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Three essays on modeling economic and fiscal change for communities under disequilibrium following natural disasters

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THREE ESSAYS ON MODELING ECONOMIC AND FISCAL CHANGE FOR COMMUNITIES UNDER DISEQUILIBRIUM FOLLOWING NATURAL DISASTERS

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DEDICATION

This dissertation is dedicated to my late mother, Shanta Adhikari, who always encouraged and supported me in every deeds of my life.

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ABSTRACT

Regional economists and policy makers are interested in forecasting economic changes that are likely to take place at local and state levels after exogenous shocks to an economy; that is, create disequilibrium conditions in terms of supply and demand. Impacts of such shocks could be observed at the level of employment, unemployment, commuting patterns, assessed property values, property and sales taxes and local level of expenditures in several categories.

The objective of the first essay was to model the employment change decompositions of different effects in two major industries using a shift share analysis technique in context of Louisiana parishes before and after hurricanes Katrina and Rita. A correlation analysis test was performed to identify whether a distinct regional industry effect can be identified separately from a sub-region local effect in shift-share analysis. Results from the test indicated that the distinctiveness of spatial neighboring region effect and the localized effect was evaluated and they were two separate effects.

The objective of my second essay was to model the Louisiana labor market for purposes of improving forecasting accuracy in regional economic modeling. Specifically, this was performed through the use of alternative regional econometric estimators in Community Policy Analysis System (COMPAS) models for Louisiana. Results suggested that panel data models increased forecasting performance compared to other models in the study, if measured in terms of traditional error measures. However, the mean comparison test suggested that panel models do not always display statistical improvement in forecasting.

The third and final objective of my dissertation was to evaluate if a fiscal module under the COMPAS framework (an equilibrium model) fits better under a disequilibrium economic environment. I found that both a simple naïve model with one year lagged expenditure as well as

a lagged expenditure model with revenue capacity variables significantly increased forecasting performance relative to the traditional supply/demand equilibrium model of the public sector. I also found weak evidence suggesting that in cases where the equilibrium model is used in a cross-sectional setting, quantile regression may improve forecasting performance given the attribute of lumpy public goods.

CHAPTER 1

INTRODUCTION

1.1 Introduction and Background Information

Pooling spatial data across different regions and localities to examine the impact of various regional drivers and shocks is a common phenomenon in regional economics (Ali, Partridge and Olfert, 2007). The prime objective of my research is to develop different frameworks in modeling the economic and fiscal change for communities that operate under disequilibrium conditions after exogenous shocks (e.g. natural disasters) for improving accuracy in regional economic modeling. The focus is on a basic theme of regional economics: spatial location matters. Regional scientists assume both the explanatory variables (X) and marginal responses to changes in explanatory variables (β) can vary across space (Ali, Partridge and Olfert, 2007). Any changes in a local community might not only result from certain shocks within the region, but also could be the impacts from the changes in neighboring/contiguous regions. Unfortunately, in many cases, regional scientists fail to take into account this concept of spatial interaction into their research because policy makers that use their research are interested in "one size fits all" policies that models with a multitude of regional parameters fails to address.

In these three essays, different strategies in modeling the economic (employment and labor market) and fiscal changes that takes place in all communities of Louisiana after a natural disaster are developed. In order to model these changes in a disequilibrium environment for improving accuracy in regional economic modeling, three essays in this dissertation will be concentrated on evaluating the impacts and their causal effects. In the case of shift-share analysis, I am modeling the decomposition of changes in an economy that would alter the employment in any sector following natural disasters through the incorporation of neighboring regional effects. I also check the validity of distinctiveness of decompositions of different effects that were earlier proposed by several researchers. In the case of Community Policy Analysis

System (COMPAS) labor force and fiscal modules (Johnson, Otto and Deller, 2006), I am modeling the equilibrium concept of supply and demand in the context of labor market and public service sectors through parametric models such as quantile regression, cross sectional ordinary least squares (OLS), three stage least squares (3sls), and panel data estimators that may increase forecasting performance. In addition, I am comparing alternative non-market models for forecasting fiscal sector changes consistent with a bureaucratic model of public sector decision making.

Regional economists and policy makers are interested in forecasting economic changes that are likely to take place at local and state levels after exogenous shocks to an economy; that is, create disequilibrium conditions in terms of supply and demand. Impacts of such shocks could be observed at the level of employment, unemployment, commuting patterns, assessed property values, property and sales taxes and local level of expenditures in several categories. They need robust analytical tools that can address these changes and develop policies based on their results to maintain an equilibrium condition.

1.2 Regional Economic Modeling: Issues and Challenges

Alternatives to fiscal models based on equilibrium conditions have rarely been framed conceptually for local governments. Concepts such as disequilibrium modeling have been incorporated more often in private sector market modeling.[1] Disequilibrium conditions might be created in several ways, some of them being but not limited to, a firm exhibiting increasing returns to scale (Deller, Chicoine and Walzer, 1988), externalities in either consumption or the

[1] See Dudley and Montmarquette (1988) for detailed disequilibrium model for private markets. They implemented maximum likelihood estimation procedure using cross sectional data for the analysis.

production side (Johnson, Otto and Deller, 2006), and non-rivalrous or non-excludable nature of public goods and services provided by local governments (Samuelson, 1955; Partridge, 2010). Some of the assumptions in the idealized world could be made on the basis of perfect competition, utility and profit maximizing behavior, firms exhibiting constant returns to scale, and achievement of pareto optimality, among many others. When any complexities or externalities of the real world are introduced, these assumptions are less likely to hold and there is a break in supply demand equilibrium framework. Most of the regional modelers in the past considered only the demand side (consumer's perspective) of the story and assumed equilibrium (Bahl, Jordan and Martinez, 1990). They did not consider the fact that the equilibrium condition might not hold with sizeable exogenous shocks to an economy. This study provides a descriptive analysis of changes that could occur by exogenous shocks (a natural disaster in our case) in an economy which can be argued to be out of supply demand equilibrium. I tend to analyze the growth decomposition, their efficacy, and seek the best possible alternatives for modeling the local government labor market and fiscal sectors in a disequilibrium condition following natural disasters, primarily based on two different types of regional models described hereafter.

1.2.1 Shift Share Analysis

Any exogenous shock to an economy might create short or long term disequilibrium, thus hindering the smooth performance of supply-demand balance chain. With various exogenous demand shocks, the comparative advantage a region has over another region may vary due to a number of factors. If a region possesses some industry sector, for example, the food services sector, it could be driven by a combination of local demand from local residents as well as export demand from tourists. If any exogenous shock hits the region (such as a natural disaster), one would expect the timing of growth in this industry to lag given the slow re-population of the historical population base necessary to support minimum efficient scale of food service places (restaurants) in the region. Further, its support establishments – those inter-connected sectors both upstream and downstream – are also highly dependent on the export base of tourism population. Hence, we might expect in a worst case scenario the loss of market share because of an exogenous natural disaster to be so great as to move the regional economy beyond a "sustain point" as described by Fujita et al (1998) such that the previous agglomeration effects in the tourism industry are no longer attainable. At best, we might see local establishments in the food services sector to temporarily move to other neighboring regions where the local population base has relocated until that population locates back to the urban core and the population base reaches a level to sustain food service establishments at a historically viable scale.

Regional modelers are interested in figuring out the changes (level and causes) that take place after any external shock. They tend to study these changes by decomposing several effects which provide a better understanding of the causal relationship. When evaluating shift share analysis, although traditional (also known as classical) shift share decomposes a region's sectoral growth for a given period of time into three effects: a national growth effect, an industry (business) mix effect, and a competitive (localized) effect, the model is criticized heavily by different authors in many aspects. One of the criticisms of the traditional shift-share methods is the temporal nature of the technique (Yasin, Alavi, Sobral, and Lisboa, 2004; Bariff and Iii, 1988). This means that the shift share technique does not account for the adjustments to the changes that might occur during other years within that pre-specified interval. The traditional shift-share model has also been criticized on the grounds that it does not take into account the interaction effect between the industry-mix effect and the competitive effect (Toh, Khan and Lim, 2004; Loveridge and Selting, 1998). A homothetic model was developed by Esteban-

Marquillas (1972) to capture the interaction effect, which essentially adds a fourth component called the allocation effect. The recognition of spatial structure is however, missing in the earlier analyses. This is a logical consequence of the fact that regions are spatial sub-units within a country. The general idea here is that the decomposed effects are not spatially independent; the performance of surrounding regions, of regions with similar structures, or of regions that are dominant trading partners, will all have an influence on the growth performance of a particular region (Nazara and Hewings, 2004).

In order to check the dependency of spatial decompositions, the distinctiveness of a regional industry effect can be identified separately from a sub-region local effect in shift-share analysis. Policy makers and regional scientists might be interested in comparing regional versus sub-regional localized effects to generate new policies to address the impacts caused by exogenous shocks in an economy. This issue could be addressed by incorporating neighboring region effects through a spatial weight matrix to the classical shift share methodology in place of the typical national industry mix effect. The spatial shift share analysis attempts to overcome some of the potential shortcomings of classical shift-share analysis; in particular, that the local competitive effect captures some of the effect that is truly a result of growth in the neighboring region's industry growth. Further, the spatial shift share analysis can be shown to be an effective tool for regional scientists and community planners interested in a bivariate presentation of economic change.

1.2.2 Community Policy Analysis Modeling

Community Policy Analysis System (COMPAS) modeling is an effective tool to estimate the fiscal impacts of different industries in a region (Scott and Johnson, 1997). Input output models such as IMPLAN (Fannin et al., 2008) are used to determine the employment impacts of commodity final demand in a region The COMPAS model uses employment change as an exogenous driver of labor market and fiscal (public revenue and expenditure) change. The model includes a system of cross sectional econometrically estimated equations estimated for rural communities and cities in respective states (Johnson, Otto and Deller, 2006). The overview of Louisiana Community Impact model is demonstrated in a flow diagram as follows:

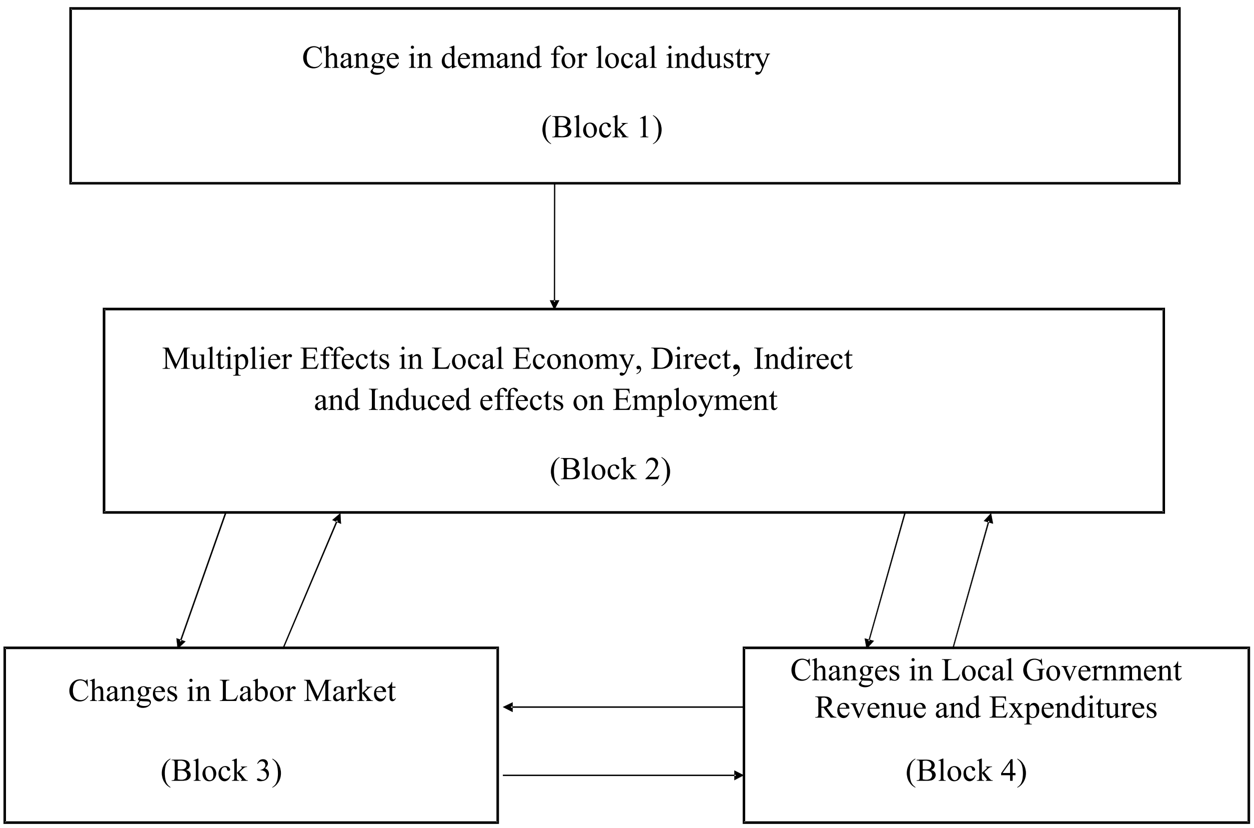

Figure 1.1. A COMPAS modeling approach

(Fannin et al., 2008)

The indicators used for the COMPAS model are based on theory, the availability of data and output needs of targeted clients of the model. An example of indicators suggested by Johnson et al. is presented in the table below:

Table 1.1. Suggested Indicators for COMPAS Modeling

Economic	Demographic	Fiscal	Social	Environmental
Employment	Population	Expenditures	Poverty Rate	Water Quality
Unemployment	Labor Force Participation	Revenues	Gini Coefficient	Air Quality
Per Capita Income	School Enrollment	Net Public Service Benefits	Social Capital	Land Use
Regional Product			Health Status	
Retail Sales			Housing Quality	

A median voter concept of modeling, based on the early voter theory of Black (1958), is often introduced to identify the level of public goods and services to be delivered. This median voter theory was used extensively to model the local public sector since the service demands of median voters were addressed by the political parties in order to carry elections. Under situations of majority rule, a median voter model has been used in many instances to analyze the fiscal behavior of a region. This approach of the median voter[2] was initially developed by Barr and Davis (1963), but then was applied by several scholars to replace the then popular ad hoc expenditure model. Median income levels, population, tax prices of public goods, and consumer's tastes and preferences at local level are assumed to determine the level of demand for local public goods and services. Any government spending far from the median will be driven away from office by an opposition that proposes an expenditure level closer to the

[2] See Shaffer et al (2004) for detailed explanation for median voter model, where the author has compared similarity between median voter model and Hotelling model by using a beach vendor example.

demands of median voter. Early voter theory (Black, 1958) is a basis for the median voter model and it assumes that voters are evenly distributed over a political spectrum and a party that acts towards the benefits of median voter's preferences can easily win the election. In other words, bureaucrats are forced to allocate the desired level of spending based on the median voters' preferences.

Although the stylized median voter model was built on an empirically tractable approach, there are a few limitations which could hinder the effectiveness of the model. Some of the factors that limit the supply demand equilibrium in the traditional conceptual framework are, but not limited to, downward sloping supply curves, the nature of private and public goods, and the non-excludability and non-rivalrous nature of public goods. Hence, applied researchers interested in providing local stakeholders valuable research tools developed an alternative framework (which will be discussed later in chapter 4) that simply attempts to forecast the movement of public expenditure between equilibrium points over time (Johnson, Otto, and Deller, 2006). At the same time, there are additional conceptual frameworks that might be considered more applicable during periods of disequilibrium with alternative empirical models. An empirical application of one of these alternative conceptual frameworks represents one of the items addressed in the proposed research presented in the next section.

1.3 Contributions of This Study

One of the major contributions in this dissertation will be the application of modern shift share methodologies to understand the distinctiveness of regional industry effects. I address this issue by incorporating neighboring region effects through a spatial weight matrix to the classical shift share methodology in place of the typical national industry mix effect. I show how using this approach provides additional information for policy makers comparing regional versus sub-regional localized effects. No study that I am aware has attempted to test whether or not the neighboring-region effect represents a truly distinct and practically interpretable effect from the traditional model's competitive effect. In Loveridge and Selting (1998), they tested a number of variations of traditional shift share at the time including the Esteban-Marquillas (EM) family of shift share models. These augmented models were developed to eliminate the proposed problem that the traditional competitive effect was actually measuring part of the industry mix effect. Loveridge and Selting used a correlation analysis to show that the EM family of models did reduce the correlation of the industry mix and competitive effect from the traditional shift share model, but the solution, the breakup of the competitive effect into a traditional competitive effect component and homothetic (industry proportion) competitive effect component, resulted in an almost perfect correlation of these components rendering their separate interpretative value meaningless. It should be noted that some of the local competitive effect explained in the traditional shift share model is actually explained by neighboring region effects. How might this be tested to know if the neighboring region effect is truly a distinct effect from the local competitive effect? I present an approach to testing this distinction in the second chapter.

In addition to shift share analysis, another major contribution is the implementation of COMPAS models for modeling the labor force and fiscal module of Louisiana. Much of the previous research in regional science combining labor market and fiscal modeling is focused on determining economic impacts and changes in regional economic activities using a conjoined input-output (I-O) and econometric model (Stevens et al, 1981; Fannin et al., 2008; Johnson, Otto and Deller, 2006). I extend the previous research by evaluating an alternative conceptual framework for empirical modeling the local public sector. The community policy analysis network (CPAN) acknowledges two alternative conceptual frameworks for modeling public service delivery: the bureaucratic approach (Niskansen, 1971; Poole and Rosenthal, 1996) and the flypaper effect (Bailey and Connolly, 1998; Knight, 2002). I present an overview of both approaches in chapter 4 and argue for a bureaucratic approach as an alternative model that should be made more empirically tractable and evaluated as an alternative model under a disequilibrium environment. These models (bureaucratic and flypaper effect) may serve as alternatives when the restrictive assumptions of the median voter model are too great or a community is in an extended period of disequilibrium. This will be an innovative study in terms of comparing static versus dynamic characteristics of a fiscal module in COMPAS type models under a disequilibrium condition. My contribution would be the addition of dynamics in the model by incorporating the lagged dependent variable for different expenditure categories. As suggested by many researchers, I will be estimating the forecasting performance by several quantitative methods where I will be analyzing different indicators like mean error, mean square error, root mean square error and Theil's coefficients as a benchmark for comparison. To my knowledge, this study is unique in that the quantile regression approach and the dynamic panel data model is used in COMPAS type models for forecasting the performance of estimators via various quantitative techniques.

1.4 Objectives

i) Identify the distinctiveness of a regional industry effect and whether it can be identified separately from a sub-region local effect in shift-share analysis by incorporating neighboring region effects through a spatial weight matrix to the classical shift share methodology in place of the typical national industry mix effect.

ii) Model the labor force module of Louisiana for purposes of improving forecasting accuracy in regional economic modeling by using alternative regional econometric estimators in Community Policy Analysis System (COMPAS) models.

iii) Assess whether the forecasting performance of the public sector expenditure under a COMPAS fiscal module (an equilibrium model) fits reasonably well under a disequilibrium environment by introducing alternative empirical model formulations.

1.5 Outline of Dissertation

The first objective will be accomplished by the introduction of spatial shift share analysis and then comparing with the traditional (classical) approach in Chapter 2. A correlation coefficient will be developed in order to analyze the results based on the correlation of industry mix effects and neighboring region effects based on an approach by Loveridge and Selting (1998).

Growth of any spatial unit is not independent of the growth of its neighboring units. Any spatial unit may be affected (positively or negatively) by the spatial spillovers transmitted from the neighboring regions (Isard, 1960). Based on this idea, Nazara and Hewings (2004) have incorporated a spatial structure within shift share analysis and developed an extensive taxonomy of regional growth decompositions. The elements of a spatial weight matrix are non negative based on different measures such as physical contiguity (Moran, 1984; Geary, 1954), measures of distance (Molho, 1995; Fingleton, 2001; Paelinck and Nijkamp, 1975) and additional economic measures. Here, the square spatial row standardized weight matrix is used to calculate the changes in employment for different sectors and the weight matrix is selected on the basis of contiguity of parishes. The interdependence between the parishes is shown by the non zero entry in the square spatial row standardized weight matrix where each row sum equals to unity. The empirical methods are explained thoroughly in Chapter 2 of this proposal.

The second objective of this paper will be accomplished in Chapter 3 by laying out the labor force module of Louisiana where the regional input-output models are conjoined with structures representing the regional labor market. I attempt to model the labor force with both cross-sectional and panel approaches. I start with an OLS/GLS framework (baseline) where I take a single year's worth of data as performed by Johnson, Otto and Deller (2006) to estimate our labor force module. Then, I introduce the three stage least squares method as it is considered to be an efficient estimator that incorporates the cross-equation correlation into parameter estimates (Pindyck and Rubinfield, 1991). The strategy incorporated here is to choose an optimal model that maximizes forecasting performance for labor force module equations in COMPAS models. Finally, a measurement and assessment of relative performance of various estimators of labor markets in Louisiana Community Impact Models (LCIM) is performed. These issues will be addressed in Chapter 3, where I develop a model to forecast local labor markets of Louisiana using alternative procedures that are capable of increasing the performance over existing COMPAS estimators.

The final objective will be addressed in Chapter 4 by constructing a fiscal module of Louisiana and then measuring the relative performance of various estimators by quantitative methods. Most of the empirical models rely on the median voter model assumption heavily for their empirical specification and alternative conceptual frameworks offer alternative empirical formulations. The underlying assumption made is that local governments consider the demands and provide the desired level of services at the lowest possible cost. My concentration in this paper is to evaluate the Louisiana fiscal module built in the equilibrium COMPAS modeling tradition to alternative empirical formulations argued to be more consistent with a bureaucratic model under a disequilibrium environment of the period immediately following the 2005 hurricane season (including the 2008 season).

As many, I will estimate traditional OLS regressions with the COMPAS equilibrium model and compare it with panel data, three stage least squares, and a quantile regression model. Any exogenous shock in an economy changes the population base and demand conditions, and these must be accounted for modeling public services by local governments by incorporating the dynamics in the model. Local governments make decisions about the total expenditures in the fiscal year based on the spending that was made in the previous year plus the total revenues that could be collected in the current fiscal year. A panel data regression (a dynamic panel) is used in order to evaluate the impacts based on multiple years' worth of data. A lagged dependent variable will be implemented for determining the impacts of other variables in the spending behavior of local governments in different categories. This solidifies the argument that, while setting policies for next year's expenditure in any category, local governments must take into account the previous year's expenditure plus the revenue that could be extracted from the upcoming fiscal year. Besides this, a concept of quantile regression is used so that the impacts can be analyzed based on small samples (quantiles) rather than the single larger aggregate (state-wide) sample.

1.6 Summary

To summarize, I highlight the research activities that will occur in succeeding chapters. In Chapter 2, I analyze whether a distinct regional industry effect can be identified separately from a sub-region local effect in shift-share analysis. I address this issue by incorporating neighboring region effects through a spatial weight matrix to the classical shift share methodology in place of the typical national industry mix effect. I show how using this approach provides additional information for policy makers comparing regional versus sub-regional localized effects. A spatial shift share analysis is thus compared to the traditional shift share analysis to observe the precision of identifying comparative advantage and other details to the economic structural change caused by the two hurricanes to regional economies following the storm.

Following in Chapter 3, I model the labor force module with cross-sectional, three stage least squares, and panel approaches. I analyze several labor force and employment variables that could be impacted by socio economic variables such as commuting patterns, land area, unemployment, among others. I start with an OLS/GLS framework (baseline) and extend to other approaches. I then evaluate the forecasting performances of different estimators to check whether they have advantages over existing traditional COMPAS estimators by several quantitative measures to check errors.

Finally, in Chapter 4, I develop a model to check whether the local government public services model (an equilibrium model) works better under disequilibrium environment. I incorporate various techniques like a dynamic panel model (a naïve model) and a hybrid (modified naïve) model and analyze the impacts of several socio economic variables by means of simple OLS/GLS regression, panel data regression and quantile regression and apply them to the fiscal indicators of the Louisiana economy. These results will be helpful to those community modelers desiring to estimate the validity of cross-section fiscal modules for forecasting expenditures by local government units. Results from this study will also identify whether continuous (OLS and Panel) models have increased performance versus non-continuous quantile regression methods in fiscal module COMPAS approaches. I end the dissertation with a short conclusion chapter highlighting the key findings as well as reviewing opportunities for future research.

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CHAPTER 2

DISTINGUISHING REGIONAL VERSUS LOCAL COMPARATIVE ADVANTAGE THROUGH SHIFT SHARE ANALYSIS

2.1 Introduction and Background Information

The purpose of this paper is to identify whether a distinct regional industry effect can be identified separately from a sub-region local effect in shift-share analysis. I address this issue by incorporating neighboring region effects through a spatial weight matrix to the classical shift share methodology in place of the typical national industry mix effect. I show how using this approach provides additional information for policy makers comparing regional versus sub-regional localized effects.

The spatial shift share analysis attempts to overcome some of the potential shortcomings of classical shift-share analysis; in particular, that the local competitive effect captures some of the effect that is truly a result of growth in the neighboring region's industry growth. Further, the spatial shift share analysis can be shown to be an effective tool for regional scientists and community planners interested in a bivariate presentation of economic change. My results suggest that the spatial shift share model does provide a more "distinct" effect between the neighboring region and local effects than the distinctiveness between the industry mix and competitive effects in the classical model for the Mining and Food Services sectors in Louisiana.

The remainder of this paper addresses how these spatial shift share techniques can be applied to understanding these differing employment patterns over time and how they provide a more precise identification of comparative advantage from trade theory. I first begin by presenting a review of historical shift share analysis using the traditional employment metric. I then present an alternative regionalized decomposition approach using spatial weight matrices as presented by Nazara and Hewings (2004). I conclude with an empirical analysis of these novel shift share techniques to local employment data from parishes (counties) impacted by Hurricanes Katrina and Rita to test the distinctness of the regionalized effect.

2.1.1 Historical Shift-Share Analysis

In order to understand why one may see differences in the growth rates among various economic indicators between regions, shift share analysis has been historically applied by regional economists. Dunn (1960) developed this analysis as a method for determining the components explaining the variations in economic magnitudes, mainly employment (Fernandez, Menendez and Suarez, 2004). Shift share analysis is a statistical tool/technique which decomposes a region's sectoral growth for a given period of time into three effects: a national growth effect, an industry (business) mix effect, and a competitive (localized) effect. It is a useful tool to identify the varying dimensions of regional growth (Hoover, 1971).

Shift share analysis at its core is a simple variance decomposition technique. However, many regional scientists over several decades have applied the technique to analyze many classical conceptual frameworks. The most common theory argued by regional scientists to be addressed through shift share has been trade theory.

Trade theory envisions economic specialization leading to economic growth and that the regional endowments vary according to different types of resources present in a region. The theory suggests that the exchange is based on regional differences in endowments and preferences and specialization in production depending on comparative advantage (Siegel, Johnson and Alwang, 1995). In shift share analysis, the expected value of sectoral activity is determined by subtracting the national average share (G) from the industry mix share (G_i), (G_i-G). The local share then determines the basis of comparative advantage which could be obtained by the differences between the expected and observed level of sectoral activity (Andrikopoulos et al., 1990; Keil 1992). While studying the decomposition of growth, comparisons are made on the basis of national average growth, industry mix growth and localized growth. Growth in any sector of an economy might result from various rapidly growing sectors or by gaining market share in slowly growing sectors if the local area has a comparative advantage (Siegel, Johnson and Alwang, 1995). Hence, even if the region has a negative share for its industry mix, the total overall growth in a particular sector can be positive if the region outperforms national average growth rates (Thompson, 1965; Hoover and Giarratani, 1985).

2.1.2 The Classical Approach

In classical shift share analysis, the national (or aggregate) growth effect is simply the share of a local area's growth in a given industry due to the overall growth of all sectors in the national economy. It explains how much of the overall growth of the national economy affects an individual industry's growth in a respective region; that is, if the nation's whole economy is growing, we would expect some changes in each industry in a given region. The classic idea is that a rising economic tide lifts all (industrial) boats. In practice, the national effect may be calculated as the total growth of all industries in a given country (such as the United States as a whole) or for an individual state or large region.

An industry mix (business mix or sectoral mix) effect isolates the fact that nationwide, some industries grow faster or slower than others. In other words, the industry mix effect characterizes the positive or negative effects of specialization of the local employment in sectors where the rate of growth at the national level varies by sector. If we subtract the national growth rate of the total economy from the national growth rate of the specific industry, we estimate the industry mix effect.

The third effect, the competitive or localized effect, shows the contribution to growth due to the special dynamism of the sector in that region compared with the average growth that such a sector has at the national level (Esteban-Marquillas, 1972). It explains how much of the total change in a given industry is due to some unique competitive advantage that the region possesses. This effect is calculated by taking a specific sector of a region and subtracting the national growth of that specific sector. If national and/or industry mix effects are negative, this effect might be positive or negative depending upon the actual job growth of the region.

2.1.3 Explanation of Classical Shift-Share

The classical model can be explained by the following. Let e_i be the total employment in i^{th} sector for a region. Similarly, the total employment of a larger geographic unit (e.g. nation) is denoted by E and the total employment for the nation for the i^{th} sector is denoted by E_i. Hence, the three components of classical shift share analysis can be obtained by the equations listed below.

For any time period from t to time period t+1, the change in employment can be calculated by

(1) Change in employment = $G + (G_i\text{-}G) + (g_i\text{-}G_i)$; where,

(2) G (national growth effect) = $(E_{t+1}\text{-}E_t)/E_t$

(3) G_i (industry mix effect) = $(E_{it+1}\text{-}E_{it})/E_{it} - G$, and

(4) g_i (competitive effect)= $(e_{it+1}\text{-}e_{it})/e_{it} - G_i$

The above approach decomposes the percent growth in employment among these three effects. Alternatively, one can decompose the total employment change by effect by simply multiplying equation (2), (3), or (4) by E_i^t. This can be better understood with a hypothetical example. Suppose a parish (county) in Louisiana experienced employment growth in the agriculture sector. Let the initial total employment in that parish for the agriculture sector in time t be 100 jobs that grew to 150 jobs in time t+1, or 50%. During the same period, the national employment grew 20%. At the same time, if the national employment in agriculture sector declined by 10%, the total effect would be calculated as follows.

For this example, let $e_i^t = 100$, $G = 20\%$, $G_i = -10\%$ and $g_i = 50\%$; resulting in the following;

National Growth Effect = $e_i^t * G = 100*0.2 = 20$

Industry-Mix Effect = $e_i^t (G_i - G) = 100* (-.1-.2) = -30$

Competitive Effect = $e_i^t (g_i - G_i) = 100* (.5-(-.1) = 60$.

The total employment growth in the agriculture sector in the parish is:

60 + 20 – 30 = 50 jobs[3].

Hence, the new level of employment for time t+1 equals 150 jobs.

The additional employment gained if the local employment in the agricultural sector i followed the overall national growth rate is 20 and is shown by the national growth effect. Similarly, the number of additional employees that is due to the national growth in the agricultural sector is -30, the industry mix effect. The negative sign portrays that the national agricultural sector grew slower than the average growth of total employment in the nation. Finally, the incremental growth in the employment because of the local specialization in the agricultural sector is 60 and is shown by the competitive effect.

2.2 Spatial Spillover and Location Effect

Economic growth of any spatial unit is not independent of growth of its neighboring units. Any spatial unit may be affected (positively or negatively) by the spatial spillovers transmitted from its neighboring regions (Isard, 1960). Based on this idea, Nazara and Hewings (2004) have incorporated a spatial structure within shift share analysis and developed an extensive taxonomy of regional growth decompositions. The general formula for their model

[3] The national growth, industry mix, and competitive effect percentage changes can be multiplied by the initial economic metric level for the sector in the initial time period to calculate each of the effects in terms of jobs.

replaces G_i with $\vec{g}_i$, which is a spatial lag variable that denotes the growth rate of sector i in the neighborhood regions.

(1) $(\text{growth})_i = G + (\vec{g}_i - G) + (g_i - \vec{g}_i)$

The spatial lag variable, $\vec{g}_i$ is a weighted average of neighboring regions, and is acquired by multiplying a square spatial weight matrix (R X R)[4], denoted as W, times the conformable column vector of neighboring values. W is therefore a spatial weight matrix whose elements w_{jk} describe the level of interdependence between spatial units j and k (Evans, 2008). An example of how the spatial weight matrix is calculated is presented in the Appendix. The first part of the right hand side (G) refers to the overall national effect that has been described earlier in the classical shift share model. The second part $(\vec{g}_i - G)$ refers to the difference between the growth rate of i^{th} sector in the neighboring region and overall national growth. This effect due to the growth in a neighboring region for any particular sector is termed as the nation-region industry-mix effect. A positive number reflects the growth of i^{th} sector in the neighboring region grows faster than the total national growth. The third part $(g_i - \vec{g}_i)$ is the difference in the growth of the i^{th} sector in any specific local area and its neighboring region. This effect is termed as neighbor-region sectoral regional-shift effect and the positive number implies that the growth of i^{th} sector in any specific region is faster than the growth of the same sector in its neighboring region.

Nazara and Hewings, 2004, have calculated the all sector employment growth rate for the contiguous region k of a particular region j, denoted by $\vec{g}$. Mathematically, the formula is written as

[4] R is the number of regions (parishes) in the system.

$$(2) \qquad \vec{g} = \frac{(\sum_{k=1}^{J} \tilde{w}_{jk} e_k^{t+1} - \sum_{k=1}^{J} \tilde{w}_{jk} e_k^{t}}{\sum_{k=1}^{J} \tilde{w}_{jk} e_k^{t}}$$

where $\tilde{w}_{jk}$ = element of a square spatial row standardized weight matrix indicating the intensity of j's interaction with region k. Similarly, the formula can be slightly modified to obtain the growth rate for region k's neighbor for a specific sector i.

$$(3) \qquad \vec{g}_i = \frac{(\sum_{k=1}^{J} \tilde{w}_{jk} e_{ik}^{t+1} - \sum_{k=1}^{J} \tilde{w}_{jk} e_{ik}^{t}}{\sum_{k=1}^{J} \tilde{w}_{jk} e_{ik}^{t}}$$

e_{ik}^{t+1} = total employment in region k for sector i for time period t+1

e_{ik}^{t} = total employment in region k for sector i for time period t

In addition to the spatial augmentation of the classical shift share analysis, Nazara and Hewings (2004) present additional alternative shift share decompositions:

(4) Growth (g_i) = $G_i + (g - G_i) + (g_i - g)$ (Augmented classical shift share 1)

(5) Growth (g_i) = $G_i + (\vec{g}_i - G_i) + (g_i - \vec{g}_i)$ (Augmented spatial shift share 2)

In Equations 4 and 5, we see an approach to augmenting the classical shift share decomposition. In Equation 4, instead of isolating the national effect G and national industry i effect G_i, we isolate in the decomposition first on G_i and second on overall employment change for all industries for a single parish, g. This is one of a number of combinations Nazara and Hewings suggest. For any given economic situation, the classical approach, one of the augmented approaches, or a spatial variant of these may provide the most appropriate decomposition for analysis. In the spatial shift share version of Equation 5, the decomposition creates a neighboring region / industry effect that compares the difference between the overall national growth of an industry against the neighboring region employment growth in that industry ($\tilde{g}_i - G_i$). Hence, this neighboring-region industry effect is unique to each parish and represents how much faster or slower a neighboring region's employment in a given industry contributes relative to the employment growth of the industry nationally. It creates a third "industry-based effect" and thereby better distinguishes where potential comparative advantage is geographically focused (nation/state, larger neighboring region, or localized area).

Since the original formulation by Nazara and Hewings (2004), there have been a number of applications of this approach. A search on Google Scholar in July 2010 identified 37 citations of Nazara and Hewings (2004). Applications have been numerous for many geographic regions including China (Chunyun, et at., 2007), Australia (Mitchell, Myers, and Juniper, 2005), Spain (Marquez, Ramajo, and Hewings, 2009), Greece (Fotopoulas, Kallioras, and Petrakos, 2009), and Texas (Tu and Sui, 2010) among others. The approach has been criticized for the potential for creation of neighboring regions that are not sufficiently large to take into account sectors driven by larger geographic region effects (Fotopoulas, Kallioras and Petrakos, 2009), and has been used to evaluate sectoral versus regional classification tradeoffs (Marques, Ramajo, and Hewings, 2009). The approach has been modified to include an exponential distance function for the spatial weight matrix (Mitchell, Myers and Juniper, 2005) and extensions of the approach to incorporate homothetic effects in the tradition of the Estaban-Marquelles approach (Pautelli et al 2006).

Unfortunately, no study has attempted to test whether or not the spatial shift share model improves on the distinctiveness of the localized effect. In Loveridge and Selting (1998), they tested a number of variations of classical shift share model at the time including the Esteban-Marquillas (EM) family of shift share models. These augmented models were developed to eliminate the proposed problem that the traditional competitive effect was actually measuring part of the industry mix effect. Loveridge and Selting used a correlation analysis to show that the EM family of models did reduce the correlation of the industry mix and competitive effect from the traditional shift share model, but the solution, the breakup of the competitive effect into a traditional competitive effect component and homothetic (industry proportion) competitive effect component, resulted in almost perfect correlation of these components rendering their separate interpretative value meaningless.

Since many of the aforementioned applications of the spatial shift share approach assume that the neighboring region spatial effect is truly differentiable from the localized effect, their interpretations of these results would be invalid if the neighboring region effect created by the spatial weight matrix was not truly distinct. Further, the practical interpretative value of the neighboring region effect suggests that validation of its distinctness is important before the approach is extended from the academic realm to the economic development practitioner. The succeeding sections attempt to identify the interpretable distinctiveness of spatial shift share through an application of employment change of selected industries along the Louisiana Gulf Coast following Hurricanes Katrina and Rita.

2.2.1 Example of Spatial Weight Matrix Creation

The elements of a spatial weight matrix are non-negative based on different measures such as physical contiguity (Moran, 1984; Geary, 1954), measures of distance (Molho, 1995; Fingleton, 2001; Paelinck and Nijkamp, 1995) or some alternative economic measure. Here, the square spatial row standardized weight matrix is used to calculate the changes in employment for different sectors and the weight matrix is selected on the basis of contiguity of parishes. The interdependence between the parishes is shown by the non-zero entry in the square spatial row standardized weight matrix where each row sum equals to unity.

We can present the following hypothetical example to show how the spatial weight matrix creates neighboring region effects. Assume there are 4 regions with the employment vector $X = \begin{bmatrix} 40 \\ 80 \\ 60 \\ 20 \end{bmatrix}$ for a specific sector i. Let us assume that the region 1 is contiguous to region2 and region 4, region 2 is contiguous to region 1 and region 4, region 3 is contiguous to region 4 only and region 4 is contiguous to region 1, region 2 and region 3. Based on these assumptions, we can create the following row-standardized contiguous spatial weight matrix A.

Table 2.1. Example Showing Row-Standardized Spatial Weight Matrix

Regions	**1**	**2**	**3**	**4**	**Total**
1	0	0.5	0	0.5	1
2	0.5	0	0	0.5	1
3	0	0	0	1	1
4	0.33	0.33	0.33	0	1

Hence, the neighboring region employment could be calculated by matrix multiplication (A*X) which produces 4x1 vector of neighboring region employment: Thus $\vec{g}_i = \begin{bmatrix} 50 \\ 30 \\ 20 \\ 59.4 \end{bmatrix}$

2.3 Economic Change Following the 2005 Hurricane Season

Katrina and Rita, two of the most deadly hurricanes in the history of the United Sates, made a landfall less than a month apart in 2005. The United States Department of Commerce, (2006) reported that Hurricane Katrina was the costliest hurricane (in the history of the United

States responsible for $81.2 billion[5] in damages. Hurricane Rita was recorded as the ninth costliest storm in U.S. history and responsible for approximately $10 billion in damages (Knabb, Brown and Rhome, 2007). These hurricanes had strong impacts on economies and employment in the affected areas. There were many incidences of mass layoffs and increases in unemployment rates after these hurricanes (Kosanovich, 2006). Severe fiscal and employment impacts of these hurricanes were recorded. Besides the decline in population and employment in many of the hurricane affected areas, significant changes in expenditure, revenues, assets and liabilities of local governments were observed in its aftermath. These changes can be examined by shift share analysis by decomposing the changes into various effects.

With natural disasters such as Hurricanes Katrina and Rita, the comparative advantage a region has over another region may vary due to a number of factors. For example, one of the key industry sectors in New Orleans, the Food Services sector, is driven by a combination of local demand from local residents as well as export demand from tourists. One would expect the timing of growth in this industry to lag given the slow re-population of the historical population base necessary to support minimum efficient scale of restaurants in the region. Further, its support establishments – those inter-connected sectors both upstream and downstream – are also highly dependent on the export base of the tourism population. Hence, we might expect in a worst case scenario the loss of market share because of an exogenous natural disaster to be so great as to move the regional economy beyond a "sustain point" as described by Fujita et al (1998) such that the previous agglomeration effects in the tourism industry are no longer attainable. At best, we might see local establishments in the Food Services sector to temporarily move to other neighboring regions where the local population base has relocated until that

[5] The amount is specified in 2005 U.S. dollars .

population locates back to the urban core and the population base reaches a level to sustain food service establishments at a historically viable scale.

On the other hand, the oil and gas extraction sector's economic base comes from a combination of a historically large supply and low cost to extract petroleum and natural gas minerals along the Gulf Coast with a support infrastructure of suppliers and transportation networks (ships, barges, pipelines, ports) to move these raw minerals from their extraction source to further processing (e.g. petroleum refineries) and eventually to end consumers. Further, the skilled labor involved in the industry is accustomed to the mobile nature of the industry. Both on-shore and off-shore drilling and related activities change geographic locations regularly leading to measurable dichotomies in place of work and place of residence employment. Hence, one might expect at worst, low producing oil or gas wells to simply be shut and removed from production due to hurricane impacts. At best, the loss and/or damage to infrastructure in the industry are quickly repaired given that the labor force supporting the industry is geographically spread over a much greater area.

Further, the importance of deep-water drilling and production as a proportion of total oil production in the U.S. increased during this period. After the year 2000, average daily deep-water offshore oil production exceeded shallow water oil production in the U.S.[6] (Nixon et al 2009). Louisiana's total offshore oil production is dominated by federal outer-continental shelf production (mostly deep-water) with 48 million barrels extracted as compared to only 6.3 million barrels in shallow-water state territorial waters. Further, the servicing of deep-water rigs is dominated in Louisiana. In particular, it is concentrated in Port Fourchon, in Lafourche Parish,

[6] Deepwater drilling is considered drilling of wells with a water depth of at least 1,000ft. Ultra-deepwater drilling is defined as drilling of wells with a water depth of at least 5,000ft.

Louisiana. It services approximately 90% of all deep-water rigs in the entire Gulf of Mexico (Scott and Associates 2008).

2.4 Data and Methodology

The analysis was performed on the basis of the classical shift share analysis and the spatial decomposition based on the contiguity of parishes. We focus on the Coastal Louisiana Region (CLR) parishes that are measurably influenced by industries geographically concentrated in this region as well as tropical storms[7]. CLR parish level employment data were drawn from Wholedata (Isserman and Westervelt 2006). Wholedata uses county business patterns (CBP) data (see http://www.census.gov/econ/cbp/index.html) that provides detailed employment by up to six digit NAICS sectors; however, since many sectors in small regions have only a small number of establishments, their employment data are not disclosed to protect confidentiality. Wholedata imputes the undisclosed data so that employment estimates are available for all detailed NAICS sectors for each county. Summed national industry employment is used for the aggregate effect; hence total national employment in the given time t is denoted by E_t. The total employment in the given time t for different sectors in the nation are denoted as E_{it} . Similarly, the overall employment for each CLR parish in time t is denoted by e_t and the employment for each sector of each CLR parish is denoted by $e_{it.}$

The spatial weight matrix is developed based on the contiguity of the parishes. The matrix is then row standardized for further application in shift share analysis. We evaluated a wide range of models developed by Nazara and Hewings (2004) in order to check the employment change for every CLR parish.

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[7] Coastal Louisiana Region includes 32 parishes chosen from US Dept of Interior Bureau of Ocean Energy Management, Regulation and Enforcement (BOEMRE) definition of parishes influenced by energy industry activities off the outer-continental shelf (Saha, Manik, and Phillips 2005).

The primary basis for spatial decomposition in this paper is the physical contiguity of parishes. Similarly, we can proceed further by creating the weight matrix on the basis of some economic variables and treating the neighboring regions on the basis of the interdependence in those economic variables. The weight matrix as constructed makes the neighboring region and local competitive effects easily interpretable by general practitioners.

2.5 Contributions of Spatial Shift Share

Nazara and Hewings (2004) suggest that some of the local competitive effect explained in the classical shift share model is actually explained by neighboring region effects. How might this be tested to know if the neighboring region effect is truly a distinct effect from the localized effect? I apply a correlation analysis test used by Loveridge and Selting (1998) to test the distinctiveness of the neighboring region effect.

I apply the same correlation analysis by taking the average of annual shift share decomposition effects between 2001 and 2006 and evaluating their pair wise correlations. My hypothesis is that if the spatial neighboring region effect is a distinct decomposition effect, we would see the correlation between the neighboring region effect and the new localized effect created from the spatial model weakly correlated suggesting their effects are distinct.

2.6 Results and Discussion

2.6.1 Results

In Table 2.2 and 2.3, we compare the classical shift share analysis against the spatial shift share model (Equation 1) in the mining sector (NAICS 21) and augmented spatial shift share model 2 (Equation 5) for two time periods – a three year period preceding the impacts of Katrina/Rita (2001-04) (Table 2.2) and a two year period during which Katrina/Rita occurred (2004-06). Columns 1-3 in both tables refer to the classical shift share case in 2001-04 and 2004-

Table 2.2. Comparing Classical versus Augmented Spatial Shift Share Analysis on Employment Growth in the Mining Sector, 2001-04

	Classical Shift Share (01-04)			Spatial Shift Share (01-04)			Augmented Spatial Shift Share (01-04)			
	G	Gi-G	gi-Gi	G	$\vec{g}_i$ -G	gi- $\vec{g}_i$	Gi	$\vec{g}_i$ Gi	gi- $\vec{g}_i$	(10)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Area name	**Nat. Effect**	**Industry Mix**	**Comp Effect**	**Nat. Effect**	**Neigh. Region Effect**	**Local Effect**	**Nat. Industry Effect**	**Neigh. Region Effect**	**Local. Effect**	**Total Growth (01-04)**
Acadia	0.0001	-0.032	0.442	0.0001	-0.281	0.691	-0.031	-0.249	0.691	0.410
Allen	0.0001	-0.032	-0.094	0.0001	0.673	-0.798	-0.031	0.705	-0.798	-0.125
Ascension	0.0001	-0.032	-0.382	0.0001	-0.178	-0.235	-0.031	-0.147	-0.235	-0.413
Assumption	0.0001	-0.032	0.240	0.0001	-0.129	0.337	-0.031	-0.097	0.337	0.209
Beauregard	0.0001	-0.032	0.410	0.0001	0.529	-0.150	-0.031	0.560	-0.150	0.378
Calcasieu	0.0001	-0.032	0.056	0.0001	-0.241	0.265	-0.031	-0.209	0.265	0.025
Cameron	0.0001	-0.032	-0.535	0.0001	-0.334	-0.233	-0.031	-0.302	-0.233	-0.566
E. Baton Rouge	0.0001	-0.032	-0.608	0.0001	-0.221	-0.418	-0.031	-0.189	-0.418	-0.639
Evangeline	0.0001	-0.032	0.395	0.0001	-0.227	0.591	-0.031	-0.195	0.591	0.364
Iberia	0.0001	-0.032	0.046	0.0001	-0.101	0.115	-0.031	-0.069	0.115	0.014
Iberville	0.0001	-0.032	-0.149	0.0001	-0.102	-0.079	-0.031	-0.070	-0.079	-0.181
Jefferson	0.0001	-0.032	-0.273	0.0001	-0.202	-0.103	-0.031	-0.171	-0.103	-0.305
Jefferson Davis	0.0001	-0.032	-0.503	0.0001	-0.001	-0.534	-0.031	0.031	-0.534	-0.535
Lafayette	0.0001	-0.032	-0.208	0.0001	-0.126	-0.114	-0.031	-0.094	-0.114	-0.239
Lafourche	0.0001	-0.032	0.107	0.0001	-0.183	0.258	-0.031	-0.152	0.258	0.075
Livingston	0.0001	-0.032	-0.380	0.0001	0.356	-0.768	-0.031	0.387	-0.768	-0.412
Orleans	0.0001	-0.032	-0.227	0.0001	-0.072	-0.187	-0.031	-0.040	-0.187	-0.259
Plaquemines	0.0001	-0.032	0.027	0.0001	-0.156	0.151	-0.031	-0.125	0.151	-0.005
St. Bernard	0.0001	-0.032	0.127	0.0001	-0.132	0.227	-0.031	-0.100	0.227	0.095
St. Charles	0.0001	-0.032	-0.589	0.0001	0.003	-0.624	-0.031	0.035	-0.624	-0.620
St. James	0.0001	-0.032	-0.254	0.0001	0.028	-0.313	-0.031	0.059	-0.313	-0.286
St. John	0.0001	-0.032	0.272	0.0001	0.096	0.144	-0.031	0.128	0.144	0.240
St. Landry	0.0001	-0.032	-0.627	0.0001	0.157	-0.815	-0.031	0.189	-0.815	-0.658
St. Martin	0.0001	-0.032	0.127	0.0001	-0.142	0.238	-0.031	-0.111	0.238	0.095
St. Mary	0.0001	-0.032	0.034	0.0001	-0.005	0.007	-0.031	0.027	0.007	0.002
St. Tammany	0.0001	-0.032	0.100	0.0001	1.464	-1.396	-0.031	1.495	-1.396	0.068
Tangipahoa	0.0001	-0.032	2.267	0.0001	0.147	2.088	-0.031	0.179	2.088	2.235
Terrebonne	0.0001	-0.032	-0.306	0.0001	0.095	-0.433	-0.031	0.127	-0.433	-0.338
Vermilion	0.0001	-0.032	-0.459	0.0001	-0.183	-0.307	-0.031	-0.152	-0.307	-0.490
Vernon	0.0001	-0.032	2.781	0.0001	0.127	2.623	-0.031	0.158	2.623	2.750
Washington	0.0001	-0.032	0.724	0.0001	1.152	-0.459	-0.031	1.183	-0.459	0.692
W. Baton Rouge	0.0001	-0.032	0.154	0.0001	-0.410	0.532	-0.031	-0.378	0.532	0.122
Average	**0.0001**	**-0.032**	**0.085**	**0.0001**	**0.044**	**0.009**	**-0.031**	**0.075**	**0.009**	**0.053**

06 respectively and columns 4-6 show the spatial shift share model results and column 7-9 augmented spatial shift share two model results.

In 2001-04, while the overall national employment was essentially flat (Table 2.2, Column 1), This contributed to the industry mix effect of -3.2% (Table 2.2, Column 2). These results from the classical shift share model suggest that any overall positive employment growth in a parish's mining sector during the period was entirely due to localized in-parish positive competitive effects.

On the other hand, by incorporating the spatial shift share model, we are able to potentially tease out more precise localized effects from larger regional effects. Take the example of Calcasieu Parish. Using the spatial shift share model (Table 2.2, Columns 4-6) we see that the new localized effect (26.5%) is much greater than the competitive effect (5.6%) in the classical model. This is driven by the difference in using the industry mix in the classical model which treats a portion of a local county's employment growth in a given industry as being driven by the overall growth in that industry nationally versus the spatial shift share model that treats a portion of that growth as driven by the same industry growth, but in the neighboring contiguous counties.

In Table 2.3, we see even greater contrasts and interpretation between the classical and a spatial shift share models. In the Calcasieu Parish case, between 2004 and 2006, the classical model shows that 19% of the 37% employment growth rate in the mining sector was attributable to local competitive effects (Table 2.3, Column 3) whereas the spatial shift share model shows that approximately 41% of the same 37% growth rate in Calcasieu Parish was due to localized effects. The underlying differences are driven by the differences between the industry mix and neighboring region effects. In the classical model, national industry growth would have contributed approximately 14% (Table 2.3, Column 2) to overall employment growth, whereas the neighboring region effect would have actually reduced employment in Calcasieu Parish by 8% (Table 2.3, Column 5).

Table 2.3. Comparing Classical versus Augmented Spatial Shift Share Analysis on Employment Growth in the Mining Sector, 2004-06

	Classical Shift Share (04-06)			Spatial Shift Share (04-06)			Augmented Spatial Shift Share (04-06)			
	G	Gi-G	gi-Gi	G	$\vec{g}_i$ -G	gi- $\vec{g}_i$	Gi	$\vec{g}_i$ -Gi	gi- $\vec{g}_i$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Area name	**Nat. Effect**	**Industry Mix**	**Comp Effect**	**Nat. Effect**	**Neigh. Region Effect**	**Comp. Effect**	**Nat. Industry Effect**	**Neigh. Region Effect**	**Local. Effect**	**Total Growth (04-06)**
Acadia	0.042	0.137	0.084	0.042	0.009	0.211	0.179	-0.127	0.211	0.263
Allen	0.042	0.137	-0.179	0.042	0.008	-0.050	0.179	-0.129	-0.050	0.000
Ascension	0.042	0.137	1.025	0.042	0.209	0.953	0.179	0.072	0.953	1.204
Assumption	0.042	0.137	-0.223	0.042	0.310	-0.396	0.179	0.173	-0.396	-0.044
Beauregard	0.042	0.137	-0.649	0.042	0.338	-0.850	0.179	0.201	-0.850	-0.471
Calcasieu	0.042	0.137	0.190	0.042	-0.081	0.408	0.179	-0.218	0.408	0.369
Cameron	0.042	0.137	0.024	0.042	0.057	0.104	0.179	-0.080	0.104	0.203
E. Baton Rouge	0.042	0.137	0.521	0.042	0.621	0.036	0.179	0.485	0.036	0.700
Evangeline	0.042	0.137	-0.872	0.042	0.260	-0.996	0.179	0.124	-0.996	-0.693
Iberia	0.042	0.137	-0.494	0.042	0.111	-0.469	0.179	-0.026	-0.469	-0.315
Iberville	0.042	0.137	0.233	0.042	0.317	0.053	0.179	0.181	0.053	0.412
Jefferson	0.042	0.137	-0.162	0.042	0.182	-0.207	0.179	0.045	-0.207	0.017
Jefferson Davis	0.042	0.137	-0.029	0.042	-0.121	0.229	0.179	-0.258	0.229	0.150
Lafayette	0.042	0.137	0.099	0.042	0.125	0.111	0.179	-0.012	0.111	0.278
Lafourche	0.042	0.137	0.043	0.042	0.147	0.033	0.179	0.010	0.033	0.221
Livingston	0.042	0.137	0.561	0.042	0.329	0.369	0.179	0.192	0.369	0.740
Orleans	0.042	0.137	-0.228	0.042	0.053	-0.144	0.179	-0.084	-0.144	-0.049
Plaquemines	0.042	0.137	0.280	0.042	-0.116	0.533	0.179	-0.253	0.533	0.459
St. Bernard	0.042	0.137	-0.370	0.042	0.163	-0.396	0.179	0.026	-0.396	-0.191
St. Charles	0.042	0.137	0.087	0.042	0.070	0.153	0.179	-0.066	0.153	0.265
St. James	0.042	0.137	-0.579	0.042	0.328	-0.770	0.179	0.191	-0.770	-0.400
St. John	0.042	0.137	-0.080	0.042	0.210	-0.153	0.179	0.073	-0.153	0.099
St. Landry	0.042	0.137	0.619	0.042	-0.002	0.757	0.179	-0.139	0.757	0.797
St. Martin	0.042	0.137	0.134	0.042	0.176	0.094	0.179	0.040	0.094	0.313
St. Mary	0.042	0.137	0.005	0.042	0.245	-0.103	0.179	0.108	-0.103	0.184
St. Tammany	0.042	0.137	-0.123	0.042	-0.415	0.428	0.179	-0.551	0.428	0.055
Tangipahoa	0.042	0.137	-0.697	0.042	0.125	-0.685	0.179	-0.012	-0.685	-0.518
Terrebonne	0.042	0.137	1.017	0.042	0.078	1.075	0.179	-0.058	1.075	1.196
Vermilion	0.042	0.137	-0.402	0.042	0.073	-0.339	0.179	-0.063	-0.339	-0.223
Vernon	0.042	0.137	0.821	0.042	-0.277	1.235	0.179	-0.414	1.235	1.000
Washington	0.042	0.137	-0.406	0.042	-0.273	0.004	0.179	-0.410	0.004	-0.227
W. Baton Rouge	0.042	0.137	0.120	0.042	0.514	-0.257	0.179	0.377	-0.257	0.299
Average	**0.042**	**0.137**	**0.012**	**0.042**	**0.118**	**0.030**	**0.179**	**-0.019**	**0.030**	**0.190**

If one prefers to include both national industry growth rate and neighboring region effects separately in the shift share decomposition, then using the augmented spatial shift share 2 models is appropriate (Columns 7-9, Tables 2.2 and 2.3). While, generating the same localized effect as the spatial shift share model, it disentangles any neighboring region effects that may be driven by national industry growth. In the Calcasieu case, when using the augmented spatial shift share model, the neighboring region effect reduces employment growth over 21% (Table 2.3, Column 8).

To better understand how the spatial shift share model interprets growth patterns, we present a breakdown of growth by sign of the neighboring region and local effects using the spatial shift share model for mining in Figures 2.1 and 2.2.

In Figure 2.1, we identify parishes based on the signs of their growth rates from both the neighboring region effect and the local effect from the spatial shift share model for the period 2001-04 for the mining sector. As can be seen from the figure, red parishes have both neighboring region effects that are positive as well as localized effects that are positive. These parishes are thriving from both localized and regional effects.

Parishes in purple represent those parishes that have positive neighboring region effects, but negative local effects. These parishes are potentially receiving spillover employment benefits from the larger region and are likely to indicate the parish may have a weaker comparative advantage in the industry as compared to what the classical competitive effect would suggest in classical shift share analysis. Parishes in orange have negative neighboring region effects but positive localized effects. These parishes are likely to have strong comparative advantage effects locally and may have a larger region that supports this parish's specific industry. Parishes in green represent poor localized conditions for employment growth and a weak regional environment to maintain existing employment in the industry.

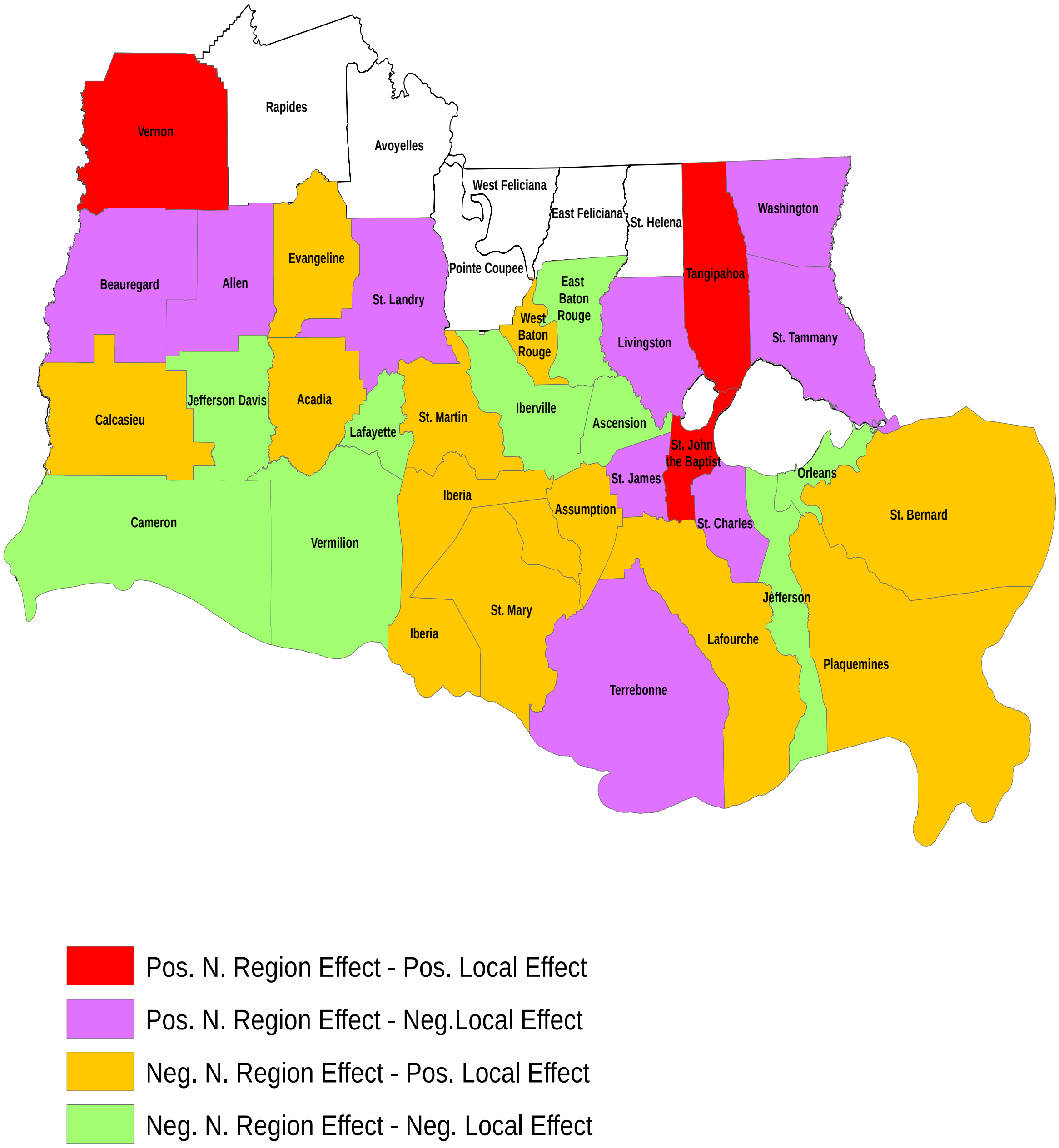

Figure 2.1. 2001-04 Spatial shift share neighboring region and local effects, mining

During this period for the mining sector, oil prices stayed in a range of $20 to $40 per barrel, which did not economically support re-investment in more mature shallow depth oil fields. Structurally, growth in the oil and gas industry was occurring in the deep-waters of the

Gulf of Mexico. The major service port for overwhelming majority of drilling activity is Port Fourchon, at the southern tip of Lafourche Parish (see Figure 2.1). This parish showed overall positive employment growth during this period (7.5%) despite its neighboring region effect contributing to an over 18% reduction in growth on the parish (Table 2.2, Column 5). Related to this port, support activity industry establishments for deep-water drilling are spread across multiple parishes along the coast. The positive spillover effect of Lafourche Parish's employment growth (driven in large part by its deep-water port activity) dampened potentially larger reductions in employment for support industry parishes such as Terrebonne and St. James. Further, Figure 2.1 highlights few spatial spillovers in mining originating from the major metropolitan centers in South Louisiana to surrounding areas. Orleans (New Orleans), East Baton Rouge (Baton Rouge), Lafayette (Lafayette) and Calcasieu (Lake Charles) core metro parishes only had one contiguous parish each that were categorized as having positive neighboring region effects.

In 2004 through 2006 (Figure 2.2), we see a changing spatial spillover landscape. In particular, we see two spatial "corridors" of thriving employment growth: a corridor along the Interstate 10/12 corridor from Livingston Parish in the east to Acadia Parish in the west, and a corridor extending through Terrebonne, Lafourche and St. Charles Parishes. Sandwiched between these two corridors is a large horizontal corridor of parishes that received positive neighboring spillover benefits driven by neighboring parishes to both the north and the south. During this period, Terrebonne and Lafourche (as well as Cameron Parish in Southwest Louisiana) were major ports involved in the repair and restoration of many of the drilling rigs, platforms, and pipeline systems within the Gulf of Mexico.

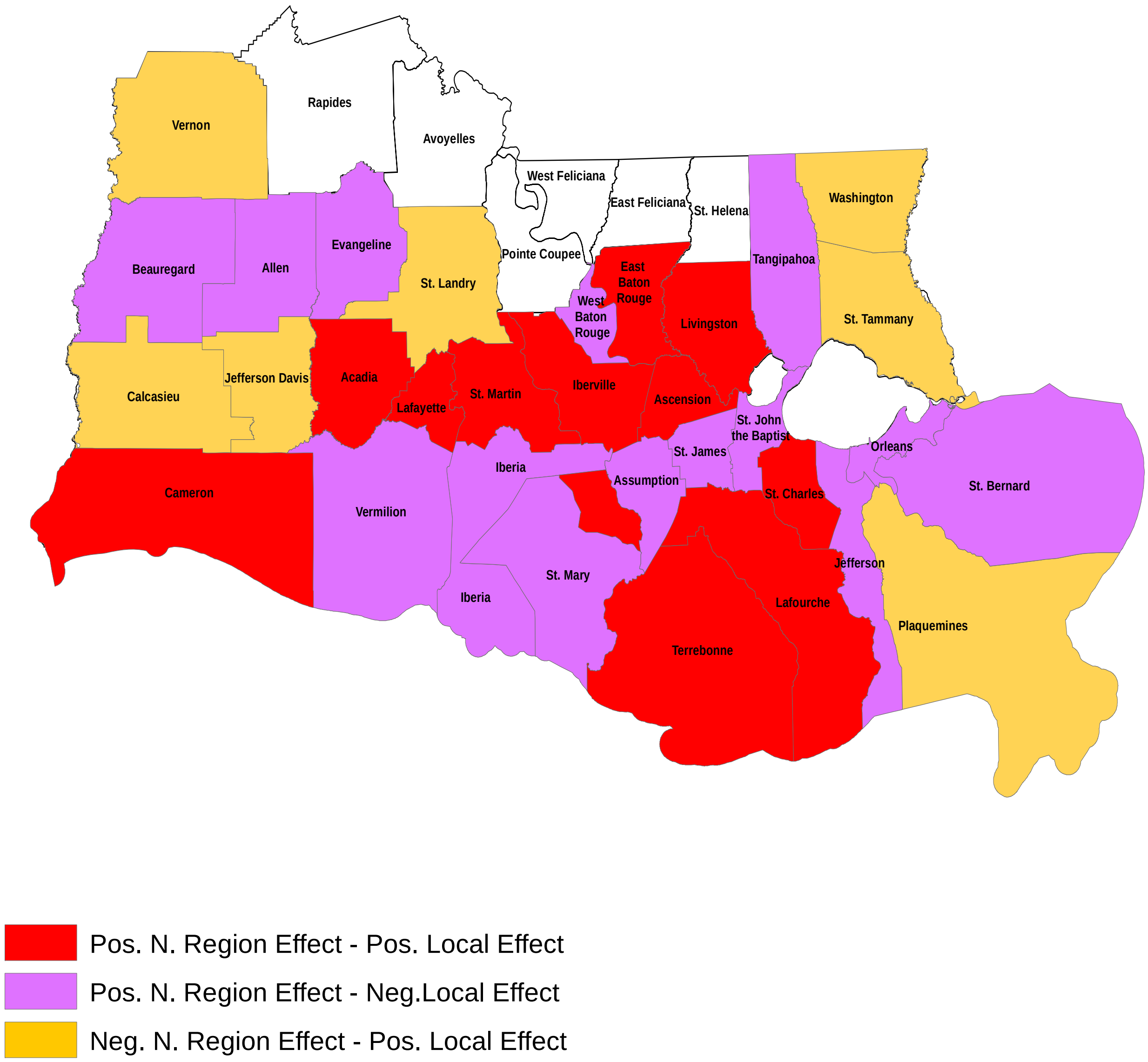

Figure 2.2. 2004-06 Spatial shift share neighboring region and local effects, mining

The I-10/12 corridor highlights a region likely benefitting from on-shore mining support industries helping in the restoration of the off-shore industry infrastructure as well as increasing oil prices during this period helping to create a mild bounce back in on-shore activities such as work-over rigs and other repair and activities on existing land-based wells to extract additional hydrocarbons from many older low producing wells.

In Figures 2.3 and 2.4, we present the combined neighboring region/local effects for 2001-04 and 2004-06 time periods respectively for the Food Services sector (NAICS 722) using the spatial shift share model. Since the Food Services sector for most places is not an export-base sector, then food service employment growth is likely to follow population growth. Further, the traditional interpretation of shift share analysis to comparative advantage from trade theory does not traditionally fit. As can be seen in Figure 2.3, we don't see any major spatial patterns that stand out during the 2001-04 time period. At most, one may see a pattern of parishes contiguous to metropolitan core parishes having both a positive neighboring region effect and positive local effect as the labor force increases its distances between where it lives and works and increases the proportion of food consumed away from home. However, after Katrina/Rita made landfall, regions of the state that were major recipients of evacuees, particularly from New Orleans, grew to accommodate the temporary migration of residents to their region.

The Food Services sector between 2004 and 2006 grew to accommodate their demand as shown in Figure 2.4. Major metropolitan centers less impacted by the storm path of Katrina/Rita saw positive regionalized and localized growth. These included portions of the Houma-Thibodaux MSA (Terrebonne Parish) Southwest of New Orleans, the Baton Rouge MSA (particularly East Baton Rouge and West Baton Rouge Parishes) Northwest of New Orleans, and the Lafayette MSA (Lafayette and St. Martin parishes), West of New Orleans. Nonmetropolitan parishes north of New Orleans (Tangipahoa and Washington) also benefitted.

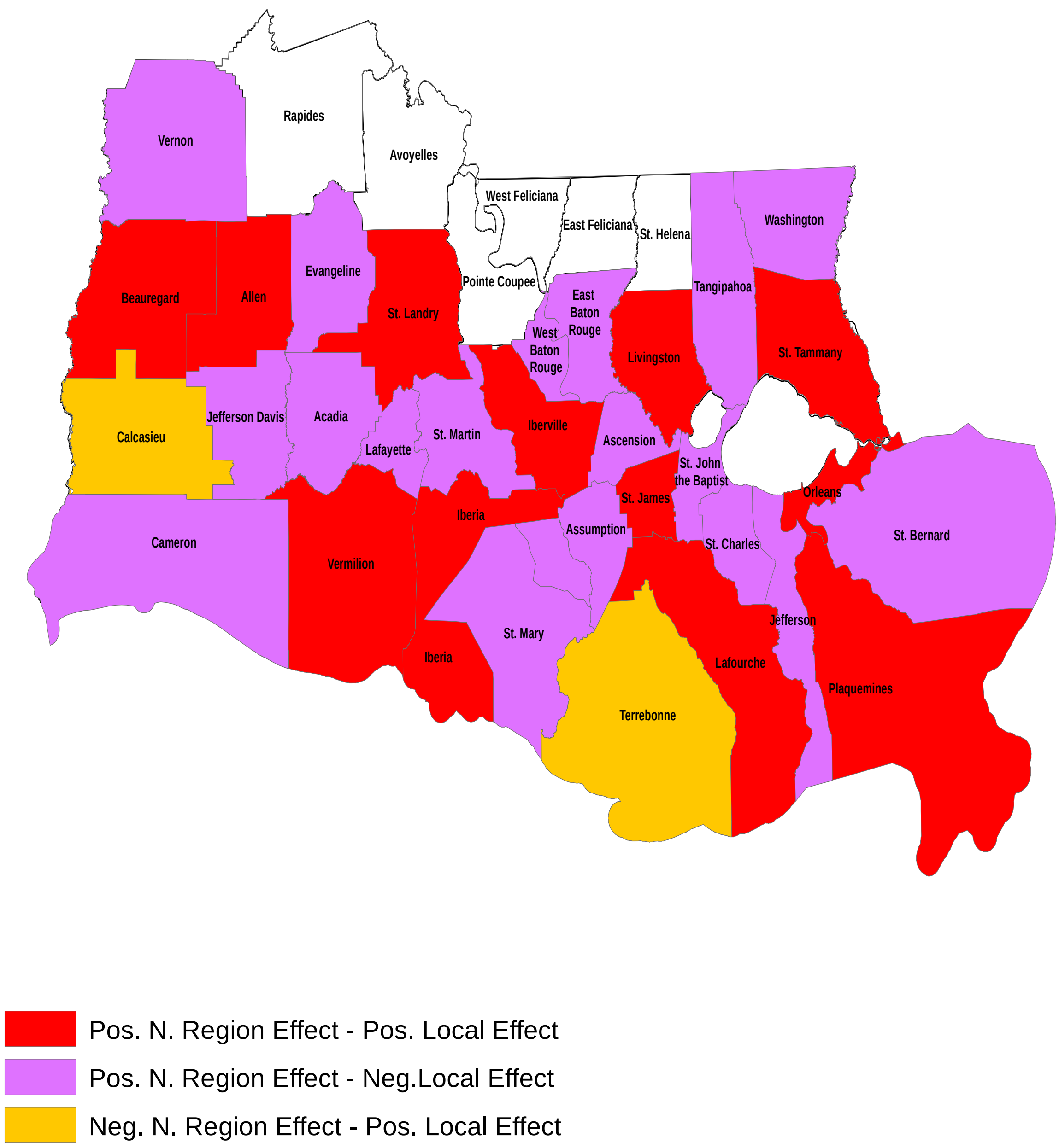

Figure 2.3. 2001-04 Spatial shift share neighboring region and local effects, food services

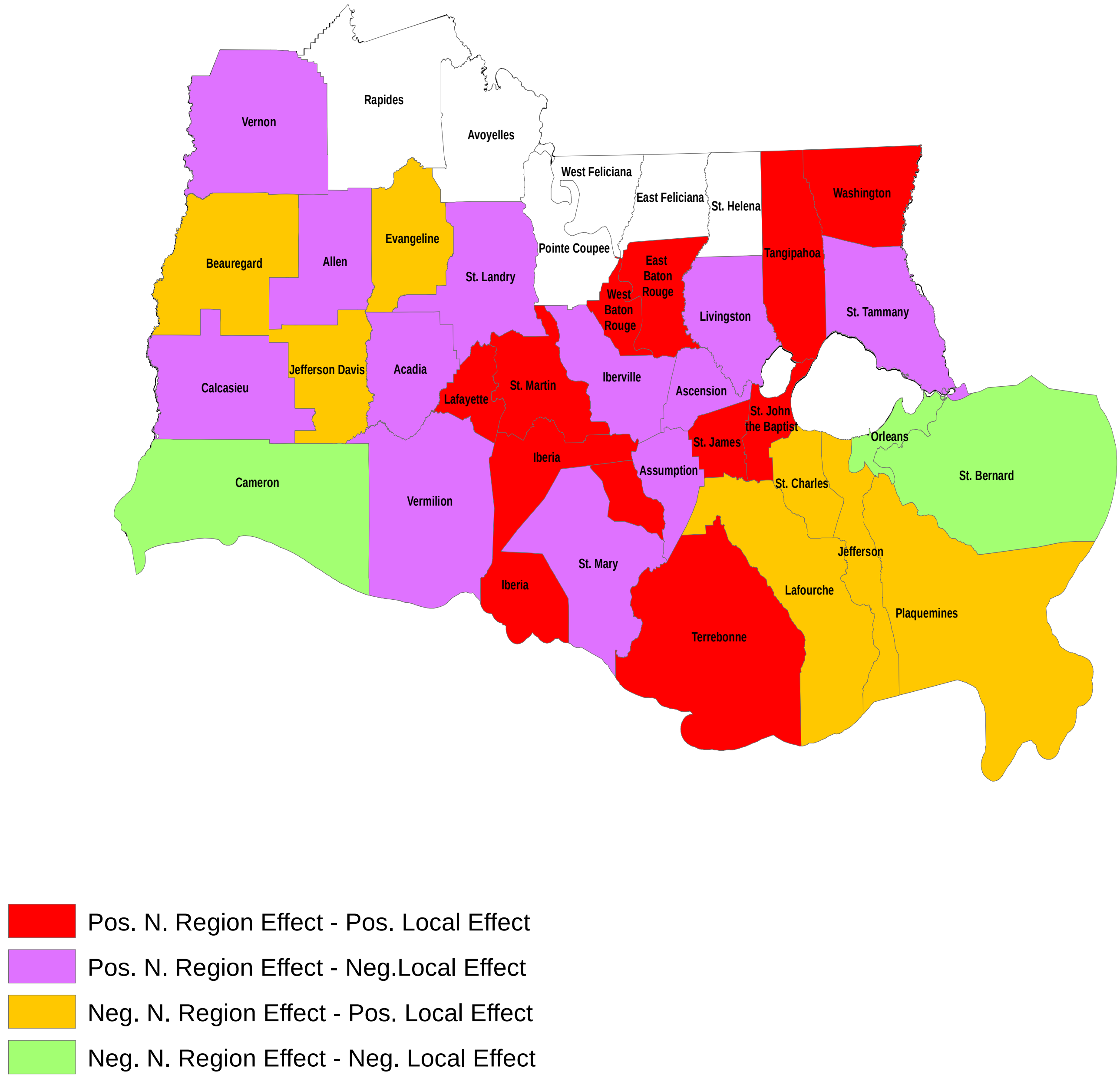

Figure 2.4. 2004-06 Spatial shift share neighboring region and local effects, food services

Results from the spatial shift share in Table 2.4 suggest that the spatial shift share model, unlike the Estaban-Marquillas (EM) approaches, tends to disentangle neighboring region ($\vec{g}_i$ -G) from truly localized competitive effects ($gi - \vec{g}_i$) without creating additional correlation issues compared to the classical model. For example, in the classical model for the Mining sector, the correlation between the industry mix (Gi-G) and competitive effect (gi-Gi) was significant at -0.297. In the spatial shift share model for Mining, the correlation between the neighboring region effect ($\vec{g}_i$ -G) and the local effect (gi- $\vec{g}_i$) was -0.013 and insignificant. Hence, these results suggest that the regional structural influence that was argued for the restructuring of the competitive effect in the EM approaches (and argued as unsuccessful by Loveridge and Selting, 1998) appears to have been mitigated with the spatial shift share method. We see a similar reduction in the Food Services correlations (Table 2.5) with the traditional correlation between industry mix and competitive effect of -0.713 reduced to -0.44 between the neighboring region and localized effect.

Table 2.4. Correlation Analysis Testing the Distinctness of Neighboring Region Effect in Mining Sector

Decompositions	National (G)	Industry-mix (G_i-G)	Competitive (g_i-G_i)	Neigh. Region ($\vec{g}_i$ -G)	Local (g_i- $\vec{g}_i$)
National (G)	1.000				
Business-mix (G_i-G)	0.994*** (0.000)	1.000			
Competitive (g_i-G_i)	-0.324* (0.070)	-0.297* (0.097)	1.000		
Neigh. Region ($\vec{g}_i$ -G)	-0.997*** (0.000)	-0.994*** (0.000)	0.325* (0.069)	1.000	
Local (g_i- $\vec{g}_i$)	0.014 (0.937)	0.042 (0.815)	0.940*** (0.000)	-0.013 (0.941)	1.000

Values in parenthesis indicate p-values. *, **, and *** indicate the significance level at 10%, 5% and 1% respectively.

Table 2.5. Correlation Analysis Testing the Distinctness of Neighboring Region Effect in Food Service Sector

Decompositions	National (G)	Industry-mix (G_i-G)	Competitive (g_i-G_i)	Neigh. Region ($\vec{g}_i$ -G)	Local (g_i- $\vec{g}_i$)
National (G)	1.000				
Business-mix (G_i-G)	0.998*** (0.000)	1.000			
Competitive (g_i-G_i)	-0.708*** (0.000)	-0.713*** (0.000)	1.000		
Neigh. Region ($\vec{g}_i$ -G)	-1.000*** (0.000)	-0.998*** (0.000)	0.708*** (0.000)	1.000	
Local (g_i- $\vec{g}_i$)	-0.439*** (0.010)	-0.445*** (0.010)	0.945*** (0.000)	-0.439** (0.011)	1.000

Values in parenthesis indicate p-values. *, **, and *** indicate the significance level at 10%, 5% and 1% respectively.

2.6.2 Discussion

The results presented above, particularly for the Mining sector, suggest that some parishes may have localized competitive advantages despite having little economic support from neighboring parishes (negative neighboring region effect, positive local effect) whereas other parishes tend to ride the coat-tails of their neighbors economically (positive neighboring region effect, negative local effect). What might be driving these varying patterns? In particular, while the interpretation of the classical competitive effect holds for interpreting the localized effect in the spatial shift share model, what may be driving the neighboring region effect?

I posit two explanations. The first is that the larger region has multiple establishments producing products that are connected together as part of a larger supply chain. There is increased demand for a product at one point along the supply chain which is located in one parish in the larger region. To the extent that establishments upstream in the supply chain are in neighboring parishes, the backward linkage effects spill over to the neighboring parish.

The mining industry in Louisiana presented above is a good case industry for this analysis in that two conditions hold for its measurement. The first is that many of the physical inputs in Mining, particularly Oil and Gas Extraction, are bulky making it cost prohibitive to transport the inputs long distances. The second is an artifact of the data. A larger proportion of the major physical and service inputs in the aggregate Mining sector from the North American Industrial Classification System (NAICS) also are classified as Mining sector industries. Consequently, when Mining is decomposed using spatial shift share analysis, the supply chain linkages can be captured. For a sector where a large proportion of its inputs come from an entirely unrelated industry sector altogether, an aggregated industry decomposition using spatial shift share analysis would fail to capture the supply chain linkages.

The second explanation suggests that a common site advantage, such as a harbor or river, may be shared by multiple parishes in a larger region to produce a similar product. Hence, if demand increases for a product that needs to take advantage of a natural site advantage, economies of scale may indicate expansion of an existing facility up to an efficient scale threshold. Beyond that point, increased demand may need to be met by a new establishment. The new establishment may take advantage of the natural site advantages in a neighboring parish possibly resulting in neighboring region spillover effects.

In both explanations, the local effect in the spatial shift share model is strictly dependent on the growth rate of the neighboring region effect for its sign and magnitude. That is, after controlling for the overall national growth of the economy, all of the remaining employment growth in a parish for a particular industry is first attributed to the neighboring region growth with the residual being the local effect. The decomposition assumes that a local parish's employment growth is dependent on its neighboring region's growth for its on growth.

Unfortunately, there are some limitations to this assumption. For example, let's assume a local port that supplies the offshore oil and gas industry grows over a period of time and reaches capacity with no possibility for further growth. Industries that use the existing port recognize the economic value of supporting their offshore activities using the canal to move finished products. If a neighboring parish's port along the same canal deepens the depth of its access points to supply the larger offshore vessels, it may generate additional employment growth from these industries.

The spatial shift share model with the neighboring region effect in the above example would assume that the first port's growth (the port that reached capacity) was dependent on the growth of the neighboring parish's port. However, the example shows that causality cannot be clearly inferred from spatial shift share analysis. That is, the causality can either run from the neighboring region to the locality or from the locality to the neighboring region. In most cases for aggregated industries, the classical shift share decomposition is mostly immune to this shortcoming because most small regions analyzed with shift share are too small to cause economic growth in the larger nation.

The choice between the classical and numerous variants of spatial shift share analysis should not be taken lightly. As mentioned previously, both regional industry structure and data structure should be considered. For industries that are very homogenous in their production process across space or typically have demand effects that evenly spread across geographic space, a classical shift share model with national industry growth may be appropriate. However, for aggregated industry classifications with very heterogeneous production processes across space, a spatial shift share model may be a preferable alternative. Also, industries that have multiple sections of a supply chain in the same industry classification may also benefit from spatial shift share models that highlight spatial spillovers from supply chain effects.

2.7 Conclusion

Shift share analysis is a constructive tool for identifying the separate contributors to economic growth as well as identifying regional comparative advantage as identified by trade theory. However, in the classical approach, there is an absence of a sub-national, or regional, influence. It assumes that a region is independent of its neighbors, even if they are geographically, fiscally or economically close to each other.

This research highlighted the application of the augmented spatial shift share model as originally outlined by Nazara and Hewings to understanding regionalized comparative advantage in core economic sectors of the state of Louisiana and regional economic shifts that occurred after Hurricanes Katrina and Rita. Our results indicated that while overall mining employment declined in the three year period prior to Katrina/Rita, the spatial shift share model identified regions that witnessed job growth and that the growth was broken into individual parishes that had localized comparative advantage. One of the possible explanations for this comparative advantage was a re-focusing of particular parishes to deep-water oil and gas exploration and development. It was argued that neighboring parishes to these parishes showing positive local comparative advantage from deep-water operations also received spatial spillovers in terms of employment growth. The same model also highlighted the shift of employment growth in the food service sector to major regional centers of evacuation after the 2005 storms.

Further, the research found that the spatial neighboring region effect was a distinct effect from the localized effect in the spatial shift share model. Hence, this research identified an alternative decomposition technique that increased distinctiveness between industry and local effects that were not achieved by Esteban-Marquillas shift share formulations.

There a few limitations that should be noted. First, the correlation test in this study is limited to two industries over five years in a single state. If spatial shift share analysis is to be adopted and used for both descriptive as well as parametric analysis, a more comprehensive test covering additional geographic areas over additional industries using a longer time period would be helpful in improving the robustness of these results.

Second, it should be noted that our focus with this spatial analysis is on more aggregate industrial groupings. While it can be argued that using a more aggregated sectoral classification is more appropriate using spatial analysis – especially when the aggregated industry sector includes more detailed sectors that are inputs in the supply chain of other detailed industry sectors – focusing on more detailed industry sectors may identify an alternative form of clustering of industries in geographic proximity to one another.

Further, one of the traditional limitations of the technique is that as a non-parametric analysis; we cannot make any inferences to the causality of the hypothesized spatial spillovers. Our research suggests that without further analysis, it may be difficult to know whether the larger neighboring region's growth causes a local area's growth or vice versa. Also, the approach is limited to the accuracy of the regions identified. Alternative measures of regionalization beyond our basic spatial contiguity approach could result in different outcomes and conclusions. However, both of these limitations can be tested through sensitivity analysis in future research. For example, results from the spatial shift share could be treated as a first step in an exploratory analysis to develop a more formal spatial model that identifies causality.

Shift share analysis has been applied over the decades to provide local policy makers and development officials a better perspective concerning what factors drive their local economic growth. By applying these and other spatial shift share approaches in novel ways, community development scholars and practitioners can provide a more sophisticated picture of the driving forces behind economic changes in rural regions.

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CHAPTER 3

MODELING THE LABOR MARKET AND ESTIMATING THE RELATIVE PERFORMANCE OF ESTIMATORS FOR LOUISIANA LABOR MARKET: A LABOR FORCE MODULE APPROACH

3.1 Introduction and Background Information

The Community Policy Analysis System (COMPAS) model is an effective tool to measure the labor and fiscal impacts of different industries in a region. The model exhibits inter-sectoral linkages, since an exogenous shock in any sector of the economy leads to series of changes in other sectors. Community Policy Models such as the Louisiana Community Impact Model (LCIM) (Fannin et al, 2008; Adhikari and Fannin, 2010) have been helpful in addressing economic impact questions to address the policy issues of a region. Other policy analysis models such as The Virginia Impact Projection (VIP) Model developed by Johnson (1991), The Iowa Economic/Fiscal Impact Modeling System developed by Swenson and Otto (2000), and the Integrated Economic Impact and Simulation Model for Wisconsin Counties (Shields, 1998) demonstrate how such a model could be used to aid local decision makers. This paper focuses in extending the results from Adhikari and Fannin (2008) using panel models and comparing to 3SLS modeling to measure the forecasting performances of estimators.

The COMPAS modeling framework can be applied across the country to address labor market and fiscal impacts from initial changes in economic activity (Johnson, Otto and Deller 2006). At its foundation, COMPAS is an employment driven model. Employment demand is generated by changes in local product demand. The definition of employment demand may vary but the exogenous shock that appears from the changes in employment demand is the basis of the modeling system in COMPAS based models. In many cases, this product is converted to employment demand through the use of input-output models. The input-output (I/O) model treats final demand as exogenous and the labor market supply as perfectly elastic to meet the labor demands generated by the product demands (Beaumont, 1990). In this I/O framework, an exogenous change in demand for the product and services interact with the rest of the economy through linkages of industrial material goods and services in an economy, its local labor market, and ultimately, its fiscal sector. See Figure 3.1 for an example of this structure.

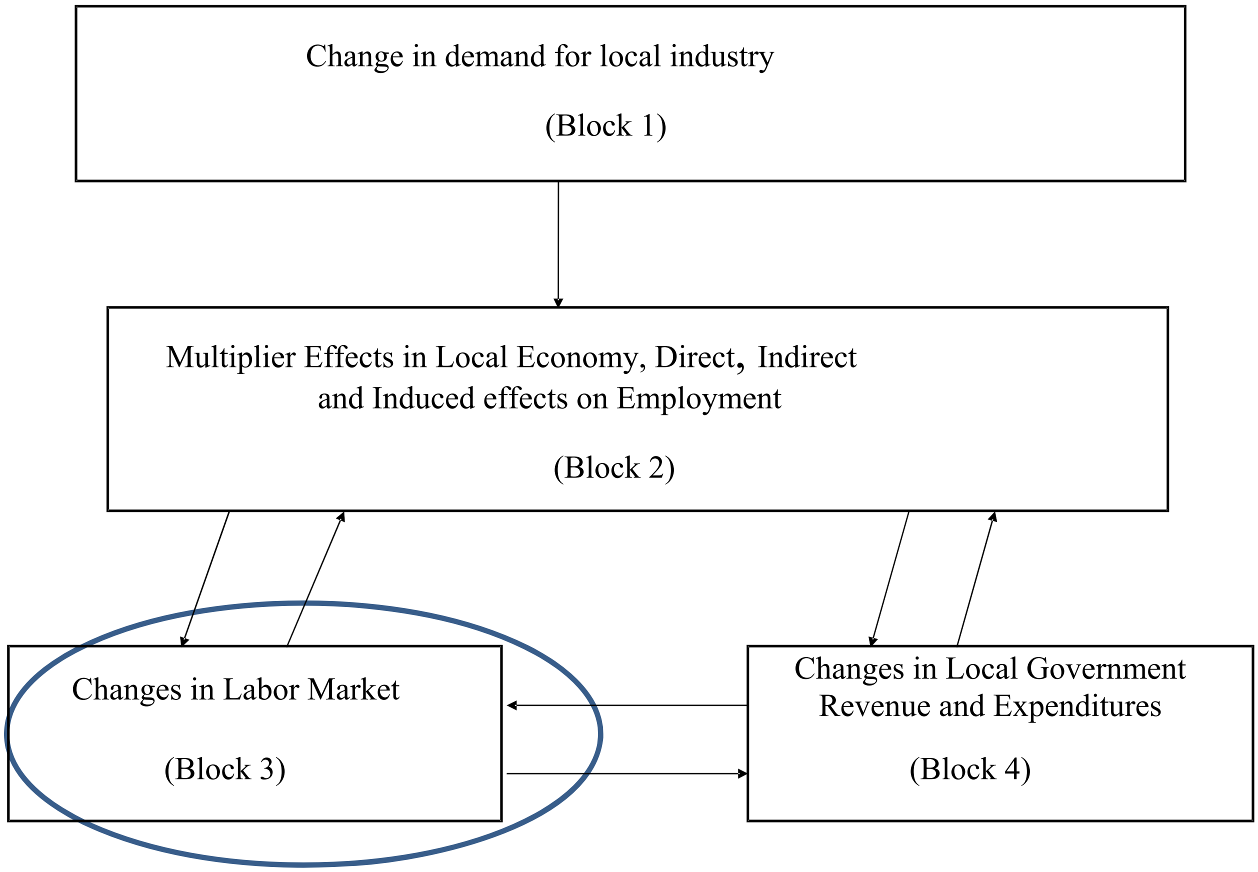

Figure 3.1. Highlighting the labor market in COMPAS modeling framework

3.2 Layout of the Study

The chapter comprises several sections. The next section is comprised of a literature review where we present the major ideas of several scholars who have conducted similar studies and lay out a foundation for the development of the remaining sections of the chapter. Then, we lay out a conceptual framework that explains the foundation of the model. This will be followed by the objectives of the study, which then will be followed by a data and methodology section where we set forth the theoretical and empirical model and describe the data and methods we will be using for accomplishment of the objectives of the chapter. These results will then be discussed and compared based on their relative performance of alternative labor market estimators.

3.3 Literature Review

The labor force module is a demand driven framework based on employment demand (Johnson, Otto and Deller, 2006; Fannin et al., 2008; Swenson, 1996). The underlying assumption is that economic growth is largely due to the exogenous increase in employment in a region. Several studies in the past have dealt with analytical methods and empirical results. Labor markets in the past were mostly focused on determination of wages and employment rather than observing the structural forms of labor force, in-commuters and out-commuters (Topel, 1986). Some of them took into account the spatial interactions of labor markets within and between neighboring regions (Cox and Johnson, 1999; Mohlo, 1995; Rouwendal, 1998) while others have ignored the spatial relationships. Also, most of the previous studies were performed to model the labor market and estimate the relationship of different variables with various determinants of the labor force module, most importantly, labor force, in-commuters, out-commuters, etc. There have not been any studies to my knowledge evaluating the relative forecasting performance of alternative labor market estimators of COMPAS models.

A concept of modeling the spatial labor market, a foundation of COMPAS type models, was developed by Johnson (2006) where he assumes that economic growth of a community is based on the labor market that distributes jobs between the in-commuters, out-commuters, currently unemployed and new entrants to the local labor market (Figure 3.2). Commuting plays a vital role while analyzing the labor market of a specific region. A small region might have a smaller resident labor force, but more commuters because of shorter travelling distance to its neighboring region. Similarly, a large and developed region might have measurable commuters because of more opportunities and job placement in the region. A labor market is conceptualized and presented in the figure below where the author has provided ample reasoning on why the labor market plays a vital role in COMPAS based models.

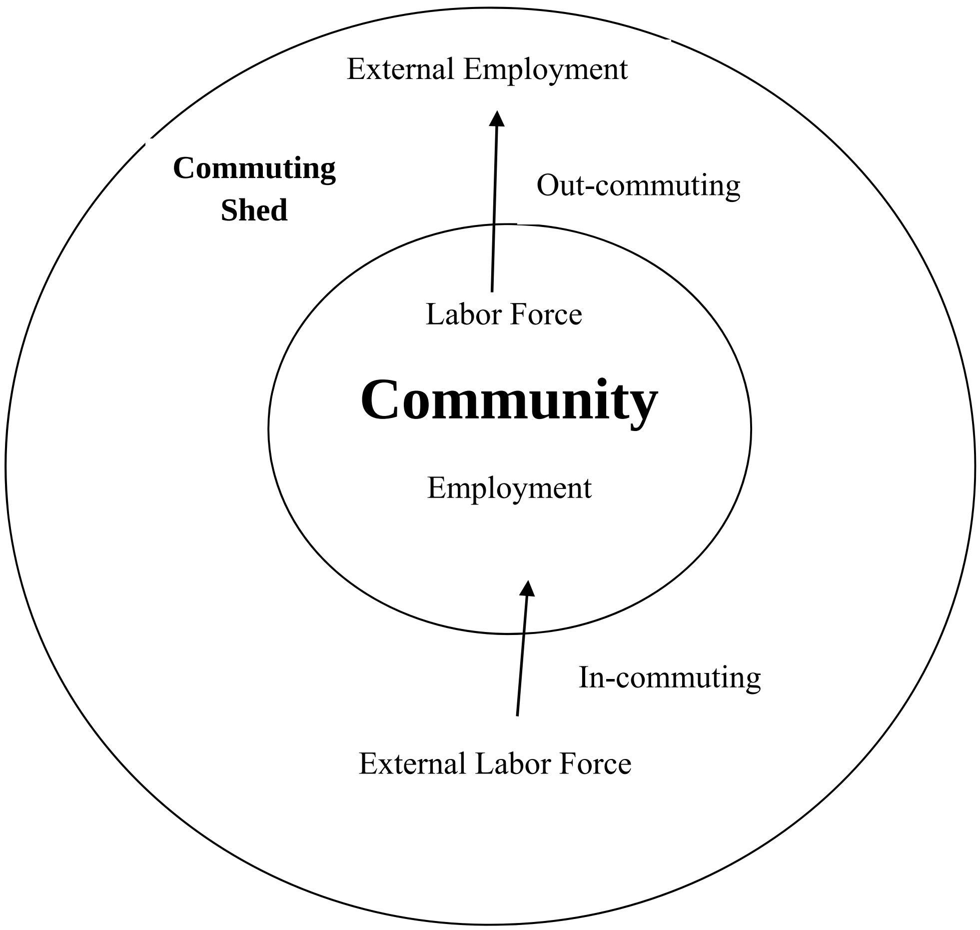

Figure 3.2. A conceptual labor market (*Johnson, 2006)*

The linking of the labor force module with input-output models such as IMPLAN (impact modeling for planning) is highlighted by Swenson and Otto (1998). They constructed an Iowa economic/fiscal impact model (IE/FIM) to generate detailed information about economic, demographic and fiscal variables to local decision makers. An inter-relationship of the labor force module and a fiscal module is presented in the sense that the changes in employment demand and the population are major factors affecting local tax bases, local revenues and expenditures. Labor force, out-commuters and in-commuters were the three dependent variables used in the model whereas population was assumed to be a function of labor force and other variables that affect labor force participation rate.

Based on the Iowa economic/fiscal impact model, Johnson and Scott (2006) proposed and analyzed another model to provide the information needs of policymakers at federal, state and local levels. The model, developed in Missouri, was named the Show Me model. They treated employment as the major driver for change in the local economy. Study of labor markets is important in allocating jobs between unemployed, in-commuters, out-commuters, in-migrants and local resident labor force. Changes in the labor market lead to changes in fiscal markets such as tax bases, retail sales, public service demands and local and state government transfers. Labor market equations were created based on the spatial labor market developed earlier by Johnson (2006) where in-commuters and out-commuters are the major source of labor supply in a region and employment by place of work equals labor demand. The model was analyzed by a simultaneous system of equations where a three stage least squares regression method was used to evaluate the model since it is an efficient estimator in checking for existence of correlation between individual equation's error terms (Pindyck and Rubinfield, 1991). An "area" term was added in the previous model to capture the spatial effects that were being ignored. Results showed that most of the expansion variables were significant; hence, they suggested that the "area" of a county has an impact on endogenous variables and should be incorporated in the

Show Me model. Employment was positive and highly significant for labor force, in-commuters and out-commuters equation.

A similar study was carried out recently by Fannin et al.(2008) to evaluate the deep water energy impacts on economic growth and public service provision in Lafourche Parish, Louisiana. Authors created a Louisiana community impact model (LCIM) in a block recursive fashion based on the COMPAS modeling framework to enumerate the linkages among local economic activity and the demand for local government services. A conjoined input-output and econometric model was used to analyze the economic impacts of the region. A labor market has been defined as a market that can provide population estimates as the local economy changes and that where the demand for labor by firms in a local economy between in-commuters, out-commuters, unemployed and new entrants are allocated. In my study, I propose modifications in variables and the estimation procedure by inclusion of a three stage least squares model, and panel regression methods that account for cross-equation correlation and multi-year variation respectively.

An extension of earlier studies was proposed by Evans and Stallmann (2006), where they proposed the Small Area Fiscal Estimation Simulator (SAFESIM) for Texas counties using a two-stage least squares procedure. SAFESIM was constructed as a spreadsheet-based simulator, which consisted of several socio-economic variables with data from county and school districts. Data in the model were obtained from a number of sources, including the U.S. Census Bureau, Woods and Poole Economics Inc., National Center for Education Statistics' Core of Common Data, and the Census of Governments. A labor force module and fiscal module were estimated using a 14-equation model. Civilian labor force was defined to be a function of employed and unemployed and results showed that that the labor force was positively affected by population and negatively by the level of unemployment. Total population was assumed to be the function of total number of jobs (positive relationship) and net commuting (negative relationship). Similarly, net commuting (In-commuters minus Out-commuters) was defined as a function of the place of work employment and the level of unemployment. Results indicated that there was a positive and significant relationship of place of work employment with net commuting. As the number of jobs in a region increase, the number of in-commuters increase and out-commuters decrease and thus the net commuting is positive. The effect was opposite in case of the increased levels of unemployment.

Many of the earlier studies in other disciplines used different techniques for evaluating forecasting performance. Cicarelli (1982) proposed a new method of evaluating the accuracy of economic forecasts where the probability of correctly forecasting directional change was introduced. Values of this measure were computed for eleven well-known macro econometric forecasting models. An inequality-type index of relative directional accuracy based on this measure was presented and used to evaluate the models in terms of their relative accuracy. Hsu and Wu (2008) performed a similar study for interval data with different evaluation techniques. They defined a criterion which was more efficient to evaluate forecasting performance for interval data, where they presented evaluation techniques for interval time series forecasting. The forecast results were compared by the mean squared error of the interval and mean relative interval error.

Amirkhalkhali et al. (1995) examined the relative forecasting performance of different estimators proposed for a structural equation in a large system using Monte Carlo experiments with antithetic varieties. The performance of the estimators was compared in terms of the accuracy of the within-sample as well as post-sample predictions for 10 structural equations by using the mean absolute percentage error (MAPE) of forecasts. It was concluded that the ridge-type estimator performed consistently better than other estimators in both the within-sample predictions and ex-post forecasts. While many forecast evaluation techniques are available, most are designed for the end user of the forecasts. Most statistical evaluation procedures rely on a particular loss function. Forecast evaluation procedures, such as mean squared error and mean absolute error, that have different underlying loss functions, may provide conflicting results. Diersen and Manfredo (1998) developed a new approach of evaluating forecasts, a likelihood scoring method that does not rely on a particular loss function. The method takes a Bayesian approach to forecast evaluation and uses information from forecast prediction intervals.

Most of the earlier community policy models dealt with the modeling issues and estimating relationships of several variables with labor market variables. Only few of them have tried to evaluate the forecasting performance of community policy models, Kovalyova and Johnson (2006), being one of them. They suggested that forecasting performance could improve model accuracy and validation. They ran simulations with all satisfactory models and looked for the best model (in terms of minimum error) from a statistical point of view to generate realistic economic predictions. They used several indicators to validate the Missouri Show Me model developed by Johnson and Scott (2006), which was estimated on the basis of cross-sectional data. They used several quantitative indicators for each equation and each county in the sample to analyze the forecasting accuracy. Results showed that the “best” model performed with about 10 percent error, as indicated by root mean square percent error and mean absolute percent error and concluded that the model produced forecasts of acceptable quality.

Traditionally, most of the COMPAS models were built on cross-sectional frameworks. Data availability was one of the biggest issues while constructing COMPAS type models in different states. Commuting data were historically added in the model based on the census journey to work data that is released once every decade. This results in two constraints while constructing a model. First, one is forced to model the commuting patterns only in the census year if one is to have data used in the model to be consistent across the same year. Second, one might have to assume that the commuting relation holds to the rest of the years when we take the census year of data, which incorporates some level of measurement error into the model. One of the major contributions of this study is the addition of newly available annual commuting data by county (parish) which allows increasing reliability of off-census year cross-sectional models as well as provides the opportunity to develop a panel data estimator as an alternative in COMPAS labor market module estimation.

Our concentration in this paper is to model the Louisiana labor market based on earlier developed community policy analysis models and then compare and contrast performance of alternative estimators using several approaches. As suggested by many researchers, we will be estimating the performance using several quantitative methods where we analyze different indicators like mean error, mean square error, root mean square error and Theil's coefficients as a benchmark for comparison. This will be a novel study in terms of comparing performance of several estimators of the labor force module in COMPAS modeling.

3.4 Conceptual Framework

Labor markets involve a structural system where employment supply and employment demand are constantly changing between regions creating a constant change in the flow of the labor force to meet demand both within and between regions. Neoclassical economics suggests that equilibrium in the labor market is the result of interactions between profit-maximizing firms and utility maximizing laborers. This interaction determines the price (wage in case of the labor market) and the quantity (number employed in case of labor market). One of the most common approaches of labor supply and labor demand could be the cases in Figure 3.3 and Figure 3.4 where a region faces an upward sloping (positively sloped) labor supply and downward sloping labor demand (negatively sloped). In such case, wage is determined where labor supply intersects labor demand (Hamermesh, 1993).

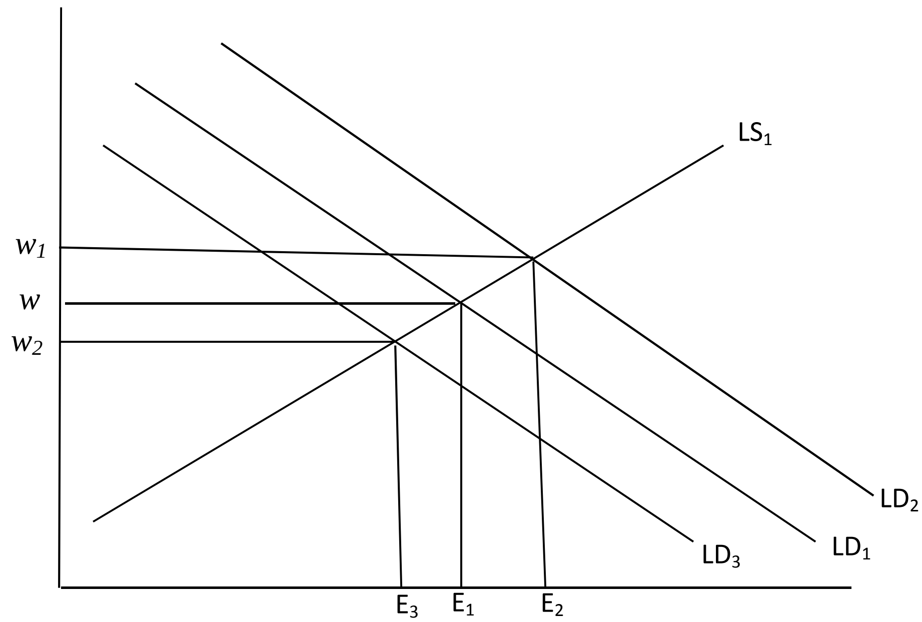

Fig 3.3. Result of labor demand change in employment and wages, supply being constant

In the figure 3.3, LS_1 and LD_1 determine labor supply and labor demand in an equilibrium condition. If labor demand increases (with constant labor supply), we see that the labor demand curve moves outward (LD_2) and thus both the employment and wages increases from E_1 to E_2 and w to w_1 respectively. If the labor demand decreases (again, labor supply being constant), labor demand curve shifts inwards (LD_3) and hence the employment decreases to E_3 and wages decreases to w_2. In case of Figure 3.4, LS_1 and LD determine labor supply and labor demand in an equilibrium condition. If there is an increase in labor supply (labor demand holding constant), labor supply curve moves to right (LS_2) and thus the employment increases from E_1 to

E_2 but wage decreases from w to w_1. On contrary, if the labor supply decreases, the labor supply curve moves to the left (LS_3), resulting in the increase in wages to w_2 but the decrease in employment to E_3 (Figure 3.4). The magnitude of change in the employment and wages depend on the shift of the curve.

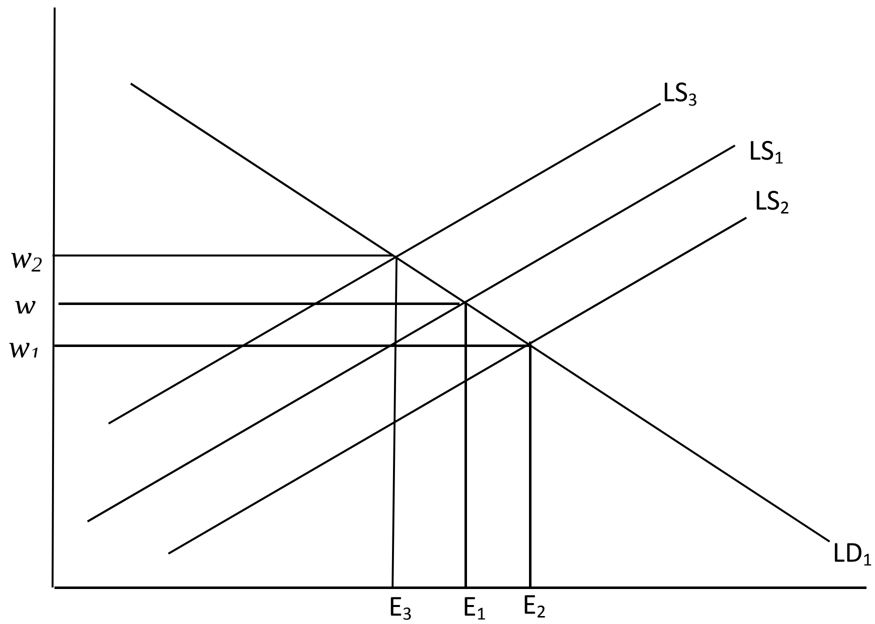

Fig 3.4. Result of labor supply change in employment and wages, demand being constant

Another approach that we explain here is an approach demonstrated by Johnson (2006), where individual labor faces a perfectly elastic labor supply, perfectly inelastic labor demand and exogenous wage[8] (Figure 3.5). This approach is more relevant in the context of the COMPAS modeling framework since the model is implemented in a small open economy region, for example, a county or a city. Such a region faces a perfectly elastic labor supply because of its residents, in-commuters and in-migrants (Bhandari, 2003).

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[8] Here, we consider a small region, say county, and thus the change is labor demand may not necessarily change the wage rate. Hence, wage in such a case is exogenously calculated.

In Figure 3.5, which is a case of a small economy, labor supply is displayed as L_S (which is infinitely elastic, as shown by horizontal line) and labor demand is displayed as L_D (which is completely inelastic, as shown by vertical line). Wages are exogenous and shown as *w* in the vertical axis. An increase in labor demand from L_D to L_{D1} would not change the wage rate but changes the total employment from E_1 to E_2.

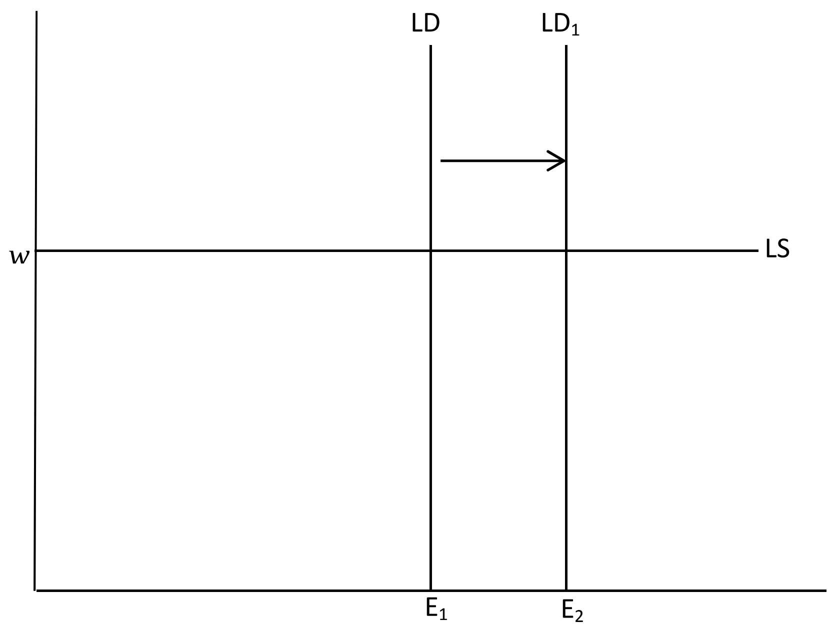

Fig 3.5. Result of perfectly elastic labor supply and perfectly inelastic labor demand

Changes in labor markets and how it is influenced by the changes in employment demand are described hereafter. Estimation of the labor force module plays a key role in our model, as is also the case with other COMPAS- based models. The Louisiana labor force module estimates structural equations for labor force, in-commuters and out-commuters, which closely explains the relationship between employment demand and the supply of labor needed to meet that demand. In the COMPAS modeling framework, labor supply is a function of labor force, unemployment, out-commuters and in-commuters within a region. Similarly, labor demand is the function of the wage rate. As can be seen in Figure 3.1, the labor force module lies between exogenous changes in employment and the ultimate fiscal effects (local government revenue and expenditures that occur in the local economy) in the COMPAS framework (Block 3).

Local and regional labor markets play a vital role in COMPAS-based models. These models assume that economic growth is caused mostly by an exogenous increase in employment. Conceptually, the labor force module intersects labor force demand and labor force supply:

$$L_D = L_S \qquad (1)$$

where L_D is labor force demand and L_S is labor force supply (Johnson 2006). The demand curve for the labor force is a function of the wage rate:

$$L_D = f(w) \qquad (2)$$

where w is the wage rate. We can invert the labor demand equation to obtain

$$w = g(L_D) \qquad (3)$$

We can also evaluate the supply as disaggregated into the following components:

$$L_S = LF - U - OC + IC \qquad (4)$$

where LF is the total labor force, U is the total unemployment, OC is the total number of out-commuters, and IC is the total number of in-commuters. We can then evaluate each component of the total labor supply as a function of employment as well as a vector of supply shifters (Johnson, Otto and Deller, 2006).

$$LF = f_L\,(w, Z_{LF}) = f_L\,(g\,(L_D), Z_{LF}) \qquad (5)$$

$$OC = f_L\,(w, Z_{OC}\,) = f_L\,(g\,(L_D\,), Z_{OC}\,) \qquad (6)$$

$$IC\;= f_L\,(w, Z_{IC}\,) = f_L\,(g\,(L_D\,), Z_{IC}\,) \qquad (7)$$

where Z is a vector of supply shifters for labor force, out-commuters, and in-commuters.

3.5 Objectives of the Study

This study aims to develop a model to forecast labor demand in terms of labor force, in-commuters, and out-commuters for the labor force module of Louisiana Community Impact Model (LCIM) using alternative procedures that are capable of increasing the performance over traditional COMPAS estimators. The specific objective includes modeling the labor force module (labor force, in-commuters and out-commuters) for all parishes of Louisiana with cross-sectional, three stage least squares (3sls), and panel approaches to compare the relative forecasting performance of the alternative estimators.

3.6 Data and Methodology

Estimation is based on the COMPAS model for all parishes of Louisiana that includes all 64 parishes[9], where the variables for the labor force module were selected on the basis of Fannin et al (2008) and were modified depending upon the requirements of our model. Louisiana is a good candidate for such a test because of the heterogeneity of the local labor force within the state. Seven different equations are estimated by a cross-section Ordinary Least Square (OLS) model as a base control with three stage least squares and the panel data model also estimated. We estimate the model using data mostly from the Bureau of Economic Analysis (BEA) regional economic data series (www.bea.org). In-commuting and Out-commuting Data come from the US Census Bureau's new Local Employment Dynamics Project

[9] Few outliers were removed using the r-student procedure

(http://lehd.did.census.gov/led/led/led.html). The entire regression analysis is analyzed using STATA. The forecasting performance is evaluated based on the procedures outlined in Johnson, Otto and Deller (2006), and Kovalyova and Johnson (2006).

3.6.1 Empirical Specification of Labor Force Module

The labor market equations in this module are based on the conceptual labor market discussed earlier in the paper. A cross-sectional OLS model is used as a base control model using the sample year of 2008. A panel data method is applied to observe whether the model performs better with increased observations, and the three stage least squares method is used to both improve model specification by explicitly modeling endogeneity between equations in the model, and to correct for any correlation, present between each individual equation's error terms. Following the work by Johnson (1996); Shields (1998); Swenson (1996); and Fannin et al. (2008), the Louisiana labor force module empirically specifies several equations for these variables.

Equations for Louisiana labor force module could be specified as:

$$WAGE= \beta_{20}+\beta_{21}EMP+ \beta_{22}UNEMP+ \beta_{23}WAGLAG+ \varepsilon \tag{8}$$

$$POP= \beta_{30}+\beta_{31}EMP+ \varepsilon \tag{9}$$

$$UNEMP = \beta_{40}+\beta_{41}EMPOP+ \beta_{42}WAGE+ \beta_{43}UNEMPLAG +\varepsilon \tag{10}$$

$$INCOMM = \beta_{50}+\beta_{51}RELLOCWA+ \beta_{52}RELLOCUN+ \beta_{53}EMPOP +\varepsilon \tag{11}$$

$$\text{OUTCOMM} = \beta_{60}+\beta_{61}\text{RELLOCWA}+ \beta_{62}\text{RELLOCUN}+ \beta_{63}\text{EMPOP} + \varepsilon \tag{12}$$

$$\text{LABFOR} = \beta_{70}+\beta_{71}\text{POP}+ \beta_{72}\text{ELDPOP}+ \beta_{73}\text{WAGE} + \varepsilon \tag{13}$$

where, LABFOR (labor force), UNEMP (unemployment), WAGE (average wage per job), POP (population), OUTCOMM (out-commuters), INCOMM (in-commuters) are endogenous variables and EMP (place of work employment), WAGLAG (wage lag), EMPOP (employment opportunities), UNMPLAG (unemployment lag), RELLOCWA (relative local wage), RELLOCUN (relative local unemployment), and ELDPOP (percentage of elderly population) are exogenous variables. The expected signs based on previous studies (Shields, 1998; Johnson, Otto, and Deller, 2006; Fannin et al., 2008) for these variables could be seen in the Table 3.1 below.

The labor market equation provides the information on all the components of labor supply and labor demand. Most employed (including self-employed) workers commute some distance. The data that we use are organized as if jobs and workers were located in discontinuous locations. When data are recorded, some workers are identified as residents of a different location than that of their jobs. These workers are defined as commuters. This definition, however, is very much dependent on the arbitrary boundary of data cells; especially the size of the data cells. In practice, these data cells are typically counties or census places. Functional forms for each of the equations were based on Fannin et al., (2008); however, I also tested the functional forms for each equation by the box-cox test and results suggested the log-log form to be the most appropriate functional form based on the data.

Table 3.1. Expected Signs for Different Variables for Labor Force Module Equations

Dependent Variables	Independent Variables		
WAGE	EMP	UNEMP	WAGLAG
	(+)	(-)	(+)
UNEMP	EMPOP	WAGE	UNEMPLAG
	(+)	(-)	(+)
POP	EMP		
	(+)		
INCOMM	RELLOCWA	RELLOCUN	EMPOP
	(+)	(-)	(+)
OUTCOMM	RELLOCWA	RELLOCUN	EMPOP
	(-)	(+)	(-)
LABFOR	POP	ELDPOP	WAGE
	(+)	(-)	(+)

As stated earlier, the primary purpose of this chapter is the performance measurement of alternative estimators based on newly available datasets and to check whether the uniqueness of cross-sectional units matter. This is performed by evaluating different estimators of the general labor force module of Louisiana. We are interested in choosing an optimal model that maximizes the forecasting performance for the labor force module equations of the Louisiana COMPAS model. A cross-sectional OLS, 3sls, and a panel approach will be applied in order to model the labor force. Based on the results, we evaluate if the model specification addressing endogeneity (as observed from 3sls) or additional time series data (panel data set that incorporates both spatial and temporal dimensions) is relatively more important for increasing the forecasting performance.

We start with the OLS/GLS framework where we take a single year's worth of data as performed by Johnson et al. (2006). The base year as a sample for estimation is 2008. Next, we take into account three stage least squares model (2000-2008) and a panel model (2000-2008) that takes into account the newly available annual data on commuting.

Comparing the performance of different estimators is an important step in the model building process since it can suggest the best model to be selected and different ways in which the model can be improved. Because of the availability of actual data for 2008, it is a simple matter to determine the accuracy and degree of discrepancy between generated outcome and the actual data. The performance of estimators is compared on the basis of quantitative evaluation methods. These methods include analysis of mean simulation error (ME), mean percent error (MPE), mean absolute error (MAE), mean absolute percent error (MAPE), mean square error (MSE), root mean square error (RMSE), root mean square percent error (RMSPE), and Theil's coefficient U1 and U2 (Johnson, Otto and Deller, 2006; Pindyck and Rubinfield, 1991, 1998; Theil, 1970, 1975). These performance metrics will be provided for both in-sample years (2008) and selected year's out-of-sample (2000-2008).

3.7 Results and Discussion

Results from table 3.2 demonstrate the descriptive statistics of variables used in the labor market equations of the labor force module of Louisiana. As can be seen, there is measurable variability in the data. It should be noted that unlike other COMPAS type models that incorporate only a subset of the counties (parishes) in a state for analysis, this model incorporates all parishes, large and small, resulting in greater variability.

Table 3.2. Variable Description and Summary Statistics, Louisiana

Variable	Variable Description	Mean	Standard Deviation	Min	Max
EMP (#)	Place of work employment	30,165	43,908	1,944	221,739
WAGE ($)	Average wage per job	30,072	7,156	17,653	55,730
UNEMP (#)	Unemployment	1,615	2,189	114	13,931
POP (#)	Total Population	69,315	95,303	5,671	483,663
INCOMM (#)	Total In-commuters	10,754	19,890	272	118,882
OUTCOMM (#)	Total Out-commuters	10,552	13,194	488	86,044
LABFOR (#)	Total labor force	31,555	40,133	2,196	236,340
WAGLAG ($)	Wage lag	29,222	6,615	17,653	51,685
UNEMPLAG (#)	Unemployment lag	1,640	2,224	114	13,931
RELLOCWA ($)	Relative local wage (avg local wage/avg continuous wage)	1.009	0.147	0.718	1.507
RELLOCUN (#)	Relative local unemployment (local unemployment/contiguous unemployment)	0.305	0.569	0.010	4.512
EMPOP (#)	Relative employment opportunities (local employment/contiguous employment)	0.318	0.561	0.012	4.997
ELDPOP (%)	% Population over 65 years of age	12.64	2.28	6.96	18.05

Results from table 3.3 demonstrate parameter estimates comparison of the OLS estimators, 3sls estimators, and panel estimators for all equations of the labor force module of

Louisiana. Most of the signs in the parameter estimates are as expected; however, there are some counter-intuitive estimates.

Table 3.3. Parameter Estimates for OLS, 3sls and Panel Regressions of Louisiana Labor Force Module

Labor Force Module	Linear (OLS)		3SLS		Panel	
	Coeff.	t-stat	Coeff.	z-stat	Coeff.	z-stat
Wage						
Employment	0.008	0.62	-0.002	-0.21	0.024***	4.73
Unemployment	-0.010	-0.72	0.001	0.11	-0.026***	-4.50
Wage lag	1.00***	59.86	1.008***	94.18	0.990***	127.03
Intercept	0.051	0.34	-0.025	-0.28	0.092	1.22
Unemployment						
Employment opportunities	0.008	0.44	0.042**	3.14	0.036***	4.11
Wage	0.103	1.32	-0.072	-1.58	-0.066***	-3.20
Unemployment lag	0.995***	37.70	0.926***	56.38	0.945***	85.04
Intercept	-0.874	-1.29	1.316***	2.86	1.112***	4.45
Population						
Employment	0.906***	32.57	0.889***	50.22	0.881***	35.27
Intercept	1.788***	7.01	1.979***	11.45	2.050***	8.92
In-commuters (Dep var) (log-log model)						
Relative local wage	1.534**	2.35	1.673***	6.38	0.701	1.64
Relative local unemployment	-0.630***	-5.73	-0.443***	-6.27	-0.283**	-2.46
Relative employment opportunities	0.172	1.49	0.158**	2.26	0.202***	4.05
Intercept	10.286***	51.21	9.536***	122.48	9.400***	35.16
Out-commuters (Dep var) (log-log model)						
Relative local wage	-0.242	-0.43	-0.257	-1.36	-0.481	-1.10
Relative local unemployment	0.515***	5.15	0.334***	6.87	0.306***	4.49
Relative employment opportunities	0.110	1.24	0.055	1.14	0.126	1.04
Intercept	10.336***	78.51	9.531***	158.27	9.714***	63.07
Labor Force (Dep var) (log-log model)						
Population	1.024***	22.56	0.888***	49.65	0.858***	12.87
% Population over 65 years of age	0.110	0.48	-0.139***	3.19	-0.415**	2.02
Wage	-0.280	-1.04	0.676***	10.32	0.128***	2.57
Intercept	1.695	0.59	7.022***	10.31	-1.620**	-2.22

*****/**/*** indicate statistical significance at 1%, 5%, and 10% levels respectively

Parameter estimates for the labor force module is presented in the table 3.3. Predictably, in the **wage** equation, the current wage rate is significantly related to its lagged value. Parameter estimates for lagged wages close to one suggest that almost all effects are captured by the lagged variable and that the lagged wages are considered to be important determinants of current wages. Similar interpretation could be made in the case of **unemployment** equation that the current unemployment rate is significantly related to its lagged value and the parameter estimates for lagged unemployment close to one suggest relative year-to-year stability of labor markets. Negative sign (3sls and panel model) for wage is consistent with the theory suggesting that an increase in wage would attract more people and that would be an incentive for a decrease in unemployment.

Place of work employment is considered to be the primary variable that drives changes in variables from the labor force module, since it determines the changes in population in the regions of study. Results from the **population** equation suggest that economic opportunity, as measured by the number of local jobs, has an important influence on the number of local residents. This is consistent with the theory since people tend to live close to their place of work. Hence, as new local jobs are created, people migrate into the region: here 100 new jobs result in about 90 additional local residents.

In case of the **in-commuters** equation (for all models), we see that an increase in the relative local wage would attract more in-commuters. When a region A has more jobs compared to its contiguous regions B, C, and D, people in-commute to region A from B, C, and D in search of employment opportunities. Similarly, a negative sign for the relative local unemployment is consistent with theory, as it depicts that an increase in unemployment in a region A compared to regions B, C, and D would decrease the number of in-commuters into region A since the workers from B, C, and D would substitute working in their place of residence rather than commuting to the region A. Furthermore, a positive sign for the employment opportunity depicts that an increase in employment in a region A compared to regions B, C, and D would increase the in-commuters of region because there would be increased supply of jobs in region A and thus people from regions B, C, and D would out-commute to region A to meet this newly available supply.

In case of the **out-commuters** equation, the negative sign of the relative local wage variable indicates that an increase in the local wage of region A compared to regions B, C, and D would lead to a decrease in out-commuters from region A. This is also consistent with the theory because an increase of local wages in region A works as an incentive for the workers of region A to live and work in their own region which certainly would decrease the number of out-commuters. Similarly, a positive sign for the relative local unemployment is consistent with theory, as it depicts that an increase in unemployment in a region A compared to regions B, C, and D would increase the out-commuters of region A as they would explore for jobs in their contiguous regions. While the signs on the coefficients for relative employment opportunities run counter to theory, they are not statistically significant.

Not surprisingly, population is the largest determinant of the local labor force, as evident from the **labor force** equation. As observed from the panel data model, 100 additional residents lead to around 85 person increase in the local labor force. The negative sign on the percent population above 65 years of age depicts that an increase in elderly population leads to decrease in the labor force of a region since fewer at this age will continue to work. Similarly, results show that an increase in wages lead to an increase in the labor force, which is consistent with the theory, since an increase in wages would be an incentive for people to starting looking for jobs and hence join the labor force.

Table 3.4. Average Performance Estimation Measures for Dependent Variables in Labor Force Module

Labor Force Module	Linear (OLS)	3sls	Panel
Wage			
Mean Percent Error	0.002	-0.003	0.0005
Mean Absolute Percent Error	0.026	0.020	0.019
Root Mean Square Percent Error	0.004	0.002	0.001
Theil's Coeff (U1)	0.010	0.048	0.046
Theil's Coeff (U2)	0.021	0.276	0.275
Unemployment			
Mean Percent Error	0.027	0.027	0.026
Mean Absolute Percent Error	0.181	0.173	0.172
Root Mean Square Percent Error	0.068	0.068	0.068
Theil's Coeff (U1)	0.141	0.140	0.140
Theil's Coeff (U2)	0.689	0.690	0.689
Population			
Mean Percent Error	0.044	0.054	0.038
Mean Absolute Percent Error	0.183	0.191	0.174
(Table 3.4 contd.)			
Root Mean Square Percent Error	0.059	0.067	0.054
Theil's Coeff (U1)	0.077	0.081	0.075
Theil's Coeff (U2)	0.176	0.192	0.385
In-commuters			
Mean Percent Error	0.300	0.434	0.422
Mean Absolute Percent Error	0.711	0.892	0.855
Root Mean Square Percent Error	1.698	1.688	1.685
Theil's Coeff (U1)	0.246	0.267	0.206
Theil's Coeff (U2)	0.745	0.707	0.798
Out-commuters			
Mean Percent Error	0.291	0.317	0.257
Mean Absolute Percent Error	0.632	0.651	0.617
Root Mean Square Percent Error	0.845	0.915	0.815
Theil's Coeff (U1)	0.264	0.138	0.136
Theil's Coeff (U2)	0.475	0.634	0.626

(Table 3.4. contd)

Labor Force			
Mean Percent Error	0.051	0.097	0.042
Mean Absolute Percent Error	0.233	0.281	0.215
Root Mean Square Percent Error	0.128	0.143	0.107
Theil's Coeff (U1)	0.051	0.052	0.047
Theil's Coeff (U2)	0.281	0.282	0.264

When testing the relative performance between the models, for most cases, the panel data model outperformed both the ordinary least squares and three stage least squares models in terms of mean error, root mean square percent error and Theil's coefficients[10] (Table 3.4). Theil's coefficients are calculated based on root mean square error and zero value of the coefficient indicates perfect prediction and any value up to 10% is considered effective.

Referring to Figure 3.6, a comparison is made on the off-years forecasting performance between these models for the labor force equations. My OLS model is based on a cross-sectional data for the year 2008. My 3sls and panel data are based on years ranging from 2000 to 2008. Results display similar pattern in most cases (2005 and 2006 display some unusual pattern which might have resulted from the effects of hurricanes Katrina and Rita)-panel data model outperforming both the OLS and 3sls model, measured in terms of average absolute mean percent error measures.

[10] See Appendix 1 for diagrammatical comparisons between models for five sample equations based on error measures mentioned earlier

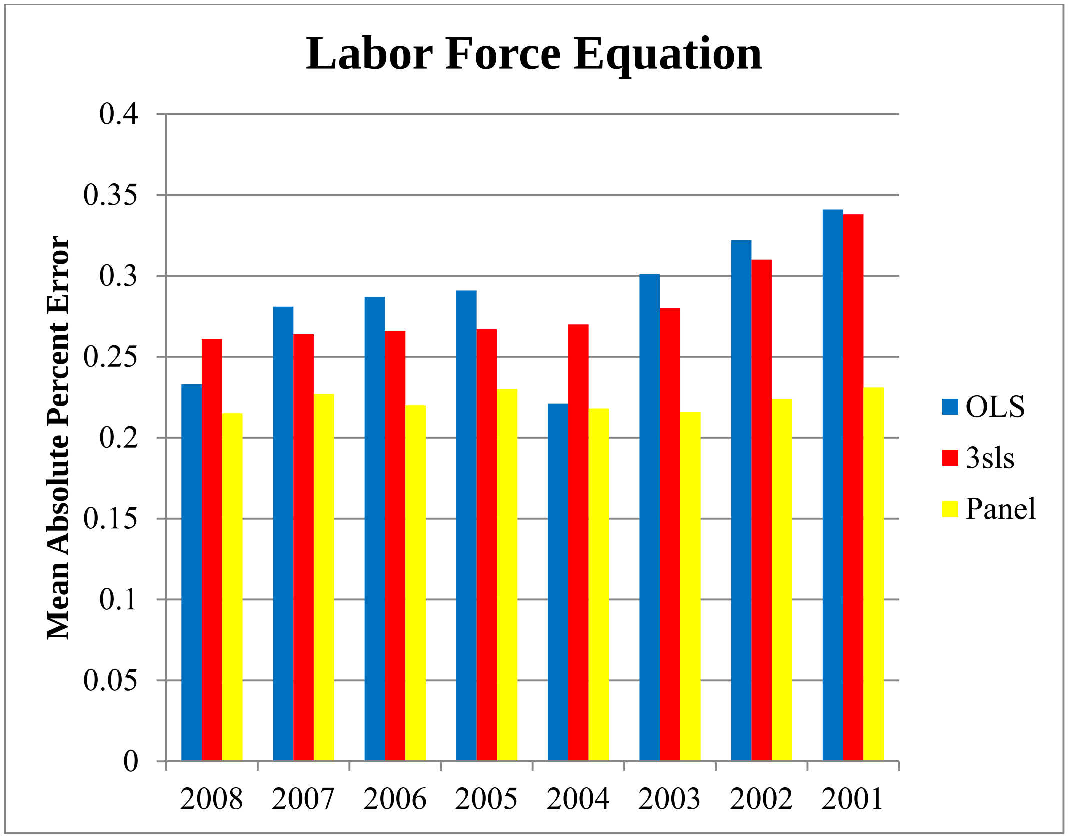

Fig 3.6. Comparing off-years MAPE by OLS, 3sls and panel data models

While comparing OLS and 3sls by same sets of error measures, 3sls seems to outperform OLS on all three equations. This might be consistent with the theory because 3sls procedure improved model specification (by incorporating endogenous regressors) increased forecasting performance. Further, as expected, inaccuracy of forecasts increased as we back-casted further from the cross-sectional date from which the parameter estimates were constructed (2008).

Although error measures were suggested by Kovalyova and Johnson (2006) to evaluate what would be considered quality forecasting performance, I conducted a mean comparison test in STATA to compare the base OLS model with 3sls and panel data models for four different equations (wage, in-commuter, out-commuter, and labor force) of the labor force module. The test performs a comparison of means for all possible combinations of groups. For instance, we have 3 types of models (OLS, 3sls, and panel) and we would like to see if there are differences in means between groups, this test computes the t-test for all three possible combinations. The output is presented in a table of differences in means (as denoted by magnitude) and includes the value (as denoted by t-stat), and significance level of the t-test (as denoted by single, double and triple asterisks for indicating statistical significance at 10%, 5%, and 1% respectively. These results are presented in Tables 3.5 – 3.8.

Table 3.5. Mean Comparison Test for Wages Based on MAPE

Wages					
	OLS	3sls		Panel	
		Magnitude	t-stat	Magnitude	t-stat
OLS		-127	-4.35***	-0.002	-1.74**
3sls				127	4.35***
Panel					

*****/**/*** indicate statistical significance at 1%, 5%, and 10% levels respectively

Table 3.6. Mean Comparison Test for In-commuters Based on MAPE

In-commuters					
	OLS	3sls		Panel	
		Magnitude	t-stat	Magnitude	t-stat
OLS		0.106	2.22**	0.069	1.132
3sls				-0.036	-1.37
Panel					

*****/**/*** indicate statistical significance at 1%, 5%, and 10% levels respectively

Table 3.7. Mean Comparison Test for Out-commuters Based on MAPE

Out-commuters				
	OLS	3sls		Panel
		Magnitude	t-stat	Magnitude	t-stat
OLS		0.020	0.521	0.035	0.860
3sls				0.014	1.36
Panel					

***/**/* indicate statistical significance at 1%, 5%, and 10% levels respectively

Table 3.8. Mean Comparison Test for Labor Force Based on MAPE

Labor Force					
	OLS	3sls		Panel	
		Magnitude	t-stat	Magnitude	t-stat
OLS		-0.088	-4.064***	-0.051	-2.338**
3sls				0.036	1.236
Panel					

***/**/* indicate statistical significance at 1%, 5%, and 10% levels respectively

Overall, results from these tables suggested that although the panel data model is always lower in magnitude in terms of error measures as compared to the base OLS model and the 3sls model for all five labor force module equations, it is not always significantly lower (in terms of absolute mean percent error) than the OLS or 3sls model. Hence, one should not conclude that panel data model outperforms the OLS and 3sls models. For wages equation (Table 3.5), one can statistically conclude whether the panel data model outperforms OLS and/or 3sls model because the test shows that there is significant difference between OLS, 3sls and panel data models. For example, if we look at the fourth and the fifth column, we found that the magnitude of differences between the mean values of OLS and the panel model is -0.002. A test statistic for the difference between the means of two different groups is calculated as:

$$t = \left(\frac{\bar{Y}_{OLS} - \bar{Y}_{3SLS}}{SE(\bar{Y}_{OLS} - \bar{Y}_{3SLS})} \right), \tag{15}$$

where, $\bar{Y}_{OLS}$ *and* $\bar{Y}_{3SLS}$ are the average absolute mean percent error for OLS and 3sls model respectively, and SE is the standard error.

Hence, results for the wages equation (Table 3.5) show that both the panel data and 3sls model seem to outperform OLS model and the panel model also outperformed the 3sls model. However, for the in-commuter equation (Table 3.6), it seems that 3sls model outperformed the OLS model but the supremacy between 3sls model and the panel model is ambiguous based on significant differences. For the out-commuter equation (Table 3.7), supremacy between all three models is ambiguous as we could not see significant differences between these models. Finally, for the labor force equation (Table 3.8), both 3sls and the panel model seems to outperform the OLS model but the supremacy between the panel model and 3sls model seems ambiguous.

Average error measures are not a perfect method for evaluating the performance of entire region. We can, therefore, take individual parish data and evaluate the performance of estimators in terms of quantitative measures like mean error, mean percent error and root mean square error to figure out how much the predicted value deviates from the actual value. For the labor force equation (in case of OLS), we could see that the average mean percent error, average absolute mean percent error, and average root mean square percent error are 0.051, 0.233, and 0.128 respectively (Table 3.4). However, because of the heterogeneity in space, some parishes like

West Feliciana, Plaquemines, Assumption, East Baton Rouge, Iberville, and Orleans are not performing as well on average, since their predicted values are measurably different than their actual values and thus are the reason for higher error values. On the contrary, parishes like Calcasieu, Bossier, Caldwell, Claiborne, Richland, St. Helena, Terrebonne, Union, and Madison are performing better than the average error measures as the difference between the predicted and actual values are close to zero.

3.8 Conclusion and Limitations

This research identified newly available data from which to evaluate alternative models for improving forecasting performance for labor market module estimators in Community Policy Analysis System-type models. In particular, we applied new labor market data on commuting from the census bureau to apply more time accurate commuting data for OLS and three stage least squares models as well as develop a panel dataset of commuting to apply a panel data estimator to estimate and forecast labor force, in-commuting and out-commuting.

Panel data models, in most of the cases, have advantages over cross-sectional OLS regressions in improving the model performance. Also, three stage least squares models showed minimal performance improvements as compared to the base OLS model. This might be the case that the sample year (2008) might not be a good year for the labor force module. From these findings, our analysis suggest that over the time period analyzed, there is higher returns to forecasting performance from incorporating additional data through a panel specification than incorporating endogeneity in the model. Results suggested that incorporating endogeneity in the model actually reduces forecasting performances relative to ignoring the endogeneity with the panel model. The reduction in the forecasting performances might have been the result of misspecification of the model, which is one of the limitations of three stage least squares model.

One of the limitations of this study is the exclusion of spatial econometric analysis to build the models that might take into account the spatial behavior in terms of distance measures. These spatial estimators could also be used as alternatives to the COMPAS model to evaluate whether these estimators would increase the forecasting performance by taking including the space variable in the model. Their inclusion would be a future extension of this research.

An additional limitation of this research is the unfortunate timing of the exogenous shock of Hurricanes Katrina and Rita during the modeling period. The 2005 and 2006 years are likely outliers in terms of temporary labor market shifts that did not settle out until 2007. Including these two years in our panel dataset may have reduced the forecasting performance of the panel data estimator. Future research may investigate panel data windows that exclude this period.

An evaluation of the alternative methodologies performed in this study are expected to give regional economic modelers better information from which to choose econometric models for labor force modeling in COMPAS-type models. Using the data from different sources, this study developed a model to forecast different sectors of the labor force module using cross-sectional linear, three stage least squares, and panel data regression. Future optimal applications of these estimators will improve forecasts and increase the demand and application of these models by local governments and other constituencies.

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CHAPTER 4

MODELING THE LOUISIANA LOCAL GOVERNMENT FISCAL MODULE IN A DISEQUILIBRIUM ENVIRONMENT: A MODIFIED COMPAS MODEL APPROACH

4.1 Introduction and Background Information

Most of the public service expenditure models under the community policy analysis system (COMPAS) are structured under an equilibrium condition assumption, i.e., supply equals demand. Based on Inman (1978), the expenditure equations tend to describe the equilibrium of public expenditure demand and supply. First, the demand side is explained which determines how revenue is raised to pay for goods and services and/or how the goods and services will be produced. Second, the supply (production) side is explained by the process of transforming inputs to outputs. These models have rarely been tested in an environment where the public sector may be argued to be operating in a disequilibrium environment.

The primary objective of this study is to assess whether the forecasting performance of the public sector expenditure under a COMPAS fiscal module (an equilibrium model) fits reasonably well under a disequilibrium environment. Conceptually, the fiscal module under a COMPAS framework represents an equilibrium concept and this equilibrium is operationalized by demand shifters modeled empirically. These shifters, however, may not work well in a disequilibrium environment, where exogenous shocks push the public sector into an intermediate period (or long-term period) where local government public sector supply in less sensitive to traditional demand curve shifting conditions. In such a case, one should consider alternative models for forecasting local government revenues and expenditures during the period of supply-demand disequilibrium. This study is focused on evaluating the conceptual framework for modern day local government revenue and expenditure forecasting along with the strengths and weaknesses of such modeling in terms of empirical specification. We compare the traditional COMPAS model with a modified COMPAS model (a dynamic model) and analyze the forecasting performance of several indicators under disequilibrium conditions. The study evaluates forecasting performance during the time frame of proposed disequilibrium, where the data represents a period of major exogenous shock (hurricanes Katrina, Rita and Gustav)[11] to local government.

A traditional equilibrium public service model is tested versus the naïve model (that incorporates dynamics with inclusion of lagged dependent variable) where I evaluate public service expenditure forecasting in a disequilibrium environment. The naïve model (lagged dependent variable) is then tested against the naïve plus model (an inclusion of revenue capacity variables in the naïve model) and the modified naïve model (a hybrid type of model that includes the naïve plus model as well as demand shifter co-variates from the traditional COMPAS empirical specification). Unlike traditionally applied COMPAS models, these models allow for multiple years' worth of data to be considered in the form of a panel structure. In addition, a comparatively newer approach (quantile regression) is also introduced to test the shortcomings of existing COMPAS estimators.

The chapter comprises several sections. The next section deals with the background of local fiscal modeling, where I present the major ideas of several scholars who have done similar studies and lay out a foundation for the development of my paper. I also explain the theoretical and conceptual background of local public service modeling in terms of COMPAS frameworks and alternative frameworks in this section. The following section includes general and specific objectives of this study. This will be followed by the empirical specifications of fiscal module, where I set forth the empirical model with revenue capacity and expenditure equations. The succeeding section describes the data and methodology used for the analysis. I will then analyze

[11] Hurricanes Katrina and Rita made a landfall in Louisiana in 2005 and Hurricane Gustav made a landfall in Louisiana in 2008.

the data and discuss the results and key findings of the regressions and the performance comparison of different estimators from various underlying models and compare them based on their relative forecasting performances. Finally, I conclude the study by pointing out some limitations of the study and the future prospect of this research.

4.2 Background on Local Fiscal Modeling

There have been several studies focused on the construction and evaluation of fiscal modules by local governments to determine the level of public services to be provided to its residents. In 1960s and most of 1970s, ad hoc expenditure models dominated the modeling issues of local public sector. Other models developed during these periods with the concept of modeling public services were concentrated on empirical analysis and mostly were lacking a conceptual framework. We present a snapshot of some of these studies built on the empirical frameworks used to model local public service delivery in Table 4.1.

Table 4.1. Summary of Determinants of Local Public Service Expenditures in 1960s and 1970s

Author (Year)	**Model Used**	**Objectives of the Study**	**Dependent Variables**	**Major Regressors**	**Major Findings**
Fisher (1961)	Simple linear regression	To estimate per capita expenditure of state and local government	Per capita expenditure of state and local government	Population, Population density, Per capita income	Income positive and significant, population density negative and significant
Sacks and Harris (1964)	Ordinary least squares	To analyze total direct expenditures on several categories of local government	Total direct expenditures, health and hospital, education and other expenditures	Population, Federal and state aids, Per capita income, % urban	Income and federal and state aids significantly describe local government expenditures

(Table 4.1 contd.)

Barr and Davis (1966)	Simple and multiple regression	To analyze determinants of several expenditure categories of Pennsylvania counties	General government expenditure, Highways expenditure, Judicial expenditure, and other expenditure	Property holdings, Median income, Median education, Voting preferences	Differences in preferences for expenditures significantly explains several local government expenditure
Bahl and Saunders (1966)	Ordinary least squares, Non-linear regression	To analyze the temporal pattern of determinants of state and local government expenditures	State and local government expenditures	Per capita federal grant, Per capita income, Population, % urban	Per capita federal grant, income, population density and % urban were all positive and significant
MacMohan (1970)	Ordinary least squares	To analyze determinants of public primary and secondary education expenditures by cross-sectional and time series data	Public primary and secondary education expenditures	Pupil per teacher, Assessed value, Federal and state aids, Personal income, Population	Federal and state aids, pupil enrollment over time significantly explain growth of public primary and secondary education expenditures
Bergstrom and Goodman (1973)	Ordinary least squares	To estimate demand functions for municipal public services	General expenditures, police expenditures, parks and recreation expenditures	Tax share, Population change, Crowding parameter, Income	Expenditures on different categories depends on locality. Income plays major role in most localities

The introduction of IMPLAN (impact model for planning) (Alward et al., 1989) created a revolution in regional economics for studying impact analysis in late 1970s and the 1980s. IMPLAN was a major modeling accomplishment through its creation of local input-output models based on secondary data that could be updated annually as compared to other models dependent on primary data for construction that were for typically larger regions and costly to construct and update (Johnson, Otto, and Deller, 2006). Unfortunately, despite IMPLAN's success at generating contribution and impact projections for community-wide current account variables such as output, value-added, labor income, and employment, it was less effective in providing valuable information for a community's public sector.

Consequently, researchers then focused on building models that could cater to the customized needs of communities for public sector impacts and forecasting based on secondary data. In an effort to develop advanced fiscal models for local communities, the regional rural development centers and the Rural Policy Research Institute (RUPRI) supported several rural studies that were intended to generate an empirically tractable approach to local public sector modeling (RUPRI, 1995). RUPRI then extended its help and support for conducting multistate interdisciplinary research by building an outreach network, known as community policy analysis network (CPAN) (Scott and Johnson, 1998). The network comprised a group of social scientists who attend periodic meetings to help develop new models and support tools on emerging issues that were important to rural communities. Their efforts began by developing a stylized model that was originally intended to develop a true general equilibrium type fiscal model where one could formally model separately local public sector demand and supply. In an effort to explore a model that accounts for both the empirical as well as the conceptual framework and could be customized based on the needs of local public supply and demand, they (CPAN members) introduced a model in 1980s, today known as community policy analysis system (COMPAS) models (Johnson, Otto and Deller, 2006). These models originated from mostly CPAN researchers from Midwestern states developing models for rural counties in their respective states where these regions were quite homogenous and that were likely to have the equilibrium assumptions that empirically operationalized their models hold during the slow steady growth of these rural regions in the 1990s.

4.2.1 Mathematical Derivation of Stylized Model

The supply and demand side of local goods and services market could be integrated to gain more insights in this median voter model. First, if we look at the supply side, let us assume a Cobb Douglas production function by local governments and they are a price taker in terms of factor inputs. Mathematically,

$$Y = AL^{\beta}K^{1-\beta}, where 0 < \beta < 1 \qquad (4.1)$$

where Y denotes total output and L and K are labor and capital inputs. A is assumed to be constant and refers to level of technology. Budget constraint could be expressed as :

$$B = TC = wL + rK \qquad (4.2)$$

where w is the wage rate of labor and r is the rental rate of capital. B denotes total budget and TC refers to total cost. The optimization problem could be set up as a Lagrangian function ℓ(L, K, λ):

$$\max\ \ell = AL^{\beta}K^{1-\beta} + \lambda(TC - wL - rK) \qquad (4.3)$$

Solving first order conditions and setting them equal to zero,

$$MRTS_{L,K} = \frac{w}{r} \qquad (4.4)$$

The marginal rate of technical substitution between labor and capital equals the ratio of wages and rents. Local governments tend to consume factor inputs until the point where the marginal products equal input factor costs. Factor demand equations could be solved and by substituting the factor demand equations in the original production function, we can solve for marginal cost function, which is required for the demand side of the model. The marginal cost function in this case looks like:

$$MC_y = \left(\frac{1}{\alpha}\right)\left(\frac{w}{\beta}\right)^{\beta}\left(\frac{r}{1-\beta}\right)^{1-\beta} \tag{4.5}$$

Now, if we look at the demand side, a concept of price must be well defined. Prices equal marginal costs in case of perfectly competitive markets. But, in case of local government's public sector, payment is made through some form of taxes (mostly property taxes) and thus the taxpayers' (median voter) burden must be taken into account along with the cost of production while determining the price. Thus, price could be expressed as:

$$s = \varphi MC_y \tag{4.6}$$

where, φ is the tax share of median voter.

An utility maximization equation could thus be set up to analyze the demand side of the model. With some income and price constraints, we could express the optimization model as:

$$\max U(X, Q) \qquad s.t. \quad I = pQ + \varphi MC_y Y \tag{4.7}$$

where, Y denotes public goods and Q denotes private goods. I represents money income and p represents the price for composite private goods. Working through Lagrangian and solving the first order conditions, we can derive a demand equation for public goods as:

$$q = \alpha(\varphi MC_y N^{\rho})^{\eta} I^{\partial} \tag{4.8}$$

where, q is the quantity consumed by an individual and N is the population of local government jurisdiction where the good is consumed. ρ is the measure of congestion and ranges between 0 to 1. Higher value of ρ indicates overcrowding and thus the consumption of public goods become more difficult.

4.2.2 COMPAS Modeling Framework

The COMPAS model is an effective tool to estimate the fiscal impacts of different policy/development scenarios on a region (Scott and Johnson, 1997). COMPAS models are regional economic models that combine two different approaches (typically input-output and parametric econometric modeling) to build an integrated, or conjoined, model of rural economic structure (Johnson, Otto and Deller, 2006). These models are mostly used to evaluate the impacts within a small city, region or a county. COMPAS models typically treat employment demand as an exogenous driver of changes in the labor market which ultimately impact the fiscal sector. The fiscal module in this research is an extension to the module used by Fannin et al., (2008) and Adhikari and Fannin (2010).

COMPAS models use statistically estimated relationships to forecast changes in demographic, economic and fiscal conditions under exogenous changes in economic activity. The model includes a system of cross sectional econometrically estimated equations estimated for communities in respective states (Johnson, Otto and Deller, 2006). These estimates, though in some cases statistically significant, might not perform well in terms of forecasting performance. These equilibrium COMPAS estimators could be tested under disequilibrium conditions in order to compare the relative forecasting performance based on multiple quantitative evaluation methods. The block recursive diagram of the COMPAS model is displayed below:

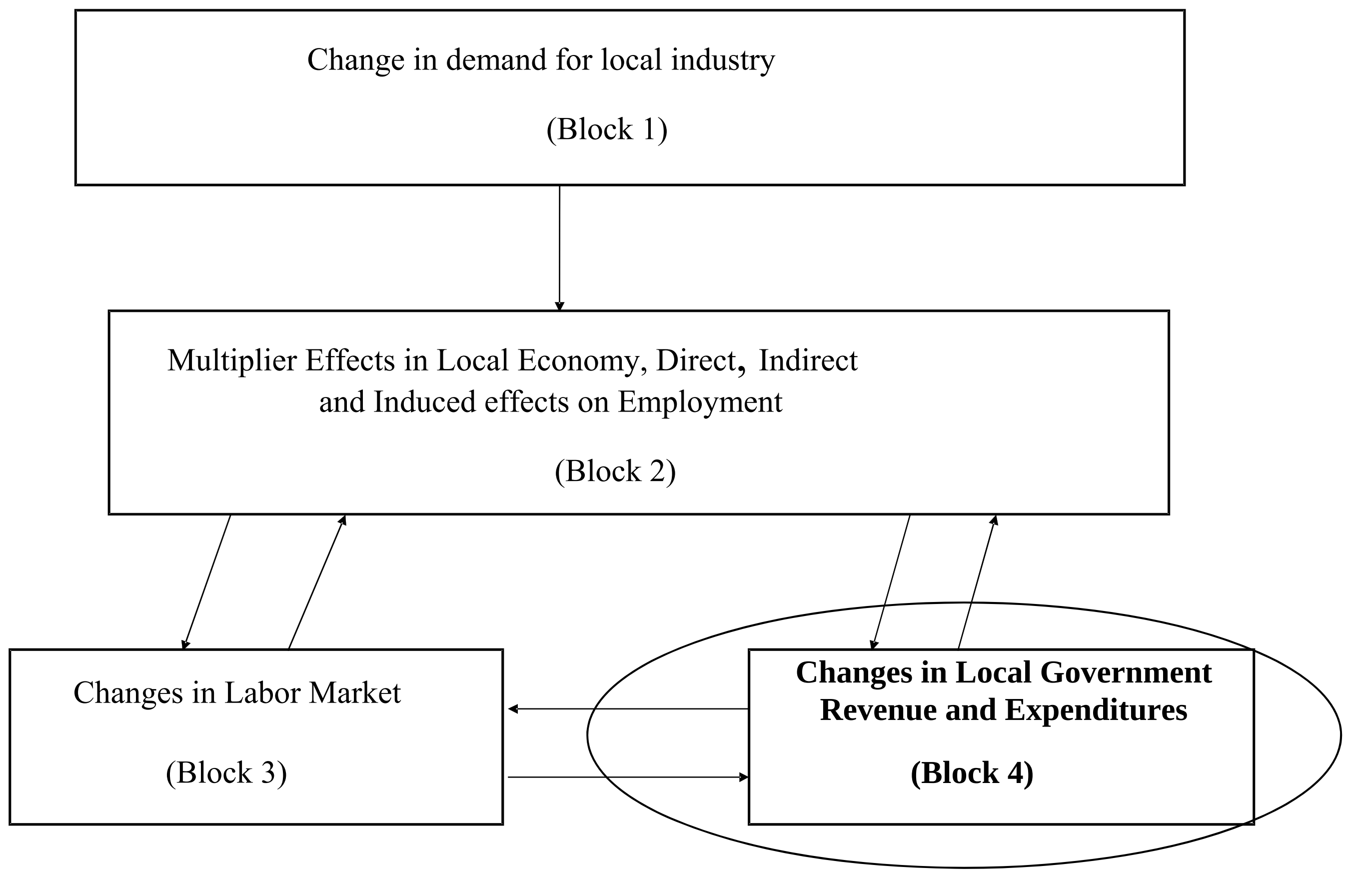

Fig 4.1. Highlighting the fiscal module in COMPAS modeling framework

The median voter model was introduced to develop the conceptual framework of public sector demand and supply based on the early voter theory of Black (1958). This median voter theory was used extensively to model the local public sector since the service demands of median voters were addressed by the political parties in order to carry elections. As stated earlier, the local government's fiscal behavior is demand driven (for public goods and services). Under situations of majority rule, a median voter model has been used in many instances to analyze the fiscal behavior of a region. This approach of the median voter[12] was initially developed by Barr and Davis (1963), but then was applied by several scholars to replace the then popular ad hoc

[12] See Shaffer et al (2004) for detailed explanation for median voter model, where the author has compared similarity between median voter model and Hotelling model by using a beach vendor example.

expenditure model. Median income levels, population, tax prices of public goods, and consumer's tastes and preferences at the local level are assumed to determine the level of demand for local public goods and services. Any elected officials approving government spending far from the median will be driven out of office by an opposition that proposes an expenditure level closer to the demands of the median voter. Early voter theory (Black, 1958) is the basis for the median voter model and assumes that voters are evenly distributed over a political spectrum and a party that acts towards the benefits of median voter's preferences can easily win the election. In other words, elected officials are forced to allocate the desired level of spending based on the median voter's preferences. Although the stylized median voter model was built on an empirically tractable approach, there are a few limitations which could hinder the effectiveness of the model. Some of the factors that limit the supply demand equilibrium in the traditional conceptual framework are, but are not limited to, downward sloping supply curves, the nature of private and public goods, and the non-excludability and non-rivalrous nature of public goods (Buchanan, 1965). Hence, applied researchers interested in providing local stakeholders valuable research tools developed an alternative framework that simply attempts to forecast the movement of public expenditure between equilibrium points over time (Johnson, Otto, and Deller, 2006).

In particular, they described an equilibrium point where structural demand meets structural supply. We can thus estimate a set of equations that models these equilibrium points based on its location and behavior as proposed by Johnson, Otto and Deller, (2006):

$$e = \beta_1 + \beta_2 \varphi + \beta_3 N + \beta_4 I + \sum_{i=5}^{n} \beta_i Z, \tag{4.9}$$

where, e is the expenditure (spending) of local governments,βs are regression coefficients to be estimated, φ is the tax share of median voters, N is the population of local government jurisdictions, I is income and Z are vectors of exogenous variables in the model.

A plethora of studies were then developed based on these empirical applications of modern COMPAS modeling built on the foundation of the conceptual foundations of the median voter model. A comprehensive fiscal impact model for Virginia counties was estimated by Swallow and Johnson (1987) where they developed a model to forecast the economic, demographic and fiscal impacts of regional economic shocks. The entire analysis was carried out by estimating sets of local government revenue capacity and local government expenditure equations. An extension and a slight modification of this work was presented by Shields (1998) where he estimated different sectors of the local economy using two revenue capacity equations, six expenditure equations and two housing market equations. A seemingly unrelated regression (SUR) model was then used to estimate the local government expenditures on a per capita basis on the health sector, government administration, public safety, public works and other amenities. His findings showed that local government expenditures were significantly impacted by variables such as income, assessed property values and property taxes.

Johnson and Scott (2005) proposed the Show Me Community Policy Analysis model, where they collected data from county and city governments of Missouri to estimate the labor market and the fiscal module coefficients. The model was actually a spreadsheet-based model that was used in conjunction with the IMPLAN model. They regressed police expenditure, jail expenditure, court expenditure, road expenditure, administrative expenditure and other expenditure with several socio-economic variables that served as demand shifters. Major results showed that demands for public services were a function of income, wealth, age, education and few other factors such as input and other demand conditions. Based on this conceptualized framework and data for the model, Johnson and Scott (2006) constructed and estimated a labor force module and fiscal module for all counties of Missouri using three stage least squares. Their fiscal module included two revenue base equations, three revenue equations and six expenditure equations.

Swenson and Otto (1999) provided continuity from earlier research and estimated an economic/fiscal impact modeling system for Iowa counties, where they introduced the concept of housing market equations. The fiscal module was quite similar to the one used by Swallow and Johnson(1987), where they included six revenue capacity equations and various sets of expenditure equations. An extension of earlier studies was proposed by Evans and Stallmann (2006), where they proposed the Small Area Fiscal Estimation Simulator for Texas counties using a two-stage least squares procedure. A labor force module and fiscal module were estimated using a 14-equation model.

Most of the empirical models rely on the median voter model assumption heavily for their empirical specification. Further, COMPAS modelers assume that local governments consider the demands and provide the desired level of services at the lowest possible cost. When tax bases and demand for expenditures are known, local governments are assumed to adjust tax rate to balance their budget. Public services may be subject to increasing and/or decreasing returns to size. Unit costs of public services could be hypothesized to be a function of the level, and quality of services, input and output factors, input prices and the rate of population growth.

4.2.3 Alternative Conceptual Frameworks for Public Service Delivery

The CPAN network acknowledges two alternative conceptual frameworks for modeling public service delivery: the bureaucratic approach (Niskansen, 1971; Poole and Rosenthal, 1996) and the flypaper effect (Bailey and Connolly, 1998; Knight, 2002). I present an overview of both approaches below, and argue for a bureaucratic approach as an alternative model that should be made more empirically tractable and evaluated as an alternative model under a disequilibrium environment.

A bureaucratic approach of the local budget allocation decision was set forth initially by Niskansen (1971) and concentrates more on political practices rather than economic approaches. Bureaucrats regulate the local level budget request and allocation process and present them to the elected officials. It depends on the bureaucrats whether or not to inflate the budget requests taking into account the behavior of elected officials who might cut-off some portions of the proposed request. A regional economic modeler must consider the fact that the political aspect of modeling in addition to the economic aspect comes into play while modeling the local public sector. The supply/demand equilibrium model that I described earlier focuses more on the economic backgrounds and thus the political aspect of decision making is ignored.

Besides taking into consideration the political approach while modeling, regional economic modelers must also gain some insights on the flow of intergovernmental grants and aids in the model. These intergovernmental transfers, grants and aids are important sources of revenue to a local economy which ultimately impacts the overall spending behavior at the local level (Gramlich and Galper, 1973). Basically, it is assumed that the lump-sum grant[13] money income is re-distributed to the local taxpayers in the form of rebates or via a reduction in local taxes (Johnson, Otto and Deller, 2006). However, several scholars do not placate this one-to-one relationship of grants to income and local spending and suggest that the effect of total grants/aids to an economy has greater effect on local government spending than the effect of equal increase

[13] Lump-sum grant is one of the grant types that is awarded from higher level of government to lower level of governments for developing sectors like highways, health, education, etc.

in individual income of residents. This is termed as "flypaper effect." Some suggested that the flypaper effect is the result of the monopoly behavior of local officials while formulating budgetary decisions while others claim it to be the result of incorrect use of statistical methods (Bae and Feiock, 2004). These models (bureaucratic and flypaper effect) may serve as alternatives when the restrictive assumptions of the median voter model are too great or a community is in an extended period of disequilibrium.

My concentration in this paper is to evaluate the Louisiana fiscal module built in the equilibrium COMPAS modeling tradition to alternative empirical formulations argued to be more consistent with a bureaucratic model in the disequilibrium environment of the period immediately preceding and following the 2005 hurricane season in Louisiana. I will estimate traditional OLS regressions with the COMPAS equilibrium model and compare it with panel data and a quantile regression model. Local governments may make decisions about the total expenditures in the fiscal year under a bureaucratic model conceptual framework based on the spending that was made in the previous year plus the total revenues that would be projected available in the current fiscal year. My contribution would be the addition of dynamics in the model by incorporating the lagged dependent variable for different expenditure categories. I will be estimating the forecasting performance by several quantitative methods where I will be analyzing different indicators like mean error, mean square error, root mean square error and Theil's coefficients as a benchmark for comparison. This will be an innovative study in terms of comparing static versus dynamic characteristics of a fiscal module in COMPAS type models under disequilibrium market conditions.

4.3 Empirical Specification of Fiscal Module

The fiscal module in a COMPAS model is composed of two components, local government revenue and local government expenditures that use outcomes from the labor force module as exogenous variables. The endogenous variables from the labor force module (in-commuter earnings, out-commuter earnings) serve as exogenous variables in the fiscal module that determine the factors contributing to total revenue. Local government revenue is generated by different forms of tax revenues (typically property taxes and sales taxes which are dependent on assessed property value and retail sales) as well as self-generated revenue (fees) as well as intergovernmental transfers (block grants from the federal and state governments, etc).

Two equations measure revenue capacity in a fiscal module –assessed property value and retail sales.

$$ASDVAL = f(LNDNSTY, OUTCERN, RESEMPERN) \qquad (4.10)$$

$$RETSALE = f(LNDNSTY, INCERN, OUTCERN, RESEMPERN) \qquad (4.11)$$

Expenditure equations are explained by factors that measure the quantity of public services, quality of public services, demand conditions related to public services and input conditions (Johnson, 1996). Based on Inman, 1978, the expenditure equations tend to describe the equilibrium point of public expenditure demand and supply. First, the demand side is explained which determines how revenue is raised to pay for goods and services and/or how the goods and services will be produced. Second, the supply (production) side is explained by the process of transforming inputs to outputs. Following the block recursive nature of COMPAS model, output from the revenue capacity equations are used as explanatory variables in the local government expenditure equations. For this study, four expenditure equations are accounted for through regression analysis, where a total of seven explanatory variables are used. The expenditure equations are presented as:

$$GG\ EXP = f(ASDVAL, RETSALE, TOTINC, LNDNSTY, LCLRDMLS, POP) \tag{4.12}$$

$$HW\ EXP = f(ASDVAL, RETSALE, TOTINC, PERAFAM, POPPLUS, LCLRDMLS, POP) \tag{4.13}$$

$$PS\ EXP = f(ASDVAL, RETSALE, TOTINC, PERAFAM, POPPLUS, POP) \tag{4.14}$$

$$PW\ EXP = f(ASDVAL, RETSALE, TOTINC, PERURB, LNDNSTY, LCLRDMLS, POP \tag{4.15}$$

(Variable descriptions are provided in Table 4.2)

4.4 Data and Methodology

4.4.1 Methods

An initial comparison is made by modeling each of the equations using Ordinary Least Squares (OLS) regression, panel regression, and the quantile regression approach. As an alternative approach for the COMPAS models, OLS, panel, and quantile regressions are useful in measuring forecasting performance. OLS (and to a lesser extent panel) regression has been historically applied in COMPAS fiscal modeling. The inclusion of quantile regression represents an additional iteration (or sensitivity analysis) in COMPAS regression modeling.

For a distribution function, one can determine the probability of occurrence for a given value of a for a dependent variable y. Quantiles, however, are meant to do exactly the opposite. That is, one wants to determine for a given probability of the sample data set the corresponding value y. In OLS, one has the primary goal of determining the conditional mean of random variable Y, given some explanatory variable x_i, $E[Y \mid x_i]$. A cross-sectional data is used in the analysis process.

Quantile Regression goes beyond this and enables one to pose such a question at any quantile of the conditional distribution function. It focuses on the interrelationship between a dependent variable and its explanatory variables for a given quantile. Hence, quantile regression overcomes various problems of OLS and panel models. Frequently, error terms are not constant across a distribution, thereby violating the axiom of homoscedasticity. Also, by focusing on the mean as a measure of location, information about the tails of a distribution is lost. Also, OLS and panel regressions are sensitive to extreme outliers, which can distort the results significantly. As has been indicated in the small example of Boston Housing data (Besley, Kuh and Welsch, 1980), sometimes a policy based on OLS might not yield the desired result as a certain subsection of the population does not react as strongly to this policy or even worse, responds in a negative way, which was not indicated by OLS. Finally, quantile regression addresses a specific issue of public service delivery, which is that public services are often "lumpy" in their delivery. For example, a given highway or a given water well can have additional cars and hookups added respectively resulting in reduced average total costs for the public service. However, once capacity for the highway or well is reached, an additional lane or well is added resulting in increased capacity but also higher average total costs over all consumers of the public service. Quantile regression represents an empirical strategy to address this issue by segmenting parishes at different average total cost thresholds.

This section also develops and demonstrates a model evaluation process for community policy analysis models and highlights a number of key steps in this evaluation process. In particular, the study evaluates, via theoretical discussion and through empirical investigation, the quality of forecasts generated by one particular module, the fiscal module of the Louisiana Community Impact Model (LCIM). Evaluation of this COMPAS type model is different than typical model validation in a number of ways. Although these models involve evaluation of temporal simulation capability of cross-sectional models and are primarily forecasted for accuracy of time series models, I am evaluating the performance of different estimators of one time period on a cross-sectional basis. Since the study focuses on evaluating a community impact model, the unit of analysis is the parish (county), rather than regions or firms. The base year for estimation is 2007, which is a desired time period because many parishes were measurably recovered from the serious damages caused by hurricanes Katrina and Rita and was not impacted by another big hurricane, Gustav (that made a landfall in 2008). Although base year for estimation of OLS and quantile estimators is cross-sectional 2007 data, the study also assesses multi-year data (from 2004 to 2009) for forecasting purposes to compare the performance within and outside of the in-sample year (see Appendix A 4.3 for on and off sample year forecasting performances comparison for different sets of models for the general government expenditure category).

The performance of estimators is compared on the basis of quantitative evaluation methods. These methods include analysis of mean simulation error (ME), mean percent error (MPE), mean absolute error (MAE), mean absolute percent error (MAPE), mean square error (MSE), root mean square error (RMSE), root mean square percent error (RMSPE), and Theil's coefficient U1 and U2 (Johnson, Otto and Deller, 2006; Pindyck and Rubinfield, 1991; Theil, 1970, 1975).

Estimation is based on the COMPAS model for Louisiana that includes all 64 parishes, where the variables for the fiscal module were selected on the basis of Fannin et al (2008) and were modified depending on the requirements of our model and applied geographically to all Louisiana parishes. Louisiana parish level fiscal module data are obtained from audited financial statements of parish governments. Within the fiscal module, different expenditure equation data on public safety, public works, general government, and health and welfare sectors are estimated. These equations are estimated by a cross-section Ordinary Least Square (OLS) model as a base control with quantile regression, and panel data regressions also estimated. Other major data sources for the co-variates include the Louisiana Department of Education, U.S. Census Bureau, and Bureau of Economic Analysis. I apply OLS regression and quantile regression using STATA. The forecasting performance is evaluated based on the procedures outlined in Johnson, Otto and Deller (2006), and Kovalyova and Johnson (2006).

4.4.2 Forecasting Evaluation Techniques

Although evaluation techniques include both qualitative[14] and quantitative techniques, we concentrate on quantitative methods for the purpose of this study. Quantitative evaluation techniques include, but are not limited to, mean simulation error (ME), mean percent error (MPE), mean absolute error (MAE), mean absolute percent error (MAPE), mean square error (MSE), root mean square error (RMSE), root mean square percent error (RMSPE), and Theil's coefficients U1 and U2 (Kovalyova and Johnson, 2006; Pindyck and Rubinfield, 1991; Theil, 1970, 1975). Roughly, in the increasing order of intricacy, these error measures are explained below for better understanding the results.

The first sets of measures of the model performance are ME and MPE, which calculate cumulative error. These error measures provide the indication whether forecasts are biased or not, i.e., whether they tend to be disproportionately positive or negative. These error measures for any given dataset are expressed as:

$$ME = \frac{1}{n}\sum(\hat{Y}_t - Y_t) \qquad (4.16)$$

[14] See Theil (1970, 1975) for more details about qualitative evaluation of models

where $\hat{Y}_t$ = predicted value at time t

Y_t = actual value at time t

N = number of periods in simulation

$$MPE = \frac{1}{n}\sum\left(\frac{\hat{Y}_t - Y_t}{Y_t}\right) \quad (4.17)$$

In case of ME and MPE, negative errors could be offset by the positive ones and that the results could be conflicting, if based on an average. MAE and MAPE are therefore considered better measures for error estimation, as they correct the 'canceling out' effects. They could be expressed as:

$$MAE = \frac{1}{n}\sum(|\hat{Y}_t - Y_t|) \quad (4.18)$$

$$MAPE = \frac{1}{n}\sum\left(\frac{|\hat{Y}_t - Y_t|}{Y_t}\right) \quad (4.19)$$

Different statistical models could be compared using their MSEs, $RMSE_{S,}$ and $RMSPE_s$ as measures of how well they explain a given set of observations. The unbiased model with the smaller (or smallest, if compared more than two models) values of MSEs, $RMSE_{S,}$ and $RMSPE_s$ are generally interpreted as "best" explaining the variability in the observations and are treated the 'best unbiased estimator.' They indicate average deviation of the predicted value from the actual value. These statistics are calculated using the following formula:

$$MSE = \frac{1}{n}\sum(\hat{Y}_t - Y_t)^2 \quad (4.20)$$

$$RMSE = \sqrt{MSE} \quad (4.21)$$

$$RMSPE = \sqrt{\frac{1}{n}\sum\left(\frac{\hat{Y}_t - Y_t}{Y_t}\right)^2} \tag{4.22}$$

Measures based on the squared error such as MSE, RMSE and RMSPE penalize large forecast errors more than small forecast errors. They are naturally associated with the quadratic loss function. An MSE of zero, meaning that the estimator predicts observations of the parameter with perfect accuracy, is the ideal, but is practically never possible.

The final set of error measures for the model performance is the Theil's U coefficients, also known as Theil's inequality coefficient. These coefficients are derived from RMSE indicators. Theil (1958) proposed an accuracy measure in forecasting, popularly known as U1. Regardless of how data are defined, this value is bounded to an interval of 0 and 1. Theil's U1 normalizes RMSE with sum of root squares of actual and predicted values. A value of 0 indicates perfect prediction and the value of 1 corresponds to inequality or negative proportionality between actual and predicted values.

$$U1 = \frac{\sqrt{\frac{1}{n}\sum(\hat{Y}_t - Y_t)^2}}{\sqrt{\sum Y_t^2} + \sqrt{\sum \hat{Y}_t^2}} \tag{4.23}$$

or, $$U1 = \frac{RMSE}{\sqrt{\sum Y_t^2} + \sqrt{\sum \hat{Y}_t^2}} \tag{4.24}$$

Theil (1966) proposed another modified error measure (U2) that addresses some shortcomings of U1. The statistics U2 is bounded below by 0, same as the case in U1 but the upper bound is lacking in this case and would thus it is constrained to take the values between 0 and $+\infty$. The choice of using U1 or U2 depends on the researcher and the objectives of the study. Again, if the prediction is perfect, it takes the value of 0 (smaller the better).

$$U2 = \frac{\sqrt{\frac{1}{n}\sum(\hat{Y}_t - Y_t)^2}}{\sqrt{\frac{1}{n}\sum Y_t^2}} \tag{4.25}$$

or, $$U2 = \frac{RMSE}{\sqrt{\frac{1}{n}\sum Y_t^2}} \tag{4.26}$$

4.4.3 Data

OLS regression uses cross-sectional data and accounts for different activities by taking the average value of each activity and lumping them in one dataset. It provides an insight on the impacts that the independent variables have on the dependent variables by taking the averages over thousands of repeated trials. OLS depicts conditional mean of random variable Y, given some explanatory variable x_i, $E[Y \mid x_i]$. Quantile regression is employed in varying the parameter based on the size of dependent variables we are estimating. The specific heterogeneity we are trying to model could be elaborated by couple of examples. First, the quantile regression approach may capture the differences in the quality of the public service delivered. For example, some parishes in Louisiana, solid waste disposal is handled through house-to house garbage pick-up paid by a fee to a private firm (not tax); yet for others, the house-to house garbage pick-up is paid through a tax which shows up as increased public expenditure. Still others are provided public waste disposal through regional dumpsters (lower quality). Similarly, it would be the case when dealing with the "lumpy" goods.[15] Thus, quantile regression goes beyond the

[15] See Taylor and Ward (2006) for descriptive analysis of lumpy goods

average values and divides these activities into distinct quantiles so that the heterogeneity in each activity is accounted through each quantile.

The panel regression model has not been historically applied in COMPAS modeling due to local public sector expenditure because of the lack of consistent (and reliable) time series data. Early COMPAS models were constructed from expenditure data that was common across all states (five years U.S. Census Bureau Census of Governments). However, in later years, those incorporating COMPAS models sought administrative data at the state level on local public sector expenditure that may be measured with greater precision that would have the potential to increase forecasting precision. In this project, I use audited financial statement data of parish (county) governments in Louisiana. The data collected used a common federal accounting standard (Government Accounting Standards Board Standard 34). It has been collected annually by the Louisiana Legislative Auditor since 2004 and allows for a panel dataset of common local government expenditure categories to be created and used for modeling purposes.

4.5 Results and Discussion

Descriptions of variables used in the study are presented in Table 4.2. The average spending for Louisiana parishes is about $13 million for general government, $3 million for health and welfare, $12.5 million for public safety and $14.5 million for public works categories respectively. Average assessed value and retail sales turn out to be about $418 million and $901 million respectively. Average total income of 64 parishes of Louisiana is about $2 billion with measurable variation from as low as $163 million (Tensas) to $19 billion (Jefferson). Average parish population totaled just over 68,000.

Table 4.2. Variable Description and Summary Statistics, Louisiana

Variables	Description	Mean	Standard Deviation	Min	Max
GG EXP	General Government Expenditure	12,907,252	37,669,961	593,955	210,722,026
HW EXP	Health and Welfare Expenditure	3,357,312	7,399,740	5,664	13,602,439
PS EXP	Public Safety Expenditure	12,561,498	40,169,582	232,882	189,130,903
PW EXP	Public Works Expenditure	14,526,595	31,200,493	847,070	65,739,927
GG6	*GG EXP* lag	9,097,823	25,819,736	555,209	191,462,016
HW6	*HW EXP* lag	2,894,097	5,003,084	5,016	28,751,486
PS6	*PS EXP* lag	11,361,581	30,625,856	178,617	17,260,2185
PW6	*PW EXP* lag	12,895,400	29,179,849	685,291	20,744,981
ASDVAL	Assessed Value	418,151,563	553,860,439	36,056,864	3,466,560,930
RETSALE	Retail Sales	901,353,145	1,355,501,809	29,883,946	7,612,001,075
LNDNSTY	Arable Land Density	770	431	190	2,413
LCLRDMLS	Local Road Miles	1,513	717	284	3,635
POP	Population	68,376	90,951	5,788	440,339
TOTINC	Total Income (in thousands)	2,447,161	3,864,120	163,901	18,996,431
PERAFAM	Percent African American	32	14	3	68
PERURB	Percent Urban	48	28	0	99
POPPLUS	Population above 65 years of age	8,290	10,291	660	58,362

Results from Table 4.3 demonstrate parameter estimates comparison of the panel estimator, OLS estimator and quantile estimators, divided in three quantiles (0.33, 0.66 and 0.99) for four different expenditure categories within 64 parishes of Louisiana. Most of the signs in the parameter estimates are as expected; however, there are some counter-intuitive estimates. If one focuses on the general government category, it is as expected; an increase in assessed value leads to an increase in the expenditure of general government. That is, general government is somewhat of a normal good that as income (or in this case, wealth) increases, consumption of the public service increases. The difference between the panel, OLS and quantile estimates could be clarified by comparing the estimates for public safety. We could see that an increase in total income leads to increases in expenditure in the public safety for all the three models. This is consistent with the theory since public safety is also a normal good and as a result, an increase in income would lead to an increase in the consumption of public safety services. One observes that the magnitude keeps increasing for higher quantiles. This means that if per capita income for counties with lower income category increases, there is less increase in public safety expenditure compared to the intensity of increase for counties with higher total incomes.

Results are mixed in identifying a superior model for forecasting when comparing panel, OLS and quantile regression (Table 4.4) in our traditional COMPAS model. In the general government category, the lowest quantile (0.33) in the quantile regression is found to be performing better (lower the better) than OLS and panel models in terms of mean percent error, mean absolute percent error, mean square percent error and Theil's coefficient (U1). Higher quantiles are far higher in terms of error measures (which demonstrates poorer model fit and performance and thus could be a possible reason of making OLS and panel regression inferior (since OLS is based on conditional mean) to the quantile regression.

Table 4.3. Parameter Estimates for Panel, OLS and Quantile Regressions, Louisiana

Expenditure Category	Panel		OLS		Quantile Regression 0.33		Quantile Regression 0.66		Quantile Regression 0.99	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
GG EXP										
Constant	0.051	0.96	-2.049	0.28	-2.590	0.46	-2.768	0.29	0.637	0.78
ASDVAL	0.425***	0.001	0.175	0.36	0.067	0.82	0.338	0.28	0.195	0.60
RETSALE	0.252***	0.009	0.415*	0.07	0.584	0.26	0.361	0.43	0.242	0.56
TOTINC	0.213*	0.09	1.988***	0.001	2.025***	0.003	2.049***	0.01	1.239*	0.07
LNDNSTY	0.227**	0.06	0.120	0.28	0.103	0.72	0.061	0.69	0.234	0.30
LCLRDMLS	-0.45***	0.003	-0.309*	0.06	-0.359	0.32	-0.223	0.33	-0.437*	0.09
POP	0.047	0.62	-1.98***	0.001	-0.207**	0.03	-2.201***	0.001	-0.884	0.29
HW EXP										
Constant	-0.488	0.84	-8.612**	0.04	-10.244	0.19	-6.966	0.18	-6.243	0.59
ASDVAL	0.494**	0.015	0.617***	0.009	0.520	0.33	0.449	0.40	0.772	0.45
RETSALE	0.410*	0.09	0.085	0.81	0.540	0.34	0.423	0.39	0.066	0.96
LCLRDMLS	-0.580**	0.02	-0.120	0.70	-0.073	0.90	-0.260	0.61	0.209	0.79
PERAFAM	0.0006	0.99	0.279	0.12	0.104	0.63	0.169	0.56	0.059	0.91
POP	0.017	0.96	-1.946*	0.06	-1.776	0.24	-3.817**	0.02	1.230	0.68
TOTINC	-0.385	0.29	1.878**	0.02	1.647	0.26	2.311	0.13	-0.333	0.89
POPPLUS	0.705**	0.02	0.363	0.63	-0.144	0.91	1.572	0.23	-0.583	0.82
PS EXP										
Constant	-8.40***	0.001	-15.92***	0.001	-12.62***	0.003	-17.49***	0.001	-17.52***	0.008
ASDVAL	0.633***	0.001	0.528**	0.02	0.765*	0.09	0.454	0.28	0.247	0.31
RETSALE	0.012	0.92	0.316	0.19	-0.198	0.77	0.505	0.24	0.555	0.28
TOTINC	0.791***	0.001	3.795***	0.001	0.018	0.95	0.045	0.77	0.171	0.68
POPPLUS	-0.621*	0.06	-1.018**	0.05	-0.009	0.99	-1.546**	0.04	-2.623**	0.02
PERAFAM	0.126	0.46	0.152	0.23	3.705***	0.001	3.993***	0.001	3.289***	0.001
POP	0.406	0.25	-2.929***	0.003	-3.369**	0.02	-2.782***	0.005	-0.67*	0.09
PW EXP										
Constant	-0.373	0.77	-0.219	0.89	0.398	0.92	0.369	0.89	1.912	0.56
ASDVAL	0.459***	0.003	0.304	0.11	0.251	0.54	0.555	0.11	0.113	0.71
RETSALE	0.223*	0.06	0.258	0.25	0.372	0.42	-0.011	0.98	0.182	0.70
PERURB	-0.077*	0.09	-0.020	0.68	-0.014	0.86	-0.027	0.58	0.028	0.88
LCLRDMLS	-0.28***	0.002	-0.064	0.60	-0.175	0.56	-0.226	0.20	0.035	0.90
POP	-0.42**	0.05	-0.759	0.20	-1.143	0.32	0.192	0.86	-1.268	0.29
TOTINC	0.625***	0.009	0.870*	0.09	1.063	0.30	0.180	0.82	1.486	0.19
LNDNSTY	0.110	0.35	0.194*	0.06	0.198	0.59	0.336***	0.01	0.128	0.56

*****/**/*** indicate statistical significance at 1%, 5%, and 10% levels respectively

For the health and welfare category of expenditure, again the mean percent error, mean absolute percent error, mean square percent error and Theil's coefficient (U1) is the least in the lowest quantile(0.33), as compared to other higher quantiles and any other models (lower error measures and lower Theil's coefficient indicates better prediction). Public Works and public safety categories follow an almost similar pattern as other categories described earlier. However, OLS has the advantage over panel regression in cases of both the public works and public safety expenditure categories. These are all the average values of the error terms for entire parishes for the panel model and OLS model and for around twenty one parishes each for the three quantiles of the quantile regression model. OLS regression is performed with the base year 2007. However, I have performed a sensitivity analysis with every year and compared it with the panel and quantile regressions in Appendix 4.3. Results are again mixed in identifying a superior model for forecasting.

In addition to average error measures, we can, review individual parishes forecasts and evaluate the performance of estimators in terms of quantitative measures like mean percent error, absolute mean percent error and mean square percent error to figure out how much the predicted value deviates from the actual value.

For the public safety category for 66th quantile, we could see that the mean percent error, absolute mean percent error and mean square percent error are 0.51, 0.62 and 0.88 respectively (Table 4.5). However, because of the heterogeneity in space, some parishes like Acadia, Iberia, Vernon, and West Feliciana are not performing as well on average, since their predicted values are measurably different than their actual values and thus the reason for higher error values. Alternatively, parishes like Avoyelles, Cameron, East Feliciana, Jefferson Davis, and Webster are performing better than the average error measures as the difference between the predicted and actual values are close to zero.

Table 4.4. Average Performance Estimation Measures for Different Categories of Expenditure

Expenditure Category	Panel	OLS	Quantile Regression		
			0.33	0.66	0.99
GG EXP					
Mean Percent Error	0.054	0.084	0.047	0.201	0.581
Mean Absolute Percent Error	0.365	0.341	0.323	0.319	0.790
Mean Square Percent Error	0.211	0.201	0.148	0.211	1.321
Theil's Coeff (U1)	0.285	0.246	0.183	0.206	0.583
HW EXP					
Mean Percent Error	0.443	0.276	0.271	0.524	2.097
Mean Absolute Percent Error	0.888	0.682	0.562	0.749	2.097
Mean Square Percent Error	2.354	0.846	0.645	1.305	10.934
Theil's Coeff (U1)	0.278	0.261	0.260	0.401	0.469
PS EXP					
Mean Percent Error	0.188	0.130	-0.063	0.512	2.254
Mean Absolute Percent Error	0.570	0.439	0.306	0.624	2.254
Mean Square Percent Error	0.678	0.337	0.176	0.876	12.051
Theil's Coeff (U1)	0.209	0.372	0.200	0.343	0.347
PW EXP					
Mean Percent Error	0.132	0.089	0.077	0.478	0.446
Mean Absolute Percent Error	0.441	0.365	0.274	0.575	0.547
Mean Square Percent Error	1.322	0.236	0.135	0.978	0.641
Theil's Coeff (U1)	0.184	0.194	0.174	0.326	0.325

Table 4.5. Performance Estimation of 66th Quantile for Public Safety, 2007

b1	b2	b3	b4	b5	b6
-17.493	0.454	0.5056	0.0451	-1.546	3.993

Areaname	Y	Yhat	yhat-y	Abs (Yhat-y)	(yhat-y)/y	Abs (Yhat-y)/y	(yhat-y)^2	{(yhat-y)/y}^2	y^2	yhat^2
Avoyelles	760963	731179	-29784	29784	-0.04	0.04	8.87E+08	0.00	5.79E+11	5.35E+11
Washington	768591	1022928	254337	254337	0.33	0.33	6.47E+10	0.11	5.91E+11	1.05E+12
West Feliciana	797606.6	1934250	1136643	1136643	1.43	1.43	1.29E+12	2.03	6.36E+11	3.74E+12
Madison	818261	356842	-461419	461419	-0.56	0.56	2.13E+11	0.32	6.7E+11	1.27E+11
Acadia	1052581	2256535	1203954	1203954	1.14	1.14	1.45E+12	1.31	1.11E+12	5.09E+12
St. Martin	1139754	2115733	975979	975979	0.86	0.86	9.53E+11	0.73	1.3E+12	4.48E+12
St. Landry	1224563	2467141	1242578	1242578	1.01	1.01	1.54E+12	1.03	1.5E+12	6.09E+12
East Feliciana	1234880	1234890	10	10	0.00	0.00	94.80119	0.00	1.52E+12	1.52E+12
DeSoto	1343235	1879691	536456	536456	0.40	0.40	2.88E+11	0.16	1.8E+12	3.53E+12
Pointe Coupee	1369996	2551059	1181063	1181063	0.86	0.86	1.39E+12	0.74	1.88E+12	6.51E+12
Assumption	1388278	1964934	576656	576656	0.42	0.42	3.33E+11	0.17	1.93E+12	3.86E+12
Jefferson Davis	1445394	1445406	12	12	0.00	0.00	146.5802	0.00	2.09E+12	2.09E+12
Beauregard	1640590	1278936	-361654	361654	-0.22	0.22	1.31E+11	0.05	2.69E+12	1.64E+12
Vernon	1793828	6174108	4380280	4380280	2.44	2.44	1.92E+13	5.96	3.22E+12	3.81E+13
Webster	2011698	1927147	-84551	84551	-0.04	0.04	7.15E+09	0.00	4.05E+12	3.71E+12
Natchitoches	2136326	1825393	-310933	310933	-0.15	0.15	9.67E+10	0.02	4.56E+12	3.33E+12
Iberia	2329147	7426970	5097823	5097823	2.19	2.19	2.6E+13	4.79	5.42E+12	5.52E+13
Vermilion	2883739	2578341	-305398	305398	-0.11	0.11	9.33E+10	0.01	8.32E+12	6.65E+12
Cameron	2979528	2979546	18	18	0.00	0.00	321.2887	0.00	8.88E+12	8.88E+12
Livingston	3565513	4614907	1049394	1049394	0.29	0.29	1.1E+12	0.09	1.27E+13	2.13E+13
		SUM	16081466	19188942	10.26	12.49	5.41E+13	17.5288	6.55E+13	1.77E+14
		Sqrt						4.19	8090497	13319348
		Avrg	804073	959447	0.51	0.62	2.71E+12	0.88	3.27E+12	8.87E+12

ME	16081466
MPE	10.2556
MAE	19188942
MAPE	12.48953
MSE	5.41E+13
RMSE	7357682
RMSPE	4.186741
U1	0.343659
U2	0.909423

Although the lower quantiles displayed superior forecasting performance relative to other quantiles and other two models in all four categories of expenditure, it would be preferable to identify a more robust model to estimate and forecast public sector expenditure. As suggested by Johnson, Otto and Deller (2006), the best way to validate model performance is by comparing the forecasts with those of the naïve extrapolation. As such, I applied a naïve model (cross-sectional) where all four categories of expenditures were regressed with its one year lagged value. This approach makes for a reasonable baseline because it suggests that any model estimated should forecast at least as well as simply using the information from last year's expenditure. In addition, this approach forms the basis for a bureaucratic model approach to public sector expenditure given that that local governments often make decisions on their spending for the fiscal year based on the spending that was made last year plus some adjustment for the current year. Besides, there are a few major variables that are important to account for while making the expenditure decision by local governments for the fiscal year. Depending on last year's spending and the total revenue that could be generated in a fiscal year, total expenditure to any category must be allocated by local and state governments. Thus, revenue capacity variables are added in the naïve model to develop a new model (Naïve plus) for comparing the forecasting performance. We further introduced a modified naïve model which includes the original COMPAS covariates to compare with naïve and naïve plus model. The expenditure equations in the new models are now expressed as:

4.5.1 NAÏVE MODEL

$$GG\ EXP = f(GG6) \tag{4.8}$$

$$HW\ EXP = f(HW6) \tag{4.9}$$

$$PS\ EXP = f(PS6) \tag{4.10}$$

PW EXP = f(PW6) (4.11)

4.5.2 NAÏVE PLUS MODEL

GG EXP = f(GG6, ASDVAL, RETSALE) (4.12)

HW EXP = f(HW6, ASDVAL, RETSALE) (4.13)

PS EXP = f(PS6, ASDVAL, RETSALE) (4.14)

PW EXP = f(PW6, ASDVAL, RETSALE) (4.15)

4.5.3 MODIFIED NAÏVE MODEL

GG EXP = f(GG6, ASDVAL, RETSALE, TOTINC, LNDNSTY, LCLRDMLS, POP) (4.16)

HW EXP = f(HW6, ASDVAL, RETSALE, TOTINC, PERAFAM, POPPLUS, LCLRDMLS, POP) (4.17)

PS EXP = f(PS6, ASDVAL, RETSALE, TOTINC, PERAFAM, POPPLUS, POP) (4.18)

PW EXP = f(PW6, ASDVAL, RETSALE, TOTINC, PERURB, LNDNSTY, LCLRDMLS, POP) (4.19)

Results from Table 4.6 demonstrate the parameter estimates comparison of the OLS and panel estimators of the naïve, naïve plus and modified naïve model for four different expenditure categories within 64 parishes of Louisiana and results from Table 4.7 display parameter estimates for the naïve model, naïve plus model and modified naïve model based on three quantiles (0.33, 0.66, and 0.99) via quantile regression. The results are quite similar to what we saw in the earlier models. However, results seem to be superior as compared to earlier COMPAS equilibrium models as we observe the forecasting performance increases with inclusion of the lagged variable (as a naïve model) in our earlier model.

Table 4.6. Parameter Estimates for Naïve Model, Naïve Plus Model and Modified Naïve Model, OLS and Panel Data Regressions

	OLS			Panel		
	Naïve	**Naïve Plus**	**Modified Naive**	**Naïve**	**Naïve Plus**	**Modified Naive**
GG EXP						
Constant	-0.23	-0.45	-0.04	0.15*	-0.54***	-0.49
ASDVAL		0.08	0.11***		0.11**	0.07
RETSALE		-0.03	-0.11**		-0.03	-0.01
TOTINC			0.06			0.29***
LNDNSTY			-0.01			0.04
LCLRDMLS			-0.03			-0.09
GG6	1.02***	0.97***	0.95***	0.99***	0.93***	0.88***
POP			0.04			-0.24**
HW EXP						
Constant	0.004	-1.33**	-4.71***	0.40*	-1.32***	-1.06
ASDVAL		0.25***	0.22***		0.12**	0.12**
RETSALE		-0.14***	-0.16		0.03	0.06
TOTINC			0.78**			-0.007
LCLRDMLS			-0.16**			-0.05
POPPLUS			-0.16			0.09
PERAFAM			0.19**			-0.002
HW6	0.99***	0.94***	0.91***	0.97***	0.87***	0.86***
POP			-0.64			-0.10
PS EXP						
Constant	0.23	-1.10**	-2.84***	0.70***	-1.58***	-1.89***
ASDVAL		0.13*	0.08		0.22***	0.20**
RETSALE		-0.05	-0.01		-0.004	-0.07
TOTINC			0.64**			0.19
POPPLUS			-0.16			-0.28*
PERAFAM			0.12***			0.02
PS6	0.98***	0.97***	0.90***	0.95***	0.82***	0.79***
POP			-0.46			0.20
PW EXP						
Constant	0.47	0.05	-1.63**	1.06**	-0.49	-0.61
ASDVAL		0.01	-0.003		-0.23***	-0.16***
RETSALE		0.05	0.15**		0.06	0.004
TOTINC			0.27*			0.35*
PERURB			0.01			-0.006
LNDNSTY			0.07*			0.07*
LCLRDMLS			0.13**			-0.03
PW6	0.98***	0.92***	0.89***	0.93***	0.66***	0.66***
POP			-0.46***			-0.24

Table 4.7. Parameter Estimates for Naïve model, Naïve Plus Model and Modified Naïve Model, Quantile Regression

	Naïve			Naïve Plus			Modified Naive		
	0.33	**0.66**	**0.99**	**0.33**	**0.66**	**0.99**	**0.33**	**0.66**	**0.99**
GG EXP									
Constant	-0.52**	-0.19	-4.77*	-0.87***	-0.54	2.04	-0.69	-0.36	-0.94
ASDVAL				0.11***	0.14	0.22	0.10	0.12	0.17
RETSALE				0.16	-0.09	0.03	-0.05	-0.16**	-0.19
TOTINC							0.05	0.29	0.14
LNDNSTY							-0.002	-0.01	-0.10
LCLRDMLS							-0.01	-0.02	0.14
GG6	1.03***	1.02***	1.38***	0.96***	0.99***	1.13***	0.95***	0.95***	0.99***
POP							-0.01	-0.17	-0.04
HW EXP									
Constant	0.02	-0.11	-1.01	-1.22	-1.12	-1.52	-4.08**	-5.66***	-2.04
ASDVAL				0.25***	0.19	0.09	0.20*	0.15	0.33
RETSALE				-0.14*	-0.11	0.06	-0.09	-0.07	-0.18
TOTINC							0.26	0.94***	-0.29
LCLRDMLS							0.25*	0.20	0.07
POPPLUS							-0.71	-0.42	0.24
PERAFAM							0.19	0.17*	0.04
HW6	0.99***	1.01***	1.12***	0.95***	0.97***	0.92***	0.94***	0.92***	0.89***
POP							0.24	-0.59	0.23
PS EXP									
Constant	-0.01	-0.11	1.86***	-1.78	-0.31	-1.34	-1.32	-3.01**	-2.12
ASDVAL				0.20	0.02	0.24	0.004	0.04	-0.01
RETSALE				-0.09	-0.005	-0.09	0.04	0.01	0.06
TOTINC							0.31	0.79*	0.78*
POPPLUS							0.14	-0.19	-0.42
PERAFAM							0.11	0.10	0.11
PS6	1.00***	1.01***	0.92***	0.96***	1.00***	0.93***	0.97***	0.93***	0.85***
POP							-0.48	-0.64	-0.14
PW EXP									
Constant	0.47	0.41	1.17***	0.03	-0.08	1.27	-1.13	-2.33**	0.123
ASDVAL				0.05	-0.06	-0.03	0.01	-0.06	-0.04
RETSALE				-0.0006	0.08	0.02	0.07	0.22**	0.08
TOTINC							0.53	0.29	0.02
PERURB							0.02	0.002	0.07*
LNDNSTY							0.04	0.066	0.08
LCLRDMLS							0.03	0.16*	0.19
PW6	0.97***	0.98***	0.95***	0.93***	0.99***	0.96***	0.86***	0.95***	0.89***
POP							-0.60	-0.54**	-0.12

*****/**/*** indicate statistical significance at 1%, 5%, and 10% levels respectively

The lagged variable is highly significant for all models and for all categories of expenditure which explains that the previous year's expenditure plays an important role in determining the future year's expenditure. Except for the public works category, assessed value is positive which indicate an increase in assessed value leads to increase in the expenditure of the general government, public safety and health and welfare categories.

There is again a mixed result in performance between OLS and quantile regression models (Table 4.8). All models including a lagged dependent variable are found to be outperforming the baseline COMPAS models; however, performance varies in the quantile regression with lagged dependent variables. In most of the models, lower quantiles (0.33) are found to be performing better as compared to the middle (0.66) and higher quantiles (0.99). The OLS model outperforms the panel model (except in case of public works category) in most of the expenditure categories for naïve, naïve plus and modified naïve, as measured in terms of specified error measures. Although the naïve model is found to be superior as compared to our earlier model, the naïve plus model is displaying better forecasting performance than the naïve model (and naïve plus model as well) measured in terms of mean percent error, absolute mean percent error, mean square percent error and Theil's coefficient. It is hypothesized that the greater performance in the lower quantile (0.33) suggests that local parish governments that spend less in these categories are delivering a much more homogeneous public service in a given expenditure category than those in the middle (0.66), and especially highest (0.99) quantile.

Table 4.8. Average Performance Estimation Measures for Different Categories of Expenditure (2004-2009)

Error Measures	Panel			OLS			Quantile Regression								
	Naive	Naïve Plus	Modified Naive	Naive	Naïve Plus	Modified Naive	Naive			Naïve Plus			Modified Naive		
							0.33	0.66	0.99	0.33	0.66	0.99	0.33	0.66	0.99
GG EXP															
Mean Percent Error	0.17	0.13	0.11	0.12	0.11	0.05	-0.09	0.08	0.41	-0.06	0.06	0.32	-0.05	0.05	0.25
Mean Absolute Percent Error	0.16	0.12	0.12	0.10	0.10	0.08	0.10	0.16	0.43	0.08	0.13	0.32	0.08	0.11	0.25
Mean Square Percent Error	0.14	0.10	0.09	0.13	0.09	0.06	0.03	0.09	0.19	0.02	0.03	0.16	0.01	0.02	0.09
Theil's Coeff (U1)	0.11	0.09	0.07	0.06	0.04	0.04	0.05	0.08	0.31	0.03	0.07	0.21	0.03	0.07	0.20
HW EXP															
Mean Percent Error	0.13	0.13	0.09	0.10	0.05	0.03	0.07	0.17	0.61	0.02	0.10	0.66	0.01	0.09	0.54
Mean Absolute Percent Error	0.37	0.26	0.17	0.33	0.20	0.18	0.25	0.29	0.58	0.12	0.27	0.66	0.14	0.22	0.54
Mean Square Percent Error	0.83	0.14	0.14	0.91	0.10	0.07	0.23	0.24	0.77	0.04	0.20	0.72	0.06	0.11	0.58
Theil's Coeff (U1)	0.26	0.19	0.16	0.23	0.17	0.12	0.18	0.29	0.23	0.06	0.18	0.18	0.08	0.16	0.17
PS EXP															
Mean Percent Error	0.12	0.14	0.11	0.08	0.08	0.06	-0.07	0.14	0.36	-0.05	0.13	0.34	0.03	0.11	0.23
Mean Absolute Percent Error	0.33	0.19	0.15	0.25	0.15	0.14	0.25	0.15	0.31	0.24	0.16	0.34	0.11	0.14	0.23
Mean Square Percent Error	0.39	0.09	0.06	0.32	0.09	0.08	0.12	0.09	0.21	0.07	0.05	0.16	0.05	0.04	0.09
Theil's Coeff (U1)	0.28	0.16	0.11	0.21	0.11	0.08	0.14	0.15	0.17	0.11	0.07	0.07	0.06	0.06	0.03
PW EXP															
Mean Percent Error	0.08	0.03	0.03	0.05	0.04	0.04	-0.05	0.13	0.33	-0.03	0.10	0.27	-0.03	0.09	0.21
Mean Absolute Percent Error	0.21	0.11	0.09	0.16	0.14	0.12	0.12	0.17	0.31	0.10	0.18	0.27	0.08	0.13	0.21
Mean Square Percent Error	0.09	0.03	0.02	0.04	0.03	0.02	0.04	0.07	0.17	0.02	0.04	0.13	0.01	0.03	0.10
Theil's Coeff (U1)	0.16	0.05	0.04	0.10	0.07	0.06	0.08	0.14	0.18	0.07	0.10	0.14	0.04	0.07	0.09

To gain a better understanding of the relative performance of these estimators, I performed mean comparison test in STATA, where I compared the base OLS cross-section model with the cross-section models of each of the equations with a lagged dependent variable (naïve, naïve plus, and modified naïve). These results are presented in Tables 4.9 – 4.12.

Table 4.9. Mean Comparison Test Based on OLS Model for General Government Expenditure

General Government							
	Base	Naïve		Naïve Plus		Modified Naive	
		Magnitude	t-stat	Magnitude	t-stat	Magnitude	t-stat
Base		0.209	6.01***	0.223	6.55***	0.261	6.92***
Naïve				0.014	1.38*	0.052	1.75**
Naïve Plus						0.038	0.69
Modified Naïve							

***/**/* indicate statistical significance at 1%, 5%, and 10% levels respectively

Table 4.10. Mean Comparison Test Based on OLS Model for Public Safety Expenditure

Public Safety							
	Base	Naïve		Naïve Plus		Modified Naive	
		Magnitude	t-stat	Magnitude	t-stat	Magnitude	t-stat
Base		0.189	2.32**	0.289	5.50***	0.299	6.19***
Naïve				0.102	1.54*	0.112	1.79**
Naïve Plus						0.010	1.04
Modified Naïve							

***/**/* indicate statistical significance at 1%, 5%, and 10% levels respectively

Table 4.11. Mean Comparison Test Based on OLS Model for Health and Welfare Expenditure

Health and Welfare						
Base	Naïve		Naïve Plus		Modified Naive	
	Magnitude	t-stat	Magnitude	t-stat	Magnitude	t-stat
Base	0.352	1.38*	0.482	5.54***	0.502	5.84***
Naïve			0.130	1.53*	0.150	1.68**
Naïve Plus					0.021	1.17
Modified Naïve						

*****/**/*** indicate statistical significance at 1%, 5%, and 10% levels respectively

Table 4.12. Mean Comparison Test Based on OLS Model for Public Works Expenditure

Public Works						
Base	Naïve		Naïve Plus		Modified Naive	
	Magnitude	t-stat	Magnitude	t-stat	Magnitude	t-stat
Base	0.205	4.81***	0.225	5.12***	0.245	5.38***
Naïve			0.023	1.21	0.041	1.57*
Naïve Plus					0.020	0.90
Modified Naïve						

*****/**/*** indicate statistical significance at 1%, 5%, and 10% levels respectively

In considering only the lowest magnitudes (highest forecasting performance), the modified naïve model displayed superior results as compared to the naïve and naïve plus model, if measured in terms of absolute mean percent error. Overall, results from Tables 4.9-4.12 suggested that lagged models are significantly lower in terms of error measures as compared to the base OLS model in all four categories of expenditure. However, the modified naïve model is not always significantly lower (in terms of absolute mean percent error) than the naïve and naïve plus model and thus one should not infer that modified naïve model outperforms the other lagged dependent variable models. In Table 4.9, one can statistically observe that modified naïve model is displaying better forecasting performance as compared to base OLS model and naïve model but the test shows that there is no significant difference between naïve plus and the modified naïve model. Also, naïve plus model display significantly better performance compared to base OLS and naïve model. For public safety and health and welfare category of expenditure, test results show a similar pattern (Table 4.10 and 4.11). In the case of public works category of expenditure (Table 4.12), the modified naïve model performs significantly better than base OLS and naïve model but one could not statistically infer that the naïve plus model is better than the naïve model and modified naïve models are better than naïve plus model. These results are consistent with the story that during this period, Louisiana parish governments were driven more by bureaucratic forces than median voter model preferences.

4.6 Conclusion

In this study, I tried to evaluate whether the forecasting performance of the public sector expenditure under a COMPAS fiscal module (an equilibrium model) fits reasonably well under a disequilibrium environment. This study was focused on evaluating the conceptual framework for modern day local government revenue and expenditure forecasting along with the strengths and weaknesses of such modeling in terms of empirical specification. We compared the traditional COMPAS model with the modified COMPAS model (a dynamic model) and analyzed the forecasting performance of several indicators under disequilibrium conditions. The study evaluated forecasting performance during the time frame of supply demand disequilibrium, where the data represents a period of major exogenous shocks (hurricanes Katrina, Rita and Gustav) to local government operations. Different models were compared parametrically using the cross-sectional OLS, panel data, and the quantile regression.

Most of the original COMPAS models were developed in Midwestern states where there was measurable homogeneity in economic and fiscal structure of rural regions (the focus of many of these models). Our results identify whether continuous (OLS and Panel) models have increased performance versus quantile regression methods in fiscal module COMPAS approaches. Results showed that the newer alternative methods are now available to address the limitations of cross sectional OLS models. Quantile regression has some statistical advantages over COMPAS model and panel and OLS regression in improving the model performances (as evidenced by our original model). Quantile regressions are hence proposed as another COMPAS estimator alternative since they provide varying parameter estimates to be applied in forecasting depending on a county's relative position within the distribution of all counties in a state.

Overall results indicate that a bureaucratic model may have been a more appropriate conceptual framework during this public service delivery period of Louisiana local government history. However, these results are limited in that one cannot infer that the bureaucratic model is superior in all disequilibrium environments. In particular, due to data limitations, one cannot evaluate the pre-Katrina/Rita forecasting performance between traditional COMPAS models and the bureaucratic model. The panel dataset starts from the year 2004, the first year in which there were quality comparable public sector data across all parish jurisdictions. That is, Louisiana parish public sector spending may have followed a more bureaucratic model prior to the disequilibrium period brought about by the storms.

Further, the research results indicate that segmenting parishes for modeling purposes does have value for forecasting performance. The consistent increased performance by the lowest quantile showed that greater homogeneity of governmental units helps when modeling local government units. While early COMPAS models may have segmented based on rural/urban, these results suggest that segmentation may also occur on spending levels which may or may not always follow population size.

An evaluation of the alternative methodologies performed in this study are expected to give regional economic modelers better information from which to choose when seeking to construct models projecting different modules. Using the data from different sources, this study developed a model to forecast different sectors of expenditure in the fiscal module using OLS, panel, and quantile regression. Future research should focus on a further narrowing of the confidence interval around forecasts. Besides the comparison (between non-spatial models) made in this paper, future research should consider spatial models such as the spatial error model and the spatial lag model in order to compare the performances between spatial and non-spatial estimators. As increased quantity and quality of public sector data become available due to compulsory reporting requirements, researchers should be able to construct models with increasing forecast reliability that can be used by analyst-deficient local governments for more informed public sector decision making. Future research should also focus on applying rational expectations model because of the fact that local governments would depend on the past expenditures and future expected revenues to make budgetary decisions for any fiscal year.

4.7 References

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CHAPTER 5

CONCLUSION

The prime intent of this research is to explore the issues and challenges of regional modeling and to address those issues with the available resources using theoretical and empirical analysis. Regional economic modelers and policy makers at the local level are interested in assessing impact analysis and forecasting the economic changes that could likely occur at the state or local level after certain exogenous shocks to an economy. These impacts might be observed in many facets of economy such as employment, income, labor force, commuting patterns, contiguous employment, population, revenues, and expenditures, among many others. Also, such exogenous shocks might disrupt the supply demand equilibrium and hence robust analytical tools must be applied to address these changes. This research concentrates on building economic models that are appropriate to assess such changes and suggest policy makers to adjust their decisions accordingly.

Secondary objectives of this study include modeling the economic and fiscal changes that take place in coastal communities of Louisiana after occurrence of a natural disaster. Three different essays were developed in this study to model these changes in a disequilibrium environment for improving accuracy in regional economic modeling for the purpose of evaluating economic and fiscal impacts and their causal effects. The first essay (chapter 2) highlights the modeling concept of the decomposition of changes in an economy that would alter the employment in any sector following natural disasters through the incorporation of traditional and spatial shift-share analysis. In the process, the analysis also tends to evaluate the distinctiveness of decompositions of different effects that were earlier proposed by several researchers. The second and the third essay (chapter 3 and 4 respectively) develop strategies to model labor force and fiscal modules of COMPAS models based on the equilibrium concept of supply and demand in the context of labor market and public service sectors through parametric models such as quantile regression, cross sectional ordinary least squares (OLS), three stage least squares (3sls), and panel data estimators that may increase forecasting performance.

Changes in employment in the mining and food services sectors were evaluated by decomposing different traditional and spatial effects in the second chapter. The concept of a neighboring region effect and sub-regional localized effects were introduced in the spatial effect to evaluate the spatial dependence between regions. Results showed that the local effect in the spatial shift share model is dependent on the growth rate of the neighboring region effect for its sign and magnitude. Results also indicated that while overall mining employment declined in the three year period prior to Katrina/Rita, the spatial shift share model identified regions that witnessed job growth and that the growth was broken into individual parishes that had localized comparative advantage. Further, the distinctiveness of the spatial neighboring region effect was evaluated and results suggested that spatial neighboring region effect and the localized effect in the spatial shift share model were two separate effects. Hence, this study identified an alternative decomposition technique that increased distinctiveness between industry and local effects that were not achieved by Esteban-Marquillas shift share formulations.

Modeling the Louisiana parish labor market was introduced in chapter 3 for purposes of improving forecasting accuracy in regional economic modeling. The study concentrated on modeling Louisiana labor markets using alternative procedures, i.e., ordinary least squares, three stage least squares, and panel data that are capable of increasing the performance over existing COMPAS labor market estimators. These models also evaluated commuting patterns of labor and their effects on total labor force of a region. Results showed that panel data estimators were comparably the best fit for forecasting purposes, if model performance is strictly judged on the basis of average error measures. However, mean comparison tests suggested that one cannot statistically infer that the panel data model to be a better fit when compared to OLS and 3sls model in case of the labor force equation.

The fiscal sector of the Louisiana community impact model was introduced in the third chapter to evaluate the forecasting performance of estimators during periods of supply demand disequilibrium. The chapter evaluated whether the forecasting performance of the public sector expenditure under a COMPAS fiscal module (an equilibrium model) fits reasonably well under a disequilibrium environment. A comparison was made between the traditional COMPAS model with the modified COMPAS model (a dynamic model) and analyzed the forecasting performance of several indicators under assumed disequilibrium conditions. The stylized model based on the median voter concept was proposed by earlier researchers. The model was followed with an extension of alternative conceptual frameworks of public service delivery, i.e., the bureaucratic approach and flypaper effects approach. An argument was made to apply the bureaucratic approach as an alternative model that should be made more empirically tractable and evaluated as an alternative model under a disequilibrium environment. These models (bureaucratic and flypaper effect) may serve as alternatives when the restrictive assumptions of the median voter model are too great or a community is in an extended period of disequilibrium. A lagged dependent variable was introduced in the model based on the prior assumption that local governments would make spending decisions for any fiscal year based (partially or fully) on last year's expenditure. Three different models (naïve, naïve plus and modified naïve) were evaluated for forecasting performance using ordinary least square regression, panel data, and the quantile regression approach and were compared to the base OLS model. The modified naïve model appeared to outperform the base OLS, naïve and naive plus model in most cases. However, when the mean comparison test was performed to compare between the base model and three different lagged dependent models based on the cross-sectional linear regression framework, results showed that the modified naïve model do not always significantly outperform all other models.

This study makes a few contributions to the regional science/rural development literature. First, a contribution is made applying shift share analysis by testing the existence of spatially distinct regional effects in Chapter 2. No study that I am aware prior to this one has attempted to test whether or not the neighboring-region effect represents a truly distinct and practically interpretable effect from the traditional model's competitive effect.

The second contribution could be observed from the third chapter, by developing new panel data labor market COMPAS models. No study until this one applied a panel data framework for labor force module using annually available commuting data. Further, no research to date on COMPAS modeling has attempted to identify the tradeoff of alternative estimators for forecasting purposes in labor market models like was performed in this study.

The third contribution observed in the fourth chapter was to test forecasting performance of fiscal expenditure models driven by alternative assumptions about how public sector expenditure decisions are made. Related to this contribution, this study was the first to the author's knowledge that incorporated quantile regression to address the lumpy good limitations inherent in modeling the public sector in COMPAS modeling.

The study holds some limitations. In the case of shift share analysis, results do not. The correlation test in this study was limited to two industries over five years in a single state. If spatial shift share analysis is to be adopted and used for both descriptive as well as parametric analysis, a more comprehensive test covering additional geographic areas over additional industries using a longer time period would be helpful in improving the robustness of these results. Also, industrial aggregation is limiting factor in this study because the mining sector is considered to have several forward and backward linked industries and focusing on more detailed industry sectors may identify an alternative form of clustering of industries in geographic proximity to one another. Causality is another limitation that must be considered while analyzing the spatial shift share analysis as we cannot make rigid interpretations on causality of spatial spillovers from this nonparametric analysis.

While modeling the labor force and fiscal module, data availability is a major limiting assumption. When modeling the public service sector for Louisiana, results indicate that a bureaucratic model may have been a more appropriate conceptual framework during this public service delivery period of Louisiana local government history. However, because of data limitations, it is difficult to make an inference that the bureaucratic model being superior in all disequilibrium environments, especially prior to Hurricanes Katrina and Rita. This interpretation limitation occurs because the comparative data structures used to model the public sector (audited financial statements under Government Accounting Standards Board Rule Number 34) were not adopted across all Louisiana parishes until 2004. It may have been the case that Louisiana parish governments may have followed a bureaucratic approach to public sector expenditure decisions during periods prior to the 2005 hurricane season.

There are several opportunities for future research that could be carried to extend the results of this research. When modeling the change decompositions by spatial shift share analysis, this study employed contiguity measures to develop a weight matrix. Some other measures such as distance, distance squared, economic characteristics, etc. could be applied to build the weight matrix for evaluating the sensitivity of the results to the form of spatial proximity defined. Several decompositions, other than spatial and augmented spatial used in the study, could also be constructed to evaluate the distinctiveness of different effects. The shift share analysis was built on two industries for Louisiana parishes, but could be extended to more regions and industries depending on the availability of data. When modeling the labor force module, an “area” variable could be added in the model to unmask the spatial effects that could have been ignored and that the spatial differences in parameters are allowed. The model could also be tested with several other econometric specifications built on spatial and non-spatial formulations. The modeling of public service delivery in Louisiana context could be further extended by inclusion of spatial models such as the spatial error model and the spatial lag model in order to compare the performance between spatial and non-spatial estimators. This provides regional economic modelers better information to construct models with narrow confidence intervals to forecast.

APPENDIX 1: ERROR MEASURES, LABOR FORCE MODULE

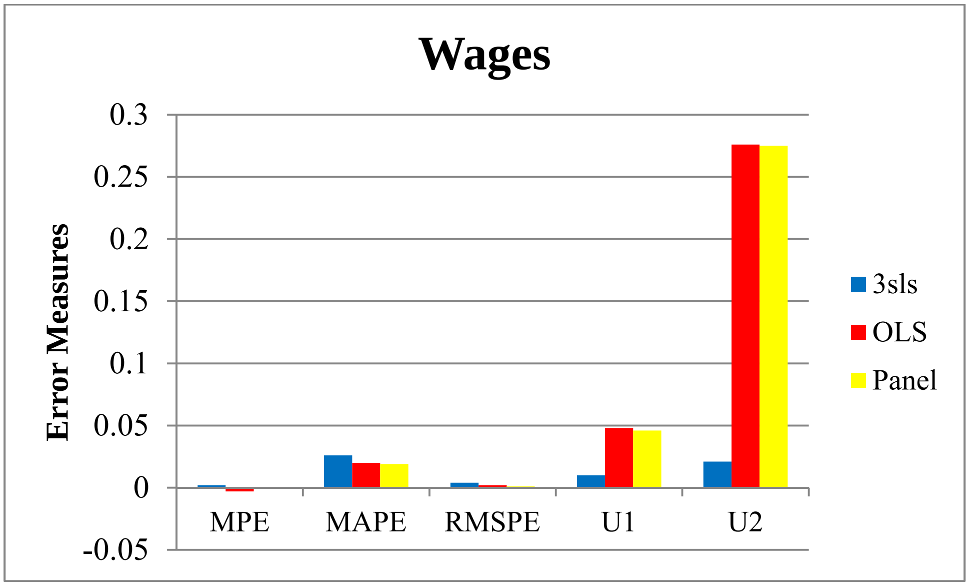

Fig A 1.1. Comparing OLS, 3sls and panel estimators of wages by different error measures

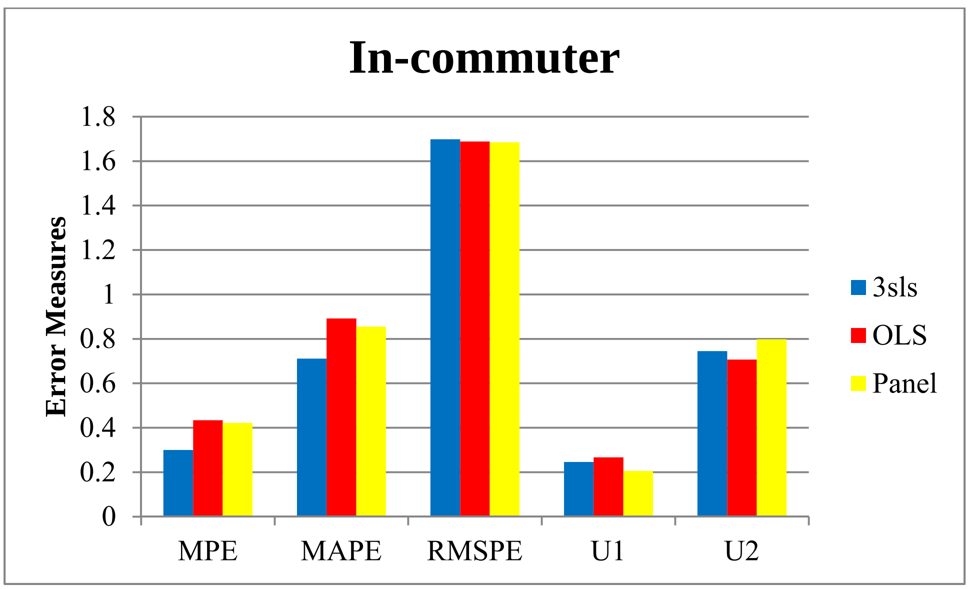

Fig A 1.2. Comparing OLS, 3sls and panel estimators of in-commuter by different error measures

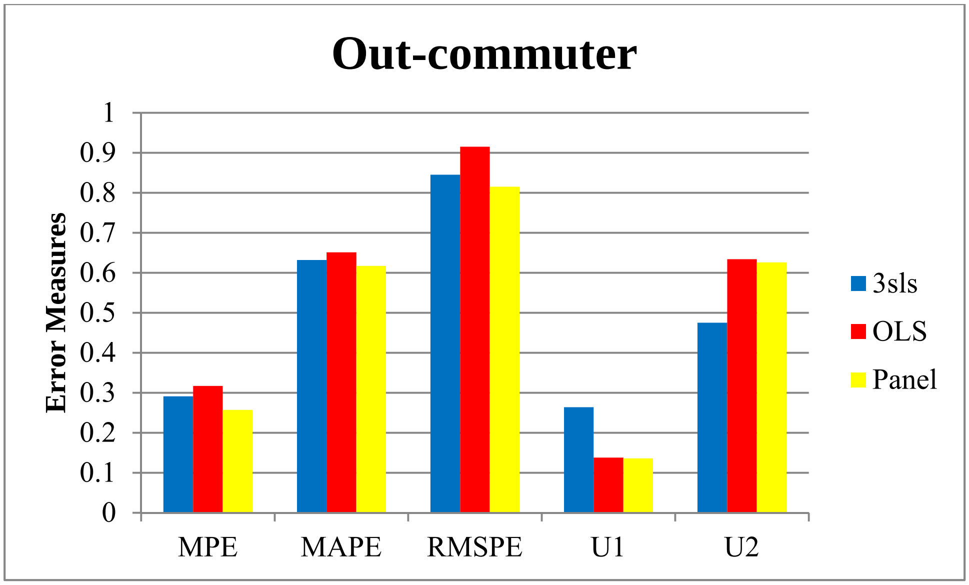

Fig A 1.3. Comparing OLS, 3sls and panel estimators of in-commuter by different error measures

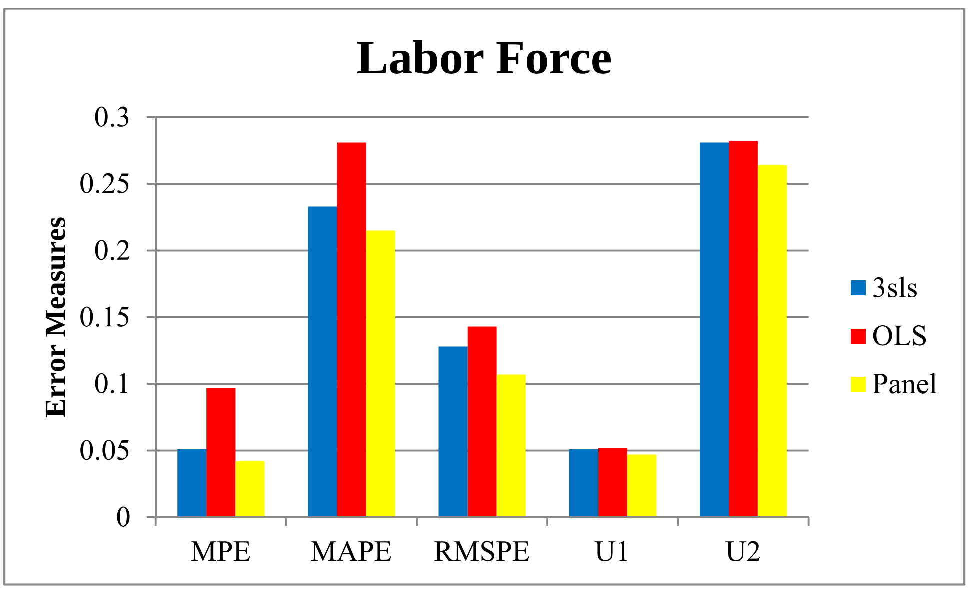

Fig A 1.4. Comparing OLS, 3sls and panel estimators of labor force by different error measures

APPENDIX 2: MPE EVALUATION, FISCAL MODULE

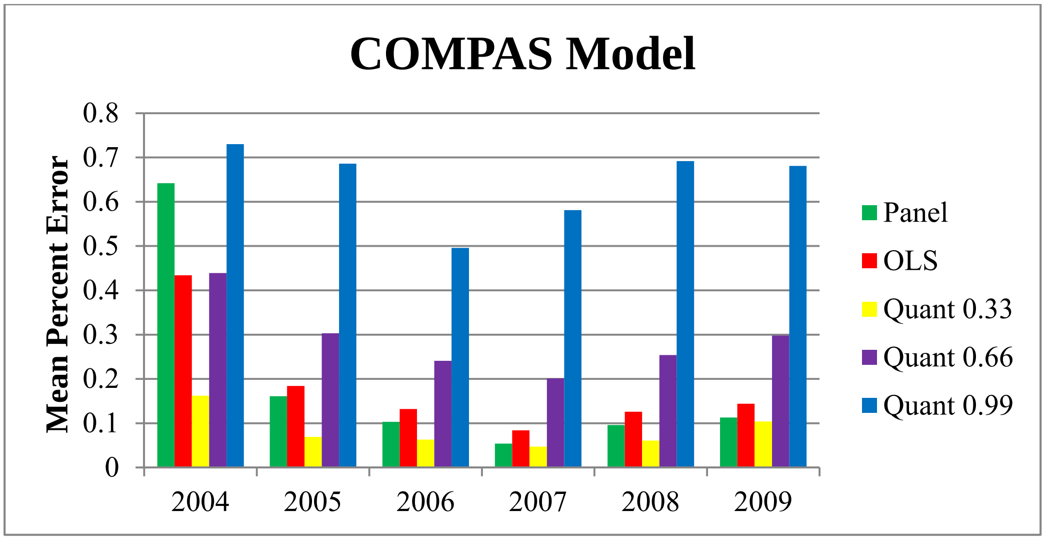

Fig A 2.1. Comparing OLS, panel and quantile estimators of COMPAS model for general government expenditure

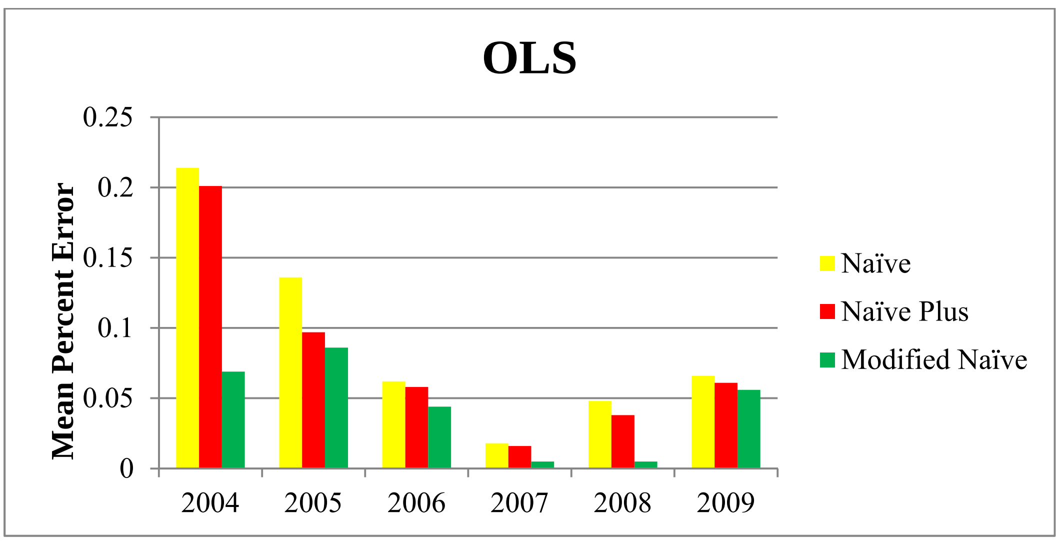

Fig A 2.2. Comparing naïve, naïve plus and modified naïve models by OLS for general government expenditure

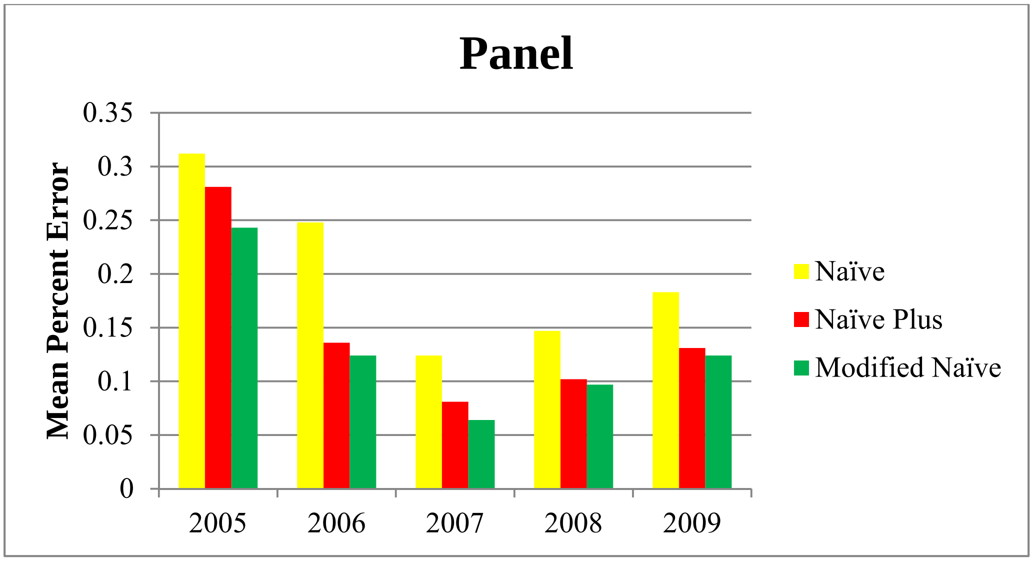

Fig A 2.3. Comparing naïve, naïve plus and modified naïve models by panel model for general government expenditure

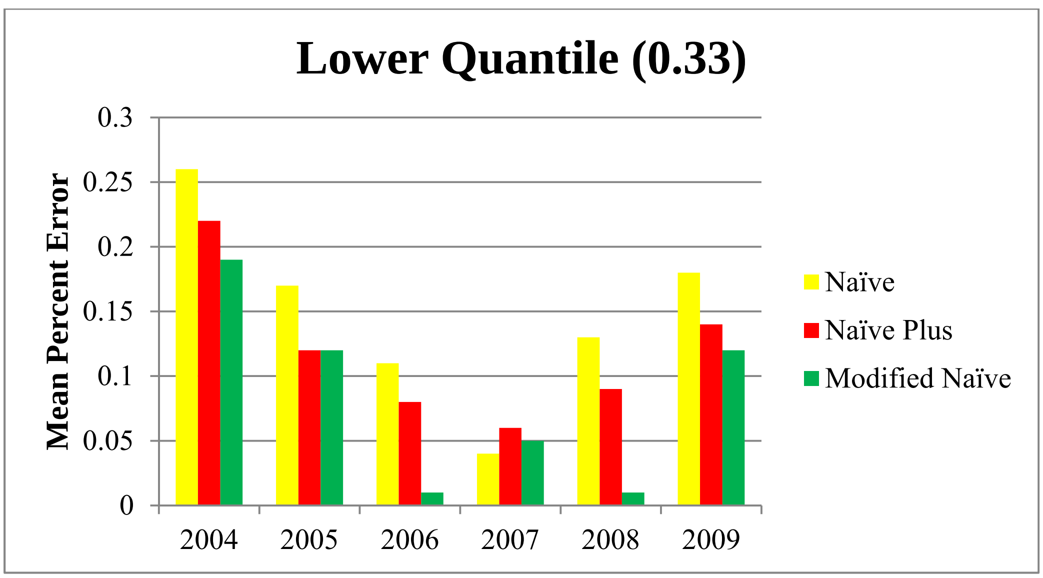

Fig A 2.4. Lowest quantile (0.33) comparing the naïve, naïve plus and modified naïve models by quantile regression model for general government expenditure

VITA

Arun Adhikari was born and raised in a rural area of Tanahun district of the Himalayan kingdom of Nepal. The family later migrated to the capital of the country, Kathmandu, where he acquired his high school degree from L.R.I. school. Later, he completed his undergraduate degree in agricultural science from the only agricultural institute of Nepal, namely, Institute of Agriculture and Animal Science, Rampur Campus, Chitwan, Nepal. He then joined a multinational company, AC Nielsen, ORG MARG, Nepal, as a Research Associate for one year before he moved to the University of Idaho, USA to acquire his master's degree in agricultural economics, where he was provided with the graduate research assistantship for two years. He pursued his master's degree under the guidance of Dr. Christopher McIntosh and submitted a thesis titled "Economic Impacts of Green Industries in Idaho." After receiving his master's degree in 2007, was offered an assistantship in the Department of Agricultural Economics at Louisiana State University to pursue his doctorate degree. Mr. Adhikari enrolled into a doctorate program under the supervision of Dr. J. Matthew Fannin in the Department of Agricultural Economics at Louisiana State University and Agricultural and Mechanical College.