AN EXAMINATION OF COUNTY-LEVEL LABOR MARKET RESPONSES TO ECONOMIC GROWTH IN KANSAS

by

JANET A. SCHLOSSER

B.S., California Polytechnic State University, San Luis Obispo, 2006

A THESIS

submitted in partial fulfillment of the requirements for the degree

MASTER OF SCIENCE

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2008

Approved by:

Major Professor
Dr. Jeffrey Peterson

Abstract

State and local economic development policies are often created with the goal of stimulating local economic activity through employment growth. The success of these policies is commonly measured by the number of jobs they create. Because labor markets are not bound by county lines, commuting and migration are important factors to consider when measuring employment growth in a region.

This study used county-level data from the 2000 Census to predict labor force participation, unemployment, in-commuting, and out-commuting. The model was estimated using Ordinary Least Squares regression and was simulated to predict changes in labor force, unemployment and commuting as a result of a change in employment for all 105 Kansas counties. An increase in employment was found to increase the labor force participation, in-commuting, and unemployment, while decreasing the number of out-commuters.

The increase in in-commuting causes many of the economic benefits expected to accrue to the county where the job growth occurred to be essentially exported to the county where the in-commuters live. Failure to account for the proportion of new jobs filled by in-commuters would lead to significant over estimations of local impacts of employment growth. These results suggest that regional coordination of economic development policies, through the use of tools such as tax-base sharing, would provide substantial gains to otherwise competing local governments.

Table of Contents

List of Figures

List of Tables

Acknowledgements

I would like to thank my major professor, Dr. Jeff Peterson, for his guidance and patience with me throughout the process of writing my thesis. His ability to allow me to take a problem and work through it, while providing helpful advice along the way is the reason this work was accomplished. I would like to acknowledge the contributions of my committee members, Dr. John Leatherman and Dr. John Crespi, as well. I am very appreciative of Dr. Leatherman's insight into the world of regional economic development and thankful for Dr. Crespi's patience while helping me to understand the nuances of econometric modeling more thoroughly. I would also like to acknowledge the Kansas NSF-EPSCoR project, "Ecological Forecasting in the Central Plains," as the funding source for this project.

Secondly, I would like to thank my friends and colleagues on the 4th floor of Waters Hall. Their friendship and support was the reason I looked forward to coming to school every day and the reason I have thoroughly enjoyed this experience. Without their help I would not have completed this endeavor.

Finally, I would like to thank my family for their constant support throughout my entire college experience. Without the love and encouragement of my parents I would not be the person I am today or have had the life changing experiences that come along with graduate school and living in a new place. I would also like to thank my grandma for always reminding me no matter what I do or where I go I will always be welcomed home.

CHAPTER 1 - **Introduction**

1.1 Background

State and local economic development policies are often created with the goal of stimulating local economic activity through employment growth. The success of these policies is commonly measured by the number of jobs they create. The push for job creation is especially strong in rural communities where jobs in traditionally important industries, such as agriculture and extractive industries, are declining. In these communities, manufacturing and service industries often provide new sources of employment. Local policies can alternately encourage or discourage the opening of new business and plants in a community; therefore it is important for policy makers to be able to measure the costs and benefits of policies that affect economic development.

In order to realize the impact of economic development policies, local officials need accurate information about their economy. Because labor markets are not bound by county lines, commuting and migration are important factors to consider when measuring employment growth in a region. If a new company invests in a county, the demand for labor in that county increases. This demand can be met by currently underemployed or unemployed residents of that county. These new jobs may also be captured by workers living in a surrounding county who are willing to commute to the county where new jobs are available (in-commuters). Both situations have implications for changes in county population and public service demands, but they are quite different. Local officials invest considerable amounts of scarce local resources with the expectation that the benefit of economic growth and tax revenues will accrue to the community.

But, to the extent new jobs are taken by in-commuters rather than local residents, much of the benefit is functionally exported.

The debate as to who is actually reaping the benefit of local job growth is long standing. Two contributors to the discussion are Batrik (1993) and Blanchard and Katz (1992), which are reviewed in more depth in Chapter 2. Both papers examine benefits of local job growth across the United States, but their conclusions about who benefits are very different. Batrik estimated that about one-quarter of new jobs go to local workers whereas Blanchard and Katz found that in five to seven years almost all new employment is filled by the inflow of new migrants. This is an important distinction in that enhancing the welfare of the locally unemployed and otherwise needy is one of the important objectives of many local economic development programs.

1.2 Objectives

The overall goal of this study is to identify the impacts of job growth on county level labor markets in Kansas. Specifically, the research objectives are:

1. Quantify the relative contribution of county demographic and fiscal characteristics on labor market migration and commuting patterns.
2. Assess in-sample and out-of-sample prediction performance of the model.
3. Predict the impact of a change in county employment on labor force, commuting, and unemployment.
4. Illustrate use of the model by comparing observed and simulated labor force changes due to an employment event.

In order to accomplish these goals an econometric model was estimated from Kansas data, with variables defined in such a way that the estimated equations can be conjoined with an input-output model to simulate labor market impacts in particular situations. After testing for consistency, the econometric model was estimated using the Ordinary Least Squares (OLS) method from county-level demographic and labor force information from the 2000 Census. Next, the model was validated using a 10-fold cross validation procedure to make out-of-sample predictions. Error statistics were then calculated and compared for the in-sample and out-of sample predictions to validate the model.

Finally, a common regional economic impact tool, called Input-Output (I-O) analysis, was used to predict employment shocks and build scenarios that can be inserted into the econometric model to measure changes in labor force, commuting, and unemployment. Software such as Impact Analysis for Planning (IMPLAN) track endogenous linkages between production, labor and capital income, trade, and household expenditures, and then provide estimated effects on sector output, value added, household income, and employment, given estimates of direct economic change (MIG, 1999).

The I-O model provided estimates of not only the scale of total employment impacts, but also those sectors most directly affected. However, IMPLAN does not tell us who is taking the jobs and how the employment change will affect the local population or labor force. The model developed here is meant to answer some of these questions by using IMPLAN predictions in conjunction with an econometric model. The total employment change including direct, indirect and induced changes predicted by IMPLAN is input into the econometric model as an exogenous shock in the labor market. The econometric equations then predict changes in labor force, in-commuting, out-commuting, and unemployment in a county as a result of this employment shock. These predictions will allow the reader to determine if the jobs are being filled by local residents or commuters and, therefore, infer whether wages earned are staying in the county or are being essentially exported elsewhere.

1.4 Organization of the Thesis

This thesis is organized into eight chapters. Chapter 2 is a review of previous studies regarding local economies. This chapter has an overview of some other regional economic models, including conjoined input-output econometric models. It also contains reviews of articles that discuss commuting in labor markets. Chapter 3 is devoted to the theory behind the estimated model. The data set, data sources, definitions of the variables used, and model specification are discussed in Chapter 4. Chapter 5 presents the methods and procedures used for estimating and validating the model. Specifically, it discusses the justification for using OLS as well as the functional form of the model. Next, in Chapter 6 the results of the estimation are presented and its performance is assessed with the results of the 10-fold validation procedure. Chapter 7 will present the results of different exogenous employment shock scenarios on Kansas counties. Finally, Chapter 8 will report conclusions garnered from this study and discuss suggestions for future research.

CHAPTER 2 - **Literature Review**

2.1 Introduction

The purpose of this chapter is to review literature relevant to regional economic analysis models and labor force commuting patterns. There is extensive literature on regional analysis models thanks to the efforts of the members of the Community Policy Analysis Network (CPAN). CPAN was originally sponsored by the Rural Policy Research Institute, a collaborative endeavor of several Midwestern Land Grant Universities. Many of the members of CPAN have used their models to analyze changes in the labor market and commuting patterns. The following section will review some of these models as well as findings of other researchers who have studied labor markets and commuting.

2.2 Regional Economic Models

Regional economic models are used for many different purposes. Bolton (1985) outlines four types of model applications: pure economic science, economic forecasting, government revenue forecasting, and policy assessment. All models, however, can be classified as either nonstructural or structural (Treyz, 1993). Nonstructural models use past values of variables such as population, employment, and income to predict future values. They make predictions based on past trends, analysis of regional changes based on national industry changes, and shifts in the local industry share of these national changes. Shields (2006) points out that nonstructural models are useful but inflexible because they cannot be easily manipulated. Structural models investigate cause and effect relationships in the economy (Treyz, 1993). With these models, assumed behavior is used to predict how various actors will respond to changes in the economy. The advantage of these types of models is that they give the ability to simulate policy (Shields, 2006). By including variables that are subject to local policy, such as tax rates or spending, the modeler can perform analysis under different policy scenarios.

There are three ‘pure’ approaches for modeling regional economies: computable general equilibrium (CGE) models, input-output models (I-O), and regional econometric models (Shields, 2006). CGE models are typically used for impact assessments and policy analysis by regional economists. CGE models fully incorporate the supply side of the economy, which gives users additional flexibility to impose capacity constraints. I-O models take estimates of direct economic impacts (the original economic shock) and estimate endogenous linkages between production, labor and capital income, trade, and household expenditures, providing estimated effects on sector output, value added, household income, and employment (MIG, 1999). An I-O model will provide estimates of not only the scale of total employment impacts, but also those sectors most directly linked to the employment sector of interest. These models are popular because they provide easily interpreted results and are readily available commercially. The final modeling approach is a regional econometric model. These models consist of a series of simultaneous equations. Since there are usually multiple equations, they are grouped into modules. Once the structure of the equations is decided upon, regional data is used to econometrically estimate the parameters (Shields, 2006).

2.3 Conjoined Input-Output Econometric Models

All three types of models have strengths and weaknesses. In an effort to take advantage of the best attributes of each model, researchers have developed hybrid models. One of these is a conjoined input-output econometric model, in which a regional econometric model is estimated in such a way that it may be linked to an I-O model for policy simulation. Such a regional econometric model was estimated for this research. The conjoined model is a hybrid approach that takes direct, indirect, and induced employment impacts as predicted by I-O analysis and inputs the employment predictions into an econometrically estimated model to simulate changes in factors such as labor force, commuting, school enrollment, and tax revenues and expenditures in a region. This type of model has been used to estimate economic models for states across the country. The remainder of this section reviews some of these models and the advantages and disadvantages of using this modeling strategy.

Yeo and Holland (2000) developed a regional econometric model for Washington counties. A static labor and fiscal model was developed for all 39 Washington counties that was simulated in conjunction with a county-scale I-O model. The I-O model estimates changes in place-of-work employment and county income. This information was then used in the econometric model to estimate the change in local labor force, population, commuting patterns, and local government revenues and expenditures. Labor force, unemployment, in-commuters, and out-commuters were assumed to be a function of employment and determined endogenously. Government revenues and expenditures were considered a function of population as well as personal income and also were determined endogenously.

The model was estimated using cross-sectional data from 39 Washington counties as reported in the 1990 U.S. Census. Seven equations were estimated using seven endogenous and seven exogenous variables. The equations were in log linear form so that the coefficient could be interpreted as elasticities. The seven endogenous variables were: population, labor force, in-commuters, out-commuters, per capita general government revenue, per capita general government expenditure, and unemployment. The right hand sides of the equations had two random variables: endogenous variables and error terms. Because these two random variables may be correlated, the equations were estimated using the Three Stage Least Squares method.

Missouri's Show Me model (Johnson and Scott, 2006) was built to address the information needs of policymakers at federal, state, and local levels. The Show Me model was based on assumptions about the way in which rural and small city economies work, about the way in which local governments make decisions, and about the conditions under which local public services are provided. Given these assumptions the model was estimated with a labor module and a fiscal module.

In this county-scale model, labor supply consisted of locally employed residents as well as in-commuters, which are locally employed non-residents. Labor demand was equal to employment by place-of-work. The labor module equations were estimated using the three-stage least-squares procedure. Four Missouri counties were determined to be outliers and deleted from the data before estimating the module. The labor force module estimated labor force, in-commuters, out-commuters, and second jobs. It also predicted unemployment using the identity that unemployment is equal to labor force plus in-commuters and second jobs minus employment and out-commuters.

The Show Me labor module is different from other community impact models because of the equation for second jobs. Employment can be measured by the number of people in a county who are employed or by the number of jobs in a county. Knowing and modeling the number of jobs in a county is usually most important for policy analysis. Using this measure gives the number of jobs, but not necessarily the number of people employed because it does not account for the people who work more than one job. The second jobs variable was calculated as a residual that contains various measurement errors as well as the actual number of people who hold two or more jobs.

Swenson and Otto (1998) developed the Iowa Economic/Fiscal Impact Modeling System (IE/FIM) as a tool for local policy makers. It provides detailed economic, demographic, and fiscal information that can be used to assist with decision making. This model identifies changes in city and county income, employment, population, school enrollment, and fiscal impact as a response to changes occurring in regional or local economies.

The model for the local labor market was based on the assumption that economic growth is largely affected by exogenous changes in employment. Total labor demand was assumed to be perfectly inelastic at an exogenous level of employment, and total labor supply was perfectly elastic at a wage level. Local labor supply was comprised of locally-employed residents and in-commuters. The number of locally employed residents was found by subtracting out-commuters from the total residential labor force. Labor supply was composed of two positive factors, labor force and in-commuters, and a negative factor, out-commuting. In this model unemployment was a residual component of supply. Labor force, in-commuting, and out-commuting depend heavily on employment in the local economy; however, they will also be affected by relative housing conditions, costs of living, quality of public services, tax levels, and the job mix in the local area.

2.3.1 Advantages and Disadvantages of Conjoined Input-Output Econometric Models

There are advantages and disadvantages of using these conjoined input-output econometric models. According to Shields, Deller and Stallmann (2001), using a conjoined model allows the analyst to take advantage of the best elements of the range of modeling approaches incorporated in the hybrid model. One useful attribute of I-O models is that the results are categorized by employment sector, which allows the analyst to pinpoint the sectors most impacted by a change. The econometric equations are able to model spatial characteristics such as unemployment and commuting, as well as the associated changes in government revenues and expenditures that are of interest to policy makers. By using a hybrid model, the "full employment" assumption of I-O models can be relaxed. I-O models assume that labor supply is infinitely elastic and therefore every member of the labor force is employed. This assumption does not have to hold when using econometric models because they allow for unemployment. Using the econometric model gives a better representation of how economic agents act and captures the complex spatial dimensions of regional interactions both implicitly and explicitly.

The authors also point out some limitations of conjoined I-O econometric models. This modeling approach is demand driven and incorporating supply responses can be challenging. Another concern is that relative price changes must be built explicitly into the model framework. In order to do this, the wage or income of a region should be included in the regression. The model depends on marginal analysis and does not clearly address structural change, which prohibits the model from examining how existing local capacity will accommodate change. Lastly, although economic theory gives insight into how the model should be built, much discretion is left to the modeler.

2.4 Labor Market and Commuting

Policy makers often encourage business growth to provide new jobs for their constituents. Studies are conducted to predict how many jobs are created in a region as the result of a new business. However, these jobs are often times filled by workers outside the community investing in development. For this reason, it is important to take commuting patterns into account when predicting labor force impacts of employment growth in a region.

Bartik (1993) stated that most new jobs are filled by either local residents or in-migrants (those who move, rather than commute, to a region in response to jobs). Through a survey of the research literature regarding who fills new jobs that are a result of labor growth, Bartik concluded that local job growth does have important effects on, and implications for, the local labor force. Specifically, new jobs are more likely to be filled by local residents in a region with low participation and employment rates. The size of the local labor market also affects who takes new jobs. Larger cities contain a variety of skilled workers to fill specific job requirements, making in-migration unnecessary. Areas that have high costs, often large cities, are less attractive to those considering migrating and therefore new jobs are filled by current residents.

All research on this topic, however, does not agree with Batrik's conclusion. Renkow (2003b) estimated a county-level labor market model to determine who gets new jobs when there is growth in the labor market. His model consists of four equations estimated using 3 stage least squares. These equations estimate the change in county labor force size, in-commuting, out-commuting, and unemployment, given an exogenous change in the demand for labor (or employment).

Using county-level data for the years 1980 and 1990, Renkow estimated that when new jobs are created two-thirds to four-fifths of them are filled by commuters. He also found that most of the remainder of the new employment was filled by in-migrants. The study also found that rural and urban county commuters behave differently. Results showed that a higher percentage of new jobs were filled by in-commuters in urban counties whereas in rural counties the jobs were filled by residents of that county, thereby reducing the number of out-commuters.

Also, labor force growth in rural counties was affected more by employment growth in nearby counties. Overall, Renkow estimated that a significant portion of new jobs, one-third for rural counties and one-half for metro counties, were filled by in-commuters.

The fact that so many jobs in a county are often filled by residents from other counties has serious policy implications. Local government officials often try to enhance job growth for their residents. However, if new jobs are filled by those outside the jurisdiction, then this goal is not met. Renkow also cautioned that overlooking commuting patterns can also have fiscal impacts. Employment increases in a location that draws in-commuters can have spillover effects to the surrounding communities where the employees may prefer to live. This 'bedroom' community phenomenon seems to be a growing issue in rural counties located near large economic centers.

Blanchard and Katz (1992) estimated a series of dynamic econometric models using data from all 50 states. The paper researches many questions related to employment, wages, and regional migration. The section of interest for this thesis estimated a model that examined how different amenities (such as relative wages) offered by different states to workers or firms led to differences in migration. A log linear model was regressed over the period 1952-1990 to determine employment change as a function of the labor force, wages, unemployment, and the working age population.

From this model the authors found that a negative shock to employment initially led to an increase in unemployment and a small decline in the labor force participation rate. Over time, the effect on employment increased, but the effect on unemployment and participation disappeared after five to seven years. This indicated to the researchers that a state labor market returned to normal after an adverse employment shock not because employment recovered, but because workers left the state. This conclusion also worked the other way. In five to seven years a response to an increase in employment consisted almost entirely of the inflow of new immigrants.

Renkow (2003a) focused on a smaller region by looking at employment and commuting impacts in thirteen states comprising the Southern United States. Renkow built a county-level labor market model to quantify the spatial aspects of employment growth during the 1990s. His model accounted for movement of workers across county lines when a labor demand shock took place. The model estimated equations for in-commuting, out-commuting, labor force, and local unemployment.

Renkow's results indicated that about one-quarter of new rural jobs and one-half of new metro jobs are filled by in-commuters. Failure to account for in-commuters could lead to significant overstatement of changes in final demands resulting from employment shocks. Also, between 60 and 70 percent of the adjustment of labor supply to new employment opportunities is accounted for by changes in commuting flows, and that in-migrants account for the remainder of the change. From these results, Renkow concluded that fiscal impacts associated with residential demands for public services will be smaller than is usually supposed.

Fisher (2003) used 2000 Census data to observe commuting patterns of workers in a single state, Minnesota. Seventeen laborsheds were constructed, each containing a primary county where commuters are employed and a number of surrounding counties where the workers live. The laborsheds were built based on the percentage of workers commuting into and out of the counties. After determining the laborsheds, Fisher was able to make several conclusions about the employment and commuting patterns of Minnesota residents by analyzing the number of workers, where they live, and where they work.

Because the laborsheds were based on percentages of the population commuting, some small counties appeared to have more in-commuters than would be expected. Essentially, a smaller town in a more rural area may have a higher in-commuting percentage and appear to be more of an employment magnet, compared to a larger town in a more populated region of the state. A smaller regional hub in a rural area benefits from being the only job center within a reasonable commuting radius. Fisher's second finding was that when workers had the choice between two economic centers, a smaller closer center and one larger but farther away, they choose to commute farther to the larger center. Two reasons were given for this. There may be more jobs available in the larger center, or wages may be higher in the larger economic center.

Seventeen Minnesota counties were not included in any laborshed because they did not have a significant population commuting to any of the primary employment counties. These counties were the most rural. They tended to have lots of acres in forests and lakes or farmland. There were no large cities in these counties, just a few small towns. For the most part the residents worked close to home.

When comparing 1990 Census data to that of the 2000 Census, Fisher found that workers were becoming increasingly mobile. More employees are willing to travel to work, and those that do travel are willing to go further distances. As a result, the number of 'bedroom communities' (counties with 25 percent more working residents than jobs) surrounding economic centers has also grown.

Shields and Swenson (2000) examined the relationship between employment opportunities and in-commuting in 65 Pennsylvania counties. The authors focused on commuters because they can impact the level of demand for local public services and are a source of income 'leakage' in a community (i.e. they spend their earned income back in their community of residence). A county-level econometric model was estimated where in-commuting is a function of the relative wage, relative unemployment, employment, relative housing prices, external labor, and external employment.

This model was different from other literature in residential and workplace choice in that it disaggregated commuting by industry. A Tobit model was used to estimate ten variations of the model, one for each of the ten different industries studied. The industries examined were: farming; agricultural services and mining; construction; manufacturing; retail and wholesale trade; services; finance, insurance, and real estate; transportation, communication, and public utilities; state and local government; and federal government.

The results suggested that the proportion of jobs filled by in-commuters varies by industry, ranging from 0.036 in farming to 0.498 in the federal government sector. The authors also found that in 9 of the industries the number of in-commuters increases as relative housing prices increase. This suggests that households may be sensitive to the regional housing market when making residential and workplace location decisions.

2.5 Summary

Many different types of econometric techniques have been used to estimate regional economic models. One type of model often used is conjoined input-output econometric models. Many such models have been estimated to research the question of who takes new jobs. This question has been of interest at the country, state, and county level and there is disagreement in the literature as to whether the majority of new jobs go to residents or commuters. This research will add to the literature by answering this question at the county-level in Kansas using a conjoined input-output econometric model to predict changes in labor force, unemployment and commuting when there is an increase in demand for workers.

CHAPTER 3 - **Theoretical Model**

3.1 Introduction

Analysis of labor market commuting patterns has been done in various regions using a variety of methods resulting in sometimes contradictory conclusions. This research uses a conjoined input-output econometric model to estimate labor force impacts, including commuting, in urban and rural Kansas counties. The model is based on a conceptual framework laid out by the members of CPAN (Johnson, Otto, and Deller, 2006). The conceptual foundation for the model to be estimated is provided in this chapter.

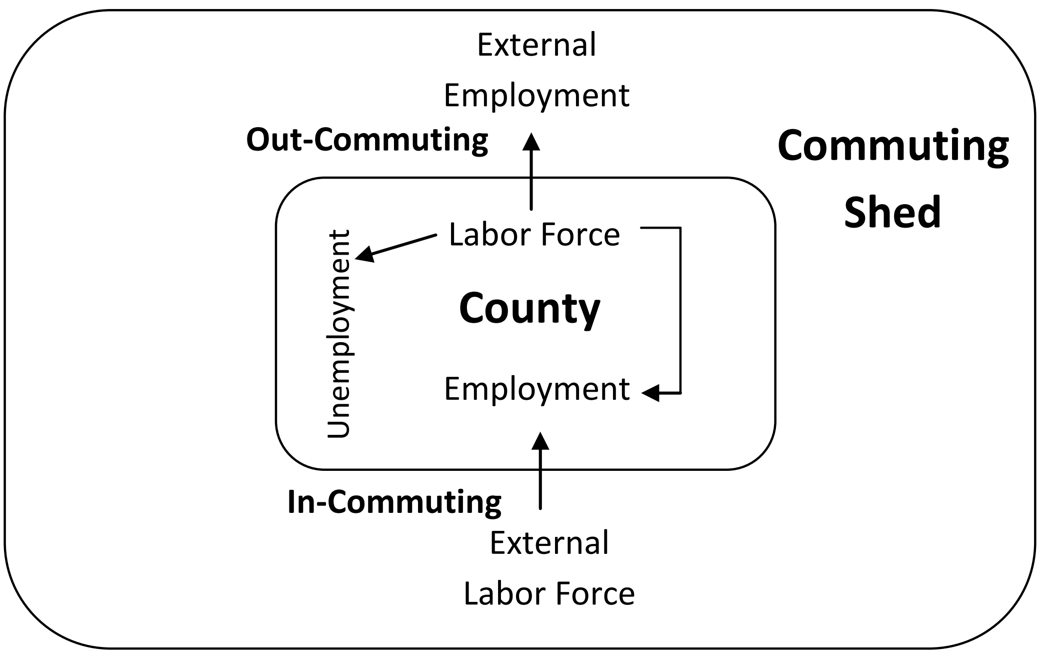
3.2 Theoretical Model

Building on previous regional economic analysis models, a static Kansas labor impact model is developed. The model is centered on local and regional labor markets, as is the case with most Community Policy Analysis Modeling (COMPAS) based estimations that have been promoted through the Rural Policy Research Institute. At the most basic level, the motive for economic change at the local level is employment, and the fundamental unit of the spatial economy is the labor market (Johnson, 2006).

The model is based on the assumption that an exogenous change in employment drives changes in the labor market. The labor market allocates new jobs among the locally unemployed, locally-employed non-residents (in-commuters), residents who currently work in other counties (out-commuters), and new entrants to the labor force. Growth in the demand for labor can result from either new public investment or new private investment.

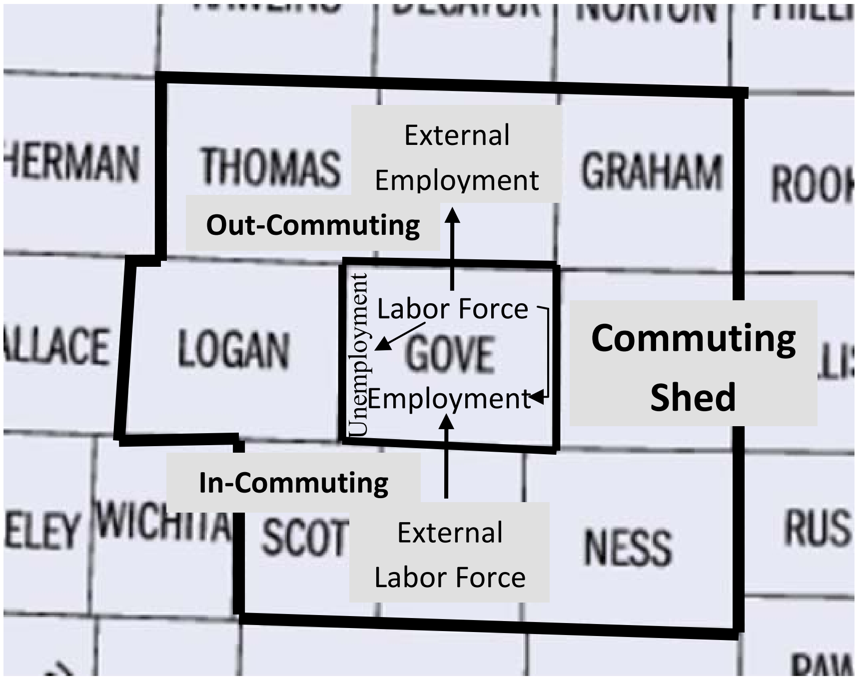
In this model, demand can be viewed as perfectly inelastic at an exogenously determined level of employment (Swenson and Otto, 2006). Figure 3.1 depicts the local labor market relationships for a generic county. Local jobs are taken by locally-employed residents and in-commuters; in the figure these flows of labor are represented by the arrows from the Labor Force to Employment and from the External Labor Force to Employment. The local labor force is composed of locally employed residents, out-commuters, and the unemployed; thus the arrows in the figure emanating from the Labor Force show that it is distributed among Employment, External Employment, and Unemployment.

Figure 3.1 Conceptual Labor Market



Defining the commuting shed for a county as the counties contiguous to it, the relationship for Gove County, Kansas, one of the counties in this model, is illustrated below in Figure 3.2.

Figure 3.2 Labor Market for Gove County, Kansas



In- and out-commuters are not aggregated into net commuters in the conceptual model because they are not equal in the long term. The difference over time shows preferences for public services, occupational characteristics of households, and the fact that submarkets for different labor skills exist in different counties (Johnson, 2006). The relationships depicted above imply an identity that accounts for local labor flows; labor force and in-commuters add to the supply of labor and unemployment and out-commuters subtract from it:

Employment = Labor force + In-commuters – Unemployment – Out-commuters. (1)

Following previous work, the model is formally developed starting with labor demand and supply. Let X_D denote the exogenous (perfectly inelastic) demand for labor, also referred to as employment, and let X_S denote the local labor supply.

Decomposing labor supply, equation (1), into its components gives:

$$X_S = X_{LF} + X_I - X_U - X_O \quad (2)$$

where X_{LF} is the resident labor force, X_I is the number of in-commuters, and X_U is the number of unemployed person, X_O is the number of out-commuters. Each component of supply is a function of the wage rate and a vector of supply shifters:

$$X_{LF} = f_L(w, Z_{LF}) \tag{3}$$

$$X_O = f_O(w, Z_O) \tag{4}$$

$$X_I = f_I(w, Z_I) \tag{5}$$

$$X_U = f_I(w, Z_U) \tag{6}$$

where the Z vectors contain supply-shift variables for the various components of supply. The individual variables in these vectors and their expected direction of impact on the supply components are described below.

Market clearing in the local labor market requires that $X_D = X_S$. Substituting the component functions from (3)-(6) into equation (2) gives,

$$X_D = f_L(w, Z_{LF}) - f_U(w, Z_U) - f_O(w, Z_O) + f_I(w, Z_I) \tag{7}$$

Equation (7) implicitly defines an equilibrium wage function, $w^*(X_D, Z)$, where the value of the function is the unique wage that clears the local labor market when employment is X_D and the supply-shift variables are $Z = (Z_{LF}, Z_U, Z_O, Z_I)$. Substituting the wage function into equations (3) - (5) gives

$$X_{LF} = f_L(w^*(X_D, Z), Z_{LF}). \tag{8}$$

$$X_O = f_O(w^*(X_D, Z), Z_O). \tag{9}$$

$$X_I = f_I(w^*(X_D, Z), Z_I)\ . \tag{10}$$

Unemployment, equation (6) can be computed residually from the other model variables by rearranging the identity from equation (2):

$$X_U = X_{LF} + X_I - X_O - X_D \tag{11}$$

This is a system of equations, each of which depends on employment, X_D, and other variables, Z, which is the basis of the econometric model to be estimated. The wage rate is substituted out of the system, avoiding the difficult issue of finding a variable that measures the local wage rate. In practice, wages vary widely within a county across a range of job types and skill levels. As specified in chapter 4, equations (8) – (10) are estimated while equation (11) is an omitted identity.

As noted above, all three components of labor supply depend on employment at the location in question. The other supply shifters include housing conditions, costs of living, quality of public services, tax levels, and job mix in the location of employment relative to alternate locations within a commuting shed. The geographic size of the region (in our case county) may be an important variable to consider. Smaller counties will have a smaller resident labor force and have more in- and out-commuters because they will have to cross county lines to get to work. Larger counties will have more employment opportunities as well as more places of residence, therefore more laborers will live and work in the same county and there will be fewer commuters. Commuting will also depend on the distance between place of residence and place of work. Taking these variables into account the theoretical equations can be expressed as follows:

Labor force = *f*(employment, housing conditions, cost of living, public services, taxes, industry mix, area)

Out-commuting = *f*(employment, external employment, external labor force, housing conditions, cost of living, public services, taxes, industry mix, area, distance to jobs)

In-commuting = f(employment, external employment, external labor force, housing conditions, cost of living, public services, taxes, industry mix, area, distance to jobs)

These equations have been the building blocks of numerous state-sanctioned community policy economic models. All states have been cooperating with the Community Policy Analysis Network under the leadership of the Rural Policy Research Institute.

3.3 Theoretical Effect of Change in Employment

The main driver behind a change in labor force and commuting is a change in employment. Using the theory laid out above we can predict how a change in employment will affect labor force, in-commuting, out-commuting, and unemployment.

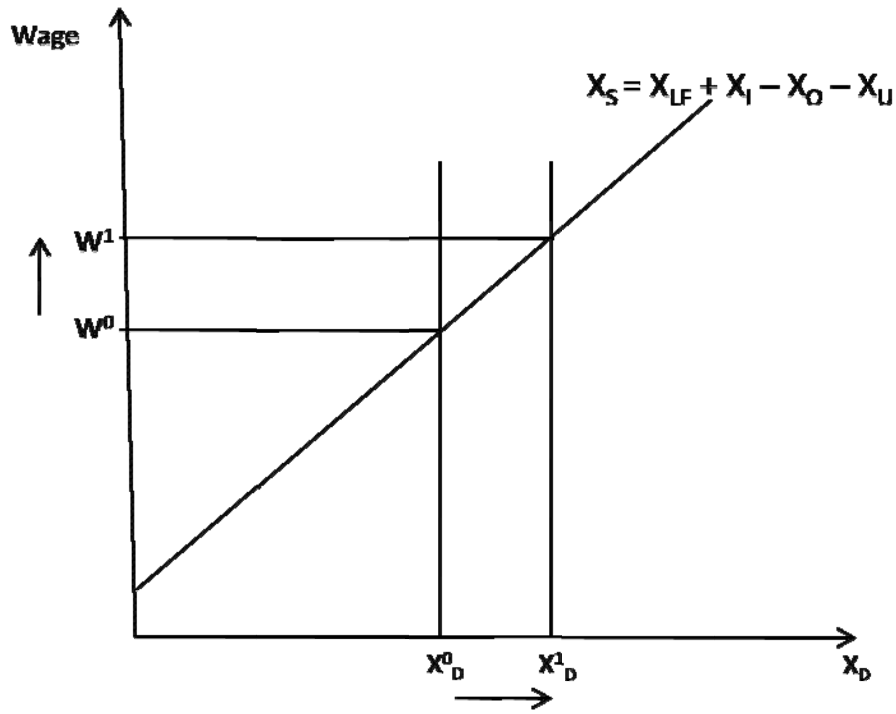
Equation 8 shows labor force as a function of wages and a vector of other supply shifters. By taking the derivative of this equation with respect to labor demand (i.e. employment) the effect of a change in employment on labor force can be observed.

$$X_{LF} = f_L(w^*(X_D, Z), Z_{LF})$$

$$\frac{\partial X_{LF}}{\partial X_D} = \underset{(+)}{\frac{\partial f_L}{\partial w}} \times \underset{(+)}{\frac{\partial w*}{\partial X_D}}$$

The first part of this derivative, $\frac{\partial f_L}{\partial w}$, is the slope of the labor force supply curve and is positive. The second part, $\frac{\partial w*}{\partial X_D}$, shows what happens to the equilibrium wage when there is an exogenous change in the demand for labor. This term is positive, as an outward shift in the inelastic labor demand will cause an upward movement along the labor supply curve, which means the equilibrium wage will increase. (Figure 3.3) Thus, labor demand and labor force are positively related. An increase in employment will cause an increase in labor force.

Figure 3.3 Effect of an Increase in Labor Demand on Wage



The same steps can be followed to find employment's effect on in-commuting, out-commuting, and unemployment. In-commuting is assumed to be positively related to the local wage and therefore will have the same signs as labor force. Out-commuting has a negative relationship with the local wage so an increase in demand for employees will cause decrease in out-commuting. The derivatives can be seen below.

$X_I = f_I(w, Z_I) = f_I(w^*(X_D, Z), Z_I)$

$$\frac{\partial XI}{\partial XD} = \underset{(+)}{\frac{\partial fI}{\partial w}} \times \underset{(+)}{\frac{\partial w*}{\partial XD}}$$

$X_O = f_O(w, Z_O) = f_O(w^*(X_D, Z), Z_O)$

$$\frac{\partial X_0}{\partial X_D} = \frac{\partial f_0}{\partial w} \times \frac{\partial w*}{\partial X_D}$$

(-) (+)

To find how a change in labor demand affects unemployment we use equation (11):

$X_U = X_{LF} + X_I - X_O - X_D$

Taking the complete derivative we get

$$\frac{\partial X_U}{\partial X_D} = \frac{\partial X_{LF}}{\partial X_D} + \frac{\partial X_I}{\partial X_D} - \frac{\partial X_0}{\partial X_D} - \frac{\partial X_D}{\partial X_D}$$

Substituting in the values derived above

$$\frac{\partial X_U}{\partial X_D} = \frac{\partial f L}{\partial w} \times \frac{\partial w*}{\partial X_D} + \frac{\partial f_I}{\partial w} \times \frac{\partial w*}{\partial X_D} - \frac{\partial f_0}{\partial w} \times \frac{\partial w*}{\partial X_D} - 1$$

(+) (+) (+) (+) (-) (+)

The sign of $\frac{\partial X_U}{\partial X_D}$ is ambiguous and depends on the magnitudes of the terms on the right hand side of the equation. If $\frac{\partial f L}{\partial w} \times \frac{\partial w*}{\partial X_D} + \frac{\partial f_I}{\partial w} \times \frac{\partial w*}{\partial X_D} - \frac{\partial f_0}{\partial w} \times \frac{\partial w*}{\partial X_D}$ adds up to less than one then the change in unemployment will be negative. This seems intuitive. However, if $\frac{\partial f L}{\partial w} \times \frac{\partial w*}{\partial X_D} + \frac{\partial f_I}{\partial w} \times \frac{\partial w*}{\partial X_D} - \frac{\partial f_0}{\partial w} \times \frac{\partial w*}{\partial X_D}$ adds up to a value greater than one, the change in unemployment will be positive. This also makes sense. If new jobs are filled by people who move to the county, they might not migrate in alone. For example, if a husband and wife move to a county for the husband to fill a new job if the wife does not also have a job she will add to the number of unemployed.

CHAPTER 4 - **Model Specification and Data**

4.1 Introduction

This chapter describes the data used for this research. Section 4.2 discusses the sources of the data and how they were collected. Section 4.3 then presents the empirical model specification. Next, Sections 4.4 and 4.5 define the variables specified in the labor force, in-commuting, out-commuting, and unemployment equations. Finally, Section 4.6 describes some important characteristics of the data set.

4.2 Data Sources

The majority of the data used for this research were extracted from the 2000 Decennial Census. The original Census, in 1790, was a simple headcount of Americans classified by age, sex and race. During the twentieth century, the Census Bureau became the chief statistical agency of the United States government, surveying on behalf of other federal agencies as well as itself. Currently, in addition to administering the Census of Population and Housing, the Census Bureau conducts more than 200 annual surveys classified under either the demographic or the economic program (census.gov).

Every ten years, the United States Department of Commerce Census Bureau conducts the Decennial Census to collect information regarding the status of the country's people and economy. The most recent Decennial Census of the U.S. was conducted in 2000. A survey with seven questions for each household was sent out to American families. A 20 percent sample of households also received a longer questionnaire that asked 52 questions relating to socioeconomic factors of the population. Due to a wide-spread advertising campaign that was estimated to have reached 99 percent of U.S. residents and an aggressive non-response follow-up program, the response rate to the survey was about 67 percent. Households who received only the short form survey could respond by Internet, telephone, or mail. The 2000 Census was the first time respondents could reply by email and 70,000 households took advantage of this medium (census.gov).

Several variables in this study including labor force, housing values, per capita income, unemployment, and the metropolitan or micropolitan statistical area classification came directly from the Census data tables. Data on in- and out-commuting were calculated from information provided by the Journey to Work portion of the 2000 Census. The commuting portion of the Census offers information regarding where people work, how they get there, amount of time spent commuting, and carpooling information.

The employment by workplace data was available through the Regional Economic Information System (REIS) compiled by the Bureau of Economic Analysis (BEA). The REIS data breaks down information such as gross domestic product and personal income by state and local regions, which provides a consistent framework for analyzing and comparing individual state and local area economies (http://www.bea.gov/regional).

The next section describes the precise variables in the labor force equation and the commuting equations presented conceptually in chapter 3. A complete listing of variables used in this study along with their respective sources is in Table 4.1.

Table 4.1 Description, Derivation, and Source of Variables

Variable	Scale	Description	Derivation	Source
LF	Number of Persons	Total county labor force, 2000	Given	U.S. Census, 2000
IN	Number of Persons	Employees commuting into a county to work, 2000	No. of persons employed in county - No. of persons employed in and living in county	BEA Journey to Work, 2000
OUT	Number of Persons	Residents of a county commuting to another county for work, 2000	No. of employed persons in county - No. of persons employed persons living and working in county	BEA Journey to Work, 2000
EMP	Number of Persons	Place of Work Employment, 2000	Given	BEA Regional Economic Information System, 1969-2006
RESUN	Number of Persons	Total county residual unemployment, 2000	Labor Force + In-commuters - Out-commuters - Employment	U.S. Census 2000
INC	Dollars	Aggreagate County Income from Wage/Salary	Given	U.S. Census 2000
CEMP	Number of Persons	Countiguous employment, 2000	Σ employment in countiguous counties	BEA Regional Economic Information System 1969-2006
CLF	Number of Persons	Contiguous labor force, 2000	Σ labor force in countiguous counties	U.S. Census 2000
RIPC	None	Relative per capita income, 1999	County per capita income/Average per capita income of contiguous counties	U.S. Census 2000
RHOUSE	None	Relative owner occupied housing value, 2000	County median owner occupied housing value/ Average owner occupied housing value of contiguous counties	U.S. Census 2000
METRO	Dummy Variable	Metropolitan/Micropolitan statistical area, Yes=1, 2000	County population > 10,000 has a value of 1	U.S. Census 2000

4.3 Model Specification

The equations estimated in this study were specified based on the conceptual model in chapter 3. For county i, the equations explaining the size of the labor force LF_i, out-commuting, OUT_i, in-commuting, IN_i, and unemployment, $RESUN_i$, are specified as

$$LF_i = f_L(EMP_i, CEMP_i, INC_i, RHOUSE_i, RIPC_i, METRO_i, e_{1i}) \quad (12)$$

$$OUT_i = f_O(EMP_i, CEMP_i, INC_i, RHOUSE_i, RIPC_i, METRO_i, LF_i, e_{2i}) \quad (13)$$

$$IN_i = f_I(EMP_i, INC_i, RHOUSE_i, RIPC_i, METRO_i, CLF_i, LF_i, e_{3i}) \quad (14)$$

$$RESUN_i = LF_i + IN_i - OUT_i - EMP_i$$

where e_{ji} are random estimation errors and, for county *i*,

- EMP_i, = employment
- $CEMP_i$ = total employment in contiguous counties
- INC_i = wage/salary income
- $RHOUSE_i$ = housing value relative to contiguous counties
- $RIPC_i$ = income relative to contiguous counties
- $METRO_i$ = a binary variable indicating a metro/micro-politan county
- CLF_i = total labor force in contiguous counties

The empirical definitions of the variables also are described in detail by equation below. The functional forms of $f_L(.)$, $f_O(.)$, and $f_I(.)$, as well as the properties of the errors, e_{ji}, are discussed in chapter 5.

4.4 Definition of Variables in Labor Force Equation

For this study, cross sectional data from all 105 Kansas counties were used. Most variables are explicitly provided by or calculated from the 2000 Census data. Labor force (LF) is defined as the number of people residing in a given county classified as employed or unemployed. These people are 16 years old or older and currently working, actively looking for work or are in the U.S. armed forces. As discussed in Chapter 3, labor force is hypothesized to be a function of employment, industry mix, housing conditions, cost of living, public services, taxes, and area. In reality not all of these variables are available on a county level. The variables that were available and specified in equation (12) to explain the variation in labor force are described below.

Employment is represented by two variables, EMP and CEMP. EMP is employment in a given county by place of work. This is the number of full-time and part-time employees on the payroll at yearend. If the employment of a parent or an affiliate was unusually high or low because of temporary factors (such as a strike) or large seasonal variations, the number that reflected normal operations or an average for the year is shown. Place of work employment was chosen rather than place of residence employment because this number allows us to measure the number of jobs filled in a county and accounts for people who may hold more than one job.

CEMP is the contiguous employment for a county. It is calculated by adding the place of work employment in every county contiguous to the county of interest. For this paper a contiguous county is one that borders the county of interest. This variable, along with employment, represents total labor demand for a county's residents.

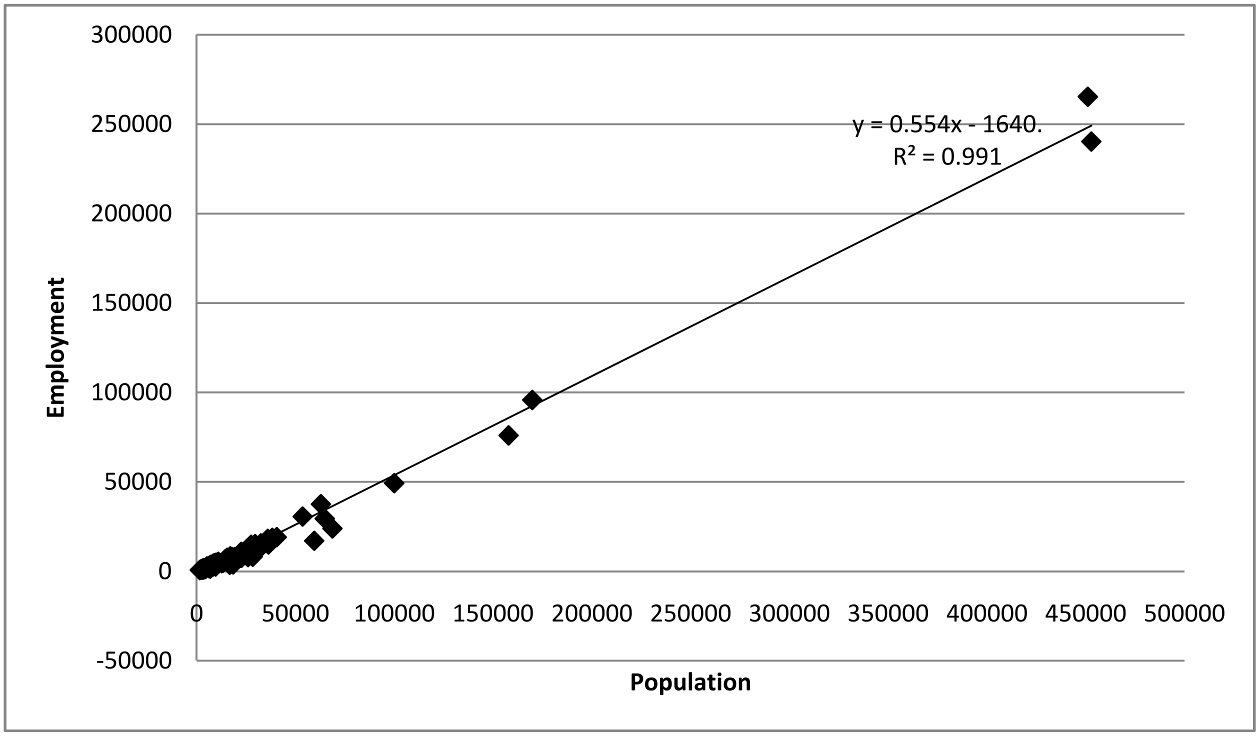
The variable INC is defined as the aggregate income in the county that comes from wages and salaries. This variable is meant to measure the types of jobs (industry mix) in the county. Higher paying jobs usually require specialized skills, so an increase in higher paying jobs in the county may have a different effect on who fills the new jobs compared to an increase in lower paying jobs.

The variable RHOUSE is the relative value of a county's owner-occupied housing. It is calculated by dividing the median value of owner occupied housing in a county by the average of the median values of owner occupied housing in contiguous counties. This variable is meant to account for housing conditions as well as the cost of living in a county compared to the counties around it.

The variable RIPC is the per capita income for each county relative to surrounding counties. This variable was calculated by dividing the per capita income for a county by the average per capita income of its contiguous counties. This variable is a proxy for the local tax base and the level of public services; better public services should increase labor supply in a county by drawing more workers into the local labor force.

To find the best econometric model, many variables that in theory are suggested to be important were examined for inclusion in the model. However, due to the lack of availability or the high correlation of some of these exogenous variables not all variables thought to be theoretically important could be used. Plots and correlation matrixes were used to indentify explanatory variables that may be correlated and therefore cause multicollinearity. For example, population was hypothesized to be an important explanatory variable in the labor force equation but it is very highly correlated with EMP; these two variables have a correlation coefficient of 0.996. This relationship can be seen in Figure 4.1.

Figure 4.1 County Employment vs. County Population



Given this apparent correlation, a metropolitan dummy variable (METRO) was used as an explanatory variable in the equations to account for differences in population while avoiding multicollinearity.

A metro area contains a core urban area of 50,000 or more population, and a micro area contains an urban core population of between 10,000 and 50,000. As defined by the 2000 Census, each metro or micro area consists of one or more counties and includes the counties containing the core urban area, as well as any adjacent counties that have a high degree of social and economic integration (as measured by commuting to work) with the urban core. This variable also is a proxy for cost of living and the level of public services.

4.5 Definition of Variables in Commuting and Unemployment Equations

Equations are also estimated for in-commuting and out-commuting. These equations share many of the same variables, but vary slightly. The Journey to Work data, which provide the number of people living and working in a given county, are used to calculate the number of people commuting into and out of a county for work. The variable IN (number of in-commuters) is calculated by subtracting the total number of working persons living and working in a county from the total number of persons employed in that county. The variable OUT (out-commuters) is derived by taking the total number of employed persons living in a county and subtracting the total number of employed persons that live and work in the county. Theoretically, both equations should depend on employment, external employment, external labor force, housing conditions, cost of living, public services, taxes, industry mix, area, and distance to jobs/residence.

As with the labor force equation, employment (EMP) is included in both commuting equations as a proxy for labor demand. In the out-commuting equation the variable CEMP represents demand for labor in the counties surrounding the county of interest. This variable is used in the out-commuting equation because the more jobs available in surrounding counties the more likely workers are to commute to work outside their county of residence.

Once again the aggregate income variable, INC, is included to help determine the types of jobs available in the county. Relative income per capita, RIPC, and relative housing values, RHOUSE, are used in the commuting equations, as well. The relative income variable proxies differences in tax revenues and thus public services between a county and those surrounding it. The housing variable is meant to take into account relative housing conditions as well as the relative cost of living in a county. The METRO dummy variable is included to take into account population. Also, the unemployment variable is again a residual value included to account for the labor force identity.

The labor force variable (LF) is used as an explanatory variable in both commuting equations to account for the number of available workers in the county without commuting. The size of the labor force will logically influence the number of workers leaving the county to find employment or entering the county to take available jobs. In addition, the number of in-commuters in a given county would depend on the number of available workers in a given county's commuting shed; the more people in the surrounding counties' labor forces, the more likely they may commute into the county of interest to find employment. The number of people in the labor force in the counties surrounding the county of interest is measured by the variable CLF, which was calculated from the 2000 Census data.

The final value estimated by the model is unemployment (RESUN). This variable is a residual value derived from the identity equation:

Unemployment = Labor Force + In-commuters - Out-commuters - Employment

By Census definition unemployment is all civilians in a county 16 years or older who are not working, but are looking for employment and are available to start a job.

4. 6 Characteristics of the 2000 Census Data Set

The census collects county level data on all 105 Kansas Counties. This is a cross-sectional study using only one year of data, so there are a total of 105 observations. As a group the counties are fairly similar in size, demographics, and labor force characteristics. Two counties, Johnson and Sedgwick, can be regarded as outliers as they are much larger than the rest in terms of population and labor force. These counties both have a larger number of commuters, as well. Although the population, labor force, and commuting observations are much larger than the rest of the counties they are included in the estimation because removing them did not make a significant difference. Summary statistics for all variables can be seen in tables 4.2 and 4.3.

The counties vary widely in population with the most populous county having 452,869 residents and the least populous having 1,534 residents. The average county population is 25,604 with a standard deviation of 65,337.

Counties range in size from 151 square miles to 1,428 square miles. The average county is 779 square miles with a standard deviation of 214 square miles. Like population itself, the population density varies over a wide range, from 1,043 people in metropolitan areas to 2 people per square mile in rural counties. The average population density is 46 people per square mile.

The labor force in each county ranges from 720 to 253,160 participants. The average labor force size is 13,236 people with a standard deviation of 34,981. Labor force divided by population gives us the labor force participation rate. This number indicates the proportion of the available "working age" population that is willing and able to work and is either employed or actively seeking employment. The labor force participation rate ranges from 52.1% to 73.9%. The average labor force participation rate is 63.9% with a standard deviation of 3.9% across all counties.

Employment in the counties ranges from 735 jobs to 265,363 jobs. The counties with the most jobs available also have the largest populations. The average number of jobs available in a county is 12,543. The standard deviation for employment is 36,343. Unemployment ranges from 2 people to 11,159 people. The average number of unemployed people in a county is 556 with a standard deviation of 1,407.

All counties have some residents that commute across county lines for work. The average number of in-commuters is 2,882 people. In-commuting ranges from a minimum of 93 people to 99,439 people commuting into a county for work. The standard deviation for in-commuting is 10,961 people across all counties. The number of people commuting out of their county of residence to work in another county ranges from 66 to 77,984 people. The average number of out-commuters in each county is 2,828 with a standard deviation of 8,489 people across all counties.

Median housing values range from $29,000 to $149,300 for the counties. The average housing value is $58,334 with a standard deviation of $19,108. Income per capita ranges from $17,569 to $41,557. The average income per capita of the counties is $23,625 with a standard deviation of $4,095.

Table 4.2 Dependent Variable Descriptive Statistics

Variable	Mean	Standard Deviation	Min	Max
LF	13,236	34,981	720	253,160
IN	2,882	10,962	93	99,439
OUT	2,828	8,490	66	77,984
UNEMP	556	1,408	2	11,159

Table 4.3 Independent Variable Descriptive Statistics

Variable	Mean	Standard Deviation	Min	Max
EMP	12,544	36,344	735	265,363
CEMP	109,675	163,014	13,599	1,031,707
CLF	85,180	122,841	10,462	762,016
INC	379,755,576	1,293,648,047	15,855,200	10,911,976,000
RHOUSE	58,334	19,108	29,000	149,300
RIPC	23,626	4,095	17,569	41,557

CHAPTER 5 - **Methods and Procedures**

5.1 Introduction

This chapter discusses the methods and procedures used to estimate and validate the labor market equations. Section 5.2 describes the functional forms of the equations and the expected signs of the empirical model. Section 5.3 explains the method used to estimate the model and the sub-sections give justification for its use.

5.2 Functional Form

No theoretical functional form exists in this field, however some previous studies (Johnson, Scott, Shields) have used a linear specification. Others (Yeo and Holland) have used log-transformed variables to account for the large variability in their raw data. Originally I ran the model using a linear specification with the raw variables. When estimated, this model had a very high fit with an R-squared in the labor force equation of .998. The shortcoming of this model was that most of the explanatory power was driven by the employment, EMP, variable which had a very large t-statistic.

The reason for employment's high explanatory power is that counties with high population will have large employment and a large labor force. That is, there is a spurious relationship between LF and EMP, caused purely by the scale of population. This resulting model is a misleading representation of the cause-effect relationship between those two variables. A further problem is that the explanatory contributions of the other variables in the LF equation were all overwhelmed by the EMP variable. To remove the scale illusion and provide a meaningful interpretation of the coefficients on other variables, LF, EMP and several other variables that are logically related to population were scaled (normalized) by the 1990 Census population for each county. The 1990 Census population can be regarded as a predetermined variable for all counties, ensuring the normalization did not introduce additional endogeneity. The dependent variables as well as employment, contiguous employment, and aggregate income, in the labor force and out-commuting equations were scaled by the counties' 1990 population. The dependent variable as well as employment, contiguous labor force, and aggregate income in the in-commuting equation were scaled by the 1990 population in contiguous counties because that is where the in-commuters originate from. The new set of variables and their definitions are provided in table 5.1.

Table 5.1 Description of Variables

Variable Name	Variable Description	Variable Name	Variable Description
LFS	Labor Force/1990 County Population	INSC	In-Commuters/1990 Contiguous County Population
OUTS	Out-Commuters/1990 County Population	EMPSC	Employment/1990 Contiguous County Population
EMPS	Employment/1990 County Population	CLFSC	Contiguous Labor Froce/1990 Contiguous County Population
CEMPS	Contiguous Employment/1990 County Population	INCSC	Aggregate Income/1990 Contiguous County Population
INCS	Aggregate Income/1990 County Population	UNEMPSC	Unemployment/1990 Contiguous County Population
UNEMPS	Unemployment/1990 County Population	UNEMP	Unemployment
LFSC	Labor Force/1990 Contiguous County Population	LF	Labor Force
RIPC	Relative Income Per Capita	IN	In-Commuters
RHOUSE	Relative Owner Occupied Housing Value	OUT	Out-Commuters
METRO	Metropolitan County	EMP	Employment

The equations are estimated as follows:

$$\mathrm{LFS} = c_1 + \alpha_1 * \mathrm{EMPS} + \alpha_2 * \mathrm{RIPC} + \alpha_3 * \mathrm{RHOUSE} + \alpha_4 * \mathrm{METRO} + \alpha_5 * \mathrm{INCS} + \alpha_6 * \mathrm{CEMPS} + e_1$$

$$\mathrm{OUTS} = c_2 + \beta_1 * \mathrm{EMPS} + \beta_2 * \mathrm{CEMPS} + \beta_3 * \mathrm{RIPC} + \beta_4 * \mathrm{RHOUSE} + \beta_5 * \mathrm{METRO} + \beta_6 * \mathrm{INCS} + \beta_7 * \mathrm{LFS} + e_2$$

$$\mathrm{INSC} = c_3 + \gamma_1 * \mathrm{EMPSC} + \gamma_2 * \mathrm{CLFSC} + \gamma_3 * \mathrm{RIPC} + \gamma_4 * \mathrm{RHOUSE} + \gamma_5 * \mathrm{METRO} + \gamma_6 * \mathrm{INCSC} + \gamma_7 * \mathrm{LFSC} + e_3$$

$$\mathrm{UNEMP} = \mathrm{LF} + \mathrm{IN} - \mathrm{OUT} - \mathrm{EMP}$$

The normalization preserved the linear functional form, but alters the interpretation of some of the individual coefficients.

5.2.1 Expected Signs

Local employment is measured by EMPS and CEMPS in the labor force and out-commuting equations and by EMPSC in the in-commuting equation. As these variables serve as proxies for labor demand, they are expected to have a positive impact labor force and in-commuting and negative impact on out-commuting. An increase demand for workers will be met with an increase in the supply of workers. This extra supply can be met through migration, which would be seen as an increase in the labor force, or through an increase of in-commuters. The increased demand for workers can also be filled by out-commuters who chose to begin working inside the county.

The relationship between relative income per capita variable, RIPC, and labor force, in-commuting, and out-commuting is unclear. This variable is a proxy for public services and better public services should attract more people to live and work in a county. However, if relative incomes are higher, cost of living expenses might also be higher, causing members of the labor force to live in surrounding counties and commute to work. The relative aggregate income variables, INC and INCS, are expected to positively impact the labor force and in-commuting, while negatively impacting out-commuting. A greater proportion of high paying jobs in a county should increase the labor supply by drawing more workers into the labor force through stimulating in-migration, in-commuting, and increased labor force participation rates (Renkow, 2003). The higher paying local jobs should also make job opportunities in surrounding counties less attractive to out-commuters.

Higher relative housing costs in a county, i.e., an increase in RHOUSE, would encourage those that work in that county to live elsewhere where housing is less expensive and commute to the county they work in. Following this logic the sign of the coefficient on this variable is expected to be positive in the in-commuting equation and negative in the labor force and out-commuting equations.

The METRO dummy variable is expected to have a positive sign in all three equations. If there is a higher population in the county it is expected there are more members of the labor force. Metropolitan areas usually have more jobs available but may be more expensive to live in; therefore we would expect to have more workers commuting into the area. Also, since there are more people living in the area we would expect to see more people commuting outside the county to work elsewhere.

Contiguous labor force, CLFCS, is expected to have a positive relationship with in-commuting. Contiguous labor force is essentially the supply of potential in-commuters. The more people willing and able to work in surrounding counties the more will come to the county of interest for employment. Contiguous employment is expected to have a positive relationship with out-commuters because it represents the demand for laborers to work in nearby counties.

It is unclear how labor force, LFS and LFSC, will be related to in- and out- commuting. The signs of the coefficients depend on whether commuting and migration are substitutes or complements. If these are substitutes then an increase in a county's labor force would be associated with an increase in the number of in-commuters and a decrease in the number of out-commuters. In this case the strong regional economy pulls in new residents, attracts more in-commuters, and also attracts former out-commuters who now find local employment. If this were the case the in-commuting coefficient would be positive and the out-commuting negative. However if commuting and migration are complements the signs would be reversed. This could happen if a community becomes a suburb of a larger metropolitan area. In this case we would see an increase in the labor force, but the new workers would be out-commuting to the metropolitan area for work.

5.3 Method of Estimation

After the appropriate variables were identified the next step was to identify the appropriate method of estimation. Previous models (Yeo and Holland, Renkow, Johnson and Scott) have estimated labor force equations using the two stage least squares (2-SLS) or three stage least squares (3-SLS) methods. This was because the right hand sides of the equations involve two kinds of random variables, endogenous variables and an error term. This suggests that these two variables may be correlated, thus violating the classical GLM assumptions necessary to use the ordinary least squares (OLS) method of estimation. To correct for this problem modelers have used 2-SLS or 3-SLS to simultaneously estimate the equations.

5.3.1 Hausman Test

Following previous work, this model was originally estimated using 2-SLS. To be complete the model was also estimated using Ordinary Least Squares (OLS). The Hausman test was then preformed to determine which model was the best fit. Hausman (1978) developed a test for the consistency of an estimator. In this test two estimators are compared. One is consistent and efficient under the null hypothesis, but inconsistent under the alternative hypothesis. The other estimator is consistent under both the null and alternative (Kennedy, 1993).

In the test preformed for this study under the null of no correlation between the regressors and the error term the OLS estimator was consistent (and efficient), but is inconsistent in the presence of correlation, whereas the consistency of an instrumental variable estimator (as used in 2 and 3 SLS) is not affected by correlation error. Therefore if the null hypothesis is true (and there is no correlation) both estimators should produce similar estimates. If the null hypothesis is false (and there is estimation error) the estimates should differ.

When run, the Hausman test indicated that the equations in this paper are best estimated using OLS. For this test there were 16 degrees of freedom so at a 99% level of confidence the critical value is 32.0. The test had a t-statistic of 2.47 which is less than the critical value. Therefore we fail to reject the null hypothesis that the OLS and the 2SLS estimators produce similar results, so OLS is a consistent estimator of the equations. In this case it is the preferred estimator because it has a higher statistical efficiency.

5.3.2 Recursive System

The reason the model can be estimated using OLS even though it appears there may be endogeneity is because it is a recursive system. A recursive system has a unidirectional dependency among the endogenous variables. The equations of a recursive system can be ordered such that the first equation is determined only by exogenous variables. The second equation is determined by the first endogenous variable and exogenous variables, the third equation is a function of the first two endogenous variables and exogenous variables, and so on. (Kennedy, 1993)

This works as long as there is no feedback from an exogenous variable to one lower in the causal chain. For example, a change in the disturbance in the third equation directly affects the third endogenous variable which in turn would affect the higher-ordered endogenous variables in the system (i.e. the 4th equation's endogenous variables), but would not affect the lower-ordered endogenous variables (i.e. the 2nd equations endogenous variables). Because only lower-ordered variables appear as regressors in the third equation, there is no simultaneous correlation between the disturbance and the regressors in the third equation. As long as there is no correlation between the disturbances in different equations OLS estimation is consistent. If no lagged endogenous variables appear among the exogenous variables in the equation it is also unbiased (Kennedy, 1993). The model estimated for this thesis has all the characteristics of a recursive model and is estimated using OLS.

CHAPTER 6 - **Results**

6.1 Introduction

Chapter 6 presents and discusses the results of the OLS regression and 10-fold cross validation procedure. In section 6.2 the estimated equations for labor force, in-commuting, and out-commuting are presented followed by a discussion of how the equations compare to the expected results. Next, in 6.3 elasticities are calculated to facilitate interpretation of the relative contribution of the different regressors on the dependent variables. Finally, to determine how well the model works, model performance measures are calculated and compared for the validation estimations and the model estimations in section 6.4.

6.2 Estimated Equations

To predict the effect that an increase in employment, as well as other factors, has on a county's workers, three equations were estimated. The labor force equation estimates how a county's labor force is affected by a change in many factors, including the employment level in each county and the counties surrounding it. The in-commuting and out-commuting equations estimate the impact of changing factors on the workers that commute to and from a county for employment. The unemployment identity equation uses these predictions as well as the change in employment to calculate the change in unemployment.

The equations estimated by OLS and the identity are shown below. Some of the coefficients are not easily interpreted because certain variables in the labor force and out-commuting equations were scaled by the 1990 county population and some variables in the in-commuting equation were scaled by the 1990 contiguous county population. The estimated equations are reported below with standard errors and significance levels reported in tables 6.1-6.3.

$$\mathrm{LFS} = 0.29068 + 0.09250 * \mathrm{EMPS} - 0.05091 * \mathrm{RIPC} + 0.04318 * \mathrm{RHOUSE} - 0.02712 * \mathrm{METRO} + 0.00002 * \mathrm{INCS} + 0.00047 * \mathrm{CEMPS}$$

$$\mathrm{OUTS} = 0.01064 - 0.75666 * \mathrm{EMPS} + 0.00114 * \mathrm{CEMPS} + 0.00545 * \mathrm{RIPC} - 0.02104 * \mathrm{RHOUSE} + 0.01290 * \mathrm{METRO} + 0.000007 * \mathrm{INCS} + 0.71810 * \mathrm{LFS}$$

$$\mathrm{INSC} = -0.01741 + 0.49500 * \mathrm{EMPSC} + 0.02671 * \mathrm{CLFSC} + 0.00052 * \mathrm{RIPC} + 0.00756 * \mathrm{RHOUSE} + 0.00289 * \mathrm{METRO} + 0.000006 * \mathrm{INCSC} - 0.54478 * \mathrm{LFSC}$$

$$\mathrm{UNEMP} = \mathrm{LF} + \mathrm{IN} - \mathrm{OUT} - \mathrm{EMP}$$

Although some of the coefficients are not easily interpreted, expected signs and significance levels can be discussed. With the labor force equation, the adjusted R^2 is .8071 and all variables are significant at the 5% level, except contiguous employment (Table 6.1). Because the dependent variable, LFS, and the employment and aggregate income variables (EMPS, CEMPS, and INCS) are scaled in identical ways, the coefficients on those variables can be interpreted directly. *Ceteris paribus*, an increase in a county's employment by 1,000 jobs increases its labor force by 92.5 people, while an increase in employment in contiguous counties by 1,000 jobs increases the home county's labor force by just 0.47 persons (the latter is not statistically different from zero). An increase in a county's aggregate income of $100,000 will increase its labor force by 2 persons, *ceteris paribus*.

The theoretical impact of relative income per capita on labor force was ambiguous in sign, but its estimated impact was negative. This suggests that the income per capita variable was strongly related to households' perceived cost of living in a given county, causing members of the labor force to live in surrounding counties and commute to work. The METRO variable was expected to have a positive relationship with labor force, but its estimated coefficient was negative. This negative coefficient indicated that metropolitan counties have a smaller labor force relative to their 1990 population as compared to nonmetropolitan counties. This may be a result of 'bedroom communities' outside the metropolitan county. The bedroom counties surrounding a metropolitan county grew in both population and labor force between 1990 and 2000, so that the measured value of LFS is larger in these counties than in metropolitan counties.

Table 6.1 Labor Force Equation Parameter Estimates and Standard Errors

Variable	Estimate	Standard Error
Intercept	0.29068***	0.02037
EMPS	0.09250**	0.04087
RIPC	-0.05091***	0.01433
RHOUSE	0.04318***	0.01305
METRO	-0.02712**	0.01230
INCS	0.00002***	0.0000013
CEMPS	0.00047	0.00045

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

For the out-commuting equation the adjusted R^2 is .8353. All significant coefficients had the expected signs, with the exception of aggregate income variable (Table 6.2). INCS was hypothesized to have a negative relationship with out-commuting, but its estimated impact was positive. This could be because the higher-paying jobs in a county draw more specialized workers in dual-career households and therefore some local residents have to drive to other counties to find employment. In this equation the relative income and metropolitan dummy variables were not statistically significantly different from zero.

Once again, LFS, EMPS, CEMPS, and INCS were scaled using the 1990 population and their coefficients can be interpreted directly. *Ceteris paribus,* an increase in employment in a county of 1,000 jobs will result in a decrease in out-commuting of 756 people, while an increase in employment in contiguous counties will cause an increase in out-commuting of 1 person. An increase of aggregate income in a county of $100,000 is estimated to increase the number of out-commuters by less than one person, *ceteris paribus*. Out-commuting was found to be a complement to migration; a *ceteris paribus* increase in a county's labor force of 1,000 persons would lead to an estimated 718 additional out-commuters.

Table 6.2 Out-Commuting Equation Parameter Estimates and Standard Errors

Variable	Estimate	Standard Error
Intercept	0.01064	0.04279
EMPS	-0.75666***	0.05020
CEMPS	0.00114**	0.00054
RIPC	0.00545	0.01823
RHOUSE	-0.02104*	0.01648
METRO	0.01290	0.01509
INCS	0.000007***	0.0000024
LFS	0.71810***	0.12097

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

The adjusted R^2 for the in-commuting equation is .8591. All coefficients have the expected sign, however not all are significantly different from zero (Table 6.2). Employment, contiguous labor force, aggregate income, and labor force are significant at the 99% confidence level. Relative housing value, relative income per capita, and the metropolitan dummy variable are not significant variables.

Labor force (LFSC), employment (EMPSC), contiguous labor force (CLFSC), and aggregate income (INCSC) are scaled in identical ways so the coefficients on those variables can be directly interpreted. *Ceteris paribus*, an increase in a county's employment by 1,000 jobs will increase the number in-commuters by 495 people. An increase of 1,000 participants in the labor force of contiguous counties will result in an increase of 26.7 in-commuters, *ceteris paribus*. An increase in a county's aggregate income of $100,000 will result in an increase in in-commuting of less than one person, *ceteris paribus*. Finally, a *ceteris paribus* increase in a county's labor force of 1,000 persons leads to an estimated reduction of 545 in-commuters.

Table 6.3 In-Commuting Equation Parameter Estimates and Standard Errors

Variable	Estimate	Standard Error
Intercept	-0.01741	0.00914
EMPSC	0.49500***	0.14836
CLFSC	0.02671***	0.00427
RIPC	0.00052	0.00847
RHOUSE	0.00755	0.00639
METRO	0.00289	0.00589
INCSC	0.000007***	0.000001
LFSC	-0.54478***	0.14769

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

6.3 Variable Elasticities

In order to compare the relative importance of employment and other variables on labor force, in-commuting, and out-commuting, it is helpful to measure their impacts as elasticities. The elasticity is defined as:

$$\varepsilon = \frac{\partial y_j}{\partial x_i} * \frac{x_i}{y_j},$$

where y_j is the j^{th} dependent variable and x_i is the i^{th} independent variable. The elasticity measures the percentage change in y_j in response to a 1 percent change in x_i. The elasticity formula was evaluated at the sample mean values of y_j and x_i, where the estimated coefficient on x_i was inserted as the derivative $\frac{\partial y_j}{\partial x_i}$. The results are reported in Table 6.4.

The advantage of calculating the elasticities is that they show which variables have the biggest effect on the dependent variable. Looking at table 6.4, it appears that aggregate income appears to be the most important determinant of labor force, a result not clear when examining the coefficients. The largest determinant of both in- and out-commuting is labor force. The effects of labor force and employment on in- and out-commuting are considerably higher than any of the other variables in the commuting equations.

The elasticities with the most implications for this study are those that measure the response of the dependent variables to a change in employment. These numbers predict what effect a percent change in employment will have on labor force, in-commuting, and out-commuting. A 1% increase in employment will, on average, increase the labor force by 0.08%. This increase could be through migration or an increase in the labor force participation rate. A 1% increase in employment is also estimated to decrease out commuting by 2.87% on average. This means 2.87% of residents who previously commuted to surrounding counties now stay in their home county to work. The incomes earned by the new members of the labor force and those that now work in the county directly benefit county residents, which is often the goal of new job creation. A 1% increase in employment is also estimated to result in a 2.72% increase in in-commuting. This means that an increase in employment causes non-residents to come into the county and take the new jobs. This is the portion of new jobs and their benefits that are essentially exported to surrounding counties via in-commuters.

As one would expect, the labor force response is highly inelastic with respect to a change in employment while commuting patterns are elastic. This result reflects the fact that relocation is much more costly and difficult for households than changes in commuting. While the commuting elasticities are very large compared to the labor force elasticity, it is important to keep in mind that elasticities measure percentage changes, and that in- and out-commuting are small values compared to a county's labor force. Thus, a given change in commuting, of say 100 workers, represents a much larger percentage change in those variables, compared to the percentage change in labor force from a change of 100 workers. Additionally, the elasticities do not account for the endogeneity of the labor force variable in the in- and out-commuting equations. An employment change that increases the labor force would also decrease in-commuting and increase out-commuting, somewhat offsetting the estimated elasticities of employment in those equations.

Table 6.4 Elasticities at the Sample Mean

	Employment	Contiguous Employment	Contiguous Labor Force	Relative Income per Capita	Relative Housing Values	Aggregate Income	Labor Force
Labor Force	0.08076	0.01418		-0.10443	0.08683	0.35018	
In-Commuting	2.71798		0.91386	0.02759	0.39452	0.95609	-3.11582
Out-Commuting	-2.86575	0.08664		0.04849	-0.18351	0.69695	3.11497

Perhaps a more meaningful way of assessing the impact of an employment change is to consider how new jobs in a county would be distributed across its labor force, its in-commuters, its out-commuters, and the currently unemployed. These can be calculated by imposing an employment change and then calculating the percentage of that change that is accounted for by each dependent variable. These percentages can be seen in Table 6.5. A change in employment would increase labor force size by an estimated 9.25% of the employment change. This is consistent with the relatively small estimated employment coefficient in the labor force equation.

Table 6.5 Proportion of Employment Growth Accounted for by Different Activities

Activity	Change
Increased Labor Force Size	9.25%
Increased In-commuting	44.46%
Decreased Out-commuting	69.02%
Decreased Unemployment	-22.73%

Because in-commuting and out-commuting are dependent on the change in labor force, the percentage change in these dependent variables will not be the same as the employment coefficients for their respective estimations. Accounting for the endogeneity of labor force, a change in employment is estimated to increase in-commuting by 44.46% of the employment change and decrease out-commuting by 69.02% of the employment change. Using the identity, the residual unemployment can be calculated. The model predicts the changes in employment, labor force size, and commuting will result in a negative reduction (i.e., an increase) in unemployment by 22.73% of the change in employment. The increase in unemployment is likely a result of in-migration and/or labor force participation to fill the new jobs. As discussed in more detail in chapter 7, however, the predicted change in unemployment is small when measured as a change in a county's unemployment rate. Most of the new jobs in a county are captured by in-migrants, residents who used to out-commute, or in-commuters who live in surrounding counties.

6.4 Model Performance

To test the accuracy of the model a statistical technique called K-fold cross validation was used. With this procedure the observations are randomly divided into K equal subsets of data. One subset of data is then put aside and the remaining K-1 sets are used to estimate the model. After the equations have been estimated using the K-1 subsets the subset that was set aside was treated like a "new" dataset and the estimated equations with their estimated coefficients are used to predict the dependent variables of the held back subset using the explanatory variables from the held back subset. Using the "new" data the squared error between the actual and predicted values are then calculated to assess the out-of-sample prediction performance of the model. This process is repeated K times holding back a different data subset each time.

According to previous research (Breiman and Spector, 1992 , Kohavi, 1995) 10-fold cross-validation is optimal in most cases. Therefore the 105 observations were randomly separated into 10 subsets with 10 or 11 observations in each subset. The K-fold cross-validation process was then used to re-estimate the labor force, in-commuting, and out-commuting equations so that calculations can be made to assess the accuracy of the estimations. These calculations were then compared to error calculations for the in-sample predictions (i.e., the errors using the coefficients when the complete dataset is used for estimations) to determine how well the model is functioning.

The data were split into 10 subgroups and the models were re-estimated leaving out one subgroup each time. The out-of-sample predictions for labor force, in-commuting, and out-commuting were then calculated for the subgroup of counties not included in the regression using the 10 new estimated equations. Then, a number of performance measures were calculated for the in-sample predictions and the out-of-sample predictions to determine how accurately the models simulate the dependent variables.

6.4.1 Performance Statistics Calculations

The first measure of model performance calculated was the root-mean-square (RMS) simulation error. The RMS simulation error for a dataset with N observations, $Y_{1,\ldots,}Y_N$ is defined as:

$$\text{RMS error} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(Y_n^s - Y_n^a)^2}$$

where Y_n^s = simulated value of Y_n
Y_n^a = actual value
N = number of observations

The RMS error is a measure of the average deviation of the predicted value from its actual value. The magnitude of this error can be evaluated by comparing it with the average size of the variable in question (Pindyck and Rubinfeld, 1998).

A measure of performance that compares the error to the average size of the variable in question is the RMS percent error. This statistic is calculated using the following formula:

$$\text{RMS percent error} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(\frac{Y_n^s - Y_n^a}{Y_n^a}\right)^2}$$

The mean simulation error and the mean percent error were also calculated. However, it is important to remember one drawback to calculating mean errors is that if large positive errors cancel out large negative errors they may be close to 0 (Pindyck and Rubinfeld, 1998). The formulas for these statistics are:

$$\text{mean simulation error} = \frac{1}{N}\sum_{n=1}^{N}(Y_n^s - Y_n^a)$$

$$\text{mean percent error} = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{Y_n^s - Y_n^a}{Y_n^a}\right)$$

Finally, Theil's inequality coefficient (U) was calculated. Theil's inequality coefficient is calculated as:

$$U = \frac{\sqrt{\frac{1}{N}\sum_{n=1}^{N}(Y_n^s - Y_n^a)^2}}{\sqrt{\frac{1}{N}\sum_{n=1}^{N}(Y_n^s)^2} + \sqrt{\frac{1}{N}\sum_{n=1}^{N}(Y_n^a)^2}}$$

This coefficient will always fall between 0 and 1. If U = 0, $Y_n^s = Y_n^a$ for all n and the model is a perfect fit. If U = 1 the performance of the predictive model is as bad as it could possibly be. In this case the predicted values are always 0 when actual values are nonzero, or nonzero predictions are made when the actual values are zero, or simulated values are positive (negative) when actual values are negative (positive) (Pindyck and Rubinfeld, 1998).

6.4.2 Performance Statistics Results

Table 6.6 shows the results for the calculated performance statistics discussed above. These statistics were calculated for the in-sample and the out-of-sample model predictions for each of the three regression equations. The in-sample predictions are those estimated from the equations presented in section 6.2. The out-of sample predictions are those estimated using the 10-fold cross validation equations. By definition, the in-sample predictions are the best that can be obtained from the dataset, given the specification of the model; the danger is that the model is too tailored to the dataset from which it is estimated and would predict poorly if brought to new data. If the model as specified is robust, the in-sample and out-of-sample predictions will be very similar.

As seen in Table 6.6, the labor force model performs well and the error calculations for the in-sample and out-of-sample estimations are similar. The root mean square error was only 0.0041 higher for the out-of-sample predictions than for the in-sample predictions. Theil's inequality coefficient was also 0.0041 higher for the out-of-sample predictions.

Table 6.6 Measures of Prediction Error

	Mean	RMSE	RMS % E	ME	M%E	U	R^2
Labor Force							
In-Sample	0.498432	0.028071	0.053684	-0.000083	0.002745	0.027975	0.818200
Out-of-Sample	0.499489	0.032212	0.059402	0.000973	0.004512	0.032053	0.708665
In-Commuting							
In-Sample	0.018855	0.015825	1.086351	-0.000339	0.263211	0.202369	0.868600
Out-of-Sample	0.017601	0.029336	1.242395	-0.001593	0.287879	0.386091	0.362233
Out-Commuting							
In-Sample	0.114905	0.037666	0.660336	-0.000019	0.162820	0.138244	0.846400
Out-of-Sample	0.114074	0.036456	0.637979	-0.000850	0.137243	0.133598	0.777880

Where RMSE is the root mean square error, RMS%E is the root mean square percent error, ME is the mean error, M%E is the mean percent error, U is the Theil's inequality coefficient, and R^2 is the R-Square.

The prediction errors differ more for the in-commuting and out-commuting equations. The difference between the in-sample and out-of-sample root mean square error for the in-commuting equation was 0.0135. The Theil's inequality coefficient was 0.1837 higher for the out-of sample in-commuting equation than for the in-sample predictions. For the out-commuting equation the difference in root mean square errors was 0.0012 and the difference in Theil's inequality coefficient was 0.0046.

Part of the reason for the jump in prediction errors for the in-commuting and out-commuting equations can be found in the raw data. Two counties, Johnson and Sedgwick, are obvious outliers in the data set. They have much larger populations, labor forces, and number of commuters. When conducting the out-of-sample estimations these counties are not included as data for the regression in one of the 10 "folds", but then the resulting model is used to predict labor force and commuting. Naturally, in this case the model will perform poorly in predicting the dependent variables for these atypical counties.

This error in prediction for the higher populated counties is not of too much concern because, for this study, the focus is on labor force changes in rural counties. Keeping this in mind, the prediction errors were re-calculated, ignoring the predictions for Johnson and Sedgwick counties. This removed much of the difference in simulation errors for the in-sample and out-of-sample predictions. These errors are reported in Table 6.7.

With these counties removed from the calculations the difference between the root mean square errors for the in-sample and out-of-sample estimations of labor force was only 0.0013. The difference in the Theil's inequality coefficients was also reduced to 0.0013 for the labor force equations.

The error differences were also considerably reduced for the commuting equations. For the in-commuting equation, the difference between the root means square errors was reduced to 0.0057. For the out-of-sample predictions the Theil's coefficient was 0.2974 and it was 0.2128 for the in-model estimations. This is a difference of 0.0846, which is less than half of the difference in Theil's coefficients when the outlying county estimations were used in the calculations.

With the out-commuting estimations the difference in root mean square errors is reduced to 0.0037. The Theil's coefficient for these models was 0.1366 for the in-sample predictions and 0.1219 for the out-of-sample predictions. In this case the difference in coefficients is actually higher, with a value of 0.0148, than when Johnson and Sedgwick counties were used in the error calculations.

Table 6.7 Measures of Prediction Error, Johnson and Sedgwick County Estimations Omitted

	Mean	RMSE	RMS % E	ME	M%E	U	R^2
Labor Force							
In-Sample	0.494743	0.027078	0.052658	-0.000909	0.001550	0.027459	0.818200
Out-of-Sample	0.495019	0.028395	0.055422	-0.000638	0.002209	0.028787	0.773623
In-Commuting							
In-Sample	0.016477	0.012424	1.085403	0.000953	0.269468	0.212806	0.868600
Out-of-Sample	0.016564	0.018147	1.239383	0.001038	0.298810	0.297437	0.755955
Out-Commuting							
In-Sample	0.113928	0.036700	0.491176	-0.000892	0.119536	0.136649	0.846400
Out-of-Sample	0.114382	0.032971	0.442683	-0.000446	0.098494	0.121887	0.818317

Where RMSE is the root mean square error, RMS%E is the root mean square percent error, ME is the mean error, M%E is the mean percent error, U is the Theil's inequality coefficient, and R^2 is the R-Square.

CHAPTER 7 - **Simulation**

7.1 Introduction

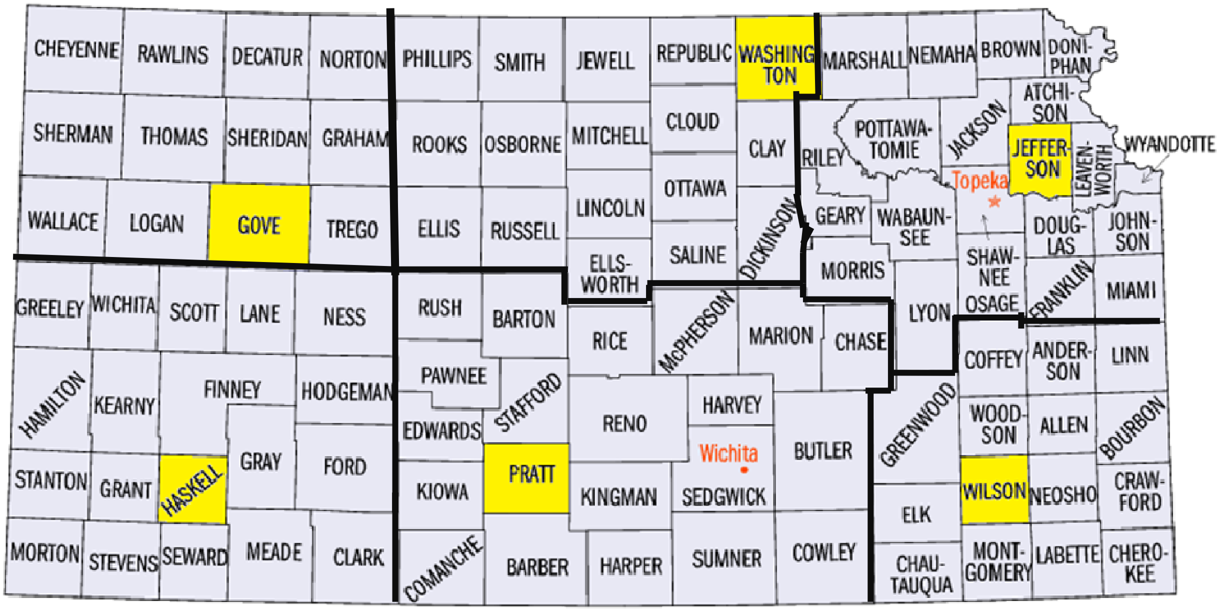
To assess the impact of economic growth in Kansas counties a simulation experiment was conducted by increasing labor demand 5% in each county. Six representative counties are selected to observe the changes in labor force, unemployment, and commuting as a result of this exogenous employment shock. Next, the success of the model is tested by forecasting changes in labor force in three Kansas counties as a result of actual firms that opened or closed in that county. The model predictions are then compared to actual labor force changes that occurred during the five years following the employment event.

7.2 Simulation with 5% Increase in Employment

To assess the impact of economic growth on county labor market adjustments, a simulation experiment was conducted. To shock the labor market, it was assumed that the economic growth of a region was manifested by an exogenous increase in employment demand. Therefore, the simulation involves increasing the labor demand by 5% for each of the counties.

Six representative Kansas counties, one from each geographic region, were selected to give an illustration of the effects of a 5% increase in labor demand throughout the state. The counties selected were Gove, Haskell, Jefferson, Pratt, Washington, and Wilson. These counties were selected by dividing the state into 6 geographic regions and then selecting the county with the median population in each region. The location of the counties can be seen in Figure 7.1. The populations of the representative counties range from 3,068 people (Gove) to 18,426 people (Jefferson).

Figure 7.1 Representative Counties from Six Kansas Regions



7.2.1 Baseline Estimates

To gauge the effect of a 5% increase in employment, baseline values for the equations first must be estimated. These estimations were made by inserting the 2000 Census values of each variable for each county into the model. This allowed the model to make (in-sample) predictions for labor force, unemployment, in- and out-commuting. These predictions served as the starting point against which the effects of the employment change were measured.

These predictions are in the "Baseline Value" columns in tables 7.1- 7.3. As discussed in chapter 6, these predictions are a fairly accurate representation of observed values. However, many of the unemployment estimations stand out as unreliable due to the fact they are negative. One reason for the incorrect estimations is that unemployment was not estimated using an econometric equation. It is calculated as a residual value of employment, labor force, in-commuting and out-commuting; therefore it contains all the errors associated with these estimations. Also, in many counties unemployment is very small so even a relatively small error in estimation of one of the other values may appear very large when it is applied to unemployment. Obviously, it is impossible to have a negative number of people unemployed in a county. These negative estimations also magnify the size of unemployment changes later calculated.

7.2.2 Employment Increase Estimates

After baseline estimates are made, a 5% increase in employment demand was imposed on each county. The difference between these two estimates represents the simulated impact of economic growth. The simulated values and impacts from the baseline values are shown in Tables 7.1-7.3. The simulated employment growth caused an increase in labor force, in-commuting, and unemployment and a decrease in out-commuting in every county. The increase in unemployment is likely a result of in-migration to fill the new jobs. This implies that most of the new jobs are captured by in-migrants, residents who used to out-commute, or in-commuters who live in surrounding counties.

The increase in labor force and in-commuting and decrease in out-commuting for every county was expected, however the magnitudes of these changes are of interest. The percentage increase in the labor force is considerably smaller than the percentage changes in commuting for every county. On average, labor force increased by 0.40% in response to the 5% increase in employment. This is a small adjustment compared to the average 16.43% increase in in-commuting and average 20.41% decrease in out-commuting. These results indicate most of the new jobs are filled by adjustments in commuting decisions of residents and non-residents, rather than by in-migrants or current residents entering the labor force.

Unemployment was estimated to increase in a county as a result of a 5% increase in labor force. In the tables the percent change in unemployment is very large (89%) due to the fact that unemployment in most counties is fairly small to begin with. For this reason the resulting percent change in unemployment due to a slight increase in the number of unemployed people looks exceptionally large. To better represent this change, the change in the unemployment rate (unemployed persons as a share of the labor force) was also calculated. This statistic is much more reasonable. On average, a 5% increase in employment results in .99% increase in the unemployment rate.

Table 7.1 Simulation Results for Employment and Labor Force

County	Employment				Labor Force			
	Baseline Value	Simulation Value	Net Impact	Percent Change	Baseline Value	Simulation Value	Net Impact	Percent Change
Allen	6769	7107.45	338.45	5.00	6950.13	6981.43	31.31	0.45
Anderson	2648	2780.40	132.40	5.00	3795.74	3807.99	12.25	0.32
Atchison	7874	8267.70	393.70	5.00	8310.49	8346.91	36.42	0.44
Barber	2451	2573.55	122.55	5.00	2669.24	2680.57	11.34	0.42
Barton	13538	14214.90	676.90	5.00	13508.69	13571.30	62.61	0.46
Bourbon	7585	7964.25	379.25	5.00	7445.83	7480.91	35.08	0.47
Brown	4836	5077.80	241.80	5.00	5235.00	5257.36	22.37	0.43
Butler	17088	17942.40	854.40	5.00	29516.03	29595.07	79.03	0.27
Chase	911	956.55	45.55	5.00	1456.20	1460.41	4.21	0.29
Chautauqua	1328	1394.40	66.40	5.00	1977.11	1983.25	6.14	0.31
Cherokee	7591	7970.55	379.55	5.00	10507.63	10542.74	35.11	0.33
Cheyenne	1397	1466.85	69.85	5.00	1457.64	1464.10	6.46	0.44
Clark	1055	1107.75	52.75	5.00	1158.38	1163.26	4.88	0.42
Clay	3527	3703.35	176.35	5.00	4232.03	4248.34	16.31	0.39
Cloud	4789	5028.45	239.45	5.00	5226.48	5248.62	22.15	0.42
Coffey	4594	4823.70	229.70	5.00	4626.17	4647.42	21.25	0.46
Comanche	942	989.10	47.10	5.00	997.02	1001.38	4.36	0.44
Cowley	15025	15776.25	751.25	5.00	18612.97	18682.46	69.49	0.37
Crawford	18736	19672.80	936.80	5.00	18310.52	18397.17	86.65	0.47
Decatur	1519	1594.95	75.95	5.00	1726.13	1733.16	7.03	0.41
Dickinson	7988	8387.40	399.40	5.00	10172.61	10209.56	36.94	0.36
Doniphan	3274	3437.70	163.70	5.00	3958.56	3973.70	15.14	0.38
Douglas	49301	51766.05	2465.05	5.00	49861.48	50089.50	228.02	0.46
Edwards	1407	1477.35	70.35	5.00	1619.91	1626.42	6.51	0.40
Elk	999	1048.95	49.95	5.00	1482.54	1487.16	4.62	0.31
Ellis	14883	15627.15	744.15	5.00	15225.93	15294.76	68.83	0.45
Ellsworth	2891	3035.55	144.55	5.00	3158.21	3171.58	13.37	0.42
Finney	19139	20095.95	956.95	5.00	19494.84	19583.36	88.52	0.45
Ford	15663	16446.15	783.15	5.00	15535.78	15608.22	72.44	0.47
Franklin	9871	10364.55	493.55	5.00	12197.23	12242.88	45.65	0.37
Geary	11521	12097.05	576.05	5.00	14760.27	14813.55	53.29	0.36
Gove	1546	1623.30	77.30	5.00	1520.54	1527.69	7.15	0.47
Graham	1269	1332.45	63.45	5.00	1541.52	1547.39	5.87	0.38
Grant	3505	3680.25	175.25	5.00	3965.90	3982.11	16.21	0.41
Gray	2525	2651.25	126.25	5.00	2824.21	2835.89	11.68	0.41
Greeley	735	771.75	36.75	5.00	830.37	833.77	3.40	0.41
Greenwood	2703	2838.15	135.15	5.00	3606.24	3618.74	12.50	0.35
Hamilton	1222	1283.10	61.10	5.00	1149.20	1154.85	5.65	0.49
Harper	2679	2812.95	133.95	5.00	3195.12	3207.51	12.39	0.39
Harvey	13962	14660.10	698.10	5.00	16079.90	16144.47	64.57	0.40
Haskell	1744	1831.20	87.20	5.00	1987.70	1995.77	8.07	0.41
Hodgeman	914	959.70	45.70	5.00	1024.95	1029.18	4.23	0.41
Jackson	4620	4851.00	231.00	5.00	6524.62	6545.99	21.37	0.33
Jefferson	3876	4069.80	193.80	5.00	8884.19	8902.11	17.93	0.20
Jewell	1468	1541.40	73.40	5.00	1757.50	1764.29	6.79	0.39
Johnson	265363	278631.15	13268.15	5.00	279759.93	280987.25	1227.32	0.44
Kearny	1709	1794.45	85.45	5.00	2097.62	2105.52	7.90	0.38
Kingman	3201	3361.05	160.05	5.00	4436.18	4450.98	14.80	0.33
Kiowa	1528	1604.40	76.40	5.00	1693.87	1700.94	7.07	0.42
Labette	10574	11102.70	528.70	5.00	11572.70	11621.61	48.91	0.42
Lane	1054	1106.70	52.70	5.00	1098.69	1103.57	4.87	0.44
Leavenworth	23977	25175.85	1198.85	5.00	34922.39	35033.29	110.89	0.32
Lincoln	1462	1535.10	73.10	5.00	1675.43	1682.20	6.76	0.40
Linn	2728	2864.40	136.40	5.00	4686.54	4699.16	12.62	0.27

Table 7.1 (con't) Simulation Results for Employment and Labor Force

County	Employment				Labor Force			
	Baseline Value	Simulation Value	Net Impact	Percent Change	Baseline Value	Simulation Value	Net Impact	Percent Change
Logan	1414	1484.70	70.70	5.00	1442.27	1448.81	6.54	0.45
Lyon	18211	19121.55	910.55	5.00	18498.32	18582.55	84.23	0.46
McPherson	15207	15967.35	760.35	5.00	15119.71	15190.04	70.33	0.47
Marion	4860	5103.00	243.00	5.00	6375.20	6397.67	22.48	0.35
Marshall	5322	5588.10	266.10	5.00	5456.99	5481.61	24.61	0.45
Meade	1666	1749.30	83.30	5.00	2072.98	2080.69	7.71	0.37
Miami	8224	8635.20	411.20	5.00	14265.54	14303.57	38.04	0.27
Mitchell	3638	3819.90	181.90	5.00	3482.82	3499.64	16.83	0.48
Montgomery	17911	18806.55	895.55	5.00	19152.50	19235.33	82.84	0.43
Morris	2465	2588.25	123.25	5.00	3004.83	3016.23	11.40	0.38
Morton	1775	1863.75	88.75	5.00	1822.20	1830.41	8.21	0.45
Nemaha	5183	5442.15	259.15	5.00	5110.06	5134.03	23.97	0.47
Neosho	8452	8874.60	422.60	5.00	8525.56	8564.65	39.09	0.46
Ness	1703	1788.15	85.15	5.00	1812.87	1820.74	7.88	0.43
Norton	2629	2760.45	131.45	5.00	2792.78	2804.93	12.16	0.44
Osage	3693	3877.65	184.65	5.00	7989.79	8006.87	17.08	0.21
Osborne	2076	2179.80	103.80	5.00	2112.49	2122.09	9.60	0.45
Ottawa	1794	1883.70	89.70	5.00	2951.64	2959.93	8.30	0.28
Pawnee	3269	3432.45	163.45	5.00	3710.83	3725.95	15.12	0.41
Phillips	2956	3103.80	147.80	5.00	3089.14	3102.81	13.67	0.44
Pottawatomie	7907	8302.35	395.35	5.00	9260.80	9297.37	36.57	0.39
Pratt	4802	5042.10	240.10	5.00	5010.97	5033.18	22.21	0.44
Rawlins	1277	1340.85	63.85	5.00	1462.82	1468.73	5.91	0.40
Reno	29466	30939.30	1473.30	5.00	33230.91	33367.19	136.28	0.41
Republic	2705	2840.25	135.25	5.00	2914.40	2926.91	12.51	0.43
Rice	4157	4364.85	207.85	5.00	5025.50	5044.72	19.23	0.38
Riley	37572	39450.60	1878.60	5.00	34816.01	34989.78	173.77	0.50
Rooks	2432	2553.60	121.60	5.00	2702.00	2713.25	11.25	0.42
Rush	1347	1414.35	67.35	5.00	1746.29	1752.52	6.23	0.36
Russell	3475	3648.75	173.75	5.00	3543.13	3559.20	16.07	0.45
Saline	30664	32197.20	1533.20	5.00	28090.59	28232.41	141.82	0.50
Scott	2700	2835.00	135.00	5.00	2928.35	2940.84	12.49	0.43
Sedgwick	240333	252349.65	12016.65	5.00	237731.82	238843.38	1111.55	0.47
Seward	10907	11452.35	545.35	5.00	10515.29	10565.74	50.45	0.48
Shawnee	95850	100642.50	4792.50	5.00	88703.51	89146.82	443.31	0.50
Sheridan	1256	1318.80	62.80	5.00	1340.17	1345.98	5.81	0.43
Sherman	3253	3415.65	162.65	5.00	3489.82	3504.87	15.05	0.43
Smith	1890	1984.50	94.50	5.00	2212.13	2220.87	8.74	0.40
Stafford	1908	2003.40	95.40	5.00	2368.24	2377.07	8.82	0.37
Stanton	1332	1398.60	66.60	5.00	1171.50	1177.66	6.16	0.53
Stevens	2352	2469.60	117.60	5.00	2612.23	2623.11	10.88	0.42
Sumner	7974	8372.70	398.70	5.00	13245.87	13282.75	36.88	0.28
Thomas	4190	4399.50	209.50	5.00	4396.81	4416.19	19.38	0.44
Trego	1363	1431.15	68.15	5.00	1687.38	1693.69	6.30	0.37
Wabaunsee	1556	1633.80	77.80	5.00	3441.82	3449.02	7.20	0.21
Wallace	868	911.40	43.40	5.00	852.53	856.55	4.01	0.47
Washington	2682	2816.10	134.10	5.00	3166.49	3178.90	12.40	0.39
Wichita	1175	1233.75	58.75	5.00	1221.57	1227.01	5.43	0.44
Wilson	4508	4733.40	225.40	5.00	4918.45	4939.29	20.85	0.42
Woodson	1189	1248.45	59.45	5.00	1756.93	1762.43	5.50	0.31
Wyandotte	76028	79829.40	3801.40	5.00	77752.82	78104.45	351.63	0.45
Average	12543.52	13170.70	627.18	5.00	13467.88	13525.90	58.01	0.40
Max	265363.00	278631.15	13268.15	5.00	279759.93	280987.25	1227.32	0.53
Min	735.00	771.75	36.75	5.00	830.37	833.77	3.40	0.20

Table 7.2 Simulation Results for In-Commuters and Out-Commuters

County	In-Commuters				Out-Commuters			
	Baseline Value	Simulation Value	Net Impact	Percent Change	Baseline Value	Simulation Value	Net Impact	Percent Change
Allen	760.87	911.35	150.48	19.78	961.26	727.65	-233.61	-24.30
Anderson	272.55	331.42	58.87	21.60	1340.03	1248.65	-91.39	-6.82
Atchison	3152.35	3327.39	175.04	5.55	1505.21	1233.47	-271.75	-18.05
Barber	372.56	427.05	54.49	14.62	471.23	386.64	-84.59	-17.95
Barton	1361.74	1662.70	300.95	22.10	2152.23	1685.01	-467.22	-21.71
Bourbon	1399.43	1568.05	168.62	12.05	832.07	570.29	-261.77	-31.46
Brown	699.13	806.64	107.51	15.38	856.68	689.78	-166.90	-19.48
Butler	3941.62	4321.49	379.87	9.64	15244.00	14654.26	-589.74	-3.87
Chase	564.71	584.97	20.25	3.59	679.38	647.94	-31.44	-4.63
Chautauqua	1253.62	1283.14	29.52	2.35	776.49	730.66	-45.83	-5.90
Cherokee	2760.84	2929.59	168.75	6.11	3377.01	3115.03	-261.98	-7.76
Cheyenne	223.68	254.73	31.06	13.88	175.79	127.58	-48.21	-27.43
Clark	427.48	450.93	23.45	5.49	230.35	193.94	-36.41	-15.81
Clay	379.59	458.00	78.41	20.66	1059.70	937.98	-121.72	-11.49
Cloud	370.00	476.47	106.46	28.77	867.37	702.10	-165.28	-19.05
Coffey	1223.67	1325.80	102.13	8.35	683.81	525.26	-158.55	-23.19
Comanche	215.49	236.43	20.94	9.72	140.31	107.80	-32.51	-23.17
Cowley	-2261.86	-1927.85	334.01	-14.77	4999.77	4481.24	-518.54	-10.37
Crawford	2886.32	3302.83	416.51	14.43	1700.15	1053.54	-646.61	-38.03
Decatur	240.42	274.19	33.77	14.05	323.58	271.16	-52.42	-16.20
Dickinson	1305.70	1483.27	177.58	13.60	2711.81	2436.13	-275.68	-10.17
Doniphan	1668.00	1740.78	72.78	4.36	1058.93	945.94	-112.99	-10.67
Douglas	14930.71	16026.69	1095.98	7.34	9903.52	8202.06	-1701.46	-17.18
Edwards	192.81	224.09	31.28	16.22	363.53	314.97	-48.56	-13.36
Elk	45.83	68.04	22.21	48.45	611.82	577.35	-34.48	-5.64
Ellis	2093.45	2424.30	330.85	15.80	1617.05	1103.41	-513.64	-31.76
Ellsworth	590.60	654.87	64.27	10.88	656.27	556.50	-99.77	-15.20
Finney	2316.29	2741.75	425.47	18.37	2596.60	1936.08	-660.52	-25.44
Ford	1933.82	2282.02	348.19	18.01	1674.74	1134.18	-540.56	-32.28
Franklin	4308.68	4528.11	219.44	5.09	4021.97	3681.31	-340.67	-8.47
Geary	266.42	522.54	256.12	96.13	4128.75	3731.14	-397.61	-9.63
Gove	241.96	276.33	34.37	14.20	157.43	104.08	-53.36	-33.89
Graham	-320.46	-292.25	28.21	-8.80	362.15	318.35	-43.80	-12.09
Grant	665.12	743.04	77.92	11.71	881.63	760.67	-120.96	-13.72
Gray	646.33	702.46	56.13	8.68	605.71	518.56	-87.14	-14.39
Greeley	297.27	313.61	16.34	5.50	164.84	139.47	-25.37	-15.39
Greenwood	215.84	275.93	60.09	27.84	1164.38	1071.10	-93.29	-8.01
Hamilton	406.08	433.25	27.17	6.69	91.75	49.58	-42.17	-45.97
Harper	238.46	298.01	59.56	24.98	730.79	638.33	-92.46	-12.65
Harvey	5951.74	6262.12	310.38	5.21	4770.60	4288.75	-481.85	-10.10
Haskell	495.70	534.47	38.77	7.82	532.96	472.78	-60.19	-11.29
Hodgeman	398.74	419.05	20.32	5.10	243.53	211.99	-31.54	-12.95
Jackson	1267.20	1369.90	102.70	8.10	2530.04	2370.60	-159.44	-6.30
Jefferson	761.49	847.65	86.16	11.32	5446.15	5312.38	-133.77	-2.46
Jewell	104.95	137.59	32.63	31.09	407.34	356.68	-50.66	-12.44
Johnson	67989.98	73889.10	5899.12	8.68	79726.90	70568.75	-9158.14	-11.49
Kearny	294.32	332.32	37.99	12.91	576.00	517.02	-58.98	-10.24
Kingman	2838.34	2909.50	71.16	2.51	1847.94	1737.47	-110.47	-5.98
Kiowa	291.43	325.40	33.97	11.66	316.56	263.82	-52.73	-16.66
Labette	1317.95	1553.02	235.06	17.84	2104.96	1740.04	-364.93	-17.34
Lane	255.17	278.60	23.43	9.18	187.49	151.12	-36.38	-19.40
Leavenworth	7618.61	8151.63	533.02	7.00	14846.12	14018.63	-827.49	-5.57
Lincoln	292.45	324.95	32.50	11.11	390.01	339.55	-50.46	-12.94
Linn	82.57	143.22	60.64	73.44	2089.60	1995.45	-94.15	-4.51

Table 7.2 (con't) Simulation Results for In-Commuters and Out-Commuters

County	In-Commuters				Out-Commuters			
	Baseline Value	Simulation Value	Net Impact	Percent Change	Baseline Value	Simulation Value	Net Impact	Percent Change
Logan	232.38	263.81	31.43	13.53	194.36	145.56	-48.80	-25.11
Lyon	922.34	1327.18	404.84	43.89	2351.85	1723.35	-628.49	-26.72
McPherson	3168.84	3506.90	338.06	10.67	1786.68	1261.86	-524.82	-29.37
Marion	672.59	780.63	108.04	16.06	1994.45	1826.73	-167.73	-8.41
Marshall	1046.63	1164.94	118.31	11.30	832.93	649.26	-183.67	-22.05
Meade	364.06	401.10	37.04	10.17	599.41	541.91	-57.50	-9.59
Miami	7033.21	7216.03	182.82	2.60	7856.88	7573.06	-283.82	-3.61
Mitchell	595.10	675.98	80.87	13.59	200.99	75.44	-125.55	-62.47
Montgomery	1921.49	2319.66	398.17	20.72	2776.43	2158.29	-618.14	-22.26
Morris	279.23	334.03	54.80	19.62	821.68	736.61	-85.07	-10.35
Morton	578.87	618.33	39.46	6.82	275.15	213.89	-61.26	-22.26
Nemaha	904.20	1019.42	115.22	12.74	557.85	378.98	-178.87	-32.06
Neosho	903.48	1091.37	187.89	20.80	1065.50	773.81	-291.69	-27.38
Ness	385.20	423.05	37.86	9.83	327.40	268.63	-58.77	-17.95
Norton	399.96	458.40	58.44	14.61	387.61	296.88	-90.73	-23.41
Osage	662.29	744.39	82.10	12.40	4615.95	4488.50	-127.45	-2.76
Osborne	196.53	242.68	46.15	23.48	247.35	175.70	-71.65	-28.97
Ottawa	316.19	356.07	39.88	12.61	1320.03	1258.11	-61.91	-4.69
Pawnee	327.40	400.07	72.67	22.20	706.28	593.46	-112.82	-15.97
Phillips	381.71	447.42	65.71	17.22	359.00	256.98	-102.02	-28.42
Pottawatomie	1955.58	2131.36	175.78	8.99	2440.57	2167.69	-272.88	-11.18
Pratt	880.32	987.07	106.75	12.13	712.92	547.20	-165.73	-23.25
Rawlins	231.22	259.60	28.39	12.28	298.94	254.86	-44.07	-14.74
Reno	4923.03	5578.07	655.04	13.31	7368.11	6351.19	-1016.92	-13.80
Republic	432.32	492.45	60.13	13.91	394.56	301.21	-93.35	-23.66
Rice	383.13	475.54	92.41	24.12	1311.94	1168.47	-143.47	-10.94
Riley	4887.76	5723.00	835.24	17.09	598.47	-698.20	-1296.68	-216.66
Rooks	169.33	223.39	54.06	31.93	496.98	413.05	-83.93	-16.89
Rush	49.56	79.51	29.94	60.42	565.64	519.15	-46.49	-8.22
Russell	536.77	614.02	77.25	14.39	419.14	299.21	-119.93	-28.61
Saline	5368.36	6050.03	681.67	12.70	1596.54	538.27	-1058.27	-66.29
Scott	580.44	640.47	60.02	10.34	582.95	489.76	-93.18	-15.98
Sedgwick	40267.44	45610.13	5342.69	13.27	42743.63	34449.32	-8294.31	-19.40
Seward	1838.03	2080.49	242.47	13.19	1075.12	698.70	-376.42	-35.01
Shawnee	18305.52	20436.30	2130.78	11.64	11586.62	8278.67	-3307.95	-28.55
Sheridan	97.85	125.78	27.92	28.53	187.41	144.06	-43.35	-23.13
Sherman	565.06	637.38	72.32	12.80	576.30	464.03	-112.27	-19.48
Smith	158.81	200.82	42.02	26.46	445.98	380.75	-65.23	-14.63
Stafford	216.83	259.25	42.42	19.56	676.56	610.72	-65.85	-9.73
Stanton	532.60	562.21	29.61	5.56	41.32	-4.65	-45.97	-111.25
Stevens	606.46	658.75	52.29	8.62	539.27	458.09	-81.17	-15.05
Sumner	2376.10	2553.37	177.26	7.46	6157.95	5882.75	-275.20	-4.47
Thomas	460.95	554.10	93.15	20.21	565.59	420.98	-144.60	-25.57
Trego	142.13	172.43	30.30	21.32	413.78	366.74	-47.04	-11.37
Wabaunsee	902.16	936.75	34.59	3.83	2149.09	2095.39	-53.70	-2.50
Wallace	227.18	246.48	19.30	8.49	88.44	58.48	-29.96	-33.87
Washington	606.40	666.02	59.62	9.83	778.52	685.96	-92.56	-11.89
Wichita	327.56	353.68	26.12	7.97	201.25	160.70	-40.55	-20.15
Wilson	537.14	637.36	100.21	18.66	868.82	713.24	-155.58	-17.91
Woodson	19.96	46.39	26.43	132.41	611.00	569.97	-41.03	-6.72
Wyandotte	24009.71	25699.84	1690.13	7.04	16157.90	13534.04	-2623.86	-16.24
Average	2629.86	2908.71	278.85	16.43	3045.96	2613.06	-432.90	-20.41
Max	67989.98	73889.10	5899.12	132.41	79726.90	70568.75	-25.37	-2.46
Min	-2261.86	-1927.85	16.34	-14.77	41.32	-698.20	-9158.14	-216.66

Table 7.3 Simulation Results for Unemployment

County	Unemployment				
	Baseline Value	Simulation Value	Net Impact	Percent Change	Rate Change
Allen	-19.26	57.69	76.94	399.53	1.10
Anderson	80.26	110.36	30.10	37.50	0.79
Atchison	2083.63	2173.13	89.51	4.30	1.07
Barber	119.57	147.43	27.86	23.30	1.04
Barton	-819.80	-665.91	153.89	18.77	1.13
Bourbon	428.20	514.42	86.22	20.14	1.15
Brown	241.46	296.43	54.97	22.77	1.05
Butler	1125.65	1319.89	194.24	17.26	0.66
Chase	430.53	440.88	10.36	2.41	0.71
Chautauqua	1126.24	1141.33	15.10	1.34	0.76
Cherokee	2300.47	2386.76	86.29	3.75	0.82
Cheyenne	108.53	124.41	15.88	14.63	1.08
Clark	300.51	312.50	11.99	3.99	1.03
Clay	24.92	65.01	40.09	160.90	0.94
Cloud	-59.89	-5.46	54.44	90.89	1.04
Coffey	572.03	624.25	52.22	9.13	1.12
Comanche	130.21	140.91	10.71	8.22	1.07
Cowley	-3673.67	-3502.88	170.79	4.65	0.91
Crawford	760.69	973.66	212.98	28.00	1.16
Decatur	123.97	141.24	17.27	13.93	1.00
Dickinson	778.50	869.30	90.80	11.66	0.89
Doniphan	1293.63	1330.85	37.22	2.88	0.94
Douglas	5587.67	6148.08	560.41	10.03	1.12
Edwards	42.20	58.19	15.99	37.90	0.98
Elk	-82.45	-71.09	11.36	13.77	0.76
Ellis	819.33	988.51	169.18	20.65	1.11
Ellsworth	201.54	234.40	32.86	16.31	1.04
Finney	75.53	293.09	217.56	288.03	1.11
Ford	131.87	309.91	178.04	135.02	1.14
Franklin	2612.94	2725.14	112.21	4.29	0.92
Geary	-623.06	-492.10	130.96	21.02	0.88
Gove	59.07	76.64	17.57	29.75	1.15
Graham	-410.09	-395.66	14.42	3.52	0.93
Grant	244.38	284.23	39.84	16.30	1.00
Gray	339.83	368.53	28.70	8.45	1.01
Greeley	227.81	236.16	8.35	3.67	1.00
Greenwood	-45.31	-14.58	30.73	67.82	0.85
Hamilton	241.54	255.43	13.89	5.75	1.20
Harper	23.79	54.24	30.45	128.01	0.95
Harvey	3299.04	3457.75	158.71	4.81	0.98
Haskell	206.44	226.26	19.82	9.60	0.99
Hodgeman	266.16	276.55	10.39	3.90	1.01
Jackson	641.78	694.30	52.52	8.18	0.80
Jefferson	323.53	367.58	44.06	13.62	0.49
Jewell	-12.89	3.79	16.69	129.41	0.95
Johnson	2660.02	5676.45	3016.43	113.40	1.07
Kearny	106.95	126.37	19.43	18.16	0.92
Kingman	2225.58	2261.96	36.39	1.63	0.82
Kiowa	140.75	158.12	17.37	12.34	1.02
Labette	211.69	331.89	120.20	56.78	1.03
Lane	112.37	124.35	11.98	10.66	1.09
Leavenworth	3717.89	3990.44	272.55	7.33	0.78
Lincoln	115.88	132.50	16.62	14.34	0.99
Linn	-48.49	-17.48	31.01	63.95	0.66

Table 7.3 (con't) Simulation Results for Unemployment

County	Unemployment				
	Baseline Value	Simulation Value	Net Impact	Percent Change	Rate Change
Logan	66.29	82.37	16.07	24.25	1.11
Lyon	-1142.18	-935.17	207.01	18.12	1.11
McPherson	1294.87	1467.73	172.86	13.35	1.14
Marion	193.33	248.58	55.24	28.57	0.86
Marshall	348.69	409.19	60.50	17.35	1.10
Meade	171.64	190.57	18.94	11.03	0.91
Miami	5217.86	5311.35	93.48	1.79	0.65
Mitchell	238.93	280.28	41.35	17.31	1.18
Montgomery	386.56	590.16	203.60	52.67	1.06
Morris	-2.62	25.40	28.02	1068.85	0.93
Morton	350.92	371.10	20.18	5.75	1.10
Nemaha	273.41	332.32	58.92	21.55	1.15
Neosho	-88.47	7.61	96.08	108.60	1.12
Ness	167.66	187.02	19.36	11.55	1.06
Norton	176.13	206.01	29.88	16.97	1.07
Osage	343.12	385.10	41.98	12.23	0.52
Osborne	-14.33	9.27	23.60	164.68	1.11
Ottawa	153.80	174.19	20.39	13.26	0.69
Pawnee	62.95	100.11	37.16	59.03	1.00
Phillips	155.85	189.45	33.60	21.56	1.08
Pottawatomie	868.81	958.69	89.88	10.35	0.97
Pratt	376.36	430.95	54.59	14.50	1.08
Rawlins	118.10	132.61	14.52	12.29	0.99
Reno	1319.82	1654.76	334.94	25.38	1.00
Republic	247.15	277.90	30.75	12.44	1.05
Rice	-60.31	-13.06	47.25	78.34	0.94
Riley	1533.30	1960.38	427.09	27.85	1.22
Rooks	-57.66	-30.01	27.64	47.94	1.02
Rush	-116.78	-101.47	15.31	13.11	0.87
Russell	185.76	225.26	39.50	21.26	1.11
Saline	1198.41	1546.97	348.56	29.09	1.23
Scott	225.85	256.54	30.69	13.59	1.04
Sedgwick	-5077.36	-2345.46	2731.91	53.81	1.14
Seward	371.20	495.18	123.98	33.40	1.17
Shawnee	-427.60	661.95	1089.54	254.81	1.22
Sheridan	-5.38	8.90	14.28	265.44	1.06
Sherman	225.59	262.56	36.98	16.39	1.06
Smith	34.96	56.44	21.48	61.46	0.97
Stafford	0.51	22.20	21.69	4249.93	0.91
Stanton	330.78	345.92	15.14	4.58	1.29
Stevens	327.43	354.16	26.74	8.17	1.02
Sumner	1490.03	1580.67	90.64	6.08	0.68
Thomas	102.18	149.81	47.63	46.61	1.08
Trego	52.73	68.22	15.49	29.38	0.91
Wabaunsee	638.90	656.58	17.69	2.77	0.51
Wallace	123.27	133.14	9.87	8.00	1.15
Washington	312.38	342.86	30.49	9.76	0.96
Wichita	172.88	186.24	13.36	7.73	1.09
Wilson	78.77	130.01	51.24	65.05	1.04
Woodson	-23.11	-9.60	13.52	58.48	0.77
Wyandotte	9576.63	10440.86	864.22	9.02	1.11
Average	508.26	650.85	142.58	89.18	0.99
Max	9576.63	10440.86	3016.43	4249.93	1.29
Min	-5077.36	-3502.88	8.35	1.34	0.49

In the six representative counties, the 5% increase in employment resulted in an increase of 77 to 240 new jobs, depending on the county. This change resulted in an average increase in labor force of 0.39%, with values ranging from 0.20% to 0.47%. The model also estimated an average in-commuting increase of 12.33%. The increase of in-commuters ranges from 8%, in Haskell County, to 19%, in Wilson County. The average decrease in out-commuting in the six counties was 16.78%. The county with the largest decrease in out-commuting was Gove County, with 34%. Jefferson County had the lowest predicted change, which was a 2% decrease in out-commuting. This result makes sense because many residents of Jefferson County currently commute to the Kansas City metro area for employment. A relatively small increase of 5% in employment will probably not be enough to draw a majority of residents to stay in the county for work. While the predicted changes in unemployment were large in percentage terms (an average of 89%, ranging from 1% to 4250%), they represent relatively modest changes in the unemployment rate (an average change of 0.99%, ranging from 0.49% to 1.29%).

The predictions of these changes can be seen in figures 7.2 and 7.3. Table 7.4 shows the same information that is represented in figure 7.2, but in tabular form. The changes in labor force, commuting, and unemployment as a percent of the change in employment were reported in table 6.5 and discussed in chapter 6.

Figure 7.2 Change in Employment, Labor Force, Commuting, and Unemployment due to a 5% increase in jobs

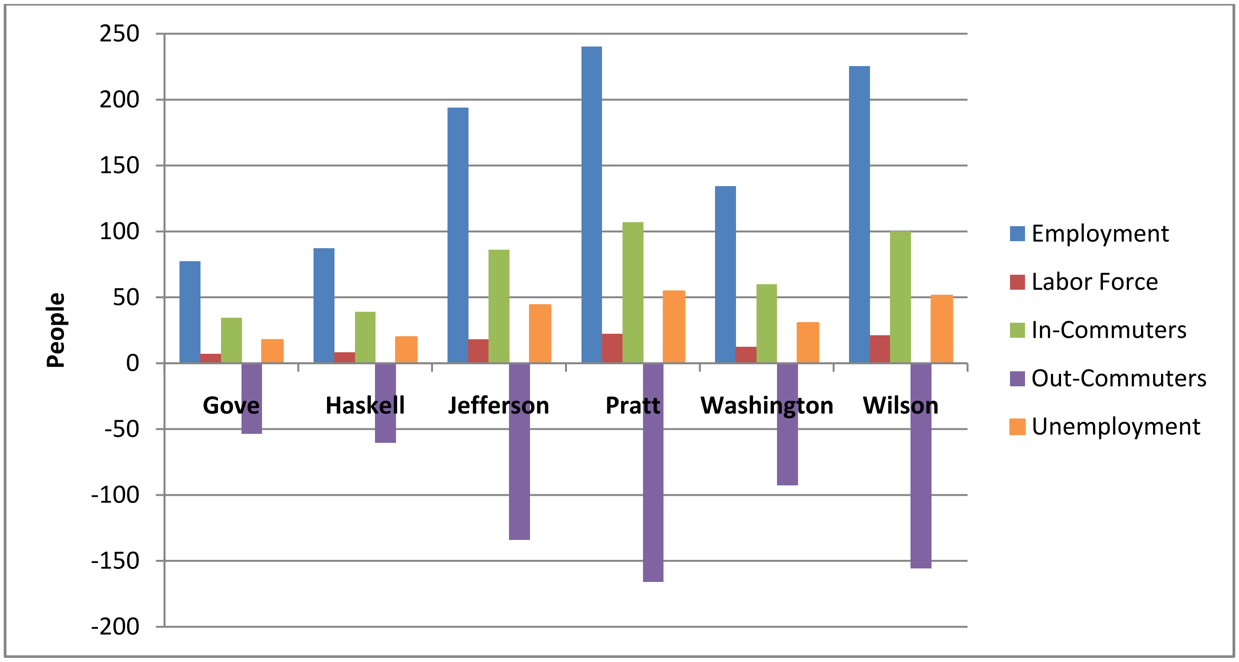
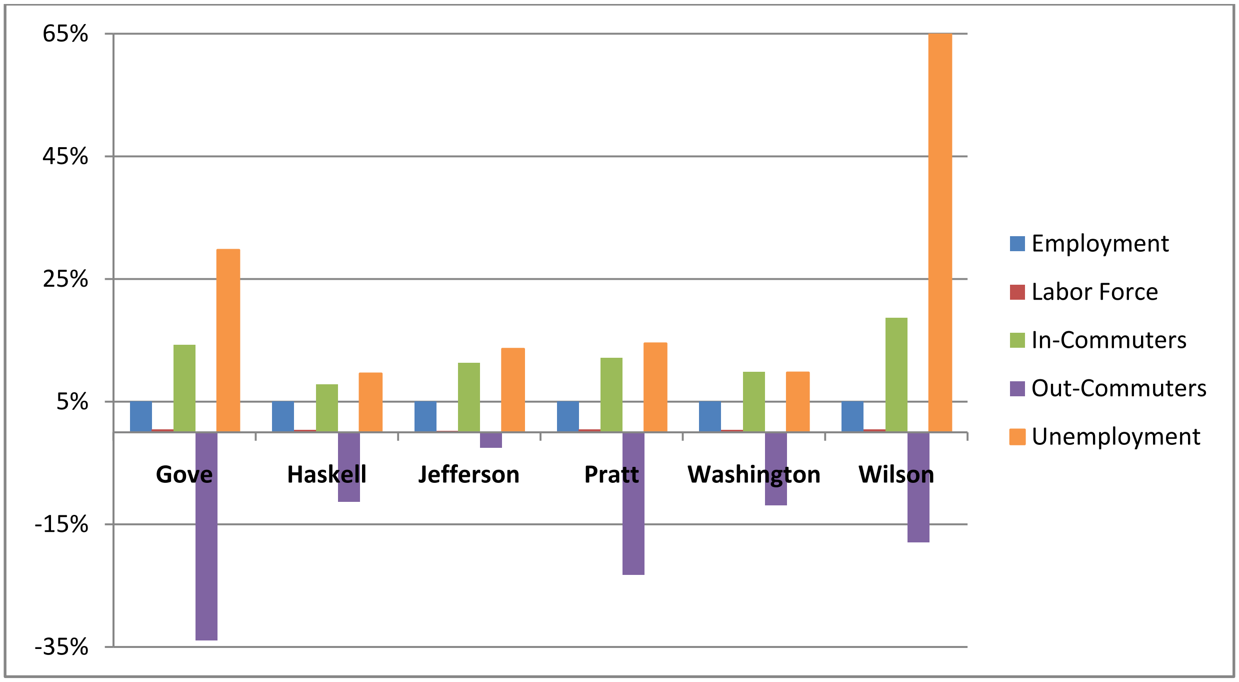


Table 7.4 Change in Employment, Labor Force, Commuting, and Unemployment due to a 5% increase in jobs

County	Employment (Jobs)	Labor Force (People)	In-Commuters (People)	Out-Commuters (People)	Unemployment (People)
Gove	77.30	7.15	34.37	-53.36	17.57
Haskell	87.20	8.07	38.77	-60.19	19.82
Jefferson	193.80	17.93	86.16	-133.77	44.06
Pratt	240.10	22.21	106.75	-165.73	54.59
Washington	134.10	12.40	59.62	-92.56	30.49
Wilson	225.40	20.85	100.21	-155.58	51.24

Figure 7.3 Percent change in Employment, Unemployment, Labor Force, and Commuting due to a 5% increase in jobs



7.3 Labor Force Changes

One way to illustrate the usefulness of the model is retrospectively compare the estimated labor market impacts for an existing employer in a county to the actual number of new jobs created after the employer began operation. Ideally, the employer would have begun operation around the year to which this model is calibrated, 2000. There were three major employment events that occurred around this time in Kansas.

This first event analyzed was the opening of a biofuel plant in Russell County, Kansas in October 2001. The second was the burning down of a beef processing plant in Finney County on Christmas night in 2000. The third event examined was the opening of a Cessna production facility in Montgomery County in 1996. It would be ideal to examine the accuracy of all the equations in the model, but county labor force is the only variable available yearly. County level commuting data is only available for census years. Due to this limitation, only the labor force predictions are presented in this section.

7.3.1 Biofuel Plant, Russell County

In October 2001, a 40 million gallon per year biofuel plant opened adjacent to a currently operating wheat gluten plant in Russell County, Kansas. The facility directly employed 73 people and had total sales of $202,255,495. This information was used to predict total effects of the biofuel plant using IMPLAN. IMPLAN tracks endogenous linkages between production, labor and capital income, trade, and household expenditures, and then provide estimated effects on sector output, value added, household income, and employment, given estimates of direct economic change (MIG, 1999). The total employment and income changes including direct, indirect and induced changes predicted by IMPLAN were an increase of 219 jobs and $10,717,095 in total income (Leatherman, 2008).

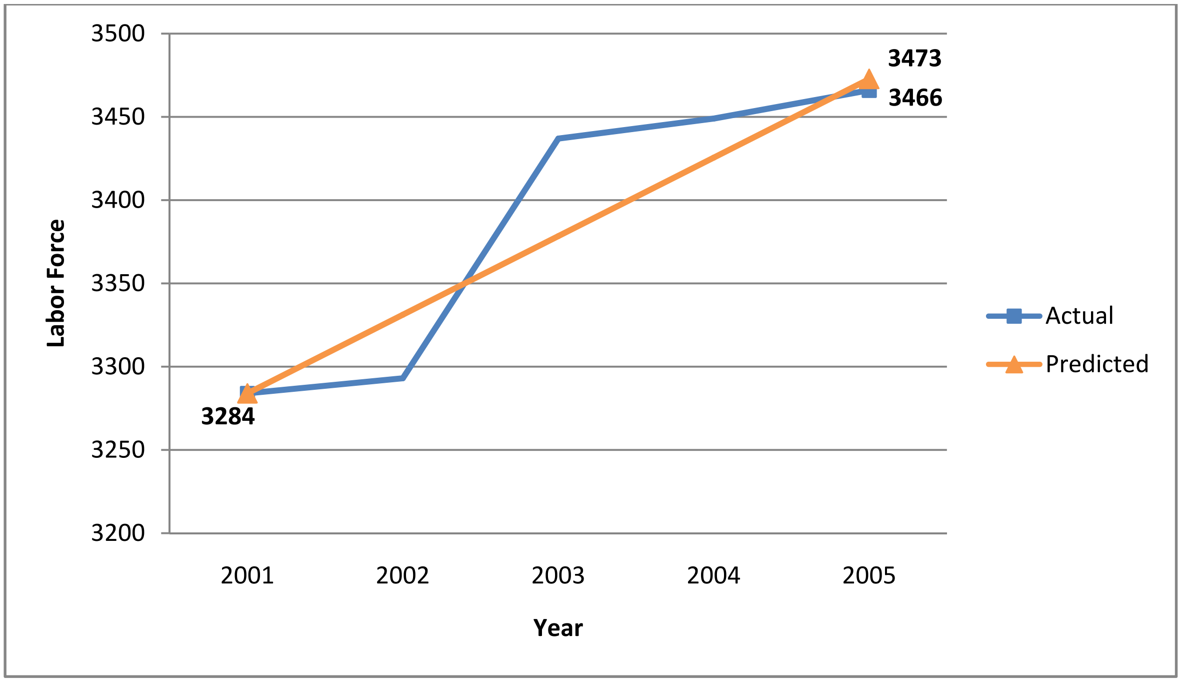
These predictions for employment and income change were entered into the estimated equation for labor force and the difference between the baseline estimates and the new estimates were examined. The model did not exactly predict the labor force values for the starting year. In order to compare the changes predicted by the model to the changes that actually occurred in Finney County the estimates were adjusted by the difference between the baseline estimate for the first year and the actual labor force. This adjustment allows us to compare the changes that occurred over 5 years after the plant opened.

The model predicted a baseline value of 3,543 people in Russell County's labor force. The actual labor force size in 2001 was 3,284 people (Bureau of Economic Analysis), so the estimates were adjusted by 259 to allow for comparisons. With the IMPLAN estimations entered into the model the new labor force is estimated to be 3,732. Therefore, the model predicted a labor force increase of 189 people in Russell County as a result of the new biofuel plant.

Assuming it takes 5 years for the total labor force effects of the plant to play out in the local economy, the actual labor force in Russell County after the plant opened increased by 182 people. Realistically, it was not expected that the labor force model would predict the actual labor force changes. This is because the estimations assume there is no other labor activity occurring in the county during this time. It is possible another firm opened or closed during that five year period that would have also have had an effect on the labor force size in the county.

With this scenario, the labor force model predicted a change fairly close to what was actually occurring in Russell County at that time. The difference between the predicted and the actual labor force changes was only 7 people. The actual and predicted changes in labor force as a result of the biofuel plant opening are compared in Figure 7.4.

Figure 7.4 Predicted and Actual Labor Force Changes in Russell County, 2001-2005

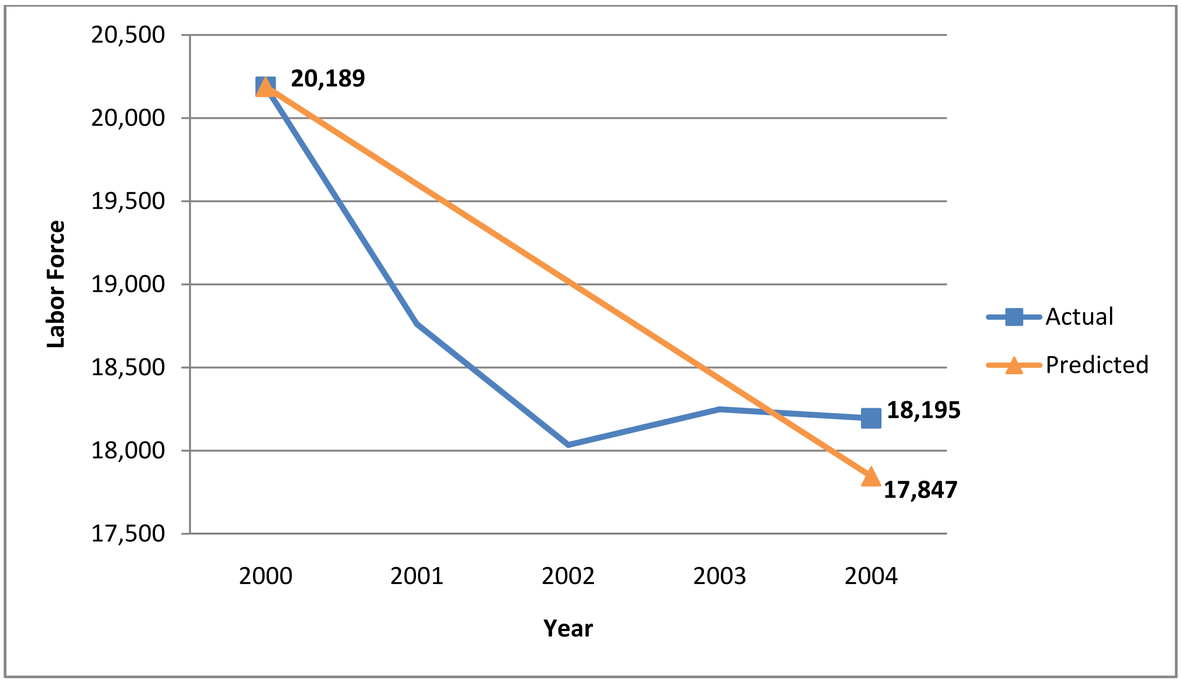


7.3.2 Packing Plant, Finney County

The impacts of the closure of a beef packing plant, owned by ConAgra, in Finney County were also examined. The plant was destroyed by a fire in December 2000 resulting in 2,300 people put out of work (Broadway and Stull, 2006). According to IMPLAN estimations, the direct loss of 2,300 jobs in the meat packing industry in Finney County would result in a total impact of a 4,367 decrease in employment and a decrease in total labor income of $123,269,247 in the county (Leatherman, 2008).

Figure 7.5 shows how the estimated labor force impacts compare to the actual changes in labor force over the five years after the beef packing plant closed. The labor force equation estimated a baseline labor force value of 19,495 people. According the Bureau of Economic Analysis the labor force in Finney County in 2000 was 20,189 people. Once again the baseline value was adjusted to match the actual labor force in 2000 so that the estimated change in labor force could be compared to the actual change.

Figure 7.5 Projected and Actual Labor Force Changes in Finney County, 2000-2004



After inputting the IMPLAN estimated changes in employment and income the labor force equation projected a decrease in the labor force of 2,342. Once again assuming it took 5 years for the labor force impacts to play out the estimated change in labor force was compared to the actual change in labor force in Finney County between 2000 and 2004. In 2004 Finney County had a labor force of 18,195, a decrease of 1,994 people (Bureau of Economic Analysis).

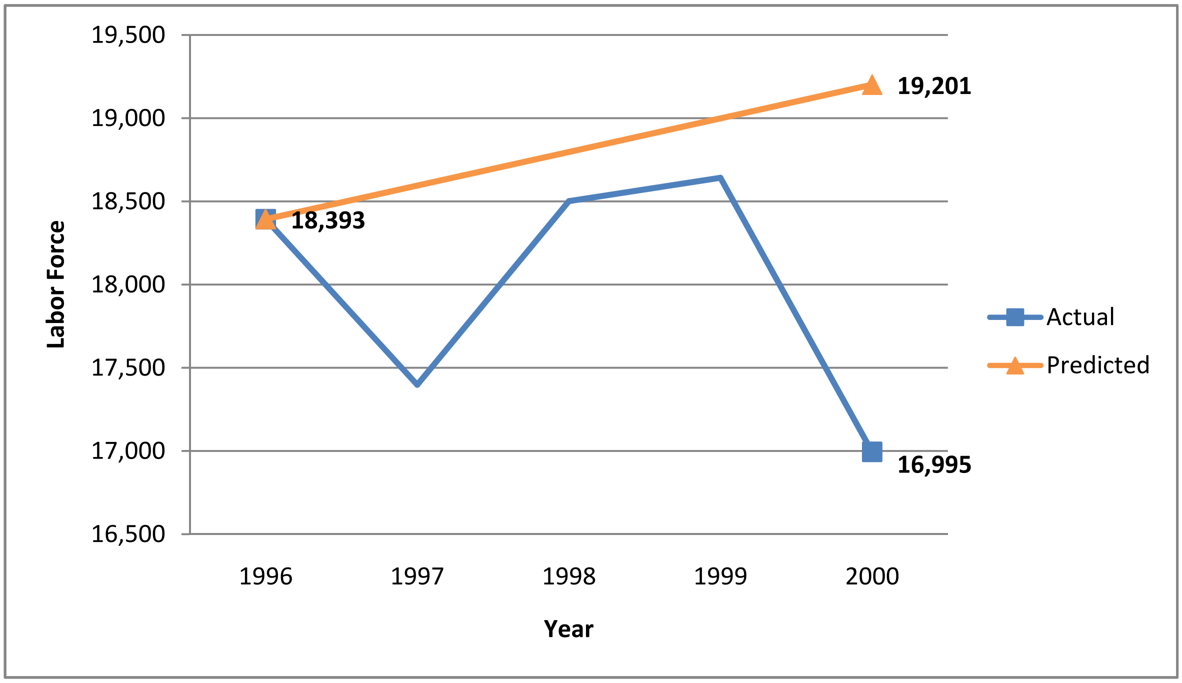
Looking at Figure 7.6 it appears that it may have taken less than five years for Finney County to begin to recover from the plant's destruction. The labor force stabilized beginning in 2002, which may have been the result of some other economic activity in the county. Despite this other activity, the model did a fairly accurate job of predicting the decrease in labor force as a result of the beef packing plant's closure.

7.3.3 Cessna Factory, Montgomery County

In July 1996 Cessna opened an aircraft manufacturing facility in Montgomery County, Kansas. This facility began production line flow in July 1996, employing 625 people who earned a combined salary of $171 million (Wings Over Kansas, 2004). Using this information, IMPLAN predicted the opening of the Cessna plant created a total of 1,481 jobs and a total labor income impact of $42,686,484 (Leatherman, 2008).

These IMPLAN predictions were input into the labor force equation to obtain an estimated change in labor force in Montgomery County as a result of the Cessna plant opening. The estimated changes can be seen in Figure 7.6. The baseline labor force estimation for Montgomery County was 19,152 which was 759 people higher than the actual labor force in 1996 of 18,393 people. The estimated change in labor force as a result of the Cessna plant was an increase of 808 participants.

Figure 7.6 Actual and Predicted Labor Force Changes in Montgomery County, 1996-2000



The actual change in labor force between 1996 and 2000, the estimated period it takes for labor force effects to play out, can also be seen in Figure 7.6. It is apparent there was economic activity in Montgomery County during this period other then the Cessna facility opening. During this period the actual labor force fluctuates considerably, and the labor force model did a poor job of predicting what was actually occurring in Montgomery County. Unfortunately no information on what caused the labor force fluctuations during this time was found.

7.4 Conclusion

As was expected, the labor force model did not exactly estimate the changes in labor force in a county after the creation or destruction of jobs. This was because the model assumed the only economic activity in the county at that time is the activity being analyzed. Of course this is rarely the case, therefore the model will probably never perfectly predict labor force changes.

There are no numbers available to determine how accurate the labor force, commuting, and unemployment change estimations were as a result of a 5% increase in employment. However, if the model can give a reasonably close estimate of labor force impacts it can be used as a planning and analysis tool for local policy makers. It is important local officials have realistic expectations for economic development through job creation. The goal of this model was to provide realistic projections for labor force impacts when jobs are created.

CHAPTER 8 - **Conclusions and Implications**

8.1 Introduction

The objective of this research was to determine the labor market impacts of employment growth in Kansas counties. Employment growth is often the goal of local development policies, but it is not always clear who benefits from this growth. New jobs may be filled by the currently unemployed, by additions to the labor force in the county where the growth occurs or by residents that used to commute out of the county for employment. These new jobs may also be captured by workers living in a surrounding county who are willing to commute to the county where new jobs are available (in-commuters).When in-commuters take jobs, many of the economic benefits expected to accrue to the county where the job growth occurs are essentially exported to the county where the in-commuter lives.

8.2 Results and Implications

To determine the changes in labor force, unemployment, and commuting when a labor demand shock takes place, a labor market model was econometrically estimated. The model predicted labor force in a county as a function of employment, income, housing values, metropolitan status and unemployment of a county as well as the employment available in contiguous counties. In- and out- commuting were estimated as a function of employment, income, housing values, metropolitan status, labor force, and unemployment in a county, as well as the employment available and labor force size in contiguous counties. Unemployment was estimated using the identity that unemployment is equal to the sum of labor force and in-commuting minus the sum of employment and out-commuting.

The results of the estimation indicated that approximately 48% of new jobs are filled by in-commuters. The model also estimated that 9% of new jobs are filled by an increase in labor force size and the number of out-commuters decreases by 69% of the new employment. It was found that the estimated increases in employment, labor force and in-commuting as well as the decrease in out-commuting would result in an increase in unemployment equivalent to 26% of the increase in employment.

Failure to account for the proportion of new jobs filled by in-commuters would lead to significant over estimations of local impacts of employment growth. First, fiscal impacts associated with residential growth in a county would be much smaller. If in-commuters are filling jobs, there will be much smaller demand for schools, healthcare facilities, and other family facilities because the employees' families will be living in another county. Also, residential tax revenues, such as property taxes, will be much lower than expected for the county of employment because its employees will be paying taxes on land in other counties. This indicates the importance of considering spatial effects when analyzing the impacts of job growth.

If spatial effects and commuting are as important as indicated by the model, it may benefit local governments to work collaboratively when planning economic development policies. If the consequences of economic change are spread regionally, it would be logical for economic development programs to be approached on a regional basis.

One example of a regional development policy is tax-base sharing. Under regional tax-base sharing all of the municipalities within a metropolitan area agree to share tax proceeds from new development. This eliminates interregional competition; facilitates other planning goals such as preserving open space or maintaining a vibrant downtown; encourages suburbs and central cities to cooperate on regional economic development goals; and leads to a more equitable distribution of tax burdens and public services (Institute for Local Self Reliance). Tax-base sharing has been adopted in the Twin Cities area of Minnesota and the Hackensack Meadowlands area in New Jersey. It has also been proposed in the Sacramento metropolitan area of California. Such a policy makes sense if regions are competing against one another for revenue-generating development that actually has consequences for all regions due to commuting and migration.

8.3 Model Limitations

As highlighted by Section 7.3, it is important to remember the model assumes all other economic activity is held constant when looking at an employment shock. This is often not the case and sometimes the opening of one facility may cause the closing of another. These interactions are important to consider when making predictions using the model.

Another limitation of the model is that if it is used in conjunction with I-O modeling any errors in the I-O predictions are essentially magnified by the econometric model. If the I-O model over-predicts the total number of jobs or wage income created by new employment these over predictions will lead to inflated predictions of changes in labor force, commuting, and unemployment. This issue emphasizes that care and skill in the modeling exercise is essential.

8.4 Opportunities for Future Research

This research answers a few questions, but opens the door to many others. One topic worth examining further is if there is a difference in commuting impacts for metropolitan and non-metropolitan counties. This topic could be examined more carefully by estimating different models for metropolitan and nonmetropolitan counties. If there are differences based on population density, then it would be beneficial to extend this research to include one model examining the effect of an employment shock for metropolitan counties and a different model for rural counties.

This model could also be expanded to estimate labor force changes as a result of an employment shock for different industry sectors. I-O analysis programs often break down estimated employment and income changes by different industry sectors. This information could be input into an industry-specific labor force model. The results of such a model would be of importance to officials looking to increase economic activity in their county through employment growth. Local officials may use this information to take steps to make their county more attractive to industries estimated to create more jobs that are filled by local residents.

8.5 Summary

A common goal of many local officials is to strengthen the local economy through job growth. However, when job growth occurs it is not always apparent who is taking the new jobs. Often, residents of neighboring counties commute in to fill some of these positions. When in-commuting occurs many of the estimated benefits of job growth are not realized by the county where the jobs are available. This results in inflated expectations of increases in local economic growth. By being able to predict the percentage of new jobs filled by commuters, local residents, and in-migrants, local officials can better plan for future economic expansion.

References

Bartik, T.J. 1993 . "Who Benefits from Local Job Growth: Migrants or the Original Residents?" *Regional Studies*. 27:297-311.

Blanchard, J.B. and L.F. Katz. 1992. "Regional Evolutions." *Brookings Papers on Economic Activity*. 1:1-75

Bolton, R. 1985. "Regional Econometric Models." *Journal of Regional Science*. 25: 495-520.

Breiman, L. and P. Spector. 1992. "Submodel Selection and Evaluation in Regression. The X-Random Case." *International Statistical Review*. 60:291-319.

Broadway, M.J. and D.D. Stull. 2006. "Meat Processing and Garden City: Boom and Bust." *Journal of Rural Studies*. 22:55-66.

"Cessna Expands Its Independence, Kansas, Facility." 2004. Wings Over Kansas. Access Date: November 2008. Available at: http://www.wingsoverkansas.com/news/article.asp?id=390.

Cox, A.M. and D. Swenson. 2006. "Data Issues." In T.G. Johnson, D.M. Otto, S.C. Deller, ed. *Community Policy Analysis Modeling*. Ames IA: Blackwell Publishing, pp. 181-194.

Davis, E.E., L. S. Connolly, and B.A. Weber. 2003. "Local Labor Market Conditions and the Jobless Poor: How Much Does Local Job Growth Help in Rural Areas?" *Journal of Agricultural and Resource Economics* 28:503-518.

Davis, E. and F.N. Bachewe. 2004 ."Employment Growth and Commuting Patterns in Rural Labor Markets." Paper presented at the American Agricultural Economics Association annual meeting, Denver CO, 1-4 August.

Fisher, A. 2003. "Where Do Workers Come From?" Minnesota Department of Employment and Economic Developlment. Minnesota Employment Review, June.

Greene, W.H. 1993. Econometric Analysis, 2nd ed. New York: Macmillan Publishing Company.

Institute for Local Self Reliance. "Regional Tax-Base Sharing." Access date: December 2008. Available at: http://www.newrules.org/retail/taxbasesharing.html.

Johnson, T.G. 2006. "Modeling the Local Labor Market." In T.G. Johnson, D.M. Otto, S.C. Deller, ed. *Community Policy Analysis Modeling*. Ames IA: Blackwell Publishing, pp. 85-96.

Johnson, T.G, D.M. Otto, and S.C. Deller. 2006. "Introduction to Community Policy Analysis Modeling." In T.G. Johnson, D.M. Otto, S.C. Deller, ed. *Community Policy Analysis Modeling*. Ames IA: Blackwell Publishing, pp. 3-16.

Johnson, T.G. and J.K. Scott. 2006. "The Show Me Community Policy Analysis Model." In T.G. Johnson, D.M. Otto, S.C. Deller, ed. *Community Policy Analysis Modeling*. Ames IA: Blackwell Publishing, pp. 119-130.

Kennedy, P. 1993. *A Guide to Econometrics*, 3rd ed. Cambridge: The MIT Press.

Kohavi, R. 1995. "A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection." International Joint Conference on Artificial Intelligence, pp. 1137-1143.

Leatherman, J.C. 2008. Personal Interview.

Li, P. 2006. "Simulated Prediction of excess stock returns using a forecasted macroeconomic factor and Capital Asset Pricing Models." Unpublished, University of California, Berkley.

Minnesota IMPLAN Group, Inc. (MIG). 1999. *IMPLAN Professional Software, Analysis, and, Data Guide*. Stillwater, MN: Minnesota IMPLAN Group, Inc.

Pindyck, R. and D. Rybinfeld. 1998. *Econometric Models and Econometric Forecasts*, 4th. ed. Boston: Irwin McGraw-Hill.

Renkow, M. 2003a. "Employment Growth and the Allocation of New Jobs: Evidence from the South." Paper presented at the American Agricultural Economics Association annual meeting, Montreal, Canada 27-30 July.

Renkow, M. 2003b."Employment Growth, Worker Mobility, and Rural Economic Development." *American Journal of Agricultural Economcis.* 85:503-513.

Scott, J.K. and T.G. Johnson. 2006. "A National Infrastructure for Community Policy Analysis." In T.G. Johnson, D.M. Otto, S.C. Deller, ed. *Community Policy Analysis Modeling*. Ames IA: Blackwell Publishing, pp. 51-56.

Shields, M. 2006. "The Philosophy Underlying Community Policy Models." In T.G. Johnson, D.M. Otto, S.C. Deller, ed. *Community Policy Analysis Modeling*. Ames IA: Blackwell Publishing, pp. 57-84.

Shields, M. and D. Swenson. 2000. "Regional Labor Markets: The Relationship Between Industry Level Employment and In-commuting in Pennsylvania Counties." *The Journal of Regional Analysis and Policy*.30:81-94.

Shields, M., S.C. Deller, J. I. Stallmann. 2001. "Comparing the Impacts of Retiree versus Working-Age Families on a Small Rural Region: An Application of the Wisconsin Economic Impact Modeling System." *Agricultural and Resource Economics Review*. 30:20-31.

Swenson, D. and D.M. Otto. 1998."The Iowa Economic/Fiscal Impact Modeling System." The *Journal of Regional Analysis and Policy*. 28:64-75.

Swenson, D. and D.M. Otto. 2006. "The Iowa Economic/Fiscal Impact Modeling System." In T.G. Johnson, D.M. Otto, S.C. Deller, ed. *Community Policy Analysis Modeling*. Ames IA: Blackwell Publishing, pp. 131-146.

Treyz, G. 1993. *Regional Economic Modeling*. Boston: Kluwer Academic Publishers

U.S. Department of Commerce, Bureau of the Census. "Your Gateway to Census 2000." Access date: August 2008. Available at: http://www.census.gov/main/www/cen2000.html.

U.S. Department of Commerce, Bureau of Economic Analysis. "Regional Economic Accounts." Access date: August 2008. Available at: http://www.bea.gov/bea/regional/reis/.

U.S. Department of Commerce, Bureau of Economic Analysis. Access date: August 2008. Available at: http://www.bea.gov/.

Yeo, J. 2000. "Economic Growth in Washington: An Examination of Labor Market-Population Relationships." PhD dissertation, Washington State University.

Yeo, J. and D.W. Holland. 2002. "Economic Growth in Washington: An Examination of Labor Market and Fiscal Response." *The Journal of Regional Analysis and Policy*. 32:1-31.

Yeo, J., J.C. Leatherman, and T.L. Marsh. "Understanding the Engine of Economic Growth: Cointegration Analysis of the Kansas Labor Market." Unpublished, Kansas State University.