DISSERTATION

ESSAYS ON THE ECONOMICS OF NATURAL DISASTERS

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Yuchen Hu

Department of Economics

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Doctoral Committee:

Advisor: Harvey Cutler

Sammy Zahran
David Mushinski
John van de Lindt

ABSTRACT

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Natural hazards occur frequently, and the costs associated with these events are well into the billions of dollars. The rising frequency and costs from natural disasters require a comprehensive understanding of its impacts on the economic system and mitigation strategies for local communities that can minimize these losses.

The purpose of Chapter 1 is to demonstrate a linkage between civil engineering and economic models to accomplish these objectives. To do this, I build a spatial computable general equilibrium model (SCGE) for Shelby County in Tennessee that requires an extensive data set dependent upon eight different data sources. I then develop advanced methods that integrate simulation models from engineering and economics. Civil engineers have created a range of simulation models that estimates the impact of a hypothetical earthquake on damages to buildings, utilities, and transportation network. These damages are integrated into the SCGE model to simulate a range of economic outcomes. I find that the SCGE model is more advanced in capturing the adjustment behaviors of businesses and households to external shocks compared to previous attempts. I also find that to better estimate the economic impacts, we need to simulate the model with the three types of physical damages jointly and not individually.

Chapter 2 investigates a hidden layer of the impact of natural disasters, which is the spillover effect due to disaster-induced migration on the receiving areas' labor markets. Using the difference in difference approach, I empirically compare the hourly wage rates in areas that

received the evacuees from Hurricane Katrina to areas that didn't. I find that in the export-oriented industry, the inflow of migrants due to Katrina slightly reduces the hourly wage rates for both the low and the high-skilled workers. However, in the localized industries where the inflow of the migrants also increased the demand for local goods and services, the inflow of evacuees raises the hourly wage rates the high-skilled workers and imposes no significant impacts for the low-skilled workers. These results are consistent with previous literature in that immigrants did impact the local labor markets but at a small magnitude.

Chapter 3 proposes the setup of a Rainy-Day Fund (RDF) through tax increase/hikes for local governments in preparing for external shocks in the future. To minimize the costs of tax hikes to the economy and achieve the target amount of RDF, I use the SCGE model developed in Chapter 1 to solve for an optimal path of tax hikes over time. The process starts with an endogenized cost function measured by the foregone output that could be produced had there been no changes in the tax system. Built on the profit and utility maximization in response to changes in taxes, the cost function expands the theoretical setup of Barro (1979) and Ghosh (1995) by allowing any factors that influence the output to enter the optimization process. Moreover, the cost function in any period depends on not only the tax rates in that period but also the tax rates in previous periods, since any changes to the tax rates previously can influence the current economy through changes in investment and capital. I find that the optimal trajectory of the tax hikes tends to be rising in time. The rate of the increase depends on the magnitude of labor supply elasticity to real wages, and the interest of the regional planners to include economic outcomes beyond the planning horizon.

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Introductory Chapter

Natural disasters impose large costs on the functioning of local economies. In the U.S., NOAA (National Oceanic and Atmospheric Administration) keeps track of the extreme weather events that they call "Billion-Dollar Weather and Climate Disasters", as the costs of these events were no less than 1 billion. From 2015 to 2019, the annual average number of the billion-dollar events has more than doubled, compared to the long-term average from the 1980s. The total cost over the last 5 years exceeds $353 billion. The recovery path from natural disasters can be months or years. For instance, one year after Hurricane Harvey that occurred in 2017, 30 percent of the residents from the heavily damaged area reported their life was still being disrupted (Lee (2019)). Nearly 20 percent of local businesses had to wait more than 6 months to re-open, and 5 percent closed permanently (Hamel et al. (2018)).

Improving local communities' level of resilience requires modules that include a comprehensive understanding of how natural disasters affect local communities and quantitative measurement on community resilience. Under this background, in 2014, the National Institute of Standards and Technologies (NIST) funded a five-year grant to create a "Center for Risk-Based Community Resilience Planning". The center is unique in merging the disciplines of engineering, social sciences, and economics. 31 faculty members and more than 60 graduate students from 10 universities (Colorado State University, University of Oklahoma, Oregon State University, Rice University, Texas A&M University, the University of Illinois, the University of Washington, the University of South Alabama, California Polytechnic University, Pomona and Texas A&M-Kingsville) are working closely with an aim to empower regional planners with optimal community resilience planning and disaster mitigation strategies. This grant has been recently renewed for another 5-year period to continuously committed to such an aim. Research in this dissertation is also funded by this project for a deeper understanding of economic resilience to natural hazards.

In Chapter 1, I build a spatial computable general equilibrium model (SCGE) for Shelby County, TN, an area with a potential risk of earthquakes to estimate the economic losses due to natural hazards. The spatial feature of the model addresses the phenomenon that natural disasters can damage a region unevenly. In a hypothetical earthquake scenario, the engineers provide a comprehensive portrait of physical damages from buildings, utilities, and road networks. I then come up with means by which these damages can be transformed and integrated into the SCGE model for economic loss estimation. Given the varying post-disaster conditions among regions in Shelby County, firms will adjust their intermediate inputs demand from one region to another in searching for lower-priced products. The spatial feature also includes an aspect that is typically ignored in previous studies, which is the commuting flows across regions. In the aftermath of a natural disaster, households will also adjust their commuting decision among regions in the county searching for maximum employment opportunities and wages. Therefore, an important contribution of Chapter 1 is the framework that can be translated both to engineers and economists in terms of how their models integrate so that future researchers from related disciplines are aware of what to deliver and how to interpret the outcomes from these models.

The simulation results suggest that modeling the above behavior changes allows it to better mimic the real-world inherent responses to natural disasters. I also find that the joint economic impacts from building, transportation network, and utility damage are smaller than the sum of the individual impacts, which implies the possibility that when the economy copes with one type of damages, it automatically protects itself from other damages to some degree.

In Chapter 2, a hidden layer of the economic influence of natural hazards is examined, which is the spillover effects caused by the disaster-induced migration. Examples of such migration in the U.S. happens frequently: the American Dust Bowl in the 1930s caused 12 percent population decrease in high erosion counties relative to low erosion counties (Hornbeck (2012)); Over the 18 years and 19 Hurricanes in Florida, counties that were directly hit experienced a growth rate reduction in the population of 74.8 percent on average (Belasen and Polachek (2011). There are extensive empirical studies on the impact of migration on the local labor market, while most studies identified modestly or slightly negative impact on the wage rates as migration shifted the labor supply to the right. De Silva et al. (2010) argued that it is due to the ignorance of the simultaneous demand-side impact. The rising amount of in-migration also pushes up the demand for localized goods and services such as retail and housing, and as a result of demand rise, wages can go up. In the meantime, studies that looked at the Hurricane Katrina only investigated the labor markets in the city of Houston, TX, since in absolute terms, it received the largest number of evacuees. Nevertheless, according to the author's calculation, except for Houston, there are many other counties that also received the Katrina evacuees. Relatively speaking, regarding the ratio of the evacuees to the population size, Houston was outside the list of the top 10 largest receiving areas. What happened in these areas remains unknown to the public.

Chapter 2 addresses the above issues using a Difference in Difference approach that compares the hourly wage rates in all areas that received these evacuees to areas that didn't in four separate markets. These four markets are distinguished by workers' skill sets and the attributes of industries being export-orientated (traded industry) or not (localized industry). The reasons for such distinction are the considerations that the demand side impacts mentioned above are only present in the localized industries and the fact that people who were less likely to return due to

Katrina were disproportionally young and less-educated. I find that the inflow of the migrants reduces the wage rates in the market of the traded industry, but the impact is relatively larger for the high-skilled workers. I also find that migration slightly increases the wages of high-skilled workers in localized industries but causes no impact for the low-skilled workers. However, when controlling for the demand hikes, the positive wage gain disappears in the high-skilled group and the negative impact on low-skilled workers shows up, though not statistically significant.

In Chapter 3, I propose the setup of a Rainy Day Fund (RDF) through tax hikes in preparing for adverse events. Regarding natural disasters, the purpose of this fund is to reduce the amount of waiting time for local communities to receive the financial assistance, where previous studies found both the waiting time for disaster assistance and the cost of waiting are non-trivial. Earlier studies (Barro (1979); Lucas and Stokey (1983), Sahasakul (1986); Zhu (1992)) concluded that raising taxes imposes distortions to the economy, with the objective of developing theoretical foundations for the optimal fiscal policy at the national levels. These authors came up with a theory of tax smoothing, meaning that the government should use a combination of taxation and debt issuing to smooth the tax rises over time. However, little is known whether the same theory can be extended to local governments, especially when they do not have monetary policy levers (debt issuing) and have limited fiscal policy options.

Therefore, Chapter 3 uses the SCGE model developed in Chapter 1, together with the proper setup of the simulations to investigate the optimal tax hikes overtime at the local level as communities prepare for future natural disasters. In approaching such questions, Barro (1979) would pre-assume a cost function that depends positively, with a positive second derivative on tax rates. Moreover, to derive a closed-form solution, Barro (1979) made additional assumptions: 1) taxable income/resource is exogenous, and doubling the taxable resources in the economy is also going to double the cost of taxation if the tax rate remained unchanged; 2) the cost of taxation in period t only depends on the tax rate and total taxable income in that period. For a more generalized result, I relax all the assumptions regarding the cost function in Barro (1979) in Chapter 3. In particular, the cost function measured by the foregone output that could be produced had there been no changes in the tax system is endogenized in the system. It is built on the profit and utility maximization problems of firms and consumers in response to different levels of tax rates in the system. The cost function then will depend on a set of parameters that influence the level of output today and tomorrow. The results in Chapter 3 suggest that the optimal path of tax hikes tends to be backloaded, or in other words, the tax hikes should be rising in time. The rate of the increase in tax hikes over time depends on the elasticities of labor supply to real wages and whether the regional planner will take future periods or the periods beyond the planning horizon and for how long.

Finally, the three chapters come back to the idea of economic resilience, which is defined by Rose (2004) being the inherent and adaptive responses to hazards that allow communities to avoid potential loss and/or to recover from shocks more quickly. The SCGE model built in Chapter 1 takes the inherent resilience and turns it into behavior changes of firms and households. Firms are substituting their intermediate inputs demand from more damaged regions to less damaged regions that are guided by relative prices. Similarly, households will reconsider their decision on where to work given the spatial natural disaster reduces the quantity of labor demand to varying degrees. Chapter 2 deals with the spillover impacts as a result of local communities being less economically resilient to external shocks. That is, if the population cannot restore to its pre-disaster level from extreme events, temporary evacuation from the damaged area will turn to permeant migration. The case study used in Chapter 2 is a perfect example: Hurricane Katrina displaced between 700,000 to over 1 million people in the New Orleans area, and about 13 months after the storm, only slightly more than 50 percent returned (Groen and Polivka (2010)). Sastry (2009) suggested that among the people who did not return in a year, they may never return over the longer term. This migration flows provided a rise in the supply of labor in other parts of the U.S. In Chapter 2, I use the difference in difference approach where I compare the hourly wage rates in areas that received these evacuees to areas that didn't. The results suggest that in areas where these people went, the wage rates followed a different trend, but the difference is small. Chapter 3 is related to policies that can improve local communities' adaptive resilience to hazards. In this chapter, I propose the setup of Rainy-Day Fund through tax hikes in preparing for external shocks in the future. However, raising the taxes imposes distortions to the economy, so the major purpose of chapter 3 is to solve for an optimal trajectory of tax hikes for a certain amount of Rainy-Day Fund within the planning horizon.

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Chapter 1: Economic Losses Due to Earthquake Under Integrated Building, Utility, and Transportation Nexus: A Spatial CGE Model of Shelby County, TN

1.1 Introduction

In 1986, the National Science Foundation established a national center (Multidiscipline Center for Earthquake Engineering Research, MCEER) at the State University of New York, Buffalo. The objective was to conduct research using a multidisciplinary approach to provide an integrated understanding of the factors that can result in a larger degree of resilience for a community in response to an earthquake.

Over the years, researches were conducted in the Memphis Metropolitan Area (New Madrid Seismic Zone) and Portland Metropolitan Area (ocean floor Cascadian Subduction Zone). Studies on economic losses contain both direct costs and indirect costs recognition and estimation, however, one of the limitations in previous studies was examining individually the impact due to building damages, transportation networks interruption, electricity transmission and water/wastewater pipeline damages.

Subsequent studies were also limited in combining losses from all types of damages that could occur, but they focused on other aspects such as improvements in validating model parameters (Kajitani and Tatano (2018)) or improvements in incorporating a dynamic feature of recovery (such as reconstruction investment) (Shibusawa and Miyata (2011); Xie *et al.* (2014); Gertz and Davies (2015)).

Under this background that there are currently no models that consider all aspects of how a natural disaster affects a community and measure community resilience quantitatively, in 2015, the National Institute of Standards and Technologies (NIST) funded a five-year grant to create a Center for Risk-Based Community Resilience Planning, with a final aim that public users can optimize community disaster resilience planning and post-disaster recovery strategies based on their newly developed computational environment known as IN-CORE (Interdependent Networked Community Resilience Modeling Environment). The center is unique in merging the disciplines of civil engineering, sociology, and economics to model community resilience comprehensively.

The work done by Cutler *et al.* (2016) within the center built a Spatial Computable General Equilibrium (SCGE) model for a virtual community called Centerville, which offered means to integrate engineering models and their outputs into the economic system to assess the economic impact of disasters. Over the years, other actual community testbeds were established to look at different natural disasters such as tornados in Joplin, MO, earthquakes in Shelby County, TN, and tsunamis in Seaside, OR. The work in this paper builds upon the SCGE model developed by Cutler *et al.* (2016) and creates a SCGE model for Shelby County TN, an area with potential risks of earthquakes. The objective is to further improve the economic model as well as methods of the integration between engineering and economic models for natural disaster impact assessment.

Work done in this chapter has the following contributions: firstly, it improves the SCGE model in Cutler *et al.* (2016) by extending the spatial aspect to a larger extent, with behavior changes of firms substituting same types of intermediate input materials among regions based on price differences, and the behavior changes of households working and consuming among regions based on post-disaster conditions; secondly, it provides more detailed and more comprehensive descriptions on the means that integrates simulation models from engineering and economics. Civil engineers have created a range of simulation models that estimates the impact of a hypothetical earthquake on damages to buildings, utilities, and transportation network. These damages are integrated into the SCGE model to simulate a range of economic outcomes; thirdly, it examines jointly the economic impact from building damages, electricity transmission, and water/wastewater pipeline damages, transportation networks disruptions, given the limitations that previous studies only looked at one type of these physical damages at a time.

Results in this chapter suggest that modeling the above behaviors allows the model to better mimic the real-world responses of the agents after external shocks. By adjusting to the spatial damages and shifting demand/supply to areas that are less damaged or areas that are more resilient to the external shocks, it helps to reduce the loss for the economy. Moreover, such behaviors echo the concept of inherent resilience that was brought up by Rose (2004), through which the local communities have their potential to avoid additional losses after any external shocks.

Meanwhile, when looking at the joint impact from building, utility, and transportation network damages, the results suggest that the total impact could be overestimated by examining the impacts individually and then summing the losses together. The intuition is the Leontief production technology that reduces the efficient level of a second and third type of physical damages. Trying to estimate the losses from one aspect of the damages in natural disasters by assuming other conditions stay the same would not provide the most accurate acknowledgment of the influences from such external shocks.

This chapter is organized as follows: section 1.2 reviews current literature on economic impact analysis due to natural hazards; section 1.3 describes the economy of Shelby County, TN, and the corresponding SCGE model; section 1.4 illustrates the steps in transforming engineering outputs into economic inputs to simulate our SCGE model for short-run influences; section 1.5

presents the simulated results concerning changes in major economic variables after the earthquake and section 1.6 concludes.

1.2 Literature review

The history of measuring economic losses due to natural disasters started with the work done by Cochrane (1974). He used an Input-Output model to study the economic impact of a hypothetical earthquake in California. In such models, industries or firms are linearly linked with intermediate input demands from each other based on the Input-Output (I-O) coefficients. And the I-O coefficients, in general, describe the value of inputs required from all industries to produce a certain value of outputs in each industry. When some industries are directly damaged by the earthquake, it also created supply bottleneck to other undamaged industries that demand their outputs as production inputs. Cochrane (1974) calculated this additional loss to be about $4 billion followed by the direct loss of $10 billion worth of outputs.

Rose *et al.* (1997) also used an I-O model to quantify the direct and indirect economic loss from electricity outage after a hypothetical earthquake in Shelby County, TN. The results revealed additional/indirect losses of 29 percent of gross output during the first week of electricity outage, besides the direct loss of 50 percent in gross output. Okuyama (2004) used a combination of an I-O model and a sequential interindustry model to estimate both the spatial and dynamic process of the impact of natural hazards. This is an extension of the previous I-O models that are not able to identify the impact over space and time. Hallegatte (2008) used an adaptive regional I-O model to study the influence of Hurricane Katrina with improvements in the model so that losses from both the initial reduction in the capital stock and the subsequent recovery of that capital stock through rebuilding efforts are considered.

Downsides to I-O models included linearity, rigidity, and lack of behavior content. For example, I-O models do not allow for substitution between capital and labor in production and between different commodities in consumption. Rose and Liao (2005) transitioned to a Computable General Equilibrium (CGE) model to study natural disasters and specified that there are several advantages of using a CGE model to analyze the economic impact of natural hazards. First, CGE models not only contain features from other modeling techniques such as Input-Output model or linear programming, but also allow for substitution between inputs (intermediate inputs, land, labor, and capital). In other words, CGE models can be disaggregated to different industries or production sectors just like other approaches do, meanwhile allow industries to adjust between various types of inputs. Second, CGE models can address the role of price and scarcity, which are used by firms and consumers to adjust their behavior accordingly. Last, CGE models are better in evaluating the role of lifelines and infrastructure by placing a valuation on such services. Hence, CGE models are more realistic than I-O models because of both the behavioral adjustments and the valuation process in lifeline and infrastructure.

However, CGE models do have some disadvantages which include the assumption of optimizing behavior from consumers and producers and the assumption of an immediate return to equilibrium by allowing flexibility in prices or wages during a brief period of response. This makes the CGE model harder to capture very short-run post-earthquake responses. Hence in Rose and Liao (2005), they provided one refinement by fixing the price and the supply of water service to gauge the losses from water outages that range from three to nine weeks. Such a refinement is limited to disequilibrium in the market of water, but all other markets are still in equilibrium. Other utility line damages such as electricity power outages were not analyzed in this study.

One limitation of Rose's work is that he and his colleagues can only provide direct and indirect economic loss from one aspect of the adverse condition in earthquakes in isolation, such as water outage or electricity outage. Other damages from earthquakes such as building damages or transportation network damages are not considered. Part of the limitation is resolved by Chang and Chamberlin (2004). In the paper, they were able to translate the building damages, water, and electricity outage status to different levels of disruptiveness for businesses to estimate economic losses. Still, in this case study for Los Angeles County, the adverse impact from road network damages was not included. For areas like Los Angeles that are densely populated and go through heavy traffic every day, the normal functioning of the road network is more essential.

Subsequent studies didn't focus on improving the combination of different channels of impact from natural hazards but were able to provide improvements/contributions that can be summarized in four categories: the first one is validating key model parameters using real-world observations; the second one is building a spatial CGE model to better capture multiplier/spillover impacts due to business interruption; the third one is the extension in natural hazards type (from earthquakes to other types of hazards such as flooding or drought) or damage type (from lifeline disruption to road/highway damages); the last one is extending the CGE model to a dynamic framework where both immediate damages and long-run recovery process can be studied. Next, I will illustrate these improvements by one or two representative papers in each category.

A recent paper by Kajitani and Tatano (2018) was one of the first papers tried to validate a disaster-related short-run CGE model by applying it to The Great East Japan Earthquake and Tsunami in 2011. They calculated the root mean square errors between the estimates from the CGE model and the real-world observations in terms of monthly Indices of Industrial Production, meanwhile, they altered the value among a certain set of key parameters[1] in the model to see which values can generate the most-closest-to-reality results, implied by the smallest root mean square errors. Finally, the optimal value for a certain set of parameters was picked to represent what happened to the real-world after the shocks from the earthquake and the subsequent tsunami. Their results suggest that the substitution parameters for interregional trade should be smaller, and in some sectors such as automobile parts, even be zero, to better match the model estimates with the real-world data.

Tatano and Tsuchiya (2008) developed an SCGE model for Japan that divided the country into nine regions and three sectors for each region, where interregional flows of freight were considered. They used the model to estimate the loss due to transportation network disruption, which increased the cost of inputs and commodities across regions. They found a cumulative total loss of 28.2 billion yen, 66 days after the earthquake. Among the total loss, 40 percent came from the region that was directly hit by the earthquake, and the rest 60 percent came from the other eight regions.

Flooding is another area that drew researchers' attention. Haddad and Teixeira (2015) used a SCGE model for Brazil to assess the total economic loss due to the flood in Sao Paulo in 2008. Direct loss in output was first calculated and then feed into the SCGE model to estimate the spillover impact that came from trade flows to other areas in Brazil. The results suggested a total GDP loss of 2.63 percent for the city of Sao Paulo and 0.7 percent for the country.

Shi *et al.* (2015) attempted to understand how output loss from transportation sector propagate to other sectors by developing a CGE model for Shifang, an area heavily damaged by the Wenchuan Earthquake in China in 2008, and the results suggested that a 21 percent loss in

[1] The set of parameters contains elasticity of substitution between different intermediate inputs and elasticity of substitution between different consumer goods.

outputs in the transportation sector can induce additional output losses for other production sectors that range from 0.68 to 6.8 percent.

Most CGE models analyzed short-run prompt effects without addressing how economic impacts grow and diminish over time (Chang *et al.* (2002)). Time is a key dimension because the timing of reconstruction activities and disaster assistance can significantly influence the economic recovery process and economic resilience. Including time in CGE models may require an extension on the static CGE models. By adapting endowments/exogenous variables from the previous period to the next period or by maximizing profit/consumption over lifetime periods, a static CGE model can be extended to a dynamic CGE model.

Xie *et al.* (2014) was an application to the above techniques. They modeled reconstruction activities through changes in investment, which directly determined the level of capital stock for the beginning of the next period. The model was able to generate an economic loss immediately after the earthquake and a path of recovery for local economies in each year after the earthquake. For Gertz and Davies (2015), dynamics depend on the fact that lifetime consumption combinations are chosen to maximize the discounted summation of utilities over time. When the level of capital stock availability is influenced by the flooding, the level of investment will change, especially the increase in reconstruction investment. This will result in a new decision on lifetime consumption. Under this new consumption pattern, a dynamic path of the economy can be generated, which will reflect the recovery process of the economy as well as a new status of the economy.

Even though improvements have been made under different categories discussed above, there were no models that can consider how physical, economic, and social infrastructure systems interact and affect the recovery efforts. In the earlier stage of the NIST project, a virtual community (Centerville) was established to integrate both engineering, economic, and social outputs of an earthquake. A dynamic spatial CGE (DSCGE) model was built for Centerville and the means by which outputs from the engineering model can be integrated to estimate the economic and social impact was developed.

Over the years, substantial improvements were made both by the engineering team and the economics team in the NIST project. The area of study went from the virtual community to real communities that are under risks from different types of natural disasters such as tornados, hurricanes, and tsunamis. For the earthquake, the real community testbed is Shelby County, TN, an area that is close to the New Madrid Seismic Zone. The engineering team built better methods in portraying earthquake damages and reconstruction status at smaller geographical units and at detailed time steps that considered the physical damages that include lifeline, building, and transportation network damages. The economics team worked on building better local level CGE models which considered a wider range of behavior channels to mimic real-world adjustments of an economy before and after an earthquake, such as commuting behaviors and migration behaviors, meanwhile, methods to integrate the engineering model outputs were also improved to a more detailed level with better portraits both in theory and in practice. This chapter reflects part of the improvements from the economics team.

To be more specific, this chapter improves the SCGE model developed in Cutler *et al.* (2016) by being able to capture firms' substitution behavior in intermediate inputs among regions based on the changes in relative prices. When the earthquake damages these regions unevenly, firms will shift their intermediate input demand from regions that are severely damaged to regions that are slightly damaged, so that cost of production can be minimized after the earthquake. Meanwhile, for households, since they commute to work both within and (in)outside the study region, their decision on where to work will change accordingly when different regions experience different levels of damages from the earthquake. The model in this chapter also captures this commuting and the associated consumption behavior adjustments endogenously to post-disaster conditions.

What's more, as suggested earlier in this section, a lot of papers that tried to estimate the economic losses in natural disasters tend to look at one type of physical damages. But natural hazards are associated with a combination of building, utilities, and transportation network damages. For example, an undamaged factory cannot run if there is no electricity or water. Currently, studies cannot justify that the individual losses from building, utilities and transportation damages would sum to the total losses of natural hazards if looking at them jointly. Because of the works done by the engineering team, the building-level physical and lifeline damages, and regional level transportation network damages can be obtained from a hypothetical earthquake. These can then be used to develop methods for estimating the total costs jointly.

Lastly, this chapter provides a comprehensive theoretical framework that can be translated both to engineers and economists in terms of how bridges are built to transport the outputs from engineering models into economic models. And researchers from related disciplines will know what to deliver and how to use these outputs to obtain a trajectory of the direct and indirect economic losses immediately after the natural hazards.

1.3 Shelby County, TN and the SCGE model

Shelby County is in the southwest corner of Tennessee, and adjacent to the borders of Arkansas and Mississippi. The county head is the city of Memphis, which was founded in 1819 by three prominent Nashvillians and located along the Mississippi River in the southwest part of Shelby County. (More details about the history of Memphis can be found at P13-P14, Shinozuka *et al.* (1998)). Memphis is known as the American's distribution hub because of the Memphis International airport, the second largest cargo operations next to Hong Kong. FedEx is headquartered in Memphis and is one of the contributing employers in this area.[2]

Other social and demographic features for Shelby County can be found in Table 1.1 The total population in Shelby County as of 2017 was about 937,847, and the median rent is less than $900 per month, which is a little bit higher than the state level median rent but is still 9 percent less than the national median rent ($982). The poverty rate is about 4 percent higher than the state's, but the education attainment measured by percent of high school graduates or higher are at the same level compared to the whole state.

Table 1.1 Social and Demographic Features for Shelby County, TN (2017)

	Shelby County	Tennessee
Total population	937,847	6,597,381
Median rent	$894	$808
Poverty rate (%)	20.8	16.7
Education (% High school graduate or higher)	87.6	86.5

Important economic sectors are illustrated in Table 1.2 below. Health care is the most important industry in Shelby County (12.2 percent of total income) that supports numerous hospitals including the Methodist and Baptist Memorial health systems, two of the largest private health systems in the country. Famous hospitals include Baptist Memorial Hospital and St. Jude Children's Research Hospital. The transportation industry is also essential because of the Memphis International Airport, as suggested above. Other contributing industries include Manufacturing, Finance, and Wholesale Trade.

[2] According to Great Memphis Chamber, FedEx, International Paper, AutoZone, Service Master and St. Jude Children's Research Hospital are the major employers in local area. https://memphischamber.com/live-in-memphis/work/major-employers/#1496687787757-199f4a12-0523

Table 1.2 Important Sectors in Shelby County, TN

Industries	Percent of total income as of 2017
Health Care Service	12.20%
Transportation and Warehousing	10.70%
Manufacturing	8.90%
Finance, Insurance and Real Estate	7.70%
Whole Sale Trade	6.70%

Another important feature for Shelby County is its commuting pattern within the area and inflow/outflow to/from this area. For instance, according to the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES), approximately 28.8 percent of jobs within Shelby County are taken by people who live outside of Shelby County, and for people who live in Shelby County, the likelihood of working outside is 14.7 percent, as of 2015.

In Figure 1.1, Shelby County is divided into eight PUMA (Public Used Micro Areas) regions, and Table 1.3 calculated that, for industries in each PUMA region, their employees' place of residence distribution using LODES data. For example, among the people who work in PUMA region A, 18 percent of them live in that region, 12 percent live in PUMA region B, and the rest 70 percent live in PUMA regions C to H or outside the county.

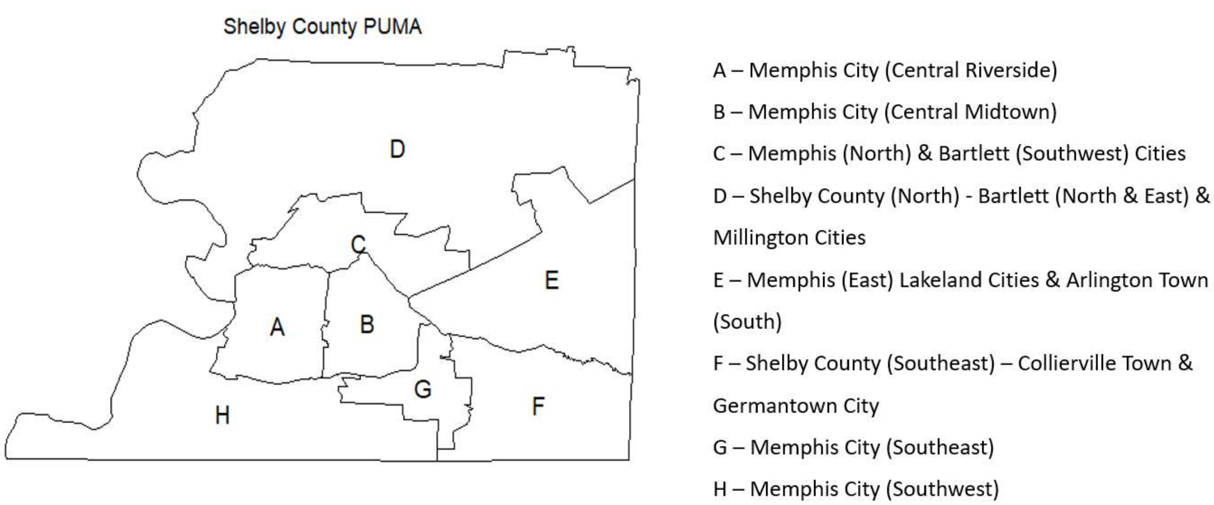

Figure 1.1 Eight PUMA regions in Shelby County, TN

Table 1.3 Commuting Pattern for Shelby County, TN (2012)

Work	A	B	C	D	E	F	G	H
Live								
A (3201)	**18%**	12%	9%	6%	7%	5%	9%	10%
B (3202)	12%	**19%**	11%	8%	10%	8%	11%	8%
C (3203)	9%	9%	**16%**	12%	10%	6%	7%	7%
D (3204)	10%	8%	15%	**23%**	12%	7%	8%	6%
E (3205)	10%	11%	13%	16%	**21%**	12%	11%	7%
F (3206)	11%	11%	7%	9%	12%	**28%**	16%	12%
G (3207)	8%	9%	8%	5%	8%	10%	**13%**	13%
H (3208)	7%	5%	4%	3%	4%	4%	6%	**12%**
Outside	15%	14%	17%	18%	17%	20%	19%	27%
Total	100%	100%	100%	100%	100%	100%	100%	100%

Regarding the potential earthquake risks, Shelby County is in the so-called New Madrid Seismic Zone with its northwest corner closer to the epicenter. Figure 1.2 provides a hypothetical Earthquake scenario for Shelby County, and darker brown indicates a higher level of ground motion in the earthquake. Comparing this with Figure 1.1 implies the eight PUMA regions will be impacted differently under the earthquake. In the meantime, given the commuting pattern in Table 1.3, if PUMA region A is damaged more than other regions, the impact from workers being laid off will spread out not only to people who live in region A, but also to other regions as people commute to region A for work.

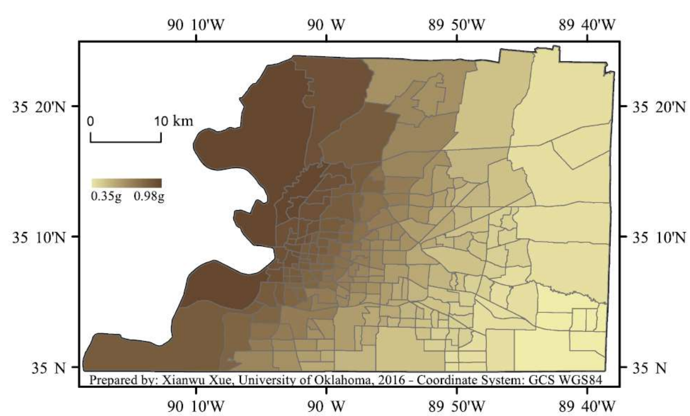

Figure 1.2 Shelby County Under a Hypothetical Earthquake
Source: Zhang et al. (2018)

1.3.1 Data

To construct the SCGE model, a social accounting matrix (SAM) is required (Figure 1.3).[3] The SAM is an integrated system of accounts that wage and capital income inflows, consumption and investment outflows, and the public finance and expenditures in a consistent form. Since the earthquake impacts the region unevenly, it is necessary to construct a spatial SAM to account for it. In summary, the spatial SAM is composed of spatial commuting and wages, spatial capital stock, and spatial intermediate input demand information. I start with the spatial commuting worker flow and their wages construction, which is accomplished by using the combination of LODES and ACS (American Community Survey) data[4].

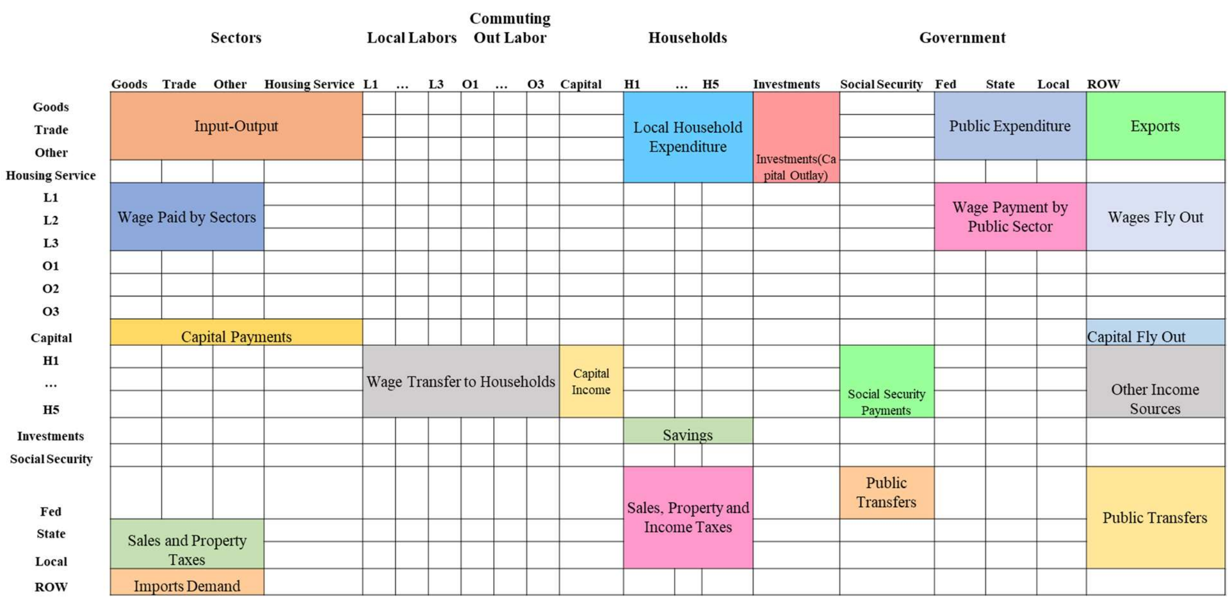

Figure 1.3 Social Accounting Matrix

First, ACS microdata provides information on employment and wages at the household/individual level based on where people live at the PUMA region level. The ACS microdata for Shelby County in 2012 is used to assign all workers in each household, their

[3] A complete description of SAM can be found in Schwarm and Cutler (2003).
[4] Noted here that both LODES and ACS are publicly available.

associating labor groups (L1, L2, and L3) using the reported annual wage income thresholds defined in Table 1.4. All the households in the eight different PUMA regions are assigned into five income groups based on the thresholds outlined in Table 1.4. Hence, there are a total of forty household groups for the SCGE model (five income groups times 8 PUMA region of residence). The microdata was then aggregated based on the labor groups and the household groups defined above. For workers who work in Shelby County but live outside the county, ACS data is also collected and aggregated using the same labor group distinctions in Table 1.4.

Table 1.4 Thresholds for Labor and Household groups

Labor Groups
L1 < $15,000
$15,001 < L2 ≤ $40,000
$40,000 < L3
Household Groups
HH1 ≤ 15,000
$15,001 < HH2 ≤ $35,000
$35,000 < HH3 ≤ $70,000
$70,000 < HH4 ≤ $120,000
$120,000 < HH5

For each household group, we know how many workers are supplied to the three labor groups— L1, L2, and L3 and their associated total annual wages after the aggregation. This can be found in Appendix Table A.1. For instance, in PUMA region A, HH1 (household annual income below $15,000) provided 7054 workers in L1 (workers whose annual wages are below $15,000) in 2012.

Next, the distribution of labor groups across different commercial sectors is required. This information is also available from the ACS survey data, where the worker’s industries are identified at the individual level based on North American Industry Classification System (NAICS). But the locations of individual industries are not available at the PUMA region level within Shelby County[5]. As a result, the LODES data is now utilized for such information.

The LODES data describes commuting flows for different groups of workers between each possible pair of census block of residence and census block of work. For confidentiality purposes, the workers are aggregated into three composite sectors: "Goods", "Trade", and "Other", which we will refer to as "commercial sectors" in our model (see Appendix Table A.2 of crosswalks between the three sectors "Goods", "Trade", and "Other" sectors and NAICS two-digit sectors).

The raw data describes that, for a census block of work, how many workers come from that block and among those workers, the distribution of workers in three income groups (L1, L2, and L3) and three commercial sectors ("Goods", "Trade", and "Other") separately. The LODES data is then aggregated from census block level to PUMA level using geographic crosswalks provided by the Census Bureau.

One challenge of using LODES data is the lack of information on the linkages between the labor group and the commercial sector. For instance, we know from LODES that there is a total of 100 workers who live in PUMA region A and work in PUMA region B, and among those workers, 40 of them belong to L1 and 60 of them belongs to L2. We also know that 30 of them work in the "Goods" sector and 70 work in the "Trade" sector. However, we do not know for the 30 workers who worked in the "Goods" sector, how many of them are L1 versus L2. To solve this, we assume that the probability of having L1 equals to dividing the total number of L1 workers by the total number of workers (40/100=0.4), and the probability will be applied to both the "Goods" and "Trade" sector to come up with the distribution of their workers among different labor groups (L1,

[5] From ACS, we know, for instance, a person is working in Retail Trade Industry, but we do not know the place of work for this person at the PUMA region level.

L2, and L3). Similarly, the probability of having L2 equals to dividing the total number of L2 workers by the total number of workers (1-0.4=0.6), so for the 30 workers in our example who work in "Goods" sector, 12 (=30×0.4) of them belongs to L1 and 18 (=30×0.6) of them belongs to L2.

The second challenge of using LODES data is the aggregation of commercial sectors into "Goods", "Trade", and "Other" due to confidentiality issues. This means that we cannot disaggregate the three commercial sectors if we want to consider more a disaggregated industry such as manufacturing, which is part of the "Goods" sector in the current scheme.[6]

Besides the spatial information on laborers, spatial information on capital stocks is also needed. The Shelby County assessor's office keeps records on the use of each parcel of land in the county in terms of the address, the acreage of the parcel, the assessed value of the parcel, and the value of the structure (commercial and residential buildings) on the parcel. The residential properties are straightforward to deal with because the addresses for each property are available, and for each PUMA regions, homes are grouped into three different residential groups (HS1, HS2, and HS3) based on the property value (HS1 ≤ \$100,000, HS2 > \$100,000, HS3 – rentals). Households demand services from these properties (such as maintaining the house, paying the mortgage or rent, repairing the house).

Organizing commercial properties is slightly more complicated. The county assessor's data is augmented with the Quarterly Census of Employment and Wages (QCEW) data, which supplies the address of each firm, the number of workers, the total wage bill, and the NAICS industry classification code. These data are then aggregated into the "Goods", "Trade" and "Other" sectors for each of the eight PUMAs in Shelby County.

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[6] We hope that in the future, such information will be available to the public with further development in software that could allow us to obtain information at the PUMA level.

The firm's intermediate inputs demand or I-O matrix comes from the Bureau of Economic Analysis, where it supplies a national I-O matrix based on NAICS codes. I then scale the national I-O matrix to the local I-O matrix using the location quotient (LQ) for Shelby County, an index that measures the level of concentration for an industry in a region. To be more specific, if the LQ for the industry is larger than 1, then this industry is more concentrated in the region than the national average, I then use the national I-O to represent the local I-O for that industry; on the other hand, if the LQ is smaller than 1, I then scale down the national I-O using the LQ for that industry in the region. However, the LQ is only available at the county level, not the PUMA level that we want. Hence, I use the workers commuting information as weights to decompose the LQ for each PUMA region.

The engineering team generated a hypothetical earthquake at a magnitude of 7.7 and an epicenter located at 35.3 N; 90.3 W. They offered us the parcel level information on buildings and utility damages, which will then be aggregated to PUMA level for our model. They also provided us the PUMA to PUMA travel efficiency losses due to road network damages. I will describe these data in detail in section 1.4 below when I build the crosswalk of transforming these engineering outputs to input variables that can be used for simulations in the SCGE model developed here.

1.3.2 Basic features of the SCGE model

Households

The SCGE model has forty household groups which are categorized by income (indexed by $h, h \in H, H = (H1, H2, \ldots, H5)$) and PUMA region (indexed by $s\ or\ r, s\ and\ r\ \in \mathrm{S}, \mathrm{S} = (\text{Puma region A, B, ... H})$. Households live in certain PUMA regions will consume not only in their region of residence but also in all other regions. For simplicity, I assume that consumption outside their region of residence only comes from their place of work PUMA region. For example, a household who both live and work in PUMA region A will not consume outside PUMA region A, but a household who live in PUMA region A and work in PUMA region B will consume in PUMA region A and B with a fixed proportion among A and B, and this proportion is the same among all households. Hence their utility maximization problem can be expressed in equation (1.1) to (1.5) below:

$$V_h^s = \max U_h^s \left(F_{1,h}^{r,s}, \dots F_{n,h}^{r,s}\right) \tag{1.1}$$

$$\text{s.t.} \sum_{r\in S} \sum_{j\in N} P_{F_j^{r,s}} F_{j,h}^{r,s} = I_h^s \tag{1.2}$$

$$for\ each\ r\ and\ r' \in S, and\ both\ r, r' \neq s,\ \frac{P_{F_j^{r,s}} F_{j,h}^{r,s}}{P_{F_j^{r',s}} F_{j,h}^{r',s}} = \left(\frac{\delta_h^{r,s}}{\delta_h^{r',s}}\right)\left(\frac{Jobcore_h^{r,s}}{Jobcore_h^{r',s}}\right) \tag{1.3}$$

$$for\ each\ \ r' \in S, and\ r' \neq s,\ \frac{P_{F_j^{r,s}} F_{j,h}^{s,s}}{P_{F_j^{r',s}} F_{j,h}^{r',s}} = \frac{\delta_h^s Jobco\quad_h^{s,s} + \sum_{r\in S}(1-\delta_h^r) Jobcore_h^{r,s}}{\delta_h^{r'} Jobcore_h^{r',s}} \tag{1.4}$$

$$\delta_h^r = \delta_h^{r'} = \delta, for\ each\ r\ and\ r' \in S \tag{1.5}$$

where $V^{h,s}$ is an indirect utility function, $U^{h,s}$ is a direct utility function, $F_{j,h}^{r,s}$ is the quantity demanded on outputs produced by sector j in region r from households h who live in region s, $j \in J$, $J = (Goods, Trade, Other, Housing\ service\ sector 1, \dots, Housing\ service\ sector\ 3)$, $P_{F_j^{r,s}}$ is the price for outputs produced by sector j in region r, $\delta_h^{r,s}$ is the percentage of total consumption that goes to the place of work—region r, when households live in region s and work in region r, and $Jobcore_h^{r,s}$ is the number of workers supplied per household from region s to region r.

Equation (1.4) implies that for all households who live in region s, their consumption in region r and r' depends on the relative distribution of households who work in region r and r' respectively. Also, households who work outside their region of residence only spend part of their income in where they work, the rest proportion $(1 - \delta_h^r)$ still goes to their region of residence, as suggested by equation (1.4).

When an earthquake happens, the relative distribution of households working in each region ($Jobcore_h^{r,s}$) will change, and their decision to work in one region versus another now will depend on the labor demand status after the earthquake. This implies that if one region experiences severe damages due to the disaster and demand in labor in that region decreases, the household will adjust their labor supply behavior accordingly by reducing their labor supply to this region. And equations (1.6) -(1.7) below describe this behavior change. What's more, when labor supply to the damaged region is reduced, the work-related consumption will also decrease, and equation (1.3) and (1.4) can take this impact into account.

$$\frac{Jobco\ _h^{r,s(1)}}{Jobcore_h^{r',s(1)}} = \left(\frac{FD^{r(1)}}{FD^{r'(1)}}\right) \tag{1.6}$$

$$s.t. \sum_{r,r \in S} Jobcore_h^{r,s(1)} = \overline{Jobcore_h^{s(1)}} = \overline{Jobcore_h^{s(0)}} \tag{1.7}$$

where $Jobcore_h^{r,s(1)}$ is number of workers supplied per household from region s to region r after the earthquake, $FD^{r(1)}$ is the factor demand for labor in region r after the earthquake, and $\overline{Jobcore_h^{s(0)}}$ is the total number of workers supplied per household, which for simplicity is assumed to be constant before and after the earthquake.

Firms

Firms use labor services and capital stock as inputs, labor is measured in the number of workers while capital is measured in real dollar terms. The capital stock is essential, as substantial portions of it consist of buildings and types of equipment that can be damaged or destroyed in natural disasters. Firms also require intermediate inputs in production, and different from traditional non-spatial CGE models or the spatial model developed in Cutler *et al.* (2016), firms can obtain the same type of intermediate inputs, say inputs from the agriculture sector, from different regions with certain levels of substitution. Figure 1.4 below illustrates the firms' production structure.

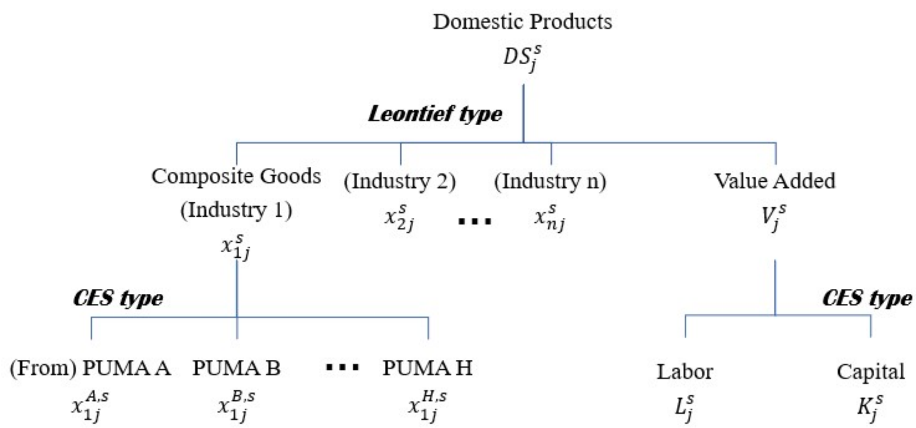

Figure 1.4 Production Techniques for Firms

Final products at the first layer in Figure 1.4 is determined by inputting composite goods and value-added based on a Leontief production function given by:

$$\mathrm{DS}_j^s = \min\left(\frac{V_j^s}{a_{vj}^s}, \frac{x_{1j}^s}{a_{1j}^s}, \ldots \frac{x_{Nj}^s}{a_{Nj}^s}\right) \tag{1.8}$$

where DS_j^s is the total output produced in sector j region s, V_j^s is the amount of value-added, $x_{ij}^s$is the amount of intermediate inputs demanded by sector j from sector i, and a_{vj}^s, a_{ij}^s are the I-O coefficients. V_j^s is determined by solving the cost minimization problem in equation (1.9) to (1.12) below,

$$\mathrm{C}(\mathrm{w}_j^s, r_j^s)V_j^s = \min_{FD_l^s, FD_K^s} \mathrm{w}_j^s L_j^s + r_j^s K_j^s \tag{1.9}$$

$$\text{s.t. } f(L_j^s, K_j^s) = \eta_j^s\{\alpha_L(L_j^s)^\rho + \alpha_K(K_j^s)^\rho\}^{1/\rho} \tag{1.10}$$

$$L_j^s \le \overline{LS_j^s} \tag{1.11}$$

$$K_j^s \le \overline{KS_j^s} \tag{1.12}$$

where η_j^s is total factor productivity, α_L and α_K are share parameters of labor and capital inputs, and $(1/(1-\rho)$) is the elasticity of substitution between labor and capital. LS_j^s and KS_j^s are the initial endowments of labor and capital stock in region s.

After the earthquake, production capacity would be reduced by the decrease in labor and capital endowments ($\overline{LS_j^s}$ and $\overline{KS_j^s}$), infrastructure disruption, transportation inefficiency, or other adverse conditions.

Composite goods on the left-hand side at the second tier of Figure 1.4 are assumed to follow the CES production techniques, and the composite goods consist of the same type of intermediate inputs from all eight PUMA regions. The use of each type of intermediate input from each region is determined by the cost-minimization problem in equation (1.13) -(1.14):

$$C_{x_{ij}^s} x_{ij}^s = min \sum_{r \in S} P_i^r x_{ij}^{rs} \tag{1.13}$$

$$s.t.\ \ x_{ij}^s = \emptyset_{ij}^s \left(\sum_{r \in S} \beta_{ij}^{rs} (x_{ij}^{rs})^{\varphi}\right)^{1/\varphi} \tag{1.14}$$

where $\emptyset_{ij}^s$ is the scale parameter, β_{ij}^{rs} is the share parameter, and $(1/(1-\varphi)$) is the elasticity of substitution parameter.

Solving for the cost-minimization problem in equation (1.13) -(1.14) gives the optimal demand on product i produced in region r by firm j located in region s as illustrated in the second tier of Figure 1.4 in the production process, and the optimal solution is expressed in equation (1.15) -(1.16) below:

$$x_{ij}^{rs} = \Gamma_{ij}^{rs} \left[(\beta_{ij}^{As})^{\frac{1}{1-\varphi}} \left(\frac{P_i^A}{P_i^s}\right)^{\frac{\varphi}{\varphi-1}} + (\beta_{ij}^{Bs})^{\frac{1}{1-\varphi}} \left(\frac{P_i^B}{P_i^s}\right)^{\frac{\varphi}{\varphi-1}} + \cdots + (\beta_{ij}^{Hs})^{\frac{1}{1-\varphi}} \left(\frac{P_i^H}{P_i^s}\right)^{\frac{\varphi}{\varphi-1}} \right]^{\frac{-1}{\varphi}} \tag{1.15}$$

$$where\ \Gamma_{ij}^{rs} = \frac{1}{\emptyset_{ij}^s} \left[\beta_{ij}^{rs}\right]^{\frac{1}{1-\varphi}} (a_{ij}^s DS_j^s) \tag{1.16}$$

When external shocks happen, especially when the external shocks are spatially distributed, firm j located in region r can re-adjust their intermediate input demand on product i produced in region $r - x_{ij}^{rs}$, based on relative prices of the same product i produced in all other regions $(\frac{P_i^A}{P_i^S}, \frac{P_i^B}{P_i^S}, \ldots \frac{P_i^H}{P_i^S})$ to minimize the cost of production. Unlike the original set up from the spatial model in Cutler *et al.* (2016), where intermediate inputs demand on the same product i produced in different regions followed the Leontief type, this CES type in the second tier in Figure 1.4 of the production process implies the firms' inherent resilience toward external shocks.

Government

The government is decomposed as federal, state, and local governments. The federal government collects federal income taxes from local households, state government collects sales and income taxes from firms and households separately. Local government is further broken down to the city of Memphis and all other cities (Arlington Town Bartlett City, Collierville Town, Germantown City, Millington City, and Lakeland City). The local government collects property taxes, local sales tax, and all other taxes and fees such as license taxes and permits.

Government sectors also buy commodities produced from commercial sectors and demand labor. In Shelby County, the governments run a balanced budget, meaning that they do not run any type of deficits or surpluses.

Rest of the world (ROW)

Shelby County trades with neighboring local economies (area named "Exports" in the upper right corner of Figure 1.3 as well as foreign sectors to import goods and services that are consumed by local households (area named "Imports Demand" in the lower-left corner of Figure 1.3). Also, it demands workers from neighboring economies and these workers will bring their wage income from Shelby County to the neighboring area. Similarly, local households supply workers to Shelby County as well as to the neighboring economies, and those who commute to work outside of the Shelby County will bring income into Shelby County[7].

Spatial Behaviors in Labor Market and Model Closure

Different from previous spatial CGE models that only allow for the intra-regional trade of intermediate inputs, the model in this chapter also allows for intra-regional commuting of workers. As a result, the supply of labor depends both on wages provided locally and outside Shelby County. Equation (1.17) is the labor supply decision made by households:

$$LS(HW_{h,s}/HH_{h,s}) = F(\textstyle\sum_{s'} \beta_h^{s,s'} w_h^{s'}, w_{commuting\ out}, t, g) \quad (1.17)$$

where $HW_{h,s}$ is the number of working households and $HH_{h,s}$ is the number of total households for household group h in region s. The variable w_h^s is the average wage of labor groups L1 to L3 in PUMS region s', and weighted by percent of workers supplied from household group h in PUMA region s to PUMA region s', or $\beta_h^{s,s'}$, $w_{commuting\ out}$ is the wage offered outside the Shelby County, t is the income tax, g is government transfer, and α is a weighting parameter.

The modified labor supply equation takes wage, total government transfer, and taxes into account. What is different from the conventional CGE model is the consideration of out-commuting wage. If wages outside Shelby County increases, denoted by $w_{commuting\ out}$, the proportion of working households will also increase because of this change.

Decision making for people who commute from outside and work in Shelby County is as follows:

$$\mathrm{CMI}_j^s = CMI0_j^s * \left[\frac{(w_j^s)}{EXWGEI}\right]^{Ecomi} \quad (1.18)$$

[7] For the year 2012, 84,014 number of workers went out of Shelby County for work, which is about 18.5% compared to the number of workers in Shelby County, and they brought a total of 1882 million of dollars of income into Shelby County, which also means on average, each worker brought in about 22,401 dollars annual income.

where $CMI0_j^s$ *and* CMI_j^s are respectively the number of people who commute in after and before the earthquake simulation to region s sector j. The variable w_j^s is the wage earned by in-commuters working in PUMA region s; $EXWGEI$ is the wage outside Shelby County; $\mathrm{E}comi_L$ is the labor supply elasticity to wages. Their decision making is impacted by the relative wages they can earn inside Shelby County versus wages that offered outside Shelby County. The sensitivity of this decision is measured by the elasticity, $Ecomi$.

The amount of people who live in Shelby County and work outside is determined in the following equation:

$$\mathrm{CMO_h} = CMO0_h * \left[\frac{FD}{FD}\right]^{Ecomo} \tag{1.19}$$

The variables $CMO0_h$ and $\mathrm{CMO_h}$ are the number of people who commute out before and after the earthquake. The variables $FD0$ and FD are total factor demand in labor before and after the earthquake in Shelby County. The elasticity $Ecomo$ is the labor supply elasticity with respect to factor demand. The decision-making process for out-commuters depends on local factor demand. When factor demand decreases after the earthquake, more people will choose to work outside the county for more employment opportunities.

Finally, the labor market clearing condition will be the following:

$$\sum_{s'} HW_h^s * Jobcore_{s,s'} + CMI_{s'} = \sum_{j\in N} \mathrm{FD_{j,s'}} \tag{1.20}$$

The variable $HW_{h,s}$ is the number of working households in group h and region s, $Jobcore_{s,s'}$ is the number of workers supplied by each working household to puma region s', $CMI_{s'}$ is the total number of in-commuters to the region s' and $\mathrm{FD_{j,s'}}$ is the factor demand for labor from sector j in region s'. Labor demand for firms in one region equals to labor supply from workers in different region PUMS region s in Shelby County plus workers who commuting in

Shelby County. Notice that $Jobcore_{s,s'}$ doesn't include workers who live in Shelby County but work outside Shelby County.

Other markets closure conditions include:

a) The factor demand and factor supply (including intermediate inputs) are equal;

b) The supply of goods equals the demand for goods in each sector;

c) The government sector's budget is balanced.

1.4 Modeling earthquake impact

1.4.1 Overview

This section describes the channels through which different types of physical damages can result in economic losses, and how I map the physical damages data as external shocks to the SCGE model to obtain economic losses. Generally speaking, as illustrated in Figure 1.5 below, there can be three different channels of the physical damages that negatively impact the economy: the first one is the functionality loss of the commercial buildings, which is caused by structure/non-structure building damages or loss of water or electricity supplies. Commercial building in the economy is treated as a factor of production called capital, and the loss of capital can reduce firms' production capacity and employment, causing a shortage in supply and higher product prices that reduce the equilibrium output and income level in the economy; the second one is the functionality loss of residential buildings, which will cause a large outmigration so that labor supply will be largely reduced as well as final demand on commodities; the last one is the damages to road and highway networks, which will impact travel efficiency and increase travel cost for commodity flows, labor flows as well as shopping trips. And as costs of these flows go up, decreased demand in intermediate inputs, labor, and consumption will cause losses in total output and total income.

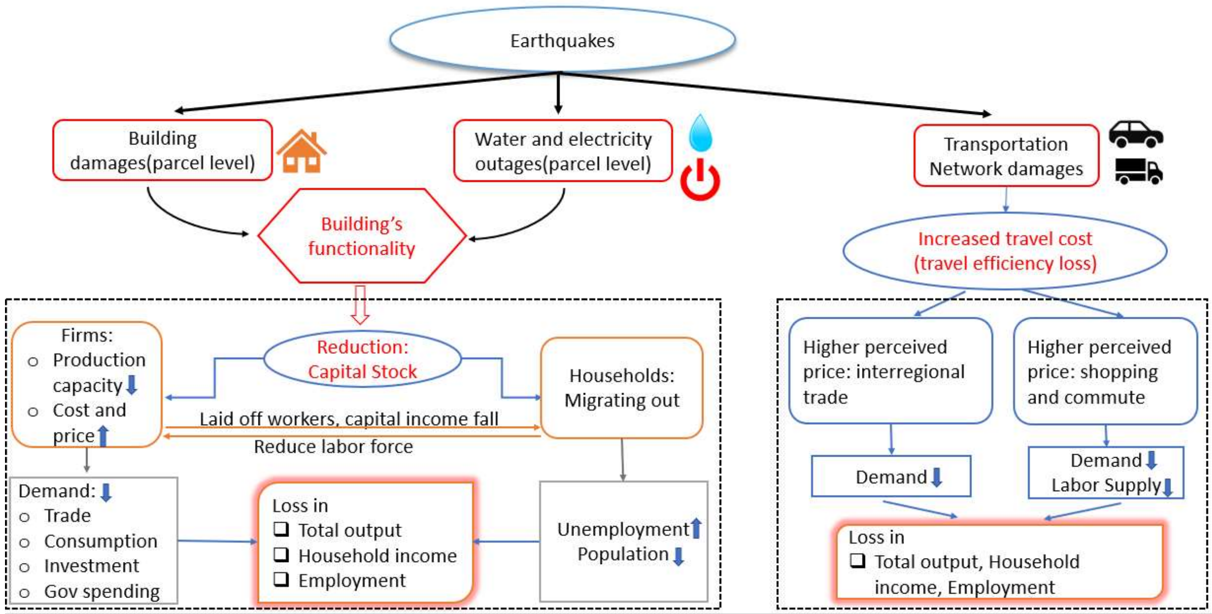

Figure 1.5 Economic Impacts of Earthquakes

Next, I will describe in detail how I use the outputs provided by the engineers and turn them into external shocks for the SCGE model developed in the chapter.

1.4.2 Commercial Building, Water/Wastewater, and Electricity damages

It is commonly accepted that earthquakes can damage the buildings at different levels of severity. For a SCGE model, buildings are treated as a factor of production which is called capital stock. Its value is measured by the county assessor's office as mentioned above in section 1.3. To use the capital stock, firms must pay the rental rate, which is similar to the wages paid to the workers.

When water pipelines or electricity transmission lines are damaged by the earthquake, buildings cannot be used as functional capital stock for production. For almost all states, when water or electricity is not functioning for commercial buildings, state regulations prevent commercial businesses from opening, and I model this as a loss/reduction in capital stock. In this case, the loss in the capital may be as short as a few days or weeks but the modeling resembles when buildings are physically damaged. In all these cases and another situation is when the structure of the commercial buildings is physically damaged by the earthquake to a safety threatening condition, regardless of the availability of the utilities, the buildings cannot be used as functional capital stock for production. In both conditions, there will be a decrease in the economy's endowment in terms of capital stock.

If one or both above situations happen, the firm's production capacity is reduced, and workers are laid off. For the rest capital stock that is still functional, the rental rate of it will increase to reflect scarcity. Firms will suffer from losses in total output and face a higher cost of production, which will lead to higher prices and smaller quantity-demanded for their output. The workers who are laid off will increase the unemployment rate and reduce the total level of household income in the economy.

To estimate the above losses, I need to identify to what extent the capital stock will be reduced using data provided by the engineering team. Previous studies, when introducing their data on building damages, were not explaining carefully whether the damages are caused by the structural damages of the buildings or by the damages of lifelines to the buildings. (Shibusawa and Miyata (2011), Xie *et al.* (2014)), or was just choosing one type of damages alone (Haddad and Teixeira (2015)). Two studies that did consider both are Pauw *et al.* (2011) and Kajitani and Tatano (2018), but they were looking at other types of natural hazards or had observed physical damage data using the actual event that happened in other counties. For the U.S., since the earthquake didn't happen very often, the simulated data from the engineers are required to estimate the capital stock damages.

The building data from the engineering team, which are outputs in terms of building damages under different levels of functionality status at the parcel level, are used to determine the level of capital stock reduction for each commercial sector in each PUMA region. The engineers defined building functionality being the suitability of a building for its intended purposes, determined by whether a building is structurally safe to be occupied and whether basic utilities are available on site (Lin and Wang (2017)). They further describe five functionality states as (Lin and Wang (2017), p.98):

1. Restricted Entry (RE): extensive structural or non-structural damage that threatens life safety regardless of utility availability.

2. Restricted Use (RU): Moderate structural or non-structural damage that doesn't threaten life safety, regardless of utility availability

3. Ro-occupancy (RO): Minor to moderate structural and non-structural damage, but utilities are the unavailability

4. Baseline Functionality (BF): Minor cosmetic structural and nonstructural damage with critical utilities available (power, water, fire sprinklers, lighting, and HVAC systems)

5. Full Functionality (FF): no damages and all utilities are available.

In the above definitions, the two types of capital stock reduction mentioned above are both considered, with buildings under RE and RU not functional as a result of structural or non-structural damages and with buildings under RO not functional as a result of utility service outage only. To obtain the level of capital stock after the earthquake ($\overline{KS_j^{s(1)}}$), for a building b in commercial sector j in PUMA region s, I first assign a dummy variable $\mu_{b,j}^s$ that indicates its functionality (0=not functional, with functionality status RE, RU and RO, =1 functional with functionality status BF and FF). Then I use that dummy variable times its assessed value $\overline{Value_{b,j}^s}$ and aggregate it to PUMA level for each sector j. Finally, I calculate the availability ratios ζ_j^s for each sector j in region s using the equation (1.21) below. Table A.3 in Appendix A lists the calculated loss ratio ($1 - \zeta_j^s$) for all the commercial sectors, which will then be used for simulation results in Section 1.5.

Based on the availability ratio, I can get the capital stock after the earthquake ($\overline{KS_J^{s(1)}}$) using the equation (1.22) below.

$$\zeta_j^s = \frac{\sum_{b \in \mathrm{B}} \mu_{b,j} \overline{Value_{b,J}}}{\sum_{b \in \mathrm{B}} \overline{Value_{b,J}}} \tag{1.21}$$

$$\overline{KS_J^{s(1)}} = \zeta_j^{s(1)} \overline{KS_J^{s(0)}} \tag{1.22}$$

where $\overline{KS_J^{s(0)}}$ is the capital stock endowment for sector j in the region s before the earthquake.

The new level of endowment in capital stock, $\overline{KS_J^{s(1)}}$, will go back to the cost minimization problem for firms in equations (1.9) -(1.12), to re-optimize and solve for the post-disaster level of output, factor demand of labor, and capital respectively.

Again, I assume that buildings under the functionality state of RO (re-occupancy), where there are no or minor structural damages except for unavailability in utilities, are not functional. Even though in reality, such buildings may be under a situation where some types of utilities are available but not all of them. This may allow them to maintain some level of production at smaller capacities. At this point, I am not able to capture such margins. Future studies can try to relax this and make buildings under the functionality state of RO available to use under the reduced level of productivity because of utility outages. This will require data on the level of business disruptiveness due to one or more types of utility service outage, which could allow studies to reduce firms' productivity accordingly[8].

[8] But there will also be some issues in terms of whether it is legal to open a business under water or electricity outage. If, after looking into detailed regulations and the findings suggest such behavior is illegal, there will be no need to relax this assumption.

1.4.3 Residential building damages

When residential buildings are damaged, people may be forced to migrate out of the damaged area, and such behavior can cause a large reduction in population, which will lead to a decrease in aggregate demand and labor supply. Similarly, the percentage of residential buildings that are not functional, due to significant damages to the structural and non-structural components, is calculated using equation (1.23) based on the same criteria used in subsection 1.4.2, i.e., a residential building is functional when it is under functionality status BF and FF, and not functional when it is under functionality status RE, RU, and RO. The residential capital stock damages that will be used for the simulation results in Section 1.5 are summarized in Table A.4 in Appendix A.

$$\eta_h^{s(1)} = \frac{\sum_{b \in \mathrm{B}} \mu_{b,h}^{s(1)}}{\overline{N_h^s}} \tag{1.23}$$

where $\mu_{b,h}^{s(1)}$ is the dummy variable indicating the functionality status of building b in region s, and $\mu_{b,h}^{s(1)} = 1$ if the building is functional, $\mu_{b,h}^{s(1)} = 0$ if it is not functional after the earthquake. $\overline{N_h^s}$ is the total number of buildings in the region s for household h.

Then this functionality ratio is going to impact household migration decision based on the following equation below:

$$\frac{HH_h^{s(1)}}{HH_h^{s(0)}} = \left(\eta_h^{s(1)}\right)^{\nu 1_h} \left(\frac{YD_h^{s(1)}}{YD_h^{s(0)}}\right)^{\nu 2_h} \left(\frac{UE_h^{s(1)}}{UE_h^{s(0)}}\right)^{\nu 3_h} \tag{1.24}$$

where $HH_h^{s(0)}$ and $HH_h^{s(1)}$ are the number of households h in region s before and after the earthquake respectively, $YD_h^{s(0)}$ and $YD_h^{s(1)}$ are the real disposable income per household in region s before and after the earthquake, and $UE_h^{s(0)}$ and $UE_h^{s(1)}$ are the unemployment rate for household h in region s before and after the earthquake respectively. $\nu 1_h$, $\nu 2_h$ and $\nu 3_h$ are elasticities of household migration regarding housing damages, disposable income, and unemployment rate respectively.

Household migration decision is a function of disposable income and unemployment rate based on Berck *et al.* (1996), as well as the percentage of housing that is functional after the earthquake. Several studies that looked at New Orleans's evacuees and their returning decision after hurricane Katrina found that the probabilities of returning to New Orleans are related to housing damages. (Paxson and Rouse (2008); Fussell *et al.* (2010); Groen and Polivka (2010)).

1.4.4 Transportation network damages

The civil engineering team uses the travel time and travel efficiency for each PUMA pairs to portrait the transportation network damages after the earthquake. For example, right after the earthquake, the estimated travel efficiency between PUMA region A and PUMA region C is 88 percent of the pre-disaster condition, i.e. the travel time increased by 12 percent between PUMA region A and C. This increase in travel time is denoted by $TT^{r,s\,(1)}$. Table A.5 in the Appendix lists the detailed percent increase in travel time for each PUMA pairs. Next, I will describe in detail how I model this increase in travel time influences the firms' production, households' labor supply, and consumption behavior respectively.

Firms: Damages to the transportation network and increased travel time can bring a negative impact on the economy. For firms, they need to buy intermediate inputs from all regions and the damaged transportation network increases the shipping costs among regions as well as the waiting time to obtain materials needed for production. When the costs of production go up, we will see the decreased output and increased price levels, and also decreased income as a result of road network damages.

To model these impacts, a perceived price inflator ($PI_{firm}^{r,s(1)}$) is used to reflect the rising travel costs of intermediate inputs in each origin and destination pair. Recall from equation (1.15) in section 1.3, firms' demand for intermediate inputs is a function of its own price and the prices of the substitutes. I multiply the prices with the perceived price inflator to capture the impact from road network damages, and equations (1.25) -(1.26) below describe how the perceived price inflator can change the firms' decision on intermediate input purchase.

$$x_{ij}^{r,s(1)} = f(PI^{A,s(1)}P_i^{A(1)}, \dots, PI^{r,s(1)}P_i^{r(1)}, \dots PI^{H,s(1)}P_i^{H(1)};\ \beta, \emptyset, x_{ij}^{rs(0)}, P_i^{A(0)}, \dots, P_i^{H(0)}) \quad (1.25)$$

$$\frac{\partial x_{ij}^{rs(1)}}{\partial P^{\ r\prime s(1)}} \geq 0\ for\ r' \neq s, and\ \frac{\partial x_{ij}^{rs(1)}}{\partial P^{\ rs(1)}} \leq 0 \quad (1.26)$$

where$PI^{r,s(1)}$ is the price inflator between PUMA region r and s due to road network damages, and $PI^{r,s(1)} \geq 1$; $P_i^{r(1)}$ and $P_i^{r(0)}$ are the prices of product i in region r before and after the earthquake respectively, $x_{ij}^{r,s(0)}$ is the demand for product i in region r by firm j in region s before the earthquake, and $\beta, \emptyset$ are parameters that are defined earlier in section 1.3.

Imagine that $PI^{r,s(1)} > 1$ and $PI^{r',s(1)} = 1, for\ r' \neq r$, which implies that only the road to region r is damaged. Then the perceived price on product i produced in region r goes up, meaning that firm j now would want to substitute more product i from other region r' ($r' \neq r$) instead, and this is equivalent to $\frac{\partial x_{ij}^{r\prime s(1)}}{\partial P^{\ rs(1)}} \geq 0, r' \neq r$ and $\frac{\partial x_{ij}^{rs(1)}}{\partial P^{\ rs(1)}} \leq 0$.

The price inflator for the firms is calculated using the equation (1.27) below:

$$PI_{frim}^{r,s(1)} = (1 + \tau^{firm} \times \mathrm{TT}^{r,s}) \quad (1.27)$$

where τ^{firm} measures the contribution of shipping time in the valuation of the intermediate inputs. According to the empirical work done by Hummels and Schaur (2012), a one day delay of the transit time is equivalent to 0.6 to 2 percent value of the good, based on the US monthly import data from 1991 to 2005. At the average level of transit time (19 days), an additional day of shipping is about 5 percent of the total shipping time. Hence, it is equivalent to say that a one percent increase in shipping time is equivalent to 0.12 to 0.4 percent value of the good. Therefore, I apply the high-end value of 0.4 as the value of τ^{firm} in equation (1.27) for the perceived price inflator calculation regarding firms' intermediate input purchases.

Meanwhile, the damaged road networks can postpone the time that firms receive their intermediate inputs, as a result, reduce the total factor productivity (TFP) of firms. Since the intermediate inputs come from all eight PUMA regions, only the inputs that arrive at the latest will matter in influencing the firms' production process. The shock to the total factor productivity η_j^s is modeled in equation (1.28) below:

$$\eta_j^{s(1)} = \eta_j^{s(0)}(1 - \tau^{TFP} \times \max_r \mathrm{TT}^{r,s}) \tag{1.28}$$

where the $\eta_j^{s(0)}$ and $\eta_j^{s(1)}$ are the level of TFP for firm j in region s before and after the earthquake, τ^{TFP} is the contribution of transportation for TFP, and $\mathrm{TT}^{r,s}$ is the percentage increase in travel time from region r to region s after the earthquake. For the value of τ^{TFP}, a survey of literature by Isaksson (2010) suggested that infrastructure contributes 15 percent to TFP changes, which implies that $\tau^{TFP} = 0.15$.

Labor Supply: For households who need to commute to work, damaged transportation networks will change the likelihood that households supplying labor to different PUMA regions. For example, if average wages paid are the same for similar commercial sectors in PUMA region A and B, when an earthquake increases the cost of travel to region B more than to region A, households would prefer to work in A instead, and firms in PUMA region B will need to pay higher wages to attract workers which lead to an increase in the cost of production. To model this, the labor supply decision that is defined earlier in equation (1.6) now becomes the equation (1.29) below. Besides the relative demand for labor after the earthquake, relative changes in travel time among different regions after the earthquake also plays a role in determining where households want to supply their labor.

$$\frac{Jobcore_h^{r,s(1)}}{Jobcore_h^{r',s(1)}} = \left(\frac{(1+\varepsilon_h^{time} TT_h^{r,s(1)})}{(1+\varepsilon_h^{time} TT_h^{r',s(1)})}\right)\left(\frac{FD^{r(1)}}{FD^{r'(1)}}\right) \tag{1.29}$$

where $TT_h^{r,s(1)}$ is the percentage increase in travel time from region r to region s after the earthquake, and $FD^{r(1)}$ is the factor demand in labor after the earthquake in region r, ε_h^{time} is the responsiveness of labor supply with respect to commuting time for household h.

For a reasonable estimate of the responsiveness of labor supply decisions to changes in commuting time, Black *et al.* (2014) tested the effect of commuting time on female's labor force participation decisions. The empirical strategy focused on female workers and the regression results suggested that a 1-minute increase in commuting time is associated with a 0.3 and 0.15 percent reduction in the labor force participation rate for high-school graduates and those with a bachelor's degree respectively. The Federal Reserve Bank of St. Louis calculated the daily average commuting time for workers by year in Shelby County, and in 2018, this number is 46 minutes, which implies that a 1-minute increase in commuting time is equivalent to 2 percent increase from the average commuting time. Therefore, the responsiveness/elasticity of labor supply decision to commuting time ranges from -0.075 to -0.15 in Shelby County. For household groups 4 and 5, whose annual income is above $70,000, I apply the responsiveness value of -0.075, as they are more likely to have a bachelor's degree. And for household groups 1 to 3, I use the responsiveness value of -0.15.

Household Consumption: For households who consume in different regions, travel costs will also increase when the road network is damaged. The actual price paid for a commodity considering the travel cost will go up, holding everything else equal. This will reduce the aggregate consumption demand in the economy. To model this consumption demand change, a price inflator ($PI_h^{r,s(1)}$) is also imposed on the household's consumption function, the same idea as the price inflator imposed in the firms' intra-regional demand on intermediate inputs in equation (1.25) before. The calculation of the price inflator to households is also similar to equation (1.27), but with a different level of τ^h, which measures the contribution of travel time in the perceived value of commodities by households.

To quantify the level of importance of the driving time in determining the price inflator for consumers, I first obtain estimates on the percentage of gasoline spending in total consumption expenditure from the Consumer Expenditure Survey. I then multiply it by the relative weight of driving time on consumption trips, accounting for the fact that total gasoline spending comes not only from shopping trips or traveling, but also from driving to work[9]. The relative weight of driving time spent on consumption versus working is calculated from the American Time Use survey. It offers estimates for different times spent in primary activities within a 24-hour time frame. According to the survey in 2018, average driving time related to consumption is about 37 minutes per person and 185 minutes per household, and average travel time related to commuting is about 17 minutes per person and 48 minutes per household, meaning that relative weight of driving time spent on consumption is about 74 percent, if taking the average of the per person and per household estimates.[10] As a result, the process of calculating the perceived price inflator for households can be summarized in equations (1.30) -(1.31) below:

$$PI_h^{r,s(1)} = (1 + \tau^h \times \mathrm{TT}^{r,s}) \tag{1.30}$$

[9] Note that consumption behavior also includes leisure related activities.
[10] Detailed information about time spent in primary activities from American Time Use Survey can be found at Bureau of Labor Statistics with the link https://www.bls.gov/tus/a1-2018.pdf.

$$\tau^h = gas_h \times \frac{driving_c}{driving_c + driving_w} \tag{1.31}$$

where gas_h is the percent of expenditure spending on gasoline for household h, $driving_c$ is the average driving time for consumption, $driving_w$ is the average driving time for work.

1.5 Results

This section has four subsections. The first subsection focuses on the simulation results due to building damages using the Cutler *et al.* (2016) model specification (original model), as well as the distributional impact from the earthquake. The second subsection compares simulation results from the new model specification developed in this chapter to those from the original model. The new model specifications consider the spatial behavior of firms purchasing intermediate inputs from different regions, the commuting behavior at sub-county-level as well as the spatial consumption behavior of households in different regions. And the third subsection provides the simulation results under both building functionality loss and transportation network damages using the new model.

1.5.1 Results with original model specification

Table 1.5 presents the simulation results for major economic outcomes in Shelby County with loss in capital stock. As we expected, when Shelby County experiences an earthquake, the total output produced/domestic supply falls, as well as the employment and household income. People also migrate out of the county due to housing damages/loss in residential capital, as expressed in equation (1.24) in subsection 1.4.3. When looking at the magnitude of the impact, percentage loss in total output is the largest and the percentage loss in household income is the smallest. The intuition is the offsetting effects from wages and rental rate of capital. When the buildings are damaged and the households are forced to leave, capital and labor inputs both become more expensive for firms. The rise in wage rates and the rate of return on capital offsets the drop of employment and capital regarding household income.

Table 1.5 Simulation Results for Original Model under Capital Stock Losses

Economic Variables		Capital stock reduction
Domestic Supply	Change (million)	-8160.67
	percent change	-12.50%
Employment	Change (number)	-32187.27
	percent change	-7.09%
Household Income	Change (million)	-482.29
	percent change	-2.16%
Out Migration	Change (number)	16058.44
	percent change	5.19%

Table 1.6 describes the residential housing stock damages and the corresponding net out-migration rate in each of the eight PUMA regions. Results indicate that the larger the residential capital stock/building damages, the higher the rate of net out-migration. For instance, PUMA region A experiences the largest extent of residential building functionality losses, and the net out-migration rate is the largest, while for PUMA region F, where the residential buildings are damaged to the smallest extent, the net out-migration rate is the smallest. However, because housing damage is not the only determinants for migration (other factors are the unemployment rate and real disposable income per household as expressed in equation (24)), the rank of the extent for capital stock reduction is not exactly the rank of the net out-migration rate among the eight PUMA regions.

Table 1.6 Distributional Impacts on Out-Migration Rates

PUMA regions	Capital stock reduction (residential)	Net migration
A	46.14%	-6.14%
B	42.10%	-5.08%
C	44.20%	-5.41%
D	42.18%	-4.73%
E	36.04%	-3.44%
F	32.62%	-2.76%
G	35.83%	-3.81%
H	41.60%	-5.21%

Table 1.7 continues with the distributional impacts on total output and household income by PUMA regions. First, we can observe that larger capital stock damages come with a larger fall in total output produced, and larger capital stock damages imply larger household income fall.

Table 1.7 Distributional Impacts on Output, Income, and Employment

PUMA regions	Capital stock reduction (commercial) (1)	Domestic Supply loss (2)	Household Income Loss (3)	Employment loss (4)
A	41.84%	-12.88%	-9.20%	-7.24%
B	33.42%	-12.66%	-4.37%	-7.66%
C	33.39%	-12.75%	-4.95%	-7.78%
D	31.41%	-11.79%	-3.00%	-7.45%
E	17.48%	-8.60%	0.30%	-7.40%
F	16.22%	-7.48%	3.57%	-6.30%
G	19.35%	-8.69%	-1.34%	-7.20%
H	31.30%	-11.27%	-5.70%	-7.15%
Correlation coefficient	—	0.96	0.94	0.49

An interesting result in table 1.7 column (3) is that while households in region A and H experience the largest income fall, households in region F experience an income rise after the simulation. For households, their income comes from both labor and capital income, and the Table A.6 in the Appendix decomposes household income loss by capital and labor income to further understand the income loss in different regions. Table A.6 suggests that the regional difference in household income losses mainly comes from the difference in capital incomes.

For capital income, Figure 1.6 presents the distributions for low-income and high-income households by each region before the earthquake. It indicates that region F is a rich community with more high-income households whose income relies heavily on the return on capital. When capital is damaged, the rate of return for the remaining available capital skyrockets. This leads to a rise in nominal capital income, and households in region F benefit the most from this rise as they owned more capital stock than households in other regions. For labor income, since PUMA region F is the region with the smallest extent of damages in both commercial and residential capital, the total net-outmigration (about 2 percent) is the smallest, as suggested by Table 1.6. Meanwhile, the wage rate rises after the earthquake because of the reduction in labor supply. With the average wage rise being around 8 percent, the combination of a smaller loss in employment and a larger rise in wages produced a small labor income rise instead of fall in region F.

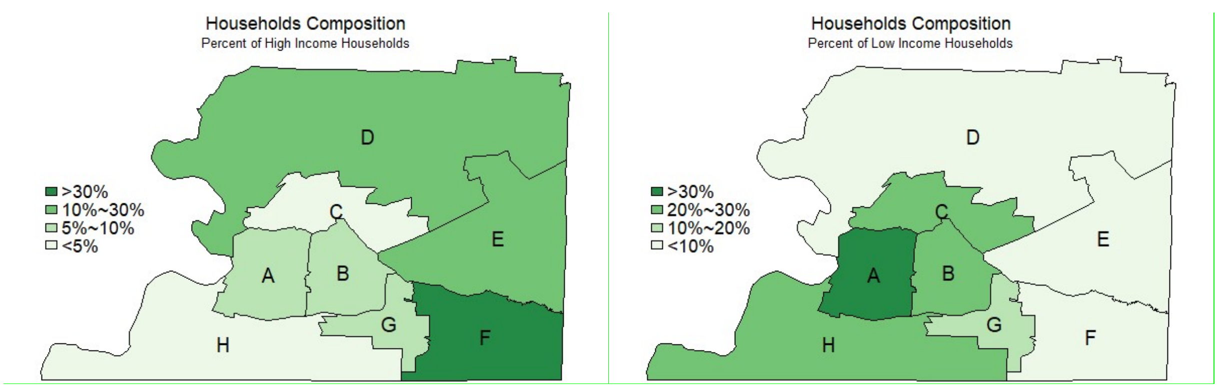

Figure 1.6 High-Income and Low-Income Households Distribution by PUMA regions

Column (4) of Table 1.7 provides the employment loss by region, unlike the output and income losses, where the correlation coefficient of them with respect to the damages in capital stock is over 0.9, the correlation coefficient of loss in employment with respect to damages in capital stock is only 0.5. This can be explained by the substitution effect between labor and capital.

Equations (1.32) to (1.34) solve for the optimal level of labor demand using the cost minimization problem expressed in equation (1.9) to (1.12) in subsection 1.3.3.

$$L_j^s = \left(\frac{\overline{Y_j^s}}{\eta_j^s}\right)\left(\alpha_k^{\frac{1}{1-\rho}} r_j^{s\frac{\rho}{\rho-1}} + \alpha_L^{\frac{1}{1-\rho}} w_j^{s\frac{\rho}{\rho-1}}\right)^{-\frac{1}{\rho}} \left(\frac{w_j^s}{\alpha_L}\right)^{\frac{1}{\rho-1}} \tag{1.32}$$

$$where\ \overline{Y_j^s} = \eta_j^s\{\alpha_L(\overline{L_j^s})^{\rho} + \alpha_K(\overline{K_j^s})^{\rho}\}^{1/\rho} \tag{1.33}$$

$$and\ \alpha_L + \alpha_K = 1, \rho = 0.67 \tag{1.34}$$

When capital ($\overline{K_j^s}$) is damaged, firm's level of output ($\overline{Y_j^s}$) is reduced and this is the output loss we see in column (2) of Table 1.7. The loss in output leads to a reduction in labor demand. Meanwhile, when capital is damaged, the price of the rest available capital stock (r_j^s) goes up to reflect this scarcity. The firm will be substituting capital into labor since capital is more expensive, and this leads to an increase in labor demand. This substitution effect can make the final employment loss, in general, to be smaller compared to total output loss, and the larger the capital stock damage is, the larger the substitution effect will be to offset the negative employment loss.

Although some regions have a smaller loss in employment when the damage to capital is smaller, this is not always the case from Table 1.7. The outliers are region A, E, and G, and to be more specific, region A and H experience much larger damages in capital stock compared with region E (41 and 31 percent compared to 17 percent), but their loss in employment is smaller. When looking at equation (1.32), other factors determine the final demand for labor include total factor productivity (η_j^s), the share of labor (α_L), and the endowment on labor ($\overline{L_j^s}$). Doing partial derivatives to equation (1.32) leads to the following conclusion,

$$\frac{\partial L_j^s}{\partial \eta_j^s} < 0; \quad \frac{\partial L_j^s}{\partial \alpha_L} < 0; \quad \frac{\partial L_j^s}{\partial \overline{L_j^s}} > 0 \tag{1.35}$$

Table A.7 in the appendix lists the values on η_j^s, α_L and α_K for these three regions. Larger values of η_j^s and α_L for region E indicates a larger loss in employment for region E when compared with region A and H, all else equal. Moreover, for region H, Table 1.3 suggests that 27 percent of its workers come from people who live outside Shelby County. But for the rest regions, this number is less than 20 percent. This implies that the endowment on labor ($\overline{L_j^s}$) is less impacted for firms in region H after the earthquake, which also explains the small loss in employment for region H compared to region E.

When looking at the losses in employment, initial capital stock reduction can only partially explain the outcome. Other features that are different across different regions will also impact how firms can maintain their level of labor demand after the earthquake shock. And we do observe that firms in some regions are very resilient to capital damages regarding their behavior on labor demand. This special phenomenon will also carry over in our new model and determine some of the gains and losses for different regions in the new model, as you will see in the next section.

1.5.2 Results with the new model

To better capture the behavior changes after an earthquake, I model two behavior changes in our new model,

1) the firm's substitution behavior among the same type of intermediate inputs produced in the eight PUMA regions as illustrated by the second layer in Figure 1.4;

2) households' decision of where to work and consume based on endogenous changes in labor demand conditions after the earthquake.

The same simulation used in subsection 1.5.2 is conducted again under the new model and Table 1.8 puts both the results for the original and the new model together to compare the difference in terms of the impact on the economy.

Table 1.8 Simulation Results for the Original and the New Model

Economic Variables		Original Model (1)	New Model (2)
Domestic Supply	Change(million)	-8160.67	-8010.64
	percent change	-12.50%	-12.27%
Employment	Change (number)	-32187.27	-30815.95
	percent change	-7.09%	-6.79%
Household Income	Change (million)	-482.29	-574.29
	percent change	-2.16%	-2.57%
Unemployment Rate	Change	2.18%	1.95%
Net Migration	Change (number)	-16058.44	-16059.35
	percent change	-4.64%	-4.64%

Generally speaking, if firms and households could adjust their behavior accordingly after the earthquake, then these behavior adjustments, or the idea of inherent resiliencies defined in Rose (2004), could reduce their losses to some extent. This is one of my expectations for the performance of the new model. Secondly, regarding where the firms and households would change their decision to buy intermediate inputs or search for jobs, it should be the places that can maintain their product with a lower price increase and a smaller fall in labor demand respectively. For firms to maintain a lower price increase after the earthquakes, they should experience less capital stock losses so that the rental rate of capital wouldn't skyrocket as well as the cost of production. However, concerning a smaller fall in labor demand, as discussed in Table 1.7 above, it will not necessarily be the places with less capital stock losses to be able to maintain less job loss after the earthquake. An example would be region H, where it experienced relatively large damages of capital but small employment loss. Hence, regions with fewer damages or regions that are more resilient to damages would benefit more when I model the two behavior changes for firms and households, and this is my second expectation.

Now looking at column (2) versus column (1) of Table 1.8, as I expected, the inclusion of the behavior adjustment for firms to substitute their input demand on the same type of product from more damaged regions to less damaged regions helps reduce the total loss in firms' output and employment. The out-migration maintains the same amount because the residential housing damages to both models are the same. The rise in the unemployment rate for households is also smaller in the new model compared to the original model. But unlike what I would expect, the new model causes a larger fall in household income (from 482 million of dollars to 574 million dollars).

To understand the additional income loss in column (2) of Table 1.8, recall the fact that both the wages and the rental rate of a capital go up to reflect the scarcity of resources for labor and capital inputs. These increases can offset the loss in household income. But in the new model, when firms can re-adjust their purchase of intermediate inputs, the cost of production is reduced as well as the cost of living. As a result, this leads to a smaller reduction in the labor supply. Combined with the second behavior change in the new model, which is the re-adjustment of workers going to regions where they can maintain their loss in labor demand as much as they can, make the labor input more easily to obtain for firms. And this has two impacts: when firms find it easier to hire workers, the wage rate will not go up as much compared to the original model; meanwhile, it allows firms to offset more of the negative impact from losses in capital, and the rental rate of capital will rise by a smaller amount since firms can now substitute into labor with a lower cost.[11] Therefore, when the wage and rental rate of capital do not rise as much compared to the outcome in the original model, the new model brings a larger fall in household income.

My second expectation of the new model is that for a spatial earthquake where regions are damaged unevenly, regions with fewer damages or regions that are more resilient to damages

[11] For the original model, the weighted rise in rental rate of capital and wage rate are 3.74% and 13%, but the rise in rental rate of capital and wage rate in the new model are 3.69% and 12%, smaller than the rise compared to the original model

would benefit more. Table 1.9 below provides the regional output loss for the original and the new model. Regions that have smaller damages are regions E, F, and G. And two of them, regions F and G, benefit from the new model by having a smaller loss in output. This is consistent with my second expectation. But region E doesn't gain in the new model. Recall from section 1.5.2 that region E experiences a relatively larger fall in employment compared to region G even though the capital stock damages in region E is only 17 percent, while the capital stock damage in region G is 31 percent. Therefore, the regions that are more resilient to damages, which is region G, benefits from the new model by having a smaller loss in output while region E doesn't.

Table 1.9 Output Losses by Region for the Original and the New Model

Economic Variables	PUMA regions		Original Model (1)	New Model (2)
Domestic Supply	A	Change (million)	-2484.32	-2512.71
		percent change	-12.88%	-13.03%
	B	Change (million)	-700.46	-733.12
		percent change	-12.66%	-13.25%
	C	Change (million)	-449.29	-474.94
		percent change	-12.75%	-13.47%
	D	Change (million)	-325.95	-338.13
		percent change	-11.79%	-12.23%
	E	Change (million)	-290.22	-301.68
		percent change	-8.60%	-8.94%
	F	Change (million)	-376.50	-259.72
		percent change	-7.48%	-5.16%
	G	Change (million)	-803.64	-767.49
		percent change	-8.69%	-8.30%
	H	Change (million)	-1490.28	-1382.79
		percent change	-11.27%	-10.46%

1.5.3 Results for transportation network damages

Now with the new model developed in this chapter, I further consider the impact of transportation interruption on labor supply, consumption, and intermediated input purchases, beyond the impact of building functionality loss. I run two additional simulations in this subsection which is the simulation that only considers the transportation network damages followed by the process discussed in subsection 1.4.4 (column (2) in Table 1.10), and the simulation that combines both the building, utilities and transportation network damages (column (3) in Table 1.10). Column (1) in Table 1.10 is the previous results of the simulation that only considers the capital stock reduction, which is listed here for comparison.

Table 1.10 Simulation Results under Different Types of Damages

Economic Variables		New Model (Building) (1)	New Model (Transportation) (2)	New Model (Building and Transportation) (3)
Domestic Supply	Change (million)	-8010.64	-77.59	-8068.93
	percent change	-12.27%	-0.12%	-12.36%
Employment	Change (number)	-30815.95	-673.95	-31349.42
	percent change	-6.79%	-0.15%	-6.91%
Household Income	Change (million)	-574.29	-2.53	-575.30
	percent change	-2.57%	-0.01%	-2.57%
Out Migration	Change (number)	-16059.35	-35.41	-16087.35
	percent change	-4.64%	-0.01%	-4.65%

Results in column (2) of Table 1.10 suggest that the increase in travel time due to road network damages causes a loss in the total output of about $77 million and a drop of employment at about 674 workers. Real household income falls by $2.53 million, and about 35 households migrate out of the county. Comparing column (2) with the economic losses in column (1), the negative impact of transportation is much smaller. It is first because that the percentage loss in travel efficiency is smaller than the building stock. The average percentage loss in travel efficiency is about 9 percent, while the loss in the capital is more than 35 percent. Second, the impacts of travel efficiency are indirect. As indicated above in section 1.4.4, the loss in travel efficiency is mapped to an increase in the perceived price for intermediate inputs and final products, but it is deflated by the contribution of transportation costs in determining the prices of these products.

When looking at the results that sum column (1) and column (2) in Table 1.10, the estimated loss is larger than the results in column (3). For instance, individual simulation from building functionality and travel efficiency loss produce a loss in output of $8011 million and $78 million, respectively. Summing the two numbers gives a total loss of about $8089 million, which is different from the simulation that jointly combined the two types of losses, which is 8069 million. This implies that the joint impact from building functionality loss and transportation network damages doesn't simply equal to the sum of running the two simulations individually. Adding the two individual simulation results would lead to a small overestimation of the negative impact.

An explanation for the above situation is that, recall from Figure 1.4, at the upper level of the production tier, the technology is a Leontief Type, which suggests that the production capacity is determined not by total resources available, but by the scarcest resource (limiting factor inputs). When the road network is damaged, trade flow across regions is limited, and as a result, firms will also reduce their demand for capital and labor due to their Leontief Type production technology. When adding additional reductions to the capital stock due to building and utility destructions, the efficient level of reduction in capital stock that is going to negatively impact the economy is smaller, as firms' demand on capital has already been reduced due to the road-network damages. As mentioned in the literature review, previous studies often focused on one type of physical damages and few papers would consider these impacts jointly. The results here inform us that it is worthwhile to consider all channels of the negative impacts that an earthquake can bring at the same time, to avoid the overestimation when considering these impacts individually.

1.6 Conclusion

In this chapter, a SCGE model is developed based on the model in Cutler *et al.* (2016), and I extend the spatial feature of the model by considering two behavioral changes, with the first one being the firms' substitution among the same type of intermediate input produced in different regions and the second one being households' decision of where to work and consume based on endogenous changes in labor demand conditions after the earthquake. The intuition of these extensions is the application on the idea of inherent resilience brought up by Rose (2004). This inherent resilience is defined as the inherent responses to hazards that allow communities to avoid potential losses.

Then I describe in detail both in theory and in practice how the physical damages from an earthquake can be used to simulate the economic losses in the SCGE model. I find that when different regions within the economy are damaged differently by the earthquake, some type of losses are highly correlated with the level of capital stock damages to each region, such as regional output and regional net-outmigration, while other types of losses are less correlated with the level of capital stock damages to each region, such as employment because of the substitution between labor and capital as well as different resilient abilities based on firms' production techniques.

When applying our new model with the two behavior changes, I find that the losses to firms and households are reduced concerning the total output and unemployment rate. I also find that regions with fewer damages or regions that are more resilient to damages would benefit more from modeling these two behavioral changes. Both findings are consistent with the fact that communities have the potential to reduce the losses after the natural hazards, or the idea of inherent resilience.

Finally, when I simulate jointly the impact from the combinations of building, utility, and transportation network damages, I find that the total losses are smaller than the sum of the simulations by the damage types individually. This implies that the economy is working together to cope with different damages and all components in the economy are impacting each other to produce the best results for the whole economy when facing external shocks. Meanwhile, for future studies that are going to examine the path of the recovery after the natural disasters, the difference in the timelines of the transportation network versus building functionality restorations can interact with each other and influence the recovery path of the economy. For example, quicker restoration of the transportation network can speed up the repairs of buildings or utilities, and vice versa. Therefore, studies should consider the interdependence of difference types of physical damages when examining the recovery of local communities from natural disasters.

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Chapter 2: Impact of Migration on Local Labor Markets: Evidence from Hurricane Katrina

2.1 Introduction

On Aug 29th, 2005, Hurricane Katrina made landfall on the Gulf Coast, causing tremendous damages to the city of New Orleans and its surrounding areas. The Levees collapsed, flooding millions of homes and induced displacing between 700,000 to 1 million people (Vigdor (2007); Groen and Polivka (2008a); Zissimopoulos and Karoly (2010)). One year after the Hurricane, only about 50 percent of the evacuees had returned to their pre-disaster county of residence. By late 2007, the population of the city of New Orleans was still about 70% of its pre-Katrina level (Sastry (2009)).

The slow return of the New Orleans' population indicated that the temporary evacuation may have turned to permeant migration. If they stayed and looked for jobs in their new locations, it would create a labor supply shock to the labor markets that pushes down the wage rate. Studies suggested that evacuees who were less likely to return, they tended to be young and less educated (McIntosh (2008); De Silva *et al.* (2010); Groen and Polivka (2010)), so we would expect and the magnitude of the shock to be disproportionally larger for the low-skilled workers than for the high-skilled workers. Except for the supply shocks, the sudden rise in the population could also drive up demand for local-base goods and services. As a result, local-base industries would increase their demand for labor inputs. The rise of the demand in labor markets would push up the wage rates that offset the impacts of the labor supply increase. Those demand-side effects wouldn't appear in the export-base industries.

To test the above hypotheses, I first use the difference in difference approach where I compare the hourly wage rates in areas that received these evacuees with areas that did not receive evacuees in four different categories of industries. These categories consist of (i) export-base industries which use low-skilled labor, (ii) export-base industries which use high-skilled labor, (iii) local-base industries which use low-skilled labor, and (iv) local-base industries which use high-skilled labor. I find that in export-base industries, a one percent increase in the inflow of the evacuees led to a 0.07 and 0.15 dollar fall in hourly wage rates for industries which use low-skilled labor and industries which use high-skilled labor, respectively, but the impact is not statistically significant for industries which use low-skilled labor. For the local-base industries, a one percentage increase in the inflow of evacuees leads to a 0.16 dollar rise in the hourly wage rates for the high-skilled workers, and no significant impact on the low-skilled workers.

An important empirical concern with documenting the above relationship is that, areas where the evacuees decided to settle in greater numbers, could have been on a different trajectory in terms of their wage rates prior to Hurricane Katrina. To handle this, I include the interaction between a series of potentially important characteristics related both to the labor supply decision and the migration decision as controls in my baseline specification. These characteristics contain regional education attainment, employer size, and English proficiency. I also use the non-employer sales data as a proxy for the demand rise in local-base industries to uncover the supply side impact, if any. When controlling for this demand side impact, I find no empirical evidence that the increase in the supply of labor reduced the wage rates in the local-base industries. One explanation for this is the level of substitutability among the migrants and the local people is not large, at the disaggregated level of the industries and occupations in the local-base industries.

Next, I use a fully flexible specification that includes years prior to the event to show that there are no discernible pre-Hurricane trends in wage rates between areas that got evacuees or not. In addition to the fully flexible specification for examining pre-Hurricane trends, I also use it to analyze how the effect of evacuees' presence on wage rates changes over time. I find that the impact on wages is diminishing over time.

The rest of the chapter is organized as follows. Section 2.2 presents a survey of the literature. Section 2.3 provides the background information for Hurricane Katrina accompanied by the theoretical analyses for such an external shock. Section 2.4 describes the data and empirical strategy. Section 2.5 discusses the results and Section 2.6 concludes.

2.2 Related Literature

There is an extensive literature on the effects of migration on regional labor market outcomes. Among these studies, some of the changes in labor supply are endogenous (meaning that people self-select themselves to areas with job opportunities) while others are quasi-experimental (meaning that their migration behavior is independent of other factors that can determine the labor market outcomes). Quasi-experimental data is preferred because it eliminates potential endogeneity problems.

Exogenous events such as natural disasters, wars, or political events can result in large geographic shifts in population. These events can serve as natural experiment to researchers who are interested in the effects of migration on regional labor market outcomes. Card (1990) looked at the immigration impact of Latin Americans in Mariel Boatlift (an event that sent about 125,000 Cuban immigrants to Miami) on the Miami economy. He found little evidence of an effect on local low-skill workers' wages. Kugler and Yuksel (2008) investigated the impact of less-skilled Latin

American migration on wages and employment of natives and earlier immigrants in the U.S. following Hurricane Mitch. They found the substitution effect from the recent immigrants toward earlier Latin American immigrants. They also found that the arrivals of the immigrants induced an out-migration of earlier Asian, European, and Australian immigrants. When controlling for this outmigration, previously identified significant wage increase of skilled natives disappeared. McIntosh (2008) looked at the impact of Katrina evacuees on the Houston labor market and found a negative but small (less than 2 percent) wage impact on native Houstonians.

Outside the U.S., Hunt (1992) explored how the repatriated people from Algeria in 1962 influenced the French labor market. Friedberg (2001) explored the migration flow to the country of Israel due to the lifting of immigration restrictions in the Soviet Union to examine how this 12 percent increase in Israel's population between 1990 and 1994 impacted the labor market outcomes. The author also argued that the migration behavior was exogenous, considering the unstable political and economic climate in the Soviet Union. Glitz (2012) analyzed the effect of the inflows to Germany with the fall of the Berlin Wall on natives' employment and wages. The fact that these immigrants were exogenously allocated to different regions upon arrival helped to eliminate the potential endogeneity problem. The forced immigration from Northern Syria because of the civil conflict allowed Ceritoglu *et al.* (2017) to investigate its impact on Turkish labor markets. Although some of the studies here reported a negative impact on employment opportunities from migration to their competing workers, all the four studies found a negligible impact on wages from immigration.

De Silva *et al.* (2010) argued that the modest or slight impact on wages is due to the ignorance of the simultaneous demand-side impact. The rising amount of in-migration also pushes up the demand for local goods and services such as retail goods, and as a result of this demand rise, wages can go up. When controlling for this, De Silva *et al.* (2010) found that the wage falls for low-skilled workers in Houston due to Katrina-induced migration can be as low as 3 percent. On the other hand, understanding the impacts of migration flows on recipient communities is important in the following sense: If the outmigration behavior from the evacuees has significant spillover impacts on those communities, then (for studies that explored or seeking to explore the direct loss of natural hazards), it is necessary to distinguish the areas that were directly hit by natural hazards, areas that were indirectly impacted due to the hazards-induced migration, and areas that were not impacted by the natural hazards.

For example, Belasen and Polachek (2008) analyzed how hurricanes in Florida impact counties' employment and wages. They pointed out the importance of control groups being identified correctly. Hence, they divided counties into three cohorts: directly impacted, neighbors of the directly impacted and unimpacted. They further argued that hurricanes caused people to flee to neighboring areas which pushed the wages down in these areas. Their results support this by a negative and significant four percent drop in the growth of wages for neighbor areas on average. Another study by Coffman and Noy (2011) made sure that counties in their control group did not receive Hurricane Iniki evacuees from the disaster area to ensure that there was no contamination when constructing a synthetic control group for analyzing the impact of Hurricane Iniki on Kauai's economy.

However, some studies acknowledged the possibility of spillovers with less careful identification of the spilled areas and other studies did not even consider the possibility. Xiao (2011) mentioned that areas within 60 miles of the flooded area in the Midwest flood of 1993 should not be included as candidates for the control group, but they did not examine the robustness of their choice for the 60 miles. After Hurricane Katrina, a large number of studies (Vigdor (2007), Groen and Polivka (2008b), and Zissimopoulos and Karoly (2010) explored the labor market behavior of evacuees and compared it with unaffected areas in the same state or other states using the Current Population Survey. These studies ignored the fact that Katrina resulted in somewhere from 700,000 to over 1 million evacuees (Coker *et al.* (2006), Groen and Polivka (2008b), Holzer (2006)). This could contaminate their control group if the influx of the evacuees had significant influences on the regional labor markets.

The current literature on the impact of Hurricane Katrina on neighboring labor markets only looked at the city of Houston, TX. Nevertheless, according to the author's calculation, except for Houston, many other counties also received the Katrina evacuees. Relatively speaking, regarding the ratio of the evacuees to the population size, Houston was outside the list of the top 10 largest receiving areas.[12] What happened in these areas remains unknown to the public. Hence, this chapter extends current literature by looking into all possible areas where the Katrina evacuees migrated to, in order to see if the negative wage impact observed Houston can be generalized to these areas.

As noted by De Silva *et al.* (2010), most studies have ignored the simultaneous rightward shift of the demand in labor due to migration. As a result, the effect of migration on labor supply can be underestimated if such a demand effect is present. However, the demand increase would not be present in the export-oriented industries. Using this fact, this chapter contributes to the migration-related literature by identifying the impact of migration separately on local-base industries and export-base industries. This chapter also accounts for the supply shock on the local-

[12] I chose eight heavily damaged counties/parishes as Katrina region in Louisiana and Mississippi according to Xiao and Nilawar (2013). Using the county to county annual migration flows, for each county, I aggregate the number of people migrated from the Katrina region to obtain the number of evacuees it received. The top 10 counties/parishes that received the largest evacuees in terms of their population base are: St. John the Baptist Parish, LA (6.42%), Pearl River County, MS (6.09%), St. Charles Parish, LA (5.71%), Stone County, MS (3.99%), Tangipahoa Parish, LA (3.98%), East Baton Rouge Parish, LA (3.24%), Ascension Parish, LA (2.72%), St. Helena Parish, LA (2.71%), Washington Parish, LA (2.66%), St. James Parish, LA (2.34%).

base industries by controlling the demand-side effects using the non-employer sales data. Before going into the details on the empirical strategies used in this chapter, I will first describe the background and the theoretical analysis of the changes in wage rates due to Katrina-induced migration.

2.3 The Background of Hurricane Katrina and Theoretical Analysis

Katrina made landfall on August 29th, 2005 near Buras, Louisiana, and led to catastrophic damage in Alabama, Louisiana, and Mississippi. There were roughly 138 counties and parishes impacted by the storm with an area of 93,000 miles (Garber (2006)). The estimated damage reached around $96 billion and the number of casualties reached more than 1000 (Gabe *et al.* (2005), Garber (2006) and Dolfman *et al.* (2007)). The huge waves brought by the wind damaged the levees and the floodwalls in New Orleans, subsequently flooding hundreds of thousands of homes in the Gulf Coasts area with huge displacement. It was estimated that 80% of the city of New Orleans was flooded and the entire population in the city was forced to evacuate (McCarthy *et al.* (2006)).

With estimates ranging from 0.7 million to over 1 million on the volume of the displaced people, the story of recovery was not encouraging. Nearly 50 percent of the evacuees came from New Orleans, a place with a high level of poverty and a negative growth rate of employment. Displaced residents were first allowed to return to the city of New Orleans at the end of September 2005 (Fussell et. Al. (2010)). By October 2005 (approximately two months after the storm), 53 percent of evacuees had returned to their pre-Katrina counties (Groen and Polivka (2010)). About 13 months after the storm, slightly more than 50 percent returned to New Orleans. This number is similar across other data sources. (e.g., the Current Population Survey (CPS), American

Community Survey (ACS), Displaced New Orleans Residents Pilot Survey (DNRPS), and Survey of Low-income parents who attend two Community Colleges in New Orleans (Paxson and Rouse (2008)). Studies have suggested that among the people who did not return in a year, they may never return over the longer terms. For example, two years after Katrina, the population of the city of New Orleans was about 70% of its pre-Katrina level (Sastry (2009)). Hence, we have a reason to believe that those people who didn't return may have decided to relocate in the area they were evacuated to, and as a result, cause an increase in the supply of labor in those areas.

Basic economic labor market theory predicts that migration will shift the labor supply curve to the right and result in decrease in the equilibrium wage rate. This comes from the neo-classical economic theory of diminishing marginal productivity of labor and the inelasticity of labor supply.

While pursuing empirical evidence about the impact of immigration on labor markets, most studies recognized that the labor markets are heterogenous with respect to skill sets. The leading economic scholar of immigration—George Borjas, suggested in Borjas (2003) that the skills of workers in terms of both education and work experience can help to identify the group of native workers that the immigrants would be competing with. In other words, downward pressure on wages will be greatest for the markets in which the individuals' skills are most like those of immigrants.

For Katrina, studies found that people who are less likely to return, they tend to be younger and less educated. Groen and Polivka (2010) suggested that nearly 22 percent of the adult evacuees who did not return didn't have a high school diploma, and about 53 percent of the adult evacuees who did not return were less than 40 years old. Therefore, we would expect a larger supply shock for the market of less-skilled workers.

However, the magnitude of the downward pressure on wages also depends on the elasticity of the labor demand curve. An elastic labor demand curve would generate a smaller fall in wages than inelastic labor demand, given the same change in labor supply. Empirical studies did find that the labor demand for low-skilled workers is more elastic than for high-skilled workers. For instance, Hamermesh (1984) reviewed about 15 papers that looked at the U.S. manufacturing sectors' demand on labor and found that in most studies, demand elasticity is larger for low-skilled workers than high-skilled workers in absolute term. Freier and Steiner (2010) found that the labor demand elasticity for unskilled labor tended to be higher than the skilled labor in absolute terms, using information from 25 industries between 1999 and 2003 in West Germany. Using data for nine Western European countries between 1990 and 2004 on over 20 industries, Crinò (2012) estimated the absolute value of the own-wage elasticity of labor demand for the low-skilled workers ranged from 0.67 to 1, while this number only ranged from 0.02 to 0.1 for high-skilled workers. A meta-analysis done by Lichter *et al.* (2015) looked at over 100 studies in labor demand also concluded that low-skill worker is associated with a more sensitive demand curve. Hamermesh (1984) explained this phenomenon as the skill ties, implying that the greater amount of human capital embodied by the high-skilled workers made the labor demand less sensitive to exogenous changes in wage rates.

For the elasticity of labor supply, the empirical evidence is mixed. At the extensive margin, the labor force participation elasticity with respect to wages tended to be larger for the low-income earners, such as the secondary income earners, single female household head, and the young adults. However, at the intensive margins, hours of working with respect to wages tended to be larger for the medium or high-income earners (Saez (2002)). Hence, for the analysis here, we do not assume any difference in the labor supply elasticity between the high and the low-skilled workers.

Migration not only brought a large pool of potential workers, but also a substantial demand for retail services, transportation, and housing. For the evacuees who didn't return, their employment to population ratio was more than half of the group of people who returned (Groen and Polivka (2008a)). People were postponing their decision to enter the labor markets as many financial aids were dispersed to them. Direct disaster relief amounted to about $100 billion (Hoople (2013)). Disaster Unemployment Assistance provided unemployment benefits for a period of up to 26 weeks to evacuees who were not covered by other unemployment insurance. It is estimated that charitable donations related to Hurricane Katrina were up to $4.25 billion (Deryugina *et al.* (2018)). All the disaster-related financial aid helped to maintain the evacuees' purchasing power and as a result, increased the demand for locally produced goods and services. These indicate that compared to the size of the labor supply increase, the demand hikes on local goods and services from these evacuees are even larger.

Industries whose products are more export-oriented, on the other hand, would not be affected by local or regional demand shocks. These asymmetric impacts on demand require a closer look at the industry attributes. To be more specific, for local-base industries, the rise in the demand can increase firms' demand for labor, which can offset the impact on wage rates from the labor supply shock; while for export-oriented industries, only the supply of labor is impacted due to these expected migrations. Thus, the impact of migration on a local-base industry is ambiguous while the impact on export-oriented industries is more straightforward (wages will stay the same or fall).

In summary, the expectation with respect to the impact on labor markets due to Katrina-induced migration can be illustrated in Figure 2.1 below. Panel (a) and (b) in Figure 2.1 illustrate the impact on export-base industries by workers' skill sets. Given that most of the Katrina evacuees were young and less-educated, a larger supply shock would happen in the low-skilled labor markets. However, as illustrated in panel (a) and (b), the labor demand curve is flatter for the low-skilled workers, in other words, the labor demand on the low-skilled workers is more elastic and the margins for wage change is smaller. As a result, the fall on wage rates could be smaller in the low-skilled export-base industry, even though the shift of the supply curve is larger.

Panel (c) and (d) in Figure 2.1 illustrate the impact on local-base industries by workers' skill sets. Different from the export-base industries, there is an additional demand shift in local-base industries. The implication of both a demand and supply outward shift is that the impact on wages is uncertain. However, it is more likely to expect a rise in the wage rate for the high skilled workers since the labor supply shocks or the number of high-skilled evacuees is smaller. Table 2.1 below summarizes the expected impacts on wage rates in the four categorizations.

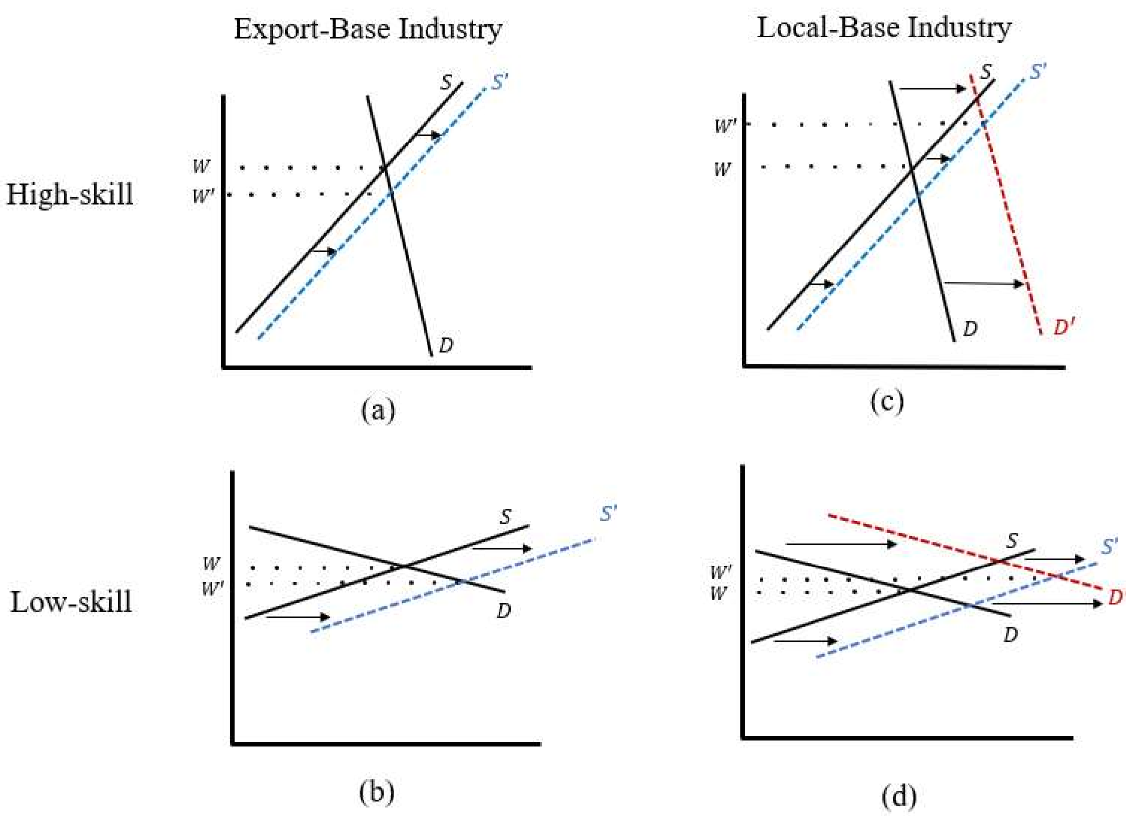


Figure 2.1 Expected Impact from Katrina Evacuees at Different Labor Markets

Table 2.1 Expected Impacts on Wage Rates

Wage rates	Export-base Industry	Local-base Industry
High-Skilled	Decrease	Uncertain (more likely to rise)
Low-Skilled	Decrease	Uncertain

In the next section, I will describe the data and the methodology used in this chapter to exploit the quantitative impact of the exogenous migration on regional labor markets.

2.4 Data and Estimation Strategy

2.4.1 Data

In this study, I combine the Decennial Census data in 2000 and the American Community Survey (ACS) data from 2005 to 2008 to examine the effect of in-migration to the local economies due to Hurricane Katrina. Census was collected every 10 years between 1790 and 2000. In 2005, the Census began gathering data every year through the American Community Survey. Essentially the Decennial Census data and the ACS data are the same sources. Since the American Community Survey was asking questions related to people's situation in the past 12 months, and Hurricane Katrina made landfall in August 2005, I choose the year 2006 to be the treatment year. Therefore, the Census data had information before (2000 and 2005) and after (2007 and 2008) the exogenous shock.

To be consistent with the geographic areas used in the Census microdata, the unit of analysis in this chapter is called PUMA—the public used microdata area. PUMA is used by the US Census for statistical and demographic information. Each PUMA contains at least 100,000 people, and there is a total of 2071 PUMAs in the 2000 Census. PUMA regions are better than counties in representing a sizable labor market due to its population lower bound being larger than

100,000, while the population level for counties in the U.S. ranges can be as low as a couple hundred.

The next question is to identify the evacuees from the survey data. In the Census survey, people were asked for their location of residence 1 year ago. Xiao and Nilawar (2013) offered a list of eight heavily damaged counties/parishes in Louisiana and Mississippi, with an average of 46.9 percent of the occupied housing under major or severe damages[13]. I then map these eight counties/parishes to the PUMA regions used in the Census data based on the population-weighted crosswalk from the Missouri Census Data Center[14]. A total of six PUMAs were identified as the "Katrina Region". The crosswalk of the eight counties/parishes to the six areas is listed in Appendix Table B.1 with the population weight.

For each PUMA, I aggregate the number of migrants from the Katrina Region to get the total number of migrants received. Among a little over 2000 PUMA regions, there are about 550 PUMAs that have people migrated from the Katrina Region. To measure the intensity of this unexpected migration flows, I construct the following variable below:

$$Evacuee_i^{2005} = \frac{No.of\ evacuees\ from\ Katrina\ Region\ to\ PUMA\ i\ in\ 2005}{Total\ population\ in\ PUMA\ i\ in\ 2005} - average\ trend_i \quad (2.1)$$

$$average\ trend_i = average_{year\ 1995\ to\ 2000}\left(\frac{No.of\ migrants\ from\ Katrina\ Region\ to\ PUMA\ i}{Total\ population\ in\ PUMA\ i}\right) \quad (2.2)$$

During normal years, there would be migrants from the Katrina Region to other places, and this normal trend will be excluded to construct the excessive flow due to Hurricane Katrina. The five-year average from the year 1995 to 2000 ($average\ trend_i$) represents the normal migration

[13] Their calculation came from reports in United States Department of Housing and Urban Development (2006).
[14] The crosswalk can be found at the following link: http://mcdc.missouri.edu/applications/geocorr2014.html

flow had Katrina not happened in 2005. Figure A.1 in Appendix plot a heat map of where the evacuees went based on the intensity variable $Evacuee_i^{2005}$ defined in equation (2.1).

The survey data also provides each worker's NAICS (North American Industry Classification System) code industry of work and his/her occupation, together with total wage income and total working hours. I then group people into the export-base industries and local-base industries based on the work of Delgado *et al.* (2016). They used the idea of geographic specialization and concentration of production activities in the U.S. to identify the export-base industries. To be more specific, export-base industries prefer to congregate with each other because of return to scale, access to transportation nodes and proximity to natural resources, as a result, their employment distribution should be more geographically concentrated than the local-base industries. For example, one of the criteria used to identify the export-base industries is that more than 50 percent of the regional-level employment is less than 10 employees, this implies that in most areas, the employment level in associated industries is almost zero, and most of the jobs are concentrated in a few areas. I then take their 6-digit NAICS industries that are export-base and match them with the NAICS code in the Census survey microdata, and the remaining industries will be the local-base industries. Table B.2 and Table B.3 in Appendix B provide the list of local-base and export-base industries in my dataset.

Using the information on the total wage income and total working hours, I calculate each worker's hourly wage rate in each PUMA. Observations whose wage rate is below the minimum wage in the year 2000 or above the maximum confidentiality level are excluded. The background analysis for Hurricane Katrina suggests that the magnitude of the labor supply shock is larger for the low-skilled workers. To test this hypothesis, I classify people into low-skilled and high-skilled workers based on their occupations. I follow the work in De Silva *et al.* (2010) to use wage rates as a standard to distinguish skills or productivity. Occupations in which the majority of the workers' wage rate is below the average wage is defined as low-skilled occupations, and the remaining occupations will be high-skilled. Table 2.2 below presents the distribution of Katrina evacuees in these four different categorizations. It is consistent with previous studies that most of the evacuees were low-skilled workers, besides, they were more likely to work on the local-base industries.

Table 2.2 Distribution of the Evacuees by Industries and Skills

	Local-base Industry	Export-base Industry
Low-Skilled	48%	20%
High-Skilled	16%	16%

After defining each worker's industry and skill category, I aggregate their wage rates to obtain a PUMA-level wage rate under the four categorizations, weighted by the personal weights in the data. Even though the locations to which that the evacuees went is exogenous of any factors related to their wage determination, there were still chances for a second or a third migration for these evacuees before they finally settled down from the impact of Hurricanes. And this additional migration may be associated with potential job opportunities or other economic factors that can determine the supply of labor as well as the wage rate in labor markets. Hence, I consider some factors that can impact both migration and labor supply.

Eyer *et al.* (2018) found that Katrina migrants tend to move to areas with higher average pay. Human capital in a region can help decide the level of average pay in the following sense: All else equal, a region with a larger percentage of college and above graduates can have higher average pay. I consider the PUMA level education attainment to proxy for the average payment level in that PUMA region.

Ehrenberg and Smith (2017) discussed the effect of employer size on labor supply. They cited the work from Oi (1983), which found that the monthly quit rate tends to decrease as employer size increases. Explanations for this phenomenon included more possibilities for transfers and promotions or higher wages from larger firms. Meanwhile, we can think of the number of large firms in a region as a measure for local amenities that attract people to migrate in. Hence, I collect the number of firms per capita by firm size using the establishment data from the County Business Pattern and map it from county to PUMA using the population crosswalk between the two[15].

According to Ehrenberg and Smith (2017), a factor that impacts immigrants' decision on whether to enter into the job market or what type of job market is their language proficiency. The level of language proficiency in the region can also influence people's migration decisions. Kugler and Yuksel (2008) found that residents migrated out after the Hurricane Mitch evacuees from Latin American arrived. Similarly, the English proficiency level can be used to proxy this kind of regional features that guide people's migration behavior. The Census survey asked about people's English proficiency level and I calculate the percent of adults who didn't speak English or speak little English for every PUMA to represent language proficiency in regional labor markets. The summary statistics of the major variables used in this chapter is in Table 2.3 below:

Table 2.3 Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Hourly Wage Rates (Low-Skill Local-base Industry)	10,220	14.12	2.12	8.75	27.53
Hourly Wage Rates (High-Skill Local-base Industry)	10,220	25.96	4.58	14.25	49.45
Hourly Wage Rates (Low-Skill Export-base Industry)	10,220	17.31	3.30	10.13	37.75
Hourly Wage Rates (High-Skill Export-base Industry)	10,220	29.06	6.28	13.49	57.61
No. Evacuee/Population in 2005	554	0.43%	0.98%	0.002%	12.79%
Percent with no more than High school Diploma	10,220	43.16%	9.68%	9.95%	65.54%

[15] The crosswalk comes from Missouri Census Data Center http://mcdc.missouri.edu/applications/geocorr2014.html.

Table 2.3 Summary Statistics continued…

Variable	N	Mean	Std. Dev.	Min	Max
Percent with Some years of College Education	10,220	16.64%	3.39%	3.13%	38.15%
Percent whose English is poor	10,220	3.99%	5.33%	0.00%	43.50%
Unearned Income per Households	10,220	2779.81	1118.58	571.69	12135.74
No. of Export-base Firms with less than 100 employees (per thousand people)	10,220	8.60	3.38	1.72	37.26
No. of Export-base Firms with 100 to 250 employees (per thousand people)	10,220	0.21	0.11	0.01	0.90
No. of Export-base Firms with more than 250 employees (per thousand people)	10,220	0.11	0.06	0.00	0.55
No. of Local-base Firms with less than 100 employees (per thousand people)	10,220	16.30	3.66	6.12	55.80
No. of Local-base Firms with 100 to 250 employees (per thousand people)	10,220	0.23	0.09	0.01	0.61
No. of Local-base Firms with more than 250 employees (per thousand people)	10,220	0.07	0.03	0.00	0.25

Notes: Hourly wage rates are the population weighted average for each of the PUMA regions in year 2000, 2005-2008, under corresponding categories that are low-skilled workers in the export and local-base industries, high-skilled workers in the export and local-base industries. The percent of evacuees in local population is calculated for the PUMA regions that received evacuees from Katrina Region from year 2005, and a total number of 554 PUMA regions reported received people from the region.

2.4.2 Methodology

To determine the impact of Hurricane-induced displacement on the regional labor market, I estimate the following baseline specification:

$$Y_{it} = \alpha\left(Evacuee_i^{2005} \times Post_t\right) + X_{it}^T\beta + \delta_i + Year_t + \epsilon_{it} \qquad (2.3)$$

where i indexes PUMAs and t indexes time-period for 2000, 2005 to 2008. Y_{it} is the outcome variable that is the wage rate for the four types of industries. $Evacuee_i^{2005}$ is the percent of in-migration to PUMA i from the heavily damaged areas in 2005, adjusting for pre-treatment trend. $Post_t$ is a dummy variable that equals 1 for years after 2005. I include both PUMA fixed effects

δ_i and time-period fixed effects $Year_t$, in my baseline specification. PUMA fixed effects account for all time-invariant characteristics that vary across counties. Time-period fixed effects account for any secular changes over time that affect all counties equally. The coefficient of interest in the equation is α. 0.01α measures the change in wage rates when the percentage of in-migration from Hurricane Katrina damaged area increases by 1 percent. As discussed in the theoretical section above, α should be negative for the export-oriented industry due to the rise in labor supply, but the sign of α is uncertain for the local-base industries with a higher chance of being positive for the high-skilled workers.

An important empirical validation of Difference in Difference is the parallel trends before treatment, which implies that there are no statistically significant differences in wage rates between the areas that the evacuees migrated to and the areas that they didn't. To determine whether the parallel trends assumption is appropriate, I examine how the relationship between Katrina-induced migration in 2005 and my outcome variables evolve over time by estimating the following fully flexible specification:

$$Y_{it} = \Gamma_t\left(Evacuee_i^{2005} \times Year_t\right) + X_{it}^T\beta + \delta_i + Year_t + \epsilon_{it} \tag{2.4}$$

where all variables are defined as in equation (2.3) with one exception that in equation (2.4), rather than interacting $Evacuee_i^{2005}$(the number of evacuees in 2005) with $Post_t$ (the post Hurricane Katrina dummy variable), I interact $Evacuee_i^{2005}$ with the full set of time-periods fixed effects from year 2005 to 2008 ($Year_t, t = 2005, 2006, 2007, 2008$). And the resulting series of the estimated coefficients Γ_t represent the relationship between migration and wage rates in each period t, compared to the reference period, which is the year 2000. If, for example, Hurricane-induced migration decreased wages, we would expect the estimated coefficient to be statistically insignificant in the pre-treatment period, i.e. Γ_{2005} should be statistically insignificant. In this way, the fully flexible specification in equation (2.4) allows for a closer examination of the patterns in the data before Katrina to determine whether there is any trend difference between the treatment and control groups before Hurricane Katrina, meanwhile decomposes the average impact of migration on wage rates in the post-treatment years (year after 2005) by each individual year.

2.5 Results

Baseline Estimates: Table 2.4 presents the coefficient estimates of α in equation (2.3). Column (1) displays the coefficient estimates for the low-skill Export-base labor markets, and column (2) is the coefficient for the high-skill export-base labor markets, column (3) shows the coefficient for the low-skill local-base labor markets and column (4) is the coefficient for the high-skill local-base labor markets.

Table 2.4 Baseline Results

VARIABLES	(1) low-skill export-base	(2) high-skill export-base	(3) low-skill local-base	(4) high-skill local-base
$Evacuee_i \times Post_t$ (α)	-7.132	-14.48*	4.112	16.02**
	(5.092)	(7.702)	(3.280)	(8.033)
Observations	10,220	10,220	10,220	10,220
R-squared	0.442	0.440	0.441	0.351
Number of PUMAs	2,045	2,045	2,045	2,045
Controls	YES	YES	YES	YES
PUMA FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Notes: Standard errors in parentheses, clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the hourly wage rates for the four labor markets that are low-skilled workers in the traded industry (column (1)), high-skilled workers in the export-base industry (column (2)), low-skilled workers in the local-base industry (column (3)), high-skilled workers in the local-base industry (column (4)). Control variables include the percent of the labor force that has no more than a high-school education, percent of the labor force that has some years of college education, percent of labor force whose English proficiency is low, and the number of firm establishments at different employee sizes.

For the Export-base industries, the results indicate a downward pressure on related markets caused by the inflow of the evacuees. For the low-skill export-base markets, a one percent increase in the excessive inflow of the evacuees leads to a 0.07 dollar fall in the hourly wage rates, but not statistically significant. The same increase also causes a 0.14 dollar fall in hourly wage for the high-skilled workers and it is statistically significant at the 10 percent significance level. The impact is twice as large for the high-skilled workers than for the low-skilled workers, which is consistent with the predictions from the theoretical analysis. The magnitude of the impact could be larger for the high skilled workers even with a smaller level of the labor supply shock, as the demand curve for high-skilled workers tends to be more inelastic or steeper. Similar results were also found in McIntosh (2008) that the negative impact on wages for people with more than high-school education was larger in the labor market of Houston, TX.

For the local-base industries, the results in Table 2.4 above suggest a small and significant rise in the hourly wage rate for the high-skilled workers, most likely driven by the increase in demand associated with the migration. And a one percent increase in the excessive inflow raises the hourly wage for the high-skilled workers by 0.16 dollars. For the low-skilled workers, there is also an increase in the wage rate, but it is not statistically significant. These results are also consistent with the theoretical analysis before, which said that the large shift in both demand and supply made the outcome on wages uncertain. The results in Table 2.4 is consistent with the theoretical expectation illustrated in Table 2.1 in section 2.3. The impact on wages should be negative in the export-base industries, while in the local-base industries, the impact on wages should be uncertain, and more likely to be positive for the high-skilled workers.

Table 2.5 presents the results for the fully flexible specification given by equation (2.4). The parameter estimates on the interaction between the evacuee inflow intensity variable and the time dummies give the influences of migration by year t. The reference year is the year 2000. Before the treatment, or in year 2005, the wage rate difference is insignificant in the low-skill export-base and high-skill local-base labor markets, and this satisfies the parallel trend assumption discussed before.

Table 2.5 Impact by Year

VARIABLES	(1) low-skill export-base	(2) high-skill export-base	(3) low-skill local-base	(4) high-skill local-base
$Evacuee_i \times Year_{2005}$ (Γ_{2005})	1.624	35.95***	-10.66**	-7.823
	(6.957)	(13.28)	(4.695)	(9.338)
$Evacuee_i \times Year_{2006}$ (Γ_{2006})	-9.371	-27.22**	2.513	20.89***
	(6.816)	(12.79)	(3.708)	(9.457)
$Evacuee_i \times Year_{2007}$ (Γ_{2007})	-6.680	-10.370	-1.939	7.172
	(6.827)	(12.81)	(3.707)	(9.455)
$Evacuee_i \times Year_{2008}$ (Γ_{2008})	-5.339	-5.948	3.428	-1.58
	(6.819)	(12.80)	(3.704)	(9.446)
Observations	10,220	10,220	10,220	10,220
R-squared	0.442	0.440	0.603	0.501
Number of PUMAs	2,045	2,045	2,045	2,045
PUMA FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES

Notes: Standard errors in parentheses, clustered at the PUMA level. *** p<0.01, ** p<0.05, * p<0.1. Dependent and control variables follow the same conventions as Table 2.4.

For the high-skill export-base markets, in 2005, the wage rate is statistically different between the areas that received the evacuees and the areas that didn't, but in the opposite direction from the labor supply shock. To be more specific, in 2005, the wage rates are statistically higher in the areas that received the evacuees, but in 2006, the wage rates becomes statistically lower, which better supports that the migration inflow in late 2005 lead to a downward pressure for the high-skilled workers in the export-base industries. For the low-skill local-base labor markets, there is a trend before the treatment, and the wage rates tended to be lower for the treatment areas, or areas that received the Katrina evacuees. However, the results in Table 2.4 above indicates that migration didn't have any statistically significant impact to the workers in this industry (low-skilled workers in local-base industries), the observed trend here before the treatment year becomes less important.

Starting from the first year of the treatment (year 2006), the magnitude of the external shock is falling by year in the export-base industries, for both the low-skilled and the high-skilled workers. Similarly, in the local-base industries, the wage gain for the high-skilled workers is only present in the year 2006. The results for the low-skilled workers in the local-base industries since the first year of the treatment is consistent with the results in the baseline regression, and no significant wage differences are observed between the treatment and the control areas. The results in Table 2.4 implies that the receiving areas were absorbing the shocks and bounce back to its normal track of growth in wage rates.

Robustness check: Table 2.6 begins a series of robustness checks. Right after Hurricane Katrina, Hurricane Rita hit the gulf coast again on September 15th, which was the fourth-most intense Atlantic hurricane ever recorded. Hence, I exclude the regions that were heavily impacted by Hurricane Rita (20 percent or larger housing units under major or severe damages) according to the report from the U.S. Department of Housing and Urban Development's Office of Policy Development and Research. I then re-run the baseline regression and the coefficient estimates of α in equation (2.3) were included in Table 2.6 below. The direction and the significance of the impacts remain unchanged and the magnitude becomes larger for the high-skilled workers in the export-base industries (from -14.5 to -19.5).

I now estimate an alternative specification that includes additional control variables that are related to people's labor supply decision. These variables include the percent of the married female with young kids, percent of the divorced or widowed female with young kids; percent of

Table 2.6 Regression with Outliers Dropped

VARIABLES	(1) low-skill export-base	(2) high-skill export-base	(3) low-skill local-base	(4) high-skill local-base
$Evacuee_i \times Post_t$	-6.61	-19.506*	5.813	16.65*
	(6.268)	(11.68)	(4.070)	(9.966)
Observations	9,895	9,895	9,895	9,895
R-squared	0.446	0.445	0.442	0.349
Number of PUMAs	1,980	1,980	1,980	1,980
Controls	YES	YES	YES	YES
PUMA FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Notes: Standard errors in parentheses, clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1. Dependent and control variables follow the same conventions as Table 2.3.

female never married; percent of married female without young kids; percent of young males aged between 16 and 19; percent of old male aged older than 65; other sources of income (except for earned income) per capita. Estimation results are included in Table 2.6 for each type of labor market. Overall, the results suggest that the estimated effect from the baseline specification in equation (2.3) is robust when controlling for additional factors related to labor supply.

Table 2.7 Regression with additional controls

VARIABLES	(1) low-skill export-base	(2) high-skill export-base	(3) low-skill local-base	(4) high-skill local-base
$Evacuee_i \times Post_t$	-7.084	-19.17**	2.666	13.69**
	(4.972)	(9.428)	(2.954)	(5.903)
Observations	10,220	10,220	10,220	10,220
R-squared	0.445	0.436	0.465	0.371
Number of PUMAs	2,045	2,045	2,045	2,045
Additional Controls	YES	YES	YES	YES

Notes: Standard errors in parentheses, clustered at the state level. Time and PUMA fixed effects included. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable follows the same conventions as Table 2.3. Control variables include the control variables in Table 2.3 plus the percent of the married female with young kids, percent of the divorced or widowed female with young kids; percent of female never married; percent of married female without young kids; percentage of young males aged between 16 and 19; percent of old male aged older than 65; other sources of income (except for earned income) per capita.

Intensity check: In the market of the export-base industry, the only shift is the labor supply curve caused by migration. Nevertheless, the number of evacuees received by these PUMA regions ranges from one or two people to close to twenty thousand people. This raises the question that what level of intensity, measured by the percent of evacuees in total population ($Evacuee_i^{2005}$), will cause significant wage changes for the export-base industries. For PUMA regions that received the evacuees, I order and divide them based on the excessive inflow of the evacuees ($Evacuee_i^{2005}$) and its percentile distribution. The thresholds used the division are the 10th percentile, 25th percentile, 50th percentile, 75th percentile, and 90th percentile. For example, PUMA regions in the group of 90 percentile and above means that the evacuees in these regions are larger than 0.9 percent of its own population. I then run the regression using the baseline specification but with one change, I replace the $Evacuee_i^{2005}$ variable with a dummy treatment variable $Treat_i$ $Treat_i = 1$ if $\mathrm{Evacuee}_\mathrm{i}^{2005} > 0, = 0\ otherwise$), as the purpose here is to find out the threshold at which the impacts on wages become statistically significant.

Table 2.7 and 2.8 below present the regression results for each group, I also plot the point estimates as well as the 95th confidence interval using the results in Table 2.8 and 2.9, and they are illustrated in Figure 2.2 below. The above results in Table 2.8/9 indicate that the negative impact on wages is statistically significant once the excessive migration inflow is above its 90th percentile level, or larger than 0.9 percent relative to the local population. While previous results suggest that for the low-skilled workers in export-base industries, the negative impact on wages due to migration is not significant, the results in Table 2.8/9 reveal the threshold and above which the impact on wages are statistically significant.

Table 2.8 Results by intensity (Dependent Variable: Wages of Low-skill Export-base Workers)

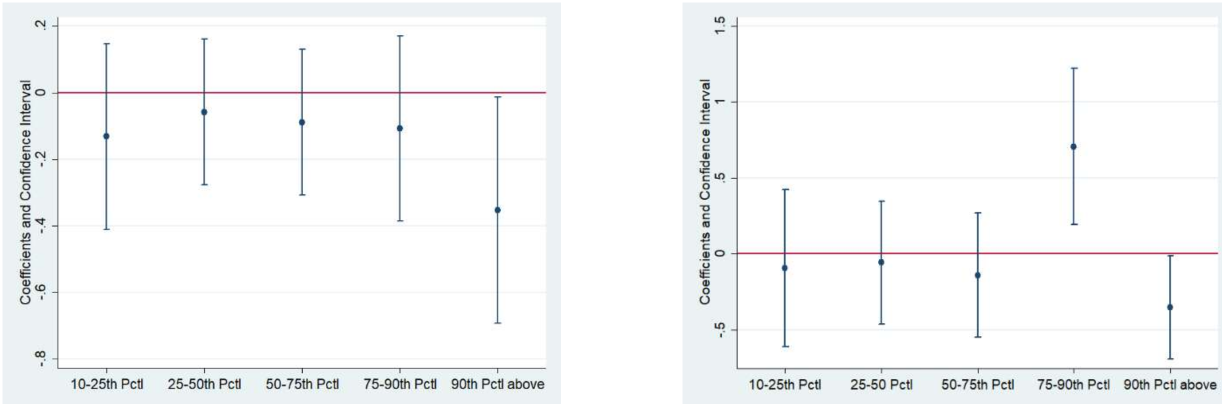
VARIABLES	(1) 0.04~0.07%	(2) 0.07~0.17%	(3) 0.17~0.4%	(4) 0.4~0.9%	(5) >0.9%
$Treat_i \times Post_t$	-0.132	-0.0580	-0.0896	-0.107	-0.353**
	(0.142)	(0.111)	(0.111)	(0.142)	(0.173)
Observations	7,855	8,145	8,145	7,865	7,725
R-squared	0.451	0.448	0.444	0.449	0.445
Number of PUMAs	1,572	1,630	1,630	1,574	1,546
Controls	YES	YES	YES	YES	YES
PUMA FE	YES	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Notes: Standard errors in parentheses, clustered at the PUMA level. Time and PUMA fixed effects included. *** p<0.01, ** p<0.05, * p<0.1. Column (1) is the regression results when comparing regions in which Katrina evacuees is between 0.04 to 0.07 percent of their population to regions that didn't have evacuees. Similarly, column (2) is the results for the regions in which Katrina evacuees is between 0.07 to 0.17 percent of their population, column (3) is the results for the regions in which Katrina evacuees is between 0.17 to 0.4 percent of their population, column (4) is the results for the regions in which Katrina evacuees is between 0.4 to 0.9 percent of their population, column (5) is the results for the regions in which Katrina evacuees is above 0.9 percent of their population. The thresholds are based on the 10th percentile, 25th percentile, 50th percentile, 75th percentile, and 90th percentile of the distribution of $Evacuee_i^{2005}, when\ Evacuee_i^{2005} > 0$.

Table 2.9 Results by intensity (Dependent Variable: Wages of High-skill Export-base Workers)

VARIABLES	(1) 0.04~0.07%	(2) 0.07~0.17%	(3) 0.17~0.4%	(4) 0.4~0.9%	(5) >0.9%
$Treat_i \times Post_t$	-0.0945	-0.0566	-0.140	0.707***	-0.562*
	(0.264)	(0.206)	(0.208)	(0.263)	(0.324)
Observations	7,855	8,145	8,145	7,865	7,725
R-squared	0.444	0.443	0.437	0.448	0.436
Number of PUMAs	1,572	1,630	1,630	1,574	1,546
Controls	YES	YES	YES	YES	YES
PUMA FE	YES	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Notes: Standard errors in parentheses, clustered by PUMA regions. Time and PUMA fixed effects included. *** p<0.01, ** p<0.05, * p<0.1. Column (1) to (5) follows the same regression strategies used in Table 2.7, but with the dependent variable being the wage rates of the high-skilled workers in export-base industries.



Panel (a) Low-Skilled Workers

Panel (b) High-Skilled Workers

Figure 2.2 Impacts at Different Level of Migration Intensities in Export-base Industry

In column (4) of Table 2.9, the high-skilled workers in areas where excessive inflow is between 0.4 to 0.9 percent experienced a wage rise due to migration. Since the coefficient estimates are the average trend from year 2006 to 2008, the significant wage rise could be in any of the three years. Table B.4 in the Appendix B decomposes the impacts by year with the reference year being 2000, and it shows that the positive wage rate is not present until the year 2007 and later. This doesn't match with the year of the Katrina event, which indicates that the observed wage gain is less relevant to the migration of the evacuees.

Control for demand shift: De Silva *et al.* (2010) used firm-level total sales data to control for potential demand-side impacts of the evacuees. Similar information is not available publicly. However, there is another set of information in the non-employer statistics (NES) from the Census, which records NACIS industry-level total sales data for businesses that have no paid employees but are subject to federal income tax. Even though these firms only account for about 4 percent of all sales nationally, the majority of the business establishments in the United States have no employees. This information might capture some of the demand-side impacts associated with the inflow of evacuees. For example, some of the real estate agents can be part of the non-***employer***

businesses and experience an increase in demand due to evacuees settling down in the new area. The NES data is reported at the county level. To transform the data to the PUMA level, I match it to PUMA level by the population weighting matrix used earlier for the construction of the Katrina Region in section 2.4.1. This construct the variable $Sales_{it}$ that is the value of total receipts from the non-***employer*** businesses in PUMA i in year t.

To account for this demand-side impact and uncover the impact on wages due to the increase in the supply of labor, I follow the estimation strategy used in De Silva *et al.* (2010) and include the $Sales_{it}$ variable and let it interact with the post treatment variable $Post_t$ and the migration variable $Evacuee_i$. The regression equation is illustrated in the following:

$$Y_{it} = \alpha_1(Evacuee_i \times Post_t) + \alpha_2 Sales_{it} + \alpha_3 Sales_{it} \times Post_t + \alpha_4 Sales_{it} \times Evacuees_i + \alpha_5 Sales_{it} \times Evacuees_i \times Post_t + X_{it}^T\beta + \delta_i + Year_t + \epsilon_{it} \quad (2.5)$$

Based on equation (2.5), $\alpha_1 + \alpha_5 Sales_{it}$ gives the impact of evacuees on wage rates at different sales level. If there is any supply side impact that pushes the wage down in the local-base industries, we would expect α_1 to be negative. We would also expect α_5 to be positive, which implies that increase in sales reduces the magnitude of the wage reduction caused by the supply shocks.

Table 2.10 below presents the estimates for the local-base industries. Column (2) shows the results for the low-skilled jobs and column (4) shows the results for the high-skilled jobs. I also include the previous baseline regression results from equation (2.3) in column (1) and (3) for compare. Using the results in column (2), at the average sales level post-treatment ($Sales_{it} = 0.4697, or\ 0.47\ billion$), the point estimates for the impact of migration on wage rate for the low-skilled labor markets is -1.129 ($\alpha_1 + \alpha_5 Sales_{it}$), suggesting that a one percent increase in migration inflow reduced the hourly wage by 0.01 dollars. However, it is both the coefficient α_1

and α_5 are not statistically insignificant, and the sign of them are not what we were expecting, as discussed above. Similarly, for the high-skilled workers, the impact of migration on wage rates due to the increase in the supply of labor is also statistically indifferent from zero. Hence, there is no evidence that migration reduces the wages for the low-skilled jobs in the local-base industry, and one explanation could be that the level of substitutability or the competition between the migrants and the locals is not strong, at disaggregated industry or occupation level.

Table 2.10 Regression with Sales Data

	(1)	(2)	(3)	(4)
VARIABLES	low-skill local-base		high-skill local-base	
$Evacuee_i \times Post_t$ (α_1)	4.11	10.760	16.02**	5.551
	(3.28)	(8.620)	(8.033)	(22.03)
Sales_{it} (α_2)		1.422***		3.683***
		(0.273)		(0.699)
$\text{Sales}_{\text{it}} \times Post_t$ (α_3)		-0.139		0.051
		(0.0956)		(0.244)
$\text{Sales}_{\text{it}} \times Evacuee_i$ (α_4)		-9.493		9.410
		(41.27)		(94.09)
$Evacuee_i \times \text{Sales}_{\text{it}} \times Post_t$ (α_5)		-25.310		0.797
		(19.08)		(48.77)
Observations	10,220	10,220	10,220	10,220
R-squared	0.441	0.609	0.351	0.506
Number of PUMAs	2,045	2,045	2,045	2,045
Controls	YES	YES	YES	YES
PUMA FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Notes: Standard errors in parentheses, clustered by PUMA regions. *** p<0.01, ** p<0.05, * p<0.1

2.6 Conclusion

In this study, I analyze the relationship between Hurricane-induced migration and the wage rates in the labor markets to which evacuees evacuated. By carefully distinguishing four types of labor markets ((i) export-base industries which use low-skilled labor, (ii) export-base industries which use high-skilled labor, (iii) local-base industries which use low-skilled labor, and (iv) local-base industries which use high-skilled labor), I find that the migration flow caused by Hurricane Katrina caused a small fall in hourly wage rate in the export-base industry, and a small rise in the hourly wage rate for the high-skill workers in local-base industries, due to the rising demand from the unexpected in-migration. To be more specific, in the export-base industry, a one percent increase in the inflow of evacuees reduced the hourly wage rates by 0.07 and 0.15 dollars for the low-skilled and the high-skilled workers, respectively. The fall in wages is caused by regions that received a significant amount of the evacuee inflows that are above 0.9 percent of the local population size. On average, in areas that the evacuees were above 0.9 percent of the local population, hourly wage rates for the low-skilled workers and the high-skilled workers are 0.35 dollars and 0.56 dollars less than the areas that didn't receive the evacuees. In the local-base industry, a one percentage increase in the inflow of evacuees leads to a 0.16 dollar rise in the hourly wage rates for the high-skilled workers, and no significant impact on the low-skilled workers.

The small magnitude of the impact of immigration on wages is consistent with studies that looked the impact of Hurricane Katrina in the Houston, TX, which received a massive number of evacuees from Hurricane Katrina (McIntosh (2008), De Silva *et al.* (2010)). Meanwhile, in the export-base industries, even though the magnitude of the labor supply shock is larger for the low-skilled workers than the high-skilled, the fall in wages is smaller due to the elastic labor demand for the low-skilled workers. This result has two implications: first, it is consistent with the empirical findings that the demand on the low-skilled workers tended to be more elastic; second, it can also explain that studies in the past found only modest or slight changes in wage rates due to migration, given the situation that immigration was shifting toward low-skilled workers in the U.S. since the 1980s (Kugler and Yuksel (2008)).

Furthermore, I make use of data from the pre-Hurricane period to show that there are either no trends in wage rate between the treated and the control groups, or the systematic trend observed could better support the wage changes since the arrival of the evacuees, among the group of workers that show statistically significant impact on wage rates. Finally, I use the non-employer business sales data as a proxy for the demand side influences on the local-base industry, to uncover any supply side impacts in the local-base industries. The inclusion of this absorbs the positive wage gain from migration, but there is no evidence of the downward pressure on wage rates due to the increase in the supply of labor in the local-base industries.

The results of this study have important implications for the relationship between migration and the outcomes in labor markets. First, the results offer empirical evidence that migration naturally brings its own demand for local goods and services, which could influence the wage rates besides the labor supply rise from the migration. Second, despite the large magnitude of the evacuation from Hurricane Katrina, its influences on wages are small. Although the elastic labor demand can explain the small magnitude of wage changes for the low-skilled workers, it is still possible that the level of substitutability between the migrants and the local workers is limited to some extent.

Chapter 2 References

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Chapter 3: Optimal Taxation Over Time in Preparing for Government Expenditure Rises: A Local-Level CGE Approach

3.1 Introduction

Individual states or local governments do not have monetary policy levers and have limited fiscal policy options in coping with economic downturns or external shocks such as natural disasters. With the increasing frequency of large natural disasters recently and the limited post-disaster finance options for local communities[16], the idea of a Rainy Day Fund (RDF) through tax hikes is proposed. The argument for such a fund is that previous studies found both the waiting time for disaster assistance and the cost of waiting are non-trivial. For instance, Almufti and Willford (2013) used information provided by experts in various fields (including engineers, building owners, contractors, cost estimators and bankers) as well as data collected from previous major disasters, and came up with estimates of delay time in different finance options. Accordingly, the median delay time for private loans is 15 weeks, and median delay time for Small Business Administration backed loans is 48 weeks. Attary *et al.* (2020) used a CGE model for Joplin, MO to demonstrate the cost of delayed federal funding, and the results suggested that waiting one more period for funding would cause a 3.4 percent loss in total output in the long run.

However, rising tax imposes distortions to the economy. To minimize the distortions over the planning period, this chapter revisits the theory of intertemporal optimal tax path within a small open regional economy context. It investigates the optimal trajectory of tax rates when using an

[16] National Oceanic and Atmospheric Administration reported the number of events that caused more than one billion damages by year, and the annual average number of billion-dollar disasters from 2015 to 2019 is more than doubled to the long-term average (1980-2019).

increase in local sales tax to finance a large amount of government expenditure in the near future. While national analyses of tax policy changes are abundant, this chapter is unique in that it addresses the level of economic activity and the relationship between output and the tax rates from a regional perspective. This is important since factors that seem meaningless in the national setting such as intra-regional migration, can become a key-factor in determining the potential labor force and total output in a region.

The formal analysis is expanded through simulation results from an intertemporal Computable General Equilibrium (CGE) model developed in Chapter 1 for Shelby County, TN, an area with potential risks of earthquakes. As of 2019, the total population in Shelby County is approximately 940,000. Studies suggested that a minimum recurrence period of a magnitude of 7 to 8 earthquake is around 200 years (Cramer (2001); Tuttle *et al.* (2002); Ogweno *et al.* (2019)). Given that insurance usually does not cover earthquakes, there will be a need from the government once we have an earthquake

In the next section, I review related literature on optimal taxation over time. Although there is an extensive body of work looking at the long run the policy suggestions at the national level, few studies have looked specifically at the local level in the short run under the context of CGE techniques. In Section 3.3 I describe the dynamic CGE model and the optimal taxation problem faced by local governments or regional planners. The model's production and household sectors are standard, but I highlight its dynamic investment dimension and the robustness of the results under ranges of elasticities used in the model. In section 3.4, I describe the simulations and results, which is accompanied by numerical examples of the optimal taxation path for the short run. My main finding is that the optimal path of tax tends to be backloaded or rising in time. The relative weights on tax hikes in each period depend on the magnitude of labor supply elasticities and the interest of the regional planners to include future economic outcomes into consideration. Section 3.5 is the conclusion.

3.2 Related Literatures

Barro (1979) introduced a method to obtain the optimal intertemporal tax path for an economy. Due to the excess burdens or the distortions brought by tax, Barro's approach began with a cost function that is assumed to be time-invariant and depend positively, with a positive second derivative, on the tax rate. This suggests that the marginal cost of taxation is an increasing function of the tax rate. The minimization of the present value of the associated cost function over time led to the outcome that optimal debt and tax policy should smooth tax rates over time.

In other words, when the government expects a future increase (decrease) in its expenditure, it increases (decreases) the tax rate today and runs a budget surplus/smaller deficit (budget deficit/smaller surplus). If the previous surplus collected is not enough for any unexpected need, the optimal policy is to issue debt instead of a sharp rise in tax rates to finance the expenditure immediately, and to pay off the debt by a smoother path of tax rise over a longer time horizon in the future.

A similar analysis was also done by Lucas and Stokey (1983) under a partial equilibrium model without capital. The same suggestion of smoothing labor income tax rates to minimize the burden overtime was made. Lucas and Stokey (1983) focused on the time-consistency issues in implementing the optimal policy which is announced today and re-evaluated in the future. They found that the optimal policy is time consistent under a barter economy but not under a monetary economy where currency and credit are available.

The empirical findings of the tax smoothing hypothesis are mixed. Barro (1979) found evidence to support the tax smoothing hypothesis. Similar results were also found in Ghosh (1995) when looking at the budget deficits or surplus for Canada and the U.S. from 1961 to 1988. However, using data for the U.S. from 1937 to 1982, Sahasakul (1986) rejected the hypothesis of uniform taxation over time and suggested that tax rate changes correspond to wars and recessions. At the state level, Strazicich (1996) found that econometrically the tax revenue over output ratio over time is nonstationary and has a unit root for provinces in Canada, which support the tax smoothing hypothesis and its implication that tax rate is a random walk. But such behavior of tax rates is not observed for the states in the U.S. Dole (2000) re-examined the behavior of the states in the U.S. and found that tax smoothing depends on states' fiscal environment.

However, according to Bohn (1990), tax smoothing came from the key assumption of the cost function being convex or having a positive second derivative. He treated this convexity as a form of risk aversion for the government, which implied tax smoothing being an optimal solution. Blanchard and Fischer (1989) suggested that uniform taxation or tax smoothing is not a generalized result since the assumption of the excess burden of tax used in Barro (1979) is too simple. They argued that the cost function should be related to the factors that caused the business cycles or the output changes. But they also concluded that the direction in which tax rates should deviate from constancy given changes in productivity is hard to predict.

Zhu (1992) extended the dynamic analysis to an economy with both capital accumulation and uncertainty. He found that the uniform taxation on labor income is only valid under certain consumer preference structures, or homogenous utility functions. Jones *et al.* (1993) studied the optimal taxation of labor and capital income under three different models in which labor is inelastically or elastically supplied, or the government expenditure is endogenized. The simulation results from the three models differ, which pointed out the importance of these factors in determining the optimal tax path. Erosa and Gervais (2002) studied the optimal taxation overtime under the overlapping generations economy. They found that uniform commodity taxation holds if the consumer preference can be characterized by an additively separable utility function between consumption and leisure. They also noticed that if the income elasticity of labor supply depends on age, then the optimal labor income tax should also change correspondingly with different levels of elasticities by putting more tax on inelastic factors.

Recent extensions to the intertemporal optimal tax path include the consideration of incomplete financial markets, social networks, and recursive preferences. According to Scott (2007), optimal labor income tax over time depends positively on the employment rate. Moreover, under incomplete markets where the government cannot issue contingent bonds, the optimal labor income tax also contains a martingale component to stress the role of the shocks to government expenditures. Arbex and Dennis (2010) stressed the role of social networks in labor markets to the optimal labor tax rates. Similar to Scott (2007), they also found optimal labor income tax is negatively related to the unemployment rate. What's more, in an economy of stronger social networks, labor income tax rate is higher because of the smaller unemployment rate in steady state. By arguing that the recursive preference can better capture the changes in asset and bond prices, Karantounias (2018) offered an optimal fiscal policy where the government should issue more bonds and tax more when there is no or little shocks to government expenditures, and pay off some debt and tax less during bad times when shocks to spending are large.

Unlike previous studies, this chapter uses a computable general equilibrium (CGE) model to study the optimal fiscal policy for local economies such as a county or a city. The purpose of raising funds can be certain and expected public infrastructure investment or uncertain events that require large government expenditures such as natural disasters.

For uncertain events, an idea called Rainy Day Fund was commonly used by the State Government to ease fiscal stress during the recession, and it became very popular in the 1980s and 1990s. About 44 states in the U.S. have some type of Rainy Day Fund as of year 1994 (Sobel and Holcombe (1996)). Such funds were set aside during booms to lessen revenue shocks during the recession through planned changes in revenue portfolio or revenue base to increase revenue. Empirical studies offered support for positive effects of Rainy Day Fund on fiscal stress at the state level (Sobel and Holcombe (1996); Douglas and Gaddie (2002); Hou (2003, 2005); Wagner and Elder (2005)). At the local level, such a fund can also be used, for example, Gianakis et al. (2007) found that the stabilization fund took about 6 percent of municipal revenues for Massachusetts in 2003.

Practically, setting up such a Rainy Day Fund is equivalent to force the government to save or spend less. However, as noted by Wolkoff (1987), cities that with more fluctuations in government spending and can benefit more by setting the Rainy Day Fund, tended to be fiscally distressed. This means that local government may have nothing to save. What’s more, restraining expenditures for local government to cope with large negative shocks in the future requires a nontrivial amount of reduction in expenditure. For example, Sobel and Holcombe (1996) suggested that 30 percent of the expenditure is needed for the Rainy Day Fund to maintain the growth for 1991 recession. Hence, instead of trying to reduce the current level of budget and government expenditure responsibilities, this chapter propose to use tax hikes for such a fund collection. Some guidance on the optimal approach to collect such a fund through tax hikes would be useful for local governments.

The general equilibrium model used here considered the consumer's utility maximization problem as well as the producer's profit maximization problem with prices, wage rates and the rental rate of capital determined endogenously. More importantly, rather than assuming a convex cost function concerning tax rates like Barro (1979) and Ghosh (1995), the cost of taxation, measured with the foregone output that could have been produced with the original tax scheme, is determined endogenously within the model. As a result, built on the optimization behavior of households and firms in response to different levels of tax rates, the cost function is linked with a set of model parameters that influence the level of output today and tomorrow. Moreover, at the national level, the effect of public policy on migration are not relevant, but it becomes important at the local level. The CGE model used in this chapter endogenizes the migration behavior through changes in regional real income per household and unemployment rate. Changes in tax rates will impact these two factors, which is then transitioned to the migration outcomes in regional economies.

Besides, previous studies were based on a simplified representative household and an aggregated production sector. The CGE model contains a range of disaggregated production sectors and a range of household and labor groups with stratified income levels. Doing so allows me to differentiate their behavior responses through a set of elasticities with different values assigned for each group. And the robustness of the results from the model can be tested through changes in these elasticities.

3.3 Overview of the Model

The CGE model used here is composed of a within-period model and an inter-temporal model. The within-period model determines a static equilibrium under different levels of external shocks to the exogenous variables, such as a change in the natural rate of population growth. The inter-temporal model accounts for the inter-period variations that drives the model dynamically, updating the values of all exogenous variables in the previous period. For instance, the current period's capital stock is determined by the depreciated capital stock from last period and current level of investment expenditure.

Agents in this model include households who maximize their utility and supply their capital and labor to firms for income, firms who maximize their profit using capital, labor, and intermediate inputs and governments who collect taxes and decide the optimal tax rates over time to minimize the distortions to the regional economy, given a target amount of fund to be raised for future use. Next, I will illustrate their behaviors in detail.

Households

Households are divided into different groups based on their income, and the same income thresholds in Chapter 1 are used here. For each group of households h, the utility maximization problem is illustrated as follows in period t:

$$V_t^h = \max U^h \left(F_{1,t}, \dots F_{j,t}, \dots, F_{N,t}, L_t\right) \tag{3.1}$$

$$\text{s.t.} \sum_j (1+\tau_c) P_{F_{j,t}} F_{j,t}^h = \sum_j (1-\tau_H) w_{j,t} H_{j,t}^h + \sum_j (1-\tau_K) r_{j,t} K_{j,t}^h \tag{3.2}$$

where V_t^h is an indirect utility function, U^h is a direct utility function, $F_{j,t}^h$ is the demand for goods in sector j in period t, L_t is the amount of leisure enjoyed in period t, $(1+\tau_c)P_{F_{j,t}}$ is the after-tax prices for commodity j with tax rate equals to τ_c, $H_{j,t}^h$ and $K_{j,t}^h$ are the amount of labor and capital supplied to sector j in period t, $(1-\tau_H)w_{j,t}$ and $(1-\tau_K)r_{j,t}$ are the after-tax wage rates and rental rate of capital with labor income tax τ_H and capital income tax τ_K.

Households own labor and capital and earn income from supplying them. Capital is supplied inelastically in the initial period. Any changes to the economic system that impact the rental rate of capital will alter the level of investment and the availability of capital in the next period. The law of motion for capital is expressed in equation (3.3) -(3.4) below. The supply of labor depends on the real wages and the income taxes imposed in the economy, and the responsiveness to these factors is characterized by labor supply elasticity for wage and tax rates separately.

$$K_{j,t+1} = (1 - \delta)K_{j,t} + I_{j,t} \tag{3.3}$$

$$I_{j,t} = f(r_{j,t}) \tag{3.4}$$

where $I_{j,t}$ is the amount of new investment in period t which depends on the rate of return of capital $r_{j,t}$ in period t, δ is the depreciation rate of capital.

Except for the normal population growth in the economy due to birth and death, households can choose to migrate in and out of the region. The specification of the migration behavior is based on the work of Berck *et al.* (1996). It is a function of real income per household and the unemployment rate in the region. Income taxes can alter both the level of real income per household and unemployment rate and make changes to the net migration rate within the region. The commodity taxes can alter the real household income through changes in the consumer price index and influence the migration outcomes within the region. As a result, taxes can impact the level of net-migration for local areas which in turn changes the availability of the labor force and total output produced in the region.

Firms

Firms use labor services and capital stock as inputs, labor is measured in the number of workers while capital is measured in real dollar terms. Firms also require intermediate inputs in production, and I assume a Leontief Production at the upper tier, which is expressed in equation (3.5) below:

$$DS_{j,t} = \min\left(\frac{V_{j,t}}{a_{vj}}, \frac{x_{1j,t}}{a_{1j}}, \dots \frac{x_{Nj,t}}{a_{Nj}}\right) \tag{3.5}$$

where $DS_{j,t}$ is the total output produced in sector j in period t, $V_{j,t}$ is the amount of value-added, $x_{ij,t}$ is the amount of intermediate inputs, and a_{vj}, a_{ij} are the I-O coefficients that remain constant over time.

$V_{j,t}$ determined by solving the cost minimization problem below:

$$\mathrm{C}(w_{j,t}, r_{j,t})V_{j,t} = \min_{L_{j,t}\ K_{j,t}} \mathrm{w}_{\mathrm{j}}^{s} L_{j,t} + r_j^s K_{j,t} \tag{3.6}$$

$$\text{s.t. } f(L,K) = \eta_j\left\{\alpha_L\left(L_{j,t}\right)^{\rho} + \alpha_K\left(K_{j,t}\right)^{\rho}\right\}^{1/\rho} \tag{3.7}$$

$$L_{j,t} \le \overline{L_{J,t}} \tag{3.8}$$

$$K_{j,t} \le \overline{K_{J,t}} \tag{3.9}$$

where η_j is total factor productivity, α_L and α_K are share parameters of labor and capital inputs, and $(1/(1-\rho)\,)$ is the elasticity of substitution between labor and capital. $\overline{L_{J,t}}$ and $\overline{K_{J,t}}$ are the endowments of labor and capital stock in period t.

Government

The government is decomposed as federal, state and local government. The federal government collects federal income taxes from local households, state government collects sales and income taxes from firms and households separately. The local government collects property taxes, local sales taxes, and all other taxes and fees such as license taxes and permits. Government sectors also buy commodities produced from commercial sectors and demand labor.

Unlike previous studies where the government can issue contingent debt, the role of the federal government here in the model is passive and act as a transit agency to collect income taxes and pay social security payments. For state government, it can authorize the local areas to change its level of sales taxes or property taxes for the idea of the Rainy Day Fund. For any amount of

Rainy Day Fund that is collected through tax hikes, the government can use it to buy financial products that offer an interest payment in each period, which means that a dollar that is collected today is equivalent to a dollar plus the interest payment in the later periods.

Rest of the world

The study area also trades with neighboring economies as well as other national or foreign producers. All of them are aggregated into a single "Rest of the World" (ROW) construct: exports flow from the study area to ROW and the study area imports from ROW. Under a small open economy context, prices outside the study area will remain unchanged.

Equilibrium

The equilibrium in period t is defined as: (1) an *allocation* of commodities consumed by households, labor services, capital stock, and intermediate inputs $(\mathrm{F}_{i,t}^{\mathrm{h}}, H_{j,t}^{h}, K_{j,t}^{h}, x_{ij,t})$; and (2) a *price vector* (i.e. final goods, factors prices) $(\mathrm{P}_{j,t}, w_{j,t}, r_{j,t})$ such that:

a) The utility maximization problem described in equation (3.1) to (3.2) is satisfied;

b) The profit maximization problem described in equation (3.5) to (3.9) is satisfied;

c) The supply and demand for final goods are equal in each sector;

d) Factor demands and factor supplies (including intermediate inputs) are equal;

e) Governments run a balanced budget;

3.4 Simulations and Results

3.4.1 Simulation set up

The general equilibrium model described above doesn't admit closed form solutions, hence the strategy is to compute the exact solutions in a deterministic setting. The data and the social accounting matrix for the study area (Shelby County, TN) developed in Chapter 1 is used here to calibrate the exogenous parameters in the model. Next, I will describe how I set-up the reference point for the economy under normal growth, and how the tax hikes fit into the model to derive the optimal path over a certain planning horizon for any target amount of the Rainy Day Fund.

Normal Growth

There is a normal growth transitioned through different periods for Shelby County. Specifically, I included the population growth and technology advances as a representation of an exogenous economic growth. Note that the total population is determined by the natural rate of population growth plus net migration, among which migration behavior is endogenized so that it will respond to changes in tax rates. The value of population growth is based on the historical data (2009-2017) from the Census Bureau. Annual growth rates are calculated among these years. Averaging them gives a 1.15 percent average annual growth rate of population for the Shelby County. For the technology advances, the Bureau of Labor Statistics listed the annual labor productivity growth for nonfarm business from 2015 to 2019. The average productivity growth is then calculated among the five years and a 1.2 percent annual growth rate is imposed in the normal growth scenario, together with the 1.15 percent population growth rate.

Tax hikes

Recall that Shelby County is under the potential risk of earthquakes. Hence imagine the following scenario: The regional planners are considering collecting some Rainy Day Fund through tax hikes to help communities improve their resiliency to earthquakes. Unlike the insurance payment that may take time to arrive for post-disaster repairs, this amount of money can be used right away. The timing and the amount of the insurance payment, as well as the insurance take up rates can influence the target level of the RDF, but it is not the focus of this study. Instead, we want to collect the RDF optimally over time so that its impact on the economy is minimized during the planned collection horizon, regardless of the level of the RDF. To quantify the impact of tax hikes on the local economy, the foregone output that could have been produced without any tax hikes is calculated. I then construct the following minimization problem:

Assume a certain planning period from period 1 to T to raise funds for the government expenditure in period $T+1$. During periods 1 to T, the governments impose a tax hike ($\Delta\tau_{c,1}, \dots, \Delta\tau_{c,T};\ \Delta\tau_{L,1}, \dots, \Delta\tau_{L,1}; \Delta\tau_{K,1}, \dots, \Delta\tau_{K,T}$) based on the current tax system (τ_c, τ_L, τ_K). The additional revenue collected from the tax hikes is saved for period $T+1$ with interest payments in each period. Excluding the additional revenue, governments still run a balanced budget in each period.

For any given amount of Rainy Day Fund $\bar{G}$, the government choose a series of taxes hikes ($\Delta\tau_{c,1}, \dots, \Delta\tau_{c,T};\ \Delta\tau_{L,1}, \dots, \Delta\tau_{L,1}; \Delta\tau_{K,1}, \dots, \Delta\tau_{K,T}$) within the planning period (period 1 to T) to minimize the discounted value of total output loss due to tax hikes in the economy. And equations (3.10) to (3.11) below illustrate the minimization problem of the government:

$$\min_{\Delta\tau_{c,t}\ \Delta\tau_{L,t}\ \Delta\tau_{K,t}} \Gamma\left(\Delta\tau_{c,t}\ \ \Delta\tau_{L,t}\ \ \Delta\tau_{K,t}\right) = \left(\sum_t \sum_j \beta^{t-1}(\overline{DS^*_{J,t}} - DS^*_{j,t}\right) \tag{3.10}$$

$$\text{s.t.} \sum_t \sum_j \beta^{t-1}(\Delta\tau_{c,t} P^*_{F_{j,t}} F^*_{j,t} + \Delta\tau_{w,t} w^*_{j,t} H^*_{j,t} + \Delta\tau_{c,t} r^*_{j,t} K^*_{j,t}) = \bar{G} \tag{3.11}$$

where β is the discount factor, $\overline{DS^*_{J,t}}$ is the optimal level of total output satisfying equation (3.1) to (3.9) without any tax hikes (the reference point and $\Delta\tau_{c,t} = \Delta\tau_{L,t} = \Delta\tau_{K,t} = 0$), $DS^*_{j,t}$ is the optimal level of total output with tax hikes. $F^*_{j,t}, K^*_{j,t}$, $H^*_{j,t}$, $P^*_{F_{j,t}}$ $w^*_{j,t}$ and $r^*_{j,t}$ are the optimal allocations of commodities, factors and price levels that satisfy equation (3.1) to (3.9). All of them are functions of exogenous variables in the model including the current tax rates (τ_c, τ_L, τ_K).

To obtain a deterministic solution, I assume the planning horizon to be 10 periods, and the discount factor β equals to 1.01, or a 1% interest rate. For simplicity, the tax rate that will increase is the commodity tax, the income taxes to labor and capital stay constant throughout the periods. Studies have discussed the efficiency of taxation on consumption versus income, with the idea of efficiency being the type of tax that can stimulate savings and growth. It has been argued that consumption tax is more favorable. In particular, the commodity tax allows the government to tax the income that is spent, without any distortions to income that is saved. As a result, the impact of taxation on the formation of capital and economic growth is eliminated.[17] For instance, Turnovsky (1996) discussed the optimal fiscal policy for an economy where government expenditure is endogenized so that it increases as the size of the economy rises. The implication of the optimal fiscal policy suggested that an increase in commodity tax accompanied by a reduction in debt had no impact on the growth rate of the economy, whereas an increase in capital taxation accompanied by a reduction in debt would lower the growth of the economy.

In the meantime, sales tax is one of the major sources of revenue for local governments, and its importance is rising over time. In 1942, local sales taxes accounted for less than 3 percent of total revenue, but in 2018, sales taxes had increased to 17 percent of total tax revenue (Sjoquist and Stoycheva (2012), 2017 Census of Government Finance). In some states, this number is even larger and can reach up 53 percent (e.g. Louisiana). Even though property taxes contribute more for local revenue than the sales taxes at the national basis, a large percent of property tax revenue is transferred to the school district. To be more specific, according to McFarland *et al.* (2018), local governments provided 45 percent of public school funding, and more than 80 percent of that came from the property tax. Using this relationship and the data from 2017 Census of Government Finance, it is calculated that about half of the property tax collected is then attributed to public

[17] For more detailed discussion on this, see Kaldor (2014)

education. Considering the transfer to school districts, sales tax is all that can be used for cities and towns to set up the Rainy Day Fund.

In the results subsection follows next, I first summarize the general features of the results from the minimization problem above. Then I present numerical examples. Finally, an explanation for such an optimal mechanism completes the section.

3.4.2 Results

For a 10-period planning horizon together with varying levels of the fund to be raised, the model is solved for the optimal path of commodity taxation. The results suggest that the tax hikes should happen only in the last period, which is period 10, and the rise in sales taxes in previous periods will be zero. One may question the robustness of the results, hence I re-run the model with different planning horizons and different model parameters that include the labor supply elasticity, migration elasticities with respect to income and unemployment rate, consumption responsiveness to commodity prices. Table 3.1 below lists the lower bound and the upper bound of these elasticities. For the labor supply elasticity, the lower bound and the upper bound come from Chetty *et al.* (2011). The rest comes from the summary by Berck *et al.* (1996).

Table 3.1 Ranges of Elasticities for Robustness Check

		Lower Bound	Upper Bound
Labor supply elasticity to real wages	ε	0.28	2.3
Migration elasticity to real wages	ν	0.83	2.3
Migration elasticity to unemployment	μ	0.1	0.83
Own-price elasticity (Agriculture, Manufacturing)		0.35	0.94
Own-price elasticity (Retail/Wholesale trade, Utilities)	λ	0.13	1.72
Own-price elasticity (Services)		0.1	1.3

Note: All the elasticities are in absolute values.

The importance of own-price elasticity is straightforward as the rise in sales tax directly increases the after-tax prices of goods and services. In the future with population and total factor productivity growth, total income rises, as well as total consumption demand. However, under a high level of price elasticity, a one percent increase in sales tax is going to reduce consumption by a larger percentage. This dampens the income and consumption demand gains in the future periods by a larger amount, which makes it more costly to impose sales tax hikes in the future.

As discussed earlier, fiscal policy at the national level differs from the one at the local level due to the cross-regional migration in response to the policy. In the CGE model developed in this chapter, migration depends on real wages and employment opportunities (unemployment rate), and both two factors will decrease when sales tax rises, which induces more outmigration from the study area. If the migration elasticities are high, outmigration is larger when tax rates go up. This reduces the potential labor force by a larger amount. In the future, due to productivity growth, losing one worker is associated with a larger output loss, which implies the cost of tax hikes is larger in the future. But because of the diminishing marginal product of labor, the larger size of the population in the future makes the cost of losing one worker being smaller. Therefore, the relative cost of tax hikes now or in the future depends on how the two countervailing effects evolve in response to a larger fall in the labor force. Similar logic can also be applied to the relative magnitude of the labor supply elasticity, since migration influences the level of the potential labor force in the economy, and the labor supply elasticity impacts the willingness to supply their labor in the economy, at any given level of the labor force.

The optimal path obtained earlier is robust under various planning horizons (5 periods, 15 periods, and 20 periods). However, it changes with a smaller level of labor supply elasticity (LSE). At a smaller level of LSE, the optimal way to collect a given amount of funding is to spread out the burden of the tax hikes in different periods with more weights on later periods. Equation (3.12) below summarizes the optimal solution.

$$
\begin{cases}
\text{when } \varepsilon > 0.5, \Delta\tau^*_{c,t} = 0 \text{ for t} < \text{T}; \ \Delta\tau^*_{c,T} = \dfrac{\bar{G}}{(\beta^T - \beta)\sum_j P^*_{F_{j,T}} F^*_{j,T}} \\
when\ \varepsilon < 0.5 \begin{cases} \dfrac{\partial\Gamma(\Delta\tau^*_{c,t}, \bar{G})}{\partial\Delta\tau_{c,t}} = \dfrac{\partial\Gamma(\Delta\tau^*_{c,t+a}, \bar{G})}{\partial\Delta\tau_{c,t+a}} \\ \Delta\tau^*_{c,t} = 0 \text{ if for any } \Delta\tau_{c,t}, \dfrac{\partial\Gamma(\Delta\tau_{c,t})}{\partial\Delta\tau_{c,t}} > \dfrac{\partial\Gamma(\Delta\tau^*_{c,t+a})}{\partial\Delta\tau^*_{c,t+a}} \end{cases}
\end{cases}
\tag{3.12}
$$

To see this difference more closely, Figure 3.1 projects the optimal path of the tax hikes in 10 periods, i.e. $(\Delta\tau^*_{c,1}, \ldots, \Delta\tau^*{}_{c,10})$, with a target of collecting \$1 billion by the end of the planning horizon at different levels of labor supply elasticities.

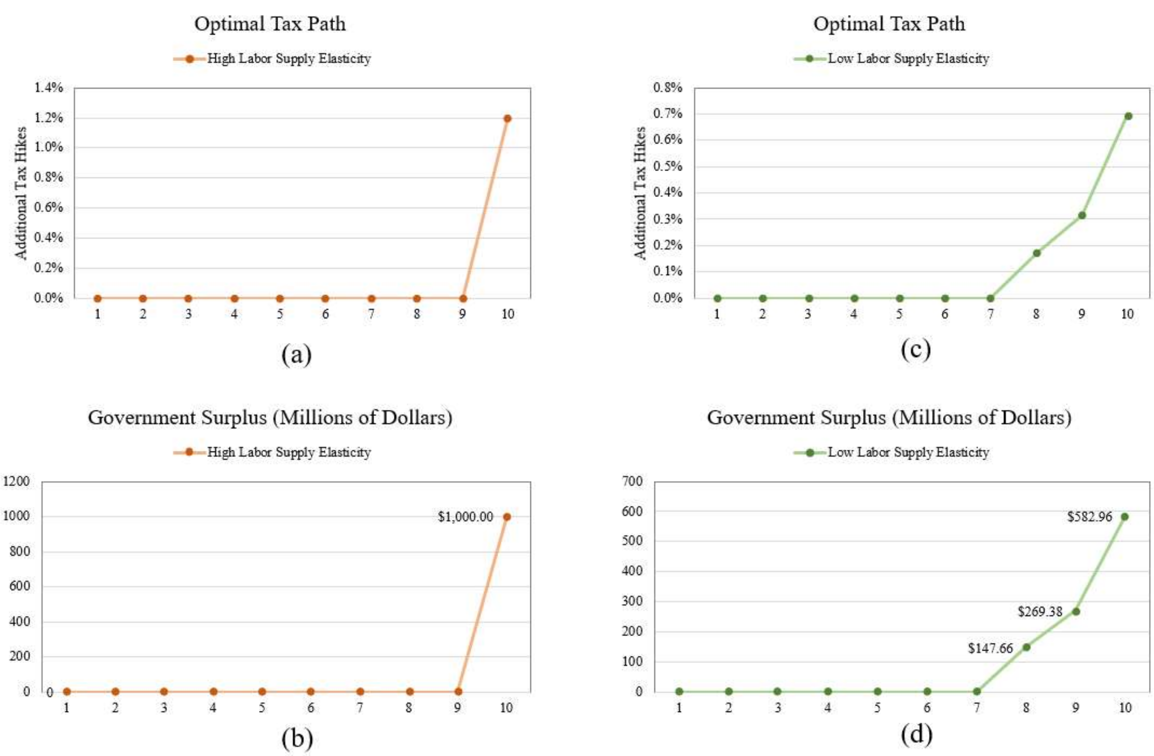

Figure 3.1 Optimal Tax Path and Government Surplus

Panel (a) in Figure 3.1 is the optimal level of the tax hikes $(\Delta\tau^*_{c,1}, \ldots, \Delta\tau^*{}_{c,10})$ when LSE is high (=1.5). From period 1 to 9, the sales tax remains at the current level, and in period 10, the sales tax rate goes up by 1.2 percentage points. This generates a government surplus that equals to \$1 billion (=\$1.09 billion if measured by future value in the 10$^{\text{th}}$ period at a 1% interest rate), as illustrated in panel (b) of Figure 3.1. But when the LSE is low (=0.5), the tax burden is shifted to periods before period 10, in periods 8 and 9 respectively. From period 8 to 10, the optimal tax policy is to gradually increase the tax rate by 0.2 percent to 0.7 percent. In panel (d), the amount of surplus that goes to the Rainy Day Fund is also increasing from \$147 million to 582 million accordingly, and the cumulative summation of the surplus from period 8 to 10 is the target amount of \$1 billion (present value). In summary, tax hikes are rising in time, with a high level of LSE, raising sales taxes should happen all in the one period before the expected government expenditure shocks, but with a low level of LSE, sales taxes should be raised in a gradually rising manner under several periods before the expected government expenditure shocks.

To quantify the improvements of planning optimally for the rises in sales taxes, I also calculate the loss/reduction in total output when planning the rises in sales taxes in the least optimal way, i.e. to resolve the optimization problem in equations (3.10) to (3.11) but maximizing the cost of the collection at different levels of collection amounts ($\bar{G}$). Table 3.2 presents the differences in the total costs when planning the tax path optimally versus least optimally, at different levels of Rainy Day Fund that ranges from \$100 million to \$1 billion of dollars. The improvements are calculated for the high and the low value of the labor supply elasticities separately.

The numbers and its magnitude measured by the percent of total output in Table 3.2 below suggest that the benefit/improvement is nontrivial, especially when the LSE is high. As an example, in column (1), when the fund to be raised is \$100 million, the improvement or the difference between the optimal and the least optimal planning is about 9 million, or 0.24 percent of the total output produced. This result argues for the attention to impose the tax hikes carefully by the regional planners. Meanwhile, when looking at the numbers along with any columns of Table 3.2, the improvement depends positively on the amount to be raised, i.e. the larger the target amount

Table 3.2 Benefit of Optimal Tax Path (millions of dollars)

	High Elasticity (ε = 1.5)		Low Elasticity (ε = 0.5)	
Fund Raised ($\bar{G}$)	Benefit (1)	As % of total output (2)	Benefit (3)	As % of total output (4)
100	9.22	0.24%	2.11	0.06%
200	18.63	0.48%	3.72	0.11%
300	28.20	0.73%	5.32	0.16%
400	37.91	0.98%	6.96	0.20%
500	47.76	1.24%	8.53	0.25%
600	57.72	1.49%	10.13	0.30%
700	67.80	1.75%	11.73	0.34%
800	77.95	2.02%	13.33	0.39%
900	88.23	2.28%	14.92	0.44%
1000	98.56	2.55%	16.52	0.48%

Note: All the numbers (except for percentages) are measured in the present value of the first period and are in millions of dollars.

of the Rainy Day Fund, the larger the improvement will be through optimal tax planning.

When comparing the numbers across the same row in Table 3.2, i.e. comparing the cost reduction for a certain amount of fund at two different levels of LSE, the results indicate that the efficiency improvement is much larger when LSE is high. The explanation for this is, when the LSE is high, tax hikes imposes a huge impact on the economy. A large LSE implies that workers' labor supply decision is very sensitive to changes in real wages. When the sales tax goes up, real wages fall, and labor supply responds very drastically to this change. As a result, total output that could have been produced is also reduced by a fair amount, which leaves more room for the optimal tax policy to ease this impact.

To fully unfold the mechanism of the optimal tax path discussed above, let's first review the impact of the tax hikes. When the sales tax rate is raised for additional revenue or surplus, it has several impacts on the economic system. Firstly, it raises the after-tax price for consumers, which reduces the total amount of consumption. Secondly, it reduces the real wage of workers and the supply of labor. Thirdly, the higher price reduces real household income and decreases the net amount of people who want to migrate to the region. As a result, the total output produced will fall which is used as the cost of the tax hikes.

Table 3.3 below provides the total and the marginal costs for raising different levels of the Rainy-Day Fund all in the first period at a high and a low level of LSE.[18] The results have a meaningful suggestion. It shows that the curvature of the cost function depends on the level of LSE used in the model.

Table 3.3 Total and Marginal Cost for Fund Raising (millions of dollars)

	High Elasticity ($\varepsilon = 1.5$)		Low Elasticity ($\varepsilon = 0.5$)	
Fund Raised ($\bar{G}$)	(1) Total Cost	(2) Marginal cost	(3) Total cost	(4) Marginal cost
100	174.61	174.61	40.23	40.23
200	347.97	173.36	80.52	40.29
300	520.12	172.16	120.88	40.36
400	691.13	171.01	161.31	40.43
500	861.08	169.94	201.81	40.50
600	1030.01	168.93	242.38	40.57
700	1197.95	167.94	283.02	40.64
800	1364.97	167.02	323.73	40.71
900	1531.10	166.13	364.52	40.79
1000	1696.37	165.27	405.38	40.86

When the LSE is high, the marginal cost of raising the second 100 million dollars (173.36 million) goes down compared to the cost of raising the first 100 million (174.61 million), according to column (2) in Table 3.3. Relate this to the cost minimization problem, when LSE is high, the cost of taxation depends positively, with a negative second derivative on tax rates. Figure 3.2 panel (a) below illustrates this type of cost function. This leads to the optimal solution that the government should collect the additional funding all in one period, because the marginal cost of additional tax hikes is going down in the same period. Mathematically speaking, the first-order

[18] The numbers are different if this experiment is under periods other than period 1, but the general features remain proportionally the same.

condition ($\Gamma'(\Delta\tau_{c,t}) = 0$) that minimizes the cost function $\Gamma(\Delta\tau_{c,t})$ is not a minimizer since the second-order condition ($\Gamma''(\Delta\tau_{c,t}) > 0$) is not satisfied, given the observations in column (2) of Table 3.3 that the cost function has a negative second derivative on tax. This implies that the optimal tax hikes ($\Delta\tau^*_{c,t}$) is either at its lower bound (=0) or upper bound ($= \frac{\bar{G}}{(\beta^T - \beta)\sum_j P^*_{F_{j,T}} F^*_{j,T}}$) at a given period t, and it depends on the unit cost of fundraising in period t versus in period $t+1$, which I will discuss later.

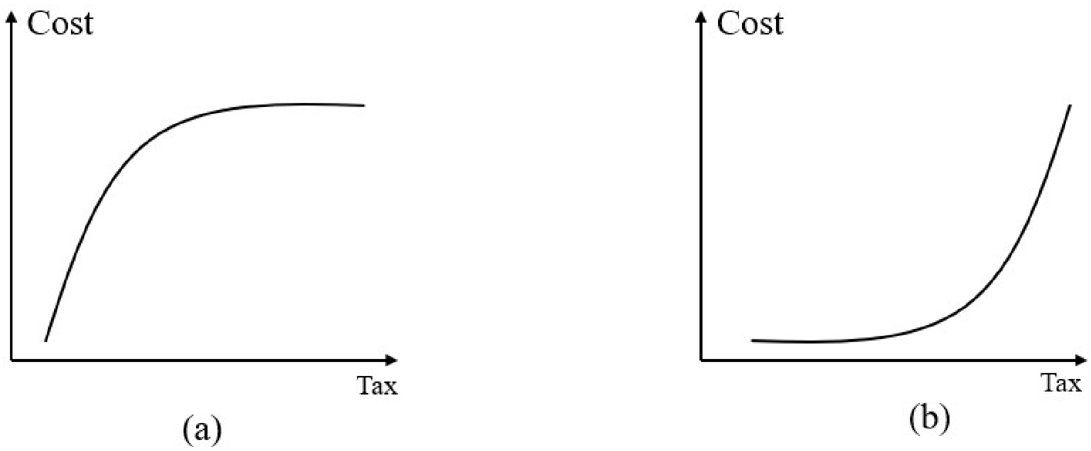

Figure 3.2 Different Shapes of Cost Function

However, column (4) in Table 3.3 suggests that, with a smaller LSE, the cost of taxation depends positively, but with a positive second derivation on tax revenues. Figure 3.2 panel (b) above illustrates such a cost function. This is consistent with the assumption in the previous literature (Barro (1979); Sahasakul (1986); Bohn (1990); Ghosh (1995)) where they assumed an explicit cost function of tax revenue, and as tax revenue increases, both the total and the marginal costs increase. Minimization of this type of cost function suggests that: The optimal solution is the point when the marginal cost of taxation is the same across all the periods to smooth out the burden of taxation. Under this situation, the second-order condition mentioned above ($\Gamma''(\Delta\tau_{c,t}) > 0$) can be satisfied, and it is sufficient to rely on the first-order condition of equaling marginal costs across periods to minimize the total cost.

The uncertainty in the sign of the second derivative of the cost function suggests that the assumption made in Barro (1979) and other papers above is a special case that is only valid at a relative low value of the labor supply elasticity. Results here expand the optimal path of taxation to accommodate different levels of parameters in the model. The intuition for the different curvatures of the cost function is, the outcomes of the CGE model are results of several opposing effects when the economic system experiences any external shocks like tax hikes. The degrees of these opposing effects depend on the value of the parameters used in the system.

To be more specific, the rise in sales tax reduces the consumption demand as well as the firm's demand for labor and increases the consumer price index in the economy. With the fall in real wages, every leisure hour represents a lower amount of forgone wages. As a result, workers may substitute more leisure for work hours (substitution effect). The second effect is that with lower real wages and reduction in labor demand, workers become poorer to afford the leisure (income effect).When the LSE is high, wages fall only slightly and the relative magnitude of the substitution effect is smaller, which implies a smaller reduction in work hours relative to leisure. For the income effect, it is determined by the changes in both the real wages and employment level. The higher level of LSE implies a smaller fall in wages but a larger fall in employment while low LSE implies a larger fall in wages but a smaller fall in employment, so the relative changes of the income effect should be similar under different levels of LSE. Therefore, the high level of LSE reduces the substitution effect more by workers substituting less leisure to work hours and offsets the negative impact of the additional rises in sales taxes.

When altering other elasticities within the ranges listed in Table 3.1, the second derivative of the cost function remains negative. One explanation of this phenomenon is that the difference between the lower and the upper bound of LSE is larger than those of the other two elasticities. It is possible that at values beyond these ranges for the other two elasticities, the curvature of the cost function changes to the shape illustrated in panel (b) of Figure 3.2.

Up to this point, equaling the marginal costs across periods doesn't offer a closed-form solution of the taxation over time. Barro (1979) made additional assumptions to conclude uniform taxation over time, and these assumptions are: 1) taxable income/resource is exogenous, and doubling the taxable resources in the economy doubles the cost of taxation if the tax rate remains unchanged; 2) the cost of taxation in period t only depends on the tax rate and total taxable income in that period. These assumptions indicate that the economy tomorrow is the constant return to scale of the economy today. Under this situation, an optimal tax rate (tax revenue over total income) in the economy today should remain unchanged in the economy tomorrow.

Limitations exist in these assumptions, especially at the local level due to the free movement of labor and capital. First, the output produced in an economy can be influenced by the level of taxation in the economy and as a result, is not exogenous. Empirical studies have found evidence that high level of taxation is associated with smaller economic growth, both at the country or the local level (Holcombe and Lacombe (2004); Lee and Gordon (2005); Arnold (2008); Johansson *et al.* (2009)). Second, if a high tax is imposed today, it can influence investment and saving decisions, which will alter the initial condition for the next period. This indicates that the cost of taxation in period t also depends on the tax rate before period t. The CGE model used here relaxes both assumptions, and the interpretation of the optimal tax path is closely related to the way the model relaxes these assumptions. Next, I will describe in detail how the changes are made and how they help to determine the optimal solutions illustrated in Figure 3.1.

As discussed earlier, sales taxes enter people's consumption, labor supply, and migration function either explicitly or implicitly, and make total output to rely on the level of taxation in the economy. If the taxable resource is endogenous, how would this change the uniform taxation results? Sahasakul (1986) found that uniform taxation is valid only if the output elasticity with respect to after-tax prices is constant over time. But factors that change the output level from one period to the next are not discussed in Sahasakul (1986), and no judgment can be made on the evolvement of the output elasticities over time. The same implication is also made by Blanchard and Fischer (1989) that factors that change the output level such as productivity, should be linked with the cost of taxation to predict how the rate of tax deviates from constancy over time.

The forces that drive the economic growth in the CGE model are the increase in the natural rate of population growth and technology advances. As these exogenous variables change, the economy tomorrow is larger, but the internal conditions also change so that the economy tomorrow is no longer a constant return to scale of the economy today. The rising population increases the total income and consumption demand, and as a result, shift out the aggregate demand curve in the economy. Meanwhile, the larger population and the higher productivity raise firms' production capacity and shift out the aggregate supply curve. The economy tomorrow is the outcome of the shifts of both curves, with a larger quantity of outputs and an uncertain change in price level. Similarly, the rising population shifts both the labor supply and demand curve outwards and changing the capital to labor ratio of firms given changes in relative rental rates and wages. When imposing a tax hike to the economy tomorrow, higher productivity indicates that losing one worker is associated with a larger output loss, but the changes in the internal conditions as discussed here may result in a smaller reduction in workers in the economy tomorrow than today, making it hard to predict whether it is more costly to collect the same value of fund in the economy tomorrow, but instead to rely on the simulation outputs produced in the CGE model under the optimal control problem listed in equation (3.10) to (3.11).

Regarding the assumption that the cost of taxation in period t only depends on the tax rate and total taxable income in that period, the dynamic setup of the CGE model here relaxes it in the following sense: The rise in sales tax reduces economic activities and the rate of return on capital investment. As a result, the new investment will decrease and the total amount of capital stock for the next period is also reduced. With a slower rate of capital accumulation, economic growth over time is limited. This lagged impact that carries to the next period makes it more costly to raise the tax earlier on in a certain planning horizon.

The results of the simulation suggest that the cost of raising the same amount of money, measured in present values, is smaller in the future. Hence, when the cost function takes the form in Figure 3.2 panel (a), where it is more efficient to collect the funding in one year, the optimal solution is to collect it in the year before the expected rise in government expenditure. But when the cost function takes the form in Figure 3.2 panel (b), which indicates that an optimal solution should be the point when the marginal cost of taxation is the same across all the periods, the situation is more complicated. Coupled with the delayed impact of tax hikes into the future, the load of the fund-collection focuses much more on the later periods to avoid the continuing slower growth over time. This is the optimal path in Figure 3.1 panel (c): within a 10-period planning horizon, the tax hikes from period 1 to 7 are zero and from period 8 to 10, the intensity of the tax hikes is getting stronger to equalize the marginal costs in the three periods.

Finally, if the tax hike only happens in the last period for any planning horizons, the lagged impact beyond the planning horizon is not considered. I then run additional simulations to look at this for 10 periods beyond, that is, even if the tax hike happens in the last period of the planning horizon which is period 10, its lagged impacts in periods 11 to 20 are also considered. For a high LSE, the optimal path of the tax hikes is the same as before. For the low LSE, the optimal path is similar, and Figure 3.3 below compares the new paths with the previous one.

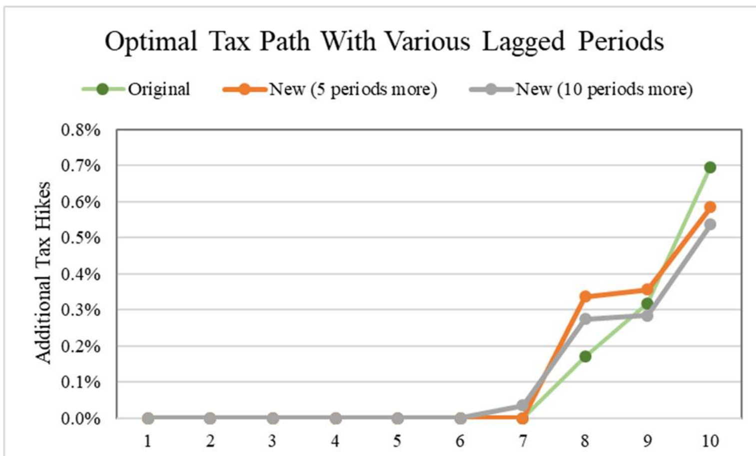

Figure 3.3

The green line is the original trajectory of the optimal tax path at the low level of LSE, the orange line is the optimal tax hikes when the regional planner considers 5 more periods after the planning horizon to capture the lagged impact, and the grey line is for 10 additional periods. When taking the economic outcomes from the periods beyond the current planning horizon (i.e. period 11 and on) into account, the comparative advantage of the tax hikes in the 10th period is diminishing. As a result, the government wants to re-allocate its tax burden by shifting some of the tax hikes to earlier periods (i.e. period 9, 8, or 7) in the planning horizon. Comparing the orange line versus the green line, the more periods beyond the planning horizon are considered (from 5 periods to 10 periods), the more tax hikes will be imposed on earlier periods in the planning horizon.

The optimal path of the tax hikes will become flattered as the regional planners become more concerned with the economic development in the long run.

The results in Figure 3.3 can also be viewed as an application to the idea of the time-consistency brought by Lucas and Stokey (1983). Time consistency means that the policy commitment carried out today is sufficient to induce the successor government to continue. According to Afonso (2014), the average length of service in local governments is about 7 to 10 years. Then the optimal paths illustrated in Figure 3.3 to include 5 or 10 additional periods besides the planning horizon become closer to a time-consistent policy that would bound the successor governments to keep this policy going.

3.5 Conclusion

In this chapter, a CGE model for a local region (Shelby County, TN) is used to discover the optimal path of tax hikes overtime in preparing for the expected rise in government expenditures in the short run. The consumer utility maximization and firm profit maximization are in the neoclassical tradition. What's more, interregional migration is considered when tax hikes change the economic conditions and job availability locally. Under normal growth, the economy grows and becomes more efficient across periods. The regional planner then chooses the proper trajectory of tax hikes within a certain planning horizon to minimize the cost of tax hikes to the economy, meanwhile making sure the target amount of funding is collected at the end of the planning period.

The simulation results and the robustness check suggested that the optimal trajectory of tax hikes depends on the elasticities of labor supply to real wages and whether the regional planner will take future periods or the periods beyond the planning horizon and for how long. In particular, when the labor supply elasticity is high, the optimal way to collect the fund is to impose the tax hikes in the last period of the planning horizon, but if the labor supply elasticity is low, the tax hikes should be spread out in different periods with more weight on later periods. The fact that tax hikes in the current period have a lagged impact in the future period through a slower rate of capital accumulation favors the optimal tax hikes to be imposed later. Also, as the size of the economy is bigger, it became less costly to collect the same amount of the fund, or the relative impact of tax hikes is weaker.

Another result found in this chapter is that, due to the lagged impact of tax hikes in the future, whether the regional planner cares about the future and to what extent is also important for the optimal path of taxes. The longer the regional planner cares about the future, the more weight should be put on the earlier periods in its contribution to the total target amount of the funding, at least in the case when the labor supply elasticity is low. Since the target of this chapter is to look at the optimal tax path for the short run, future studies could also extend it to a medium or long run until the economy fully goes back to the path where it should be, had the tax hikes never happened.

The results of this chapter have two implications. The empirical estimates for the labor supply elasticities vary. Cutler *et* al. (2018) summarized that while microeconomic approaches estimated the elasticity is less than 1, macroeconomic approaches found that this number is between 2.5 to 4.0. The results of this chapter pointed out the importance of labor supply elasticities in optimal tax path over time, and a possible new front of empirical research could focus on using regional-level data as a starting point to estimate the labor supply elasticity.

The second implication is how the planners should treat the economic outcomes in the future or the welfare of future generations. As noted by Erosa and Gervais (2002), when previous studies found that the optimal capital income tax should be as large as possible in the short-run and zero in the long-run, it is built in an environment that the individuals who bear the burden of taxation right now are the same individuals who enjoy the benefit in the future, or the benefit of the next generations is the under the interest of the current generations. If this is no longer the case, the zero capital income taxation is only valid under a certain type of consumer preferences. This is also true for the analysis here, which implies that future studies should also distinguish the notion of the short-run and long-run in making policy suggestions.

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Appendix A: Chapter 1 Additional Content

Table A.1. Total Wages and Number of Workers by Household Groups

	Total Wages (in Millions)			Number of workers		
	L1	L2	L3	L1	L2	L3
HH1A	48.70	0.00	0.00	7054	0	0
HH2A	28.32	177.90	0.00	3513	8293	0
HH3A	17.26	180.11	209.16	2590	7101	4677
HH4A	4.96	64.37	344.54	761	2754	6502
HH5A	4.14	7.37	754.33	706	330	5713
HH1B	35.36	2.63	0.00	4479	123	0
HH2B	43.21	154.13	0.00	4958	7243	0
HH3B	29.59	156.99	191.87	3217	5652	4075
HH4B	13.78	85.65	374.98	1919	3469	6510
HH5B	0.64	22.87	731.41	66	890	6339
HH1C	15.79	0.00	0.00	2021	0	0
HH2C	17.20	133.34	0.00	2280	6195	0
HH3C	30.53	185.12	190.62	4241	7368	4225
HH4C	13.43	97.68	247.02	1351	3710	4604
HH5C	2.08	13.58	268.39	394	532	2596
HH1D	4.96	0.00	0.00	915	0	0
HH2D	12.09	53.88	0.00	1768	2629	0
HH3D	20.86	167.80	116.35	2568	6168	2486
HH4D	6.57	89.62	580.43	887	3605	10215
HH5D	8.59	52.70	760.76	1591	2052	9004
HH1E	6.10	0.00	0.00	920	0	0
HH2E	21.06	88.86	0.00	2430	4048	0
HH3E	14.50	145.59	233.46	2701	6101	4881
HH4E	13.06	106.14	656.15	1790	4239	10672
HH5E	1.55	55.18	921.50	329	2259	10054
HH1F	1.80	0.00	0.00	161	0	0
HH2F	1.54	52.42	0.00	304	2442	0
HH3F	14.26	126.04	277.46	2382	4436	5615
HH4F	29.86	125.29	634.55	4793	4674	10549
HH5F	16.59	55.94	2158.99	2977	2424	17843

Table A.1. Total Wages and Number of Workers by Household Groups Continued…

	Total Wages (in Millions)			Number of workers		
	L1	L2	L3	L1	L2	L3
HH1G	25.65	0.00	0.00	2716	0	0
HH2G	31.28	185.73	0.00	3614	8697	0
HH3G	25.05	177.16	203.21	3237	7110	4482
HH4G	2.79	137.27	267.47	565	5039	4705
HH5G	5.26	11.67	332.60	673	498	2825
HH1H	28.80	0.00	0.00	3222	0	0
HH2H	16.55	124.30	0.00	2590	5347	0
HH3H	19.45	161.68	141.79	1923	6909	3185
HH4H	7.95	38.12	179.36	948	1343	3634
HH5H	4.75	19.60	144.26	476	763	1453

Table A.2 Crosswalk between Sectors and NAICS

Commercial sector	NAICS industry	NAICS code
Goods-Producing Industries (Goods sector)	Agriculture, Forestry, Fishing, and Hunting	11
	Mining, Quarrying, and Oil and Gas Extraction	21
	Construction	23
	Manufacturing	31-33
Trade, Transportation, and Utilities (Trade sector)	Wholesale Trade	42
	Retail Trade	44-45
	Transportation and Warehousing	48-49
	Utilities	22
Other sectors	Information	51
	Finance and Insurance	52
	Real Estate and Rental and Leasing	53
	Professional, Scientific, and Technical Services	54
	Management of Companies and Enterprises	55
	Administrative and Support and Waste Management and Remediation Services	56
	Educational Services	61
	Health Care and Social Assistance	62
	Arts, Entertainment, and Recreation	71
	Accommodation and Food Services	72
	Other Services	81

Table A.3 Capital Stock Reduction as A Percent of Initial Value (Production Sector)

Commercial sectors	PUMA regions	Capital stock reduction (%)
Goods-Producing Industries (Goods sector)	A	29.40%
	B	25.30%
	C	20.20%
	D	28.60%
	E	11.60%
	F	11.30%
	G	0.00%
	H	31.90%
Trade, Transportation, and Utilities (Trade sector)	A	44.90%
	B	33.60%
	C	35.40%
	D	32.60%
	E	23.60%
	F	17.30%
	G	25.50%
	H	31.90%
Other sectors	A	44.80%
	B	35.00%
	C	33.00%
	D	31.10%
	E	12.40%
	F	19.30%
	G	16.70%
	H	26.40%

Table A.4 Capital Stock Reduction as A Percent of Initial Value (Housing Sector)

Residential Sectors	PUMA regions	Capital stock reduction (%)
HS1 (Single Family Homes that are below the median market value)	A	45%
	B	42%
	C	45%
	D	44%
	E	38%
	F	33%
	G	39%
	H	41%
HS2 (Single Family Homes that are above the median market value)	A	44%
	B	40%
	C	41%
	D	41%
	E	36%
	F	33%
	G	37%
	H	40%
HS3 (Rental Homes)	A	47%
	B	45%
	C	46%
	D	44%
	E	34%
	F	29%
	G	34%
	H	43%

Table A.5 Percent Increase in Travel Time for Each PUMA Pair

PUMA	A	B	C	D	E	F	G	H
A	0%	—	—	—	—	—	—	—
B	3%	0%	—	—	—	—	—	—
C	12%	18%	0%	—	—	—	—	—
D	12%	50%	2%	0%	—	—	—	—
E	12%	20%	12%	4%	0%	—	—	—
F	5%	5%	11%	16%	4%	0%	—	—
G	10%	18%	22%	19%	8%	6%	0%	—
H	8%	5%	14%	14%	8%	5%	4%	0%

Table A.6 Household Income Loss by Labor and Capital Income

PUMA regions	Household Income Loss	From Labor Income	From Capital Income
A	-9.20%	-7.52%	-1.68%
B	-4.37%	-4.48%	0.11%
C	-4.95%	-4.81%	-0.14%
D	-3.00%	-3.70%	0.70%
E	0.30%	-1.45%	1.75%
F	3.57%	0.90%	2.67%
G	-1.34%	-2.22%	0.88%
H	-5.70%	-4.87%	-0.83%

Table A.7 Weighted share of labor and total factor productivity by region

PUMA regions	Share of Labor (α_L)	Total Factor Productivity (η_j^s)
A	0.748	0.408
B	0.798	0.460
C	0.837	0.421
D	0.844	0.353
E	0.876	0.411
F	0.898	0.381
G	0.870	0.441
H	0.856	0.348

Appendix B: Chapter 2 Additional Content

Table B.1 Crosswalk from Katrina Damaged County/Parish to Migration PUMA region

County	State	County FIPS Code	Migration PUMA	Weight
Jefferson	Louisiana	22051	1900	1
Orleans	Louisiana	22071	1800	1
Plaquemines	Louisiana	22075	1900	1
St Bernard	Louisiana	22087	1900	1
St Tammany	Louisiana	22103	2000	0.927
Hancock	Mississippi	28045	2100	0.827
Harrison	Mississippi	28047	2200	1
Jackson	Mississippi	28059	2300	1

Note: The weight means that to what extent the migration PUMA region overlaps with the county/parish boundary.

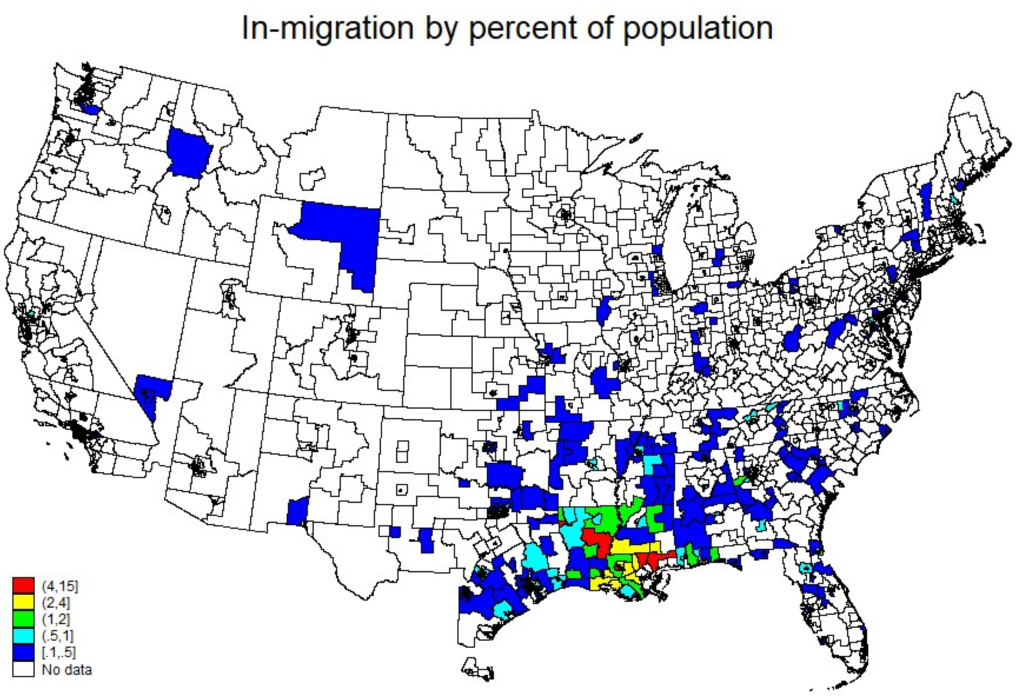

Figure B.1 Inflow of Evacuees Received by PUMA region by Intensity

Note: Only the PUMA regions whose excess inflow is larger than 0.1 percent are presented in this map, with a total of about 360 PUMA regions.

Table B.2 Local-base Industries and the Corresponding NAICS

Industry Name	NAICS
Natural gas distribution	2212P
Sewage treatment facilities	22132
Construction	23
Retail bakeries	311811
Motor vehicles, parts and supplies	4231
Lumber and other construction materials	4233
Hardware, plumbing and heating equipment, and supplies	4237
Recyclable material	42393
Groceries and related products	4244
Automobile dealers	4411
Other motor vehicle dealers	4412
Auto parts, accessories, and tire stores	4413
Furniture and home furnishings stores	442
Household appliance stores	443111
Radio, tv, and computer stores	4431M
Hardware stores	44413
Building material and supplies dealers	4441Z
Lawn and garden equipment and supplies stores	4442
Grocery stores	4451
Specialty food stores	4452
Beer, wine, and liquor stores	4453
Pharmacies and drug stores	44611
Health and personal care, except drug, stores	446Z
Gasoline stations	447
Shoe stores	44821
Jewelry, luggage, and leather goods stores	4483
Clothing and accessories, except shoe, stores	448ZM
Sewing, needlework and piece goods stores	45113
Book stores and news dealers	45121
Music stores	451M
Department stores	45211
Miscellaneous general merchandise stores	4529
Florists	4531
Office supplies and stationary stores	45321
Gift, novelty, and souvenir shops	45322
Used merchandise stores	4533
Miscellaneous stores	4539
Vending machine operators	4542
Fuel dealers	45431
Other direct selling establishments	45439
Truck transportation	484
Bus service and urban transit	485M
Couriers and messengers	492

Table B.2 Local-base Industries and the Corresponding NAICS continued…

Industry Name	NAICS
Sporting goods, camera, and hobby and toy stores	4M
Not specified trade	4MS
Newspaper publishers	51111
Wired telecommunications carriers	5171
Radio and television broadcasting and cable	51M
Insurance carriers and related activities	524
Banking and related activities	52M1
Real estate	531
Automotive equipment rental and leasing	5321
Videotape and disk rental	53223
Other consumer goods rental	532M
Legal services	5411
Accounting, tax preparation, bookkeeping and payroll services	5412
Veterinary services	54194
Employment services	5613
Business support services	5614
Investigation and security services	5616
Landscaping services	56173
Services to buildings and dwellings	5617Z
Waste management and remediation services	562
Elementary and secondary schools	6111
Offices of physicians	6211
Offices of dentists	6212
Office of chiropractors	62131
Offices of optometrists	62132
Offices of other health practitioners	6213ZM
Outpatient care centers	6214
Home health care services	6216
Other health care services	621M
Hospitals	622
Nursing care facilities	6231
Residential care facilities, without nursing	623M
Individual and family services	6241
Community food and housing, and emergency services	6242
Vocational rehabilitation services	6243
Child day care services	6244
Bowling centers	71395
Traveler accommodation	7211
Drinking places, alcohol beverages	7224
Restaurants and other food services	722Z
Car washes	811192
Automotive repair and maintenance	8111Z
Electronic and precision equipment repair and maintenance	8112

Table B.2 Local-base Industries and the Corresponding NAICS continued…

Industry Name	NAICS
Commercial and industrial machinery and equipment repair and maintenance	8113
Footwear and leather goods repair	81143
Personal and household goods repair and maintenance	8114Z
Barbershops	812111
Beauty salons	812112
Nail salons and other personal care services	8121M
Funeral homes, cemeteries and crematories	8122
Dry-cleaning and laundry services	8123
Other personal services	8129
Religious organizations	8131
Labor unions	81393
Business, professional, political and similar organizations	8139Z
Civic, social, advocacy organizations and grantmaking and giving services	813M
Private households	814

Table B.3 Export-base Industries and the Corresponding NAICS

Industry Name	NAICS
Crop production	111
Animal production	112
Logging	1133
Forestry except logging	113M
Fishing, hunting, and trapping	114
Support activities for agriculture and forestry	115
Oil and gas extraction	211
Coal mining	2121
Metal ore mining	2122
Nonmetallic mineral mining and quarrying	2123
Support activities for mining	213
Electric power generation, transmission and distribution	2211P
Water, steam, air conditioning, and irrigation systems	2213M
Electric and gas, and other combinations	221MP
Not specified utilities	22S
Sugar and confectionery products	3113
Fruit and vegetable preserving and specialty foods	3114
Dairy products	3115
Animal slaughtering and processing	3116
Bakeries, except retail	3118Z
Animal food, grain and oilseed milling	311M1
Seafood and other miscellaneous foods, n.e.c.	311M2
Not specified food industries	311S
Beverage	3121
Tobacco	3122

Table B.3 Export-base Industries and the Corresponding NAICS continued…

Industry Name	NAICS
Fiber, yarn, and thread mills	3131
Fabric mills, except knitting	3132Z
Textile and fabric finishing and coating mills	3133
Carpets and rugs	31411
Textile product mills except carpets and rugs	314Z
Cut and sew apparel	3152
Apparel accessories and other apparel	3159
Footwear	3162
Leather tanning and products, except footwear	316M
Knitting mills	31M
Sawmills and wood preservation	3211
Veneer, plywood, and engineered wood products	3212
Prefabricated wood buildings and mobile homes	32199M
Miscellaneous wood products	3219ZM
Pulp, paper, and paperboard mills	3221
Paperboard containers and boxes	32221
Miscellaneous paper and pulp products	3222M
Printing and related support activities	323
Petroleum refining	32411
Miscellaneous petroleum and coal products	3241M
Resin, synthetic rubber and fibers, and filaments	3252
Agricultural chemicals	3253
Pharmaceuticals and medicines	3254
Paint, coating, and adhesives	3255
Soap, cleaning compound, and cosmetics	3256
Industrial and miscellaneous chemicals	325M
Plastics products	3261
Tires	32621
Rubber products, except tires	3262M
Pottery, ceramics, and related products	32711
Structural clay products	32712
Glass and glass products	3272
Miscellaneous nonmetallic mineral products	3279
Cement, concrete, lime, and gypsum products	327M
Aluminum production and processing	3313
Nonferrous metal, except aluminum, production and processing	3314
Foundries	3315
Iron and steel mills and steel products	331M
Metal forgings and stampings	3321
Cutlery and hand tools	3322
Machine shops; turned products; screws, nuts and bolts	3327
Coating, engraving, heat treating and allied activities	3328
Ordnance	33299M

Table B.3 Export-base Industries and the Corresponding NAICS continued…

Industry Name	NAICS
Structural metals, and tank and shipping containers	332M
Agricultural implements	33311
Construction mining and oil field machinery	3331M
Commercial and service industry machinery	3333
Metalworking machinery	3335
Engines, turbines, and power transmission equipment	3336
Machinery, n.e.c.	333M
Not specified machinery	333S
Computer and peripheral equipment	3341
Navigational, measuring, electromedical, and control instruments	3345
Communications, audio, and video equipment	334M1
Electronic components and products, n.e.c.	334M2
Household appliances	3352
Electrical machinery, equipment, and supplies, n.e.c.	335M
Aircraft and parts	33641M1
Aerospace products and parts	33641M2
Railroad rolling stock	3365
Ship and boat building	3366
Other transportation equipment	3369
Motor vehicles and motor vehicle equipment	336M
Furniture and fixtures	337
Medical equipment and supplies	3391
Toys, amusement, and sporting goods	3399M
Miscellaneous manufacturing, n.e.c.	3399ZM
Not specified metal industries	33MS
Not specified industries	3MS
Furniture and home furnishing	4232
Professional and commercial equipment and supplies	4234
Metals and minerals, except petroleum	4235
Electrical goods	4236
Machinery, equipment, and supplies	4238
Miscellaneous durable goods	4239Z
Paper and paper products	4241
Apparel, fabrics, and notions	4243
Farm product raw materials	4245
Petroleum and petroleum products	4247
Alcoholic beverages	4248
Farm supplies	42491
Miscellaneous nondurable goods	4249Z
Drugs, sundries, and chemical and allied products	424M
Not specified trade	42S
Electronic auctions	454112
Air transportation	481

Table B.3 Export-base Industries and the Corresponding NAICS continued…

Industry Name	NAICS
Rail transportation	482
Water transportation	483
Taxi and limousine service	4853
Pipeline transportation	486
Scenic and sightseeing transportation	487
Services incidental to transportation	488
Postal service	491
Warehousing and storage	493
Publishing, except newspapers and software	5111Z
Software publishing	5112
Motion pictures and video industries	5121
Sound recording industries	5122
Other telecommunication services	517Z
Libraries and archives	51912
Other information services	5191Z
Data processing services	5142
Savings institutions, including credit unions	5221M
Non-depository credit and related activities	522M
Securities, commodities, funds, trusts, and other financial investments	52M2
Commercial, industrial, and other intangible assets rental and leasing	53M
Architectural, engineering, and related services	5413
Specialized design services	5414
Computer systems design and related services	5415
Management, scientific and technical consulting services	5416
Scientific research and development services	5417
Advertising and related services	5418
Other professional, scientific and technical services	5419Z
Management of companies and enterprises	551
Travel arrangements and reservation services	5615
Other administrative, and other support services	561M
Colleges, including junior colleges, and universities	611M1
Business, technical, and trade schools and training	611M2
Other schools, instruction and educational services	611M3
Independent artists, performing arts, spectator sports and related industries	711
Museums, art galleries, historical sites, and similar institutions	712
Other amusement, gambling, and recreation industries	713Z
Recreational vehicle parks and camps, and rooming and boarding houses	721M

Table B.4 Impacts by year for High-skill Export-base Workers

VARIABLES	(1) 0.4~0.9%
$Treat_i \times Year_{2005}$	0.194
	(0.407)
$Treat_i \times Year_{2006}$	0.201
	(0.407)
$Treat_i \times Year_{2007}$	1.086***
	(0.407)
$Treat_i \times Year_{2008}$	1.127***
	(0.407)
Observations	7,865
Number of PUMAs	1,574
R-squared	0.449
Controls	YES
County FE	YES
Cluster SE	YES
Time FE	YES

Notes: Standard errors in parentheses, clustered at the state level. Time and PUMA fixed effects included. *** p<0.01, ** p<0.05, * p<0.1. Column (1) is the regression results using equation (2.4) but restricting regions in which Katrina evacuees is between 0.4 to 0.9 percent of their population, and the control group are regions that didn't receive the Katrina evacuees.