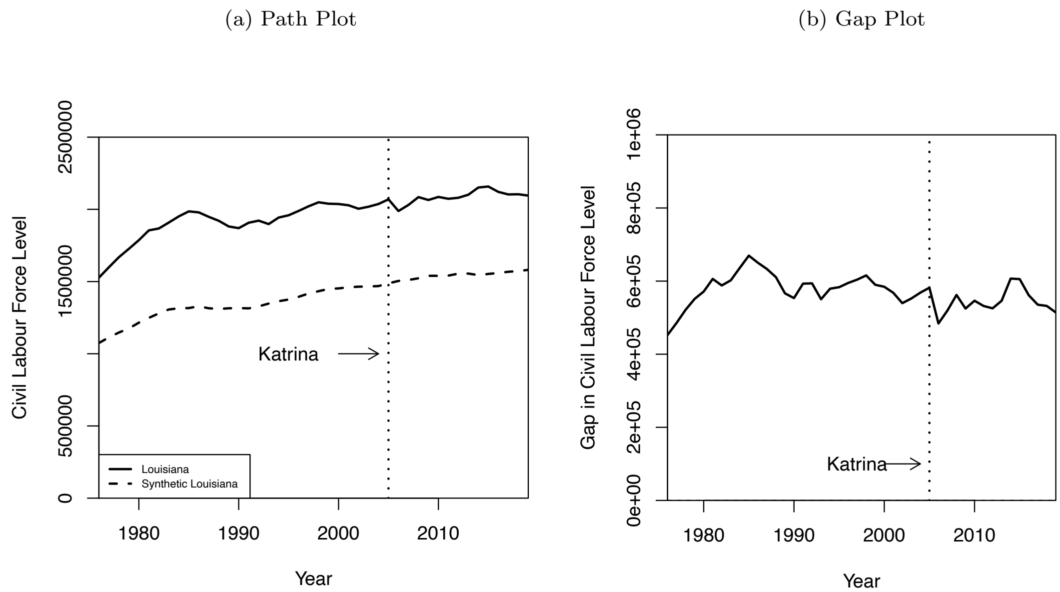


Figure 19: Path and Gap Plot of Labour Force Size 1976-2019: Louisiana versus Synthetic Louisiana

Total Employed

(a) Path Plot

(b) Gap Plot

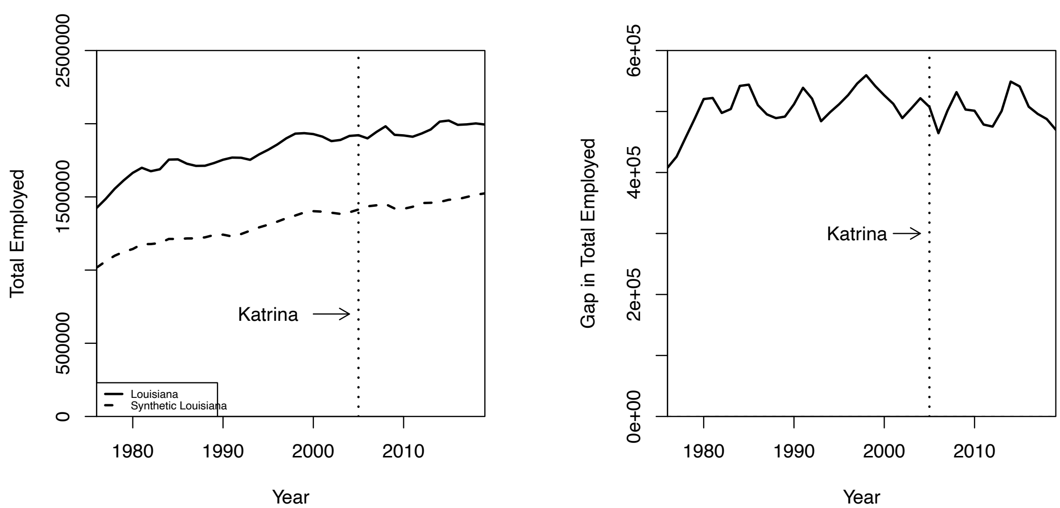


Figure 20: Path and Gap Plot of Total Employed 1976-2019: Louisiana versus Synthetic Louisiana

Civil Noninstitutional Population

(a) Path Plot

(b) Gap Plot

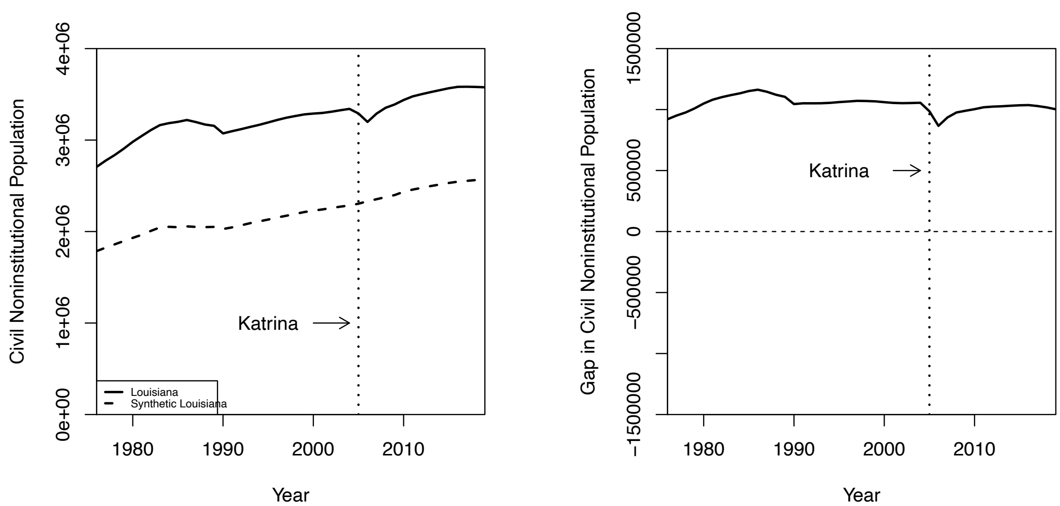


Figure 21: Path and Gap Plot of Civil Noninstitutional Population 1976-2019: Louisiana versus Synthetic Louisiana

Labour Force Participation Rate

(a) Path Plot

(b) Gap Plot

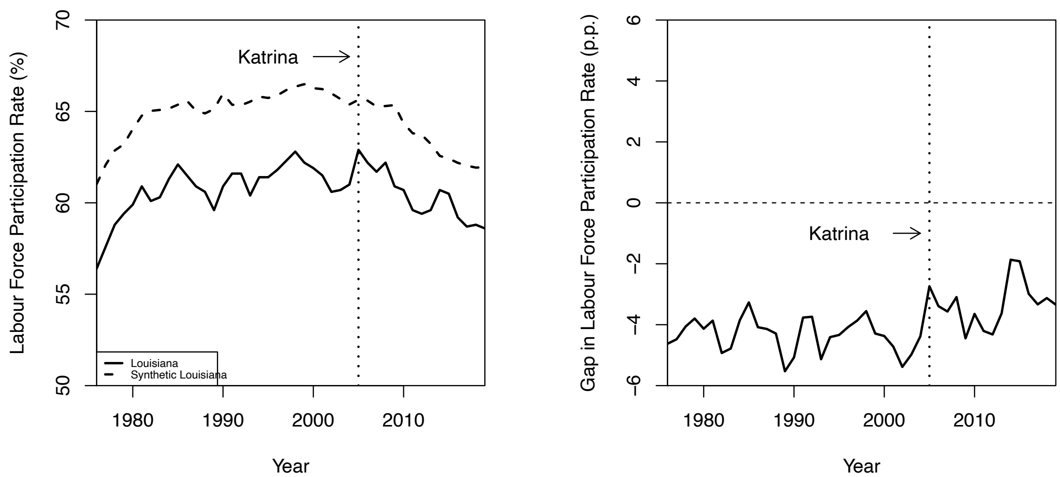


Figure 22: Path and Gap Plot of Labour Force Participation Rate 1976-2019: Louisiana versus Synthetic Louisiana

In-Space Placebo Tests – Short Run

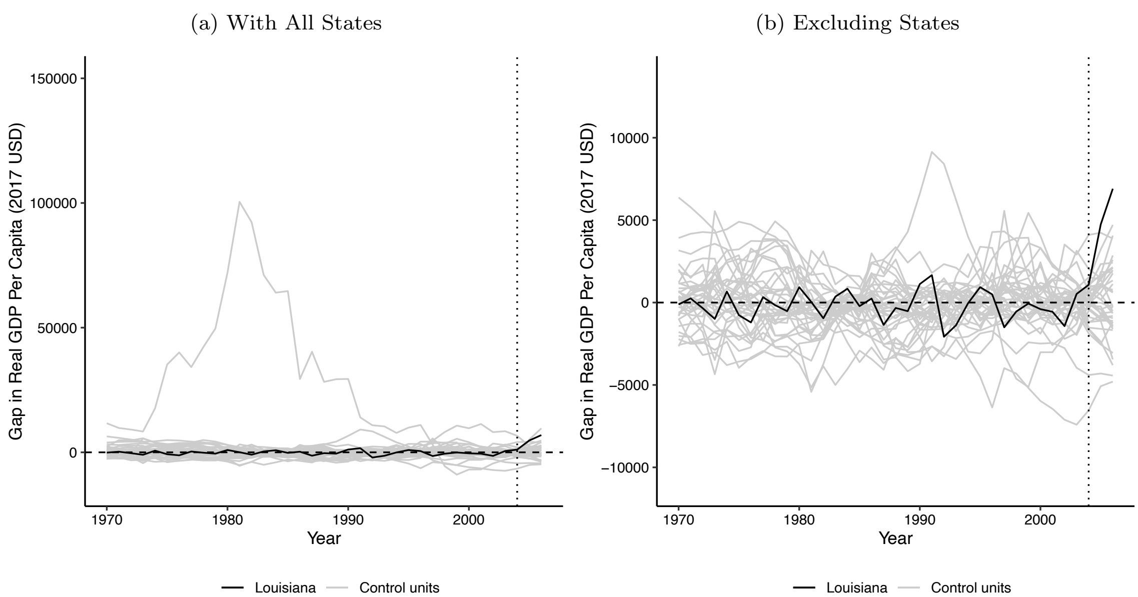


Figure 23: Short-Run. In-Space Placebo tests: Real GDP Per Capita in Louisiana and Placebo Gaps for the Control States

Note: Panel A shows the results for all states in the donor pool. Panel B visualises the exclusion of the states with a pre-disaster MSPE value that is at least 20 times larger than that of Louisiana.

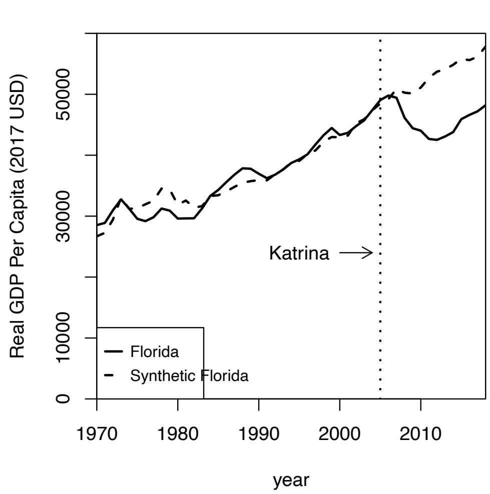
Appendix F: Synthetic Control Method on Other States

Using the SCM, we also estimate the effect on state-level economic growth on other states directly affected by Katrina. The method used are the same as for Louisiana, and we use the same predictors as we use for Louisiana. This Appendix therefore summarise the findings, and for all states we comment the results as well as the RMSPE indicating how much trust we can put in the results. We also present the weights for predictors, the weights of the synthetic counterpart, the path plot and the gap plot.

We also tested on states indirecly affected, but found no consensus.

Directly Affected – Florida: Prior to Katrina, Florida and its synthetic counterpart follow a similar trend. The pre-trend fit for both the predictors and the real GDP per capita is seen as reasonably good, although the RMSPE is higher than for Louisiana (1,488 for SCM on Florida). Therefore, we use the outcome to analyse the result on state-level economic growth in Florida. Our results show that the GDP per capita declines in Florida but not its synthetic counterpart first in 2008. At this point, the effect are more likely to be from the financial crisis than Katrina. Therefore, we are not able to see any effect of Katrina on Florida.

(a) Path Plot



(b) Gap Plot

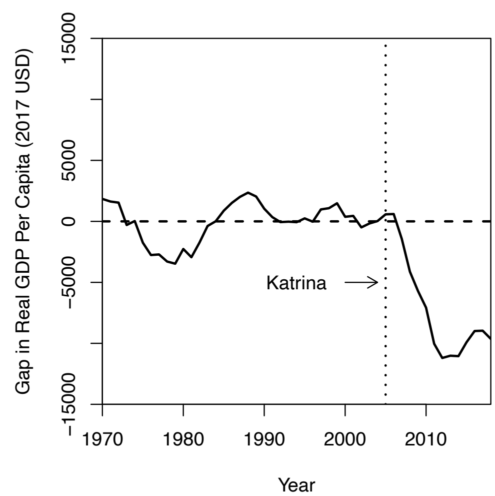


Figure 24: Path and Gap Plot of Total Employed 1976-2019: Florida versus Synthetic Florida

Table 11: Florida: Real GDP per capita Predictor Means Before Katrina

Predictors	Florida	Synthetic Florida	Sample mean
GDP per capita 1984	33,307	33,300	38,999
GDP per capita 1994	38,718	38,785	43,765
GDP per capita 2004	47,387	47,362	52,882
Bachelor's degree (%)	22.3	22.3	24.6
Industry share (%)	14.1	17.1	20.3
Savings rate (%)	7.8	7.8	8.2
TFP Proxy (%)	0.9	0.9	2.3
Government	39.7	39.6	46.2

Table 12: State Weights in Synthetic Florida

State	Weight
South Dakota	0.424
Montana	0.183
New York	0.138
West Virginia	0.105
Maine	0.057
Oklahoma	0.035
North Dakota	0.021
Hawaii	0.020
Missouri	0.002
Nevada	0.002

Note: 28 other states received 0.001 in weights

Directly Affected – Mississippi: The RMSPE for Mississippi is considerable large, 3,019, and the pre-trend fit is not follow the same trend or level. Therefore, our result are not used to indicate any effect on the regional economic growth in Mississippi.

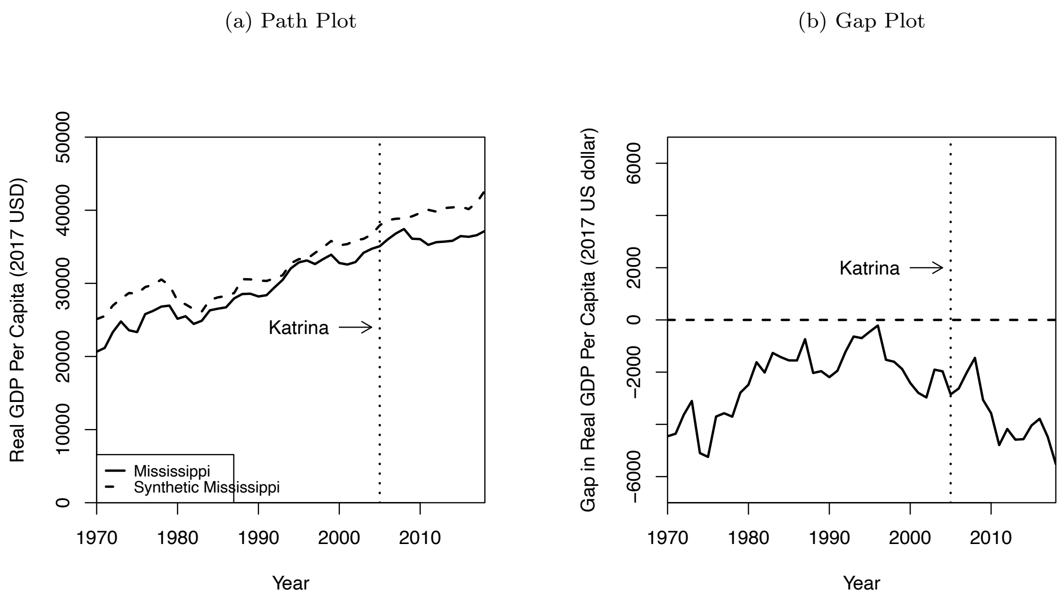


Figure 25: Path and Gap Plot of Total Employed 1976-2019: Mississippi versus Synthetic Mississippi

Table 13: Mississippi: Real GDP per capita Predictor Means Before Katrina

Predictors	Mississippi	Synthetic Mississippi	Sample mean
GDP per capita 1984	26,315	27,739	38,999
GDP per capita 1994	32,040	32,737	43,765
GDP per capita 2004	34,722	36,700	52,883
Bachelor's degree (%)	16.9	16.1	24.6
Industry share (%)	24.8	23.1	20.3
Savings rate (%)	13.6	7.8	8.2
TFP Proxy (%)	1.3	1.2	2.2
Government	52.5	53.1	46.2

Table 14: State Weights in Mississippi

State	Weight
West Virginia	0.77
South Carolina	0.23

Note: 28 other states received 0.001 in weights