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KENTUCKY FOREST SECTOR: STRUCTURAL CHANGES AND ECONOMIC IMPACTS

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KENTUCKY FOREST SECTOR:
STRUCTURAL CHANGES AND ECONOMIC IMPACTS

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Agriculture, Food and Environment at the University of Kentucky

By

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Lexington, Kentucky

2021

ABSTRACT OF DISSERTATION

KENTUCKY FOREST SECTOR:
STRUCTURAL CHANGES AND ECONOMIC IMPACTS

The Kentucky forest sector plays a key role in ensuring economic stability and enhanced livelihood for both rural and urban communities in the state. Therefore, it is important to implement policies and measures to sustain and improve the sector. One way to attract attention and engage policy makers in discussions on the need for measures to sustain the sector is to undertake comprehensive assessments that would enhance understanding of economic contributions and impacts associated with activities of the sector. To this end, appropriate analytical tools and techniques must be employed for detailed and accurate estimates. This dissertation has applied input-output (IO) and computable general equilibrium (CGE) modeling frameworks to shed light on the economic contributions and impacts of the Kentucky forest sector. This dissertation has four major essays. In essay one (Chapter 2), an impact analysis for planning (IMPLAN) IO modeling framework has been applied to conduct forest sector contribution analyses, where sectoral aggregation bias is investigated. Two commonly used approaches in forest economic contribution analysis are employed. A hierarchical clustering procedure is used to develop a new aggregation scheme for the Kentucky forest sector. The newly developed aggregation scheme is used to generate forest sector contributions estimates. The results are then compared to the sector's contributions from the currently used aggregation scheme to derive aggregation bias.

In essays two (Chapter 3) and three (Chapter 4), panel data regressions are used to examine patterns of forest industrial structural change as induced by regional input factor compositions. Forest sector shares in employment and output are used as structural variables. This analysis is conducted on a cross-country database in essay two and for Kentucky forest sector in essay three. For the cross-country analysis, a traditional catch-up growth model is also used to assess the role of the wood and paper manufacturing industries in aggregate economic growth. This analysis is rooted in factor endowment-based structural change theorems that posit that an increase in the endowment of a factor will lead to an increase in the output of the industries that use that factor more intensively.

Finally, a single-region, static CGE model is used to estimate the potential economy-wide impacts of increased demand for Kentucky forest sector products in essay four (Chapter 5). This analysis attempts to provide a broader understanding of potential impacts of the Kentucky forest sector by tracing the ripple effects of expansion in the sector as induced by increased demand of its products. Key findings of these analyses are: (i) the IMPLAN modification approach generates bias-free contributions from aggregated industries; (ii) forest-based industries grouping based on production structures introduce more bias in contribution estimates when feedback effects are captured; (iii) regional factor compositions are important determinants of forest industrial structural change; (iv) simultaneous adjustments of both labor and capital is crucial for improving forest industrial structure; and (v) the forest sector is an important contributor to Kentucky's economic growth but complementary policies may help improve household welfare as the sector expands.

Findings from this dissertation highlight evolution of Kentucky's forest sector over time. These results will enhance understanding of economic contributions and impacts of the Kentucky forest sector. These results further provide insights and guidance on IO forest sector contribution analysis on how to get more-accurate and less-biased estimates. These are critical to reliably communicate the economic stakes associated with the performance of the forest sector in the state's economy. Further, the results provide insights into the potential economic impacts of increased demand of forest sector products that could serve as evidence base for recommending policies to sustain the sector and enhance regional household welfare.

KEYWORDS: Structural Changes, Computable General Equilibrium, Input-Output Analysis, Economic Contributions and Impacts

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July 7, 2021
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DEDICATION

This dissertation is dedicated to my uncle, Mr. Charles Agyeman-Attafuah who has been a great source of inspiration and support.

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Chapter 1. General Introduction

Forests and forest product industries play an important role in providing livelihood and ensuring economic stability of many rural and urban communities around the world (Agrawal et al., 2013). About 420 million hectares of forests have been lost globally through conversion to other land uses since 1990 (FAO and UNEP, 2020). Although the rate of forest degradations and land use conversion has reduced in recent times, the current conversion rates are still high and alarming (FAO and UNEP, 2020). This threatens the stability of forest sectors and the economic stability of communities that are most dependent on the forest sector. Thus, measures to sustain forests and forest-based industries have become more imperative. One way to draw the attention of policy makers to the need for more efficient policies to sustain forest sector is to bring to light detailed economic contributions and impacts of activities related to forest industries. However, in doing so, the most appropriate methodologies must be adopted to provide accurate results.

Kentucky is home to over 12.4 million acres of forests (Oswalt et al., 2017). The forests in Kentucky provide timber for wood and paper processing centers distributed across 112 counties in the state. Together, logging, wood, and paper manufacturing activities in Kentucky provide various employment opportunities and generate billions of dollars in annual income (Stringer et al., 2020). The forest sector also serves as a source of intermediate inputs for other industries in the state and beyond. This means contractions and expansions in the forest sector may have some direct, indirect, and induced shocks on activities of other dependent industries. This dissertation employs three analytical tools to enhance understanding of contributions and impacts of the Kentucky forest sector to the state's economy and to reveal factors that drive structural changes[1] in the sector. The dissertation pays particular attention to: (1) investigating presence and extent of industry aggregation bias in Kentucky's forest sector economic contribution analysis; (2) examining factors that drive changes in forest sector shares in the state's economy; and (3) assessing potential economy-wide impacts of increased demand of Kentucky forest sector products.

1.1 Background

The US is endowed with a great amount of natural resources. Of the total 2.3 billion acres of the nation's land area, 823 million acres are forests and woodlands (Oswalt, 2019; Callahan, 2019). The forest products industry is one of the major manufacturing industries in the US. The US forest products industry accounts for approximately 4% of the nation's total manufacturing GDP, producing over $200 billion in products every year (Oswalt, 2019). According to Pelkki and Sherman (2020), forest-based industries in the US created 4,466,056 jobs and contributed about $237,445 million in employee compensation in 2016. At the regional level, Pelkki and Sherman (2020) showed that employment contribution of forest sectors ranges from 43,286 in the central plains to 1,447,077 in the southeast. The Kentucky forest sector provided about $13.97 billion in total economic contributions in 2020. The Kentucky forest sector also generated over 53,000 jobs and made about $3.1 billion in total labor wages in 2020 (Stringer et al., 2021).

[1] Structural change is defined as the change in the shares of sectors in economic activities (van Neus, 2019).

Economic contribution analysis is one of the most popular economic analyses conducted on forest sectors across states in the US. Periodic estimates of the economic contributions of forest sectors are common as they reveal the importance of the sector in sustaining rural communities, justify public expenditures in the sector's economic sustenance, and defend sustainable development (Pelkki and Sherman, 2020; Aruna et al., 1997; Flick and Teeter, 1988). According to Aruna et al. (2007), assessing the economic diversity and dependency of forest sectors in southeastern states is one of the first steps toward formulating strategies, goals, and policies for regional economic development.

Common among forest sector economic analyses is the application of input-output (IO) modeling framework such as Impact Analysis for Planning (IMPLAN) (Minnesota IMPLAN Group, 2004), RIMS II, and REMI (Lynch, 2000) to generate regional forest sector economic contributions. Among these tools, IMPLAN is arguably the most popular input-output analysis (IOA) tool used by forest economics and policy analysts in the US. IMPLAN has been used for forest sector contribution analysis in the US since 1979 (Minnesota IMPLAN Group, 2004). The long-standing popularity of IMPLAN depicts its acceptance among forest economics analysts, but there is little consensus on the methodologies, the economic indicators to report, and sometimes selection of IMPLAN forest-based industries (Parajuli et al., 2018; Joshi et al., 2017). For example, there is lack of clarity between using IMPLAN for impact analysis and contribution analysis. Understanding the difference between impact and contribution analyses is critical as these terms are often used interchangeably, yielding confusion among practitioners (Henderson et al., 2017; McConnell, 2013; Watson et al., 2007). Contribution analysis is a method used to estimate the value of a sector or group of sectors in a region at their current levels of production, while impact analysis captures the net changes of new or foregone revenues from possible entry and exit of a particular sector (Cheney, 2018; Watson et al., 2007).

Aggregation in IO analysis refers to the consolidation of several individual industries into groups to reduce the number of industries in an IO table into a smaller order (Kymn, 1990). In conducting forest sector economic contribution analysis, forest-based industries are usually aggregated into sub-sectors before their contribution estimates are generated. This aggregation makes analysis convenient but it also tends to cause loss of detailed information of the original individual industries. Therefore, using the aggregated industries for contribution analysis may introduce some bias in the resulting estimates. To avoid or minimize any potential bias of aggregation, it is important to ensure that the industry groupings are based on the similarity of industries' production structures (Olsen, 2001; Hatanaka, 1952).

In Kentucky, the aggregated wood, paper, and logging industries have experienced output growth in recent years. This growth is partly attributed to increased demand for the state's forest products. This growth means that economic contributions associated with the forest sector can be expected to increase, and such an expansion in the sector can create multiplier effects, coming from intersectoral interlinkages. Kentucky's annual forest sector economic contribution reports generated from IMPLAN IO models reveal that the sector's absolute contribution in employment, value added, and total output has been increasing for the past decade (Stringer et al., 2020). However, economy-wide impact studies that examine the broader effects of expansion in the forest sector are deficient in Kentucky. To effectively account for the impacts stemming from output or demand changes in the forest sector, economic modeling frameworks that can account for inter-industry or sector interlinkages are desirable and appropriate.

The concept of structural change has been explained from different perspectives. One of the most used definitions of structural change is the changes in the shares of sectors in economic activities (van Neus, 2019). Occasional shifts in industrial composition in economic activities are inevitable as an economy grows or develops. Theories that explain industry compositional shifts in economic activities focus on either the supply or demand side of an economy. While the demand side theorems associate changes in industrial composition to the difference in elasticities of demand among industries, the supply side theorems focus on variations in rates of technological growth and factor compositions (Ju et al., 2015; Acemoglu and Guerrieri, 2008; Ngai and Pissarides 2007; Kongsamut et al., 2001). Knowledge of the determinants of industrial structure is important to understand the basic structure and drivers of an economy (Reeve, 2006).

Several studies have analyzed the influence of factor endowments on industrial structure (e.g., Che, 2012; Reeve, 2006; Harrigan, 1997). While some of these studies have used cross-country panel data analysis to assess the linkage between factor endowments and individual industries, others have focused on combined industries in an economy. Che (2012) used panel data regressions to determine the linkage between capital endowment and industrial structure across many countries. Results from this study show that increase in capital endowment leads to an increase in the size of capital-intensive industries. Though this result from Che (2012) is revealing and confirms the supply side explanation of industrial structural change, the link between factor endowment and individual industries is masked.

Changes in forest sector shares in economic activities are commonly attributed to changes in other sectors. Lebedys and Yanshu (2014) and Agrawal et al. (2013) reported that changes in the forest sector's contributions could primarily be attributed to shifts of economic activities from agriculture and forestry to service sectors. This explanation depicts structural change concepts in that expansion in the service sector is expected to cause a decline in the shares of agriculture and forest industries' economic activities. However, empirical assessments of the role of factor compositions on changes in forest sector shares are important as it may reveal detailed information about the factors that drive growth in the sector. Such analysis may also reveal how factor endowments influence a region's comparative advantage for an industry (Rybczynski, 1955).

There are a number of economic analytical frameworks that have been applied in in assessing potential economic impacts in forest sector. Among these, partial equilibrium (PE), IO, and computable general equilibrium (CGE) models are among the most commonly used. Among these alternative analytical tools, CGE models have been identified as the most suitable (Alavalapati et al., 1998) and are increasingly being used to estimate economic impacts of forest sector policies. CGE modeling approach is considered suitable tool for impact analysis because of its economy-wide and market-based approach, where prices play a key role as the main mechanism through which supply and demand adjust following exogenous shocks such as changes in sector output (Banerjee and Alavalapati, 2014).

Against the above background, this dissertation seeks to use various analytical methods to estimate Kentucky forest sector's economic contribution while examining any potential presence of industry aggregation bias, in the process. The dissertation also investigates the influence of the factor endowments on forest industrial structure. Finally, a CGE analytical framework is applied in assessing potential economy-wide impacts of increased demand of wood products in Kentucky's economy. The motivation of these analyses stems from the identified research gaps below.

1.2 Research Gaps

Periodically, state forestry agencies and landgrant universities across the US employ IMPLAN IO models to generate forest sector economic contribution estimates that serve various purposes. In conducting such contribution analyses, various forest-based industries are aggregated into sub-sectors of interest for convenience. In Kentucky, 34 forest-based industries are aggregated into logging, primary wood manufacturing (PWM), secondary wood manufacturing (SWM), pulp and paper, paper converters (PC), and wood residue (WR). While such aggregation makes the analysis more convenient, it is known to have some potential bias in the estimates due to "loss of information" from the original unaggregated industries (Olsen, 2001). Therefore, using an aggregated industries for contribution analysis may either overestimate or underestimate contribution estimates. However, the extent of such potential aggregation bias in the estimates could be minimized if industries of similar production structures are aggregated together (Hatanaka, 1952). The current aggregation scheme used for the Kentucky forest sector economic contribution analysis is based on the similarities of forest-based industries' outputs rather than on their production structures. The current scheme has been used to generate forest sector contributions since 2010 (Stringer et al., 2020). Since 2010, no attempt has been made to investigate whether the current aggregation scheme introduces any bias in the contribution estimates or not. Examining the presence of aggregation bias is crucial for ensuring that generated contribution estimates are not misleading. Therefore, there is a need to investigate a potential presence of aggregation bias in Kentucky's forest sector economic contribution analysis.

Changes in forest sector shares in economic activities are commonly attributed to changes in other sectors (Lebedys and Yanshu, 2014; Agrawal et al., 2013). While this attribution confirms the development economics perspective of structural change,[2] empirical examination of the underlying theorems of changes in sectoral compositions is important for detailed assessments. Factor endowment-based structural change theorems posit that an increase in the endowment of a factor will lead to an increase in the output of the industries or sectors that use that factor more intensively **(**Ju et al., 2015; Acemoglu and Guerrieri, 2008; Rybczynski, 1955**).** Considerable attention has been given to the empirical assessment of the role of factor endowment industry structure (Hakobyan and Lederman, 2016; Che, 2012; Reeve, 2006; Harrigan, 1997), but these studies have used either a cross-country dataset, where characteristics of individual countries are masked or in multisector analysis where factor endowments' influence on individual sectors are masked. Analysis of the influence of factor endowment in a single region on a single sector like the forest sector is critical in revealing detailed information on how a region's factor composition influences economic contribution of the sector. Such analysis is crucial for policy makers in enhancing the understanding of what may be needed to sustain the forest sector in a particular region and make it more competitive. In Kentucky, less is known

[2] Over time, expansion of service and manufacturing sectors lead to a decline in agriculture and forest sectors shares (van Neus, 2019).

about the linkage between the region's factor composition and states forest sector's economic contributions and growth.

While annual economic contribution reports show that the Kentucky forest sector has been experiencing output growth, not much is known about economy-wide impacts of the sector's growth. Through industry interlinkages, output changes in one sector have direct, indirect, and induced impacts in other industries. Analyses that assess such economy-wide impacts are critical for providing a thorough assessment of the role that a sector plays in an economy. In Kentucky, annual forest sector economic contribution reports are used to provide information to stakeholders about the economic status of the sector. Though results from the contribution analysis are informative, they do not reveal the economy-wide impacts of the sector's activities. Recent output growth of Kentucky's forest sector can be attributed to increased demand for forest sector products. This upward trend in the demand could come from other industries' intermediate demand for forest products. This means that output growth in the forest sector is partly due to an increase in the sector's supply of intermediates to dependent industries. Economy-wide analyses that capture these potential inter-industry linkages are critical in providing a broader and indepth understanding of the sector's performance to stakeholders about what is going on in the forest sector. CGE models are well suited to depict such interactions between the forest sector and other sectors in an economy (Alavalapati et al., 1998).

1.3 Research Objectives

This project's overall goal is to enhance understanding of the economic contributions and impacts of Kentucky forest sector's growth. Specific objectives of the dissertation are to:

1. Analyze economic contributions of the Kentucky forest sector and assess presence and extent of potential industry aggregation bias.
2. Investigate the linkage between regional factor endowment and forest industrial structural change using panel data regression analysis across selected countries.
3. Investigate the linkage between regional factor endowment and Kentucky forest industrial structural change using panel data regression analysis.
4. Assess the potential economy-wide impacts of increased demand for wood products using computable general equilibrium modeling framework in Kentucky

1.4 Research Framework

This dissertation is presented in an 'article' format. The main body of the dissertation comprises four distinct but related articles. **Chapter 1** provides a general introduction with brief background information on the area of research focus. It outlines the main research objectives, and the general analytical approaches used to achieve the objectives.

Chapter 2 uses IMPLAN IO analytical framework to estimate Kentucky forest sector economic contributions, where potential presence and extent of industrial aggregation bias is assessed. Based on standard IOA aggregation theorems, a hierarchical clustering procedure is applied to Kentucky's forest-based industries' production structures to create a new aggregation scheme. The new aggregation scheme is then used to generate forest sector economic contributions. The results are then compared to the sector's economic contributions from the current aggregation scheme. The analysis was implemented through a four-step procedure: (i) aggregate forest-based industries following the currently used aggregation scheme; (ii) use hierarchical cluster analysis to identify forest-based industries with similar production structures; (iii) aggregate forest-based industries based on the similarity of their production structures to create a new aggregation scheme; and (iv) use both aggregation schemes to conduct economic contribution analysis and compare their estimates. The study was the first attempt to investigate the presence of the aggregation bias in the forest sector economic contribution analysis.

Chapters 3 and 4 employ panel data regression analyses to examine the linkage between factor endowment and forest industrial structural change. The structural variables used are employment and output shares of the forest sector. **Chapter 3** is based on a cross-country database in which two forest manufacturing industries (wood and paper manufacturing) across 11 select countries[3] are used to create a panel dataset that spans from 1980 to 2007. The panel is modified to permit the use of a cross-country "catch-up growth model" to assess the role of the wood and paper manufacturing industries in aggregate economic growth. **Chapter 4** on the other hand focuses on the Kentucky forest sector. It creates a panel data set that consists of 29 forest-based industries over a nine year period (2010-2018). The analytical methods of Chapters 3 and 4 are anchored on factor endowment-based structural change theorem that posits that an increase in the endowment of an input factor will lead to an increase in the output of the industries that use that factor

[3] The countries used in the basic estimation model are Australia, Austria, Canada, Denmark, Finland, Japan, Italy, Netherlands, Spain UK, and U.S. These countries were chosen based on the availability of data.

more intensively. This study was the first attempt to empirically test the factor endowment-based structural change theorem on the forest sector by itself.

Chapter 5 employs a single-region, CGE model to analyze economy-wide impacts of increased demand of wood products in Kentucky. Kentucky's economy is aggregated into nine sectors, including three forest-based industries (logging, wood, and paper). The model is based on traditional neoclassical economic theory, which defines (i) the behavior of economic agents, (ii) market conditions, and (iii) macroeconomic balances.

Finally, **Chapter 6** summarizes the key findings, policy implications, limitations, and future research directions that emerged from Chapters 2 to 5.

Chapter 2. Sectoral Aggregation Bias in Economic Contribution Analysis: The Case of The Kentucky Forest Sector

Abstract

Input-output models are routinely used in regional economic contribution and impact analyses across the US as a basis for policy decision making in the forestry sector. In these analyses, data of closely related industries are usually aggregated into sub-sectors for convenience and to meet user needs. Sectoral production structures drive these analyses. Industry aggregation may significantly alter the production structure through structural change. Such change may subsequently lead to biases in the resultant economic contribution/impact levels. This study investigates the extent of industry aggregation bias in the Kentucky forest sector's economic contribution analysis. A new aggregation scheme is created and compared to the current aggregation scheme based on their bias estimates. A direct output comparison indicates both aggregation schemes yield marginal bias estimates. Moreover, when accounting for the inter-industry relationships and backward linkages among forest-based industries in a contribution analysis, the current scheme yields less bias in the forest sector's contribution. These results provide insights and guidance to input-output analysts for more accurate and less-biased economic contribution analyses.

Keywords: Input-Output Analysis, Economic Contribution, Aggregation Bias, Cluster Analysis

2.1 Introduction

Input-output analysis systematically quantifies the mutual interrelationships among the various sectors of an economic system (Leontief, 1986). Since its inception, input-output models have become one of the most widely used techniques in conducting certain economic analyses. Specifically, contribution and impact analyses are among the common uses of input-output models. An economic contribution refers to the gross changes in a region's existing economy that can be attributed to a given industry, event, or policy. Whereas economic impact captures net changes to economic activity associated with arrival or departure of a new industry, policy or event (Watson et al., 2007). These two analyses provide essential information to policy makers about the driving forces of an economy. Input-output technique is by far the most commonly used technique in estimating the economic impact and contribution changes in the forest sector *(*Alavalapati et al., 1998).

Several state agencies and institutions, especially universities in the US, often use ready-made input-output models to conduct forest sector economic contribution and impact analyses. A common practice among practitioners is the aggregation of forest-based industries into convenient groups for the ease of generating contribution estimates.

2.1.1 Aggregation in Input-Output Models

Aggregation is common in input-output modeling. It involves the consolidation of several individual sectors into groups to reduce the input-output table to a smaller order (Kymn, 1990). When aggregation is performed, the group's output, input, and coefficients represent the weighted average of those of the original detailed sectors belonging to the group (Olsen, 2001). Aggregation mostly results in the loss of information and peculiarities of the original industries. A standard definition of aggregation bias is given as the difference between a vector of outputs derived from the aggregated system and those derived by aggregating the total outputs in the original disaggregated system (Theil, 1957). The problem is aggregation can lead to either overestimation or underestimation in sectoral economic contribution and impact analyses. Despite the problem associated with aggregation, frequently input-output analysts aggregate to aid analysis of the economic system which the model represents.

The Kentucky forest sector makes important economic contribution to the livelihood of the citizens of the state. In conducting an economic contribution analysis of the Kentucky forest sector, 34 forest-based industries[4] make up the Kentucky forest sector. Thirty-three of these are usually aggregated into five sub-sectors, namely, logging (LOG), paper converters (PC), primary wood manufacturing (PWM), secondary wood manufacturing (SWM), and wood residue (WR). The pulp and paper forest-based sub-sector is usually left as the only unaggregated sub-sector made up only of the paper mill industry. Table 2.1 shows the current aggregation scheme and the number of industries that make up the sub-sectors.

Using ready-made input-output models built through Impact Analysis for Planning (IMPLAN), the current definition and aggregation scheme for the Kentucky forest sector has been used to analyze the forest sector's contribution to the state's economy since 2010 (Stringer et al., 2020). The current aggregation scheme is used for grouping forest-based industries into sub-sectors for economic contribution analysis convenience. However, the loss of information from using these aggregated sub-sectors to represent the forest sector

[4] Throughout this chapter the term "industry" is used to represent detailed unaggregated or original forest-based industries. Sub-sectors refer to a group of industries. Forest "sector" refers to all forest sub-sectors or all industries together.

in a contribution and impact analyses may lead to inaccurate (biased) estimates. Aggregation bias can be minimized if appropriate grouping criteria are adopted or industries with similar production structures are grouped together. This study is concerned with assessing the impact of the current grouping of the Kentucky forest-based industries in the forest sector's economic contribution, as a case study. Further, this study creates a new grouping scheme for the Kentucky forest sector by clustering forest-based industries with closely related production structures.

2.2 Objectives

This study focuses on aggregation bias in the Kentucky forest sector contribution analysis. Specifically, the study seeks to: (1) investigate the presence of aggregation bias in Kentucky's forest sector output, (2) investigate the extent of aggregation bias in Kentucky's forest sector economic contribution analysis, and (3) develop a new aggregation scheme for grouping Kentucky forest-based industries based on industries production structures.

This study hypothesizes that grouping forest-based industries based on the similarity of their production structures should introduce less bias in forest sector economic contribution estimates.

2.3 Literature Review

2.3.1 Brief Description of An Input-Output Framework

The popular Leontief model can be summarized as a model having an intermediate transaction table $(\mathbf{D})$, a final demand vector $(\mathbf{f})$, and a value-added vector$(\mathbf{v})$. Total output $(\boldsymbol{y})$ can be obtained by either row summing intermediate output and final demand ($\mathbf{y} = \mathbf{D_i} + \mathbf{f}$), or by summing intermediate inputs and value-added $(\mathbf{y} = \mathbf{D_i'} + \mathbf{f})$. In this framework, $(\mathbf{I} - \mathbf{A})^{-1}\mathbf{f'}$ is the output required to meet a new final demand, $\mathbf{f'}$. Where $\mathbf{A} = \mathbf{D}(\mathbf{y})^{-1}$ is the direct requirement matrix and $(\mathbf{I} - \mathbf{A})^{-1}$ is a total requirement matrix or Leontief inverse (Guo et al., 2002; Leontief, 1986). The one-to-one relationship between industries and commodities defined in this framework indicates that $\mathbf{A}$ and $(\mathbf{I} - \mathbf{A})^{-1}$ produce both commodity by commodity and industry by industry matrices without distinction between commodities and industries (Guo et al., 2002)[5].

Input-output analysis is a theory of production based on a production function. Input-output models assume that: (1) sectors in an economy have linear homogenous production functions that translate to fixed technical coefficients; (2) there is a reservoir of factors of production such that increase in final demand can be met by an increase in output; (3) production in each sector in an economy is subjected to a constant rate of production. Table 2.2 is an example of a simplified input-output table from Leontief (1986).

[5] The one-to-one relationship in the original Leontief input-output system restricts an industry from producing more than one good such that a commodity can be produced by only one industry. An improvement to this original Leontief symmetric system was introduced by the United Nations in its System of National Accounts (SNA) in 1968 in a make-use matrix form which allows industries to produce more than one commodity. However, in order not to lose the importance of the symmetry and economic linkages provided by the original symmetrical system, the asymmetric make-use systems are usually converted to fit the symmetric Leontief input-output system (see Guo et al. 2002).

2.3.2 Conditions and Measures of Aggregation Bias in Input-Output Analysis

The literature on aggregation bias in input-output analysis dates back to the 1950s (see Kymn, 1990 for a survey). A large majority of developed theories for 'good' aggregation in input-output analysis is based on the similarity of industry coefficients, homogeneity of industries and similarity of production functions. Most of these requirements are implied in a condition developed by Hatanaka (1952), who developed theoretical conditions that will make aggregation consistent. He established that given a system of original unaggregated sectors, with column vectors of $\mathbf{f}$ and $\mathbf{y}$ for final demand and total output, respectively, a corresponding aggregated final demand $\mathbf{f}^*$ and an aggregated total output $\mathbf{y}^*$ can be obtained as, $\mathbf{f}^* = \mathbf{G}\mathbf{f}$ and $\mathbf{y}^* = \mathbf{G}\mathbf{y}$, respectively. This aggregation is considered consistent if Equation 2.1 holds.

$$\mathbf{A}^*\mathbf{G} = \mathbf{G}\mathbf{A} \tag{2.1}$$

$$\mathbf{G} = \begin{bmatrix} 1 \cdots 1 & 0 \cdots 0 & 0 \cdots 0 \\ 0 \cdots 0 & 1 \cdots 1 & 0 \cdots 0 \\ 0 \cdots 0 & 0 \cdots 0 & 1 \cdots 1 \end{bmatrix}$$

where $\mathbf{G}$ is a non-negative aggregation matrix, $\mathbf{A}^*$ and $\mathbf{A}$ are the technical coefficients of the aggregated system and the unaggregated system, respectively. The structure of $\mathbf{G}$ is determined by the industries to be aggregated (Theil, 1957). The aggregator matrix $\mathbf{G}$ is commonly referred to as a unit or simple matrix. This means that, as shown above, the elements g_{ij}=1 if industry j is in branch i, otherwise g_{ij} = 0.

Generally, equation 2.1 will be met when the industries to be aggregated have identical technical coefficients, a condition that is unlikely to be fulfilled or observed in real-world data. The difficulty in attaining consistent aggregation based on equation 2.1 has inspired researchers to find ways for 'optimal' aggregation. Further, researchers have, over the years, shifted attention to investigating aggregation bias based on conditions on the Leontief inverse (see Olsen, 2001 for a survey). Blin and Cohen (1977) and Cabrer et al. (1991) developed hierarchical clustering methodologies (minimizing Euclidean distances) of grouping similar industries based on the similarity of their input requirement matrices, $\mathbf{A}$ and $(\mathbf{I}-\mathbf{A})^{-\mathbf{1}}$. Clustering on the $(\mathbf{I}-\mathbf{A})^{-\mathbf{1}}$ is justified because it shows both the direct and indirect input requirement of industries, and secondly, it defines the production function at the vertically integrated industry level (Cabrer et al.,1991; Blin and Cohen, 1977).

Cabrer et al. (1991) applied six hierarchical cluster analyses to the Leontief inverse and technical coefficient matrices of the 1985 Spanish economy. An earlier study by Blin and Cohen (1977) applied hierarchical fusion algorithms to the 1967 (83 ×83) input-output table of the U.S. They compared the dendrogram obtained from a centroid algorithm with Ward's linkage method. They found the centroid method to be less discriminatory. This study is related to Cabrer et al. (1991) and Blin and Cohen (1977), as it attempts to create a new grouping of Kentucky forest-based industries through hierarchical clustering.

Chakraborty et al. (2010) used a 2003 make-use input-output table for Canada to investigate the presence of aggregation bias. They aggregated the original table of 697 commodities, 16 primary inputs, 286 industries and 168 final demand categories into 125 commodities, 11 primary inputs, 84 industries and 7 categories of final demand. The authors estimated both commodity and industry outputs from the aggregated input-output table and compared them to the original unaggregated output values. They found aggregation bias to be marginal for most sectors. Llop and Manresa (2014) investigated aggregation bias in the social accounting matrix (SAM) for the 2001 Catalan economy and compared it to that of bias resulting from aggregation in the input-output accounts of the SAM. Similar to Llop and Manresa (2014) this study isolates the traditional input-output accounts in the Kentucky SAM for analysis. This study estimates aggregated forest-based industry outputs and compares it to unaggregated output values as Llop and Manresa (2014) and Chakraborty et al. (2010) do.

2.4 Data and Method

Data for this study was obtained from the 2016 Kentucky social accounting matrix (SAM) (Table 2.3). A SAM is a detailed extension to an input-output table. A SAM is detailed extension to an input-output table (Pyatt and Round, 1985). A SAM extends an input-output table by incorporating transactions and transfers between institutions based on the distribution of income in an economy (Miller and Blair, 2009). The Kentucky SAM was extracted from the 2016 Kentucky IMPLAN database. The IMPLAN system was designed originally by the U.S. Forest Service to estimate the regional economic impacts of National Forests (Alward et al., 1985), and is currently maintained by the IMPLAN Group LLC. The IMPLAN data is constructed from several data sources like the U.S. Bureau of Economic Analysis (BEA), U.S. Bureau of labor statistics (BLS), and the U.S. Department of Agriculture (IMPLAN Group, 2016). The IMPLAN system provides data on industries at the county, state, and national levels. Classification of industries in IMPLAN follows the North American Industry Classification System (NAICS) codes. The number of industries reported depends on the data year. For example, the number of industries reported in the database was 544 for 2018 while 536 industries were reported for 2015-2017. These changes in the IMPLAN industry scheme are usually induced by occasional

BEA's updates in their input-output accounts which serve as one of the major sources of data for constructing the IMPLAN database (Clouse, 2020). Out of 536 industries in the SAM, 34 traditional forest-based industries were separated for analysis. Details of all 34 forest-based industries are reported in Appendix 1.

2.4.1 Standard Aggregation of An Input-Output Matrix

Let , **A,** and **G** be the original unaggregated matrices of transactions, technical coefficients, and an aggregation matrix, respectively. Let $\mathbf{f}$ and $\mathbf{y}$ represent column vectors of unaggregated exogenous new final demand and total output, respectively. For an n sector economy, the following matrices can be used to formulate an input-output framework,

$$\mathbf{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}, \mathbf{D} = \begin{bmatrix} d_1 1 & \cdots & d_1 n \\ \vdots & \ddots & \vdots \\ d_n 1 & \cdots & d_n n \end{bmatrix}, \mathbf{f} = \begin{bmatrix} f_1 \\ \vdots \\ f_n \end{bmatrix}, \text{and } \mathbf{G} = \begin{bmatrix} 1 \cdots 1 & 0 \cdots 0 & 0 \cdots 0 \\ 0 \cdots 0 & 1 \cdots 1 & 0 \cdots 0 \\ 0 \cdots 0 & 0 \cdots 0 & 1 \cdots 1 \end{bmatrix}$$

where the relationship between $\mathbf{y}$, $\mathbf{D}$ and $\mathbf{f}$ can be compactly written as $\mathbf{y} = \mathbf{Di} + \mathbf{f}$ and, $\mathbf{D} = \mathbf{Ay}$. Hence, the total unaggregated column vector output follows the static Leontief system and can be specified as:

$$\mathbf{y} = (\mathbf{1} - \mathbf{A})^{-\mathbf{1}}\mathbf{f} \tag{2.2}$$

where $(\mathbf{I} - \mathbf{A})^{-\mathbf{1}}$ is the Leontief inverse. Equation 2.2 illustrates one of the primary focuses of input-output analysis, which is to determine the amount of output needed to meet an exogenous final demand in a sector(s) in a defined economy.

Using the aggregation matrix $\mathbf{G}$ an aggregated exogenous final demand $\mathbf{f}^*$ can be estimated as $\mathbf{f}^* = \mathbf{Gf}$. Therefore, following equation 2.2, the aggregated total output vector needed to meet the aggregated final demand $\mathbf{f}^*$ is,

$$\mathbf{y}^* = (\mathbf{1} - \mathbf{A}^*)^{-\mathbf{1}}\mathbf{f}^* \tag{2.3}$$

where $\mathbf{A}^*$ is an aggregated technical coefficient matrix estimated as $\mathbf{A}^* = \mathbf{GAW}'$. $\mathbf{W}$ is a weighting aggregation matrix with weights $w_{ij} = y_j / y_i^*$ if industry j is in branch i, otherwise $w_{ij} = 0$.

2.4.2 Standard Measurement of Aggregation Bias in Input-Output Models

Using a unit weight aggregation matrix $\mathbf{G}$ the total output of the original unaggregated system is aggregated as $\mathbf{G}\,\mathbf{y}$. Therefore, the standard definition of aggregation bias employed in this study can be specified as the difference between Equation 2.3 and $\mathbf{G}\,\mathbf{y}$ (see Theil, 1957). That is,

$$\boldsymbol{\varepsilon} = \mathbf{y}^* - \mathbf{G}\,\mathbf{y} \tag{2.4}$$

$$\boldsymbol{\varepsilon} = [(\mathbf{I} - \mathbf{A}^*)^{-1}\mathbf{G} - \mathbf{G}(\mathbf{I} - \mathbf{A})^{-1}]\mathbf{f} \tag{2.5}$$

McManus (1956) and Olsen (2000a) developed conditions that the net production approach should be considered for aggregation and that the simple grouping matrix $\mathbf{G}$ is appropriate for aggregating net production. A weighted matrix is recommended for gross production. This study focused on the net output of forest-based industries to investigate aggregation bias. The net production is obtained by setting the diagonals of the transaction matrix $\mathbf{D}$ to zero.

2.4.3 Application to the Kentucky Forest Sector

The traditional input-output accounts were extracted from the 2016 IMPLAN industry-by-industry social accounting matrix (SAM) for Kentucky (Table 2.3). With our focus on the forest sector, all forest-based industries were isolated and all other industries were grouped as the rest of the economy (ROEC). As mentioned earlier, 34 forest-based industries were separated from a total of 536 industries in the SAM. From Table 2.3 a matrix of structural coefficients of all the SAM accounts has the form of matrix **B**:

$$\mathbf{B} = \begin{bmatrix} \mathbf{A_{11}} & \mathbf{0} & \mathbf{A_{13}} \\ \mathbf{A_{21}} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{A_{32}} & \mathbf{A_{33}} \end{bmatrix}$$

where $\mathbf{A_{11}}$ is a matrix of intermediate demand coefficients. $\mathbf{A}_{13}$ is a matrix of expenditure coefficients. $\mathbf{A}_{21}$ is a matrix of value-added shares or factors of production coefficients. $\mathbf{A}_{32}$ is a matrix of factor income coefficients. $\mathbf{A}_{33}$ is a matrix of coefficients of the transactions between consumers in the economy (Llop and Manresa, 2014; Miller and Blair, 2009). The matrix **B** structure shows that the input-output relationships are limited to a subset of the accounts in a SAM. Following the estimated coefficients matrix **B**, the unaggregated (equation 2.2) and aggregated (equation 2.3) input-output models can be written as, $\boldsymbol{y} = (\mathbf{I} - \mathbf{A_{11}})^{-\mathbf{1}}\mathbf{f}$ and $\boldsymbol{y}^{*}=(\mathbf{I} - \mathbf{A}^{*}_{\mathbf{11}})\mathbf{f}^{*}$, respectively. Subsequently, the aggregation bias is estimated as,

$$\boldsymbol{\varepsilon} = [(\mathbf{I} - \mathbf{A}^{*}_{\mathbf{11}})^{-1}\mathbf{G} - \mathbf{G}(\mathbf{I} - \mathbf{A_{11}})^{-\mathbf{1}}]\mathbf{f} \tag{2.6}$$

It is worth mentioning that using the same final demand in the unaggregated and aggregated systems may likely lead to zero bias estimates as the system does not experience any shock. As such, this study employed the common approach of assuming final demand of some industries does not coincide with the base year final demand. Llop and Manresa (2014) assumed a 10% increase in the exogenous final demand for the industry-sector. Lindberg et al. (2011) imposed a unit change in the output of the disaggregated sectors considered. This type of assumption is common in applied research based on SAM database because complete information usually lags or partial information is usually reported for some projected periods. In this study, a 10% increase in the final demand was assumed on the sawmill, woodworking and paper machinery industry (IMPLAN CODE 269), and forestry and forest products industry (IMPLAN CODE 15). A positive change was imposed on the final demand due to recent increase in forest sector output which is partly driven by increased demand for Kentucky forest sector products. A shock of 10% was used because it was at this level of change in the final demand that output differences between the aggregated and unaggregated systems became apparent.

2.4.4 Industry Hierarchical Clustering

Clustering is the process of aggregating items based on their similarities. Hierarchical clustering begins by treating each industry as a single cluster, then most similar clusters are aggregated together. By employing a hierarchical clustering analysis, the number of industries and the type of industries that are aggregated in a cluster are not predetermined. Cluster analysis requires a dissimilarity measure or distance to quantify the divergence among the objects under consideration. To do this, an Euclidian Squared distance (Equation 2.7) was used. The Euclidian Squared distance is also faster and easier to work with because it eliminates the square root in the regular Euclidean distance measure[6].

$$d(\boldsymbol{x}, \boldsymbol{y}) = (x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots (x_n - y_n)^2 \qquad (2.7)$$

where $x = (x_1, x_2, \ldots x_n)$ and $y = (y_1, y_2, \ldots y_n)$ are two points or objects in Euclidean n-space. Cluster analysis techniques require a linkage approach on how to measure the distance between clusters. Distance defines how the similarity of elements or pair of units to be clustered (industries in this case) is calculated. In this study, distance measure the

[6] The regular Euclidian distance takes the form $d(\boldsymbol{x}, \boldsymbol{y}) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$

similarity of input values among forest-based industries. The Ward (1963) linkage method was chosen among other suitable linkage methods because it was more discriminatory when applied to our segmenting variables (columns of the Leontief inverse). The Ward linkage method minimizes the sum of squares distance between any pair of clusters formed in the clustering process (Equation 2.8).

$$d(\mathrm{A},\mathrm{B}) = \frac{\mathrm{n_A}\mathrm{n_B}}{\mathrm{n_A}+\mathrm{n_B}} \; \|\overrightarrow{\mathrm{m_A}} - \overrightarrow{\mathrm{m_B}}\|^2 \tag{2.8}$$

where A and B are two different clusters. $\mathrm{n_A}$ and $\mathrm{n_B}$ are the number of points in clusters A and B, respectively. $\overrightarrow{\mathrm{m_A}}$ and $\overrightarrow{\mathrm{m_B}}$ represents the average of all points that belong to cluster A and B, respectively. Finally, a dendrogram is generated from the cluster analysis to identify how the industrial clusters are grouped (aggregated).

2.4.5 Forest Sector Economic Contribution Analysis

This study uses the two most common approaches to conducting forest sector economic contribution analysis to examine the impact of aggregating forest-based industries on forest sector contributions. The first method (Method 1) involves modifying the model and industries of interest within Impact Analysis for Planning (IMPLAN) system. This approach is commonly referred to as the within IMPLAN modification approach (Parajuli et al., 2018). The modification involves restricting the industry’s commodity production and trade flows such that no backward linkages are estimated for the industries of interest. The modification involves two key steps. First, the commodity production of the industries of interest is adjusted to prevent by-product production. Second, the regional purchase coefficients (RPC) of the industries of interest are zeroed out. Editing the by-products and the RPC is done to prevent unanticipated feedback linkages and to prevent purchases from the industries of interest from going beyond their reported outputs.

The second method (Method 2) uses a matrix inversion technique, which accounts for the inter-industry relationship between forest-based industries that are grouped together. This method accounts for each industry's backward linkages by estimating both induced and indirect effects for an industry's own direct effect (Parajuli et al., 2018; Henderson and Evans, 2017). This approach preserves industry output and prevents overestimation of contribution estimates by using appropriate multiplier adjustment factors to scale reported industry outputs (Henderson and Evans, 2017).

For each method, economic contribution estimates were generated for each of the 34 forest-based industries without any prior grouping. These estimates are used as a benchmark and compared to the case where contribution estimates are generated following the current and new (following hierarchical clustering) grouping keys. Both methods involve building an input-output model through an IMPLAN system. The IMPLAN system has been used to conduct several forest-related economic contributions and impact analyses in the U.S. (e.g., Parajuli et al., 2018; Henderson and Evans, 2017; Joshi et al., 2014). The multipliers used are detailed type SAM multipliers, which account for the total economic contribution or impact of sectors (Joshi et al., 2014).

2.5 Results

2.5.1 Aggregation Bias in the Current Aggregation Scheme (Output Comparison)

As explained in the previous section, the standard definition of aggregation bias in input-output modeling is the difference between the output of the aggregated system and the aggregated output of the original or unaggregated system (Theil, 1957). Following this definition, this study starts by examining the difference between the output of the aggregated system (both current and new aggregation schemes) and output from the unaggregated systems. Briefly, the output of the unaggregated system is first compared to the output from the current aggregation scheme. Then, the output of the unaggregated system is compared to the output from the new aggregation scheme. These results are reported in Table 2.4 and Table 2.5.

The first column in Table 2.4 represents the forest-based sub-sectors aggregated under the current aggregation scheme. These are logging (LOG), primary wood manufacturing (PWM), secondary wood manufacturing (SWM), pulp and paper (PAP), paper converters (PC) and wood residue (WR). The estimated aggregation bias follows a positive direction across all the forest-based sub-sectors. However, aggregation is small across the sub-sectors in the current aggregation scheme, with a total increase in output of about 0.00015%. From personal communication with the developers of the current aggregation scheme, industries' production structures are not considered before aggregation; the industries are grouped based on the similarity of their outputs. This could explain the similarity in output of the current aggregated and unaggregated schemes.

2.5.2 Forest Industries Cluster Analysis

Though the aggregation effect on forest sector output in the current aggregation scheme is small, an inspection of a dendrogram (Figure 2.1) created from the hierarchical clustering suggests a new aggregation scheme. The new aggregation scheme resulted in four forest-based sub-sectors (F1-F4 in Table 2.5). Details of the forest-based industries that are aggregated in this scheme are reported in Table 2.8. F1, F2, and F3 consist of five forest-based industries each. F4 is made up of nineteen forest-based industries with identical columns in the Leontief inverse matrix. The commercial logging industry, and forest and forest products industry that make up the current LOG sector were separated in the clustering process. In the new aggregation scheme, the commercial logging industry is grouped together with sawmills, wood preservation, cut stock, resawing lumber and planning, and engineered wood and truss manufacturing as F1. The sawmill and wood preservation industries were two of the four forest-based industries that make up the PWM sector (Table 2.1). The paper mill industry is clustered with four other paper manufacturing-related industries to form F2. As explained above, the paper mill industry is the single industry that forms the PAP sector in the current aggregation scheme.

2.5.3 Aggregation Bias in the New Aggregation Scheme (Output Comparison)

Table 2.5 reports the estimates of aggregation bias in the "new" forest sector aggregation scheme developed (through cluster analysis) in this study; this is referred to as the new aggregation scheme. As expected, the aggregated output from the unaggregated scheme did not change much ($12803.9514 billion) as aggregations were changed. At 12803.9699 billion, the total estimated output from the aggregated scheme increased marginally. Consequently, the total aggregation bias was small at an increased output of 0.0186 (0.00015%). Similar to the estimated bias in the current aggregation scheme, Table 2.5 shows that aggregation impacts are small across the forest-based sub-sectors in the new scheme. Here, the similarity in the aggregated and unaggregated schemes' output is attributed to the similarity in the production structures captured in the columns of the Leontief inverse matrix, which were used as the segmenting variables in the cluster analysis.

2.5.4 Economic Contribution Analysis

Employment, labor income, value-added, and output are the four indicators used to represent the economic contribution of the forest sector. Employment represents the number of full time and part-time jobs created by the sector. Labor income includes employee compensation and proprietor income. Value-added accounts for the net contribution of the forest sector to the state's economy. It is measured as the difference between the sector’s total output and intermediate input cost. Output represents the total dollar value of all sales by the forest sector. The sum of direct effects, indirect effects, and induced effects make up the total economic contributions. Direct effects represent the initial change in the forest sector itself or the effects generated within the sector. Indirect effects are changes that occur due to inter-sector transactions or effects between the forest sector and other sectors. Induced effects are changes in expenditure due to income changes in the directly and indirectly affected sectors. All economic contribution estimates are reported in 2016 dollar values.

Following Method 1 (IMPLAN customization: prevents feedback effects), the contribution estimates generated under the current scheme were identical to the contribution estimates generated under the new scheme. The identical estimates (from the current and the new schemes) were the same as the contribution estimates from the unaggregated scheme. In other words, using Method 1 for contribution analysis, the current scheme, the new scheme, and the unaggregated scheme produced identical results (Table 2.6). The direct contribution of the forest sector was estimated to be about $9.044 billion. Accounting for direct, indirect, and induced contributions, about $13.157 billion was estimated as the forest sector's total contribution. Table 2.6 reports a summary of these results.

Table 2.7 reports the result of the aggregated contribution estimates using Method 2 (matrix inversion approach: permits feedback effects). Contrary to the results from Method 1 (Table 2.6), Table 2.7 reveals that both the current and new aggregations of industries reduce the contribution estimates. In parentheses (below each contribution estimate from the current and new aggregation schemes) are the percentage reductions in the current and new aggregation schemes when compared to the unaggregated system. The reduction in the current aggregation scheme is lower for all economic indicators and contribution levels than what is observed in the new aggregation scheme. Contribution estimates across the individual industries indicate that the Kentucky forest sector generated 62,521 jobs, while the current and new aggregation schemes created 61,730 and 58,901 jobs, respectively. This represents a reduction of 791 (1.27%) and 3620 (5.79%) in the current and new schemes, respectively. It is observed that the current aggregation scheme reduces the total dollar value of all sales of the Kentucky forest sector by $164 million (1.16%). In comparison, a reduction of $534 million (3.77%) is observed under the new aggregation scheme.

The reported estimates in Table 2.7 suggest that the new grouping introduces a higher bias in contribution compared to current grouping (based on similarity in industry output). This result was not anticipated as it was expected that the new scheme would have a reduced bias or generate contribution estimates closer to the unaggregated scheme. While the reason for this result is not entirely clear, it can partly be explained by the fact that the new grouping was done on the net production, which allows input supplies from a given industry to all other demand (from other industries) than its own demand for input. Another potential reason for this result could be due to some non-homogenous and/or illogical groupings that arise in the clustering process. For example, the above dendrogram depicts how the paperboard mills industry is clustered with non-paper product manufacturing industries. This is a common issue in cluster analysis encountered by a couple of studies in this line of research (e.g., Lenzen, 2019; Olsen, 2000b).

2.6 Discussion and Conclusions

Input-output models are routinely used in regional economic contribution and impact analyses across the US states as a basis of policy and management decision making in the forest sector. In these analyses, data of closely related industries are usually aggregated into sectors for convenience. Sectoral production structures drive these analyses. Industry, aggregation may lead to biases in resultant economic contribution and impact levels.

Forest sector activities are usually reflected in several industries in an economy. Hence, to capture all the economic activities that depend on the production of goods and services of the forest sector, several forest-based industries are usually aggregated for convenience based on user needs and purpose of the analysis. Though there is no standard definition and aggregation scheme for the forest sector (Lebedys and Li, 2014), it is important to aggregate detailed forest industries with similar production activities to minimize potential biases in the aggregation process. Kentucky's forest sector is made up of 34 forest-based industries. These industries are usually aggregated into six forest-based sub-sectors for convenience in conduction contribution analysis. This study investigated the extent of industrial aggregation bias in the Kentucky forest sector based on the commonly used industry aggregation scheme. Through cluster analysis on forest-based industries, this study developed a new aggregation scheme for the sector. Outputs in both the current and new aggregation schemes were compared to that of the unaggregated one. Further, an input-output model was developed in IMPLAN to perform a forest sector economic contribution analysis using the two most common approaches to conducting forest sector economic contribution analysis. The first method (Method 1) to conducting forest sector contribution analysis involves modification of the industries of interest to prevent any form of unanticipated feedback linkages. The second method (Method 2) permits feedback linkages and inter-industry relations.

A direct output comparison revealed that the current aggregation scheme used to define the Kentucky forest sector has a small bias (relative to the unaggregated scheme). However, a resultant dendrogram from a hierarchical cluster analysis suggested a new aggregation scheme. The estimated bias of the new aggregation was small as well. These results imply that the industries aggregated under both aggregation schemes follow the principle of homogeneity in production structure, as explained in the methodology section (Chakraborty et al., 2010). However, this similarity is not reflected in a total contribution analysis when the backward linkages and inter-industry relationship between the forest-based industries are considered.

Results from contribution analysis show that both the current and new definition or aggregation of industries in the Kentucky forest sector yield identical results without any bias if the IMPLAN model is modified to prevent 'buyback' effects in the forest-based industries of interest. Results indicate that both schemes lead to a reduction in estimated economic contributions of the Kentucky forest sector when backward linkages and interrelations between industries are accounted for through a matrix inversion approach. However, aggregating forest-based industries based on the similarity of their outputs (as in the current aggregation scheme) capture more total contribution within the sector with a reduced bias of 1.16% compared to a bias of 3.77% in the newly generated scheme. A similar reduced pattern of result was observed for all other reported economic indicators (employment, labor income, and value-added). In other words, following Method 2, comparing the contribution estimates from the current and new aggregation schemes to the unaggregated system (benchmark), the current aggregation scheme introduces less bias in the forest sector's economic contributions. The greater bias introduced by the new grouping scheme is partly attributed to non-homogenous and illogical groupings that arise in the hierarchical clustering process.

Though there are existing studies in literature that have used similar procedure to investigate and shed light on the issue of aggregation bias in input-output studies (e.g., Llop and Manresa 2014; Lindberg et al., 2011; Chakraborty et al., 2010), results from this study are not directly comparable to them because these works have focused on entire economies rather than isolating a single sector (forest sector) as is the case in this study. The existing studies in literature have not investigated the potential biases that could arise if an aggregated scheme is used to conduct contribution analysis. Findings from this study reveal the importance of determining the impacts of aggregation in a sector's contribution to an economy.

With respect to the Kentucky forest sector, finding from this study suggests that taking into consideration the production structure or input requirement of a group of industries is not recommended when the inter-industry relationship and backward linkages of the industries are of interest as it may substantially reduce the contribution estimates. In order words, Method 2 should be used for contribution analysis when industry groupings are based on the similarity of their outputs. Instead, grouping of industries based on the similarity of their outputs as used in the current practices generate contribution estimates which are closer to the unaggregated estimates. It is recommended that practitioners adopt the use of the lowest level of industry aggregation available for contribution analysis whether applying Method 1 or Method 2. Moreover, if industry groupings are necessary then practitioners who are comfortable with using Method 1 for contribution analysis can group industries either based on similarity in industry output or production structure.

Results from this study have some important management implications. First, while aggregation bias can be avoided in the IMPLAN system by summing up contribution estimates from individual sectors, the cluster-based approach provides objective guidelines on which sectors within IMPLAN have natural similarity and are summed together. Also, a conceptual difference between impact vs. contribution and multi-industry contribution analysis (Method 2) is a new development (Henderson et al., 2017). Many past studies (e.g., Tilley and Munn, 2007; Li and Carray, 2009) did not report how they accounted for aggregation bias in their analysis. Since retrospective economic impact analysis, while doing economic contribution trend analysis, for those studies is a cumbersome task, insights from this study can help. Further, insights from this study can serve as a guide to practitioners in deciding on the contribution analysis methodology to employ based on the criterion for grouping industries.

2.7 Tables and Figures for Chapter 2

Table 2.1 Kentucky forest sub-sectors and their detailed number of industries

Number of sub-sectors	Forest sub-sectors	Number of industries
1	Logging	2
2	Primary wood manufacturing	4
3	Secondary wood manufacturing	19
4	Paper convertors	6
5	Pulp and paper	1
6	Wood residue	2

NB: Details of the industries that make up the sub-sectors are presented in Appendix 1.

Table 2.2 Simplified input-output table for a three-sector economy

Sector	Agriculture	Manufacture	Households	Total Output
Agriculture	25	20	55	100 bushels of wheat
Manufacturing	14	6	30	50 yards of cloth
Households	80	180	40	300 person-years of labor

Source: Leontief (1986)

Table 2.3 Structure of industry-by-industry social accounting matrix

SAM	$F1 \cdots Fn$, ROEC	Factors	Institutions	World	**Total**
$F1 \cdots Fn$, ROEC	Intermediate demand		Final demand	Exports	
Factors	Value-added				
Institutions		Factor income		Transfers	
World	Imports		Imported consumer goods		
Total					

Key: ROEC includes all non-forest industries. F1⋯Fn represent all forest-based industries. n=34 in this study. Author's elaboration.

Table 2.4 Aggregation bias in the current scheme

Sub-sectors	Aggregated system (Output in $ million)	Unaggregated system (Output in $ million)	Bias	% Bias
LOG	245.4640	245.4638	0.0001	0.0001
PWM	1078.9902	1078.9896	0.0010	0.0001
SWM	2218.4180	2218.4170	0.0010	0.00004
PAP	1193.3009	1193.3003	0.0010	0.0001
PC	3813.1585	3813.1460	0.0130	0.0003
WR	4254.6383	4254.6345	0.0040	0.0001
Total	12803.9700	12803.9510	0.0185	0.00015

Bias is the difference between columns two and three. Results for all non-forest-based industries (rest of the economy) are not reported even though all industries (both forest-based and non-forest-based industries) were used in the analysis to get a full rank matrix of all industries.

Table 2.5 Aggregation bias in the new scheme

Sub-sectors	Aggregated system (Output in $ million)	Unaggregated system (Output in $ million)	Bias	% Bias
F-1[7]	1391.5334	1391.5326	0.0010	0.0001
F-2	4749.4824	4749.4694	0.0130	0.0003
F-3	2475.7749	2475.7711	0.0040	0.0002
F-4	4187.1792	4187.1783	0.0090	0.00002
Total	12803.9699	12803.9514	0.0186	0.00015

Bias is the difference between columns two and three. Results for all non-forest-based industries (rest of the economy) are not reported even though all industries (both forest-based and non-forest-based industries) were used in the analysis to get a full rank matrix of all industries.

[7] F-1 consists of IMPLAN sector codes 16, 134, 135, 137, and 140. F-2 consists of IMPLAN sector codes 147,149,150,151, and 152. F-3 is made up of IMPLAN sector codes 136,373,368,374, and 399. F-4 consists of IMPLAN codes 15, 138, 141, 142, 144, 145, 148, 153, 165, 269, 364, 368, 369, 370, 372, 375, 376, 385, and 390.

Table 2.6 Kentucky forest sector economic contribution estimates (Method 1)

Impact Type	Economic Contribution Level			
	Direct Effect	Indirect Effect	Induced Effect	Total Effect
Employment (#)	27475	13819	13858	55152
Labor Income($M)	1646	756	556	2957
Value-added ($M)	2584	1210	1000	4793
Output ($M)	9044	2322	1791	13157

NB: Contribution estimates are the same for all aggregation schemes, so one table is presented here.

Table 2.7 Kentucky forest sector economic contribution analysis: aggregated vs. unaggregated schemes (Method 2)

Impact Type	Scheme	Economic Contribution Level			
		Direct Effect (%)	Indirect Effect (%)	Induced Effect (%)	Total Effect (%)
Employment	*Current*	26817 (-1.22)	19361 (-1.36)	15551 (-1.24)	61730 (-1.27)
	New	25477 (-6.16)	18577 (-5.35)	14848 (-5.70)	58901 (-5.79)
	Unaggregated	27148	19627	15746	62521
Labor Income	*Current*	1611 (-1.10)	1021 (-1.35)	624 (-1.27)	3255 (-1.24)
	New	1517 (-6.88)	997 (-3.67)	596 (-5.70)	3110 (-5.54)
	Unaggregated	1629	1035	632	3296
Value-added	*Current*	2536 (-1.09)	1535 (-1.35)	1120 (-1.23)	5192 (-1.28)
	New	2430 (-5.23)	1501 (-3.53)	1070 (-5.64)	5001 (-4.82)
	Unaggregated	2564	1556	1134	5254
Output	*Current*	8859 (-1.09)	3135 (-1.29)	2007 (-1.23)	14001 (-1.16)
	New	8644 (-3.49)	3071 (-3.31)	1917 (-5.66)	13631 (-3.77)
	Unaggregated	8957	3176	2032	14165

NB: The current scheme reduces total effects (output) of forest sector contribution by $164 million (1.16%) ($14001-$14165). Similarly, the new scheme reduces forest sector contribution by $534 million (3.77%) ($13631-$14165).

Table 2.8 Forest industries and their aggregation in the 'new' aggregation scheme

New forest sector	IMPLAN codes
F1	16, 134, 135, 137, and 140,
F2	147,149,151,150, and 152
F3	136,373,368,374, and 399
F4	All other IMPLAN codes listed above

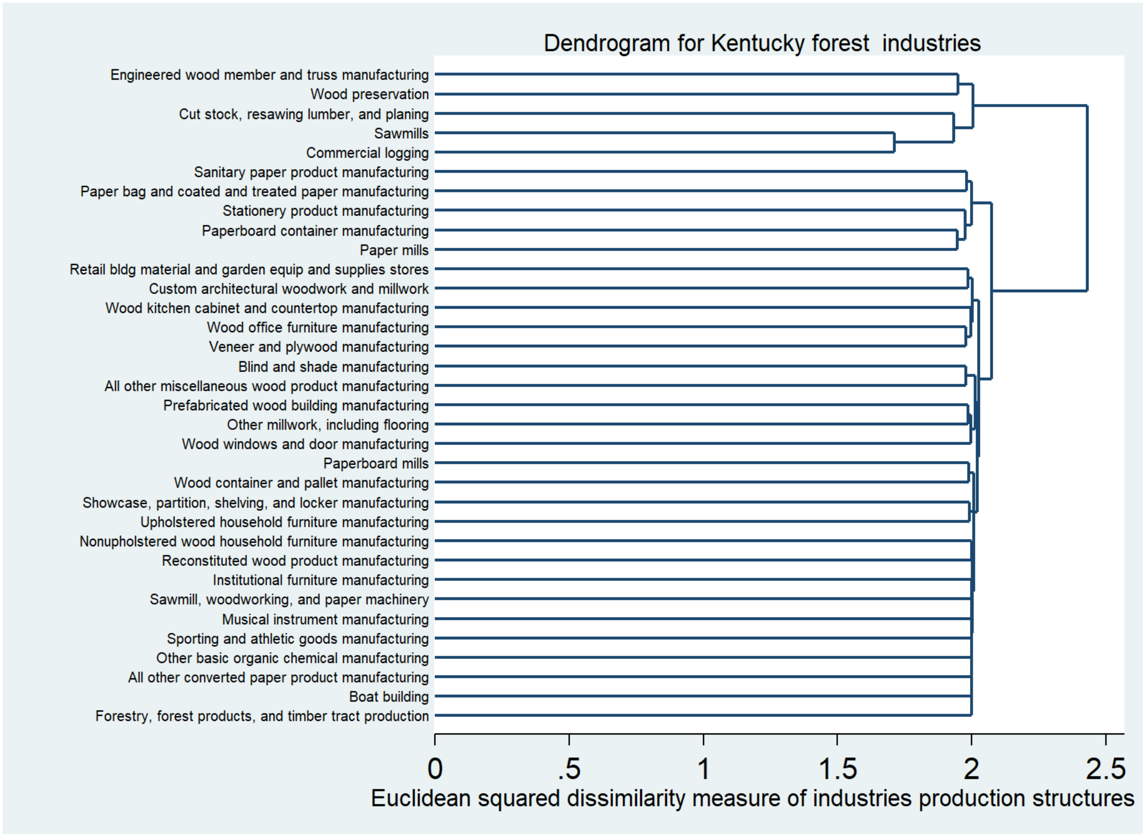

Figure 2.1 Dendrogram for Kentucky forest-based industries

Chapter 3. Factor Endowment and Forest Manufacturing Industrial Structural Change: A Cross-Country Analysis

Abstract

This study uses panel data regression analysis to examine the pattern of forest manufacturing industrial structural change induced by capital endowment changes. Also, the forest manufacturing industry's relative contribution is studied by analyzing the influence of the industry’s structure on aggregate economic growth. For the latter analysis, a dynamic panel data regression technique is employed to estimate a typical cross-country catch-up growth model. The study is guided by factor endowment-based structural change theorems that purport that an increase in the endowment of a factor will increase the output of the industries that use the factor more intensively. The study uses European Union Level of Analysis of Capital, Labor, Energy, Material, and Service (EU-KLEM) capital input data to create a panel data set consisting of two forest manufacturing industries (Wood and paper manufacturing industries) across 11 countries and spans 27 years. Using the forest manufacturing industry’s shares in employment and output as structural variables, results suggest that an increase in the capital endowment is negatively associated with forest industrial structure. The forest manufacturing industry's importance is observed through the positive influence of its structure on aggregate economic growth.

Keywords: Factor Endowment, Economic Growth, Structural Change, Forest Manufacturing Industry

3.1 Introduction

An economy's industry structure describes the relative shares of each industry in economic activities (Burfisher, 2017). Hence, industry structure changes can be measured as changes in industry shares in aggregated economic activities (van Neus, 2019). In this study, forest industry structure changes are defined as the changes in the industry's shares in employment and output relative to the entire economy totals. This study focuses on only the structure of the forest industry. But it is rooted in a large body of literature on industrial structural change, which is studied through understanding and analyses of changes in shares of the forest industry's economic activities in the overall state economy.

In the face of ongoing forest degradations and land-use change concerns, the global forest sector continues to provide economic, social, and ecological benefits to most economies (FAO and UNEP, 2020; Li et al., 2019; Agrawal, 2013; Lebedys and Li, 2014). The global forest sector provides a vast range of benefits to humans, including clean air and water, wildlife habitat, biodiversity, recreational opportunities, and aesthetic beauty. About one-third of humanity has close dependence on forests and forest products. The level of dependence on forest and forest products are expected to increase in the near future (FAO and UNEP, 2020; Forest Stewardship Council, 2013). Results from a recent global forest sector contribution analysis by Li et al. (2019) revealed that the forest sector contributed about $1298 billion to the global GDP and supported about 45.15 million jobs through direct, indirect, and induced impacts in 2011. Generally, the forest sector ensures the economic stability of rural households dependent on the sector for their economic well-being (Agrawal, 2013; Stedman et al., 2005).

The benefits provided by the global forest sector suggests that activities related to the forest sector are essential to the global economy. Therefore, changes in the structure of the forest sector may have a substantial influence on the global economy. Despite the constant absolute forest sector contributions, it appears the shares of the forest sector in aggregated economic activities has been declining in recent decades (Table 3.1 and Table 3.2). Table 3.1and Table 3.2 show declining shares of wood and paper manufacturing industries in output and employment. Given the level of dependence on the forest sector in most economies, determinants of patterns such as Table 3.1and Table 3.2 need to be investigated.

Answers to questions about the determinants of industrial structure (that is the shares of industries in economic activities) are important to understanding the basic structure and workings of an economy. Regarding the forest sector, a decline in the sector's shares in economic activities such as value-added, employment, and output, are commonly attributed to expansion of other sectors, especially the service sector. For example, in an FAO report, Lebedys and Li (2014) reported that the forest sector's global contribution to GDP had reduced from 1.2% to 0.9% between 2000 and 2011. This decline was attributed to the expansion of the service sector. Similarly, Agrawal et al. (2013) reported that changes in the forest sector contributions could be attributed to changes in economic activities of manufacturing and service sectors.

Intuitively, attributing the decline in forest sector shares in economic activities to an expansion of other sectors can be considered straightforward from a development economic perceptive. It indicates economic growth and development following changes in the industrial structure. Leading theorems on structural change attempt to understand changes in industrial structure through either supply or demand perspective. Demand side theorems attribute changes in industrial compositions to heterogeneity in industry demand structure and elasticity of demand among industries (Kongsamut et al., 2001). In contrast, supply side theorems explain changes in industrial composition based on variations in rates of technological growth (Ngai and Pissarides, 2007) and difference in factor intensities across industries (Ju et al., 2015; Acemoglu and Guerrieri, 2008). This study relies on the supply side theorem.

The supply side theorems emphasize the role of regional factor endowment and industry factor intensity in structural change. Factor endowment-based structural change theorem states that an increase in a region’s factor endowment will increase the output of industries that use the factor intensively and decrease output of industries that use the factor less intensively, consequently leading to a change in their composition in economic activities (Ju et al., 2015; Acemoglu and Guerrieri, 2008; Rybczynski, 1955). This means that changes in industrial structure is expected to align with a region's factor endowment fundamental (Ju et al., 2015; Che, 2012; Acemoglu and Guerrieri, 2008). Thus, it is important to examine the linkage between industrial structure and a region's factor endowment to confirm whether it conforms with factor endowment structural change theorems (Che, 2012).

Recent studies on the ongoing structural changes in the forest industry have considered the process as internal creative destructions, which involve consolidation and readjustment of forest-based sub-industries’ production capacity, which is induced by global interconnectedness, change in forest product demand, economic downturns, and the emergence of new forest products. The consequence of these restructuring processes is observed through changes in forest industry outputs (Hetemäki and Hurmekoski 2016; Ince et al., 2007). While the mentioned factors considered by structural change studies provide good basis for explaining changes in forest industry structure, it is critical to consider the role of other factors like regional factor compositions as suggested by standard factor endowment economic theorems (e.g., Ju et al., 2015; Che 2012; Acemoglu and Guerrieri, 2008; Rybczynski, 1955).

Drawing from the idea behind the stated factor endowment-based structural change theorem, this study seeks to examine the influence of factor endowment on forest manufacturing industry structure. This study contributes to the literature by empirically testing the factor endowment-based structural change hypothesis that a country's industrial structure shifts towards factor-intensive industries as the factor increases. Further, the study seeks to investigate the relative contribution of forest manufacturing industries by examining their structure's influence on aggregate economic growth. The latter analysis is an attempt to investigate the role of the forest manufacturing industry in economic growth.

3.2 Objectives

This study's objectives are: (1) to examine the linkage between factor endowment and forest manufacturing industry's structure and (2) to examine the influence of forest manufacturing industry's structure on aggregate economic growth.

3.3 Literature Review

This study is related to studies investigating the influence of a country's factor endowment on the output of sectors in a country. Using a two-sector model, Acemoglu and Guerrieri (2008) showed that if capital intensity varies among sectors, an increase in capital endowment would increase the relative output of the sectors use the capital more intensively. In an infinite number of industries model, Ju et al. (2015) proposed a factor endowment driven structural change theorem, which aligns to Acemolglu and Guerrieri (2008) finding. According to Ju et al. (2015), industries' structure follows a hump-shaped pattern where capital-intensive industries keep replacing less capital-intensive ones as capital endowment accumulates.

Che (2012) based his study on the theoretical assertions of Ju et al. (2015) and Acemoglu and Guerrieri (2008) and tested the hypothesis that an increase in capital endowment leads to a relative increase in the size of capital-intensive industries. Results showed that as capital endowments grow, industrial shares of employment and output become higher for capital-intensive industries. This study is closely related to Che (2012), who used a panel data regression technique to determine the linkage between capital endowment and industry structure (shares of the industry in employment and output) across countries. Focusing on forest-based industries in Australia, Austria, Canada, Denmark, Finland, Japan, Italy, Netherlands, Spain, U.K., and the U.S., a panel data regression is performed to determine the linkage capital endowment and factor forest manufacturing industry structure. This study differs from Che (2012) because it focuses on only the forest-based industries, while Che (2012) considered all industries in a country.

Though trade effects are not explicitly accounted for in this study, this study is related to a large body of international trade literature that seeks to empirically test factor endowment theorems by Heckscher-Ohlin and Rybczynski (1955)[8]. Findings from some of the studies in this research area show that changes in factor endowments (physical and/human capital and labor endowments) have a substantial influence on industrial structure (e.g., Reeve, 2006; Harrigan and Zakrajsek, 2000; Harrigan, 1997; Leamer 1984). For example, Harrigan (1997) used a cross country panel data to examine the influence of factor endowments (capital and labor) and TFP differences on the percentage shares of seven manufacturing industries (Food, Apparel, Paper, Chemicals, Glass, Metals, and Machinery) in output. Results indicated that capital and medium educated workers are generally associated with larger manufacturing output shares, while non-residential construction and highly educated workers are associated with lower output shares. Moreover, increased supply of producer durables is associated with a lower output share of the paper manufacturing industry. Results from Harrigan (1997) are identical to that of Leamer (1984) who used net exports of industries as the dependent variable.

Harrigan and Zakrajsek (2000) improved on the work by Harrigan (1997) by expanding their sample size and extending the study period (1970-1992). Results from Harrigan and Zakrajsek (2000) showed that capital abundance raises output share in the heavy capital-intensive industries, while capital abundance lowers share in less capital-intensive industries. The authors found that capital abundance lowers output share of wood and paper manufacturing industries, while abundance of labor (low and high educated

[8] Briefly, these theorems explain that increase in factor endowment will lead to more than proportional output increase in the output of the sectors that uses the factor more intensively, and for tradable goods, countries with factor abundance will have a comparative advantage in producing export goods.

workers) is associated with increased wood and paper manufacturing shares in output. Reeve (2006) used a modified factor proportion model in a general equilibrium framework to quantify the extent to which national factor endowment accumulation contributes to changes in industrial structure in a cross section of industrialized countries. Results showed that almost all manufacturing industries depend heavily on capital and moderately educated labor as source of comparative advantage. High-educated labor, on the other hand, tends to depress production output in manufacturing industries, including wood and paper manufacturing industries. Opp et al. (2009) and Suranovic (2004) demonstrated Rybcyznski theorem using graphical illustrations.

3.4 Data

Data on the factor endowment used in this study were obtained from the European Union Level of Analysis of Capital, Labor, Energy, Material, and Service (EU-KLEM) inputs database. The database provides detailed industry-level factors of production, output, output prices, and other growth accounting measures for EU and some non-EU countries, which dates back to 1970. The database is part of a research project supported by the European Commission, to analyze productivity in the European Union at the industry-level (Timmer et al., 2007). The overall capital stock in the database consists of detailed categories of assets such as computing equipment, transport equipment, residential structures, and other machinery equipment. Each capital stock is measured using the Perpetual Investment Method (PIM), which defines capital stock as a weighted sum of past investments with weights given by the relative efficiencies of capital goods at different ages (Timmer et al., 2007). Classification of industries in this database follows that of the Statistical Classification of Economic Activities in the European Community (NACE).

Based on data availability on the reported industries and their corresponding factor endowment across countries and years, this study focused on two forest-based manufacturing industries: (1) wood and wood product manufacturing and (2) pulp, paper, and paper product manufacturing. The two industries are referred together as the wood and paper manufacturing (WPM) industry throughout the text. A twenty-seven-year panel data, which spans from 1980 to 2007 was created for the two industries across 11 countries. The study period and countries included were mainly influenced by data availability on the reported capital endowments. Overall capital endowment for a country was measured as the log of real fixed capital stock. Industry capital intensity was measured as the ratio of industry capital stock to real output. Data on GDP per capita, government consumption, human capital, investment rate, population growth rate, and other country demographics used to estimate the growth model were obtained from the Bureau of Economic Analysis (BEA) database and the open-access world development data series.

3.5 Empirical Estimations

3.5.1 The Linkage Between Capital Endowment and Forest Manufacturing Industry Structure

The panel form of the basic equation used to examine the relationship between forest industrial structure and factor endowment is shown in equation 3.1. Forest-based industry shares in the total real output, total nominal output, and total employment are used as structural variables. The model specification used here follows Che (2012) closely in examining the linkage between capital endowment and industry structure.

$$lnY_{ijt} = \beta + \alpha_1 KEND_{jt}\ \alpha_2\left(K_{ijt} * KEND_{jt}\right) + \ \alpha_3 \mathbf{Z}_{ijt} + \mu_{ij} + \lambda_t + \varepsilon_{ijt} \tag{3.1}$$

where lnY_{ijt} is the log of forest-based industry $i's$ share of a country $j's$ employment or output in year t. $KEND_{jt}$ is overall capital endowment in a country. K_{ijt} is industry capital intensity. The interaction term between industry capital intensity and overall capital endowment at the national level is the main variable used to test the factor endowment-based structural change theorem. Thus, the critical parameter of interest is α_2[9]. The $\mathbf{Z}_{ijt}$ variables are controls, which include industry total factor productivity growth rate (TFP), real output per worker in a country j, and output price index of industry i. Population growth rate is used to control for country demographics (a proxy for labor growth). μ_{ij} is unobserved country-industry effect which assumes variation in an industry is country-specific. λ_t is unobserved time-specific effect and ε_{ijt} is an error term.

Equation 3.2 is estimated to allow for the potential of capital endowment growth effect, which is not accounted for in equation 3.1. All the variables in equation 3.2 are the same as those in equation 3.1 except the addition of a one year growth rate in overall capital endowment, $\Delta KEND_{jt}$.

$$lnY_{ijt} = \beta + \alpha_1 KEND_{jt} + \ \alpha_2\left(K_{ijt} * KEND_{jt}\right) + \ \alpha_3 \Delta KEND_{jt} + \ \alpha_4 \mathbf{Z}_{ijt} + \mu_{ij} + \lambda_t + \varepsilon_{ijt} \tag{3.2}$$

Following Che (2012) a standard score capital intensity was used in all regressions. Standardizing the capital intensity ensures that the intercepts α_1 and α_2 are invariant with

[9] The interaction term in this model is of interest due to its potential of suppressing industry-level endogeneity. α_1 will be biased if there is an exogenous shock that increases capital intensity and future output at the industry-level. However, for α_2 to be biased it has to be that capital intensity caused the bias, which is unlikely to happen.

respect to the level of capital endowment. The standard score was estimated by normalizing each industry's capital intensity with the mean and standard deviation of all forest-based industries' capital intensity in country j in period t. This suggests that the standard capital intensity score has a similar distribution within each country at time t. The standard score also considers the within-country variations of capital intensity across industries for each period (Che, 2012). TFP growth rate is used as a control variable as it has been identified as a significant driving factor of changes in industrial structure (Che, 2012; Ngai and Pissaridies, 2007).

From equations 3.1 and 3.2, the influence of overall capital endowment on the dependent variable can be estimated as, $\frac{\partial lnY_{ijt}}{\partial KEND_{jt}} = \alpha_1 + \alpha_2 K_{ijt}$. Since $\alpha_1 + \alpha_2 K_{ijt}$ is a linear function of industry capital intensity, K_{ijt}, it turns out that when $KEND_{jt}$ is high, then industries with high K_{ijt} should expand in terms of output. When the dependent variable is employment, the sign of α_2 depends on the elasticity of substitution between industries. For example, for capital intensive industries, α_2 would be positive if the elasticity of substitution between industrial goods is greater than 1, vice versa (Che, 2012).

The panel's unobserved heterogeneities can be controlled by using fixed effects (FE) or random effects (RE) estimators. The FE estimator assumes that the individual effects are constant. The FE estimator demeans all variables to remove all the between variations allowing only within variability. The random effect (RE) estimator assumes the individual effects are random and independent of both the right-hand side variables and the error term. A standard and commonly used Hausman (1978) test was used to test the independence of the individual effects and the error term and subsequently used to decide between the FE and RE estimators[10.]

3.5.2 Wood and Paper Manufacturing Industry Structure and Economic Growth

This study's second objective is to assess the relative contribution of the WPM industry in economic growth. To achieve this objective, the relationship between WPM industry structure and GDP per capita is examined. Specifically, this study estimates a traditional dynamic growth regression model that allows for the inclusion of traditional growth indicators and accounts for unobserved heterogeneities across countries through time. In addition, the share of WPM industry in value-added is included as a structural change indicator in the regressions. The dynamic specification is motivated by the fact that the coefficient of lagged GDP per capita accounts for potential differences in the steady-state growth rate between countries (conditional convergence) (Peneder, 2003).

$$\begin{aligned} lnG_{jt} = \beta + \alpha_1 SC_{jt} + \alpha_2 INV_{jt} + \alpha_3 POP_{jt} + \alpha_4 UNEMP_{jt} \\ + \alpha_5 EDUC_{jt} + \alpha_6 GOC_{jt} + \alpha_6 lnG_{jt-1} + \theta_j + \lambda_t + \varepsilon_{jt} \end{aligned} \tag{3.3}$$

where lnG_{jt} is the log of GDP per capita in country j at time t. SC_{jt} is the share of WPM industry in GDP in value-added. Thus, the main parameter of interest is α_1. POP_{jt} and $UNEMP_{jt}$ are population growth rate and unemployment rate, respectively. $EDUC_{jt}$ is average number of years of education in a country. INV_{jt} is growth rate in a country's investment in physical capital and GOC_{jt} is government consumption expenditure. θ_j and

[10] A missing piece of equation 3.1 and 3.2 is that it does not control for the initial influence of structural variables. Accounting for the initial influence in a dynamic specification has proven to be a good control, however the initial influence of Y_{ijt} was not controlled for in this study because when included, the model fails to pass the necessary dynamic model estimation tests.

λ_t are country and time fixed effects used to account for unobserved heterogeneities across countries and through time. ε_{jt} is an error term.

The independent variables used are standard indicators that have been used in several economic growth studies to capture different determinants of economic growth. Population growth rate (POP_{jt}) is included to control for the influence of demographic changes in the population of a country. Increase in population is expected to negatively influence GDP per capita, hence the expected sign of α_3 is negative. Unemployment rate ($UNEMP_{jt}$) is considered to account for country-specific differences in business cycles. Therefore, α_4 is expected to be negative as unemployment rate is countercyclical. INV_{jt} represents a country's investment in physical capital which reflects the influence of capital deepening of GDP per capita. α_2 is expected to be positive as increase in capital investment is positively associated with economic growth. Human capital is accounted for with the average years of education in a country ($EDUC_{jt}$) and it is expected to have a positive influence on economic growth. The effect of government consumption (GOC_{jt}) is not apparent a priori to estimation (Dreher, 2006), but the coefficient α_6 is anticipated to be negative as standard economic growth studies have found that higher government consumption can create market distortions leading to lower economic growth (e.g., Teixeira and Queiros, 2016; Moral-Benito, 2012; Dreher, 2006; Barro, 1991).

Including a lagged dependent variable as an explanatory variable in the dynamic specification (equation 3.3) causes an endogeneity problem due to the correlation between the error term (ε_{jt}) and the lagged dependent variable (lnG_{jt-1}), $E(lnG_{jt-1}, \varepsilon_{jt} \neq 0)$. The problem of endogeneity can be addressed by using a difference generalized method of moment (D-GMM) estimator (Arellano and Bond, 1991) or a system generalized method of moment (S-GMM) estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). Both estimators create special instruments for the endogenous variable. The D-GMM estimator constructs the dynamic regression equation's first differences, then forms a system of equations, one per period. Lagged levels of valid instruments or variables are then applied to the differenced equation in each period. The S-GMM estimator adds levels of the dynamic regression equation to the first differenced equation to form a system of equations. The S-GMM uses lagged levels of the endogenous variables to instrument the first-differenced equations, while lagged first-differences are used as an instrument in the level equation. Both estimators are useful in addressing endogeneity problems, however, the S-GMM is more efficient (Arellano and Bover, 1995; Blundell and Bond, 1998)[11]. Further, the S-GMM is superior to standard OLS and fixed effect models in terms of correcting unobserved country heterogeneity and omitted variable bias issues in growth models (Bond et al., 2001).

The GMM estimators are divided into one-step and two-step variants. The two-step and one-step GMM estimators differ in the weighting matrix used in their estimation process. The one-step GMM uses weight matrices independent of estimated parameters, while the two-step GMM weights the moment conditions by a consistent estimate of their covariance matrix (Windmeijer, 2005). The two-step GMM is asymptotically more efficient and robust to heteroskedasticity and autocorrelation than the one-step GMM. However, standard errors from the two-step estimation tend to be severely biased downward in finite samples (Arellano and Bond, 1991; Blundell and Bond, 1998). Windmeijer (2005) provides a finite sample correction procedure for the two-step GMM

[11] Arellano and Bover (1995) and Blundell and Bond (1998) revealed that D-GMM has a potential weakness as the simple lagged levels tend to be poor instruments for the differenced equation.

estimation process, making the two-stem GMM more efficient than the one-step GMM in finite samples. In this study, the Windmeijer (2005) correction to the two-step GMM standard errors was applied, hence it can be expected that the two-stem estimator is more efficient than the one-step GMM. Regression results for both one-step and two-step estimators are reported for comparison.

To ensure the chosen model specification and estimators yield correct estimates, recommended diagnostic tests were performed. The GMM estimators are inconsistent in the face of serial correlation in the error term. Based on the null hypothesis that there is no autocorrelation in the model, the Arellano and Bond (1991) recommended tests for first-order and second-order serial correlations were conducted to confirm the generated instruments' validity. Direct diagnostic tests of overidentification restrictions on the exogeneity of the generated instruments are provided by Hansen (1982) and Sargan (1958). The null hypothesis of these tests is that all instruments generated in the estimation process are exogenous when considered as a group. The Hansen (1982) test was used in this study because it outperforms the Sargan (1958) test in small sample sizes. The Roodman (2009) collapse option was used to avoid over proliferation of instruments.

The GMM estimators are generally more effective for dynamic panel specifications with few periods T and large individuals N. Therefore, based on the data available, a new panel was created to meet this condition, but with a reduced number of observations compared to the static equations 3.1 and 3.2. The new panel consists of twenty countries and spans from 1997 to 2007[12]. In addition to the dynamic specification, WPM industry

[12] The countries are: Australia, Austria, Belgium, Canada, Denmark, Finland, Germany, Greece, Finland, France, Japan, Italy, Ireland, Luxemburg, Netherlands, Portugal, Spain, Sweden, U.K. and U.S.

structure's influence on economic growth was assessed using the static form of equation 3.3 with a fixed effect estimator.

3.6 Summary Statistics

3.6.1 Dependent Variables

The study uses the shares of WPM industries across 11 countries in employment, real output, and nominal output as dependent variables models 3.1 and 3.2. The dependent variable in each country and for each forest-based industry was calculated as follows:

$$E_{jit} = \frac{E_{jit}^{f}}{E_{jt}} \quad \text{and} \quad O_{jit} = \frac{O_{jit}^{f}}{O_{jt}}$$

where E_{jit}, and O_{jit} are employment share and output share, respectively for forest-based industry i in country j at time t. In a respective order, E_{jit}^{f} and O_{jit}^{f} represent employment, and output of industries in forest-based industries. E_{jt}, and O_{jt} are respectively the employment and output for all industries in a country. O_{jit} was estimated for both real output and nominal output. GDP per capita is measured at purchasing power parity (PPP) of 2017. GDP at PPP is converted to international dollars using PPP exchange rates. This makes the GDP per capita estimates comparable across countries (International Comparison Program-World Bank, 2020). Summary statistics of the dependent variables used in all regressions are reported in Table 3.1. Summary statistics of the explanatory variables are reported in Table 3.2

3.7 Results

3.7.1 Linkage Between Forest Manufacturing Industry Structure and Capital Endowment

The null hypothesis of independence between the individual effects and the error term was not rejected from the Hausman tests on models 3.1 and 3.2. This means that the random effect model was considered to be more appropriate. Results from models 3.1 and 3.2, which examine the linkage between forest manufacturing industry structure and capital endowment, are reported in Table 3.3 For each dependent variable, estimates from model 3.1 are reported under column label (1) without the capital endowment growth effect. Estimates from model 3.2 with capital endowment growth effects are reported under column (2). It was observed that interaction between overall capital endowment and capital intensity is associated with lower share of WPM industry employment for all regressions. The same observation was made when the dependent variable is real output or nominal output shares. The coefficient of capital endowment growth effect (ΔKEND) reveals a negative relationship with WPM industry employment and real output. Results show that total factor productivity growth rate (TFP) is associated with low WPM industry share in employment. On the contrary, a positive and significant relationship is observed between TFP and WPM industry share in real output.

3.7.2 Forest Manufacturing Industry Structure and Economic Growth

The relationship between WPM industry structure and economic growth is reported in Table 3.4. For the GMM estimations, the null hypothesis of no first-order serial correlation is rejected following the significance of the Arrelo and Bond (1991) first-order serial correlation test (AB (1)). This is not a concern as the null hypothesis of no serial correlation is not rejected under the second-order Arrelo and Bond (1991) serial correlation test (AB (2)). The Hansen (1982) test on the GMM estimations reveals that the instruments used are exogenous. Results from both the S-GMM and D-GMM estimations show that forest manufacturing industry structure (measured as the sum of wood and paper manufacturing share in total real value-added) has a positive and significant influence on GDP per capita. This relationship is observed under both the one-step and two-step estimations. All the economic growth determinants used in the GMM estimations showed the expected signs, with the investment rate having the highest influence.

The coefficient of population showed the expected sign of a negative relationship with GDP per capita, but the coefficient estimates were not significant under the S-GMM estimations. As expected, government consumption was found to be negatively associated with GDP per capita, but this result was significant (at 10% significance level) under only the S-GMM estimation. Lagged GDP per capita had a positive and highly significant association with GDP per capita in period t. The coefficient estimates of lagged GDP per capita were less than 1 which depicts a typical conditional convergence result. Results from the static fixed effect model (column 6) were identical to the dynamic specification. The static model revealed that increase in WPM industry share in value-added leads to an increase in GDP per capita growth. Similar to the GMM estimations, the fixed effect estimation shows that capital investment growth rate and population growth rate are important determinants of economic growth with a respective positive and negative influence on GDP per capita.

3.8 Discussions

3.8.1 Linkage Between Forest Manufacturing Industry Structure and Capital Endowment

This study uses a cross-country panel data regression to examine the influence of capital endowment on forest manufacturing industry shares in economic activities. Further, the industry's relative contribution to economic growth is examined by assessing the relationship between share forest manufacturing industry in value-added and GDP per capita. In this study, forest-manufacturing consists of wood and paper manufacturing (WPM) industries. Results suggest a negative relationship between capital endowment and WPM industry shares in employment and output as the industry usage of capital intensifies. Based on the factor endowment-based structural change theorem that guide this study, an increase in capital endowment increases capital-intensive industries' size. This further explains that labor productivity will decline in labor-intensive industries if more labor is not used together with capital, leading to a reduction in output. As shown in Figure 3.3 and Figure 3.4 below, the WPM industries considered here were fairly labor-intensive over the study period. Hence, the negative relationship between capital endowment and forest sector output is consistent with the factor endowment-based structural change theorems and empirical studies. A possible explanation for the estimated negative relationship is that major displacements of WPM industry labor occur as the industries' capital usage intensifies, leading to reduced labor productivity and a consequent reduction output. As reported in Table 3.4, both the interaction term of capital endowment and industry capital intensity and capital growth is negatively associated with employment. As mentioned above, the capital-employment relationship is dependent on the elasticities of substitution of industries.

When the elasticity is above unity, employment shares of capital-intensive industries increase as capital increases (Che, 2012). However, predicting based on the elasticity of substitution across industries is difficult to apply due to differences in elasticities of substitution across different industries. Further, many industries produce intermediate goods that do not reach final consumers (Che, 2012; Oulton, 2001).

The negative relationship between capital endowment and forest industry structure observed in this study is in line with findings from other cross-country studies that focus on factor endowment differences as a source of specialization. For example, Harrigan and Zakrajsek (2000) and Harrigan (1997) found that increased capital is negatively associated with the percentage share of WPM industry output. Though trade effects are not explicitly accounted for in this study, the similarity in findings from some past studies that did and those that did not account for trade (see Harrigan and Zakrajsek, 2000; Harrigan, 1997; Leamer, 1984) points to the conclusion that, the results from this study can partly be attributed to the fact that capital endowment is not a source of comparative advantage for WPM industries. Contrary results exist (e.g., Reeve, 2006). Results indicate that increase in TFP growth is associated with a high WPM industry share in real output. This result is consistent with previous factor endowment studies (e.g., Che, 2012; Ngai and Christopher, 2007; Harrigan, 1997), and shows that industrial structure shifts toward industries with higher TFP.

3.8.2 Evolution of Factor Intensity in Wood and Paper Manufacturing Industries

An examination of the evolution of factor intensities in the forest industries throughout study revealed that both the wood and paper manufacturing industries were labor-intensive (Figure 3.3 and Figure 3.4). The ratio of factor compensation to industry output was used as a measure of both labor and capital intensities. Figure 3.3 and Figure 3.4 show that the share of labor compensation in industry output is mostly higher in both wood and paper manufacturing industries, and this is observed across all countries. The only exception is for the paper manufacturing industry in Finland, where capital compensation share rises above labor compensation share in 1995, and between 1998 and 2002. However, the industry became more labor-intensive afterward.

3.9 Summary and Conclusions

Examination of the changes in industrial structure is important in assessing growth in sectors and the workings of an economy. Further, it is essential to understand the factors that drive these changes. Standard factor endowment theorems suggest a linkage between a region's factor endowment and the structure of sectors in the region. This factor endowment and sector structure relationship reveal that an increase in a factor leads to an increase in the output of sectors that use the factor more intensively. In contrast, the output of sectors that use the factor less intensively decreases. Consequently, the sectoral composition of the economy changes as factor endowment changes. The present study attempts to empirically test this factor endowment structural change theorem on the forest manufacturing industry.

In this study, EU-KLEM physical capital input data is used to create a panel data set which consists of two forest manufacturing industries (wood and paper manufacturing (WPM)) across 11 countries. Using WPM industries shares in employment and output as structural variables, a random effect panel data regression is used to determine the linkage between national-level capital endowment and WPM industry structure. Beyond this factor endowment and WPM industry structure linkage assessment, this study determined the relative contribution of the global WPM industry by analyzing the influence of changes in the industry's shares in value-added on aggregated economic growth. For the latter analysis, a dynamic panel data regression technique was employed to estimate a typical cross-country catch-up growth model.

The results show that capital endowment growth is a significant determinant of WPM industry structure but shows a negative relationship. An investigation of the evolution of factor intensities in the WPM industries revealed that they were labor-intensive over the study period (1980-2007). Hence, these results are in line with the factor-endowment structural change theorems, which posit that industries that use a factor less intensively will contract as that factor accumulates. In this case, capital was used less intensively in the WPM industries over the study period. Finding corroborates theoretical projections of the influence of TFP growth on sector structure. According to Ngai and Pissarides (2007), sector structure moves towards industries with higher TFP. The significance of the WPM industry in an economy is observed through a positive and significant influence of their shares in value-added on GDP per capita growth. The results are also consistent with both the theoretical and empirical predictions of key economic growth indicators.

Findings from this study have important pragmatic implications and could be a source of valuable information for policy makers. The fact that regional factor endowment accumulation has a significant influence on forest-industry structure means that policies intended to sustain the industry should not only be industry-specific but should also exploit other regional factors (Reeve, 2006). The observed negative relationship between capital and forest industrial structure suggests the need for both capital and labor resources to flow across all forest-based manufacturing industries with relative ease as factor composition changes. Additionally, moving forward, capital usage in forest manufacturing industries can be expected to intensify for productivity gains. Hence, to achieve a balance between capital and labor usage there is the need for policies that invest in education of industry players on the importance of appropriately accompanying capital employment with commensurate labor. Further, policies that provide incentives to make forest industry related jobs attractive to both current and future employees are needed. This is important because it has been found that some forest industry jobs are not attractive to employees due to factors such as low wages (Abt, 2013; Baker and Greene, 2008). Further, from the economic growth analysis, an important take away from this study is that though the relative size of the forest-manufacturing industry is small it is still an important contributor of economic growth and has the potential to contribute more if needed resources are provided to ensure that the industry is sustained.

Though information on the relative contributions in output and employment and factor usage of the wood and paper industries over the study period is revealing, this study is limited by the use of small dataset which extends from 1980 to 2007. The wood and paper industries have undergone substantial changes from the study period. Hence, the estimated coefficients' magnitudes and directions might vary if more recent data is applied in future studies. Further, future research can look into other forest-based industries like logging, which contributes substantially to the total shares of forest sectors in most economies. Lastly, future studies may look into other forest-industry characteristics that would influence forest industry growth when interacted with factor endowments. An example of these characteristics could be human capital intensity.

3.10 Tables and Figures for Chapter 3

Table 3.1 Summary statistics of GDP per capita and WPM industry shares in employment and output

	Mean	Min	Max
Employment share	0.0141 (0.0084)	0.0028	0.0482
Real output share	0.0199 (0.0171)	0.0025	0.0965
Nominal output share	0.0187 (0.0155)	0.0026	0.0944
Log GDP per capita ($m)	10.6470 (0.2781)	9.8341	11.6562

NB: Author's estimates from data. Standard deviations are in parentheses.

Table 3.2 Summary statistics of independent variables in models 3.1, 3.2, and 3.3

Independent variables			
Models 3.1 and 3.2	Mean	Min	Max
Capital endowment ($m)	5.4139 (1.6180)	3.3644	9.9357
Capital endowment growth rate	0.0035 (0.0047)	-0.0078	0.0226
Industry TFP growth index (Log)	4.6001 (0.0598)	4.3912	4.7488
Industry output price index (Log)	4.4741 (0.2421)	3.4909	5.0902
Log of output per worker ($m)	1.6098 (0.2388)	1.3242	2.2869
Population growth rate	0.5832 (0.4528)	-0.1616	1.8511
Model 3.3	Mean	Min	Max
Wood and paper manufacturing share in real value-added	0.0343 (0.0425)	0.0085	0.2226
Average years of education (years)	16.0810 (1.5404)	12.4000	20.7000
Government consumption (% GDP)	18.9654 (3.2137)	10.2013	25.7127
Investment growth rate	0.0418 (0.0522)	-0.2095	0.2259
Population growth rate	0.6256 (0.5017)	-0.1337	2.8910
Unemployment rate	6.8277 (2.8788)	1.8050	17.8000

NB: Author’s estimates from data. Standard deviations are in parentheses.

Table 3.3 Linkage between forest manufacturing industry structure and capital endowment

	Employment		Real Output		Nominal Output	
	(1)	(2)	(1)	(2)	(1)	(2)
K*KEND	-0.006*** (0.0023)	-0.0059** (0.0023)	-0.0058* (0.0032)	-0.0059** (0.0031)	-0.0077** (0.0030)	-0.0077** (0.0029)
KEND	-0.0859 (0.1135)	-0.1137 (0.1142)	-0.1417 (0.1287)	-0.1469 (0.1306)	-0.1842 (0.1334)	-0.1850 (0.1383)
ΔKEND		-2.3494** (1.1692)		-2.4534* (1.4323)		-1.8182 (1.2896)
TFP	-0.80*** (0.2081)	-0.8258*** (0.1950)	0.9373** (0.3096)	0.9534** (0.3057)	0.3243 (0.3442)	0.3503 (0.3448)
Price	0.0659 (0.1415)	0.0221 (0.1401)	0.0726 (0.1533)	0.0513 (0.1507)	0.1896 (0.1566)	0.1799 (0.1565)
POP	0.0685** (0.0363)	0.0687*** (0.0351)	0.0780** (0.0364)	0.0729** (0.0350)	-0.0029 (0.0407)	-0.0085 (0.0388)
OPW	0.6765 (0.8531)	0.9808 (0.8787)	-0.6360 (1.0875)	-0.7611 (1.1286)	-0.9680 (0.9176)	-1.0055 (0.9530)
Constant	-1.5343 (1.3632)	-1.5479 (1.3271)	-7.0150*** (1.5580)	-6.7765*** (1.5888)	-3.8939 (1.5465)	-3.9457 (1.5570)
No. of Obs.	566	566	566	566	566	566

NB: K is industry capital intensity measured as the ratio of capital stock to real output. KEND is national capital endowment measured as the log of overall real capital stock for all industries in a country. K*KEND is an interaction between industry capital intensity and overall capital endowment. POP, OPW and Price and are population growth rate, country's real output per worker, and industry output price index variables. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.4 Influence of forest manufacturing industry structure on economic growth

	System GMM		Difference GMM		Fixed Effect
	Two-step	One-step	Two-step	One-step	
WPM	0.0880** (0.0326)	0.0984*** (0.0299)	0.5005** (0.2016)	0.4040*** (0.1865)	0.4120** (0.1958)
INV	0.2060*** (0.0557)	0.2107*** (0.0498)	0.2099*** (0.0703)	0.1793*** (0.0611)	0.1894*** (0.0518)
EDUC	0.0002 (0.0025)	0.0002 (0.0014)	0.0015 (0.0022)	0.0021 (0.0025)	-0.0006 (0.0021)
POP	-0.0071 (0.0067)	-0.0052 (0.0057)	-0.015*** (0.0037)	-0.0118** (0.0041)	-0.0162** (0.0045)
GOE	-0.0018* (0.0010)	-0.0020* (0.0011)	-0.0008 (0.0035)	-0.0018 (0.0026)	-0.0023 (0.0018)
UNEMP	-0.0006 (0.0014)	-0.0004 (0.0007)	-0.0015 (0.0011)	-0.0013 (0.0008)	-0.000 (0.0005)
GDP	0.9973*** (0.0390)	0.9996*** (0.0261)	0.9397*** (0.0685)	0.8796*** (0.0582)	
Time dummy	Yes	Yes	Yes	Yes	Yes
R-square					0.6483
No. of Obs.	195	195	175	175	215
AB (1)	0.035	0.041	0.024	0.039	
AB (2)	0.185	0.188	0.143	0.108	
Hansen	0.349	0.160	0.58	0.58	

NB: GDP is one period lag of GDP per capita. WPM represents the combined share of wood and paper manufacturing in total real value-added. AB (1) and AB (2) are the Arrelano and Bond (1991) serial correlation tests 1 and 2, respectively. Hansen is Hansen (1982) test for exogeneity of instruments. Within R-squares are reported for the Fixed effect regression. Robust standard errors are reported in parenthesis for all regressions. *** p<0.01, ** p<0.05, *0.1

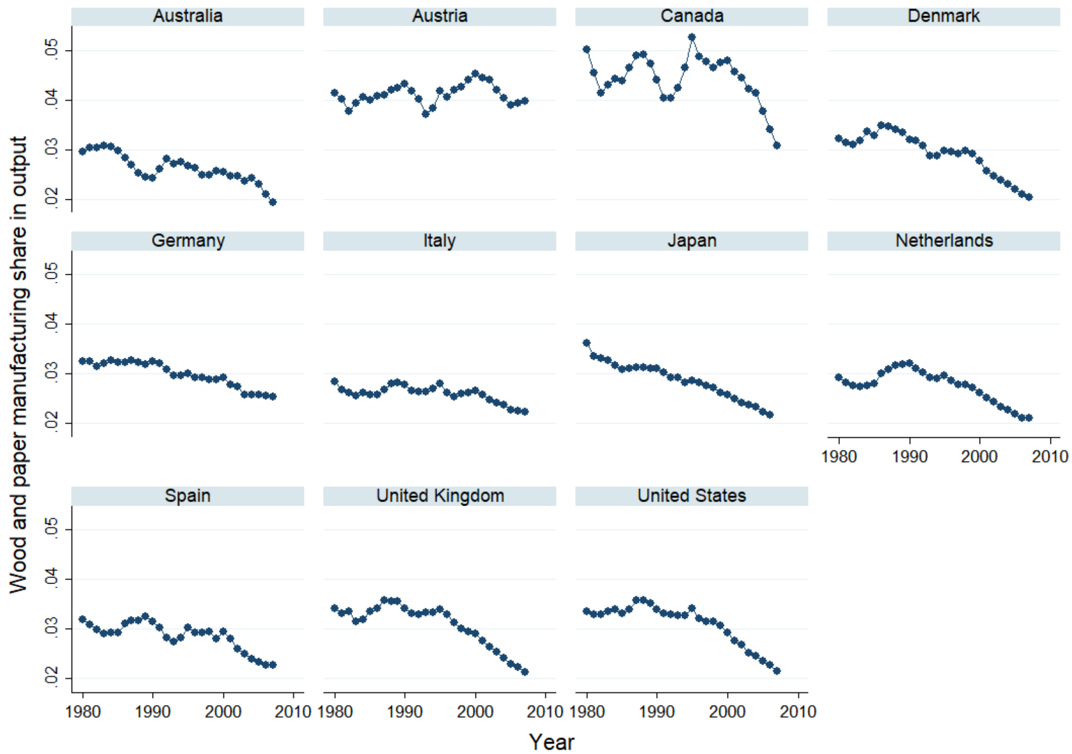

Figure 3.1 Share of wood and paper manufacturing industries in output (European Union Level of Analysis of Capital, Labor, Energy, Material, and Service data 1980-2007)

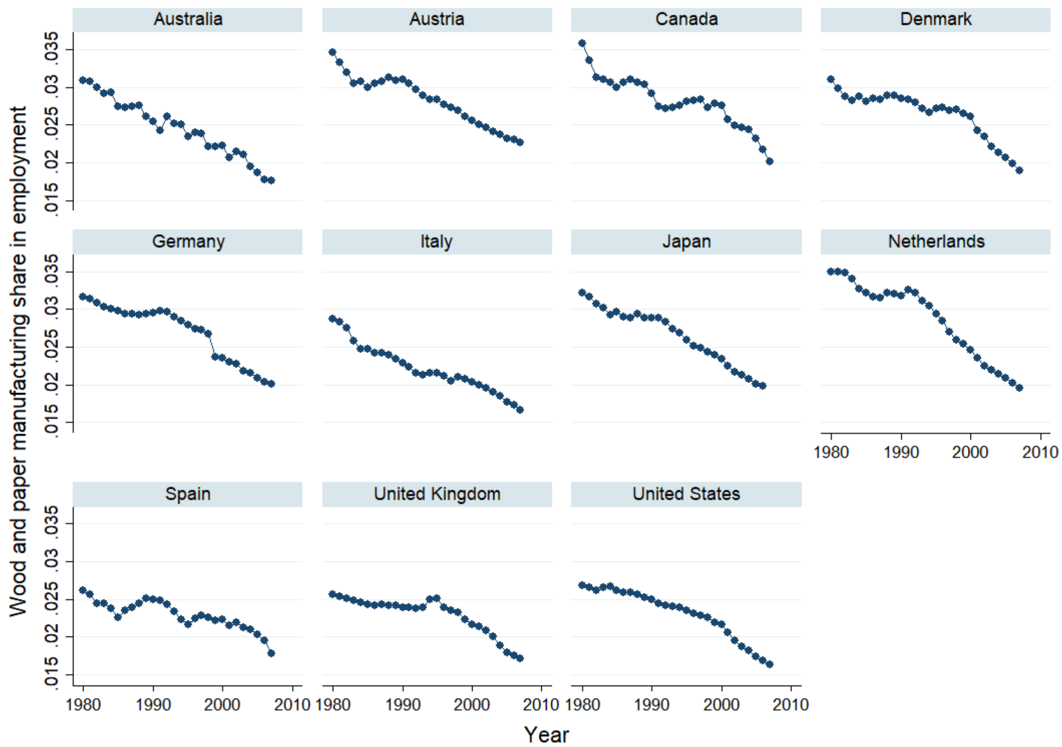

Figure 3.2 Share of wood and paper manufacturing industries in employment (European Union Level of Analysis of Capital, Labor, Energy, Material, and Service data 1980-2007)

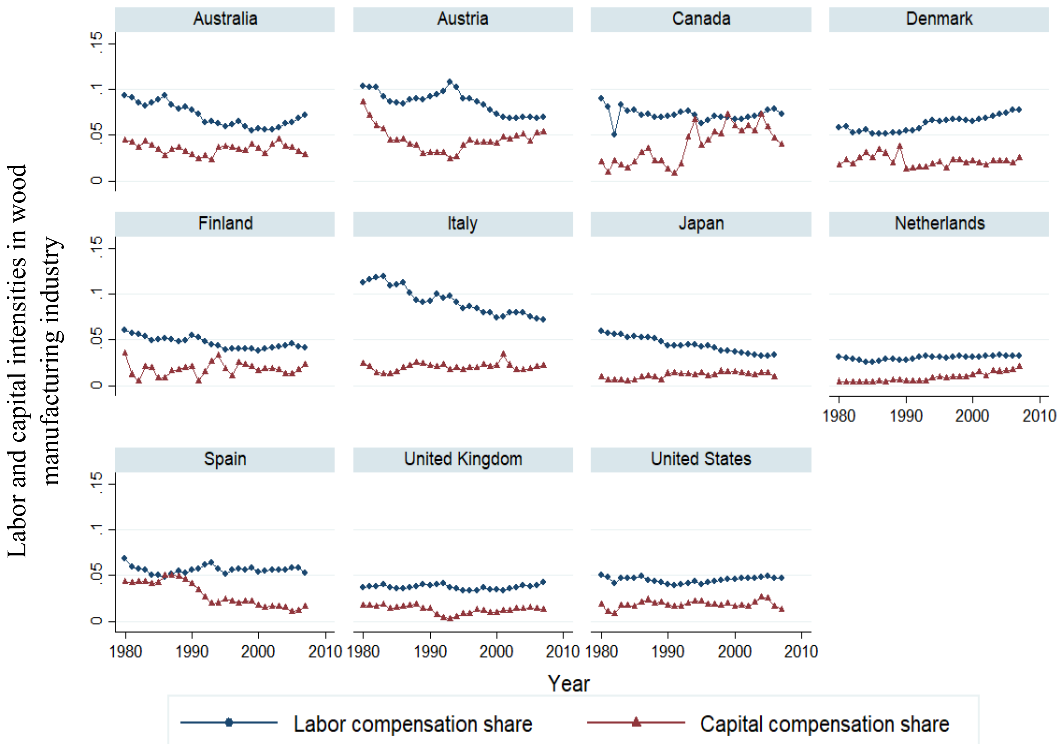

Figure 3.3 Evolution of labor and capital compensation shares in the wood manufacturing industry

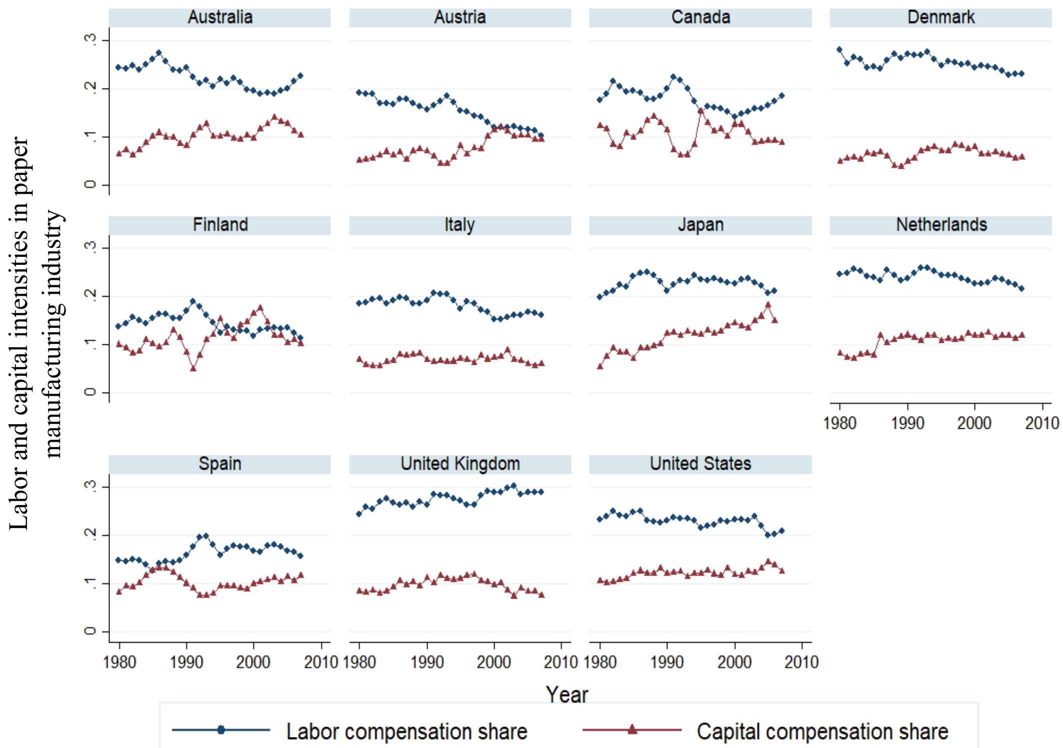

Figure 3.4 Evolution of labor and capital compensation shares in the paper manufacturing industry

Chapter 4. Factor Endowment and Structural Change in Kentucky Forest Industry

Abstract

Factor endowment-based structural change theorems posit that increases in factor endowments of a region leads to an increase in output of the industries that use the factors intensively. This study uses a dynamic panel regression analysis to examine the linkage between factor endowment and structural changes in Kentucky forest industry. The analysis uses forest-based industries' shares in employment and real output as structural variables in the regressions. Results show that increase in both capital and labor endowments positively and significantly influences forest industry structure as the industry uses the respective factors intensively. However, the magnitude of the influence of labor endowment is higher than that of the capital endowment. Finding indicates that both capital and labor compositions are important determinants of forest industrial structural change, thus simultaneously using both factors is crucial for improving forest industrial structure.

Keywords: Factor Endowment, Structural change, Forest Industry, Kentucky

4.1 Introduction

Chapter 3 above investigated the linkage between factor endowment and forest industry structure in a cross-country analysis. This chapter has a similar motivation, but the analysis is conducted in a single region (Kentucky).

An economy's industry structure describes the relative shares of each industry in economic activities (Burfisher, 2017). Hence, changes in industry structure can be measured as changes in industry shares in aggregated economic activities (van Neus, 2019). In this study, forest industry structure changes are defined as the changes in the industry's shares in employment and output relative to the entire economy totals. This study focuses on the Kentucky forest industry, however it is rooted in a large body of literature on industrial structural change, which is studied through understanding and analyses of changes in shares of the forest industry's economic activities in the overall state economy.

Collectively, southern states in the US hold about 41% of the country's timberland and contributes about 2% to the south's GDP (Brandeis and Hodges, 2015). Findings from Pelkki and Sherman (2020) revealed that 60% of the top US states with the greatest direct forest economic contribution are in the southeastern region, which indicates how important the forest sector is to southern states economies. As such, the economic analysis of changes in forest sectors in southern states is essential for southern economies. Kentucky is one of the 13 southern states in the US. Annual forest economic contribution estimates suggest that the Kentucky forest sector has consistently made a total output contribution of over $13 billion and employed nearly 60,000 people in recent years (see Stringer et al., 2020). This and many non-market forest products and ecosystem services (such as clean air and water, wildlife habitat, biodiversity, recreational opportunities, and aesthetic beauty) provided by woodlands in Kentucky make activities related to the forest sector vital to the state's economy. A notable change in the Kentucky forest industry structure is the reduction in the share of the forest-based manufacturing industries in the state's GDP. Figure 4.1 shows that the percentage shares of wood, furniture, and paper manufacturing sub-industries in state GDP have declined in recent decades, especially for paper manufacturing. However, the value-added of these sub-industries increased over the same period.

The reduction in share of the forest-based industries could be attributed to the expansion of other sectors. For example, the recent expansion of the service sector has caused forest industry shares in global GDP to reduce (Lebedys and Li, 2014; Agrawal, 2013). Such attribution can be considered straightforward from a development economic perceptive in that it indicates economic growth and development following changes in the industrial structure. Leading theorems on structural change attempt to understand changes in industrial structure through either supply or demand perspective.

Demand side theorems attribute changes in industrial compositions to heterogeneity in industry demand structure and elasticity of demand among industries (Kongsamut et al., 2001). In contrast, supply side theorems explain changes industrial composition based on variations in rates of technological growth (Ngai and Pissarides, 2007) and difference in factor intensities across industries (Ju et al., 2015; Acemoglu and Guerrieri, 2008; Rybczynski, 1955). This study relies on the supply side theorem. The supply side theorems emphasize the role of regional factor endowment and industry factor intensity in structural change.

Factor endowment-based structural change theorem states that an increase in a region's factor endowment will increase the output of the industries that use the factor intensively and decrease output of industries that use the factor less intensively, consequently leading to a change in their composition in economic activities (Ju et al., 2015; Acemoglu and Guerrieri, 2008; Rybczynski, 1955). Guided by this factor endowment-based structural change theorem, this study employs a panel data regression analyses to empirically investigate the influence of factor endowment on forest-based industry structure in Kentucky. Understanding the role of factor endowment in industrial structure changes has several advantages including, knowledge of factors that are sources of comparative advantage for industries, knowledge of the factors needed to improve industries, and understanding of the overall workings of an economy (Ju et al., 2015; Reeve, 2006).

The objective of this study is to determine the linkage between factor endowments and Kentucky forest industrial structure. This study contributes to the literature on structural change by empirically testing factor-endowment based structural change theorem in forest-based industries, which is informative for recommending policy options that will support and ensure growth and sustainability of the forest industry.

4.2 Data

Focusing on one state made it difficult to obtain a large industry-level data series to effectively determine this linkage between industry structure and factor endowment while accounting for the variation in forest-based industries over time. This is because publicly available data at the state level comes in highly aggregated forms and does not provide industry factor usage information. For example, the U.S. Bureau of Economic Analysis (BEA) provides industry capital stock information at the national level but not at the state level. This study uses data from the Impact and Economic Analysis for Planning (IMPLAN) software and database. The IMPLAN system provides annual detailed information on the industry's production activities, number of employees, value-added, and total output in input-output and social accounting (SAM) frameworks.

The IMPLAN system was designed originally by the U.S. Forest Service to estimate the regional economic impacts of National Forests (Alward et al., 1985), and is currently maintained by the IMPLAN Group LLC. There are several applications of the IMPLAN software and data in analyzing forest-based industry contribution and impact analyses, and other forests related research. The IMPLAN data is constructed from several data sources like the U.S. Bureau of Economic Analysis (BEA), U.S. Bureau of labor statistics (BLS), and the U.S. Department of Agriculture (IMPLAN Group, 2016). The IMPLAN system provides data on industries at the county, state, and national levels. IMPLAN industry schemes are based on North American Industry Classification System (NAICS) codes but represent differing levels of NAICS code rollups (Clouse, 2020). The number of industries reported depends on the data year. For example, the number of industries reported in the database was 544 for 2018 while 536 industries were reported for 2015-2017. These changes in the IMPLAN industry scheme are usually induced by occasional BEA's updates in their input-output accounts which serve as one of the major sources of data for constructing the IMPLAN database (Clouse, 2020).

Input-output and social accounting matrices report detailed information on industries in an economy while accounting for the industries' linkages. These linkages represent inter-industry transactions or dollar flows between industries needed to produce goods and services (Miller and Blair 2009). An input-output matrix of industries consists of three basic components, which include intermediate demand, value-added, and final demand. Intermediate demand shows the amount of an industry's output used as inputs by other industries in the economy. The value-added account contains industry payments for factors of production, including labor and capital. The final demand represents sales of industries output to final users (also known as institutions), including households, government, investment, and exports. A SAM extends an input-output matrix by incorporating transactions and transfers between institutions based on income distribution in an economy (Miller and Blair, 2009). Hence, the traditional input-output relationships can be considered as a subset of the accounts in a SAM (Llop and Manresa, 2014; Miller and Blair, 2009).

Since 2010, the Department of Forestry and Natural Resources at the University of Kentucky has been acquiring IMPLAN data for the state of Kentucky. This study utilized the Kentucky IMPLAN database for the years 2010-2018 (years available). For each year, the traditional input-output accounts were extracted from a detailed industry by industry SAM[13.] Focusing on the forest industry, data on all forest-based industries was isolated from other industries each year. From the value-added account, each forest-based industry's labor and capital payments were obtained and used to measure each industry's labor and capital endowments. The logs of total labor and capital payments by all industries in the economy were used to measure overall labor and capital endowments at the state-level.

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[13] The IMPLAN reported input-output tables are highly aggregated which does not show all detailed industries. Hence, an industry by industry SAM with detailed industries was first constructed for each year before extracting the information needed from the forest-based industries.

Industry's capital and labor endowments to real output ratios[14] were used as the primary measure of industry capital and labor intensities.

Due to the occasional changes in the IMPLAN industry scheme, the number of forest-based industries obtained from the database is not the same for all years. Selection of forest-based industries was based on the output claim of industries in the database. This study focuses only on industries that have 100% of their output claimed under the forest industry. This clarification is important because it is a common practice in selecting forest-based industries (especially for contribution and impact analyses), to consider industries that have forest products as part of their overall output. For example, music instrument manufacturing (IMPLAN code 390) produces both metallic and wood musical instruments. Therefore, through survey studies, the percentage of the industry's output that consists of wooden musical instruments can be obtained and used in a contribution or impact analysis. For the case of Kentucky, the percentages claimed from such industries are usually small[15] (compared to the whole) for them to be classified as forest-based in this study. Also, including such industries would require taking correct percentages of all their components in the SAM matrices. Detailed information needed for taking these percentages was not available. Further, assuming that the percentage of overall output claimed applies to the individual components of the industry in the SAM (e.g., factor endowments, intermediate demands, final demand etc.) could be erroneous because claiming 10% of an industry's

[14] The IMPLAN system automatically applies appropriate deflators to its output values, hence the reported output values are adjusted for inflation (Lucas, 2020).

[15] Information obtained through personal communication with extension personals at the Department of Forestry and Natural Resources at the University of Kentucky indicates that four industries are usually classified as forest-based due to partial claims of their output. Moreover, the output percentages claimed range from 2% to 42%. Hence, without proper proportioning, including such industries in this study could overestimate the shares of the forest-industry.

overall output as forest-related does not necessarily mean 10% of its factor endowments was used in producing the forest-related outputs. All industries with partial outputs considered as forest-related are not included in this study. Based on this criterion, the maximum number of forest-based industries obtained in a given year was thirty.

The thirty forest-based industries were selected in each year from 2013 to 2018. Twenty-six forest-based industries were obtained in the years 2010, 2011, and 2012. The reduced number of industries in the beginning years is due to two reasons. First, three forest-based industries (Sawmill, woodworking, and paper machinery; Cut stock, resawing lumber, and planning; and Other millwork, including flooring) are not reported in 2010, 2011, and 2012. Second, sawmill and wood preservation industries are combined in the first three years but are separated as individual industries from 2013 to 2018. The first reason means unavailability of data, but the second situation can be manipulated to ensure uniform information is available for the two industries (sawmill and wood preservation), especially in creating a panel dataset. The first option was to disaggregate the two industries in the first three years so that they become separated as reported in 2013 and later years. However, this was a difficult task to achieve due to unavailability of detailed information needed on the two industries to appropriately separate all their components in the SAM matrices. The second option was to consolidate the two industries in each year from 2013 to 2018. For simplicity, the second option was chosen. Hence, a single industry named 'sawmill and wood preservation' was obtained for all nine years. In sum, 29 forest-based industries were selected for the years 2010-2018. Details of all the forest-based industries all the forest-based industries used in this study and their corresponding IMPLAN codes are reported in Table 4.5.

Using the IMPLAN dataset, overall capital endowment at the state level was measured as the log of total capital payments by all industries in the economy. To see how sensitive regression results are to the choice of measurement, the net physical capital stock for Kentucky was estimated and used as an alternative measure of state-level capital endowment. The BEA make available net capital stock data at the national level, but not for individual states. Moreover, studies like Yamarik (2013) and Garofalo and Yamarik (2002), have developed techniques that can be used to create state-level capital stock estimates from the national estimates. Following Yamarik (2013) and Garofalo and Yamarik (2002), this study creates state-level net capital stock estimates by apportioning the national capital stock estimates to the state of Kentucky based on the income generated in industries (equation 4.1 and 4.2). The industries used in this study follow the one-digit NAICS industry classification.

$$c_{i,t} = \left(\frac{m_{i,t}}{M_{i,t}}\right) C_{i,t} \tag{4.1}$$

where i represents the industry ($i = 1 \ldots 19$) and t represents year ($t = 2010 \ldots 2018$). $c_{i,t}$ and $C_{i,t}$ represent net capital stock for each industry at the state and national levels, respectively. $m_{i,t}$ and $M_{i,t}$ represent industry income at the state and national levels, respectively. Net capital stock for each year is created by summing all industry estimates,

$$c_t = \sum_{i=1}^{19} c_{i,t} \tag{4.2}$$

where c_t represent state-level net capital stock for year t. Table 4.6 shows estimate of the net capital for Kentucky for 2010-2018.

Educational attainments of Kentucky employees were used as alternative measures of labor endowments. The number of employees who are between ages 25 and 64 with less than high school level of education is used to proxy unskilled labor. Skilled labor is proxied with the number of employees between ages 25 and 64 with at least a bachelor's degree. This data was obtained from the BEA–American Community Survey (BEA-ACS) database. The BEA-ACS defines an employed person as anyone 16 years old or above who either held a job or was at work during the reference week or the week during which the employment status of survey respondents is determined. Thus, the employment data includes all employees (part time and seasonal employees).

4.2.1 Dependent Variables

Table 4.1 reports summary statistics of the dependent variables. Typically, structural change is investigated by looking at the evolution of the shares of industries (van Neuss, 2019; Herrendorf et al., 2014; Che, 2012). In this study, the shares of forest-based industries in total employment and total real output were used as the structural variables. The dependent variables were calculated as follow:

$$E_{it} = \frac{E_{it}^{f}}{E_t} \quad \text{and} \quad O_{it} = \frac{O_{it}^{f}}{O_t}$$

where E_{it}, and O_{it} are employment share and real output share, respectively for forest-based industry i at time t. In a respective order, E_{it}^{f}, and O_{it}^{f} represent employment and real output of forest-based industries. E_t, and O_t are respectively the total employment and total real output across all industries in each year. Table 4.1 reports the percentage shares of forest industry output and employment.

4.2.2 Explanatory Variables

As explained in the previous section, the key explanatory variables of interest are the interactions between factor endowment (capital and labor) and industry factor intensities. Factor intensity is measured as the ratio of industry factor to output. Total factor endowment is measured as the log of total factor payments by all industries in the economy. Based on the factor-endowment structural change theorems, an increase in a factor endowment should increase the output of industries that uses the factor intensively. The influence of labor skill level on output of the forest industry is captured through the educational attainment of the employed population. Unskilled labor is measured as the number of employees between ages 25 and 64 with less than high school level of education. Skilled labor is measured as the number of employees between ages 25 and 64 with at least a bachelor's degree. Potential demand shocks on industry growth are accounted for by including the final demand of industry output as an explanatory variable. It is expected that the coefficient of the final demand will be positive when the dependent variable is real output. This is because, with available production resources assumed in the intermediate and value-added accounts of the SAM, increase in the consumption of an industry's output should increase the production output of the industry. Output per worker in industries is included to account for industry productivity. As a productivity measure output per worker is expected to have a positive coefficient when the dependent variable is output. Table 4.2 reports summary statistics of the factor endowments used.

4.3 Empirical Estimation

A dynamic model which accounts for the initial influence of forest industry structure was used to determine the linkage between forest industrial structure and factor endowment. The dynamic model in a panel form is given as:

$$y_{it} = \beta + \alpha_1 y_{it-1} + \alpha_2(k_{it} * K_t) + \alpha_3(l_{it} * L_t) + \alpha_4 \mathbf{Z}_{it} + \lambda_t + \mu_{it} \qquad (4.3)$$

where the dependent variable is the log of forest-based industry $i's$ share in total employment or total real output in time t. k_{it} and l_{it} represent industry level capital and labor intensities, respectively. These factor intensities are interacted with their state-level endowments, capital K_t, and labor L_t to examine the influence of factor endowments on the shares of forest-based industries in employment and output as the usage of respective factors intensify. Thus, the parameters of interest are α_2 and α_3. The $\mathbf{Z}_{it}$ variables include industry output per worker and final demand of industry output. Output per worker is used to account for industry productivity. Final demand for industry output is included to capture industry demand shocks. λ_t is time fixed effect. y_{it-1} is included to control for initial difference in the dependent variable. μ_{it} is an error term which can be expressed as $\mu_{it} = \varepsilon_i + \eta_{it}$. Where ε_i are unobserved industry-specific effects and η_{it} is an error term.

The interaction terms between factor endowments and industry factor intensities are considered as the variables of interest to link the study to the factor endowment-based structural change theorems explained above. By using the interaction terms, the coefficient estimates of interest from the regressions become a function of industry factor intensities. This means when capital endowment K_t increases, industries with high capital intensity k_{it} expands in terms of output. When the dependent variable is employment, the sign of α_2 depends on the elasticity of substitution between industries. For example, for capital-intensive industries, α_2 would be positive if the elasticity of substitution between industrial goods is greater than 1, vice versa (Che, 2012).

Endogeneity is a concern in equation (4.3) due to the lagged dependent variable's inclusion as an explanatory variable. This leads to correlation between the error μ_{it} and the lagged dependent variable y_{it-1} ($E(y_{it-1}, \mu_{it}) \neq 0$), making standard estimators like the ordinary least square, fixed effect and random effect inconsistent. The issue of endogeneity can be addressed by using a difference generalized method of moment (D-GMM) estimator or a system generalized method of moment (S-GMM) estimator (Blundell and Bond, 1998; Arellano and Bond, 1991). Conditions for appropriately using S-GMM and D-GMM estimators are detailed in Chapter 3 above. The S-GMM estimator is considered in this study.

S-GMM estimators are divided into one-step and two-step variants. The one-step and two-step GMM estimators differ in the weighting matrix used in their estimation process. The one-step GMM estimator uses weight matrices that are independent of estimated parameters, while the two-step GMM estimator weights the moment conditions by a consistent estimate of their covariance matrix (Windmeijer, 2005). The two-step estimator is asymptotically more efficient and robust to heteroskedasticity and autocorrelation than the one-step. Moreover, the two-step estimator only remains superior to the robust one-step estimator in finite samples when the standard errors of the former are corrected (Windmeijer, 2005)[16.] This is because the standard errors from the two-step estimation tend to be severely downward biased in finite samples (Arellano and Bond,

[16] Windmeijer (2005) provides a finite sample correction procedure for the two-step GMM estimation process which makes the robust two-stem GMM more efficient than the robust one step in finite samples

1991; Blundell and Bond, 1998). In such cases, the one-step estimator is preferred for making inferences if the standard errors of the two-step estimator are not corrected. In this study, the Windmeijer (2005) correction to the two-step estimator standard errors was applied, hence it can be expected that the two-stem estimator is more efficient than the one-step. Regression results for both one-step and two-step estimators are reported.

It would be more informative and ideal to determine for each period the influence of factor endowment on each forest-based industry or aggregated sub-industries like wood manufacturing, paper manufacturing, and furniture manufacturing. However, this cannot be achieved in this study due to data limitations. Estimating the above equation for all forest-based industries across all time provide coefficients that describe the general pattern across all forest-based industries. These coefficients can be expected to be different if the model is estimated for each forest-based industry and time. The literature on factor endowment-based structural change mostly assumes free movement of resources (capital and labor) across industries. However, instant movement of these resources is unlikely to occur. Hence, it is important to allow a slow adjustment process for resource movement. This can be done by setting the unit period in data to a higher order. For example, Che (2012) imposed a slow adjustment process by setting the unit time period in a dynamic panel data model to five years indicating that change in factor endowment and its subsequent influence on industry structure is reasonably captured within five years interval period. One-unit time period is allowed in this study due to data limitations and small sample size. Increasing the unit time period to a higher order to account for factor endowment slow adjustment process would further reduce the number of observations in this study.

4.4 Results

Table 4.3 reports the regression estimates for both one-step and two-step system generalized method of moments (S-GMM) estimations. For each dependent variable, column label (1) reports estimates for the case where IMPLAN reported capital and labor payments are used as proxies for capital and labor endowments. Column labels (2) and (3) report regression estimates where unskilled and skilled labor, respectively, are used to proxy labor endowment. The key variables of interest, the interaction term between forest-based industry capital intensity and state capital endowment (K*KEND), and interaction term between forest-based industry labor intensity and state level labor endowment (L*LEND) show a positive relationship between factor endowment and forest-based industries shares in total employment and total output. These positive relationships are observed under both one-step and two-step GMM estimations.

The positive and significant coefficients of the interaction terms between factor intensities and factor endowments suggest that an increase in a factor results in an increased output of the forest industry as the industry employs the factor more intensively. Results show that increase in labor endowment has more influence on forest-based industries shares in total employment and total output, as the coefficient estimates for the interaction terms between labor intensities and labor endowment are higher than that of the interaction term between capital intensity and capital endowment. When labor endowment is divided into skilled and unskilled labor (in separate regressions), it is observed that the positive and significant coefficients of unskilled labor is slightly higher than what is observed when labor is proxied with skilled labor endowment.

The regression results show that the final demand for forest industry output has a positive and significant influence on forest industry share in employment and output. In all regression, the null hypothesis of no first order serial correlation is rejected due to the significance of the Arellano and Bond (1991) first order serial correlation test (AB(1)) ;however, this is not a concern as the null hypothesis of no serial correlation is not rejected under the Arellano and Bond (1991) second order serial correlation test (AB(2)). For all regressions, the Hansen (1982) test for validity or exogeneity of instruments revealed the instruments are exogenous, hence valid.

Similar to Table 4.3, Table 4.4 reports the result of GMM estimations that examine the linkage between forest industry structure and factor endowments. The capital endowment used in these regressions is state-level physical capital stock estimated by allocating national capital stock estimates to the state level using industry level income data (Yamarik, 2013; Garofalo and Yamarik, 2002). Aside from a slight reduction in the coefficient of the interaction of capital intensity and capital endowment, regression estimates from Table 4.4 are identical to what is reported in Table 4.3 both in magnitude and direction.

4.5 Discussions

This study applies a dynamic panel regression model to investigate the linkage between factor endowment and forest industry structure in Kentucky. Focusing on state-level capital and labor endowments, results indicate a positive relationship between capital and labor endowments, forest-industry shares in total employment, and total output as the respective factors are used intensively. Moreover, an increase in labor endowment has more influence on forest industrial structure. An examination of capital and labor intensities among all the forest-based industries used in this study reveals that only five out of twenty-nine forest-based industries were capital-intensive over the study period (2010-2018)[17] (Figure 4.2.). The dominance of labor-intensive forest-based industries could explain why the interaction between labor endowment and labor intensity has a higher influence on forest industrial structure than capital endowment and its interaction with industry capital intensity.

Broadly, this study's result is in line with factor endowment-based structural change theorems that purport that increase in factor endowment will lead to an increase in the output of the industries that use the factor more intensively (Ju et al., 2015; Acemoglu and Guerrieri, 2008). Results show that the magnitude of unskilled labor's influence is slightly higher than that of skilled labor in all regressions. A possible explanation for this result can be attributed to the labor intensiveness of the forest industry, which could suggest the need for more unskilled labor for physical efforts to complete tasks. However, this is not always true as studies like Islam and Shazali (2011) have found stronger positive correlations between skilled labor and productivity in labor-intensive industries compared to unskilled labor. Capital-intensive industries, on the other hand, mostly require skilled workers to catch up with advancing technologies.

Results show that an increase in capital endowment leads to an increase in forest industry shares in employment and output as the industry becomes more capital intensive. The magnitude of the influence of capital on employment is lower than the magnitude of the influence of capital on output. However, the capital-employment relationship can be complicated as it may be driven by the elasticity of substitution between industries goods

[17] Commercial logging, forestry, forest products and timber, paperboard mills, paper mills and sanitary paper product manufacturing are the only capital-intensive forest-based industries.

(Che, 2012; Acemoglu and Guerrieri, 2008). Drawing from the theoretical underpinnings of structural coherence, structural change and economic growth presented by Che (2012) and Acemoglu and Guerrieri (2008), when the dependent variable is employment the influence of capital depends on the elasticity of substitution between industries goods, as the elasticity of substitution determines the degree of changes in relative prices in reponse to real output changes. If the elasticity of substitution is greater than 1, then employment shares of capital-intensive industries will also rise as capital endowment increases. However, predictions based on the elasticity of substitution among industries is hard to apply because many industries produce intermediate goods that do not target final consumers (Che, 2012; Oulton, 2001). In addition, difficulties may occur in the elasticity of substitution-based prediction due to the differences in elasticity of substitution across different industries. As explained below the positive relationship between capital and employment observed in this study can be attributed to the simultaneous use of both capital and labor in the forest industry.

The observed increase in employment as the forest industry becomes more capital intensive can be explained by the lack of displacement of labor or simultaneous labor use with capital in the industry as capital accumulates. Factor endowment-based structural change implies that an increase in capital stock leads to an increase in output of capital-intensive industries, however, more labor will be needed together with capital as the production output increases. As such, major displacement of labor following capital accumulation could reduce output in a capital-intensive industry. Therefore, the positive and significant relationship between the interaction of industry capital intensity and capital endowment and the Kentucky forest industry output and employment can be attributed to the efficient combination of capital and labor usage to maintain or increase labor productivity even as capital accumulates. This result reflects the need for more labor by the Kentucky forest industry and capital as capital accumulates. Put differently, this result is a reflection of the need for more labor by the Kentucky forest industry together with capital as capital accumulates. Aside from commercial logging, forestry, forest products and timber, and paper mills industries, the simultaneous usage of labor and capital among the forest-based industries can be observed by the closeness of their labor and capital intensities patterns in Figure 4.2

Results from this study show that an increase in final demand is associated with increase in forest industry output and employment. This result is not surprising when the dependent variable is output. It can be expected that in the face of available production resources, increased consumption of forest industry outputs will induce an increase in the industry's production output. The positive relationship between increased final demand and employment can be explained by the fact that increased demand for an industry's output creates a demand for labor to produce the output. Said differently, increase demand for an industry's output increase the industry's capacity to employ more people to produce more output to meet the increased demand. The positive demand-employment relationship is common in the literature (e.g., Şahin et al., 2013; Wah, 1997; Wilson, 1960). Demand-employment relationship is heavily dependent on the factor intensity of the industry under consideration (Şahin et al., 2013). This means that increase in demand is likely to generate more employment in a labor-intensive industry than other industries that uses labor less intensively (Şahin et al., 2013). Thus, the positive demand-employment relationship observed in this study can be attributed to the labor intensiveness of the Kentucky forest industry.

The final demand component of the SAM used in this study is made of different components including household, government, investment, and exports, hence it remains to determine which of these institutions has the highest influence on forest industry output share. This study's primary focus was to investigate the linkage between forest industry structure and factor endowments; hence, the study does conduct a detailed assessment of the different final demand components in regressions. Estimated shares of the final demand components show that exports make up the largest component of forest industry final demand for the years 2010-2018 with about 86% on average. Hence, it can be concluded that the influence of the final demand on forest industry output is mostly driven by exports.

Figure 4.2 compares factor intensities (capital and labor) across Kentucky forest-based industries. The patterns show the ratio of each industry's capital and labor payments to its output. Only five out of twenty-nine industries were capital-intensive for the years 2010-2018. The capital-intensive industries are Commercial logging (COLO), forestry, forest products and timber (FFPT), paperboard mills (PAPM), paper mills (PBCM) and sanitary paper product manufacturing (SAPM). All other industries mostly remained labor-intensive over the study period. The closeness of the two intensity patterns is an indication of a simultaneous use of both factors. Full names of industries are presented in Table 4.5.

4.6 Summary and Conclusions

This study examines the linkage between factor endowment and forest-industry structure in the state of Kentucky. This study is related to a large body of literature on the relationship between a region's factor endowment and the structure of industries in the economy. The literature on this factor endowment and industry structure relationship reveals that increase in a factor leads to an increase in the output of industries that use the factor more intensively, while the output of industries that use the factor less intensively decreases. This causes the industrial composition of the economy to change as factor endowment changes. Understanding this relationship is important in assessing and projecting growth patterns among industries as factor endowment changes in an economy.

Focusing on Kentucky, a dynamic panel model was specified to determine the influence of labor and capital endowments on the structure of the forest-based industries. Using forest-based industries shares in employment and real output as structural variables, finding reveals that increase in both capital and labor endowments leads to an increase in the forest industry's size as the industry usage of the respective factors becomes intensive. The magnitude of the influence of labor endowment is higher than that of capital endowment. A comparison of labor and capital intensities of the forest-based industries over the study period shows that most of the industries were labor-intensive. Therefore, the positive relationship between labor endowment and forest industry structure is directly in line with factor endowment-based structural change studies, and possibly explains the higher influence of labor.

An investigation of the factor intensities indicates that, though the industries are labor-intensive, both labor and capital are used at fairly constant ratios without major substitution of the other as one factor accumulates, thus the positive relationship between capital endowment and forest industry shares in employment. Considering that all the forest-based industries used in this study are manufacturing industries, a gradual shift towards automation can be expected among these industries as the forest industry seeks to increase its productivity and catch up with advancing technologies like other manufacturing industries. To facilitate increase in forest industry output, it is critical to ensure that both capital and labor resources are able to flow across all forest-based industries with relative ease.

Results from this study have policy relevance to forest sector sustainability. Broadly, this study's recommended use of capital and labor suggests that policies that make the forest industry attractive to employees are imperative. Aside from expected increased automation concerns in the future, other long-standing concerns that could hinder employment generation in forest-based industries (especially in the forestry and logging industry) includes financial concerns (low wages), reluctance to encourage children and family members to enter the field, and increase in the average age of workers (Abt, 2013; Baker and Greene, 2008; Egan and Taggert, 2004a; Egan and Taggert, 2004b). Abt (2013) projected a 2 percent increase in logging jobs in the US south by 2018. The author attributed the projected increase to increase in income per logging job resulting from increased hourly wages and increased hours per job. However, one of the major concerns raised by forest economic development researchers during the 2020 forest economic contributions summit (themed: strategies for development, communication, and education on the sector's role in the southern region, held in New Orleans, LA), was the increasing average age of forest industry workers and the lack of youth interest in forest industry jobs. This is true for the state of Kentucky. The abovementioned potential causes of employment shortage in the forest industry suggest that to maintain and or increase employment numbers in the industry, incentives such as increase in wages and insurance packages that would make the industry attractive to both current and future employees, especially among younger workers that are needed for long-run viability of the industry.

The significant influence of regional factor endowment accumulation on forest-industry structure means that policies intended to sustain the industry should not only be industry-specific but should also exploit other regional factors. Reeve (2006) shed light on this issue in a cross-country and general equilibrium analyses. According to Reeve (2006), it is important to consider industry linkages when studying industrial structure. Thus, it is recommended that policies to sustain the forest industry should also target other industries that are linked to the forest industry. Historically, the wood industry is known to be linked to the housing construction industry. The link between these two industries is strong to the extent that a major decline in the housing construction industry leads to a major decline in the wood industry (Abt, 2013; Ince and Nepal, 2012). Hence, one way to sustain the wood industry is to incentivize the housing construction industry to expand, as this would have a positive ripple effect on the wood industry. Policies that result in the expansion of the housing construction industry would indirectly expand the wood industry through increased demand for the wood industry's output. As findings from this study reveal, an increase in demand for forest industry output is positively associated with the industry's employment. However, policies intended to expand the forest industry through increased demand should be drafted with caution and predetermined plan of actions to combat potential unintended consequences such as resultant increased price effects.

A major limitation of this study is the lack of long-run data to capture the influence of factor endowment on forest industry structure over a long period. Using a short period of data limited the analysis as a slow adjustment process of factor resources could not be allowed. Increasing the unit time period to allow for a slow adjustment process would have reduced the number of observations. Future studies can improve on this study by applying a long data series on the forest industry that will permit imposing a slow movement of resources. Further, having a long data series will permit the assessment of individual forest-based industries, which will provide a more detailed insight into the relationship between factor endowment and each forest-based industry's structure. In this study, the commercial logging, and Forestry, forest products, and timber industries were identified to be highly capital-intensive, which means conducting individual analysis on these industries could potentially yield different results than the general patterns reported in Table 4.3 and Table 4.4 above. However, such individual analysis could not be performed due to data limitations. Lastly, future studies may look into other forest-industry characteristics that when interacted with factor endowment would influence forest industry growth. An example of these characteristics could be human capital intensity.

4.7 Tables and Figures for Chapter 4

Table 4.1 Summary statistics of forest industry shares in total employment and total real output

	Mean	Min	Max
Employment share	0.043 (0.494)	0.0002	0.200
Real output share	0.071 (0.001)	0.0002	0.410

Author's estimates from data. Standard deviations are in parenthesis

Table 4.2 Summary statistics of factor endowments, final demand and output per worker in Kentucky forest industry

	Mean	Min	Max
Capital endowment ($m)	11.307 (0.1000)	11.107	11.405
Labor endowment ($m)	11.340 (0.120)	11.200	11.501
Capital intensity ($m)	0.120 (0.120)	-0.132	0.732
Labor intensity ($m)	0.200 (0.083)	0.010	0.467
Skilled labor (thou)	13.050 (0.055)	12.960	13.147
Unskilled labor (thou)	11.602 (0.060)	11.534	11.713
Final demand ($m)	4.170 (1.824)	-0.885	7.170
Output per worker ($thou)	12.381 (0.655)	10.858	13.778

NB: All variables are log transformed, except factor intensities. Standard deviations are in parenthesis. Final demand consists of industry output demand by government, households, investment, and exports.

Table 4.3 Influence of capital and labor endowment on Kentucky forest industry structure

	Two-step						One-step					
	Employment			Output			Employment			Output		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
K*KEND	0.0493** (0.0206)	0.0500** (0.209)	0.0500** (0.0208)	0.0810*** (0.0253)	0.0810*** (0.0255)	0.0805*** 0.0253	0.0542** (0.0201)	0.0543** (0.0202)	0.0544** (0.0202)	0.0800** (0.0257)	0.0800** (0.0259)	0.0800** 0.0258
L*LEND	0.1466** (0.0624)			0.1640** (0.0870)			0.1610** (0.0624)			0.1589** (0.0815)		
L*USL		0.1430** (0.0587)			0.1602** (0.0866)			0.1572** (0.0613)			0.1543** (0.0806)	
L*SL			0.1277** (0.0535)			0.1426** 0.0761			0.1402** (0.0543)			0.1379** (0.0711)
OPW	-0.0984 (0.0669)	-0.0971 (0.0637)	-0.0973 (0.0660)	0.1032 (0.1022)	0.1039 (0.1034)	0.1039 (0.1028)	-0.0663 (0.0786)	-0.0658 (0.0788)	-0.0657 (0.0788)	0.1198 (0.0837)	0.1196 (0.0840)	0.1199 0.0839
FD	0.0010** (0.0002)	0.0010** (0.0002)	0.0010** (0.0002)	0.0010** (0.0003)	0.0010** (0.0003)	0.0010** (0.0003)	0.0010** (0.0003)	0.0010** (0.0003)	0.0010** (0.0003)	0.0010** (0.0003)	0.0010** (0.0003)	0.0010** (0.0003)
Constant	-0.2426 (0.9403)	-0.2458 (0.9091)	-0.2515 (0.9381)	-2.9440 (1.9603)	-2.9520 (1.9799)	-2.9528 (1.9685)	-0.6771 (0.8136)	-0.6792 (0.8133)	-0.6844 (0.8154)	-3.1365** (1.5979)	-3.1340** (1.6043)	-3.1395** (1.6004)
AB (1)	0.030	0.030	0.030	0.023	0.023	0.022	0.020	0.02	0.02	0.008	0.008	0.008
AB (2)	0.371	0.370	0.371	0.910	0.910	0.911	0.378	0.380	0.379	0.902	0.906	0.907
Hansen	0.421	0.450	0.450	0.200	0.200	0.200	0.200	0.450	0.450	0.200	0.200	0.200
No of Obs	223	223	223	223	223	223	223	223	223	223	223	223

NB: K*KEND is the interaction between industry capital intensity and state capital endowment. L*LEND is the interaction between industry labor intensity and state labor endowment. L*USL and L*SKL are the interaction terms between industry labor intensity and state unskilled labor and skilled labor endowment, respectively. USL is measured the number of employees between ages 25 and 64 with less than high school level of education. SL is measured the number of employees between ages 25 and 64 with at least a bachelor's degree. OPW represents industry output per worker. FD is industry total final demand which consists of demands from government, household, investment and exports. AB (1) and AB (2) are the Arellano and Bond (1991) first and second order serial correlation tests respectively. Robust standard errors are reported in parenthesis for all regressions. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.4 Influence of capital and labor endowments on Kentucky forest industry structure

	Two-step						One-step					
	Employment			Output			Employment			Output		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
K*KEND	0.0436** (0.0181)	0.0440** (0.0184)	0.0440** (0.0183)	0.0710*** (0.0223)	0.0710*** (0.0225)	0.0710*** (0.0223)	0.0479** (0.0177)	0.0480** (0.0178)	0.0481** (0.0180)	0.0700*** (0.0227)	0.0698*** (0.0228)	0.0700*** (0.0227)
L*LEND	0.1470** (0.0630)			0.1641** (0.0871)			0.1611** (0.0624)			0.1590* (0.0816)		
L*USL		0.1430** (0.0588)			0.1604** (0.0867)			0.1574** (0.0614)			0.1544* (0.0807)	
L*SL			0.1278** (0.0536)			0.1430** (0.0761)			0.1404** (0.0543)			0.1380* (0.0712)
OPW	-0.0986 (0.0670)	-0.0974 (0.0638)	-0.0976 (0.0662)	0.1032 (0.1021)	0.1039 (0.1033)	0.1038 (0.1027)	-0.0663 (0.0786)	-0.0658 (0.0788)	-0.0657 (0.0788)	0.1197 (0.0837)	0.1195 (0.0839)	0.1199 (0.0838)
FD	0.0010** (0.0002)	0.0010** (0.0002)	0.0010** (0.0002)	0.0010** (0.0003)	0.0010** (0.0003)	0.0010** (0.0003)	0.0010* (0.0003)	0.0010* (0.0003)	0.0010* (0.0003)	0.0010** (0.0003)	0.0010** (0.0003)	0.0010** (0.0003)
Constant	-0.2402 (0.9453)	-0.2428 (0.9140)	-0.2489 (0.9431)	-2.9448 (1.9592)	-2.9532 (1.9789)	-2.9541 (1.9675)	-0.6775 (0.8134)	-0.6795 (0.8131)	-0.6847 (0.8152)	-3.1366* (1.5981)	-3.1338* (1.6045)	-3.1395* (1.6005)
AB (1)	0.030	0.030	0.030	0.023	0.023	0.022	0.020	0.020	0.020	0.010	0.010	0.010
AB (2)	0.371	0.371	0.372	0.908	0.909	0.912	0.379	0.3790	0.380	0.904	0.910	0.910
Hansen	0.421	0.450	0.450	0.200	0.200	0.200	0.421	0.450	0.450	0.200	0.200	0.200
No of Obs	223	223	223	223	223	223	223	223	223	223	223	223

NB: K*KEND is the interaction between industry capital intensity and state capital endowment. L*LEND is the interaction between industry labor intensity and state labor endowment. L*USL and L*SKL are the interaction terms between industry labor intensity and state unskilled labor and skilled labor endowment, respectively. USL is measured the number of employees between ages 25 and 64 with less than high school level of education. SL is measured the number of employees between ages 25 and 64 with at least a bachelor's degree. OPW represent output per worker. FD is industry total final demand which consists of demands from government, household, investment and exports. AB (1) and AB (2) are the Arellano and Bond (1991) first and second order serial correlation tests respectively. Robust standard errors are reported in parenthesis for all regressions. *** p<0.01, ** p<0.05, * p<0.1

Table 4.5 Kentucky forest-based industries and corresponding IMPLAN codes

Number of industries	Industries	ABREV	IMPLAN code
1	All other converted paper product manufacturing	AOCP	153
2	All other miscellaneous wood product manufacturing	AOMW	145
3	Blind and shade manufacturing	BASM	378
4	Boat building	BOBU	364
5	Commercial logging	COLO	16
6	Custom architectural woodwork manufacturing	CAWM:	374
7	Cut stock, resawing lumber and planning	CSRP	140
8	Engineered wood member and truss manufacturing	EWMT	137
9	Forestry, forest products and timber	FFPT	15
10	Institutional furniture manufacturing	INFM	372
11	Nonupholstered wood household furniture	NWHM	370
12	Wood Office furniture	OFIF	373
13	Other millwork, including flooring	OMIF	141
14	Paper mills	PAPM	147
15	Paperboard mills	PABM	148
16	Paperboard container manufacturing	PBCM	149
17	Paper bag and coated and treated paper manufacturing	PBCT	150
18	Prefabricated wood building manufacturing	PWBM	144
19	Reconstituted wood product manufacturing	RWPM	138
20	Sanitary paper product manufacturing	SAPM	152
21	Sawmill, woodworking and paper manufacturing	SWPM	269
22	Sawmill and wood preservation	SAWP	134-135
23	Showcase, partition, shelving and locker	SPSL	376
24	Stationery product manufacturing	SPMA	151
25	Upholstered household furniture manufacturing	UHFM	369
26	Veneer and plywood manufacturing	VAPM	136
27	Wood container and pallet manufacturing	WCPM	142
28	Wood kitchen cabinet and countertop	WKCC	368
29	Windows and door manufacturing	WWDM	139

Table 4.6 Net capital stock for Kentucky for 2010 -2018

Years	Estimates ($ millions)	Growth rate (%)
2010	344,211	-1.09
2011	337,635	-1.91
2012	322,377	-4.52
2013	323,938	0.48
2014	322,745	-0.37
2015	331,595	2.74
2016	340,601	2.72
2017	340,161	-0.13
2018	343,131	0.87

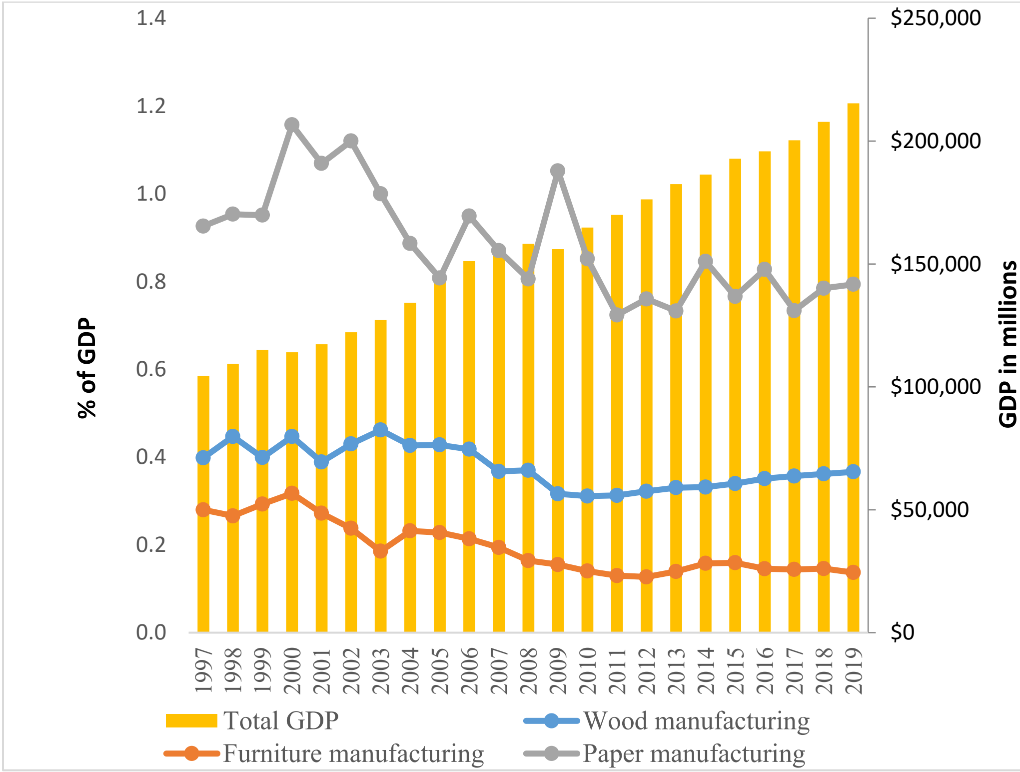

Figure 4.1 Wood, paper, and furniture manufacturing shares in Kentucky GDP. Data Source: BEA (2021)

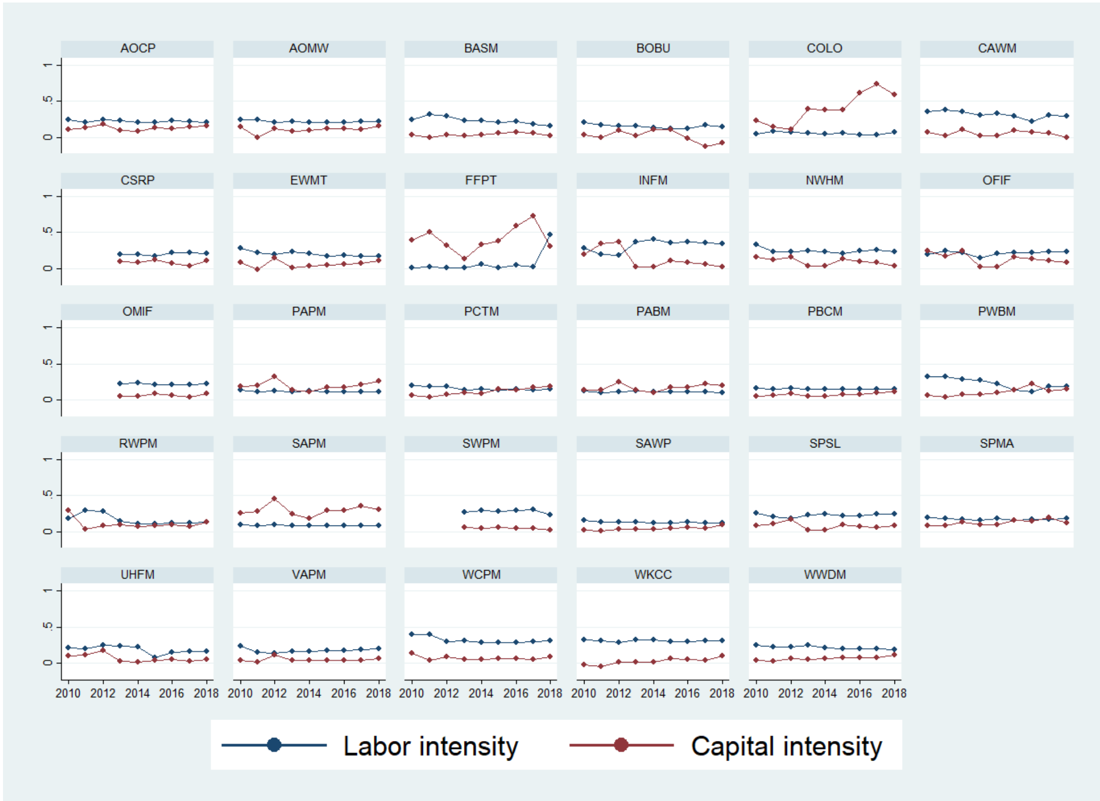

Figure 4.2 Labor and capital intensities among Kentucky forest-based industries (2010-2018)18.

[18] Full names and corresponding IMPLAN codes of industries are reported in Table 4.5.

Chapter 5. Economy-Wide Impacts of Increased Demand for Forest Products in Kentucky

Abstract

The Kentucky forest sector is projected to experience increase in outputs due to anticipated increase in demand for wood products. Through inter-industry linkages, expansion of the forest sector could have substantial economy-wide impacts. Understanding the economy-wide impacts resulting from upward demand changes in the forest sector is critical for holistically assessing the contribution and impacts of the sector. Kentucky's aggregate wood and paper product manufacturing industries have experienced output growth in recent years and expected to continue due to growing demand for the state's forest products. This study applies a computable general equilibrium model to provide a snapshot of the economy-wide impacts of increase in wood product demand in Kentucky. Two counterfactual scenarios of supply increase in the forest sector are simulated. Results show an increase in welfare of high-income households, whereas welfare of low-income households declines marginally due to increase in producer supply prices. Both federal government and state government revenues and expenditures increase. Output of most industries in the economy are positively impacted through inter-industry linkages, and gross regional product also increases. The study provides insights into the economic impacts of increased demand of forest sector products. These are valuable policy-relevant information for sustainable Kentucky forest sector.

Keywords: Computable general equilibrium, Economy-wide impacts, Kentucky forest sector

5.1 Introduction

Forests and forest products have long represented a key resource endowment in the US (Wear et al., 2016). The US is one of the leading consumers and producers of forest products (FAO, 2019; Wear et al., 2016). The US forest sector is an important part of the US economy. The paper and wood manufacturing industries constitute about 5.7% of US manufacturing GDP (Forest2market, 2019). In 2016, the US forest sector created about 2.9 million jobs and contributed about $128.1 billion in labor compensations (Forest2market, 2019). Some recent studies have listed the US forest sector among those experiencing structural changes and expected to continue on a pronounced scale due to occasional economic downturns and changes in forest products demand (Hetemäki and Hurmekoski, 2016). Notably, newsprint and graphic paper industries have been dwindling due to the shift towards electronic media (Hetemäki and Hurmekoski, 2016). However, the aggregated wood manufacturing and logging industries' outputs are projected to increase (Ince and Nepal, 2012; Abt, 2013).

Recent forest outlook projections have shown that aggregate wood manufacturing industry output will continue to increase up to 2060 primarily due to expected increase in demand for wood products especially from the housing construction industry (Ince and Nepal, 2012). For the paper manufacturing industry, the output of newsprint is expected to decline due to the shift towards electronic means of communication (Ochuodho et al., 2017; Ince and Nepal, 2012; Ince et al., 2007). However, output of other paper products such as packaging paper is projected to remain stable up to 2060, as fueled by home deliveries of online shopping. Further, employment in the wood product manufacturing industry is projected to increase due to a projected rebound in housing and modest labor productivity gains. In contrast, paper industry employment is projected to decline due to larger labor productivity gains (Ince and Nepal, 2012). These output and employment changes have potential impact other industries of the economy through inter-industry linkages.

In the US south, Abt (2013) predicted expansion in the wood manufacturing industry in conjunction with growth in housing industry. The southern logging sector is projected to experience small increases in output and jobs, while the paper manufacturing industry is expected to continue contracting (Abt, 2013). Southern states' economies are more dependent on forest sector compared to other states. The majority of jobs generated by the US forest sector are attributable to the south (Forest2market, 2019). Brandeis and Hodges (2015), show that forest sectors in the south contribute about 2% to the south's GDP. Recently, Pelkki and Sherman (2020) revealed that southeastern states make up the majority of states with the highest contribution of the forest sector to their economy. This finding further reiterates the critical role of the forest sector to the southeastern US economy. Therefore, changes in activities of the forest sector could have substantial impacts on the region's economy. Overall contributions and impacts stemming from changes in the forest sector can be holistically assessed if all industrial interlinkages are captured. The aforementioned projections are from single sector outlook studies that rarely assess the economy-wide impacts of forecasted output or demand changes. In other words, the aforementioned projections are made by examining forest-based industries in isolation and do not rigorously assess potential economy-wide impacts.

Kentucky is one of the thirteen southeastern states in the US. The state is home to over 12.4 million acres of forestland (Oswalt, 2017; Brandeis et al., 2016). The woodlands of Kentucky are very diverse, and ranks second to Florida in terms of hardwood species mix in the US. The woodlands serve as the foundation for the Kentucky forest sector that makes substantial economic contributions to the livelihood of Kentuckians and the state’s economy (Stringer et al., 2020; Thomas, 2017). Harvested timber from Kentucky forests are processed at about 671 wood and paper manufacturing facilities across 112 counties (out of 120) in the state. This distribution indicates the importance of the forest sector to local communities (Stringer et al., 2020).

Kentucky’s aggregate wood and paper product manufacturing industries have experienced growth in their outputs in recent years, but the logging industry's output has been undulating (Figure 5.1). This increase in wood and paper manufacturing industries can be attributed to the growing demand for Kentucky wood products. Driven by improvement in technology and innovation, the Kentucky construction industry is experiencing increased economic activities (Stamps, 2020). A recent report by Stamps (2020) reveals that non-residential construction activity in Kentucky increased to \$6.4 billion and \$6.5 billion in 2018 and 2019, respectively. As explained above, upward trend in construction industry drives increase in demand for wood products. Further, the wood industry may experience increased demand following the growing interest in mass timber for construction (Spence, 2021). Through inter-industry linkages, expansion of the forest sector or forest-based industries could have substantial economy-wide impacts. Understanding such economy-wide impacts resulting from demand or supply changes in the forest sector is critical for holistic assessment of the economic contribution and impacts of the sector. While recent annual reports on Kentucky forest sector economic contribution have revealed a general trend of increase in output of forest-based industries (Stringer et al., 2020), research on the economy-wide implications of the expansion of the forest sector has been lacking.

Considering the interrelations among forest-based industries and other industries in most economies, changes in forest-based industries could influence economic activities in these other industries and the economy as a whole. An economy-wide impact assessment framework, such as CGE, can effectively capture such interlinkage impacts appropriately. Focusing on the Kentucky forest sector, this study applies a static CGE model to assess economy-wide impacts of increased demand for forest products in sectors that use outputs from the forest sector. This study focuses on intermediate demand (supply) of forest sector-dependent industries that rely on wood products in their production process. This is because, in CGE modeling framework, intermediate links create a pathway through which a shock in one industry can affect the rest of the economy (Burfisher, 2017).

CGE models consist of systems of linear and non-linear equations that describe an economy as a whole and the interactions among its parts (Burfisher, 2017). They are a class of economic models that use actual economic data, usually in the form of Input-Output Table or its expanded form as Social Accounting Matrix (SAM) to estimate how an economy might react to changes in policy, technology, markets, investments, or other external factors (Dixon and Rimmer, 2016; Miller and Spencer, 1977). CGE modeling framework is the most suited for this kind of analysis because of its great flexibility as it enables substitution in production and demand; provide a more realistic treatment of factor scarcity, institutions, and the macroeconomic environment; and allow for optimization of agent behavior (Banerjee and Alavalapati, 2014; Banerjee and Alavalapati, 2010). These characteristics coupled with their ability to prospectively explain sectoral reactions and interlinkages have made them popular in economy-wide impacts studies.

CGE models assess economic impacts through comparative analysis (Ochuodho and Lantz, 2014; Pezzey, 2001; Devarajan and Offerdal, 1989). The models provide aggregated representations of an entire economy in an equilibrium in a baseline scenario, and under a policy or shock scenario. The baseline scenario represents the initial equilibrium model solution that replicates the benchmark database or expected development of the economy without any shocks. The policy scenario represents the model solution after imposing the desired shocks through model parameters. In the spirit of comparative analysis, economic impacts are estimated as the differences between the baseline and policy simulations (Ochuodho and Lantz, 2014; Pezzey, 2001). This study's objective is to assess the economy-wide impacts of increased demand of Kentucky's forest sector wood products.

5.2 Overview of Economic Impacts Analysis Models

Economic impact analysis is a quantitative analysis used to estimate how a project, policy, event, or any economic shock will impact an economy on a local, regional, or national scale (Gunton et al., 2020). Some of the commonly used methods for conducting economic impact analysis are input-output analysis (IOA), SAM modeling, partial equilibrium analysis (PEA), and general equilibrium modeling (CGE). Results from all these models are informative but their underlining assumptions and capabilities often lead to a debate about their suitability for impact assessments (Vargas et al., 2020; Alavalapati et al., 1998).

In PEA, the market for a specific industry under consideration is assessed in isolation by ignoring feedbacks that may result from related industries. In other words, PEA illustrates results or equilibrium in a single industry/sector only (Vargas et al., 2020). By ignoring feedback effects, PEA has a simplicity advantage which allows for a detailed analysis of the market conditions of specific industries (Vargas et al., 2020; Hussain et al., 2016). PEA also has the advantage of minimal data requirement which allows for fairly disaggregated or detailed level analysis in a specific industry. However, the assumptions of fixed prices and production of all other commodities except the commodity being analyzed are considered too strong as they neglect important interlinkages and factor movements across industries (Vargas et al., 2020; Hussain et al., 2016). Thus, models that permit simultaneous analysis of different markets are considered more appropriate for impact analysis when interlinkages are important (Vargas et al., 2020; Hussain et al., 2016).

Unlike PEA, IO models provide a more realistic treatment of an economy in terms of analyzing interlinkages between industries (Vargas et al., 2020; Patriquin et al., 2002). IOA relies on four rigid assumptions: (1) prices of inputs and outputs are constant; (2) there are constant returns to scale with no input substitution; (3) there are no constraints on the supply of factor inputs, and (4) final demand of each industry output is exogenous (Vargas et al., 2020; Troiano et al., 2017; Alavalapati et al., 1998). The capability of IOA effectively deriving socioeconomic impacts is limited by these underlying assumptions. The fixed prices assumption hinders the ability of IO models to capture the behavior of market agents with respect to changes in prices. The fixed prices assumption also means that supply of inputs or outputs does not influence factor or product prices (Vargas et al., 2020; Alavalapati et al., 1998). In the short run, the no input substitution assumption rules out the possibility of an industry expanding its output by combining increasing amounts of labor with its fixed capital stock (Alavalapati et al., 1998). The assumption of no input supply constraint is unrealistic. It would only be applicable in an economy where industries have excess capacity and their primary factors are not fully employed. Lastly, the exogeneity of final demand means that trading activity does not depend on relative prices. This makes IOA undesirable for international trade analysis (Alavalapati et al., 1998).

SAM modeling is another group of economic impact assessment tools. SAM models are identical to IO models as they are governed by the same assumptions (Patriquin et al., 2002). However, SAM models provide a more convenient framework to examine distributional impacts compared to IO models (Alavalapati et al., 1999). The similarity between IOA and SAM modeling stems from the fact that a SAM is an extension of an IO table. However, SAM models are not as popular as IO models in terms of conducting impact assessments. The nonpopularity of SAM modeling in impact assessments can be explained by the fact that SAMs are not often available in national statistical databases, and if they are constructed, they are specifically built as a prerequisite database for CGE modeling (Koks et al., 2016). Additionally, SAM models do not consider the special case where productive capacity of a sector is eliminated (Miller and Blair, 2009; Seung et al., 1997).

Like IO models, SAM models are typically demand driven, where changes in an exogenous final demand are estimated and the effects of these changes on an economy are computed (Seung, et al., 1997). Miller and Blair (2009) revealed a special case where regional economists use mixed exogenous/endogenous IO and SAM models in which final demand of some industries and gross output of other industries are modeled as exogenous.

The mixed exogenous/endogenous IO and SAM models are also limited by no prices and no factor substitution assumptions (Seung, et al., 1997).

5.2.1 Overview of CGE Models

Similar to IO and SAM models, CGE models assume that industries in an economy are interdependent[19]. However, CGE models relax the restrictions in IO and SAM models which makes them more suitable for impact assessments that account for industry interactions (Vargas et al., 2020; Alavalapati et al., 1998). In CGE analysis, outputs are endogenously determined and prices are assumed to be flexible to clear the commodity and factor markets. This price assumption allows CGE models to capture a more realistic behavior of economic agents. CGE models incorporate a variety of flexible production functions that allow producers to substitute factors of production. They can accommodate constraints on the availability of primary inputs and account for additional intersectoral linkages. Further, CGE models can endogenize final demand variables rather than treating them as exogenous (Vargas et al., 2020; Troiano et al., 2017; Burfisher, 2017; Alavalapati et al., 1998).

The abovementioned limitations of IOA, PEA, SAM modeling, and mixed exogenous/endogenous models coupled with the flexibility provided by CGE models have led to a growing interest in CGE application for economic impact analysis by regional economists in the last several decades. CGE models also have their limitations (Raihan, 2004). Particularly, results from CGE models are very sensitive to elasticities, model parameters, and closure rules (Ochuodho et al., 2016; Burfisher, 2017; Raihan, 2004). In

[19] IO, SAM, and CGE models' ability to capture information characterizing the interactions among and between industries and agents in an economy has earned them the name economy-wide models (Patriquin et al., 2002).

CGE modeling, it is critical to use the most appropriate elasticities to avoid overestimation or underestimation of model results (Burfisher, 2017). This study sourced from literature appropriate elasticities.

Although there are concerns about the assumptions and capabilities of all the abovementioned models, they have all been applied extensively to examine the economic impacts of agricultural-related and forest-related events or policies. However, empirical comparisons between these models suggest that CGE models are more flexible and provide more accurate results in forest-related events or policy impact analysis (Alavalapati et al., 1998). Studies like Vargas et al. (2020), Patriquin et al. (2002), Alavalapati et al. (1998), and West (1995) have provided a detailed comparison between IO, SAM, and CGE models.

To demonstrate the empirical difference between IO and CGE models, Alavalapati et al. (1998) used different variants of both models to estimate the economic impacts of a 22% increase in exports of pulp and paper products and a 1% decrease in imports of pulp and paper products Alberta, Canada. Results showed that estimates from the CGE models are much smaller than those of the IO models. The authors concluded that CGE models provide greater flexibility and have more potential for forest policy analysis when compared with IO models.

5.2.2 General Types of CGE Models

A number of distinct classifications of CGE models can be discerned. On a spatial scale, CGE models can be classified into single-region and multi-regional models (Ochuodho and Lanz 2014). Single-region models do not account for the activities and linkages between the defined region and other regions. Activities in other regions are assumed not to have any influence on the defined region's economy. Single-region CGE models can focus on one economy in a defined region, but may account for interactions with other parts of the region through trade activities. In contrast, multi-regional models analyze the performance of different interlinked regions simultaneously. Multi-regional and single-region CGE models have similar characteristics in terms of specifying a region's production, consumption, investment, import, and export structures. However, the unique features of multi-regional CGE models are: (1) each region is modeled separately as an individual economy with region-specific prices, industries, consumers etc; (2) the model reflect economic linkages and interactions across regions, such as interregional commodity flows, labor flows and capital flows etc. (Na et al., 2009).

CGE models can also be specified either as static or dynamic. Static CGE models focus on the performance of an economy within a single period (typically one year). This class of CGE models is concerned with initial (before) and final (after) comparisons after a change in economic conditions (Babatunde et al., 2017; Burfisher, 2017). They are appropriate for structural adjustment and when the analytical focus is on reaction to a one time shock (Wobst, 2001). Static models are however limited by the fact that they do not account for the adjustment path of an economy from an old equilibrium to a new equilibrium (Burfisher, 2017), spanning beyond one year. On other hand, dynamic CGE models trace the performance of an economy over multiple periods (Burfisher, 2017). Unlike static CGE models, dynamic CGE models consider time-dependent investment relationships, population/labor growth, and factor input dynamics (Kohler et al., 2006; Spence, 2005).

With the focus on the Kentucky's economy and the state's forest sector, this study employs a single-region static CGE model. The state's interactions with other parts of US and the rest of the world are accounted for through aggregate exports and imports. The CGE model captures a snapshot of economic impacts of increased demand for wood products in Kentucky.

5.2.3 CGE Applications in Forest Sector-Related Studies

Several studies have applied CGE models to examine changes in forest sectors in different regions. The studies described here are not exhaustive but they provide some insight into different applications of CGE modeling to forest sector related issues.

Das et al. (2005) used a static CGE model to investigate the impacts of environmental regulations and technical change in the US forest sector. Results suggest that welfare of the US declines following an increase in the cost of logging production in the US south, in response to environmental regulations. However, a reduction in timber harvest in the Pacific Northwest induced a shift in regional production and gains in welfare, especially in the US south. This result shows the importance of the US south forest sector to the regional and national economies. Thus, economic assessments of southern forest sectors are critical.

Banerjee and Alavalapati (2010) used a modified static CGE model from the International Food Policy Research Institute (IFPRI) to assess the economy-wide impacts of the 2006 forest concession in Brazil. The concession was to enhance forest management and thus increase available forestland by 47% to increase production of forest goods and services. The authors simulated this improvement by increasing the factor supply of forestland by 47%. Results indicate that household income and private consumption increase with the implementation of forest concessions.

Corbett et al. (2016) used a dynamic CGE model to assess the impacts of reduced annual timber harvest following a mountain pine beetle infestation in forests in British Columbia. The authors simulated this scenario by reducing stumpage price (price of standing timber) by the same percentage as the reduction in timber harvest. Results indicate a 1.34% reduction in GDP and a substantial reduction in consumer welfare, with compensating variation falling by $90 billion from 2009 to 2054.

Ochuodho et al. (2016) developed a global dynamic multi-regional CGE model to analyze the comparative economic impacts of the 2006 softwood lumber agreement between the US and Canada over the 2007 to 2013 period. The authors conducted an ex post analysis and simulated scenarios using real export values and export charge rates of Canadian softwood lumber exports to the US. Results show that the agreement was effective in reducing Canada's softwood lumber entry into the US market. The agreement benefited US producers through increased stumpage rates, but welfare of US consumers declined marginally due to increased price index.

Karttunen et al. (2018) used a dynamic CGE model to study regional socioeconomic impacts of intensive forest management due to expected increase in demand for wood biomass in eastern Finland. The forest management scenario included the assumption that wood supply will increase by 1.2 million cubic meters (Mm^3) due to the construction of a new sawmill plant and a biorefinery plant. Results indicate a 2.8% and 1.6% increase in GDP and employment by 2030. Findings provided an insight into how much regional socio-economic welfare would increase if regional wood demand combined with intensive forest management were given more attention.

Ochuodho et al. (2019) used a static CGE model to examine the potential economy-wide impacts of Virginia landowners allocating more of their lands for bioenergy biomass production. To increase biomass for bioenergy production in response to landowner decisions, they increased intermediate demand of bioenergy sector demand of biomass for bioenergy production. Results show a marginal decline in GDP but an increase in social welfare and household utility. However, increased demand of biomass from logging sector depressed the manufacturing sector, especially the wood manufacturing sub-sector.

Haddad et al. (2019) assessed the economic impacts and land use change from increasing demand for forest products in the European bioeconomy. The authors simulated increased demand for forest products through substitution of nonbio-based inputs for products and services provided from the forest sector (described as forestry, logging, and related service activities). They assumed a 1% increase in intermediate demand for forest products in all sectors that already use outputs from the forest sector. Results show that a shift to a more forest-based bioeconomy would induce small indirect land use effects globally due to existing international trade linkages and land market effects. Further, government and household demand for forest products decline following forest products price increase. These applications of CGE models in forest-related economic impact analyses is an indication of their wide application in this area of research.

5.3 Methods

5.3.1 CGE Modeling Framework

This study applies customized static single-region CGE modeling for Kentucky following the general specifications by Holland et al. (2007). The model is an adaptation of a welldocumented and widely applied International Food and Policy Research Institute (IFPRI)'s standard CGE model originally developed by Lofgren et al. (2002). Holland et al. (2007)'s customization makes the model compatible with Impact Analysis for Planning (IMPLAN) SAM dataset. Based on SAM IMPLAN dataset, the model was customized to include institutional make data, indirect business taxes, imports and exports of factors of production and institutional products. The modified model distinguishes between two sources of imports (Rest of the US (RUS) and Rest of the world (ROW)), two destinations for commodity exports (RUS and ROW), and provides a robust representation of institutional transactions and the rest of the economy (Hussain et al., 2012; Holland et al., 2007; Stodick et al., 2004).

Like most CGE models, the model used in this study is based on microeconomic and macroeconomic theories and foundations. Producers are modeled to maximize profits subject to a two-level production technology. The production function is a nested one with a Leontief function (Leontief, 1986) at the top of the production nest for both intermediate and primary inputs (capital, labor, and land). At the second level, capital, labor, and land are assumed to substitute through a constant elasticity of substitution (CES) value-added function, while the intermediate inputs are specified as a Leontief function (fixed proportions). There is no substitution between intermediate and primary inputs (Leontief function). While the assumption of no substitution between intermediate and primary factors is restrictive (Hertel and Tsigas, 1997), it is a standard practice in CGE modeling due to lack of information on reliable elasticities of substitution between intermediate and primary factors for more flexible production functions (Hussain et al., 2012). Figure 5.2

depicts the production technology of the regional model used in this study. The illustration in Figure 5.2 was obtained from Ochuodho et al. (2019).

Four major institutions are modeled: households (disaggregated into three categories based on annual income levels), government (both state and federal), general investment, and rest of the world. Households are modeled as utility maximizers of a Stone-Guery utility function constrained by a Linear Expenditure System (LES) demand function (Stone, 1954). Households derive income from the primary factors of production and transfers from other institutions; they also make payments to direct tax account, save, consume, and make transfers to other institutions. The government earns income through tax collection and transfers from other institutions. Taxes are fixed at *ad valorem* rates. Expenditures by government include transfers to households, payments to foreigners, and subsidies. Consumption by government is fixed in quantity, and government transfers to households and the investment account are normalized by a consumer price (CPI). The general investment account receives payments from the input factors and transfers from other institutions. Investment demand is fixed and defined as the product of an investment adjustment factor and the initial level of investment. Transfer payments from the rest of the world, domestic institutions, and factors are all fixed in foreign currency.

Regarding trade, consumers demand for goods is specified through a CES Armington aggregation function which captures imperfect substitution between domestic and imported goods (Armington, 1969). Based on the relative prices of domestic goods and imports, the cost-minimizing decision making of domestic consumers is used to determine the proportion of imports and domestic goods demanded. A constant elasticity of transformation (CET) function is used to model producer supply of goods (domestic or exports) or the transformation between commodities sold in the domestic and export markets. Similar to the CES aggregation for consumer demand, the CET function assumes that producer supply of goods follows an imperfect transformability between exports and domestic output sold domestically. The imperfect treatment of consumer demand substitutability and producer supply transformability permits the model to generate realistic responses (Lofgren et al., 2002; Lofgren, 2000). Imperfect substitutability and transformability may arise from differences in physical quality and differences in time and place of availability (Lofgren, 2000).

In the initial equilibrium, exchange rate and prices of commodities and primary input factors are normalized to unity. With prices normalized to one, flow values in the SAM can be interpreted as a physical index of quantity in the commodity and factor markets. New equilibrium prices are determined endogenously in counterfactual scenarios. Share and shift parameters of the CES and CET functions are calibrated with the 2016 Kentucky IMPLAN SAM dataset.

To achieve equilibrium, CGE models use standard closure rules and concepts to determine how demand and supply sides in all markets equilibrate. The choice of particular closure option depends on the context of the analysis and the user's perceptions of the economy under consideration (Lofgren et al., 2002). Typically, equilibrium is achieved in a CGE model at the micro level when all factor markets are cleared and at the macro level when savings and investment equilibrate. In equilibrium, the sum of factor demand in each sector equals total factor supply. The factor market (capital, land, and labor) in the model used in this study allows for three major alternative factor closures. The first closure assumes factors are fully employed and mobile across sectors. In this closure, quantity of each factor is fixed at the observed level and the economy-wide wage/rent is allowed to adjust until equilibrium is reached. The second closure option fixes the economy-wide wage/rent and permits unemployment of factors. The third closure alternative fixes factor demand and the economy-wide wage, but the sector-specific wage/rent and supply are variable (Lofgren et al., 2002). This study models capital as activity-specific and fixed in supply by activity, labor is considered to be flexible in supply to permit unemployment and mobile across sectors, and land is fixed in supply and mobile across sectors. The CPI is set as the reference price (numeraire) (Ochuodho et al., 2019; Hussain et al., 2012; Huan, 2010).

For savings and investment closures, three alternatives exist: the neoclassical closure, the Johansen closure, and the Keynesian closure (see Lofgren et al., 2002). The neoclassical closure is savings-driven where foreign borrowing is fixed and aggregate gross private domestic investment is determined by aggregate savings. The Johansen closure is investment-driven where foreign savings-investment balance is reached through adjustment in household consumption. Finally, in the Keynesian closure investment is fixed and all macro saving balances (ROW and RUS) are allowed to adjust (Huang, 2010; Lofgren et al., 2002). The Johansen and neoclassical closures assume no link between macrovariables and aggregate employment while the Keynesian closure establishes a link between aggregate employment and macrovariables through a Keynesian multiplier process (Lofgren et al., 2002). This study specifies the Keynesian closure as aggregate employment is linked to macrovariables. Thus, investment is fixed and macro saving balances are variable. CGE model results are very sensitive to the macroeconomic closure rules (Laborde and Traoré, 2017), hence care has to be taken to identify the most appropriate closure option. The closure concept used in this study is the same as the one adopted by Ochuodho et al. (2019) who used the same customized model and adopted the same model assumptions. The complete CGE model sets, parameters, variables, and equations are in Appendix 2.

5.4 Data

The basic framework for CGE analysis is a transaction table in the form of an Input-Output Table or a Social Accounting Matrix (SAM) based on System of National Accounts (SNA) (UN, 2008; Pyatt and Round, 1985). This study uses the 2016 SAM for Kentucky from the IMPLAN database (IMPLAN Group, 2016). The SAM has a standard industry (activity) by commodity structure (IxC) which distinguishes between accounts for activities (the entities that carry out production) and commodities. The commodities are activity outputs, either exported or sold domestically, and imports. Separating activities from commodities is preferred because it provides a more realistic representation where activities can produce multiple commodities while any commodity may be produced by multiple activities (Lofgren et al., 2002). Other major accounts in the SAM include factors used in production (labor, capital, and land) and institutions such as households, government, and the rest of the world.

The 2016 IMPLAN SAM for Kentucky consists of over 500 industries. To focus on the industries of interest in this study, industrial mapping and aggregator algorithms in General Algebraic Modeling System (GAMS) were used to aggregate the industries into nine desired industries, viz: (1) logging; (2) wood manufacturing; (3) paper manufacturing; (4) agriculture; (5) services; (6) transportation; (7) energy; (8) other manufacturing, and

(9) rest of the economy (all other industries). Table 5.1 presents a summary of the 2016 IMPLAN SAM for Kentucky.

The Kentucky IMPLAN 2016 database has nine household income classes. In this study, the income classes were aggregated into three income groups for simplicity. The three income groups were defined as: low income (with annual income less than $40,000), middle income ($40,000 to $100,000), and high income (greater than $100,000). The household population is made up of 46%, 38%, and 16% of low income, middle income, and high income household groups, respectively.

Creating the SAM for this study resulted in some imbalances in the row and column sums. CGE models can only solve without SAM imbalance errors. This study used a cross-entropy procedure based on GAMS algorithms to generate a balanced SAM (Robinson et al. 2001; Robinson and El-Said, 2000).

Elasticities are dimensionless parameters that capture behavioral responses to policy scenarios or capture behavioral responses in an economy as functions of relative prices of inputs and income (Burfisher, 2017; Blair and Miller, 2009). While a SAM database presents a static picture of an economy's equilibrium at a point in time, the elasticity parameters allow for the description of economy's movement from one equilibrium to another after a shock (Burfisher, 2017). CGE model results are sensitive to elasticities (Burfisher, 2017). Therefore, it is important to always to use the most appropriate elasticities in CGE modeling. Given the relevance of elasticities in CGE modeling and the uncertainty about their validity, many CGE modelers conduct sensitivity analysis of model results using alternative sizes of elasticities (Burfisher, 2017). While some CGE modelers estimate their elasticities to suit their model, many CGE modelers choose the most suitable elasticities based on a careful review of literature (Burfisher, 2017). This study obtained critical elasticities from (Ochuodho et al., 2019).

5.5 Experimental Shocks

The purpose of this study is to bring to light the economy-wide impacts of the Kentucky forest sector triggered by demand increase of forest sector products. This study simulates counterfactual scenarios that increase aggregate forest sector intermediate supply to sectors that use wood products in their production process. In CGE modeling, intermediate linkages create a channel through which a shock in one industry can affect the rest of the economy (Burfisher, 2017). Consider an increase in wood products demand by the construction industry as an example. This will cause a backward increase in the wood-processing industries' demand for intermediate inputs from other industries to meet the increased demand of its outputs. This will cause an increase for supply of the logging industry to supply logs to the wood-processing industries. To increase its output and supply more logs as demanded, the logging industry buys more intermediates from other industries causing an expansion in those industries. The expanded industries buy more inputs from others as they expand. If these industries depend on forest sector or forest-based industries, then the forest sector would expand and its intermediate supply would increase. Thus, by increasing forest sector intermediate supply, this study simulates this scenario through increased intermediate supply/demand in the forest sector.

Two counterfactual scenarios (from the 2016 baseline) are simulated. ***Scenario 1*** increases intermediate supply by logging, wood, and paper industries by 10%. Scenario 1 creates a situation where expansion in the forest sector is driven by increased demand for wood products in all sectors that already use outputs from logging, wood, and paper sectors (Haddad et al., 2019). Haddad et al. (2019) simulated a 1% increase intermediate demand for wood products in all sectors that depend on the forest sector to reflect increased reliance on the forest sector. Scenario 1 in this study is based on the average annual growth rate of total demand for forest sector output (logging, wood, and paper industries) as intermediate inputs by dependent industries from 2010 to 2018 (estimated from available IMPLAN data). The average annual growth rate of total intermediate demand for forest sector output is about 7.1%. This study assumes a 10% increase in intermediate demand due to the recent upward trend in the forest sector which is expected to continue, particularly due to increase in activities in housing industry which is a major consumer of wood products (Stringer et al., 2020; Wear et al., 2016; Ince and Nepal, 2012). In ***scenario 2***, intermediate supply by logging, wood manufacturing, and paper manufacturing industries are updated by -4.2%, 11.5%, and 6.5%, respectively. The shocks imposed in scenario 2 are based on the average annual growth rates of intermediate consumption from the individual forest-based industries from 2010 to 2018 (estimated from available IMPLAN data). Equation 5.1 describes the intermediate demand function.

$$QINT_{C,A} = ica_{C,A} \cdot QA_A \tag{5.1}$$

where variable is $QINT_{C,A}$ quantity of intermediate use of commodity C by activity A. QA_A is the level of activity A, and parameter $ica_{C,A}$is the quantity of C as intermediate input per unit of activity A. The CGE model is solved using general algebraic modeling system

(GAMS) software algorithm as a mixed complementarity problem (MCP) using PATH solver (GAMS Development Corp, 2020).

5.6 Results

This section presents summarized results on key microeconomic and macroeconomic indicators, including net household income, gross regional product (GRP), household welfare, supply price and quantity, government expenditure and revenue, factor demand, and imports and exports. The impacts are reported in levels ($ millions) and percentage changes from initial base equilibrium.

5.6.1 Supply Price and Quantity

As a routine in CGE modeling, all prices are normalized to unitary in the initial equilibrium before shocking the model. This means the reported price impacts are deviations from 1, which can be presented either in level or percentage change. For the 10% increase in intermediate demand by forest-based industries (scenario 1), producer (supply) commodity prices increase in all industries. The increase in producer price ranges from 0.799% to 0.002% with the logging industry having the highest percentage increase (Table 5.2). The producer prices of the logging industry, wood manufacturing industry, and paper manufacturing industry increase by 0.799%, 0.005%, and 0.013%, respectively.

In scenario 2 producer prices of the logging industry, wood manufacturing industry, and paper manufacturing industry increase by 0.144%, 0.062%, and 0.007%, respectively. The producer price of the agriculture commodities increases by 0.014% which is the highest price increase among the non-forest-based industries followed by the price of the transportation industry at 0.013%. Aside from producer price for the ROEC, producer prices for all other industries increase in scenario 2.

Table 5.3 presents commodity supply impacts in percentage and levels, respectively. For scenario 1, commodity supply is impacted positively in all industries. Commodity supply of paper manufacturing industry increases the most at 13.319% ($674.480 million), followed by the commodity supply of wood manufacturing industry and logging industry at 9.798% ($313.578 million) and 2.787% ($7.669 million), respectively. In contrast, commodity supply of logging industry decreases by 0.712% ($1.958 million) under scenario 2, while commodity supply of wood manufacturing and paper industry increase by 9.249% ($296.013 million) and 8.621% ($436.555 million), respectively. Aside from the logging industry, commodity supply is positively affected for all other industries in scenario 2. The reduction in supply in the logging industry was however expected since the industry's intermediate supply was reduced in scenario 2. Results show that the total commodity supply in non-forest-based industries increases by $866.709 million (0.196%) and $678.649 million (0.154%) in scenario 1 and scenario 2, respectively, whereas the overall commodity supply in the economy increase by $1862.435 million (0.414%) and $1409.259 million (0.313%) in scenario 1 and scenario 2, respectively.

5.6.2 Household and Welfare Impacts

Impacts on net household income are reported in Table 5.4. Net income is measured as the gross household income less household savings, household income taxes, inter household transfers, and overseas transfers. As explained in the data section above, households are classified into three income groups from low to high. However, Table 5.4 shows that the estimated net income for high income households is lower than the net income of middle household income class. This is explained by the fact that high income households are associated with high income tax rates and high savings rates than middle household income group (Holland et al., 2007). Net household income increases by $2.062 million (0.004%), $8.086 (0.013) million, and $8.127 million (0.017%) for low, medium, and high income households, respectively. A similar pattern is observed in scenario 2 where net income increases by $1.451 million (0.003%), $5.739 million (0.009), and $5.719 million (0.012%) for low, middle, and high income households.

While the change in net income is informative for examining the extent to which households are affected, it does not provide a holistic view of welfare impacts because it does not account for changes in household purchasing power stemming from the simulated shocks and the associated price effects. To measure welfare impacts this study employs the Hicksian equivalent variation (EV) which accounts for both income and price effects (Hicks, 1939) (Table 5.4). EV represents the amount of income that a household would have to be paid based on current prices that give households the same satisfaction or make households well-off in case an economic shock was to be imposed. Said differently, EV is the minimum payment a household would accept to forgo an economic shock. By accounting for both price and income changes, EV becomes a good measure for welfare impacts because both price and income changes affect household utility.

In scenario 1, EV decreases for low income households by $0.766 million while EV of increases for middle and high income households by $4.134 million and $5.152 million, respectively. EV for low income households decreases by $0.388 million, whereas middle and high income households increase by $3.146 million and $3.726 million, respectively in scenario 2. In both scenarios, the estimated EV's are consistent in direction with utility change for each household income group. Household utility decreases marginally for low income households by 0.0002% and 0.0001% in scenario 1 and scenario 2, respectively. On the other hand, household utility increases marginally for medium and high income households in both scenarios.

5.6.3 Government, Gross Regional Product, and Employment

The impacts of the counterfactual simulations on the government are presented in Table 5.6 Both federal and state government revenue and expenditure increase in both scenarios. In scenario 1, federal government revenue and expenditure increase by \$8.736 million and \$0.604 million, respectively, while the state government revenue and expenditure both increase by \$30.843 million. Similarly, federal government revenue and expenditure increase by \$6.503 million and \$0.213 million, respectively, while the state government revenue and expenditure both increase by \$23.592 million in scenario 2.Table 5.7 reports estimated impacts on gross regional products (GRP). GRP is the total of all goods and services produced in a region or an economy. It can be estimated based on factor cost that is needed to produce goods and services in an economy. This is termed as GDP at factor cost. GDP can also be estimated based on the gross value at market prices of all goods and services produced by an economy plus taxes but minus subsidies on imports. GRP increases by \$61 million (0.030%) and \$41.71 million (0.020%) in scenario 1 and 2, respectively.

The customized model used in this study permits the use of two alternative employment data from IMPLAN. For employment data, users are allowed to choose between the value of labor (initial values reported in the SAM) and aggregate employment (number of jobs) (Holland et al., 2007; Stodick et al., 2004). The second option was selected in this study, hence industry labor demand results reflect the number of jobs created or lost after the simulations. Results show a net job increase of 886 (0.0352%) and 686 (0.0273%) in scenarios 1 and 2, respectively. The service industry experiences the largest gain in jobs with 1344 and 881 jobs in scenarios 1 and 2, respectively. The number of jobs in the agriculture industry increases by 121 (0.13%) jobs and 82 (0.089%) in scenario 1 and scenario 2, respectively. In contrast, the number of jobs in the manufacturing industry declines in both scenarios. Table 5.8 below presents a summary of estimated labor demand by industry.

5.6.4 Trade and Industrial Outputs

All industries experience output increase in scenario 1. Aside from output of logging industry, outputs of all other industries increase in scenario 2. Although logging output declines, output of wood manufacturing industry increases. This is attributed to the fact that in scenario 2, intermediate supply of logging is reduced but those of wood manufacturing industry and paper manufacturing industry are increased based on the average growth rate of intermediate demand by dependent industries. Hence, in a short run analysis like conducted in this study, it can be expected that wood manufacturing output will increase regardless of its heavy dependence on the logging industry. In the long run, output reduction in logging will likely depress the wood manufacturing industry.

As explained above, trade between Kentucky and Rest of US-RUS (Domestic Trade) is distinguished from trade between Kentucky and Rest of the World-ROW (Foreign Trade). In scenario 1, results show that imports and exports from ROW increase by 0.561% and 0.410%, respectively, while imports and exports from the RUS increase by

0.690% and 0.809%, respectively. Imports and exports from ROW increase by $187.544 million (0.452%) and $106.851 million (0.312%), respectively, while imports and exports from the RUS increase by $690.281 million (0.512%) and $778 million (0.609%), respectively, scenario 2. Total imports and exports in the economy increase by $1163.874 million and $1174.351 million respectively in scenario 1, and by $877.825 million and $885.308 million, respectively in scenario 2. Table 5.9 and Table 5.10 present percentage changes in imports and exports and outputs.

5.7 Discussions

Kentucky's forest sector has experienced growth in output in recent years due to increased demand for the state's forest products. Though recent annual reports on Kentucky's forest sector highlight the consistent increase in outputs, value-added, and employment (Stringer et al., 2020), research on the economy-wide impacts associated with this upward trend in the sector has been deficient. Knowledge of the economy-wide impacts resulting from the growth in the forest sector is needed for a holistic assessment of the impacts and contributions of the sector. In this study, a static general equilibrium model (CGE) model is used to provide a snapshot of the economy-wide impacts of increased supply of the intermediate outputs by the aggregated wood, paper, and logging industries. Two counterfactual scenarios that increase the aggregate intermediate supply of the forest sector (wood, paper, and logging industries) are simulated.

Because of intersectoral linkages in the economy that the CGE modeling framework is cable of capturing, shocks in the forest-based industries have economy-wide impacts. The final SAM used as the primary database for the analysis showed that the paper, wood, and logging industries provide intermediate goods to all other industries except the transportation industry. While the transportation industry does not rely directly on logging for intermediates, however it interacts with other industries that rely on forest-based industries. Overall, an increase in intermediate supply of forest sector output impacts the Kentucky economy positively. Kentucky's gross regional product (GRP) increases following marginal increase in both federal and state government revenues and expenditures and marginal increase in total household consumption. Growth in GRP is attributed to government spending and household consumption increase.

Regarding utility and social welfare, high income and middle income households are positively impacted, while low income households experience declines in utility and welfare. The reduced welfare of low income households can be explained by the increase in producer prices which resulted in a reduction of commodity consumption by low income household category. Aside from commodities from the rest of the economy (REOC), low-income household consumption of all other commodities declined. In contrast, in the face of increased producer prices, high income households' consumption of commodities from services, wood manufacturing, agriculture, and transportation industries increases. This result indicates that although all households experience income gains, for low income households, income gains are not enough to offset price increase effects. Drawing from the fact that the welfare measure adopted in this study (equivalent variation) accounts for both price and income effects, it can be concluded that the decline in welfare of low income households is more driven by price effects than income changes. For middle and high income household groups, welfare gains stem more from income changes. In a different but related context, Holland et al. (2007), made a similar observation and conclusion on the welfare of low and high income households following energy price increase simulations which negatively affected EVs of households in Washington state. Results from this study suggest that increase in demand for forest sector products stimulates overall economic growth, but the resultant increase in producer prices dampens household purchasing power especially in low income households which consequently reduces their welfare. Thus, policies that would offset producer price increase effects such as production cost subsidies may be necessary to moderate producer prices. Also, policies that directly boost the purchasing power of low income households may be crucial to their welfare improvement as the forest sector expands. It is worth mentioning that the observed decline in welfare of low income households could be compensated by the increase in government revenue.

Generally, output, commodity supply, and producer prices of all other industries are positively impacted. This result depicts how expansion of the forest sector benefits other producers through supply price increase. The transportation industry is identified as the most positively affected industry (percent-wise) among the non-forest-based industries. This result is not surprising as the forest sector is considered transport intensive (Trømborg, 2009). For example, the logging industry relies heavily on truck transportation to move logs to processing centers. In addition to the direct link between the logging industry and transportation industry, the expansion in the transportation industry can also be attributed to the fact that both local (DT) and foreign (FT) imports and exports increase in all other industries, therefore transport activities increase.

5.8 Conclusion

An in-depth assessment of impacts and contributions of the forest sector is instrumental for policies for achieving a sustainable forest sector. This study attempts to provide a snapshot overview of the contributions and impacts of the Kentucky forest sector to the state's economy. Finding shows a positive effect on the welfare of Kentucky's economy observed through an increase in GRP. All household income groups (low, middle, and high income) enjoy income gains, however complementary policies to improve social welfare are imperative especially for low-income households due to resultant supply price increase effects. The shocks implemented in this study are not entirely hypothetical as they are based on both past and expected forest sector activities. Therefore, the results are informative and can serve as the basis for recommending policy options that sustain the Kentucky forest sector.

This study has produced important findings on the potential impacts of the Kentucky forest sector expansion, however there are areas that can be improved upon in future studies. Common to all CGE models is the sensitivity of model results to elasticities, model parameters, and closure rules. It is critical to apply elasticities estimated for a study region to get more accurate results. The elasticities applied in this study were obtained from the literature and are applicable generally to southern US (Ochuodho et al., 2019). However, it will be ideal to use elasticities estimated for Kentucky's economy. Results from different closure rules would also be informative. This study assumes capital demand is fixed by activity, therefore industries respond to shocks in the economy by adjusting labor and land demand. Exploring different closure rules which enable industries to adjust different factor combinations may provide other insightful results.

To simplify the analysis, this study aggregated industries based on the similarity of their activities (output). This aggregation masks how sub-industries are impacted. For example, the agriculture sector consists of 19 agricultural-based industries. Each of these industries may be impacted differently (depending on their relationship with the forest sector) in a disaggregated database and analysis. This study uses a static CGE model for analysis. While impact estimates from static CGE models are revealing, these models are limited by their inability to capture adjustment paths and the costs and benefits related to the transition from one equilibrium to another. With the recent projected increase in activity in the forest sector, forward looking models that take into consideration economic adjustment paths are needed for enhancing understanding of the impacts associated with forest sector activities. Such analysis can be conducted in a dynamic CGE modeling framework. Thus, future studies can improve on this study by projecting results in a dynamic CGE framework to give future insights into the impacts and contributions of the forest sector.

5.9 Tables and Figures for Chapter 5

Table 5.1 Kentucky 2016 SAM summary

Model Year	2016	Value Added	
GRP (GDP)	$203,841,876,905	Employee Compensation	$112,503,150,413
Total Personal Income	$175,258,200,000	Proprietor Income	$10,728,973,220
Total Employment	2,515,482	Other Property Type Income	$65,557,266,702
		Tax on Production and Import	$15,052,486,569
Land Area (miles^2)	39,732	Total Value Added	$203,841,876,905
Area Count (counties)	120		
		Final Demand	
Population	4,436,974	Households	$168,558,699,394
Total Households	1,775,067	State/Local Government	$28,737,289,310
Average Household Income	$98,733	Federal Government	$16,675,581,368
		Capital	$38,244,400,336
		Exports	$176,115,941,692
		Imports	($214,427,442,827)
		Institutional Sales	($10,062,591,454)
Shannon-Weaver Index	0.77621	Total Final Demand	$203,841,877,820

NB: Totals of value added may not equal to final demand due to rounding off. Source: IMPLAN (2016)

Table 5.2 Percent change in producer commodity prices from base

Industry	Scenario 1	Scenario 2
Agriculture	0.017	0.014
Logging	0.799	0.144
Wood manufacturing	0.005	0.062
Paper manufacturing	0.013	0.007
Transportation	0.018	0.013
Services	0.007	0.004
Energy	0.006	0.002
Other manufacturing	0.005	0.003
ROEC	0.002	-0.001

NB: Initial producer commodity prices = 1. Scenario 1: 10% increase in intermediate demand for forest-based industries products (logging, wood, and paper industries) in all industries that use outputs from them. Scenario 2: intermediate demand for logging, wood paper products are updated by -4.2%, 11.5%, and 6.5%, respectively.

Table 5.3 Change in commodity supply quantity

Industry	Base ($ millions)	Scenario 1 (%)	Scenario 2 (%)
Agriculture	5391.147	6.350 (0.118)	4.466 (0.083)
Logging	275.153	7.669 (2.787)	-1.958 (-0.712)
Wood manufacturing	3200.320	313.578 (9.798)	296.013 (9.249)
Paper manufacturing	5063.940	674.480 (13.319)	436.555 (8.621)
Transportation	16440.150	66.461 (0.404)	50.840 (0.309)
Services	207000.000	317.072 (0.153)	246.445 (0.119)
Energy	2071.787	3.368 (0.163)	2.655 (0.128)
Other manufacturing	146000.000	370.923 (0.253)	295.997 (0.202)
ROEC	63821.834	102.534 (0.161)	78.249 (0.123)

NB: Initial producer commodity prices = 1. Scenario 1: 10% increase in intermediate demand for forest-based industries products (logging, wood, and paper industries) in all industries that use outputs from them. Scenario 2: intermediate demand for logging, wood paper products are updated by -4.2%, 11.5%, and 6.5%, respectively.

Table 5.4 Change in net household income ($ millions)

HH category	Number of HH (% of total HH)	Base	Scenario 1	Scenario 2
Low ($0-40K)	817,639 (46%)	46503.000	2.062	1.451
Medium ($40-100K)	677,954 (38%)	64828.000	8.086	5.739
High (>$100K)	279,474 (16%)	48019.000	8.127	5.719

NB: HH represents household. Scenario 1: 10% increase in intermediate demand for forest-based industries products (logging, wood, and paper industries) in all industries that use outputs from them. Scenario 2: intermediate demand for logging, wood paper products are updated by -4.2%, 11.5%, and 6.5%, respectively.

Table 5.5 Social welfare impacts (equivalent variation in $ millions)

HH category	Number of HH (% of total HH)	Scenario 1	Scenario 2
Low ($0-40K)	817,639 (46%)	-0.766	-0.388
Medium ($40-100K)	677,954 (38%)	4.134	3.146
High (>$100K)	279,474 (16%)	5.152	3.726

NB: HH represents household. Scenario 1: 10% increase in intermediate demand for forest-based industries products (logging, wood, and paper industries) in all industries that use outputs from them. Scenario 2: intermediate demand for logging, wood paper products are updated by -4.2%, 11.5%, and 6.5%, respectively.

Table 5.6 Change in level of government expenditure and revenue ($ millions)

	Base	Scenario 1	Scenario 2
Federal government revenue	76224.018	8.736	6.503
Federal government expenditure	76223.775	0.604	0.213
State government revenue	55861.303	30.843	23.592
State government expenditure	55861.303	30.843	23.592

NB: Scenario 1: 10% increase in intermediate demand for forest-based industries products (logging, wood, and paper industries) in all industries that use outputs from them. Scenario 2: intermediate demand for logging, wood paper products are updated by -4.2%, 11.5%, and 6.5%, respectively.

Table 5.7 Change in gross regional product

	Base ($ millions)	Calculated ($ millions)	Percentage (%)
Scenario 1	203,730	203,791	0.030
Scenario 2	203,730	203,775	0.022

NB: Scenario 1: 10% increase in intermediate demand for forest-based industries products (logging, wood, and paper industries) in all industries that use outputs from them. Scenario 2: intermediate demand for logging, wood paper products are updated by -4.2%, 11.5%, and 6.5%, respectively.

Table 5.8 Change in labor demand level (number of jobs thousand)

Industry	Base	Scenario 1	Scenario 2
Agriculture	92437.631	121.470	82.186
Logging	2205.542	25.892	4.457
Wood manufacturing	15505.735	-274.383	229.148
Paper manufacturing	8748.286	296.349	208.320
Transportation	89638.067	294.037	213.789
Services	1580911.500	1344.487	881.342
Energy	1271.224	1.056	1.999
Other manufacturing	248657.350	-852.588	-555.746
ROEC	476106.920	-70.029	-379.225
Total	2515482.255	886.291	686.270

NB: Scenario 1: 10% increase in intermediate demand for forest-based industries products (logging, wood, and paper industries) in all industries that use outputs from them. Scenario 2: intermediate demand for logging, wood paper products are updated by -4.2%, 11.5%, and 6.5%, respectively.

Table 5.9 Percentage change imports and exports.

	Base	Scenario 1 (%)	Scenario 2 (%)
		Imports	
FT	41484.672	0.561	0.410
DT	135000.000	0.690	0.809
		Exports	
FT	34198.648	0.452	0.312
DT	128000.000	0.512	0.609

NB: FT represents trade between Kentucky and ROW. DT represents trade between Kentucky and RUS. Scenario 1: 10% increase in intermediate demand for forest-based industries products (logging, wood, and paper industries) in all industries that use outputs from them. Scenario 2: intermediate demand for logging, wood paper products are updated by -4.2%, 11.5%, and 6.5%, respectively.

Table 5.10 Industrial value of outputs impacts (% changes)

Industry	Scenario 1	Scenario 2
Agriculture	0.135	0.097
Logging	3.608	-0.569
Wood manufacturing	9.804	9.317
Paper manufacturing	13.334	8.629
Transportation	0.423	0.322
Services	0.160	0.123
Energy	0.168	0.130
Other manufacturing	0.258	0.205
ROEC	0.163	0.122

NB: Scenario 1: 10% increase in intermediate demand for forest-based industries products (logging, wood, and paper industries) in all industries that use outputs from them. Scenario 2: intermediate demand for logging, wood paper products are updated by -4.2%, 11.5%, and 6.5%, respectively.

Table 5.11 Percentage change in household consumption

	Scenario 1		
Industry	Low HH	Middle HH	High HH
Agriculture	-0.011	-0.003	0.002
Logging	0.000	0.000	0.000
Wood manufacturing	-0.001	0.008	0.012
Paper manufacturing	-0.013	-0.005	-0.001
Transportation	-0.018	-0.010	-0.006
Services	-0.001	0.007	0.011
Energy	0.000	0.000	0.000
Other manufacturing	-0.001	0.007	0.011
ROEC	0.002	0.010	0.015
	Scenario 2		
Industry	Low HH	Middle HH	High HH
Agriculture	-0.009	-0.004	-0.001
Logging	0.000	0.000	0.000
Wood manufacturing	-0.062	-0.056	-0.053
Paper manufacturing	-0.007	-0.001	0.002
Transportation	-0.013	-0.007	-0.004
Services	-0.001	0.005	0.008
Energy	0.000	0.000	0.000
Other manufacturing	-0.001	0.005	0.008
ROEC	0.004	0.010	0.013

NB: Scenario 1: 10% increase in intermediate demand for forest-based industries products (logging, wood, and paper industries) in all industries that use outputs from them. Scenario 2: intermediate demand for logging, wood paper products are updated by -4.2%, 11.5%, and 6.5%, respectively.

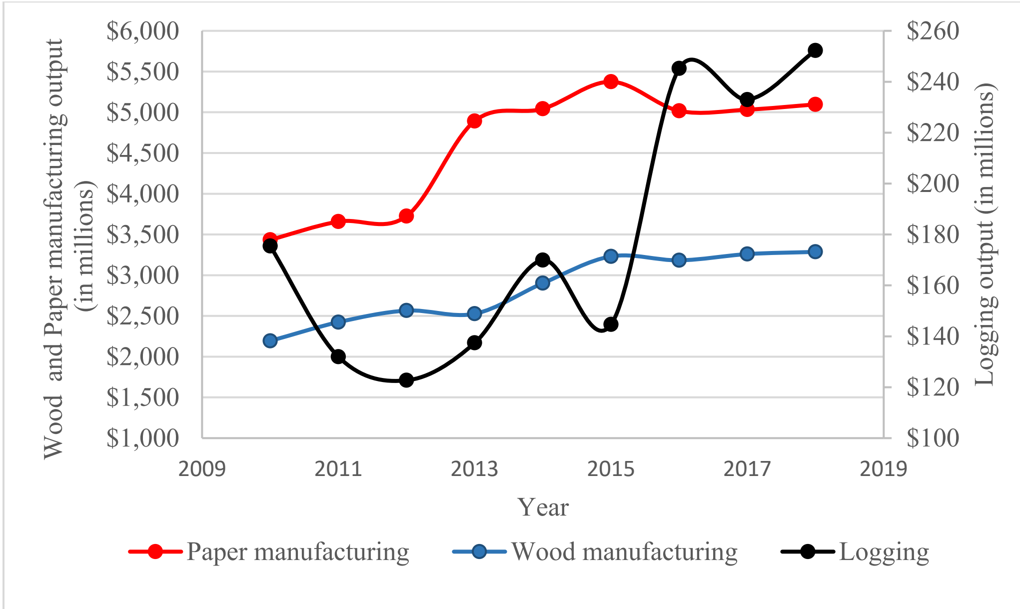

Figure 5.1 Kentucky forest sector output (IMPLAN data source 2010-2018)

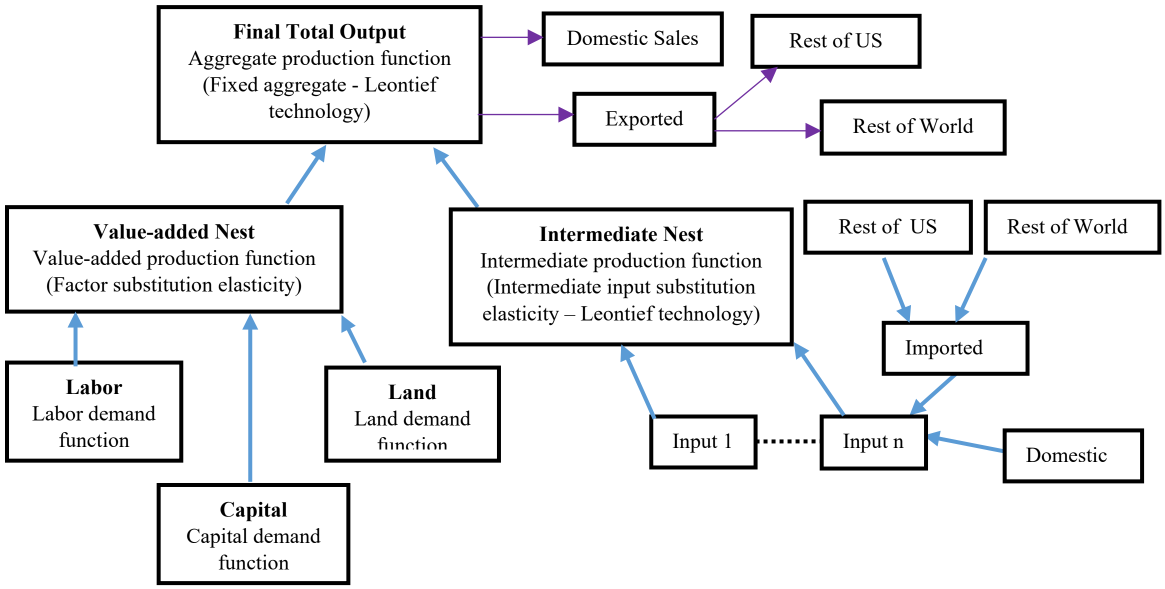

Figure 5.2 Production technology tree for regional CGE Model in US.

Source: Ochuodho et al. (2019)

Chapter 6. General Summary and Conclusions

6.1 Introduction

This dissertation focused on the structural changes and economic impacts of the Kentucky forest sector. The study applied three main analytical frameworks to shed light on the contributions and impacts of structural changes in the Kentucky forest sector. Particular contributions of this dissertation included:

(i) estimating the potential sectoral aggregation bias in Kentucky forest sector contribution analysis (Chapter 2). IMPLAN input output models are used to conduct forest sector contribution analysis where contribution estimates from a newly developed aggregation scheme (based on similarity of industry production structures) are compared to estimates from the currently used aggregation scheme (based on similarity of industry output).

(ii) assessing the influence of regional factor compositions on forest industrial structural change across countries and the role of forest manufacturing in economic growth (Chapter 3). Panel data regressions are used to highlight the relationship between regional capital endowment and shares of wood and paper manufacturing industries in output and employment in a multi-country analysis.

(iii) assessing the influence of regional factor composition on forest industrial structural change in Kentucky (Chapter 4). A dynamic panel data regression is used to examine the linkage between regional capital and labor compositions and Kentucky's forest sector shares in employment and output.

(iv) assessing the potential economic impacts of increase demand for Kentucky's forest sector products (Chapter 5). A static single region CGE model is used to trace the impacts of increased demand for forest sector products in Kentucky's economy.

6.2 Summary of Key Findings

Key findings from this study are:

Chapter 2:

(i) The IMPLAN modification approach of forest sector economic contribution analysis generates minimal to no biased estimates from aggregated industries.

(ii) Forest-based industries aggregation based on production structures introduces more bias in economic contribution estimates when feedback effects are considered.

Chapters 3 and 4:

(i) Regional factor compositions are important determinants of forest industrial structural change.

(ii) Simultaneous increase of labor and capital is crucial for improving forest industrial structure.

Chapter 5:

(i) Kentucky's forest sector is an important contributor to the state's economic growth.

(ii) Expansion of the forest sector benefits other producers through supply price increase.

(iii) Complementary policies are needed to improve household welfare in Kentucky as the as the forest sector expands.

These results provide insights and guidance to input-output analysts for more accurate and less-biased economic contribution analyses. Results also provide knowledge on how forest industrial structure can be improved based on factor usage. Furthermore, this research provides insights into the economic impacts of increased demand of forest sector products and valuable policy-relevant information for sustainable Kentucky forest sector.

6.3 Limitations of The Study and Future Research Directions

Despite comprehensive efforts and some key results, this study has some limitations and a few caveats that are worth noting. These are outlined next with suggestions of recommended future research directions for each.

(i) First, in Chapter 2, Input-Output models are demand-driven so the input-output system experiences a shock after a change in the final demand. For this reason, this study followed the common approach of assuming the final demand of some industries does not coincide with the base year final demand. This was achieved by increasing the final demand of sawmill, woodworking and paper machinery industry (IMPLAN code 269), and forestry and forest products industry (IMPLAN code 15). Adjusting the final demand of other industries in a region in future studies may provide more insights into the extent of sectoral potential aggregation bias in the Kentucky forest sector economic contributions.

(ii) Second, the data used in Chapter 3 spans from 1980 to 2007. The data period limits study in that it does not provide a more recent representation and trendlines of the wood and paper manufacturing industries. The industries may have changed in their factor intensities in recent times. Therefore, an application using updated and most recent data may provide contemporary insights.

(iii) Third, Chapters 3 and 4 are limited by the use of small datasets which span over a short period. This prevented the assessment of the linkage between factor composition and individual forest-based industries. This means the results depict general patterns which mask the influence of factor compositions on individual industries. Future studies can improve on this by using long span datasets on forest-based industries that would permit individual industry assessments and provide detailed insight into the relationship between factor endowment and individual industries.

(iv) Lastly, the static, single-region CGE modeling approach used in Chapter 5 provides a one time snapshot estimates of impacts. The static model does not take into account changes in industry structures over time. With projected growth in the forest sector, models that can project changes in the forest and all other sectors of the economy, such as a dynamic CGE model would be more suitable to capture projected changes and attendant impacts, which would be more policy-relevant and appropriate.

APPENDIX 1

Description of forest-based industries aggregated into Kentucky forest sector.

Logging

IMPLAN Code 15 -Forestry, forest products, and timber tract production. NAICS code for Timber Tract Operations is 113110 this industry comprises establishments primarily engaged in the operation of timber tracts for the purpose of selling standing timber. Forest Nurseries and Gathering of Forest Products is 113210. This industry comprises establishments primarily engaged in (1) growing trees for reforestation and/or (2) gathering forest products, such as gums, barks, balsam needles, rhizomes, fibers, Spanish moss, ginseng, and truffles.

IMPLAN CODE 16 - Commercial Logging. NAICS for logging is 113310. The Logging industry comprises establishments primarily engaged in one or more of the following: (1) cutting timber; (2) cutting and transporting timber; and (3) producing wood chips in the field.

Primary Wood Manufacturing

IMPLAN CODE 134-Sawmills: NAICS CODE for Sawmills is 321113. It comprises establishments primarily engaged in sawing dimension lumber, boards, beams, timbers, poles, ties, shingles, shakes, siding, and wood chips from logs or bolts. Sawmills may plane the rough lumber that they make with a planning machine to achieve smoothness and uniformity of size.

IMPLAN CODE 135-Wood preservation: NAICS CODE for Wood Preservation is 321114. It comprises establishments primarily engaged in (1) treating wood sawed, planed, or shaped in other establishments with creosote or other preservatives, such as alkaline copper quat, copper azole, and sodium borates, to prevent decay and to protect against fire and insects and/or (2) sawing round wood poles, pilings, and posts and treating them with preservatives.

IMPLAN CODE-136-Veneer and plywood manufacturing: NAICS CODE for Hardwood Veneer and Plywood Manufacturing is 321211. It comprises establishments primarily engaged in manufacturing hardwood veneer and/or hardwood plywood. Softwood Veneer and Plywood Manufacturing (321212) comprises establishments primarily engaged in manufacturing softwood veneer and/or softwood plywood.

IMPLAN CODE-269-Sawmill, Woodworking, and Paper Machinery Manufacturing: NAICS CODE Sawmill, Woodworking, and Paper Machinery Manufacturing is 333243. It comprises establishments primarily engaged in (1) manufacturing sawmill and woodworking machinery (except handheld), such as circular and band sawing equipment, planning machinery, and sanding machinery, and/or (2) manufacturing paper industry machinery for making paper and paper products, such as pulp making machinery, paper and paperboard making machinery, and paper and paperboard converting machinery.

Pulp and Paper

IMPLAN CODE 147-Paper mills: NAICS CODE for Paper (except Newsprint) Mills is 322121. It comprises establishments primarily engaged in manufacturing paper (except newsprint and uncoated groundwood paper) from pulp. These establishments may manufacture or purchase pulp. In addition, the establishments may also convert the paper they make. Newsprint Mills (322122) comprises establishments primarily engaged in manufacturing new sprint and uncoated groundwood paper from pulp. These establishments may manufacture or purchase pulp. In addition, the establishments may also convert the paper they make.

Secondary Wood Manufacturing

IMPLAN CODE 137-Paper mills: NAICS CODE for Engineered Wood Member (except Truss) Manufacturing is 321213. It comprises establishments primarily engaged in manufacturing fabricated or laminated wood arches and/or other fabricated or laminated wood structural members.

IMPLAN CODE 138 - Reconstituted wood product manufacturing: NAICS CODE for Reconstituted Wood Product Manufacturing is 321219. It comprises establishments primarily engaged in manufacturing reconstituted wood sheets and boards.

IMPLAN CODE 139- Wood windows and door manufacturing: NAICS CODE for Wood Window and Door Manufacturing is 321911. It comprises establishments primarily engaged in manufacturing window and door units, sash, window and door frames, and doors from wood or wood clad with metal or plastics.

IMPLAN CODE 140 - Cut stock, resawing lumber, and planning: NAICS CODE for Cut Stock, Resawing Lumber, and Planning is 321912. It comprises establishments primarily engaged in one or more of the following: (1) manufacturing dimension lumber from purchased lumber; (2) manufacturing dimension stock (i.e., shapes) or cut stock; (3) resawing the output of sawmills; and (4) planning purchased lumber. These establishments generally use woodworking machinery, such as jointers, planers, lathes, and routers to shape wood.

IMPLAN CODE 141 - Other millwork, including flooring: NAICS CODE for Other Millwork, including Flooring is 321918. It comprises establishments primarily engaged in manufacturing millwork (except wood windows, wood doors, and cut stock.

IMPLAN CODE 142 - Wood container and pallet manufacturing: NAICS CODE for Wood Container and Pallet Manufacturing is 321920. It comprises establishments primarily engaged in manufacturing wood pallets, wood box shook, wood boxes, other wood containers, and wood parts for pallets and containers.

IMPLAN CODE 144 - Prefabricated wood building manufacturing: NAICS CODE for Prefabricated Wood Building Manufacturing is 321992. It comprises establishments primarily engaged in manufacturing prefabricated wood buildings and wood sections and panels for prefabricated wood buildings.

IMPLAN CODE 145 - All other miscellaneous wood product manufacturing: NAICS CODE for All Other Miscellaneous Wood Product Manufacturing is 321999. It comprises establishments primarily engaged in manufacturing wood products (except establishments operating sawmills and preservation facilities; establishments manufacturing veneer, engineered wood products, millwork, wood containers, pallets, and wood container parts; and establishments making manufactured homes (i.e., mobile homes) and prefabricated buildings and components).

IMPLAN CODE 368 - Wood kitchen cabinet and countertop manufacturing: NAICS CODE for Wood Kitchen Cabinet and Countertop Manufacturing is 337110. It comprises establishments primarily engaged in manufacturing wood or plastics laminated on wood kitchen cabinets, bathroom vanities, and countertops (except freestanding). The cabinets and counters may be made on a stock or custom basis.

IMPLAN CODE 364 - Boat building: NAICS CODE for Ship and Repairing is 336612. It comprises establishments primarily engaged in building boats. Boats are defined as watercraft not built in shipyards and typically of the type suitable or intended for personal use. Included in this industry are establishments that manufacture heavy-duty inflatable rubber or inflatable plastic boats (RIBs).

IMPLAN CODE 369 - Upholstered household furniture manufacturing: NAICS CODE for Upholstered Household Furniture Manufacturing 337121. It comprises establishments primarily engaged in manufacturing upholstered household-type furniture. The furniture may be made on a stock or custom basis.

IMPLAN CODE 370-Nonupholstered wood household furniture manufacturing: NAICS CODE for Nonupholstered Wood Household Furniture Manufacturing is 337122. It comprises establishments primarily engaged in manufacturing nonupholstered wood household-type furniture and freestanding cabinets (except television, stereo, and sewing machine cabinets). The fur nature may be made on a stock or custom basis and may be assembled or unassembled (i.e., knockdown).

IMPLAN CODE 372 - Institutional furniture manufacturing: NAICS CODE for Institutional Furniture Manufacturing is 337127. It comprises establishments primarily engaged in manufacturing institutional-type furniture (e.g., library, school, theater, and church furniture). Included in this industry are establishments primarily engaged in manufacturing general purpose hospital, laboratory, and dental furniture (e.g., tables, stools, and benches). The furniture may be made on a stock or custom basis and may be assembled or unassembled (i.e., knockdown).

IMPLAN CODE 373 - Wood office furniture manufacturing: NAICS CODE for Wood Office Furniture Manufacturing is 337211. It comprises establishments primarily engaged in manufacturing woo d office-type furniture. The furniture may be made on a stock or custom basis and may be assembled or unassembled (i.e., knockdown).

IMPLAN CODE 374 - Custom architectural woodwork and millwork: NAICS CODE for Custom Architectural Woodwork and Millwork Manufacturing 337212. It comprises establishments primarily engaged in manufacturing custom designed interiors consisting of architectural woodwork and fixtures utilizing wood, wood products, and plastics laminates. All of the industry output is made to individual order on a job shop basis and requires skilled craftsmen as a labor input. A job might include custom manufacturing of display fixtures, gondolas, wall shelving units, entrance and window architectural detail, sales and reception counters, wall paneling, and matching furniture.

IMPLAN CODE 375-Office furniture, except wood, manufacturing: NAICS CODE for Office furniture, except wood, manufacturing 337214. It comprises establishments primarily engaged in manufacturing nonwood office-type furniture. The furniture may be made on a stock or custom basis and may be assembled or unassembled (i.e., knockdown).

IMPLAN CODE 376 - Showcase, partition, shelving, and locker manufacturing: NAICS CODE for Showcase, Partition, Shelving, and Locker Manufacturing 337215. It comprises establishments primarily engaged in manufacturing wood and nonfood office and store fixtures, shelving, lockers, frames, partitions, and related fabricated products of wood and nonfood materials, including plastics laminated fixture tops. The products are made on a stock or custom basis and may be assembled or unassembled (i.e., knockdown).

Establishments exclusively ma king furniture parts (e.g., frames) are included in this industry.

IMPLAN CODE 385 - Sporting and athletic goods manufacturing: NAICS CODE for Sporting and athletic goods manufacturing is 339920. It comprises establishments primarily engaged in manufacturing sporting and athletic goods (except apparel and footwear).

IMPLAN CODE 390 -Musical instrument manufacturing: NAICS CODE for musical instrument manufacturing is 339992. It comprises establishments primarily engaged in manufacturing musical instruments (except toys).

Paper Converters

IMPLAN CODE 148 - Paperboard mills: NAICS CODE for Paperboard Mills is 322130. It comprises establishments primarily engaged in manufacturing paperboard (e.g., can/drum stock, container board, corrugating medium, folding carton stock, linerboard, tube) from pulp. These establishments may manufacture or purchase pulp. In addition, the establishments may also convert the paperboard they make.

IMPLAN CODE 149 - Paperboard container manufacturing: NAICS CODE for Corrugated and Solid Fiber Box Manufacturing is 322211. It comprises establishments primarily engaged in laminating purchased paper or paperboard into corrugated or solid fiber boxes and related products, such as pads, partitions, pallets, and corrugated paper without manufacturing paperboard. These boxes are generally used for shipping. Folding Paperboard Box Manufacturing (322212) comprises establishments primarily engaged in converting paperboard (except corrugated) into folding paperboard boxes without manufacturing paper and paperboard. Other Paperboard Container Manufacturing

(322219) comprises establishments primarily engaged in converting paperboard into paperboard containers (except corrugated, solid fiber, and folding paperboard boxes) without manufacturing paperboard.

IMPLAN CODE 150 - Paper bag and coated and treated paper manufacturing: NAICS CODE for Paper Bag and Coated and Treated Paper Manufacturing is 322220. It comprises establishments primarily engaged in one or more of the following: (1) cutting and coating paper and paperboard; (2) cutting and laminating paper, paperboard, and other flexible materials (except plastics film to plastics film); (3) manufacturing bags, multiwall bags, sacks of paper, metal foil, coated paper, laminates, or coated combinations of paper and foil with plastics film; (4) manufacturing laminated aluminum and other converted metal foils from purchased foils; and (5) surface coating paper or paperboard.

IMPLAN CODE 151 - Stationery product manufacturing: NAICS CODE for Stationery Product Manufacturing is 322230 it comprises establishments primarily engaged in converting paper or paperboard into products used for writing, filing, art work, and similar applications.

IMPLAN CODE 152 - Sanitary paper product manufacturing: NAICS CODE for Sanitary Paper Product Manufacturing is 32229. It comprises establishments primarily engaged in converting purchased sanitary paper stock or wadding into sanitary paper products, such as facial tissues, handkerchiefs, table napkins, toilet paper, towels, disposable diapers, sanitary napkins, and tampons.

IMPLAN CODE 153 – All converted paper products: NAICS CODE for All converted paper products is 322299. It comprises establishments primarily engaged in converting paper or paperboard into products (except containers, bags, coated and treated paper, stationery products, and sanitary paper products) or converting pulp into pulp products, such as egg cartons, food trays, and other food containers from molded pulp.

Wood Residue

IMPLAN CODE 165 - Other basic organic chemical manufacturing: NAICS CODE for Cyclic Crude, Intermediate, and Gum and Wood Chemical Manufacturing is 32519. It comprises establishments primarily engaged in one or more of the following: (1) distilling wood or gum into products, such as tall oil and wood distillates; (2) distilling coal tars; (3) manufacturing wood or gum chemicals, such as naval stores, natural tanning materials, charcoal briquettes, and charcoal (except activated); and (4) manufacturing cyclic crudes or cyclic intermediates (i.e., hydrocarbons, except aromatic petrochemicals) from refined petroleum or natural gas.

IMPLAN CODE 399 - Retail - Building material and garden equipment and supplies stores: NAICS CODE for Retail - Building material and garden equipment and supply dealers is 444. Industries in the Building Material and Garden Equipment and Supplies Dealers subsector retail new building material and garden equipment and supplies from fixed point-of-sale locations. Establishments in this subsector have display equipment designed to handle lumber and related products and garden equipment and supplies that may be kept either indoors or outdoors under covered areas. The staff is usually knowledgeable in the use of the specific products being retailed in the construction, repair, and maintenance of the home and associated grounds.

APPENDIX 2

CGE Model Sets, Parameters, Variables, and Equations

Sets

A	Activities
C	Commodities
CM⊂C	Commodities which have at least one source of imports (from ROW or RUS or both)[20]
CE⊂C	Commodities which have at least one export destination (from ROW or RUS or both)
CNM⊂C	Commodities which are not imported
CNM⊂C	Commodities which are not exported
CM1⊂C	Commodities which have exactly one import source
CM2⊂C	Commodities which are imported from both sources (ROW and RUS)
CE1⊂C	Commodities which have exactly one export destination
CE2⊂C	Commodities which are exported to both destinations (ROW and RUS)
F	Factors of production and indirect business taxes
FF	Factors of production
I	Institutions
H⊂I	Households
G⊂I	Government units
HG⊂I	Households and government units
FG⊂I	Federal government units
SG⊂I	Federal government units
T	Trading regions (FT: rest of world, DT: rest of US)

[20] ROW is Rest of the world. RUS is Rest of US.

Parameters

ad_A	Shift parameter for production function
$adel_c$	Share parameter for Armington demand function
ae_C	Shift parameter for export transformation function
am_C	Shift parameter for Armington import function
aq_C	Shift parameter for Armington demand function
$arho_C$	Exponent for Armington demand function
as_C	Shift parameter for supply transformation function
$beta_{C,H}$	Marginal budget share parameter for Stone-Geary utility function
$cwts_C$	Weight of commodity C in the consumer price index
$del_{F,A}$	Share parameter for CES production function
$edel_C$	Share parameter for export transformation function
$efac_{FF}$	Demand elasticity for factors of production
$engelwt_H$	Engel aggregation weight
$erho_C$	Exponent for export transformation function
$esubd_C$	Elasticity of substitution between regional output and imports
$esube_C$	Elasticity of transformation between foreign and regional exports
$esubm_C$	Elasticity of substitution between foreign and regional imports
$esubp_A$	Elasticity of substitution for production function
$esubs_C$	Elasticity of transformation between regional output and exports
$frischh_C$	Frisch parameter for Stone-Geary utility function
$ibeta_C$	Budget share parameter for investment utility function
$ica_{C,A}$	Quantity of C as intermediate input per unit of activity A
$iengelwt$	Engel aggregation weight for commodity investment
$ifrischh_C$	Investment demand flexibility ($ifrischh_C = -1$ implies no minimum investment level)
$ilambda_C$	Subsistence level parameter for investment expenditures
$income\_ine_C$	Investment on commodities elasticity

$ine_{C,H}$	Income elasticity
$lambda_{C,H}$	Subsistence level parameter for Stone-Geary utility function
$mdel_{C}$	Share parameter for Armington import function
mps_{H}	Marginal propensity to save
$mrho_{C}$	Exponent parameter for Armington import function
$qg_{C,G}$	Government consumption
rho_{A}	Exponent for production function
$sdel_{C}$	Share parameter for supply transformation function
$sgovbal$	Initial state government budget balance
$shry_{I,FF}$	Institutional share of factor income
$srho_{C}$	Exponent for supply transformation function
tb_{A}	Indirect business tax rate
$tbshr_{G}$	Government unit share of indirect business taxes
tc_{C}	Consumption tax rate (paid only by households)
$te_{C,T}$	Export tax rate
$theta_{A,C}$	Yield of output C per unit of activity A
$tm_{T,C}$	Import tax rate
tq_{C}	Sales tax rate
$tq\_inp_{A,C}$	Sales tax rate on intermediate inputs
$trh_{H,HH}$	Inter-household transfers
$ty_{G,H}$	Household income tax rate
$wfa_{FF,A}$	Price for factor FF in activity A
$xed_{C,T}$	Elasticity of demand for world export demand function
$xshift_{C,T}$	Shift parameter for world export demand function

Variables

Price variables (endogenous)

PA_A	Activity price
PD_C	Regional price of regional output
PE_C	Composite export price in regional currency
$PER_{C,T}$	Regional export price in regional currency
$PMR_{T,C}$	Regional import price in regional currency
PM_C	Composite import price in regional currency
PQ_C	Composite commodity price
PVA_C	Value-added price
$PWE_{C,T}$	World export price in foreign currency
PX_C	Aggregate producer price for commodity
WF_{FF}	Average price for factor FF
ER_T	Exchange rate

Quantity and accounting variables (endogenous)

QA_A	Quantity level of activity
QD_C	Quantity of regional output supplied to regional demanders
QE_C	Composite export quantity
$QER_{C,T}$	Regional exports
$QF_{FF,A}$	Quantity of factor FF demanded by activity A
$QH_{C,H}$	Household consumption
$QINT_{C,A}$	Quantity of intermediate use of commodity C by activity A
$QINV_C$	Investment demand
$QINV_I$	Investment demand by institutions
QM_C	Composite import quantity
$QMR_{T,C}$	Regional imports
QQ_C	Composite quantity supplied to regional demanders

QX_C	Quantity of regional output
$DSAVM$	Rest of the U.S. savings (import row)
$DSAVX$	Foreign savings (export column)
$IINCOME$	Total investment expenditures on capital goods (commodities)
NYH_H	Net household income
$WALRAS$	WALRAS (should be 0)
$YF_{I,FF}$	Transfer of income to institution I from factor FF
YFG	Federal government income
YH_H	Gross household income
YSG	State government revenue

Exogenous variables:

QFS_{FF}	Factor supply
CPI	Consumer price index
$WFDIST_{FF,A}$	Factor price distortion factor
$IADJ$	Investment adjustment factor
$IIADJ$	Institutional investment adjustment variable
$IADJSG1_C$	Investment equation adjustment variable
$IADJSG2_C$	Stone-Geary investment adjustment variable
SADJ	Savings adjustment factor
SGADJ	State government spending adjustment factor
$SHIFTFF_{FF}$	Factor supply equation shift variable

Equations

Regional foreign import price equation:

$$PMR_{FT,CM} = pwm_{FT,CM} \cdot \left(1 + tm_{FT,CM}\right) \cdot ER_{FT} \quad \text{(A1)}$$

Regional domestic import price equation:

$$PMR_{DT,CM} = pwm_{DT,CM} \cdot \left(1 + tm_{DT,CM}\right) \cdot ER_{DT} \quad \text{(A2)}$$

Regional foreign export price equation:

$$PE_{CE,FT} = pwe_{CE,FT} \cdot \left(1 - te_{CE,FT}\right) \cdot ER_{FT} \quad \text{(A3)}$$

Regional domestic export price equation:

$$PE_{CE,DT} = pwe_{CE,DT} \cdot \left(1 - te_{CE,DT}\right) \cdot ER_{DT} \quad \text{(A4)}$$

World export demand function:

$$QER_{CE,T} = xshift_{CE,T} \cdot pwe_{CE,T}^{xed\ CE,T} \quad \text{(A5)}$$

Armington import composite equation:

$$QM_{CM2} = \left(mdel_{CM2} \cdot QMR_{FT,CM2}^{-mrhoCM2} + (1 - mdel_{CM2}) \cdot QMR_{DT,CM2}^{-mrhoCM2}\right)^{-1/mrho_{CM2}} \cdot am_{CM2} \quad \text{(A6)}$$

ROW and RUS import ratio:

$$\frac{QMR_{FT,CM2}}{QMR_{DT,CM2}} = \left(\frac{PMR_{DT,CM2}}{PMR_{FT,CM2}} \cdot \frac{mdel_{CM2}}{1-mdel_{CM2}}\right)^{1/1+mrho_{CM2}} \quad \text{(A7)}$$

Quantity for an imported commodity

$$QM_{CM1} = QMR_{DT,CM1} \cdot QMR_{FT,CM1} \quad (A8)$$

Price for an imported commodity:

$$PM_{CM1} = PMR_{DT,CM1} + PMR_{FT,CM1} \quad \text{(A9)}$$

Value of imports:

$$PM_{CM2} \cdot QM_{CM2} = \sum_T PMR_{T,CM2} \cdot QMR_{T,CM2} \quad \text{(A10)}$$

Armington export composite equation:

$$QE_{CE2} = ae_{CE2} \cdot \left(edel_{CE2} \cdot QER_{CE2,FT}^{erho_{CE2}} + (1 - edel_{CE2}) \cdot QER_{CE2,DT}^{erho_{CE2}}\right)^{1/erho_{CE2}} \quad \text{(A11)}$$

ROW and RUS export ratio:

$$\frac{QER_{CE2,DT}}{QER_{CE2,FT}} = \left(\frac{PER_{CE2,DT}}{PER_{CE2,FT}} \cdot \frac{edel_{CE2}}{1-edel_{CE2}}\right)^{1/erho_{CE2}-1} \tag{A12}$$

Value of exports:

$$PE_{CE2} \cdot QE_{CE2} = \sum_T PER_{CE2,T} \cdot QER_{CE2,T} \tag{A13}$$

Quantity for an exported commodity:

$$QE_{CE1} = QER_{CE1,DT} + QER_{CE1,FT} \tag{A14}$$

Price for an exported commodity:

$$PE_{CE1} = PER_{CE1,DT} + PER_{CE1,FT} \tag{A15}$$

Absorption equation:

$$PQ_C \cdot QQ_C = (1 + tc_C) \cdot \left(PD_C \cdot QD_C + \sum_T PMR_{T,C} \cdot QMR_{T,C}\right) \tag{A16}$$

Domestic output value:

$$PX_C \cdot QX_C = PD_C \cdot QD_C + PE_C \cdot QE_C \tag{A17}$$

Activity price equation:

$$PA_A = \sum_C PX_C \cdot theta_{A,C} \tag{A18}$$

Value added price equation:

$$PVA_A = PA_A \cdot (1 - tb_A) - \sum_C \left(\left(1 + tq\_inp_{A,C}\right) \cdot ica_{C,A} \cdot PQ_C\right) \tag{A19}$$

Leontief-CES production function:

$$QA_A = \frac{ad_A}{1 - tb_A - \sum_C ica_{C,A}} \cdot \left(\sum_{FF} del_{FF,A} \cdot QF_{FF,A}^{-rho_A}\right)^{-1/rho_A} \tag{A20}$$

Factor demand equation:

$$WF_{FF} \cdot WFDIST_{FF,A} = \frac{PA_A \cdot ad_A}{1-tb_A-\sum_C ica_{C,A}} \cdot \left(\sum_{FF} del_{FFF,A} \cdot QF_{FFF,A}^{-rho_A}\right)^{\frac{-1}{rho_A}-1} \cdot$$

$$QA_A \cdot del_{FF,A} \tag{A21}$$

Intermediate input demand equation:

$$QINT_{C,A} = ica_{C,A} \cdot QA_A \tag{A22}$$

Output function

$$QX_{C} = \sum_{A} theta_{A,C} \cdot QA_{A} + \sum_{I} IMAKE_{I,C} \tag{A23}$$

Armington commodity composite equation:

$$QQ_{CM} = aq_{CM} \cdot \left(adel_{CM} \cdot QM_{CM}^{-arho_{CM}} + (1 - adel_{CM}) \cdot QD_{CM}^{\ -arho_{CM}}\right)^{-1/arho_{CM}} \tag{A24}$$

Import (domestic) demand ratio:

$$\frac{QM_{CM}}{QD_{CM}} = \left(\frac{1-adel_{CE}}{adel_{CE}} \cdot \frac{PD_{CM}}{PM_{CM}}\right)^{\frac{1}{arho_{CM}+1}} \tag{A25}$$

Composite supply for non-imported commodities

$$QQ_{CNM} = QD_{CNM} \tag{A26}$$

Output transformation (CET) equation:

$$QX_{CE} = as_{CE} \cdot \left(sdel_{CE} \cdot QE_{CE}^{srho_{CE}} + (1 - sdel_{CE}) \cdot QD_{CE}^{\ srho_{CE}}\right)^{1/srho_{CE}} \tag{A27}$$

Export (domestic) supply ratio:

$$\frac{QE_{CE}}{QD_{CE}} = \left(\frac{1-sdel_{CE}}{sdel_{CE}} \cdot \frac{PE_{CE}}{PD_{CE}}\right)^{\frac{1}{srho_{CE}-1}} \tag{A28}$$

Output transformation for non-exported commodities:

$$QX_{CNE} = QD_{CNE} \tag{A29}$$

Factor income equation:

$$YF_{I,FF} = shry_{I,FF} \cdot \left(\sum_{A}\left(WF_{FF,A} \cdot WFDIST_{FF,A} \cdot QF_{FF,A}\right) - \sum_{T} SAM_{T,FF}\right) \tag{A30}$$

Household income equation:

$$YH_{H} = \sum_{FF} YF_{H,FF} + \sum_{C} PX_{C} \cdot IMAKEQ_{H,C} + QIINV_{H} + \sum_{T} SAM_{H,T} + \sum_{G} SAM_{H,G} + \sum_{HH}\left(trh_{H,HH} \cdot \left(1 - \sum_{G} ty_{G,HH}\right) \cdot YH_{HH}\right) \tag{A31}$$

Net household income equation:

$$NYH_{H} = YH_{H} - \sum_{HH} trh_{HH,H} \cdot \left(1 - \sum_{G} ty_{G,HH}\right) \cdot YH_{H} - \sum_{T} SAM_{T,H} - SADJ \cdot mps_{H} \cdot YH_{H} \cdot \left(1 - \sum_{G} ty_{G,HH}\right) - YH_{H} \cdot \sum_{G} ty_{G,H} \tag{A32}$$

Household consumption demand:

$$QH_{C,H} = lambda_{C,H} + beta_{C,H} \cdot \left(NYH_{H} - \sum_{CC} lambda_{CC,H} \cdot (1 + tq_{CC}) \cdot PQ_{CC}\right) / \left((1 + tq_{C}) \cdot PQ_{C}\right) \tag{A33}$$

Investment demand equation:

$$QINV_{C} = IADJ \ \cdot IADJSG1_{C} \cdot QINVO_{C} \tag{A34}$$

Institutional investment demand:

$$QIINV_{H} = IIADJ \cdot QIINVO_{H} \tag{A35}$$

Investment on capital commodities:

$$IINCOME_{H} = \left(\sum_{C} PX_{C} \cdot IMAKEQ_{INV,C}\right) + SADJ \cdot \left(\sum_{H} mps_{H} \cdot \left(1 - \sum_{G} ty_{G,H}\right) \cdot YH_{H}\right)$$
$$+(YFG - EFG) + sgovbal + FSAVX \cdot ER_{FT} + DSAVX \cdot ER_{DT} +$$
$$\sum_{FF} YF_{INV,FF} - \sum_{HG} QIINV_{H,G} - DSAVM \cdot ER_{DT} - FSAVM \cdot ER_{FT} \tag{A36}$$

Investment demand for commodities:

$$QINV_{C} = \left(ilambda_{C} + ibeta_{C} \cdot \left(\frac{IINCOMEO - \sum_{CC} ilambda_{CC} \cdot PQ_{CC}}{PQ_{C}}\right)\right) \cdot$$
$$IADJ \cdot IADJSG2_{C} \tag{A37}$$

Federal government revenue:

$$YFG = \sum_{H} \sum_{FG} ty_{FG,H} \cdot YH_{H} + \sum_{T} \sum_{FG} SAM_{FG,T} + \sum_{C} \sum_{FG} PX_{C} \cdot IMAKEQ_{FG,C} +$$
$$\sum_{FG} \sum_{FF} YF_{FG,FF} + \sum_{FG} QIINV_{FG} + \sum_{FG} \sum_{FGG} SAM_{FG,FGG} + \sum_{FG} INDT_{FG} +$$
$$\sum_{T} \sum_{C} pwm_{T,C} \cdot ER_{T} \cdot tm_{T,C} \ \cdot QMR_{T,C} + \sum_{C} \sum_{T} pwe_{C,T} \cdot ER_{T} \cdot te_{C,T} \cdot QER_{C,T} \tag{A38}$$

Federal government expenditures:

$$EFG = \sum_{FG} \sum_{I} SAM_{I,FG} + \sum_{FG} \sum_{T} SAM_{T,FG} + \sum_{FG} \sum_{C} PQ_{C} \cdot qg_{C,FG} -$$
$$\sum_{FG} SAM_{INV,FG} \tag{A39}$$

State government revenue:

$$YSG = \sum_{H} \sum_{SG} ty_{SG,H} \cdot YH_{H} + \sum_{T} \sum_{SG} SAM_{SG,T} + \sum_{C} \sum_{SG} PX_{C} \cdot IMAKEQ_{SG,C} +$$
$$\sum_{SG} \sum_{FF} YF_{SG,FF} + \sum_{SG} QIINV_{SG} + \sum_{SG} \sum_{SGG} SAM_{SG,SGG} + \sum_{SG} INDT_{SG} +$$
$$\sum_{SG} \sum_{FG} SAM_{SG,FG} + \ tc_{C} \ \cdot \sum_{C}(PM_{C} \cdot QM_{C} + PD_{C} \cdot QD_{C}) + \sum_{H} \sum_{C} tq_{C} \cdot$$
$$PQ_{C} \cdot QH_{C,H} + \sum_{A} \sum_{C} tq\_inp_{A,C} \cdot PQ_{C} \cdot QINT_{C,A} \tag{A40}$$

State government expenditures:

$$ESG = \sum_{SG} \sum_{I} SAM_{I,SG} + \sum_{SG} \sum_{T} SAM_{T,SG} + SGADJ \cdot$$
$$\sum_{SG} \sum_{C} PQ_{C} \cdot qg_{C,SG} - sgovbal \tag{A41}$$

State government budget balanced:

$$YSG \ = \ ESG \ + \ sgovbal \tag{A42}$$

Factor market equation:

$$\sum_{A} QF_{FF,A} = QFS_{FF} \tag{A43}$$

Composite commodity market equation:

$$QQ_{C} = \sum_{A} QINT_{C,A} + \sum_{H} QH_{C,H} + \sum_{FG} qg_{C,FG} + SGADJ \cdot \sum_{SG} qg_{C,SG} + QINT_{C} \tag{A44}$$

Rest of world current accounting balance:

$$\sum_{CE} pwe_{CE,FT} \cdot QER_{CE,FT} + \left(\frac{\sum_{H} SAM_{H,FT} + \sum_{G} SAM_{G,FT}}{ER_{FT}}\right) + FSAVX = \sum_{CM} pwm_{FT,CM} \cdot QMR_{FT,CM} + \left(\frac{\sum_{FF} SAM_{FT,FF} + \sum_{HG} SAM_{FT,HG}}{ER_{FT}}\right) + FSAVM \tag{A45}$$

Rest of the U.S. current account balance:

$$\sum_{CE} pwe_{CE,DT} \cdot QER_{CE,DT} + \left(\frac{\sum_{H} SAM_{H,DT} + \sum_{G} SAM_{G,DT}}{ER_{DT}}\right) + DSAVX = \sum_{CM} pwm_{DT,CM} \cdot QMR_{DT,CM} + \left(\frac{\sum_{FF} SAM_{DT,FF} + \sum_{HG} SAM_{DT,HG}}{ER_{DT}}\right) + DSAVM \tag{A46}$$

Savings investment balance:

$$\sum_{C} PX_{C} \cdot IMAKEQ_{INV,C} + SADJ \cdot \sum_{H}\left[mps_{H} \cdot \left(1 - \sum_{G} ty_{G,H}\right) \cdot YH_{H}\right] + \sum_{FF} YF_{INV,FF} + ER_{FT} \cdot FSAVS + ER_{DT} \cdot DSAVX + (YFG - EFG) + sgovbal = \sum_{C} PQ_{C} \cdot QINV_{C} + \sum_{HG} QIINV_{HG} + ER_{FT} \cdot FSAVM + ER_{DT} \cdot DSAVM + WALRAS \tag{A47}$$

Price normalization equation:

$$\sum_{C} PQ_{C} \cdot cwts_{C} = CPI \tag{A48}$$

Indirect taxes calculation:

$$INDT_{G} = tbshr_{G} \cdot \sum_{A} tb_{A} \cdot QA_{A} \tag{A49}$$

Factor supply equation:

$$QFS_{FF} = SHIFTFF_{FF} \cdot WF_{FF}^{efac_{FF}} \tag{A50}$$

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