DISSERTATION

# SPATIAL CHARACTERISTICS: IMPROVING MODEL ACCURACY AND PROVIDING REGIONAL RESEARCH INSIGHTS

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# ABSTRACT

## SPATIAL CHARACTERISTICS: IMPROVING MODEL ACCURACY AND PROVIDING REGIONAL RESEARCH INSIGHTS

The research presented in this dissertation began with an investigation of water transfers from rural Colorado to a growing urban region and how this would affect the rural economy. Chapter 1 focuses on the growing concern of water scarcity in the arid western region of the US. In this part of the country, it is widely known that water is limited, and as populations continue to increase, so will the demand for water, which is already in short supply. A multiregional Computable General Equilibrium (MRCGE) model using spatially detailed data was built to study the impact of urban growth on a rural community and is presented in Chapter 1.

The construction of the MRCGE model led to consideration of how aggregation shapes output. This evolved into a comparison of a MRCGE model that utilized spatial details that explained the differences between a rural and urban economies with a single region CGE model that aggregated these regional differences. Chapter 2 discusses identical simulations in either model, demonstrates insights gained from refining the spatial details into a MRCGE model, and identifies specific elements lost when using a broader aggregated description blending different regions together.

Different spatial qualities between locations are critical in expanding the understanding of skier behavior. Chapter 3 provides a skier behavior model of the US, which confirms the pull effect of destination snowfall shown in regional models of the ski industry. Additionally, this

research demonstrates that skier origin weather also influences skier visitation by shifting the subjective interest of traveling to another region. The result of this model provides evidence of push and pull weather variables for a winter ski destination, filling a gap generally left by travel literature that often focuses on warm weather destinations.

Chapter 1 describes a three-region CGE model that utilizes the unique spatial characteristics of urban, rural, and interface regions; the latter includes a blend of features of both the rural and urban regions. Using explicitly defined regions provides an enhanced analysis of each community's Ag and non-Ag sectors, while also describing the impact on households. This model connects the three regions via a water market, which allows for endogenous transfers of water to occur due to urban population growth. The model adds an interregional intermediate input market, allowing urban growth to demand greater domestic supply from the rural and interface industries. The interregional intermediate input market, which captures another link between the urban region and the rural region, is a new addition to the literature. These key modeling features refine the approach to investigate urban growth's influence on a rural economy by modeling multiple interregional markets and identifying regional specific characteristics. Chapter 1 allows for a more complete understanding of the dynamics between urban growth, water transfer from the rural region, and the resulting influence on the rural economy.

Chapter 1 compares a model, which includes the water market and the intermediate input market, to two restricted models, either only trade water or only trade intermediate inputs, between regions to assess the impact these markets have on the rural economy. This comparison demonstrates that both markets can increase the cost of production due to greater urban demand, but when either is restricted, rural economies can expand in respond to urban growth. When water cannot be traded between regions factor prices become relatively cheaper in the rural region because there is not the greater urban demand causing higher water prices. With cheaper factors the rural economy can expand supply to meet the growing urban demand for intermediate inputs. When the water market is the only interregional market, the rural region transfers water (primarily from the agricultural sector resulting in Ag output decline), to the urban region. The rural agricultural sector subsequently reduces their demand for land and labor making it available to the rural non-Ag sector, thus expanding their output with these relatively cheaper factors. The greater output of the non-Ag sector offsets the Ag decline in output, resulting in a total domestic supply increase. The rural economy increases output in each alternative model due to different cross-regional effects but experiences a decline in output when all interregional markets are modeled. The inclusion of both markets generates higher cost of production that cannot be offset by substitution between sectors or by the greater urban demand for intermediate inputs.

Past research has focused on how the rural region adjusts to water transfers with varied conclusions. For example, Berck et al. (1991) describes rural agriculture shifting to less water intensive production methods and benefitting from the combined payment for their water and the adjusted domestic supply. Alternatively, Seung et al. (2000) describes a decline in rural domestic supply in response to water transfers, relying on a Leontief factor substitution specification. Both research conclusions depended on the elasticity of factor substitution. The model used in Chapter 1 applies a constant elasticity of substitution that is similar to Berck et al. (1991) but describes a decline in rural domestic supply. This different economic outcome is due to the dynamics of markets that connect the multiple regions, rather than only modeling the rural region in isolation.

The Watson and Davies (2009) model includes a water market that endogenously transfers water between sectors due to urban population growth. In their model, water is a factor input for all sectors of the economy, and as urban population expands, it shifts the demand for water to non-agricultural outputs, resulting in a higher water price. The higher price of water forces the agricultural sector to shift to less water intensive production methods resulting in less output. However, the large urban population demands greater agricultural output offsetting negative supply shift. One weakness of this model is that households and industries are not regionally identified, making it unclear how rural and urban regional economic outcomes differ. The model in Chapter 1 applies a similar endogenous water market driven by urban growth but concludes that rural domestic supply and household income both decline due to regional price variations derived from the multiregional approach.

Chapter 2 compares a spatial disaggregated MRCGE model to a single region model that uses the same data to expose the importance of spatial aggregation in CGE modeling. This analysis isolates the influence of how aggregation shapes output, revealing the differences between the two models with identical simulations. The performance of the two models highlights that spatial data must be correctly leveraged by a disaggregated structure to explain unique regional output. This comparison demonstrates that qualities in the analysis are lost when CGE models use larger aggregated regions rather than a spatially sensitive MRCGE approach, which illustrates the importance of modeling spatial details.

The water model from Chapter 1 is transformed into a single region model and compared to the original specification. The same data is used in each model, leaving only the regional specification as the structural difference between them. The data used in this model is based on PUMS data that describe community level labor and household characteristics, refining the disaggregated descriptions of regional economies. Additionally, county assessor’s data provide parcel level descriptions of land and building values, thus improving the descriptions of residential and business in the model. Each of these data sets refine spatial details, which enhance the multiregional specification. When these details are aggregated into a single region, many of the county level insights are obscured. For example, rural labor markets have greater wage gains compared to similar labor groups in different regions in response to a total factor productivity increase. This outcome is unique to the rural region, and under the aggregated single region model, this labor group does not experience an increase in wages. The model comparison demonstrates how spatial characteristics represented by the MRCGE structure can shape output by preserving spatial characteristics, which determine unique model behaviors that enhance economic analysis.

The literature has recognized the benefits of the MRCGE specification. However, the justification for the MRCGE improvements over past aggregated approaches is due to adjusting the older aggregated structure with spatially descriptive data and revealing new outputs. The problem with this approach is that the new model has both a change in structure from a single region to a multi-region, and it includes additional spatial descriptive data. This method cannot determine whether improved spatial data or the spatial disaggregation is responsible for the improvement. To address this, the model presented in Chapter 2 aggregates a disaggregated model so that the spatial data values are the same but have been transformed from spatial to aspatial. This approach allows the spatial structure to be analyzed without the influence of additional data, revealing how this uniquely impacts and shapes the output.

Chapter 3 describes how weather motivates skiers to travel from one region to another in the US. It is widely known that skiing benefits from winter conditions and that skiers are willing to travel to other locations to pursue better quality ski experiences. This model considers seasonal weather variations of destination ski areas and the origin weather variables that could impact their decision-making process. Destination and origin weather variables are significant determinants of skier visits, as confirmed by the research. Snow accumulation at a destination can pull greater visits, and colder weather at the origin makes ski trips more appealing.

Chapter 3 fits within the broad literature on travel that has focused on weather's influences on travel decisions. The travel literature describes the desirable weather variables that pull travelers towards those destinations. Additionally, this literature provides push variables where the weather of a traveler's origin changes their subjective demand for leaving their home for vacation. The push and pull effects of destination and origin weather have been applied extensively to warm weather destinations, but there are many fewer applications for the winter season and cold-weather destinations. This model tests the push and pull effect for ski areas in the US and confirms that colder, snowy destination weather pulls a greater number of skier visits and that colder weather at a skier origin further pushes them to ski in any region.

The gap in the travel literature is also shared by the ski industry studies that have exclusively focused on how destination temperature and snowfall contribute to skier attendance. The ski industry research has not examined how the skier's origin influences attendance. This model addresses the smaller scope of the ski industry research that focuses on one ski area instead of skier behavior across the whole country.

Across each of the chapters in this dissertation, spatial details motivate unique economic activity. From western water markets to the differences between rural and urban labor markets to the impact of destination snowfall on skier visits, the inclusion of spatial characteristics improves model analysis and provides key insights into regional research. The diverse application in the following chapters provides strong evidence of the importance of spatial characteristics, highlighting how they shape individual behavior and drive unique research and economic outcomes.

# DEDICATION

This dissertation is dedicated to my parents, June and the original Dr. Crofton, Derek, who both relentlessly pushed me throughout my education despite the many hurdles I encountered. Their unwavering support and encouragement have been instrumental in my achievements. I also extend my deepest gratitude to my wife, Sarah, whose steadfast encouragement and support at every step of this journey have been invaluable. Thank you for believing in me. There are also countless friends and powder days that made life bearable during this unforgettable process.

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# CHAPTER 1: IMPACT OF WATER TRANSFERS ON RURAL REGIONS

## 1.1 Introduction

In August of 2017, the local Denver publication *Westword* ran an article describing where Denver transplants were coming from and why they were arriving in such vast numbers (Roberts 2017). At the time, Denver was one of the fastest growing cities in the country. This news was to the ire of Denverites who worried about overcrowding, but in rural counties adjacent to Denver urban population growth has been a concern for a different reason. As more people move toward urban centers, they demand more water which is in limited supply. Howes and Goemans (2003) estimates water demand will exceed the water supply forcing water transfers from historical agricultural usage to meet the urban demand. The concern rural communities have is: What is the cost of urban growth on rural communities? With greater competition for water, does the resulting trade of water from rural counties to urban cities generate a negative outcome for the rural area industries and households?

Berck et al. (1991), Howes and Goemans (2003), Goodman (2004), and Watson and Davies (2009) considered the cost of the raw water transfer for rural regions. The cost that rural regions bear is based on the thinking that as water is sold from a rural region, they are made worse off because of the reduced factor of production within the region. The transfer payment benefits those which own the water rights but a reduction in rural production affects many households and businesses had the water been used locally. The opportunity cost of reduced rural water impacts the agricultural producers, but also the businesses and households associated with the agricultural producers. This argument is supported by partial equilibrium (PE) models

(Howes and Goemans (2003)) while results vary when general equilibrium (GE) models are used (Berck et al. (1991), Seung et al. (1998), Goodman (2004), Watson Davies (2009)). The major difference between the PE and GE approach is what adjustments rural producers can make in response to less water availability. The GE model expands the range of choices that rural producers have access, minimize their losses and in some cases even benefits from the sale of water. The PE model's all-else-equal assumption does not consider growing urban demand for other products from neighboring regions, which could off-set the transfer of water resulting in a net benefit. A model needs to appropriately describe how changes in the urban region impact the rural region and what choices rural producers face if the impact of rural communities is to be effectively understood.

This paper will address the concern of rural impacts by stepping back and focusing on the cause for the initial transfer of water, namely urban population growth. A computable general equilibrium (CGE) model divided into regions of urban, rural, and interface can describe the urban impacts on neighboring regions. Their separation allows the growth of urban population to affect the neighboring communities through the markets of intermediate inputs and water that trade between regions. Additionally, the separation into regions allows the unique characteristics of industries, factor supply and households to be discretely identified so that impacts can be accurately measured. This paper will simulate and compare the outcomes of different market structures for water and intermediate input trade to assess how urban growth impacts the rural region. By identifying regions and the markets that connect them, policy makers can be informed of which area's residents and industries will experience the greatest effect from urban growth.

The following literature review examines previous work and how this paper will expand on the progress already made by other researchers. Further details about the improvements are also found in the description of the model section which describes the data, and the key improvement made in the CGE model. The results and discussion section describe the CGE model's output. The key finding is the rural region experiences a decline in domestic supply and household income due to water transfers to the urban region. Alternatively, restricting the transfer of water between regions limits urban growth and creates a small rural growth of domestic supply. The model also describes how the intermediate input trade could mitigate the urban population growth's negative impact on the rural region if it creates enough urban demand for rural inputs. The water and intermediate input markets each demonstrate how urban population growth causes price changes in the rural region.

### 1.2 Literature Review

Howes and Goemans (2003) explain that historically, most of the water in Colorado is owned and used by agriculture, but urban development is consuming a growing proportion of that water. As a legal requirement in Colorado, each new development needs to secure water rights for a property to be completed. The water rights of rural agricultural land can be sold to urban regions for their development. The result is water once used by Colorado agriculture is instead used by the urban region to ensure that water can be supplied to new development. The rural agricultural land can still be used for production but can no longer be irrigated. Without water, rural agricultural output is diminished and other producers that relied on the rural agriculture are affected. The concern is the water within rural agriculture could fall to an unsustainable level and diminish the output for agriculture and other industries linked to them in the rural region.

Howes and Goemans (2003) consider the effects of water transfers on two separate Colorado rural regions using an input-output model, which is a form of PE model. They find that water transfers reduced the output of each region, but transfers were less costly than additional water storage infrastructure. This model provides a description of how various producers interact with one another and the factors needed to create output. The model uses a ceteris paribus approach to simulate how a reduction of water would affect the output for the rural region. The region that depended more heavily on agricultural production experienced greater losses when water transfer occurred.

Berck et al. (1991) was the first application of CGE models used to investigate the impact of rural water transfers in a western state. Using a model of San Joaquin Valley, California they found the reduction in agricultural output ranged from $100-200 million in the most extreme case, which was less than the expected transfer payments for the water. This outcome was derived by modeling an exogenous transfer of water out of the agricultural area and then estimating the transfer payments of water was based on market rates outside of the CGE model. This indicates that the transfer payment of water is not considered in new equilibrium agricultural production decisions.

Berck et al. (1991) provides a robustness check on the substitution of various factors in agricultural production and highlighted the importance of how agriculture uses factors of production. The degree of substitution is frequently a criticism of CGE models, where the results can be manipulated to provide a desired outcome by adjusting this substitution. Berck et al. (1991) addresses this criticism by showing a range of output by using different elasticities for substitution of factors for agricultural production supported by USGS data. Given the range of elasticities, they conclude that when water supply is reduced by 20% the decline in agricultural income would be more than offset by water transfer payment. The Berck et al. (1991) analysis addresses the challenges of substitution of land, capital, and labor as inputs to agricultural production revealing a rural resilience to water transfers.

Seung et al. (1998) provides one CGE model that results in a negative rural outcome after water transfers. This case stands out as the only CGE model that counters the benefits seen for water transfers. Seung et al. (1998) focus on the Walker River Basin between Nevada and California, which is home to numerous agricultural producers and? the Walker Lake recreational area. The simulation used a shift of water from the agricultural producers to recreational uses. A decrease in water used for hay production resulted in a net loss for agricultural production. Seung concludes that the loss of agricultural output is not offset by the combination of increased recreational use and transfer payment for water for the region. However, this result is dependent on a fixed factor input assumption that causes a 30% reduction of land used in hay production in response to a 15% reduction in water use.

Goodman (2004) used a CGE model to measure the benefits of water transfers and compared it to a proposed costly water storage project in the Arkansas River Basin in Colorado. Additionally, Goodman's model includes a rural and urban region, providing separate values for the two regions' households and industries linked by a water market. The inclusion of urban buyers and rural sellers of water makes visible how water transfers can shape either community. Goodman (2004) concludes that small short-term water transfers from rural to the urban region created a 0.05% gain in welfare for both rural and urban communities and that this outcome is cheaper than water storage projects.

Goodman's results describe how transferring water out of agriculture is compensated adequately and results in a less water intensive production decision. The welfare impacts measured by equivalent variation show that both regions' household income increased by 0.05%

when transfers were allowed, which amounts to a $1.2 million increase in the rural economic activity. The analysis concludes that as water is transferred, both rural and urban areas display behavior that makes the best of the shift of resources. The modeling of separate regions provides improvement from previous works as it reveals the rural region on its own and can describe the outcomes of both buyers and sellers of water. The result can also indicate that transfers of water were a cheaper alternative than building increased water storage capacity, supporting the conclusion reached by Howe and Goemans (2003).

Davies and Watson (2009) simulate population growth in a CGE model of the Arkansas River Basin region in Colorado that creates an endogenous shift of water from the agricultural sector towards other industries. The endogenous water transfer is made possible by a detailed water market that identifies treated water demand of households and firms in addition to untreated water demand that include agricultural, manufactures, and landscape demand. The population growth causes greater household demand for water and increases production due to new cheap labor, which increases the demand of water among firms. These changes result in a higher price of water causing the agricultural sector to sell their water to other sectors. The agricultural sector experiences a decline in the production of output but an increase in price due to greater household demand. Davies and Watson concluded that a 50% increase in urban population results in a 5.7% decrease in agricultural water use but due to the greater demand of the growing population, the value of agricultural output increases in their model. The combination of higher agricultural prices and the transfer payments potentially offset the rural impacts of urban population growth. However, due to the lack of rural and urban divide in the model it is not clear how the rural household and industries change.

There are several modeling methods that can be combined to provide a better analysis of the impact of water transfers on rural communities. First, there is a need to include both the buyers and sellers of water with regional linkages. Goodman (2004) explains the economic spillover effect of water transfers on the whole rural region so that the analysis can extend beyond the agricultural sector while also describing the urban benefits. Second, the water usage in all sectors must be substitutable in production to model the behavior of adjustments available in the long term as argued by Berck et al. (1991). This can be achieved through elasticities and by using aggregated sectors to capture the varied production decisions of selecting a water intensive crop, versus a more drought resistant one. Finally, the endogenous water transfer introduces the reason for the transfers which can additionally introduce mutual benefits between rural and urban regions through increased demand for rural output. The Watson and Davies (2009) model did not have regions discretely identified, making the linkages between rural and urban output indistinguishable. The inclusion of intermediate input trade and a water market between regions make the cross-regional impact of these markets visible. Combining these modeling methods provides an in-depth description of how water transfers driven by urban growth have influenced the rural region.

## 1.3 Analytical Model Description

One of the contributions of this research is to introduce how a multiple-region structure can model the numerous agents and markets that are present in the Big Thompson River Basin of Colorado. The structure allows for interregional markets that detail the trade of water from the rural region to the urban region. The water market functions alongside the intraregional market reflecting regionally unique and isolated market characteristics of three distinct regions. This structure can become cumbersome to explain when considering all three regions, their unique factor allocations, numerous industry sectors and households. To avoid any unnecessary confusion this section will discuss the function of a simpler model that distills the necessary details to grasp the nuance of the market forces at work. Giesecke et al. (2013) argues that ", particularly large-scale CGE models, contain enormous detail, which can make it difficult to see the main mechanisms driving a set of results." Giesecke et al.'s (2013, p. 295) solution was using back-of-the-envelope (BOTE) models that distill the crucial attributes of the CGE model and reveal the narrative of what motivates the output of the model. The performance of a simple model can inform the expected behavior of a more complex model as the markets will express similar agent objectives and their influence of shifts in equilibrium price and quantities.

The previous works that focused on rural water markets (Seung et al. (1991), Goodman (2004), Watson and Davies (2009)) have each built on others CGE models dating back to Berck et al.'s (1991) paper contributing to a heritage of familiar equations resulting in the general equilibrium outcome of the models. Each paper presents their variation of equations and how they have furthered the investigation of water markets within a CGE model. Berck et al. (1991) and Seung et al. (1998) each focused on modeling only the rural region, Goodman (2004) allowed for both rural and urban regions to be separately modeled, while Watson and Davies (2009) modeled a water market that connected several components of the rural and urban regions. This paper will further this progression by modeling separate rural and urban regions with consideration of trade of water and intermediate inputs. The separation of regions with intermediate trades allows for a more robust investigation of the regional impact of water transfers. Yet across all the models mentioned above, the equations of households, or industries have not undergone any radical transformation and to introduce the same equations used by other works will not contribute anything novel to the discussion. A better explanation of this model can be performed through discussion of an analytical model.

### 1.4 The Analytical Model

The analytical model describes two regions, each with a single firm producing a good using labor and water as inputs. Each firm has a production function that allows for some substitution between labor and water. The goal of the firms is to maximize profits, while the households aim to maximize utility based on their consumption and income functions. The supply of labor and water is upward sloping, with market equilibrium reached when the supply and demand for each factor are balanced. Each household and firm interact in factor and final goods markets. Due to regional restrictions, there are two separate final goods markets, each with a different equilibrium price and quantity. Households can rent their labor to firms within their own region, creating equilibrium employment and wages, and rent their water to firms in either region, resulting in a single price for water across both regions. The only link between regions is the market for water. There are three factor markets (two for labor and one for water), with interactions between firms and households occurring in each market.

When simulating urban population growth through an increase in the exogenous labor supply, the equilibrium wage decreases while employment in the urban region increases. This is because the profit-maximizing firms demand more labor to increase output while taking advantage of the cheaper labor supply. Consequently, urban households experience a net increase in income due to the increased labor payment. Assuming that water and labor are not perfect substitutes, urban firms experience a positive shift in the demand for water. This upward shift in the demand for water increases the price of water, which generates greater water income for both urban and rural households. Overall, the simulation shows that an increase in labor supply leads to an increase in employment, output, and income for the urban region, as well as an increase in water income for both urban and rural households due to the positive shift in water demand.

When the urban firm demands more water, it connects the urban and rural regions through their shared water market. Rural households can earn more income from water rent due to the inter-regional transfer of water. However, the increased demand for water negatively affects rural firms, as they have less water available for production. This results in reduced output from rural firms since labor and water are imperfect substitutes. In other words, rural firms require a certain amount of water to maintain their production levels. Therefore, when the price of water increases all else equal, rural firms are likely to produce less output.

The mobility of water between regions enables income to be generated outside of a household's region and allows water to create final goods in another region. This inter-regional transfer of water can result in changes in the urban region that can impact the rural region positively by providing payment for water, which benefits rural household income. However, the imperfect substitution between labor and water means that rural firms face higher production costs, which can result in less output if there is less water for production.

In terms of rural household income, the impact of these changes is ambiguous. While there is an increase in income from water rent, the decline in labor demand by rural firms for production could result in a reduction in income. These two opposing effects could result in a net positive or negative impact on rural household income, depending on the firm’s ability to substitute factors and the magnitude of the income effect of higher water rents. Thus, it is necessary to use a more detailed model that accounts for the relevant factor supply of water and how firms utilize this resource in production to determine the net impact of such changes on rural household income.

Moreover, if rural household income were to rise, it could lead to an ambiguous impact on rural firm output, where the positive income effect from greater demand could overcome the negative supply shock from the water market. This indicates that the impact on rural firm output cannot be predicted without a more detailed analysis of the water market. Hence, it is essential to use a more robust model to investigate the impacts of the inter-regional transfer of water on both rural household income and firm output.

The analytical model provides a framework to study the impact of factors such as labor and water supply on regional economies. The analytical model provides insights into the intricate interactions between households and firms in both factor and final goods markets, while highlighting the pivotal role of the inter-regional transfer of water in shaping the economic outcomes of rural and urban regions. The model is used to simulate urban population growth and analyze the impacts of an increase in labor supply on employment, output, and income for both urban and rural regions. The model also highlights the imperfect substitution between labor and water and how it can affect rural firm output and income. By accounting for relevant factors such as water supply and how firms utilize this resource in production, the model allows for a more detailed analysis of the impact of changes in water price on rural household income and firm output. Overall, this analysis provides a useful tool for policymakers and researchers to understand the complex interactions in regional economies and the potential impacts of policy changes.

The analytical model used in the simulation has some limitations. It assumes that only labor and water are the inputs in production, neglecting other possible factors. Moreover, the model does not account for all the markets that link neighboring regions, which can impact rural household and firm incomes. A more detailed analysis with regionally specific data can provide a more accurate and meaningful estimation of rural income effects. Additionally, modeling the intra-regional market for final goods and the competition between urban and rural firms for water could further enhance the model's comprehensiveness.

A Computable General Equilibrium (CGE) model could be a suitable alternative to address the limitations of the analytical model used in the simulation. The CGE model is a comprehensive economic model that accounts for all sectors and factors of production in an economy. By including all relevant factors of production and incorporating the inter-sectoral linkages between different markets, it can provide a more accurate analysis of the impacts of changes in the economy. Additionally, the CGE model can capture the substitution effect between different factors of production, including water and labor, and measure their impacts on the entire economy. By accounting for multiple markets and regions, the CGE model can provide a more comprehensive understanding of how changes in one sector can impact other sectors and regions. Thus, a CGE model could help overcome the limitations of the analytical model used in the simulation and provide a more accurate and meaningful analysis of the impacts of changes in the economy.

### 1.5 The Simulation of Urban Population Growth

The specific simulation preformed within the CGE model is an exogenous increase in the urban population of 5%. This would be the equivalent of a 5% increase in the population and would have a proportional increase across household types. Note that this does not necessitate that there are 5% more jobs within the region. Since household types introduce further complexities to the analytical model the simulation will instead be a labor supply increase in the urban region. The feedbacks of an increased labor supply will still demonstrate all the necessary feedbacks presented in the CGE model with this variation in simulation.

### 1.6 Urban Impact

The urban labor market experiences the direct impact of the exogenous labor supply increase. The positive shift in labor supply depresses the equilibrium wage and increases the employment within the urban labor market. The profit maximizing objective of the firm causes greater labor demand and expand output as the input factors are relatively cheaper than before the population increase. The urban households experience a net positive change in their income; this is due to the labor payment increases necessitated by the exogenous shock to the labor supply.

Assuming that water and labor are not perfect substitutes results in a positive demand shift by urban firms for water. The positive shift in the demand for water when faced with an upward sloping supply curve results in a higher price. The higher price of water provides a greater water income for both the urban household and the rural household. Greater demand for water by the urban firm provides the cross-regional connection discussed further on within the rural impact section. This also generate greater water rent, the only other source of the household income, for the reasons stated above.

The net impact of both factor markets generates a positive shift in production of final goods by the urban firm. Cheaper labor causes the profit maximizing quantity to increase resulting in greater demand for water. The water in the rural region is transferred to meet the expanding urban demand. The combination of more water and labor results in a positive supply shift of final goods and services.

Greater labor and water income in the urban household expand their consumption creating a positive shift in the demand of goods and services. The simultaneous shift of supply and demand in the final goods market results in an explicit increase in output. The new equilibrium price is ambiguous, as the demand shift raises the price while the supply shift decreases it.

The overall impact of an increase in labor in the urban region is greater output for urban firms and greater income for their households. The additional labor creates an increase in production that contributes to both household income and expanded output. The following section explores how the water transfers caused by urban water demand affects the neighboring rural region.

### 1.7 The Rural Impact

The positive shift in the demand for water in a market shared by both rural and urban firms results in the rural firm facing a higher cost of water. Rural production is therefore more expensive compared to before the urban labor growth. The rural region uses water and labor in production similarly to the urban region where they are imperfect substitutes. As the cost of water increases the demand for labor may increase to maintain a production schedule with the lowest costs. Since water and labor are imperfect substitutes the price of final goods must increase due to the higher cost of water.

The decline in output due to more expensive water can be mitigated by using greater labor in production. The degree of substitution between the water and labor in production could result in employment increasing or decreasing. If labor can be easily substituted for water in production the new cost minimizing factor combination may involve greater labor demand. However, the cost of additional labor could result in a decline in employment based on the elasticity of substitution between factors. This cannot be determined given the detail of this analytical model and would require detailed parameterization of the fore mentioned model components.

The last component to determine the new equilibrium of the final goods market is household income. Rural household income determines how the demand for final goods will shift. The water income has increased, and the wage income is ambiguous. If water income is large enough to offset a decline in wage income rural demand will rise. Additionally, if the wages rise the demand for the final good would experience a positive shift. It becomes clear that several unknown outcomes within the rural region can result in a variety of outcomes. The goods market could experience greater output driven by the income effect that is stronger than the negative shift in final goods supplied. Alternatively, the income effect could be weak or even negative and result in a decline in equilibrium quantity for the rural final goods. It is exactly these differences of rural household income and consumption that mandate a model sophisticated enough to investigate these conflicting effects.

## 1.8 The Adaptation of the Analytical Model

The results of the analytical model provide an overview of what changes occur given urban labor growth. This model provides a description of how an interregional water market can cause changes in a rural region. The ambiguous outcome based on factor substitution, the household income effect, and negative supply shocks to the rural final goods market all contribute to how the rural region is affected by urban population growth. To clarify the ambiguous outcomes of the analytical model a CGE model can provide appropriate parameterizations of the opposing market forces. This will deliver a conclusion of whether the rural region is made worse off across their household income and consumption as well as the regional output by their firms. Additionally, the CGE model will indicate how severe the change could be.

The CGE model offers some additional detail that will not vary significantly from the behavior described within the analytical model. The inclusion of several household groups and industries does provide some heterogeneous outcomes, but the overall labor market effects does not offer a significant systemic difference from the analytical model. This is likely due to the aggregated nature of labor groups that are only distinguished by wage levels. Additionally, including capital, land and several labor groups only serve to enrich the substitution investigation that firms must make when urban labor supply increases or the price of water rises.

Alternatively, there are details that the simplified analytical model did not cover that are presented within the CGE model that should be considered as a separate aside. For instance, one of the advancements of this CGE model over previous work is the consideration of how interregional trade of intermediate input influences regional outcomes.  Introducing intermediate goods demanded between the urban and rural region offers another link between regions that could be responsible for changing the economic outcomes of the model. Realistically production is not purely driven by one firm's combination of factors but must also include other intermediate inputs in the production function. This production function is found in previous works (Berck et al. (1991), Goodman (2004)). However, instead of limiting the IO table of one region (Berck et al. (1991)) or aggregating the urban and rural industries together (Goodman 2004) this IO table would reveal how inter and intraregional firm production functions generate spillover effects like (Watson Davies 2009).

To explain how a cross-regional IO table would change the analytical model consider the following caveat to explore this additional market influence on the model. Assume first that each firm has a Leontief intermediate input demand for production, and both rural and urban firms need each other's output to generate final goods and services. The rural firm would be able to benefit from the increased output by the urban firm as rural produced intermediate output would be necessary for urban production to increase. Additionally, if the urban firm's output becomes cheaper then cost of rural production benefits from a cheaper urban intermediate input. Finally, if rural goods become more expensive, they offer a restriction to the urban expansion in the final goods market as the cost of production has increased. If cross-regional intermediate inputs demand were price sensitive as opposed to using the Leontief assumption the effect is still present. Either case could result in less water leaving the rural region for urban production as both region's firms' outputs are strongly linked. The effect of intermediate trade offers a pathway for rural to benefit from the urban growth or at the very least mitigate the loss of output by rural firms.

The intermediate input trade between regions under urban growth offers an opportunity for rural growth by supplying urban firms the use of their inputs. This shared growth opportunity is not just a model attribute it is also a distinct aspect of the region being modeled. The urban household and firm are more closely linked to each other, but they do not exist in complete isolation from their neighbor. By modeling the market connection between regions, the shared industry linkages can mitigate the reduced output on the rural region from limited water. When urban industries increase demand for rural intermediate inputs, it causes water to remain in rural communities and spreads the economic growth across regions.  However, this aspect of the region is beyond the capabilities to be effectively modeled by an analytical approach. Instead, the further details of the multiregional CGE model are called for to have a thorough understanding of the impact of this market among all the crucial market interactions.

In a broader sense the multiregional CGE model will also substantiate the effects of several details beyond the analytical model. The most looming of these is the multiple sectors of production like an agricultural, non-agricultural, and housing service sector, that can inform the behavior of regional feedback loops of firms and households. The firm's interdependency for intermediate input was not addressed within the simple model. Additionally, the CGE approach can describe the details of allocation and elasticities that would determine production substitution as well as how households would shift their consumption preferences based on changing prices and income level. All the regional aspects of preferences and parameters can take form to provide the appropriate magnitude of each market force dispelling the ambiguous outcome of the analytical model. The following section will provide a complete description of the CGE model.

### 1.9 CGE Model Description

This model improves upon the previous work (Berck et al. (1991), Goodman (2004), Watson and Davies (2009)) by having three regions with separately identified industries and households. The separate regions include a rural, urban, and interface, which each have unique mixtures of industries, factor allocations, and household characteristics. Separating these regions allows for regional impacts to be measured, utilizing their unique features. Additionally, these regions are connected by two interregional markets of water and intermediate inputs, that allow changes in one region to impact a neighboring region. The two interregional markets describe how these regions interact with one another and will provide insight into how urban population growth may change neighboring regions. Additionally, the markets themselves are compared with alternative models where the interregional markets are restricted to an urban population growth simulation of 5%. This modeling section will define the regions and the equations of the model, as both are essential in describing market improvements.

The model separately identifies three regions: rural, urban, and the agricultural interface which will be referred to as the interface region for brevity for the remainder of the paper. The rural region has the smallest population and employment and is made up of several small towns and wide open agricultural land. The urban region has the largest concentration of jobs that mostly involve non-Ag employment with high density housing and include the city of Denver. Interface has the second largest population and employment that is made up of a mixture of Ag and non-Ag firms and includes the city of Boulder and Fort Collins. The interface region shares some qualities with the urban regions, like a thicker labor market and others with the rural regions, like the Ag sector. The added benefit of including this third region, allows for two agriculturally focused regions with different industry mixtures, and both can be examined in their response to urban population growth.

The modeled areas represent the Big Thompson River Basin, which includes the metropolitan area surrounding Denver and spans north to the Wyoming border and the northeastern plains of Colorado. The map displayed in figure 1.1 shows the three-region model and the 12 counties that the model is based on. The urban region includes Adams, Arapahoe, Douglas, Denver, Elbert, and Jefferson county. The Rural region include Morgan, Logan, and Sedgwick county. The interface region is made up of Boulder, Larimer, and Weld county. Each of these regions share a border as seen in the model map on figure 1.1.

The three regions each have a unique industrial mix which justifies the need for three separate regions. Table 1.1 describes domestic supply across each region using 2013 data from Implan and county assessors' values, which will be described further in the data section. The largest domestic supply is generated in the Non-Agricultural (Non-Ag) sector within the urban region, producing 100.7 billion dollars over the course of 2013. Non-Ag domestic supply

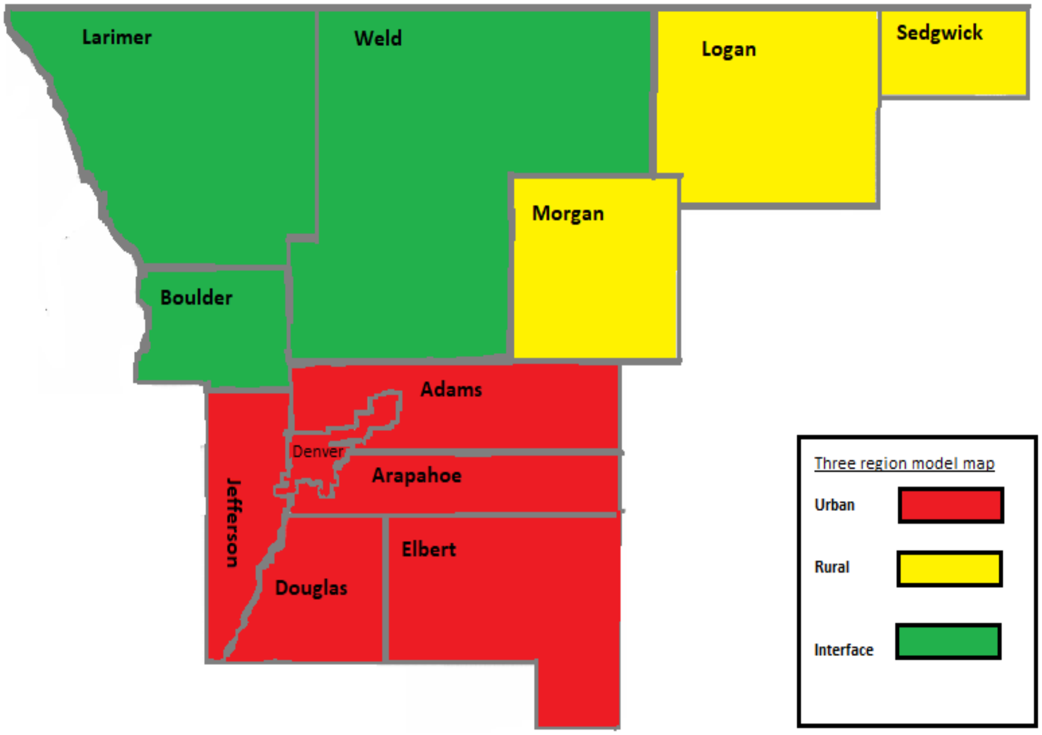


Figure 1.1 Three Region Map

Table 1.1 Regional and Industry Domestic Supply

| | Urban | | | Rural | | | Interface | | |
|---|---|---|---|---|---|---|---|---|---|
| | Ag | Non-Ag | Housing | Ag | Non-Ag | Housing | Ag | Non-Ag | Housing |
| Domestic Supply (in millions of dollars) | 167 | 100,766 | 49,392 | 221 | 3,667 | 950 | 642 | 37,488 | 18,273 |

Source: SAM

is 3.6 billion dollars and 37.4 billion dollars in the rural and interface regions, respectively. The Non-Ag sector is a composite of all industries which do not directly produce agricultural (Ag) products or housing services within the private sector. The Ag output of domestic supply per region ranges from 167 million dollars in the urban region, to 221 million in the rural region, and 642 million in the interface region. The variation in output of these two industries was the reason for creating a third classification for the interface region. The interface region has the largest output of Ag and has larger Non-Ag output than the rural region. It should also be noted that Ag production has the lowest domestic supply contribution in all the three regions.

The model also has a separate housing service sector which describes the type of lodging that households acquire. The values are derived from assessor records for each county, and then divided into a yearly payment for mortgage or rent. The urban area has the highest value of housing services at $49.4 million the rural and interface spend $950 million and $18.27 billion, respectively.

Population follows a similar trend to the housing services, where the urban region has the largest number of households of any region, with 601,124. Rural has only 40,727 and interface has 296,774 households. A household contains approximately 2.5 people, which clarifies why employment can be larger than the number of households (US Census). The housing and population data are provided by the PUMAS for this 3-region model.

Table 1.2 provides details about the employment across the different industries within the three regions. The urban region has 771,755 employees, while rural and interface each have 56,543 and 415,201 respectively (US Census). Table 1.2 shows where labor is employed between the two sectors, Ag and Non-Ag. Housing services do not employ labor but instead use Non-Ag as an intermediate input to build homes. Most labor is employed by the Non-Ag sector in all regions. The largest usage of Ag labor (by percent) is in the rural area with 4.2% while the urban and interface region only use 0.3% and 0.7%, respectively. During the simulation, the reduction in Ag output will result in both the rural and interface regions shifting their Ag labors into other sectors.

Table 1.2 Regional and Industry Employment

| | Urban | | Rural | | Interface | |
|---|---|---|---|---|---|---|
| | Ag | Non-Ag | Ag | Non-Ag | Ag | Non-Ag |
| Labor Employment (by employee) | 2,233 | 769,522 | 1,956 | 44,587 | 2,983 | 412,218 |
| Percent of Labor | 0.3% | 99.7% | 4.2% | 95.8% | 0.7% | 99.3% |

Source: PUMS

The total water in the model across all three regions sums to 1,908,721 acre-feet and is based on USGS data for water usage on an annual basis (USGS). The regional breakdown is summarized in Table 1.3 where the interface region has 1,217,870 acre-feet of water representing 64% percent of the model's total water. Rural has the next largest quantity of water with an allocation of 359,969 acre-feet, or 19%. The urban region has the least amount of water resources (17%) with 330,882 acre-feet.

The amount of land utilized across each region can also be found in Table 1.3. This demonstrates the different size of each region, with most land in the model belonging to the interface region. The model has a fixed supply of land and only considers land already in use according to the assessor's data across different industries. The table shows that urban uses the least amount of land across all three regions with 582,048 acres used. The rural region uses 653,799 acres and the interface region uses just over a million acres. The information about land usage was provided by assessors and USGS data.

Table 1.3 Land and Water Quantities Across the Three Regions

| | Acres of Land | Percent of Total Land | Acre-ft of Water | Percent of Total Water |
|---|---|---|---|---|
| Urban | 582,048 | 26% | 330,882 | 17% |
| Rural | 653,799 | 29% | 359,969 | 19% |
| Interface | 1,013,498 | 45% | 1,217,870 | 64% |
| Model Total | 2,249,346 | | 1,908,721 | |

Source: Assessors & USGS

The difference in land use between each region provides further insight to the characteristics between the regions shown in Table 1.4. Rural has the most percent of their land dedicated to Ag production at 79%, interface has the second highest with 62% and urban uses 37%. It should be noted that while rural areas dedicate a greater percent of their land to Ag than the interface, the interface region has the most total land used in Ag production. Interface uses 633,084 acres, rural uses 518,174 acres and urban uses 215,663 acres.

The remainder of Table 1.4 displays the acre-ft of water utilized across regional industries. This is calculated by dividing the acre-ft of water for each regional use by the total regional water available. Notice that the rural and interface region use different combinations of water for production, namely 94.12% for rural and 84.44% in interface. When considering this with the land usage for Ag, we can conclude that each region has a different approach to agriculture. The rural region has the highest percent of water used in the Non-Ag sector, 35.29%, but their Ag sector remains their largest user of water. The expectation is that each regions' Ag sector will lose water.

Table 1.4 Regional and Industry Land Usage

| | Urban | | | Rural | | | Interface | | |
|---|---|---|---|---|---|---|---|---|---|
| | Ag | Non-Ag | Housing | Ag | Non-Ag | Housing | Ag | Non-Ag | Housing |
| Land Acres | 215,663 | 89,702 | 276,683 | 518,174 | 122,325 | 13,300 | 633,084 | 26,439 | 353,975 |
| Land Percent | 37% | 15% | 48% | 79% | 19% | 2% | 62% | 3% | 35% |
| Water Acre-ft | 203,508 | 116,778 | 10,597 | 338,788 | 20,831 | 350 | 1,028,326 | 189,333 | 212 |
| Water Percent | 61.50% | 35.29% | 3.20% | 94.12% | 5.79% | 0.10% | 84.44% | 15.55% | 0.02% |

Source: Assessor Data and USGS Ag Data.

The three regions represent different communities with varying characteristics. The urban region has the larger population, a larger concentration of Non-Ag industry but fewer acres of land and water available to them. The rural region is the least populated and has a smaller Non-Ag sector than either of its regional neighbors. The rural region has a larger Ag sector than the urban region but is smaller than the interface region’s Ag output. The rural region has the second largest quantity of land and water of the three regions. The interface agricultural region has a unique mixture of characteristics. It has the second largest population, the largest Ag sector by output and contains the most land and water of the three regions. Each of these three regions share a border and have historically traded between each other.

The last part of describing the three regions is how they trade among each other. Trade of intermediate inputs between the three regions is shown as a matrix in Table 1.5. The rows in

Table 1.5 describe the origin, while the columns are the destination. The sum of a column represents all the intermediate inputs per region, while the rows represent where the inputs come from. Each region uses more inputs from their own region than they do from any neighboring region as seen by the diagonal from the table. Both rural and interface regions receive more inputs from the urban region than they do from each other. Rural and interface regions purchase $580 million and $6.3 billion,349 million dollars of intermediate inputs from the urban region, making the urban region the largest trading partner for each region.

Table 1.5 Local Trade Values of Intermediate Inputs (measured in millions of dollars)

| | Urban | Rural | Interface |
|---|---|---|---|
| Urban | 32,260 | 580 | 6,349 |
| Rural | 224 | 1,329 | 275 |
| Interface | 2,053 | 185 | 10,001 |
| Ag Input | 318 | 39 | 61 |
| Total Int. Inputs | 34,855 | 2,133 | 16,686 |

The last row of Table 1.5 describes the agricultural inputs used per region. Note that there is no source region specified. The reason behind making Ag supply region-less as an intermediate input removes any regional preferences for where Ag input is sourced. This specification avoids regional preferences of one region's Ag output over another. Without this specification, the urban Ag production grows alongside the urban population producing an unrealistic output. To avoid this each region's output of Ag is sold to a region-less distributor that makes each region's ag production fungible and removing preferences of where Ag inputs originate. The intermediate input demand for Ag is in the second to last row in Table 1.5 and shows that urban, rural, and interface intermediate input demand is \$318, \$39, and \$61 million, respectively.

To frame the local trade, Table 1.6 displays the percent of local trade to all inputs for the regions production. The local imports are divided by the total inputs for each regional industry. The variation between the urban region and the other two is motivated by greater inputs from the rest of the world with a larger concentration of industries within the urban regions. Additionally, the urban region depends less on the local trade from neighboring regions, using only 19% local trade proportion of total inputs for production. The rural and interface regions use a greater amount of local trade, 53% and 45%, respectively.

Table 1.6 Local Imports as a Percent of Total Production Inputs Per Region

| | Urban | Rural | Interface |
|---|---|---|---|
| Local Import Percent | 19% | 53% | 45% |

Source: SAM & Implan

### 1.10 Model Equations

The CGE model represents the interactions of a market economy for the three regions. The regions each have representative agents which seek to maximize their objective function. This model's agents are producers, households, and government. Producers seek to maximize profits; households maximize their utility function and government maximize expenditures constrained only by their need to balance budgets.  The producers are constrained by a zero-profit condition imposed by a perfect competition assumption. Household utility maximization is constrained by their income.  The behavior of each agent is quantified in dollar amounts which accounts for all interactions in the economy.  In the three-region model each of these agents are regionally specific, but they face the same equations.

The behavior of each representative agent within the CGE model can be represented in a general approach via the Circular Flow Model (Figure 1.2). Agents interact with one another through markets. The producers interact with each other by providing intermediate inputs which supply final goods and services to the households given a perfect competition assumption. The households own the factors of production and rent them to producers through the factor market which generates household income. The exchange in the two markets allows households to maximize utility, subject to their budget constraint, and the producers maximize profits subject to their production functions, prices of inputs, and consumer demand to determine their output in the market. This results in one agent's inputs becoming another agents' output and the combination of all these transactions provide an equilibrium price and quantity of all final goods, and factors in both the goods market and the factor market. Figure 1.2 below details the interactions described in this section.

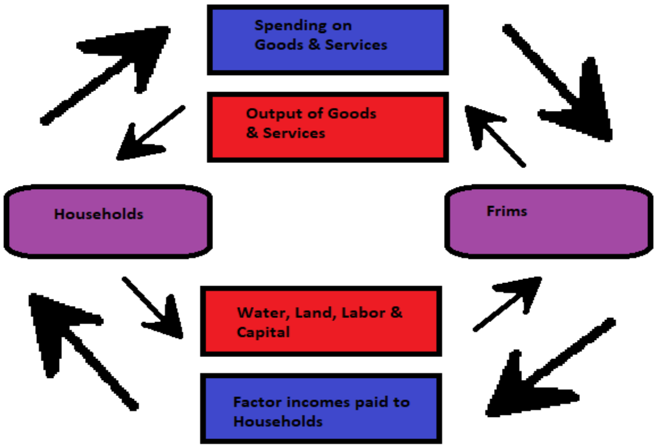


Figure 1.2 Circular Flow Diagram

The CGE model is composed of a series of equations to provide the interactions that the circular flow model describes. For more information on the complete equations refer to Berck et al. (1991). The following equations provide the necessary framework of the model to understand the simulated 5% urban population growth, factor changes and the changes in domestic supply.

The production function for firms is based on a CES function which allows for substitution of factors in maximizing the production function. This would allow a producer to switch from a labor-intensive production process to one that used a capital-intensive process, if it benefits their profit maximizing objective. The equation is illustrated below and utilizes a factor elasticity of substitution equal to 0.67. The equation describes what each industry uses to determine the optimal bundle of factors to use in production:

The industries also use other intermediate inputs in production. The intermediate input portion of the producer's production function uses inputs from its own region along with the neighboring regions and is price sensitive to these inputs. Producers combine intermediate inputs along with the basic factors of production to generate output. The description of this equation can be seen below. Note that the AD matrix describes the combination of intermediate inputs required to produce one unit of output, and the DS represents the domestic supply of these inputs.

Equation 1: $DS_i = \gamma_i(\sum_{F} \alpha_{F,i} FD^{\rho})^\wedge(\frac{1}{\rho})$

$DS_i$:Domestic supply

$\gamma_i$: Total factor productivity

$\alpha_{F,i}$: Factor coefficient

$FD^{\rho}$: Factor demand

$\rho$: elasticity of factor substitution

Equation 2: $$V_i = \sum_j AD_{i,j} * DS_j * (Pold_i / Pnew_i)$$

AD: intermediate input coefficients.

DS: domestic supply

$Pold_i$ : base price

$Pnew_i$ : new price

As noted above, water can enter the production as both a factor and an intermediate input first as raw water and then as treated water. Water as a factor of production allows for CES substitution between factors to occur, while treated water as an intermediate input only allows slight variation of input usage, based on the price changes for treated water. To reinforce the need for both forms of input, consider the example of how a golf course operates. Golf courses often water their greens using non-potable water, which is the raw water described in this model. If the price rises, the golf course may consider purchasing water efficient sprinklers and reduce the usage of raw water. This could be effectively described by the CES production function that would substitute capital for raw water. However, if the business were instead a brewery and used treated water to brew beer, an increase in treated water price could not be substituted away from with capital or any other input. The profit maximizing behavior of the brewery that faced higher cost of treated water would be to brew less beer all-else was held equal.

Equation 3 describes how households change in response to employment, labor income and the consumer price index (CPI). This equation allows for the exogenous shock of population growth to vary from the initial simulation as the three determinants each reach equilibrium. The net effect of employment, labor income and CPI determine the change in the number of people either entering or exiting a region. The population growth shock is introduced through an increase of 5% to the $HH0_{urban,}$ causing all other equations to reach their new equilibrium based on the greater households of the urban region.

Equation 3: $HW_H/HH_H = HW0_H/HH0_H * ((LRA_L)/RA0_L))/9)/(CPI_H/CPI0_H)$

HW: working households

HH: the total households

RA: new wage

RA0: base wage

CPI: consumer price index.

As the focus of this paper is about the distribution of factors of production, the remainder of the equation section will describe how factors of production are supplied within the model. This should inform how prices, and in some cases quantity, of each factor may change given the 5% urban population growth in the simulation. The model is composed of four factors of production: labor, land, capital and raw water and they are used as described in equation 1, given the CES production function.

Each of the factors of production have unique supply and market structures. For instance, the labor supply in the model is calculated with the 3rd equation, which determines in-flow and out-flow of the population based on labor income, employment, and changes in the CPI. Labor wages within an industry are fixed but are competitively determined on a regional basis. This structure results in competition between sectors for labor in each region, but not between regions. The labor market is regionally exclusive with no region-to-region migration included in the model.

Raw water is the only factor of production which can be transferred between regions. The industry price for water is fixed, while the inter-regional price for water varies. This allows the demand for water in one region to have a direct impact on the price of water in a neighboring region since they are competing for the same fixed supply of raw water. It should be noted that raw water is a factor of production, but water can be treated by the municipal productive sector and turned into an intermediate input for other industries, or as a final good for the households.

The capital supply in this model is upward sloping with independent markets specific for each industry and region. This allows capital demand in one industry to move independently of another industry. The reason for this assumption is that capital for agriculture would not be suitable to be used in non-agricultural production. The regional independence allows identical industry in another region to determine its own price without influencing the capital prices for a neighbor.

Land is substitutable between industries and housing per region, creating a single regional price of land. Since land supply is fixed if one industry demands more land it must be satisfied by other sectors using less land. The fixed land supply specification also means agricultural producers cannot use greater amounts of land in production to offset the impact of less water, which is typically the case when land is supplied is modeled with an upward sloped supply curve.

## 1.11 Model Restriction Descriptions

The model's unique combination of markets is described in Table 1.7. The original model will have access to all markets and will be referred to as the free-market (FM) model. The other two models restrict either the water market or the intermediate input market, referred to as the restricted water market (RWM) model, or restrict the intermediate input trade, referred to as the (TR) model.

The first market described on the vertical axis of Table 1.7 is the market for raw water. When the model is said to have a free water market that refers to the ability for water to be bought and sold between regions. A free water market results in one single market for water that encompasses all three regions. When the water market is restricted each of the three regions will have a separate water market, where water can only be traded between industries of that region. The FM and TR models each have a free water market while the RWM does not. The result of these two different markets also means that FM and TR have one price for water due to the market equilibrium reached across all three regions. Alternatively, the RWM model has three prices for each regional water market. The variation in prices and quantities demanded of water provide distinctly different factor demand between the three models as well as output of industries and household income.

Table 1.7 Model Characteristics

Model Descriptions

| | Local Trade | Nonlocal Trade |
|---|---|---|
| Free Water Market | FM Model | TR Model |
| Restricted Water Market | WRM Model | |

The horizontal axis of Table 1.7 describes whether there is local trade of intermediate goods and services between regions. When this market is modeled, we have intermediate inputs from all three regions used to generate output for each regional industry. For example, the urban non-agricultural sector would use inputs from the urban, rural, and interface sectors when local trade was modeled. Alternatively, when local trade is not modeled only urban intermediate inputs would be used for production. For the TR model, a local input from a neighboring region is now supplied as an import from the rest of the world. Shifting local inputs to rest of world imports means that the restricted market model has the same input costs, but not the same suppliers. Similarly, sales to a neighboring region are now added to the exports each region ships to the rest of the world. This transformation allows the three models to have the same total value per row and column within the SAM.

## 1.12 Model Data Summary

The data used by the CGE model is based on the values of the social accounting matrix (SAM), that includes all the transactions between economic agents over the course of one year (2013). Each transaction is calculated into a dollar value, and the sum of each row provides sector sales, and each column describes sector purchases. Given that there are imports and exports to the rest of the world, the matrix is balanced, with the sum of all inputs equaling the outputs, and representative of all markets over the course of one year.

The data used to build the SAM come from several sources. Many CGE modelers depend on the Implan IO table, which provides a standardized and proprietary approach generally accepted among researchers (Goodman 2000 & Davies Watson 2009). This model requires some finer detail than the Implan model, like how water is used by all sectors of the economy, so when local data sources where available, they were utilized.

The local data is typically gathered by country level sources. The government taxes and expenditures are dependent on county annual financial reports (CAFR), which is a standardized report describing sales taxes, property taxes, sales taxes as well as other miscellaneous taxes. This report also describes services funded by these taxes and divided into health, transportation, and administration. The assessor data provides information on land and building values for both the productive sectors and the housing services which is reduced to an estimated yearly payment. These sources are used to replace Implan data whenever possible.

National data is also used to build the SAM to inform household consumption and interregional trade values. The American Community Survey (ACS) describes household purchases by income level. The ACS also contributes regional data based on the public use microdata sample (PUMS), that examines the connection between labor payments and household earnings in 2013. Each PUMS identifies an area within each of the three regions that is composed of a population of 100k. This provides average home consumption information and is scaled up to the number of households that the PUMS data describes as the regional population. Additional data on the labor payments and sector level employment is provided by the Bureau of Labor and Statistics (BLS) in 2013 that informs the net employment level by industry. The Implan data provides a source for trade between regions and offers a useful input-output framework for each industry sector scaled to the land and capital values provided by county assessor data.

The model utilized in this paper provides improvements on previous research. First, there are multiple regions present which allows regional equilibrium of household and producer behavior in response to simulations of urban growth. Second, there is a market for water that describes heterogeneous buyers and sellers by regions to show how water use changes across regions and industries. Third, there is local trade of intermediate goods between each region to explain how each region's industries have cross-regional supply chains. The comparison of the three models in this paper demonstrates how each of these improvements shape the output of the model under an urban population growth. The comparison between models reveals which markets contribute to rural costs and benefits, due to urban population growth. Only through the comparison of the restricted and unrestricted interregional markets can we derive differences that occur and how this changes the impact to rural households and industries.

### 1.13 Results and Discussion

The results of the Free-Market (FM) model shown in Table 2.1 establish that urban population growth of 5% causes a 0.82% increase in urban domestic supply. The urban growth causes water demand to shift between regions where the urban region increased water demand by 0.38%, or roughly 1,262 acre-ft, and rural and interface regions lose 0.07% and 0.082% respectively, or 264 and 998 acre-ft each. The transfer of water creates decline of domestic supply among the rural and interface regions, of -0.02% and -0.01%, respectively. The shift in water and the change in output occur endogenously and meets the expected behavior of the model that describes a spillover effect of urban growth on the neighboring regions.

The reason the rural and interface regions experience a decline in domestic supply in the FM model is largely driven by a higher cost of production. The water market contributes to the cost of production across two major sources. First, there is the water cost itself, which increases by 0.15% as shown in Table 2.1. The second source of increased cost of production is due to factor substitution where firms used alternative factor combinations to generate output. Factors are imperfect substitutes in the model causing additional costs in production when firms substitute away from water. The water market generates higher cost of substitute factors as seen

Table 2.1: Change Across Regions and Models

| | Free Water Model | | | Water Restricted Model | | | Intermediate Input Trade Restricted Model | | |
|---|---|---|---|---|---|---|---|---|---|
| | *Urban* | *Rural* | *Interface* | *Urban* | *Rural* | *Interface* | *Urban* | *Rural* | *Interface* |
| Domestic Supply (Mil $) | 1,238.77 | (0.79) | (3.00) | 1,079.5 | 0.96 | 11.47 | 1,064.68 | 0.59 | 12.50 |
| | 0.82% | -0.02% | -0.01% | 0.72% | 0.02% | 0.02% | 0.72% | 0.01% | 0.03% |
| Change in Water Demand | 1262.1 | -263.6 | -998.5 | 0 | 0 | 0 | 1130.2717 | -248.964 | -881.307 |
| | 0.38% | -0.07% | -0.082% | - | - | - | 0.34% | -0.07% | -0.07% |
| Water Price | 0.15% | 0.15% | 0.15% | 0.79% | -0.06% | -0.05% | 0.075% | 0.075% | 0.075% |
| Wage | -0.59% | 0.02% | 0.00% | -0.68% | -0.01% | -0.01% | -0.70% | -0.01% | 0.00% |
| Land Price | 2.10% | 0.03% | 0.00% | 1.96% | -0.05% | -0.03% | 1.89% | -0.02% | -0.02% |
| Intermediate Input Supply (Mil $) | 559.72 | 0.17 | 4.64 | 529.97 | 0.97 | 10.05 | 542.81 | 0.25 | 5.21 |
| | 0.7% | 0.0% | 0.0% | 0.7% | 0.0% | 0.0% | 0.8% | 0.0% | 0.0% |

in the increased cost of wages and land in the FM model in Table 2.1. This effect varies between the rural and interface regions, where wages and land increase by 0.02% and 0.03% respectively for the rural region. However, the increase is practically zero for the interface region. The interface region has a greater amount of land and labor to replace the reduced availability of water resulting is smaller growth of the price of substituted factors. The greater cost of factors in rural and interface regions results in a decline in domestic supply.

The FM model includes intermediate input trade between regions allowing urban growth to increase the demand for rural and interface intermediate inputs. This market provides an opposing effect to potentially offset the additional costs urban growth creates through the factor market. At the bottom of Table 2.1 the level change of intermediate inputs increases in the FM model for the rural region by \$0.17 million and for the interface region by \$4.62 million, indicating that urban expansion is partially responsible for this growth. However, as urban demand for rural and intermediate inputs expands, the price of intermediate inputs rises, increasing the cost of production for rural and interface firms that also uses these intermediate inputs locally. There is a tradeoff between the higher prices of intermediate inputs and the greater quantity that the urban region demands. In the FM model, the combined effects of the intermediate input market do not offset the higher factor costs that rural and interface experience resulting in a decline in their domestic supply, as shown at the top of Table 2.1.

The sectoral impact of urban growth is shown on Table 2.2 where ag, non-ag, and housing services are listed by region. The first row of Table 2.2 demonstrates that in the FM model domestic supply for all sectors in the rural region decline; in the interface region Ag and housing services also decline. The water demand row establishes that water transfers in the FM model are primarily pulled from the Ag sectors in the rural and interface regions. However, each sector in the rural and interface regions experiences a decline in water demand, broadening the impact the rural community faces. The change in water demand and the impact it generates occur endogenously and is comparable to Watson and Davies' (2009) model. However, since this model identifies regional sectors, it demonstrates a negative impact on rural domestic supply across each industry that was not visible in Watson and Davies (2009), as they aggregated rural non-Ag sectors with urban non-Ag sectors.

Table 2.2: Percent Change Across Industries, Regions, and Models.

| | | Urban | | | Rural | | | Interface | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *Variables* | *Models* | *Ag* | *Non-Ag* | *Housing* | *Ag* | *Non-Ag* | *Housing* | *Ag* | *Non-Ag* | *Housing* |
| Domestic Supply | FM | -0.06% | 0.41% | 1.67% | -0.01% | -0.01% | -0.03% | -0.01% | 0.00% | -0.01% |
| | RWM | -0.08% | 0.28% | 1.62% | -0.02% | 0.02% | 0.04% | -0.02% | 0.02% | 0.03% |
| | TR | -0.06% | 0.26% | 1.63% | -0.02% | 0.01% | 0.03% | -0.02% | 0.02% | 0.03% |
| Water Demand (acre-ft) | FM | 296.4<br>0.15% | 650.4<br>0.56% | 315.4<br>2.98% | -253.1<br>-0.07% | -10.2<br>-0.05% | -0.4<br>-0.11% | -994.4<br>-0.10% | -3.9<br>0.00% | -0.2<br>-0.11% |
| | RWM | -565.3<br>0.11% | 312.5<br>0.51% | 252.8<br>2.85% | -9.9<br>-0.07% | 9.7<br>0.02% | 0.2<br>0.04% | -80.7<br>-0.09% | 80.6<br>0.00% | 0.1<br>-0.03% |
| | TR | 229.8<br>-0.28% | 598.6<br>0.27% | 301.8<br>2.39% | -244.2<br>0.00% | -4.7<br>0.05% | -0.1<br>0.06% | -879.5<br>-0.01% | -1.7<br>0.04% | -0.1<br>0.05% |
| Land Demand | FM | -1.14% | -0.76% | 1.13% | 0.00% | -0.01% | -0.04% | 0.00% | 0.01% | -0.01% |
| | RWM | -1.04% | -0.92% | 1.11% | -0.01% | 0.05% | 0.05% | -0.02% | 0.03% | 0.04% |
| | TR | -1.08% | -0.91% | 1.14% | -0.01% | 0.02% | 0.03% | -0.02% | 0.03% | 0.04% |
| Intermediate Input Price Change | FM | 0.380% | 0.090% | 0.540% | 0.050% | 0.010% | 0.020% | 0.010% | 0.010% | 0.000% |
| | RWM | 0.400% | 0.050% | 0.490% | -0.040% | 0.000% | -0.030% | -0.040% | 0.000% | -0.010% |
| | TR | 0.280% | 0.030% | 0.470% | 0.000% | 0.000% | -0.010% | -0.020% | 0.000% | -0.010% |

In the Restricted Water Market (RWM) model water can only be traded within the region but not between regions. Additionally, the RWM model allows intermediate input trade between regions, thus increasing urban demand for rural and interface intermediate inputs. The comparison of the RWM model to the FM model demonstrates how the water markets affect the rural and interface regions in response to urban growth. The rural and interface regions maintain the original allocation of water under the RWM model, resulting in regionally specific water prices that are cheaper than the FM model shown in Table 2.1. In Table 2.1, the RWM model shows an increase in intermediate inputs of $0.97 and $10.05 million for the rural and interface regions, respectively. This contributes to rural and interface's greater domestic supply growing by 0.02% for each region under the RWM model. Additionally, the greater demand for intermediate inputs from the rural and interface regions in the RWM model has a lower intermediate input price for each sector than in the FM model. This is due to the higher cost of water and other factors in the FM model compared to the RWM model. This comparison demonstrates how urban demand can benefit neighboring regions if water is maintained in the region while causing greater intermediate input demand. Keeping water local and sending the goods and services would appear to be one method for urban growth to share the benefits with its neighbors.

The output of the trade restricted (TR) model shows an increase in domestic supply for the rural and interface regions, despite a reduction of water in these regions. In the TR model, regions are only connected by the market for water, and the intermediate inputs that were once supplied by neighboring regions are now supplied by the rest of the world. This unique result becomes clear when considering sectoral outputs in Table 2.2. Ag loses water and declines in domestic supply for both the rural and interface regions. Additionally, Ag land and employment fall. This explains why land and wage prices decline in Table 2.1. Some of the land and employment that was once used by Ag sectors is now utilized by the non-Ag sectors and housing service sectors in both the rural and interface regions, resulting in an increase in their domestic supply (Table 2.2). The catalyst of more expensive water reduces Ag production and frees up many factors of production that are then employed by these alternative sectors. This results in a decline in Ag output but is offset by an increase in the domestic supply of non-Ag and housing services. Shifts in sectoral outputs within a region based on declining water is similar to Goodman (2004), but this outcome is driven purely by factor substitution instead of increased intermediate input trade. The TR model has consistently cheaper factor prices and intermediate input prices than in the FM model, indicating that the price effect of intermediate inputs is more harmful than the quantity effect.

One novel outcome across all three models is a decline in agricultural output. This decline is the result of the reduction in water and increased cost of production due to substitution of other factors of production shown in both Table 2.1 and Table 2.2. In the FM model, the increased demand from the urban growth results in a relatively larger agricultural demand. The greater growth of urban industries partial offsets the negative Ag supply shift with a positive demand shift, thus dampening the decline of the Ag sector in the FM model. Alternatively, the two restricted models do not experience the same size shift of urban demand as the FM model, and they have greater decline in Ag output as a result. Each model describes a greater opportunity cost of factors once used for Ag production resulting in a decline.

The impact of urban growth can be described by the change in household income. Under the FM model, income declines for both rural and interface households, as shown in Table 2.3. The decline is slight, 0.01% for the rural households and 0.005% for interface. This outcome differs from the conclusion of Watson and Davies (2009) and Goodman (2004), who both described where rural households were made better off by water transfers. In either the TR or RWM model rural and interface households' income increases, demonstrating that the higher costs of factors and intermediate inputs does affect the households in the communities neighboring the urban region. Additionally, the household income of urban is greatest under the FM model and is relatively smaller under either restricted model specification.

Table 2.3 Change in Real Household Income

| | Free Water Model | | | Water Restricted Model | | | Trade Restricted Model | | |
|---|---|---|---|---|---|---|---|---|---|
| | *Urban* | *Rural* | *Interface* | *Urban* | *Rural* | *Interface* | *Urban* | *Rural* | *Interface* |
| Change in Real Household Income | 1.01% | -0.01% | -0.005% | 0.76% | 0.01% | 0.02% | 0.79% | 0.01% | 0.02% |

## 1.14 Conclusion

The separate regions and cross-regional market structures used in this study indicate how urban population growth can influence the neighboring regions. A simulation of a 5% increase in urban population generated growth for the urban region but at the cost of neighboring regional output. The Free-Market model provides the closest representation of reality and shows that without intervention the rural region experiences decline in all their industries and household income. The cost of urban growth can be attributed to both the intermediate input market and the market for water, both of which cause increased costs of production for neighboring regions. This occurs despite factor substitution that results in greater prices of factors, like land, that are not traded between regions.

However, when either of these markets are restricted, the combined gain of the rural and interface regions' domestic supply comes at a cost of unrealized urban gains as its domestic supply is lower than in the FM model shown in Table 2.1 The urban output falls from $1.2

billion of domestic supply in the FM model to 1.08 in the RWM model while the rural and interface collect gains in domestic supply amount to less than $13 million. Either of the market restrictions are drastic approaches and would not be considered practical policy measures. The restriction of the water or intermediate input market demonstrate how urban growth can cause higher prices that result in less domestic supply and less household income in the rural and interface regions.

In each of the three models the agricultural production declined. This demonstrates a different result from other CGE models that include many of the multiregional structures (Goodman 2004, Watson Davies 2009). Restricting the transfer of water may not help agricultural production when agricultural production costs can be influenced by alternative markets. Agricultural production responds to several market forces when urban population grows, and while water transfers increase the cost of water, higher prices of other factors and intermediate inputs are also responsible for the decline of output. Further research on the impact of urban growth on agricultural markets and the communities they support will benefit from taking a holistic approach to how prices of all inputs into the Ag market are influenced by the urban region.

# CHAPTER 2: THE IMPACT OF AGGREGATION ON CGE MODEL OUTPUT

## 2.1 Introduction

When creating a computable general equilibrium (CGE) model, one of the most important decisions is determining the level of aggregation. The geographic aggregation decision determines the level of analysis and subsequently the detail of the region of interest. This governs what questions can be investigated and how accurately the model represents the studied area. The level of aggregation of a model dictate where sectors and geographical areas could be individually identified or combined. These decisions can either make visible specific outcomes or obscure them. These choices should be deliberate, but there can be a myriad of unintended outcomes from modeling decisions. Understanding the impact of how aggregation influences CGE models demonstrates why aggregation decisions must be made with care. The purpose of this paper is to explore how spatial aggregation shapes a CGE model's output to draw attention to the importance of this modeling decision. To explore the impact of aggregation, two models built on the same data with differing spatial aggregation specifications are employed. The variation in output between the models demonstrates how choices of aggregation generate meaningful differences in CGE analysis.

The model used for this analysis was originally created as a three-region model for the purpose of considering water markets between different regions. During the creation of this model the specification was the subject of many valuable discussions about how the model structure determines output. These discussions laid the foundation for an investigation into comparing the original three-region model to a modified specification that aggregated the spatial qualities of the three subregions to create a single region CGE model. CGE models typically go through numerous iterations to provide researchers with varying sensitivities of different parameters, yet to my knowledge there has been limited investigation of how spatial aggregation affects output. This comparison allows for the impact of model structure to be made visible so that the benefit or spatial specifications can be discussed in earnest.

Investigating the impact of model structure fits within a wider movement within CGE modeling that has been pushing the application of modeling techniques in both regional, environmental, and natural resource-focused research. Multiregional CGE (MRCGE) models have been at the forefront of the innovation as their increased granularity allows investigations in regionally specific impacts restricted by single region models. The literature review will discuss how MRCGE models can address the same level of analysis that single region models offer, while also providing interregional linkages, and regional specific output of firms and households. The increased capacity of the MRCGE has been generated by both the innovation of modelers but also from the greater availability of regional data. Innovation of model structure and the benefits of improved data each allow disaggregated details that describe unique characteristics of regions and sectors, provide enhanced model accuracy, and are the focus of the literature review. The discussion of the advancements of MRCGE will offer comparison to the single region model and examples of the unique analysis they can offer. From this discussion, the benefits of MRCGE are clear, through both regional data usage and the modeling structure they enable. The review of past research also demonstrates the need for a comparison of varied spatial aggregation, based solely on model structure to isolate the impact of this modeling decision.

This research compares simulations between a single region model and a three-region model to discuss how modeling choices affect the output. The expectation is that a single region model will be more responsive to shocks because it can access all factors of production in one centralized market, resulting in larger changes in output of domestic supply and other key variables. For example, if there was increased demand for labor in the urban subregion, the single region model can supply this demand with labor supply from the rural subregion. In the single region model the labor supply of all three regions are aggregated together to form a single market. Alternatively, the three-region model has a subregional market structure, where only the factors of that subregion can supply the factor demand. The three-region model's separated market structure limits urban demand to labor availability in the urban subregion, causing a reduced output compared to the single region's response that could use rural or interface labor supply to meet demand.

This research seeks to answer the question: does the single region model generate greater output and employment in response to shocks? The comparison confirms that the single region model does have greater responsiveness under a population growth shock but not under a total factor of productivity increase. This comparison demonstrates how aggregation can shape output, and what details are obscured when a single region is used instead of a multiple region approach. The comparison will also focus on how variation in subregional output describes heterogeneous responses to these simulations that are not observed in a single region model. Investigating the varied subregional output compared to the single region will better equip researchers using or critiquing CGE models.

The analysis begins with a brief comparison between a MRCGE model and the single region alternative. The subsequent literature review will discuss examples of the advantages that MRCGE provides, both in terms of the improvements over the single region model, and how MRCGE models expand research questions that can be addressed by the modeling specification. The model description section will cover the construction of the Social Accounting Matrix

(SAM), and the CGE model description and how a three-region model can be transformed into a single region model using the same data. The simulation descriptions provide some background on model utility and generate the basis of comparison between the two models. The results and discussion section focus on the analysis of these simulations. The paper will conclude and describe further steps to investigate the impact of aggregation decisions on CGE models.

## 2.2 The Advantages of MRCGE versus a Single Region Model

The advantage of a MRCGE model over a single region model is driven by a more intensive use of data that utilizes spatial detail. The MRCGE model provides spatial distinctions allowing each subregion to reveal different industry concentrations, population characteristics, and factor allocations that would be obscured by a single region model. The advantage of separated regions is combined with trade between subregions, making visible the spillover effects between a subregion that would be obscured by using several isolated CGE models or by a single region model.  These benefits are made possible by available data that can distinguish separate regions, describe the trade between regions, and offer greater detail on the economic agents and the factor allocations they contain. The structure and data used in MRCGE models more closely resemble the regions than a typical single region CGE model and provide greater accuracy and detailed output, making them more useful to researchers.

Separate subregions have unique characteristics and modeling these details permits researchers to construct specific regional policies. In this model, the subregions are composed of several Colorado counties that would take on different characteristics if they were aggregated to form a single region. For example, there are unique labor opportunities in an urban labor market that are unavailable in a rural labor market. When these two subregions are aggregated together it blurs how a model can accurately represent a subregion's labor markets. Separating labor markets by subregions provides a more precise view of their supply and demand of labor and offers varied market outcomes between regions. The division of labor markets into subregions provides a spatially sensitive analysis that enhances the investigation and generates different policies that cater to the characteristics of that area. MRCGE models can present the differences between rural and urban labor markets, but this is not possible in a single region model as it lacks the distinction between subregions.

Creating a model with the capacity for interregional trade enables researchers to focus on how one subregion influences another, through shifts in demand or supply of intermediate goods. For example, if the rural subregion produces most of the agricultural output, and experiences a catastrophic wildfire, the decline in agricultural output would impact the urban subregion that relies on its rural neighbor for agricultural products. The import of rural agriculture goods to the urban subregion would decline and create urban spillover effects for industries and households that rely on this good. The impact of the fire to the urban subregion is indirect, as it does not experience the same employment fall or decline in household income, compared to the rural subregion. The benefit of creating a CGE model with subregional trade, allows for interaction between regional sectors, while maintaining separate regional spillovers that are crucial to the accuracy of the model. The nuances of household and labor impacts would not be evident in a single region model, as the spillover effects would lack the detail specific to the region, which would produce inaccurate analysis of a disaster. Being able to discern linkages between subregions has been a critical element for research reference to pollution abatement, trade, and natural disasters.

Separately identified subregions can accommodate sectoral disaggregation that distinguishes key industries that have a critical impact on the economy or are the primary research focus. For example, dividing power generation into coal versus solar power can explain the carbon footprint between subregions providing a more accurate description of total CO2 output (Lenzen et al. 2004). Additionally, knowing where CO2 is generated can support regionally targeted policy to reduce CO2 emissions. The alternative to this practice would be to aggregate power generation into a single broad category of energy production, which lacks accuracy of CO2 emissions, the power generation source, or how it is utilized by varying industries as an input. Sectoral disaggregation further refines the ability to observe within regional details, which in-turn inform cross-regional and the total impact across all regions. A single region model could utilize disaggregated sectors, but not to the same level of accuracy as having the spatial characteristics that would describe the spillover impacts. Models that have multiple subregions benefit from greater detail at the sectoral level and provide further accuracy of the spillover effects between industries and regions. Informing policy is a major use of MRCGE models and using a regionally accurate aggregation scheme improves the effectiveness of policy recommendations.

The subregions themselves, the trade between them and the level of detail provided, are all informed by data that maintains a richer level of description within a multiregional structure. The papers discussed in the literature review below, describes structural improvement but also how new sources of data further refines the capabilities of the model. The data availability has undergone a renaissance as the papers cited in this review are frequently using the latest sources that can benefit from local knowledge of industry concentrations, greater detail of technology applications and more thorough explanations of factor markets to improve the accuracy of models. The data often provides insight into the subregional levels that were previously inaccessible and comparisons between previous data usage and the newer reveal improved policy recommendations. With accurate data, the structural qualities of a MRCGE model provide more meaningful representations of the region. “A structural improvement is only as good as the data is accurate,” is an argument worth repeating and is demonstrated throughout the literature review.

It is the combination of both structure innovation and data that allows MRCGE models to address a wide range of regional economic concerns, such as pollution mitigation, water management, and disaster recovery. If policy recommendations are applied uniformly, like a carbon tax in all subregions, a MRGE model can inform the system-wide impact of the policy and how the impact would vary across different subregions (Lenzen et al. (2004)). Additionally, having several subregions represented, offers the opportunity to measure how a policy applied in one subregion creates spillover effects on the others (Kajitani and Tantano, 2017; Li et al., 2009; Schwarm and Cutler, 2003). The progress of MRCGE models as a tool across several research interests reveals how model structure and regional data are each necessary to better understand policy effectiveness on some of the most vulnerable communities (Kilkenny and Otto 1994, Turner 2006, Dixon et al. 2007).

The disadvantage of applying a MRCGE is the cost of creating them. Finding new data can accrue financial cost in terms of time spent seeking new data sources. There is significant time spent appending several data sets that may be incompatible. Disaggregated data is often noisy and provides fewer alternative data sources to support observations. This costs additional time and forces careful consideration of the assumptions that must be justified to readers. This effort will lead researchers to consider if the benefits are worthwhile. The comparison between the models provides one example of gains made in exchange for analyzing more data.

## 2.3 MRCGE Literature Review

The literature review is organized into two sections: The first section will discuss how data organization and equations refine the analysis of MRCGE models through the development of sectoral disaggregation, spatial characteristics, and the interregional linkages. The organization of regional data provides disaggregated details of sectors and the regions themselves to develop a more accurate model. The second section details the equations and mathematical formulation of a MRCGE model, and how these reflect the range of decisions available across subregions and sectors. The review will discuss how the MRCGE model offers improved analysis over the single region model specification and how MRCGE can offer analysis that would be infeasible from a single region model.

Kilkenny and Otto (1994) identify a central problem of modeling a rural region which cannot be accurately represented in autarky or aggregated with suburban and urban neighbors. Their review of past rural modeling efforts presents one of the earliest arguments for using MRCGE models. They argue that an urban adjacent rural region must be represented alongside their neighbors as the markets are heavily dependent on surrounding regions for trade and as a source of competition. If the rural region were combined with its neighbors to form a single region, the rural qualities would be obscured and the ability to address research focused on the rural community would be ineffective. For example, rural characteristics like employment are a fraction of the net total employment, when aggregated with a neighboring urban center, resulting in no meaningful analysis of the rural economy. Kilkenny and Otto (1994) require the rural regions be modeled separately from its neighbors to capture the distinct qualities of the area but maintain that the neighbors must also be presented with unique markets. A MRCGE avoids inaccurately assuming rural autonomy while also differentiating rural regional characteristics.

Observing that space matters and must be addressed for accurately modeling rural regions, Kilkenny and Otto (1994) argue that a model with interregional linkages can best describe the spillover effects on distinct communities, a principle applicable to various regions with unique spatial distinctions. While referring to regional income, Kilkenny and Otto (1994, p 1130) discuss the benefits of a multiregional model stating, “the task of tracing income generated by rural people through factor markets, capital markets, tax payments, across regions, and ultimately through consumers' expenditure forces the analyst to deal explicitly with the interdependencies of economic agents in rural areas on public and private agents across region.” This same argument can be made between any two distinct regions, making the intraregional impact visible, while also allowing for interregional markets’ transactions to take place. Spatial division of regions allows for the markets and agents that operate between regions, to create cross-regional spillover effects and brings meaningful market characteristics into the model. The same reasoning is applied to numerous MRCGE and regional modeling examples throughout this literature review.

Further advocating for the use of regionally sourced data, Kilkenny and Otto (1994) contend that relying on national coefficients scaled down to rural regions as an alternative to local data is an inaccurate approach. This method fails to capture the unique characteristics of rural regions, which often differ significantly from national averages. In reference to many of the rural models, Kilkenny and Otto (1994,p 1131) argue “Too many of the existing models are basically national-type models calibrated with the region's shares of national economic activity. Too few of the models operationalize any of the many compelling theories of location.” Fortunately, there has been a growing trend, as examples from Schwarm & Cutler (2003), Lenzen et al. (2004), Turner (2006), Palatnik et al. (2011), and others within this literature search that address their concern. The benefit of regionally sourced data is it can precisely describe the details of a region that matter to those that live and work there. The data methods and sources of the data are all necessary components to properly model spatially dependent economic policies for rural modeling, but these practices are equally applicable to any region misrepresented by national data.

Illustrating how the concentration of industries and the size of a community can significantly affect model output and diversity between regions, Schwarm and Cutler's (2003) study involves creating three distinct CGE models for Colorado communities with varying population sizes and industrial characteristics. These models aim to showcase the impact of adding 250 manufacturing jobs to each community, utilizing Public Use Microdata Area (PUMA) data to provide location-specific descriptions of the labor forces in each region.

The results reveal that the regions exhibit different multiplier effects in response to the same level of employment change, both for consumption and production. This variation in output between regions underscores the importance of utilizing regionally sourced data to achieve accurate modeling results. By highlighting the need for spatially distinct models, based on region-specific data, Schwarm and Cutler's findings emphasize the significance of capturing regional nuances to better inform policy decisions and economic analyses.

The comparison of the three models in Schwarm and Cutler (2003) underscores the significant influence of regional size and industrial concentration on model output variability. The simulation, aimed at increasing manufacturing jobs by 250, adjusts each model's exports of manufactured goods accordingly. Interestingly, smaller communities exhibit a larger percentage increase in export demand compared to larger ones, despite generating fewer manufactured goods. This discrepancy in export demand does not proportionally benefit smaller communities due to leakage of purchases and employment outside of the community via commuting, which impacts each model differently.

As Schwarm and Cutler (2003) note, "The multipliers for Fort Collins, Loveland, and Windsor are 1.62, 1.32, and 1.16, respectively." These variations in estimated multipliers align with the economic structures of the municipalities. Windsor, being a relatively smaller community with limited retail and service sectors, experiences fewer indirect effects from job creation compared to Fort Collins and Loveland. Since most of Windsor's household expenditures occur in neighboring Fort Collins and Loveland, the added expenditure due to the increase in Windsor's employment leak out of the region.

This employment disparity further supports the conclusion that disaggregated CGE models have a crucial role in policy consulting and economic impact analysis (Schwarm and Cutler, 2003, p. 133). By accounting for the multipliers' variations across regions, these models provide valuable insights into how policy changes affect employment differently in distinct communities. Effective modeling of interregional linkages informs researchers about the varying spillover effects between regions. Therefore, if research interests require consideration of varied regional responses, it is imperative for MRCGE models to utilize regional data and accurately represent separate regions within the model.

Dixon et al. (2007) extend the USAGE-ITC model, originally a single-region trade model of the United States, to develop a MRCGE model that incorporates each state. This transformation enables a comprehensive analysis of tariff reductions, capturing state-specific, interstate, and national impacts on trade policy. Utilizing an exogenous source-sharing technique, the authors categorize each state's demand for over 500 commodities, considering whether they are supplied by neighboring states or the rest of the world. The state-specific industry concentration and inter-state trade dynamics reveal the heterogeneous impacts of national trade policy across states and industries, offering a sophisticated tool to investigate tariff reductions. By disaggregating to the state level, the model captures the intricate interregional interactions between states, providing insights into direct and indirect impacts of trade policy on individual states.

Through this approach, the model delineates the geographical sources of commodities and their impact on state-wide tariff reduction, offering valuable insights into supply chains and interstate trade dynamics. Additionally, it identifies winners and losers of tariff policies, such as North Carolina's vulnerability due to its concentration in high-tariff commodities like textiles. Moreover, the model highlights the significance of regional characteristics and trade interactions in assessing the effects of tariff policy. Regression analysis further enhances explanatory power, revealing the influence of factors such as port activity and proximity on state employment and competition dynamics. Overall, Dixon et al.'s (2007) model underscores the importance of state-level disaggregation in understanding the nuanced impacts of tariff policy across industries and regions.

Lenzen et al. (2004) modeled energy production and CO2 emissions across several European countries. This model demonstrates how sectoral disaggregation of the energy sector, separate regional characteristics and trade between countries are important factors to consider when measuring CO2 emissions. Lenzen et al. (2004, p 392) argues that, “Using a single-region input–output model and assuming that factor uses of foreign industries are identical to those of domestic industries can introduce an error into the CO2 multipliers.” Denmark is used as an example to demonstrate how models with different sector aggregation and international trade relationships change the emission values generated by the model and reflect an improved accuracy of model output.

The disaggregation of sectors reflects an improved accurate measure of the carbon footprint associated with different technologies, making a distinction between fuel types used, the source of energy in utility sectors, and processes employed by manufacturing sectors. Lenzen et al. (2004) compares the aggregate and disaggregated energy sectors' CO2 output and explains that varied emission levels show an upward bias for the aggregate specification within Denmark. The aggregate utility sector generated 15% more CO2 compared to a disaggregated sector of utilities, looking at the emissions from electricity, gas, and water separately. The varied outcomes of CO2 emissions based on the level of disaggregation demonstrates the importance the IO table plays in models. IO tables are a key model feature of every MRCGE model as they can be used to distinguish both regional and sectoral characteristics. If the level of detail provided by disaggregate sectors can shift output, then it should be heavily considered when constructing a model.

Just as the disaggregated sectors within a country change the output of a model, it can also reveal critical heterogeneous characteristics between regions, resulting in varied output. Using the same aggregated sector description for Denmark for other countries, would ignore the variation in technology access between nations (Lezen et al. (2004) p 409). "Norway has a low CO2 impact due to use of hydropower, Danish electricity production has a high CO2 impact due to inputs of fossil fuels, for example coal." The aggregation of utilities can generate inaccuracies when the basis for their description does not account for the regional available technology. Furthermore, the aggregation of sectors can ignore the true source of CO2 emissions when it combines renewable energy with fossil fuels. Disaggregation of sectors and regionally accurate data are necessary elements to improve the accuracy of a multiregional model.

The disaggregated sectors between countries further leverages the importance of trade between Denmark and its neighbors in terms of the carbon footprint generated. An IO table that provides the trade between countries, offers insight into the contribution of trade to CO2 emissions of each country. Lenzen et al. (2004, p 409) argues, "The case of Denmark illustrates that a significant amount of CO2 is embodied in foreign trade, and that there is an inherent conflict between a national CO2 target for domestic CO2 emissions and the aim of improving the foreign trade balance." The features of the disaggregated sectors and multiple countries represented within the IO table is compared with models that lack each of these qualities and demonstrates a more informed carbon footprint for Danish consumption. "In the case of Denmark, an 11 Mt CO2 trade surplus resulting from a single-region model turns into balance when multidirectional trade is considered." This comparison demonstrates how multiregional modeling and disaggregation of sectors can each refine modeling accuracy by correctly identifying trade and regional specific industry concentrations.

Kajitani and Tantano (2017) employed their MRCGE model to simulate the aftermath of the 2011 earthquake and tsunami in Japan. By manipulating various substitution elasticities between industries and regions, they recreated the historical output changes following the simulated catastrophe. This simulation relied on well-defined regional boundaries and sectoral classifications, facilitated by an IO table detailing each region's industries. Through this approach, the model captured the spillover effects within and between sectors, enabling a comprehensive analysis of the disaster's impact.

Their findings revealed significant differences in substitution elasticities across industries, particularly those with intricate supply chains like automotive and semiconductor sectors, which exhibited close to zero elasticity of substitution compared to other sectors with a 1/3 ratio. Moreover, Kajitani and Tantano compared these results with established substitution parameters used in medium to short-term models, finding them to underestimate the output reduction. This underscores a key challenge in MRCGE modeling: the necessity of specifying accurate elasticities tailored to regional, industrial, and temporal contexts. Overcoming these challenges holds promise for enhancing the model's precision in identifying vulnerable sectors during disaster events, such as the 2011 earthquake.

Li et al. (2009) employed a multiregional model of China to investigate the effects of targeted investment in different regions, necessitating the use of an MRCGE model due to the spatial nature of their inquiry. Their study conducted eight simulations, each applying an 8.3 percent increase in nationwide investment to individual regions. Results revealed that less developed regions exhibited greater growth both within their boundaries and for the country as a whole. In addition to examining regional growth, Li et al. (2009) analyzed the spillover effects of region-to-region trade generated by increased investment. They found that commodity trade linkages between regions facilitated the transmission of growth beyond the initially targeted areas. This underscores the interconnectedness of regions within the model and highlights the potential for a single region to trigger cascading changes across the entire system.

The study concludes that accounting for regional differences and interregional economic linkages significantly influences policy analysis, as evidenced by the varying outcomes observed between regional investment simulations. For instance, the Northwest region of China, with its abundant untapped natural resources, emerged as a major contributor to the country's simulated growth, showcasing the importance of regional-specific characteristics and interdependence in shaping economic outcomes. Moreover, the inclusion of detailed regional information and the analysis of variations between regions enhance the depth and accuracy of policy assessments. By capturing the distinct economic structures and dependencies of each region, MRCGE models provide valuable insights into the differential impacts of policy interventions across diverse geographical contexts. This nuanced understanding enables policymakers to formulate more targeted and effective strategies that address the specific needs and challenges of individual regions, ultimately leading to more equitable and sustainable development outcomes.

Turner (2006) highlights the significance of regionally sourced data and sectoral disaggregation through a comparison of two models of the Isle of Jersey—one based on regional data and the other on nationally adjusted values. The comparison reveals stark differences in pollution emissions from energy production, industrial output, and consumption, depending on the data source employed. Specifically, the model using national data tends to overestimate Jersey's pollution levels due to its broad aggregation of fuel types, failing to account for sustainability improvements made within the region. In contrast, the regional data offers fuel-specific processes that capture regional sustainability choices, resulting in a more accurate depiction of emissions.

While the national data suggests a focus on land transit policies, the regional-specific data identifies electricity production as the primary source of CO2 and other emissions. Turner's (2006) comparison underscores the divergent policy recommendations that each model would yield regarding emission reduction strategies.  This discrepancy highlights the importance of measuring emissions by sector rather than regional agglomeration, as it informs more targeted and effective policy interventions aligned with national emission reduction goals. Turner's findings thus question the suitability of using national energy efficiency data for multiregional models of the UK to inform emission reduction policy.

The improved accuracy of the regionally supported data in Turner (2006) is due to the disaggregated sector description, which relies on more refined SIC classification. Unlike the top-down disaggregation approach employed by the national data, which adjusts national data to fit the regional level of the Isle of Jersey but loses regional characteristics, the bottom-up approach preserves regional data through sectoral refinement. Consequently, regional data utilized in a bottom-up approach offers a more precise model capable of providing nuanced and contextually relevant policy recommendations.

The literature showcases the diverse applications of MRCGE models and regional data across various research topics. By innovatively organizing data within CGE models, researchers have been able to capture the unique characteristics of different regions, including industry mixtures, factor markets, and interregional trade. Through comparisons with traditional methods, such as those demonstrated by Lenzen et al. (2004) and Turner (2006), the advantages of MRCGE and regional data approaches are clearly illustrated. Moreover, studies by Schwarm and Cutler (2003), Dixon et al. (2007), Li et al. (2009), and Kajitani and Tantano (2017) have highlighted the invaluable insights and analyses made possible by these approaches. These examples collectively underscore the enhanced quality of output and the deeper level of investigation achievable through the utilization of well-organized data in MRCGE models.

The increased availability of detailed regional data is applied by leveraging key equations within the MRCGE model. Having a model develop regionally informed behaviors furthers the usefulness of the model to generate meaningful output. The following section of the literature review will discuss the adjustments of equations within MRCGE models based on regionally sourced data and how this has revealed greater detail in model output and further refines the utility of a MRCGE model.

The degree of substitutability of a factor can shape a model's output and should represent the production decisions available to the sector within the region. In Seung et al. (2000) the impact of water redistributed from one agricultural region in Nevada to a recreational use in a neighboring region is considered. A CGE model is used to explore the immediate impact of water transfer to determine the impact on the agricultural sectors. The immediate time frame provides justification to use a Leontief production function, which fixes the proportions of factors used to create agricultural output. This assumption results in a dramatic decline of agricultural output because water is no longer available, and producers are unable to substitute other factors to maintain production. Time is an important component in the decisions of economic agents and accurate modeling is crucial for analysis. The temporal component of a model cannot be completely addressed by the construction of data but must rely on properly specified equations to be modeled effectively in a CGE model.

To address the immediate impact of water transfer, Seung et al. (2000) makes several modeling decisions to describe the choices available to producers. First, there is no mobility of land between different agricultural sectors to model the short time frame agricultural producers must react to the reduction of water. Second, the land and water ratio have a fixed proportion per each agricultural sector's production function to model the short-term decision-making producers face. This means that if each acre of land used an acre-foot, land use would fall equally with the reduction of water. Finally, the simulation pulls water only from hay production as it is likely to be the first to be dried. These choices constrain the substitutability of production decisions to reflect the immediacy of water transfers on the agricultural sector.

Seung et al. (2000) expresses concern for how labor and capital would respond to the transfer of water as these factors will have the greatest impact on regional agricultural output. To best address this concern, Seung et al. (2000) uses three variants of the model, each describing different mobility of labor and capital. When labor was mobile between sectors and regions, the simulated 15% decline in water use for hay production, resulted in a 32% decline in hay output and a decline of 8% in agricultural production overall. Factoring in the transfer, payments of water and the increased leisure revenue from water recreation, a net loss in regional output of 0.08% was calculated when labor was mobile, and capital was restricted. The variance between the different mobility of labor and capital revealed that when both had no mobility, the region only declined by 0.06% output for the whole region. The change in output between the differences in factor market assumptions shows the impact of factor mobility. The region experiences greater decline in output when factors can move out of the region.

The varied access to mobility and the degree of substitution available can provide a method of capturing the time sensitive nature of many research questions. Seung et al. (2000) demonstrates that the feedback loops differ based on the limitations of labor mobility. This process can only be achieved via adjustments to the equations of the CGE model, and while this can be improved by regional data, this data is not found with the SAM or the IO table, but only in the equations that animate a CGE model.

Goodman (2004) uses a MRCGE model of Colorado to investigate the impact of water transfers between a rural agricultural community and a growing urban center. Rural Colorado, which owns most water rights in the region, has been steadily transferring this valuable factor of production to satisfy the demand for urban growth. The concern is that if enough water leaves the rural region, agricultural production will decline, and that this would have a negative impact on the rural region. To investigate this issue, Goodman (2004) creates an interregional water market that connects the two regions and simulates the impact of water transfers between them. This process was used to compare the outcome of water transfers versus a costly storage capacity project, which the results of this model deemed to be an inefficient solution for both rural and urban users.

The key innovation to the Goodman (2004) model is identifying how water is utilized in either community. Using a constant elasticity of substitution (CES) production function per firm permits the factors of land, labor, capital, and water to be substituted imperfectly with respect to an elasticity of substitution parameter. The CES production function replaces the Leontief production discussed earlier, providing the ability to vary factors of production. This specification allows agriculture to continue to maintain production, despite a higher price of water and a reduction in access to water within the region. The model demonstrates that across a range of elasticities of substitution of agricultural production, the water transfer results in a modest output decline from 1-5%. The drop in rural agricultural production was mitigated by the ability to substitute to a less water intensive production. Additionally, the transfer payments of water sold to the urban region mitigated the impact to the rural region, justifying the cost of switching to alternative production methods in the agricultural sector. The conclusion of simulated water transfer demonstrated that the rural region was better off in terms of total output. Additionally, a modest increase in household income level was mainly attributed to the factor payment of water transferred.

The Goodman (2004) model demonstrates that definition of the water market between regions allowed for regionally relevant research to take place. A single region would not be able to accurately describe the significant supply and demand effects of the cross-regional issue of water transfer between regions. Having both regions present allows for the regional impact of the water allocation to provide the spillover effects to pass through each region's economy. For instance, Goodman (2004) can describe that the rural households are not negatively affected, as they have their own connection with the rural agricultural economy, as well as other sectors, all contained within the rural region of the model. The regional spatial distinctions and the interregional interaction of this model are both dependent on the definition of the water market that links the two regions.

Watson and Davies (2009) refine the modeling of rural water transfers in Colorado by identifying the specifications of water ownership and usage and making the transfer of water an endogenous response to urban growth. This model recognizes the agricultural sectors and municipal utilities have varying degrees of substitutability for water in their production decisions, and that the market equations for water should reflect each of their behaviors. The model uses a simulation of urban population growth that expands urban output and household demand, thus making the transfer of water between uses an endogenous result of the water market. The simulated population growth demonstrates a legitimate reason for the water transfer from agricultural to non-agricultural usages. Additionally, the simulation introduces further changes to the economy driven by the urban population growth that accompany the transfer of water. Urban population growth shifts the demand and the supply of several markets within the model, some of which mitigate the impact of water transfer from rural agricultural sectors. Watson and Davies (2009) conclude that water transfers do not occur in isolation and use of a model and simulation that reflect this reality, are critical to informing policy on this subject.

The endogenous pull of water from the rural agricultural region to the urban region moves as expected because the equations for the water market are designed to reflect the behavior of the firms within the regions. The MRCGE does not just model the transfer of water in a vacuum, but rather due to population growth the urban region has a burgeoning labor supply, which changes the way firms maximize their production process. This allows Watson to conclude that "economic growth in Colorado's Platte River Basin will, in equilibrium, create a pull-on land and water and will take them out of extensive crop production and into other sectors in the economy" (Watson and Davies 2009, p 344). The way the model creates the transfer of water between regions highlights the importance of having equations that effectively generate the interregional interactions. Furthermore, this analysis produces output with greater nuance and shows agricultural sectors lose water due to the expanded urban activity of both household consumption and production. However, agricultural production increases, driven by higher urban demand.

The Watson and Davies (2009) model includes 18 sectors, which range from several kinds of agricultural, manufacturing, and commercial sectors, but these are not divided between their rural and urban locations. The model does not hold strict regional identification of all sectors. Instead, the rural and urban classification are applied only to the households and their factors of production, including a rural and urban labor market that works for the firms. This designation of regional characteristics allows the trade between firms of regions without regional classification, intertwines the trade between regions for intermediate trades but has a strict regional designation of household factor allocations between sectors. For heavily interregional trade with different regional factor allocation, this structure can address the net impact across all regions, while also measuring the impact on regional households and the firms they supply with factors. This structure does not provide a clearly defined amount of trade between regions of intermediate goods, nor would it be able to designate how rural or urban commercial or manufacturing changed as these sectors have been aggregated together. For a spatially specific impact of a region's industries the sectors would need to be regionally classified.

Palatink et al. (2011) pioneers the use of ICES (Inter-temporal Computable Equilibrium System) and partial equilibrium tools to inform the substitution of factors in agricultural production given a simulated forecast of climate change. Palatink et al. (2011) consider the impact of forecasted climate change on several Mediterranean countries with a focus on agricultural production and how they adapt, using a dynamic MRCGE model. Palatink et al. (2011) argues that the equations describing the production decision in agriculture for CGE models are based on strong assumptions that can be biased in either direction. Palatink et al. (2011) suggest using local data instead of strong assumptions, to improve the model's accuracy. This process utilizes regionally specific data to better inform the model of key decisions agricultural producers need to make. The model is dynamic and shows the changes in the production types for Italy and Israel over the course of a 50-year analysis. This process offers insight into how climate change will impact the country and the regional characteristics of their land.

There are two key innovations in the production function presented in Palatink et al.'s (2011) model. First, the partial equilibrium method used regression analysis of the effects of temperature, precipitation, and salinity of the land to inform agricultural production type suitability. The second innovation is the application of the elasticities, in a nested constant elasticity of transformation (CET) production function. The production function is modeled after a decision tree that first considers land use, and then narrows down several agricultural products that share similar land characteristics. Regarding the decision tree, Palatink et al. (2011, p 16) states, "In general, at each stage of the decision-making process, the CET parameter increases, reflecting the greater sensitivity to relative returns amongst crops. This means that it is relatively easier to change the allocation of land within upper nests, while it is more difficult to move land out of the group into a lower nest, such as into sugar cane and rice." Having a production function that models the decision process that is informed by a regional spatial distinction offers an improvement over simpler assumptions based on more aggregated data.

The model demonstrates that equations about agricultural production and regionally informed information on the quality of agricultural inputs, can be used to study the impact of climate change. Recognizing that both the land use and the available land are needed to model shifts in the competition for this resource, as its quality changes based on climate change, is a clear benefit of regional spatial distinction, as both aspects are more accurately described at finer levels of disaggregation. This model demonstrates the long-term progression of land usages within each country, to shift based on the profit maximization decision of the agricultural firm. The decision in agricultural production follows a dynamic path as the climate warms for Mediterranean countries, demonstrating that a decision tree is more effective when it considers the relevant long-term trends of climate while also factoring in the availability of land and its qualities. This process reveals that land substitution increases the cost of producing fruits and vegetables. Wheat appears to decline significantly in the face of higher temperatures and more competition from other products that can make use of the changing climate. The impact of each of these changes creates a cascading effect on the country and its trading partners which would be obscured without an agricultural production equation that is informed by regionally specific data.

Alexeeva-Talebi et al. (2011) compares the results of an aggregate and disaggregate model to investigate CO2 emissions among EU countries and the implementation of a carbon tax. The aggregate model is based on data sourced from the GTAP, a global source of economic data that sets sectoral classification at a higher aggregate level. The criticism of this approach is that sector-specific technology, country-wide behaviors in consumption and production techniques, and the trade between nations would collectively shift the outcome of a model compared to an aggregated model that cannot model these features. Alexeeva-Talebi et al. (2011, p 128) argues, “the importance of heterogeneity of selected energy-intensive and trade-exposed sectors for the implementation of border tariffs. Therefore, sufficient sector-specific details must be introduced which are generally not available in global economic datasets used for the impact assessment of climate policies.” Regional data is used to inform the variance of household utility across regions and the production methods of disaggregated industries, which reveals behaviors that are obscured within the original aggregate.

The disaggregation data is provided by ExioPol, estimates country-specific energy usage per sector, with additional information on trade. This provides a single source disaggregation strategy making the per-country equivalence easier than using unique data for each country. The challenge was how to inform the household and production substitution decision. Alexeeva-Talebi et al. (2011) uses Armington equations with varied elasticities based on energy sources used in production and consumption decisions. The model then performs three different levels of substitution given the simulated emission reduction targeted by the EU. Including information on the energy used by each process will have a clear connection to the carbon emitted and the increased price that a carbon tax would be shared by producers and consumers.

The output of the disaggregate model provided instances of sub-sector industries that show opposite signs of change in output when compared to the general result from an emission reduction simulation, with the aggregated model. For example, the disaggregate model revealed that metal manufacturing and mining decline in output, while the aggregate model, which includes these disaggregated sectors and additional mining and manufacturing sectors, shows a net increase in output.  This result was found to hold across several different degrees of production function elasticities. Variation within the sub-sector for CO2 policies collectively resulted in a different aggregate measure of CO2 emission, which is an important benchmark for policy makers. The price of CO2 and the welfare effects showed significant differences and can be attributed to the sectoral disaggregation, the trade substitution, and the technology specified at the sector level. This result provides merits for this approach as it would contribute to varied policy recommendations between the two models.

The contrast between the aggregate and disaggregate models showed that outside of the CO2 emissions, macroeconomic indicators moved in the same direction. The similarity demonstrated that the disaggregate model can effectively inform at the macroeconomic level but would strongly advise the use of a disaggregate effort for questions requiring further detail as is the case with CO2 emissions. Alexeeva-Talebi et al. (2011) argue that sector-specific policies need appropriately aggregated sector classifications to model meaningful output. To achieve this goal Alexeeva-Talebi et al. (2011, p 141) concludes, “the usage of new data, enriched with a detailed sequence of CO2 and trade intensities at the sub-sectoral level, is a necessary but not a sufficient condition for a proper assessment of carbon price implications. We find that assumptions about the underlying technology specifications and trade elasticities matter most for sub-sectoral, sectoral and macroeconomic implications.” This information, informing the production and consumption decisions, must be included if the model is to accurately describe the impact within regions, between regions, and across the entire EU.

The equations of a MRCGE can be used to further express regional characteristics through market definition, production, and consumption functions. The second section of the literature review has demonstrated how the equations of a CGE model can utilize regional data to solidify the link between the observed behaviors of different regions, and how the model will operate. Seung et al.(2000), Goodman (2004), and Watson and Davies (2009) each offered different considerations of water markets and the use of water to reveal how rural agricultural water not only impacts the agricultural output but the communities they inhabit. The various outcomes of these three works reveal the importance of regional data informing the model, and what degree of substitution is allowed within the model which will have a significant impact on the output. Palatnik et al. (2011) also grappled with the importance of factor markets as the model considers the shift in agricultural land availability between various agricultural producers over the course of a climate change simulation. Alexeeva-Talebi et al. (2011) carbon tax model is similar to the Lenzen et al. (2004) approach with regards to disaggregated sectors.  It provides additional consideration for how consumption decisions are influenced by carbon taxes, and therefore the fuel type of production was a crucial component which influenced both producer and consumer behavior. How the economic agents of the model operate is regionally defined, and the markets they have access to will have profound effects on the outcome of a model. Making these equations representative of the regions they model is as valuable as the SAM and IO table used.

This literature review provides numerous examples for how MRCGE models and regional data have been coupled together to provide more accurate regional modeling. Regional data can add value for the model in the form of SAM's and IO tables, but it must also be used to inform the structure of markets and the equations within a CGE model. Lenzen (2004), Turner

(2006) and Alexeeva-Talebi (2011) each provided comparisons with models that lacked some of the advancements of regional data which highlight the benefits of sectoral disaggregation and the interregional interaction.

The benefits of utilizing regional data have been made clear but comparing the pros and cons of a multiregional model compared to a single regional model can be examined further. In each case, going back to Dixon et al. (2007) there has not been an effective comparison of the same data used in a single region model compared to a multiregional model. To do so would offer a case study in how structure can influence outcomes of the model, which can be used to consider omissions from single region models or when they are even necessary. Isolating the structure of the model without varying the data used to create it, would make clear the benefit of how regional data can be leveraged.

The use of the same data between a single and multiple region CGE model means that only structural modeling decisions would influence the varying output between the models. The comparison could enlighten when multiregional models are needed and what aspects of a model are sensitive to spatial characteristics. The comparison could also be used to clarify missing elements when multiregional descriptions are not utilized. For all these reasons, there is a need to investigate how the definition of regions within a CGE model influences the output.

### 2.4 Model Description: CGE Basics

A CGE model describes the market interactions between representative agents in an economy. The agents in the economy are households, producers, and government, as described in the circular flow diagram in Chapter 1. The households rent the factors of production via the factor market to the producers and government, which in turn produce goods and services provided to the households via the goods market. The exchange in the two markets finds a simultaneous solution for prices and quantities as each agent achieves the optimal solution of their object function. The household's objective function is to maximize their utility based on a consumption function, subject to a budget constraint. The producers and government agents maximize profits given their production function and operate under an assumption of a perfectly competitive market that results in zero profit. General equilibrium is achieved when all agents cannot be made better off.

The standard CGE model is based on real world data organized into a social accounting matrix (SAM) which describes the economic transactions between agents over a set period, measured in dollars. The SAM is a square matrix, which allows each agent's output to become another agent's input, describing the complete history of transactions in the economy. The total sum of each column of the SAM is equal to the total sum of the row for each economic sector, describing a balanced matrix and equilibrium in the model.

The equations of the CGE model represent the behaviors of the economic agents and the markets that connect them to provide a general equilibrium state of the modeled economy. The equations solve for the prices and quantities given the values of the SAM. Once the equations reproduce the values in the SAM, the CGE model is calibrated. The calibrated CGE model can then simulate changes to the economy and solve for a new optimal solution, given the simulated exogenous shock. This results in new prices and quantities of all market exchanges as a new general equilibrium is found by the model, subject to all the equations and their constraints. The benefit of this approach is that all markets are simultaneously responding to the shock and generating an output for the model subject to economic agent behavior. would behave.

Additionally, the new equilibrium can be compared to the calibrated equilibrium and describe how different sectors of the model have changed in relation to each other.

The typical CGE model described above resembles a single region model, whereas the three-region model used in this research has a few differences. First, agents and markets are regionally identified for each of the three subregions. The three subregions are identified as rural, urban and interface have their own unique allotment of households and firms. The urban region includes a greater population and industry concentration but a small agricultural sector. The rural region is sparsely populated with a relatively large percent of its output coming from the agricultural sector. The interface region has a blend of rural and urban characteristics like that of a suburb but includes a sizable agricultural sector. Additionally, the households in the three-region model can only buy goods and services from their region's producers, resulting in three separate goods and service markets, for each subregion's household group. Producers can only use factors located in their subregion except for raw water, which is traded between subregions. The factor market for all other factors, besides water, then has three subregional factor markets, resulting in separate quantities and prices. The subregions are also connected via their intermediate input trade market, which allows producers of different subregions to buy and sell goods and services. The water market and the intermediate input market, distinguish the three-region model from three separated SAMs via connection nuances covered in the analytical sector in Chapter 1.

The comparison of a single region SAM and the multiregional SAM in Figure 2.1 and 2.2 provides insight into regional characteristics represented in either model. Figure 2.1 provides how a single region model would be structured and Figure 2.2 describes a multiple regional model. The subregions in the multiregional SAM are identified as 1 through 3 and identify the sectors, labor, capital, households, and government. The columns and rows of subregional sectors are summed together to form the single region model, thus maintaining the same total SAM value between both models. The variation between subregional firm’s factor demand is lost when they are aggregated together. If one subregion’s firm used a higher capital-to-labor ratio compared to the other two subregions, this variation is obscured when they are aggregated together. Regional characteristics from government expenditures, taxes, household consumption and factor earnings all vary between subregions, and when aggregated together to a single region mode they no longer accurately represent the behavior of any specific subregion.

The variation between subregions will determine different responses to simulated shocks. For example, the variation in factors employed by rural and urban firms reflect different profit maximizing choices, if labor supply increases. If the rural firm has a more labor-intensive production function, it will be positioned to use new workers in a more efficient manner, compared to the urban firm. However, when both regions are aggregated together, the subregional production characteristics are combined, inaccurately describing the subregional profit maximizing choices in response to new labor.

A model including subregions versus one that does not, respond differently to shocks because they have different general equilibrium conditions. A rural marketplace will have different availability of factors and different firms demanding these factors from neighboring subregions. The unique regional supply and demand determine subregion-specific prices and quantities. When two subregions are aggregated there are fewer prices and quantities, and they must now represent both subregions. The imprecision of aggregation described here, is like the concerns raised by Lenzen et al. (2004) and Palatnik et al. (2011). The inaccuracy of aggregation described in subregional factor markets, can also be applied to other subregional details such as household consumption, income, and firm behavior.

The multiregional model can also express the intermediate input trade between regions shown in the top left corner of the multiple region SAM in figure 2.1 where inputs are sources for neighboring subregions. The subregional trade intermediate inputs describe the concentration of firms and how supply chains link subregions. When they are aggregated together the single region could no longer describe how one subregion specializes in a specific production, or how another subregion relies heavily on a firm in a neighboring subregion for production. The subregional detail can describe bottlenecks in the supply-chain, as opposed to aggregating away any fragile relationship in separate regions. The cross-regional relationships are lost when they are aggregated together, potentially biasing the results to be less sensitive.

| Single Region SAM | | | | | |
|---|---|---|---|---|---|
| | Firm | Labor | Capital | HH | Government |
| Firm | X | | | X | X |
| Labor | X | | | | |
| Capital | X | | | | |
| HH | | X | X | | |
| Government | X | | | X | |

Figure 2.1 Single Region SAM Structure

Multiregional SAM

| | Firm1 | Firm2 | Firm3 | Labor1 | Labor2 | Labor3 | Captial1 | Captial2 | Captial3 | HH1 | HH2 | HH3 | Government 1 | Government2 | Government3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Firm1 | X | X | X | | | | | | | X | | | X | | |
| Firm2 | X | X | X | | | | | | | | X | | | X | |
| Firm3 | X | X | X | | | | | | | | | X | | | X |
| Labor1 | X | | | | | | | | | | | | | | |
| Labor2 | | X | | | | | | | | | | | X | | |
| Labor3 | | | X | | | | | | | | | | | X | |
| Captial1 | X | | | | | | | | | | | | | | X |
| Captial2 | | X | | | | | | | | | | | | | |
| Captial3 | | | X | | | | | | | | | | | | |
| HH1 | | | | X | | | X | | | | | | | | |
| HH2 | | | | | X | | | X | | | | | | | |
| HH3 | | | | | | X | | | X | | | | | | |
| Government 1 | X | | | | | | | | | X | | | | | |
| Government 2 | | X | | | | | | | | | X | | | | |
| Government 3 | | | X | | | | | | | | | X | | | |

*note: sub-regions are identified by 1,2,3*

Figure 2.2 Multiregional SAM Structure

## 2.5 Model Description and Data Sources

The three-region model is based on the front range in Colorado, which includes 12 different counties that are categorized as either urban, rural, or interface. These three regions share a border with each other, making trade possible. The urban region is 6 counties surrounding the city of Denver and is the most populated area. The urban region also employs the greatest amount of nonagricultural production of the three regions. The rural region is composed of three sparsely populated neighboring counties east of Denver, where agricultural production makes up a large part of the output of the region. The interface region shares characteristics between urban and rural regions. The interface region has three large counties which include Fort Collins and Boulder, home to many tech companies and universities, but also surrounded by productive farmland. Each of the three region industries' have unique market structures for their industries, their household consumption, and the quantity of resources that they can utilize.

The data used to build this model is organized into the SAM, which was described in the previous chapter. The SAM is primarily derived from a hybrid of an IMPLAN SAM, which has been modified with additional data. IMPLAN provides a standardized regional SAM using proprietary software. However, since the model is specifically focused on studying water transfers between regions and IMPLAN lacks water-related information, many aspects of the model rely on local data sources. These sources include county-level data from the American Community Survey (ACS), Bureau of Labor Statistics (BLS), county assessor's offices, and county annual financial reports (CAFR), all sourced from 2013. Information from these sources, such as property values, taxes, and government expenditures, was collected on a per-county basis whenever feasible. Household and labor data were sourced from Public Use Micro Samples

(PUMS) and BLS data. Average household purchases are based on ACS findings, which were adjusted to align with PUMS estimates of total households per region.

While the IMPLAN data provided an input-output table for intermediate inputs, it was scaled to align with the factors from the alternative sources mentioned above. Additionally, the IMPLAN data helped establish the amount of intermediate input trade between regional producers. Finally, the SAM is balanced by adjusting the imports and export totals to the rest of the world, or in areas not included in the three regions.

The final aspect of the model addresses how to transform the three-region model into a single region model. Since all three regions have the same number of representative economic agents, converting the multiple region model to a single region model involves only a few steps. Each row and column for the three regions SAM is summed into one entry to create the single region. The 27 household rows and columns, which represent three sets of 9 different household types are summed into one set of 9. This operation is performed for all industries, factors, and government sectors. Some sectors do not have a regionally unique identity, like that of the federal government and state government, so the number of sellers in the SAM is not completely reduced by 2/3rds. The SAM transforms from a 182 by 182 matrix to one of only 61 by 61. The sums of the total value of each SAM are equal.

Both models use their respective SAMs to calibrate the CGE model. Calibration in CGE models uses this SAM as an input, and the equations generate equilibrium prices and quantities which recreate the SAM values. Prices are normalized to one in the initial calibration. This allows for changes in both prices and quantity to occur across sectors when simulations are applied.

## 2.6 Simulation

A simulation in a CGE model allows for some exogenous change to occur in the model that requires the system of equations to resolve into a new equilibrium state. The new equilibrium is determined by all agents maximizing their objective function, subject to their constraints, which have been altered by the exogenous shock. The new equilibrium provides different quantities and prices for all markets based on agent responses to the shock. The new equilibrium is compared to the unchanged equilibrium, to provide percent changes in different sectors of the economy to inform what markets, industries, or groups of people are affected by the simulation.

## 2.7 NRPG Simulation

The natural rate of population simulation involves an exogenous increase in households by 5 percent. This growth in households has a profound impact on economic output, which can be examined from two perspectives. Firstly, as the number of households rises, there's a positive shift in labor supply. This means a larger pool of potential workers enters the labor market, creating more job opportunities. To quantify this impact within our simulation, we analyze the marginal product of labor, represented by the partial derivative of the production function with respect to labor ($\partial Q/\partial L$). This derivative allows us to assess how changes in labor supply affect production levels and economic output. However, with the increase in labor supply outpacing demand, wages tend to decrease. This decline in wages translates to reduced production costs for firms, enabling them to increase domestic supply at a lower cost, as demonstrated in Table 1A. This illustrates the inverse relationship between labor supply and wages, where an increase in labor supply leads to lower wages but higher domestic supply, reflected by a positive $\partial Q/\partial L$.

Secondly, household growth also stimulates demand for final goods and services. As the number of households increases, so does the overall demand for consumer goods and services, as indicated in Table 1H. Firms and the household sectors each demand the non-agricultural sector, but households are the sole consumer of housing service that increases by 1.91% for the three-region model and 1.5% for the single region model. Growth in demand positively impacts demand sides of the economy, resulting in greater overall output. This shift fosters economic activity, encouraging firms to produce more goods and services to meet the rising demand. Consequently, the economy experiences an expansion in output, driven by increased consumption resulting from household growth.

**Production function:**

$$Q = \beta L^{\propto}(1-\beta)K^{1-\propto}$$

Where:

Q is the output of the production function

β is the proportion of labor used between 0 and 1 and (1-β) represent the proportion of capital used in production

L is the labor input

K is the capital input

∝ is the output elasticity of labor and (1-∝ ) is the output elasticity of capital

**The marginal product of labor**

$$\frac{\partial Q}{\partial L} = \beta \propto L^{\propto}(1-\beta)K^{1-\propto}$$

| Table 2.1A Model Output Comparisons | | |
|---|---|---|
| | Three-region | Single region |
| Percent change in number of households | 3.64% | 3.82% |
| Percent change in domestic supply | 0.78% | 1.28% |
| Percent change in employment | 1.06% | 1.68% |

In the context of labor market competition, the single region model exhibits greater competition and, subsequently, larger declines in wages and higher employment rates compared to the three-region model. By combining separate labor markets, individuals from more remote regions can fill jobs in denser urban areas, which leads to more competition among laborers. Table 2.1B presents the percent changes in wages for both models and reveals that the single region model's wage total decreased by 1.12%, compared to 0.73% in the three-region's weighted results. The nine columns in Table 2.1B describe labor groups by earnings and demonstrate a relatively greater decline in percent change of wages for the single region model compared to the three-region model. The findings suggest that the three-region model incurs a relatively higher cost of employing new labor compared to the single regional model when facing population growth. The distinct labor markets across the three regions reduce overall employment for the three-region model compared to the single region model, resulting in smaller relative gains in employment, domestic supply, and household retention (as shown in Table 2.1A).

The difference in labor outcomes between the single region and three-region models can be explained by the heterogeneity of labor characteristics across different regions. In the single region model, the rural labor market is combined with the urban labor market, resulting in the dominance of urban labor characteristics due to a larger population size. However, this approach fails to accurately describe the level of labor competition when rural and urban workers are combined within a single labor market. Moreover, the single region model cannot capture the unique employment opportunities available within each of the three regions.

Table 2.1B shows that the labor market structure affects both the magnitude and direction of wage changes among labor groups. The three-region model reveals regionally specific labor outcomes that are not observed in the single region model, with all labor groups experiencing wage decline in the single region model, compared to wage decline in all labor groups except for groups seven and eight in the three-region model. The smaller overall decline in wages and the instances of wage growth in the three-region model demonstrate that using separate labor markets disrupts the level of competition and provides labor-specific outcomes not seen in the single region model. The wage growth of labor groups seven and eight between models further demonstrates how regional markets can lead to growth when disaggregated regional characteristics are considered. The three-region model's ability to disaggregate regional

Table 2.1B: Percent Change in Labor Payments

| | L1 | L2 | L3 | L4 | L5 | L6 | L7 | L8 | L9 | Weighted Average |
|---|---|---|---|---|---|---|---|---|---|---|
| Single Region | -1.68% | -1.40% | -1.60% | -1.29% | -0.98% | -0.73% | -0.38% | -0.41% | -0.51% | -1.12% |
| 3-Region Weighted Average | -1.35% | -1.20% | -1.19% | -0.92% | -0.57% | -0.33% | 0.14% | 0.12% | -0.01% | -0.73% |
| Urban | -1.08% | -1.01% | -1.08% | -0.89% | -0.59% | -0.42% | -0.01% | -0.04% | -0.16% | -0.66% |
| Rural | -1.86% | -1.87% | -1.75% | -1.23% | -0.93% | -0.52% | 0.12% | -0.38% | -2.21% | -1.33% |
| Interface | -1.61% | -1.41% | -1.30% | -0.94% | -0.46% | -0.10% | 0.49% | 0.43% | 0.44% | -0.78% |

characteristics allows for a more accurate depiction of labor market complexities and provides insights into how labor markets function in different regions.

The differences in labor groups seven and eight between the two models illustrate how the labor market structure expresses important spatial characteristics that contribute to varied output. The three-region model has unique regional shares of labor groups, with smaller shares in rural and interface regions for labor groups seven and eight. Table 2.1B's bottom three rows offer regional wage percent changes across the nine labor groups, revealing regional asymmetric responses to increased labor supply that are not visible in the single region model. For example, labor group seven shows wage gains in rural and interface regions but wage declines in the urban region. The variation in wage changes for these labor groups is due to the regional scarcity of this labor group, as described in Table 2.1C's base distribution of labor between regions. Labor group seven is disproportionately concentrated in the urban region compared to the other two regions, indicating that the wage growth of rural and interface regions is due to the relative scarcity of this labor group. When all regions are combined into a single labor market, regional

Table 2.1C: Base Labor Distribution

|  | L1 | L2 | L3 | L4 | L5 | L6 | L7 | L8 | L9 | TOTAL |
|---|---|---|---|---|---|---|---|---|---|---|
| Single Region | 236,288 | 98,903 | 167,503 | 170,402 | 184,670 | 200,575 | 99,468 | 83,803 | 54,960 | 1,296,572 |
| Urban | 121,126 | 59,621 | 103,327 | 108,638 | 122,155 | 135,182 | 69,539 | 54,723 | 39,356 | 813,667 |
| Rural | 9,312 | 6,457 | 8,785 | 9,057 | 8,141 | 5,923 | 2,091 | 761 | 538 | 51,065 |
| Interface | 105,850 | 32,825 | 55,391 | 52,707 | 54,374 | 59,470 | 27,838 | 28,319 | 15,066 | 431,840 |

scarcity does not result in a higher wage because there is more of this group available to meet the demand between regions. These details demonstrate how model structure shapes output and how enriching the model with regional characteristics provides a more nuanced understanding of labor market dynamics.

The total employment change of the three-region model has variations between regions contributing to lower employment gains. Each region has lower employment growth than the single region model (Table 2.1E), meaning that no single region is responsible for slower employment growth. There are variations among the regional total employment, with rural having the smallest gains of 0.99% and urban having the largest with 1.08% growth. The differences among the regions' total employment are much smaller than the 1.68% of employment in the single region model, which corresponds to a relatively cheaper input in production.

Table 2.1E: Percent Change in Labor Employment

| | L1 | L2 | L3 | L4 | L5 | L6 | L7 | L8 | L9 | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| Single Region | 2.06% | 1.87% | 2.00% | 1.79% | 1.59% | 1.43% | 1.19% | 1.20% | 1.25% | 1.68% |
| 3-Region Weighted Average | 1.50% | 1.40% | 1.38% | 1.20% | 0.94% | 0.77% | 0.46% | 0.46% | 0.56% | 1.06% |
| Urban | 1.41% | 1.35% | 1.38% | 1.24% | 1.01% | 0.89% | 0.61% | 0.62% | 0.69% | 1.08% |
| Rural | 1.40% | 1.39% | 1.31% | 0.92% | 0.67% | 0.37% | -0.07% | 0.19% | 1.70% | 0.99% |
| Interface | 1.61% | 1.48% | 1.41% | 1.15% | 0.82% | 0.54% | 0.15% | 0.17% | 0.17% | 1.03% |

The limitations of the single region and three-region models to accurately reflect employment changes depend on their respective assumptions. The single region model cannot capture wage gaps between rural and urban labor markets or how wage declines vary between regions. Conversely, the three-region model assumes strict separation of labor markets by region, which may not reflect the choices of laborers who may choose to commute. In the case of the rural region consisting of Morgan, Sedgewick, and Logan County, where 66.2% of workers both live and work in the area, it is difficult to assume that all rural labor competes with urban laborers in a single labor market. Therefore, neither model is entirely adequate in describing employment changes in this region when faced with population growth.

The variation in the labor market outcomes between the two models causes greater domestic output in the single region model. Table 2.1A shows that the domestic supply is 1.28% for the single region model and 0.78% for the three-region model. Relatively cheaper labor expands the profit-maximizing quantity of production, further resulting in greater output and more employment in the single region model. Additionally, a larger household retention in the single region model generates greater household demand for final goods and services. The single region model has a larger positive shift in supply and demand of the final goods, and in the service market, than in the three-region model.

However, the labor market outcome in the three-region model has subregional variations that contribute to differences in domestic supply, when the sectors are divided by industry. In Table 2.1H, domestic supply is separated into agricultural, non-agricultural, and housing sectors to denote differences between each model and subregion. The single region model has greater non-ag and housing services but has a smaller increase in agricultural output than the three-region model. The greater agricultural output of the three-region model is caused by the rural subregion, as this is the only subregion with a growing agricultural output as shown in Table 2.1H. The greater agricultural output in the three-region compared to the single region model signifies the importance of maintaining regional characteristics in a model, as it can change whether a sector is growing or declining. If specific sector output is necessary, this comparison shows how a MRCGE can change the net output based on regional characteristics.

Table 2.1H: Change in Domestic Supply by Sectors (due to a 5% increase in households)

| Percent Change | AG | NONAG | HS | TOTAL |
|---|---|---|---|---|
| Single Region | 0.01% | 0.99% | 1.91% | 1.28% |
| Three-Region | 0.09% | 0.44% | 1.50% | 0.78% |
| Urban | -0.07% | 0.42% | 1.67% | 0.83% |
| Rural | 0.16% | 0.81% | 1.22% | 0.72% |
| Interface | -0.03% | 0.45% | 1.06% | 0.65% |
| Level change (in $m) | AG | NONAG | HS | TOTAL |
| Single Region | 0.15 | 1411.77 | 1312.25 | 2724.16 |
| Three-Region | 2.00 | 620.00 | 1031.97 | 1653.98 |
| Urban | -0.12 | 419.57 | 825.87 | 1245.32 |
| Rural | 2.34 | 29.87 | 11.59 | 43.80 |
| Interface | -0.21 | 170.56 | 194.52 | 364.87 |

## 2.8 Total Factor Productivity Simulation

A simulated 1% increase in TFP could be conceptualized as a technological breakthrough that enables a more efficient utilization of all factors of production, thereby resulting in an increase of domestic supply. Producers expand their domestic supply to a greater profit-maximizing quantity, by increasing their factor demand beyond the pre-simulation level. The positive shift in demand factors results in higher prices ceteris paribus. The increased demand for factors also contributes to the growth of household income, resulting in greater demand for goods and services. The behavior of producers and consumers creates positive shifts in the supply and demand curves in the final goods market.

The differences in the two models' labor markets cause different outcomes in employment and wages in response to the TFP increase. In the single region model, sectors ranging from rural or urban regions are aggregated, causing sectors located in different regions to compete with one another for labor in a single labor market. The aggregation across different regional characteristics in the single region model, obscures the unique concentration of labor groups per region. For example, the concentration of high-income workers is greater in the urban region, than in the rural region, but when they are aggregated together this distinction is not observable in the model.

In the three-region model, the rural labor market does not compete with the urban labor market, allowing each region to develop unique labor equilibriums. When labor markets are disaggregated the increased factor demand of a rural producer does not influence the wages paid by urban firms. Regionally separated labor markets allow each region to expand factor demand at a lower cost compared to a single region model, because increased demand in one region does not generate a shift in demand of the labor market in a neighboring region.

Diverse labor distributions across regions yield varied employment and wage outcomes, with each region responding differently to the simulated increase in TFP. Refer to Table 2.1C for a breakdown of the distinct labor distributions across the three regions. Notably, the rural region exhibits the lowest concentration of L8 and L9, the two highest-paid labor groups, in comparison to its neighboring regions. The two highest paid rural labor groups are less than 3% of the total labor employment in the rural region, which is lower than the other two regions described on Table 2.2A. The labor distribution describes the regional scarcity of labor groups and allows the rural labor market to respond according to regional characteristics. Due to the rural regional scarcity of the highest paid labor group, the TFP shock causes a smaller growth of their employment and a higher wage growth compared to the same group in other regions. The variation of labor distribution creates varied responses in employment and wage percent changes between regions.

Table 2.2A: Distribution of Employment Between Labor Groups

| | L1 | L2 | L3 | L4 | L5 | L6 | L7 | L8 | L9 |
|---|---|---|---|---|---|---|---|---|---|
| Single Region | 18.2% | 7.6% | 12.9% | 13.1% | 14.2% | 15.5% | 7.7% | 6.5% | 4.2% |
| Urban | 14.9% | 7.3% | 12.7% | 13.4% | 15.0% | 16.6% | 8.5% | 6.7% | 4.8% |
| Rural | 18.2% | 12.6% | 17.2% | 17.7% | 15.9% | 11.6% | 4.1% | 1.5% | 1.1% |
| Interface | 24.5% | 7.6% | 12.8% | 12.2% | 12.6% | 13.8% | 6.4% | 6.6% | 3.5% |

The variation in labor distribution between the three regions is obscured when aggregated together to create the single region. For example, rural labor group 8 has only 761 employees out of a total 83,000 across all three regions. Their small contribution for labor groups is minor in comparison to the larger urban and interface regions. Table 2.1C above provides the actual employee count per region across the labor groups, revealing that both urban and interface are the largest contributors of labor. This would indicate the rural group is not accurately represented by a single region model.

In addition, the varied amount and concentration of labor groups between urban and interface means that neither of the larger regions are accurately described in the single region model. For example, the aggregated proportion of labor group one is much larger than the urban proportion. Alternatively, the top five labor groups in the aggregate are below the urban proportion for these groups. The aggregation of regional labor characteristics is not consistently over or underrepresented in any of the regional labor distributions, which questions the accuracy of the labor market output of the single region model when representing heterogeneous labor markets.

Table 2.2B shows the employment growth per labor group, and Table 2.2D provides the wage percent change for the TFP simulation across each of the three regions. Each table demonstrates that the individual regions have different outcomes of employment gains and wage growth across the labor groups. Rural and interface have the greatest respective gains in employment for the bottom 4 lowest paid labor groups. These lower earning labor groups have a greater wage increase in the urban region than the interface or rural regions, shown on Table 2.2C. Alternatively, urban's top four higher earning labor groups have the greatest employment gains out of the three regions, but they also have the slowest wage growth. When contrasting the output of both Table 2B and Table 2.2C, a trend occurs where greater wage gains occur in the region with the lowest growth of employment.

Table 2.2B: Percent Change in Employment

| | L1 | L2 | L3 | L4 | L5 | L6 | L7 | L8 | L9 | TOTAL |
|---|---|---|---|---|---|---|---|---|---|---|
| Single Region | 0.10% | 0.11% | 0.11% | 0.11% | 0.11% | 0.12% | 0.12% | 0.15% | 0.13% | 0.11% |
| Three-Region | 0.16% | 0.15% | 0.16% | 0.16% | 0.17% | 0.18% | 0.19% | 0.22% | 0.20% | 0.17% |
| Urban | 0.14% | 0.14% | 0.15% | 0.15% | 0.16% | 0.19% | 0.20% | 0.23% | 0.21% | 0.17% |
| Rural | 0.19% | 0.18% | 0.21% | 0.19% | 0.17% | 0.16% | 0.15% | 0.14% | 0.07% | 0.18% |
| Single Region | 0.17% | 0.17% | 0.17% | 0.17% | 0.17% | 0.18% | 0.18% | 0.19% | 0.19% | 0.17% |

| Table 2.2C: Percent Change in Labor Payments | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Percent Change | L1 | L2 | L3 | L4 | L5 | L6 | L7 | L8 | L9 | Weighted Average |
| Single Region | 0.16% | 0.16% | 0.15% | 0.16% | 0.15% | 0.13% | 0.13% | 0.10% | 0.12% | 0.14% |
| Three-Region (weighted average) | 0.14% | 0.15% | 0.13% | 0.13% | 0.11% | 0.08% | 0.08% | 0.05% | 0.06% | 0.11% |
| Urban | 0.15% | 0.15% | 0.13% | 0.13% | 0.10% | 0.06% | 0.05% | 0.01% | 0.03% | 0.10% |
| Rural | 0.13% | 0.14% | 0.10% | 0.14% | 0.14% | 0.18% | 0.21% | 0.17% | 0.30% | 0.14% |
| Single Region | 0.13% | 0.14% | 0.14% | 0.13% | 0.13% | 0.13% | 0.14% | 0.13% | 0.12% | 0.13% |

The growth in employment per regional labor group also coincides with differences in the regional labor proportions. For example, there are fewer high wage workers in the rural region compared to the other regions, and this group experiences the smallest employment growth and the largest wage gains. The most extreme example is rural employment gains of only 0.07% for labor group 9 compared to the urban's 0.2%, yet rural wages increase by 0.3% compared to urban's 0.03%. This comparison describes the importance of maintaining regional characteristics, like the relative scarcity of one labor group in a region. Heterogeneous regional labor impacts demonstrate the benefits of having separate regional labor markets, that can explain wage gaps between regional labor markets, and varied employment trends often seen between rural and urban areas.

The variation across regions in wage growth contributes to a different net impact across the three regions. The wages of the highest earning labor group rise by 0.12% in the single region, compared to 0.06% in the weighted results on the three-region model. The weighted results of the three-region model have used the regional labor distribution, which explains the differences in this labor group between regions and offers a lower wage gain than the single region model. The different regional characteristics create unique output between regions causing the multiregional models to generate different output from a single region model. Regional characteristics describe the barriers between labor location and job openings that will shape model output and could be critical to shaping labor policy.

The three-region model shows one instance where wage increase is greater in the rural region compared to the single region model. Among the top four labor groups as seen on Table 2C the rural groups' wage growth ranges from 0.17-0.30% compared to the single region's 0.10-13%. The advantage of using a multiregional model is that it can more accurately represent the larger labor groups, like the urban region. It also captures the unique outcomes and scarcity of the rural high wage earners. When regions are modeled separately, and their output is then combined to create a multiregional output, regional insight inclusive of the regional characteristics are gained so that this can be scaled up.

Using a single region model to discuss individual regional effects is not accurate even if one region makes up a larger contribution compared to the single region. The urban region and the single region model are only similar in terms of how the lowest earning labor group behaves as observed in Table 2B and 2C. The urban region represents more than 60% of the labor in the single region model, but the characteristics of urban regions are not maintained with the addition of these other regions. Since the single region model shows no clear similarity to the urban region, the usefulness of the single region to provide region specific output is limited. The same is true for the interface region, which shares no trends of employment of wage percent changes across the labor groups. This result is driven by the diverse labor distribution between regions, muddying the ability for the single region to represent any of the individual regions accurately when they are aggregated together.

Aggregating the individual regions of the three-region model allows for a comparison to the single region model. In Table 2B, the aggregation is the sum of the regional employment growth, and in Table 2C regional wage gains are weighted by that regional labor groups' employees. In terms of each labor group, the three-region model results in greater employment than the single region model. When comparing the total employment gains the three-region model has a 0.17% growth compared to the single region's 0.11%. The single region model has greater gains in wages than the three-region model, with a weighted average wage gain of 0.14% compared to 0.11%. In Table 2C, every labor group has a relatively higher wage gain in the single region versus the three-region model. This provides a similar relationship to the region-to-region comparison, where lower employment is paired with greater wage gains.

The intuition behind the three-region and single region comparison shares similarities to the NRPG simulation results. The regional markets of the three-region model allow for unique regional employment and wage equilibriums to occur independently of each other compared to a single region model. Each model has greater labor demand, but in the three-region model, labor employed in the rural region does not affect the wages of the urban region. This creates a relatively cheaper market in which to hire labor and utilize the increased productivity of the TFP shock, because the marginal increase in rural labor does not shift the wages for urban labor. This outcome is like the NRPG simulation where a single market compared to a three-region labor market provides different responsiveness in both wages and employment percent change. The single region model labor market has fewer barriers to competition, resulting in a TFP shock with greater wage growth and a NRPG shock that generates a larger decline in wages. The single region model has higher wage elasticity than the weighted results of the three-region model based on the output of these two simulations.

The single region model structure misrepresents the individual regional labor market because it cannot express the key characteristics of each of the three regions. Aggregation was identified by Lenzen et al. (2004) as a source of bias in measuring greenhouse gas production for the energy producing sectors. When all energy production types ranging from coal power to hydroelectric were aggregated together the greenhouse gas intensity was misrepresented and produced 3 (metric tons) more carbon in comparison to a model using disaggregated energy sectors. Similarly, when production sectors are disaggregated as in Alexeeva-Talebi et al. (2011), heterogeneous impacts occurred between sectors, providing different policy options to lower greenhouse emissions that would not be visible in an aggregated model. Like these examples, the heterogeneous characteristics between regional labor markets in this paper are susceptible to misrepresentation when aggregated together. The unique concentration of labor present per region is not easily aggregated in a way that would provide accurate descriptions of labor impacts at the individual region.

The unique regional allocation of each labor group per region would be obscured in a single region model, as it combines thin rural labor markets with a robust urban one which would consequently smooth the regional concentration of specific labor groups. Regional scarcity of individual labor groups means that some regional labor groups experience a different wage and employment change, compared to similar groups in neighboring regions. The individual regional labor outcomes contribute to a different total labor impact in contrast to an aggregated model, making the three-region approach valuable in assessing subregional and total regional effects, as it is based on more accurate data.

Contrasts in the labor group enable further differences in output between the single region and three-region model. The percent change in real household income in Table 2D is directly influenced by the varied employment and wages. In terms of the total percent change of real household income across the aggregated three-region model, we see 0.28% growth compared to 0.26% in the single region model. Across the individual household this effect is not so clear, as households appear to have a greater increase in real income in the single region model for the bottom six household groups, but smaller gains in the top three. Disaggregating the three-region model into the individual region demonstrates that household income growth is diverse across the regions. Rural household income grows greater than their neighbors for all but the last few household groups, exceeding the single regions output for the bottom earning household. The interface and urban regions each provide slower household income growth compared to the single region's bottom six household groups. The differences in household income growth based on model and subregion of three-region model, demonstrates how spatial characteristics shape output.

Table 2.2D: Percent Change in Real Household Income

| | HH1 | HH2 | HH3 | HH4 | HH5 | HH6 | HH7 | HH8 | HH9 | TOTAL |
|---|---|---|---|---|---|---|---|---|---|---|
| Single Region | 0.22% | 0.20% | 0.24% | 0.26% | 0.24% | 0.27% | 0.19% | 0.31% | 0.26% | 0.26% |
| Three-Region | 0.20% | 0.19% | 0.23% | 0.25% | 0.23% | 0.26% | 0.22% | 0.33% | 0.29% | 0.28% |
| Urban | 0.20% | 0.19% | 0.22% | 0.25% | 0.23% | 0.25% | 0.22% | 0.34% | 0.29% | 0.29% |
| Rural | 0.26% | 0.22% | 0.33% | 0.38% | 0.34% | 0.35% | 0.29% | 0.34% | 0.29% | 0.32% |
| Single Region | 0.19% | 0.20% | 0.23% | 0.26% | 0.25% | 0.27% | 0.21% | 0.27% | 0.27% | 0.26% |

The combined effect of greater household income and greater employment, results in relatively more domestic supply in the three-region model than in the single region model. Table 2E describes the percent change of domestic supply and the level change in millions of dollars for each model, and for the subregions of the three-region model. Each of the three regions have a greater percent in domestic supply than the single region model. The rural region's 0.13% is the greatest percent change of any of the regions providing evidence of unique regional outcomes, based on the disaggregated approach of the three-region model. The variation of domestic supply by subregions is a result of the regional labor markets that employed more labor and increased household incomes compared to the single region model. These variations result in a domestic supply growth of 0.11% for the entire three-region model in comparison to the single region model's 0.03%.

Table 2.2E: Domestic Supply

| | Percent Change | Level Change (in millions of dollars) |
|---|---|---|
| Single Region | 0.03% | 62.62 |
| Three-Region | 0.11% | 224.09 |
| Urban | 0.11% | 164.31 |
| Rural | 0.13% | 8.01 |
| Interface | 0.09% | 51.77 |

## 2.9 Conclusion

The comparison between the single-region and three-region models underscores the significant impact of data organization and regional characteristics on simulation outcomes. The three-region model, by offering both a net impact across regions and regional-specific output, provides a nuanced analysis that elucidates behavior contingent upon varying concentrations of labor groups and industries responding differently to exogenous shocks. Through the simulations presented, this model effectively describes unique regional responses, highlighting how a disaggregate approach enhances accuracy compared to an aggregate model by considering regional labor supply and demand dynamics.

Contrarily, aggregating across regions with heterogeneous characteristics obscures the distinct regional responses and undermines the accuracy of aggregate models. This finding aligns with broader trends in the CGE literature, as observed in studies by Lenzen et al. (2004), Turner et al. (2006), and Alexeeva-Talebi (2011), indicating that the level of aggregation significantly influences simulation results. The use of disaggregated data, which retains critical and unique details, ultimately enhances model accuracy, albeit requiring intensive effort in data management and modeling decisions.

The comparison between the three-region and single-region models serves as a critical exercise in understanding how aggregation alters output. The spatial delineation of labor markets influences wages, employment, and other model-wide measures at the subregional level, illuminating diverse regional characteristics that differentiate rural and urban labor market behaviors in response to exogenous shocks. These findings serve as a cautionary note to CGE modelers, urging them to critically evaluate the interpretation of current aggregated models and encouraging the retention of regional characteristics in their specific models for improved accuracy and relevance.

# CHAPTER 3: REGIONAL SKIER BEHAVIOR BASED ON CROSS-REGIONAL WEATHER CHANGE

## 3.1 Introduction

The ski industry has long recognized the pivotal role that weather plays in influencing skier visits. While destination weather has traditionally taken center stage in shaping skier behavior, the impact of a skier's origin weather conditions has been somewhat overlooked. In other sectors of the tourism industry, the relationship between weather and travel decisions, specifically the "push" of origin weather and the "pull" of destination weather, has been well-established (Scott et al., 2003, 2007; Hamilton et al., 2007). This research seeks to bridge the gap by analyzing how these dual influences impact skier visits across the United States.

Historically, colder weather and increased snowfall have translated into enhanced skiing conditions at the destination, prompting a surge in skier visits. However, the same climatic conditions back home significantly influence skiers' considerations for embarking on ski trips. This study delves into the intricate interplay of these push and pull effects of weather variables on skier behavior, a dynamic that has already found application in models of warm-weather travel (Bigano et al., 2005; Day et al., 2012). It is reasonable to suspect that these effects extend to the ski industry.

This research reveals a compelling connection between unfavorable origin weather conditions – characterized by declining snowfall and rising temperatures – and a reduction in the number of ski trips. This observation underscores the growing importance of origin weather in shaping skier travel behavior, challenging ski areas and the communities they support to consider not only how their customers perceive their region's climate change but also how climate change may affect the skier's originating point. By examining the combined influence of origin and destination weather variables on skier behavior, this research offers a unique perspective into the cross-regional impacts of climate change. As climate change unfolds, its effects will vary across regions, impacting each differently in terms of temperature and precipitation. Skier behavior, already attuned to respond to regional weather variations, will play a pivotal role in understanding the spillover effects of climate change on neighboring regions and the ski industry.

The response to climate change poses myriad challenges, and studying the ski industry can provide valuable insights into how consumers adapt. Climate change, characterized by unprecedented shifts, forces researchers to look to past weather events for insights into the economic consequences of both behavioral shifts and physical damages. The ski industry stands out as an ideal subject for such studies because it exhibits diverse regional climates and interregional connections. Skiers, who may traverse the country for a day of skiing, embody cross-regional behavior influenced by regional climate change. These qualities position the ski industry as an invaluable tool for comprehending the interregional impacts of varying climate change and how consumers respond to real physical changes and their perceived impacts. Through this focused study, policymakers can gain clarity on the stakes involved in future climate change responses and identify areas that warrant further research.

In terms of economic significance, the US ski industry drew in over 57 million skier visits in 2019 and is estimated to be worth 3.5 billion dollars according to the National Ski Area Association (NSAA). This industry is an integral component of the broader tourism sector, often the primary economic contributor within a region (World Travel and Tourism Council, 2016). On a global scale, tourism accounts for an average of 10.5 percent of global GDP (WTTC, 2019). Tourists' climate sensitivity will shape the fortunes of various vacation destinations in response to climate change. For example, some areas may experience diminished tourist demand due to climate-related changes, such as extreme temperatures or excessive rainfall. Conversely, other regions may see increased demand if they are perceived as less vulnerable to climate change risks, such as hurricanes or wildfires. Behavioral changes in response to climate change will dictate where skiers choose to visit, ultimately determining which destinations benefit from their patronage. Understanding these behaviors becomes even more critical as climate conditions become increasingly unpredictable, affecting both communities and industries that rely on tourism.

This study will examine the influence of weather on travel decisions within the tourism industry and its link to potential climate change impacts. The research will also highlight the challenges faced by the ski industry, which has limited available data for assessing the threats it confronts. Our model offers an original national perspective on skier behavior, illustrating that winter weather, both at the origin and destination, serves as a key motivator for skier demand. By providing region-specific impacts across various weather variables, our model sheds light on how these factors collectively shape the national impact of weather on the ski industry.

### 3.2 Literature review

The following literature review examines the methods used to investigate climate change's effect on tourism. Interviews, surveys, and quantitative approaches have been applied by various travel and tourism journals and recreation-focused publications. These interdisciplinary fields have collectively advanced our understanding of how changing weather patterns impact tourism. Researchers have explored how weather influences travelers' decisions both before and after their journeys, including the role of an origin's climate in determining the choice between regional and international trips. These diverse perspectives and methodologies have shed light on the intricate relationship between weather and tourism, and its implications for the economic effects of climate change on the industry.

The review is structured as follows: it will first explore the theoretical underpinnings of weather's influence on travel decisions, delving into the causal factors connecting climate change and tourism demand. It will then provide examples of how travelers' behavior is influenced by weather patterns, discussing various methods used to model how weather affects travel choices. These works offer valuable insights into the decision-making process of leisure travelers in response to weather conditions and highlight the significant role of weather in shaping tourist behavior. Additionally, the review will address climate and travel arteries, considering the impact of origin weather on travel choices. It will conclude with a focus on the ski industry, which is particularly vulnerable to the forecasted global warming when compared to warm-weather destinations.

The emphasis on the ski industry is essential due to its unique characteristics. The communities surrounding ski areas are often remote and rely heavily on these areas as primary employers. Winter tourist destinations differ substantially from other forms of leisure travel, thus presenting distinctive challenges when observing shifts in weather patterns' impact. By examining travel choices from various regions and considering a wide range of research methodologies, this review aims to provide a more comprehensive and nuanced approach to climate change research in the context of winter tourist destinations.

### 3.3 Literature Review: Exploring the Dynamics of Push and Pull Factors in Tourism

John Crompton's 1979 landmark study laid the foundation for understanding travel motivations, introducing a critical distinction between "pull factors," attributes that make a destination appealing, and "push factors," internal motivations driving travelers away from their usual environment. Crompton highlighted weather as a significant pull factor, demonstrating its power to attract travelers to certain destinations. This research illuminated the complex interplay between the allure of a destination's weather and the competing comforts of familiar routines.

Expanding on Crompton's work, recent studies, such as the development of the INDECIS Snow Tourism Index (ISTI) by Olano Pozo et al (2020)., focus on the specific climate dependencies of the ski industry. The ISTI represents a sophisticated synthesis of meteorological data, infrastructure characteristics, and seasonal dynamics, aiming to optimize conditions for snow tourism in the Pyrenees. Created in collaboration with local stakeholders, the ISTI exemplifies the application of climate services to tourism, addressing the unique challenges and opportunities presented by weather conditions in a specific region.

The conversation between push and pull factors offers a predictive framework for tourist behavior, emphasizing weather's pivotal role. As climate change becomes an increasingly critical issue, this nuanced understanding of motivational forces is essential for both researchers and industry stakeholders to navigate the shifting landscape of travel preferences. Crompton's initial insights into travel motivations, enriched by contemporary studies like the ISTI, enhance our comprehension of tourism dynamics, particularly in the context of the ski industry's response to climate change. This integration of past and present research supports the broader themes of this chapter, underscoring the importance of examining both the attractions of destinations and the motivations for departure from the origin in understanding tourism behavior in a changing climate.

### 3.4 Literature Review: Pull Factor Travel Research

Exploring the influence of weather on tourism, research from Førland et al. (2013), Bigano et al. (2005), and Day et al. (2013) provides compelling evidence that destination weather significantly affects tourist demand. Through an analysis of historical weather data, travel attendance figures, and survey responses, these studies collectively underscore weather's pivotal role in shaping travel intentions.

Førland et al. (2013) conducted a survey among tourists in the Arctic Circle, revealing how anticipated climatic changes could alter the tourism landscape. The survey, carried out at two Norwegian ferry sites, delved into tourists' weather preferences and how these affect their travel decisions and destination choices. A key finding was the high value placed on visibility, underscoring the critical role of weather in enhancing the appeal of travel destinations, especially those known for their scenic beauty and celestial phenomena. Interestingly, the study observed that international tourists exhibit greater tolerance to cold weather compared to their domestic counterparts, suggesting that accessibility and travel flexibility may influence sensitivity to weather conditions. The research concludes that favorable weather conditions—characterized by sunshine, warmer temperatures, and minimal precipitation—significantly boost tourism by making destinations more attractive to leisure travelers, thus emphasizing weather's crucial impact on the tourism industry's economic vitality.

Through their work on the WISE project, Bigano et al. (2005) uncovered a strong "pull" effect of favorable weather on European tourism, focusing on how Italy's warmer seasons boost coastal visits while warmer winters dampen winter sports activities. This research highlights tourism's seasonal dependencies and the significant influence of even slight summer temperature increases on boosting domestic holiday planning by 0.8% to 4.7%. It emphasizes the crucial role of weather expectations in shaping tourist behavior.

Bigano et al. (2005) delve into weather anomalies, discovering that extreme summer heat waves detrimentally affect Italian resort occupancy, while mild seasonal shifts elicit a positive tourism response. This dichotomy highlights a sophisticated tourist sensitivity to weather, extending beyond mere temperature to encompass broader weather conditions. Their study suggests that travel preferences are intricately linked to personal weather experiences, advocating for in-depth research into how weather patterns across different times and locations influence tourism. It underlines the importance of advancing beyond simple temperature analyses to grasp the complex interplay between weather and tourism dynamics.

Day et al. (2013) present a quantitative analysis aimed at unpacking the short- and medium-term effects of weather variables on the economic landscape across five U.S. cities. Employing regression analysis against a backdrop of variables like employment, payroll, and output values across tourism-related sectors, the study reveals that both hot weather and significant precipitation levels serve as critical predictors of economic vitality, signaling a notable pull effect. The distinction between weekly and annual data in showcasing weather's influence underscores the necessity of further research into the nuanced, lagged effects of weather phenomena on tourism trends.

In exploring pull factors within tourism, the studies by Førland et al. (2013), Bigano et al. (2005), and Day et al. (2013) underscore how destination weather significantly impacts tourist demand, illustrating weather's vital role. These investigations pave the way for a nuanced understanding of how weather conditions, both seasonal and anomalous, influence traveler preferences and decisions.

In Scott et al.’s 2016 Holiday Climate Index (HCI), they refined climate impact analysis on tourism by considering a wider array of destinations. This approach acknowledges that different types of destinations have unique climate preferences, offering a nuanced perspective on the subjective nature of pull factors. By applying a standardized methodology across diverse locales, HCI uncovers how variations in weather conditions can subtly influence travelers' destination choices, offering enhanced predictive accuracy over the Tourist Climate Index (TCI). This comprehensive view allows for an understanding of how relative climate differences between destinations serve to either attract or deter tourists, highlighting the subjective evaluation of climatic allure. The HCI's ability to differentiate the climatic requirements of various destination types further enriches its contribution to tourism studies, making it a pivotal tool for gauging the pull effect of climate on global tourism trends. This innovative index paves the way for future research to explore cross-regional comparisons, identifying how weather contrasts can promote one destination over another in the competitive landscape of tourism.

### 3.5 Literature Review: Push Factor Travel Research

In travel decision-making, the contrast between "push" and "pull" factors, particularly in the context of weather's influence on tourism, is vital. "Push" factors, stemming from unfavorable conditions at a traveler's origin, motivate the search for new experiences. In contrast, "pull" factors attract travelers to destinations with enticing attributes, such as pleasant weather. This interplay significantly shapes tourism economics, with weather acting as both a motivator to leave one's starting point and a lure to desirable locations. Studies by Agnew et al. (2006), Ridderstaat et al. (2014), and Chen et al. (2017) offer insights into how adverse weather at origins drives tourists towards more favorable climates, thus impacting tourism dynamics.

Agnew et al. (2006) utilized Google Trends to reveal how mild and sunny conditions in the UK diminished interest in destinations like Majorca, suggesting that desirable weather at home can overshadow even the inherent appeal of the destination. This discovery not only illuminates the strong motivational force of origin weather conditions but also illustrates how favorable weather can sometimes divert potential international travel towards domestic tourism instead. The study's exploration of the lag effect of weather—a revelation that weather experiences in the year preceding travel can shape future travel plans—adds a layer of complexity to understanding the push factors in tourism. It indicates that weather's influence on travel decisions extends beyond immediate conditions to include the residual effects of past weather experiences.

Expanding this discussion by exploring how both origin and destination weather conditions affect tourism flows, Ridderstaat et al. (2014) and Chen et al. (2017) analyze hotel occupancy and travel patterns to destinations like Aruba and Hainan Island, respectively. These studies underscore the nuanced responses of tourists to weather variables, demonstrating that both push and pull factors play a pivotal role in shaping travel decisions. For instance, rainy weather at the origin leads to an uptick in travel demand, suggesting a reflexive move away from less desirable conditions. Chen et al. (2017) demonstrates that the push effect varied between travelers from separate locations that had different weather conditions. These insights contribute to a broader understanding of the dynamic interplay between environmental conditions at both the starting point and the destination, further complicating the traditional push-pull narrative in tourism research.

By juxtaposing the compelling pull of favorable destination weather against the push of adverse weather at home, this body of research underscores the intricate balance between push and pull factors in tourism. It calls for a more granular investigation into how weather patterns, both current and historical, act as critical determinants in the tourism decision-making process. This expanded view also enriches our comprehension of tourism dynamics but also emphasizes the need for a nuanced approach in assessing the multifaceted influences of weather on global tourism trends, particularly in the context of climate change and its variable impacts on different regions.

Utilizing lagged weather measurements, Juschten et al. (2019) explored how residents of Vienna, Austria, were influenced by past seasonal experiences when shaping their travel preferences. They considered heat-related predictors, uncovering that experiencing high-temperature summers in Vienna intensified the inclination to travel to cooler rural destinations in the following months. This research extended and enhanced the findings of Agnew et al. (2006) by underscoring the profound influence of past experiences on shaping travel decisions.

The exploration of weather's dual influence on tourism through the lens of push and pull factors reveals a subtle, multifaceted dynamic that significantly shapes travel behavior. Studies highlighted in this review, such as those by Agnew et al. (2006), Ridderstaat et al. (2014), Chen et al. (2017), and Juschten et al. (2019), collectively underscore the profound impact of both origin and destination weather conditions on tourism flows. These investigations offer critical insights into how adverse weather at the traveler's origin can act as a potent catalyst for seeking out destinations with more favorable climates, thus affecting overall tourism dynamics. The interplay between the push of less desirable origin weather conditions and the pull of appealing destination climates complicates traditional understandings of travel motivation, calling for a deeper examination of the temporal and spatial nuances of weather's impact on tourism.

This body of research validates the importance of considering both immediate and residual weather effects in tourism studies. The findings from these studies enhance our understanding of the complex decision-making processes behind tourism and also underscore the need for further research. As climate change continues to alter weather patterns globally, the need to understand its impact on tourism becomes increasingly critical. Future studies should aim to develop more comprehensive models that account for the varied and evolving nature of weather influences, bridging the gap between theoretical frameworks and the lived realities of tourists.

The emerging patterns of adaptation among tourists, as observed in the preference shifts towards destinations offering relief from unfavorable weather conditions, indicate a significant area for future inquiry. It is essential to investigate how changing global climate conditions might further influence these adaptive behaviors. Additionally, the role of technology and data analytics, as exemplified using Google Trends in capturing real-time shifts in tourist interests, points towards innovative approaches for tracking and predicting tourism trends in response to environmental changes.

### 3.6 Literature Review: Weather Impact on Ski Tourism

Exploring the nexus between weather impacts and ski tourism shifts our focus from the broader spectrum of travel behavior to the specific context of skiing destinations. These areas, unlike their warm-weather counterparts, rely on cold temperatures and ample snowfall for their allure and operational viability. The precarious balance between optimal weather conditions and the thresholds of sustainability (as discussed by Hamilton et al. (2007) and Scott et al. (2004, 2006)) highlights the unique challenges faced by ski resorts. Extended periods of unfavorable weather threaten the immediate operational status of these areas and poses a significant risk to the economic stability of communities that depend heavily on ski tourism.

The scarcity of readily available attendance data within the ski industry complicates efforts to quantify the impact of climate change on ski tourism. Researchers have navigated this challenge by adopting two primary methodologies: case studies that apply theoretical push and pull factors to the context of ski tourism, and predictive models that estimate the effects of climate change on the skiing season and skiers' expectations. These methods reveal the vulnerability of ski areas to fluctuations in participation and operational duration in response to changing climate conditions.

The study by Hamilton, Brown, & Keim (2007) forms a cornerstone for understanding how weather influences ski tourism demand, demonstrating that weather variables significantly predict daily variations. Their research reveals the substantial impact of both ski resort conditions and urban area weather on visitor numbers, aligning with the "backyard hypothesis" that urban snow conditions affect perceptions of skiing conditions. This study not only highlights the critical role of destination and origin weather in ski area attendance but also foreshadows the challenges ski destinations may face with climate change, predicting a potential shift in peak seasons and impacting the industry's economic stability. Integrating these insights, the discussion evolves to emphasize the necessity for further research in adapting ski tourism to changing climate conditions, suggesting a deeper exploration into weather's influence from both a push and pull perspective.

However, projecting these findings into the context of climate change forecasts presents a concerning scenario. Predictions of warmer temperatures and reduced snowfall accumulation could potentially delay the start of the ski season, undermining one of the industry's peak revenue-generating periods. The lack of a corresponding rise in attendance during the latter phases of the season, highlighted by the failure to adjust to delayed season commencements, exacerbates the difficulty, indicating a bleak outlook for ski areas in the context of climate change.

Despite the valuable insights these studies provide, they also illuminate significant limitations within ski tourism research, notably the reliance on scarce and often proprietary attendance data and the assumption of uniform skier responses to weather variables. Future research efforts should aim to develop more nuanced models that account for diverse skier behaviors and the complex economic ecosystems of ski resort communities. Such endeavors will be crucial in devising strategies to mitigate the impact of climate change on this vulnerable sector of the tourism industry, ensuring its resilience and sustainability in the years to come.

Shih et al. (2008) offers an illuminating case study from southern Michigan, spotlighting the significant pull effect of snow depth on ski area ticket sales. This study parsed through a variety of weather variables, including temperature extremes and snowfall, across two ski areas over several seasons. Unlike expectations, weather conditions at the tourists' origins showed no significant correlation with visitation rates. Instead, an increase in snow depth directly correlated with heightened ticket sales, underscoring the direct link between adequate snow coverage and the appeal of ski destinations. This finding emphasizes the critical role of destination-specific weather conditions in attracting visitors and brings to light the regional challenges and potential benefits that climate change predictions hold for the Great Lakes area.

In dissecting their data further, Shih et al. (2008) differentiated between peak and off-peak seasons to analyze variances in skier demographics and behaviors. The analysis revealed that peak seasons, marked by holidays and significant family attendance, exhibited a lesser sensitivity to daily weather fluctuations, given the advanced planning typically involved. Conversely, the off-peak season, favored by skiing aficionados and those desiring a less crowded experience, demonstrated a pronounced responsiveness to snow depth, affirming the nuanced dynamics within ski tourism that extend beyond a simple binary of good or bad weather.

The collective findings of Hamilton et al. (2007) and Shih et al. (2008) converge on the importance of snowfall and depth in enriching the skiing experience and potentially extending the season. However, these insights predominantly reflect local participant behavior, presenting a challenge in extrapolating these findings to a wider context due to the reticence of many ski areas to share detailed visitor data.

Pivoting to a different methodology, Scott et al. (2004, 2006, 2007) adopted a predictive lens to estimate the season lengths of ski areas across Ontario, Quebec, and the Northeastern US. By integrating historical data with climate projections, these studies assess the efficacy of snowmaking as a countermeasure to the anticipated impacts of climate change. Despite the promise of snowmaking, its utility is bounded by practical limitations such as water access, infrastructure capabilities, and optimal temperature conditions, highlighting the precarious balance between technological solutions and the inherent challenges posed by climate change.

The literature discussed affords critical insights into how weather variables—both push and pull factors—interact to shape tourism patterns and the operational realities of ski resorts. While the acknowledgment of weather's dualistic role in influencing skier decisions is a valuable takeaway, the scope and scale of the studies' mentioned pose limitations to a full understanding of the intricate relationship between climate change, weather phenomena, and their collective impact on the ski tourism industry. This gap underscores an urgent call for more expansive research that not only delves deeper into the specifics of winter tourism but also embraces the complexity of regional weather variations. Such endeavors are essential for a comprehensive grasp of how climate change will reshape the landscape of ski tourism, prompting a reevaluation of strategies to ensure the long-term viability and sustainability of ski areas amidst evolving environmental conditions.

### 3.7 Skier Utility Model

The travel literature examined weather's role in travel decisions, focusing predominantly on warm-weather destinations with limited exploration of cold-weather destinations. Skiing studies, such as Shih et al. (2008) and Hamilton et al. (2007), delved into the pull and push factors of skier behavior, with varying conclusions about the significance of push weather variables. This research aims to bridge the gap by combining cross-regional and winter destination research, examining how weather affects skier choices, and emphasizing the role of push factors.

A utility model is presented to explore the relationship between weather and skier visits. This model builds upon previous research (Hamilton et al. 2007, Scott et al. 2007) and focuses on the behaviors of skiers traveling across the US, requiring new assessments of push and pull variables. The model describes skiers' utility in relation to destination and origin weather and other relevant factors. Weather introduces subjective and objective qualities to skiing, shaping the perceived benefit of a destination ski trip. This model seeks to uncover the impacts of weather on the skiing experience and set a foundation for understanding a priori expectations.

The utility model's organization covers destination weather variables, origin weather variables, and alternative variables, as depicted in Figure 3.1.

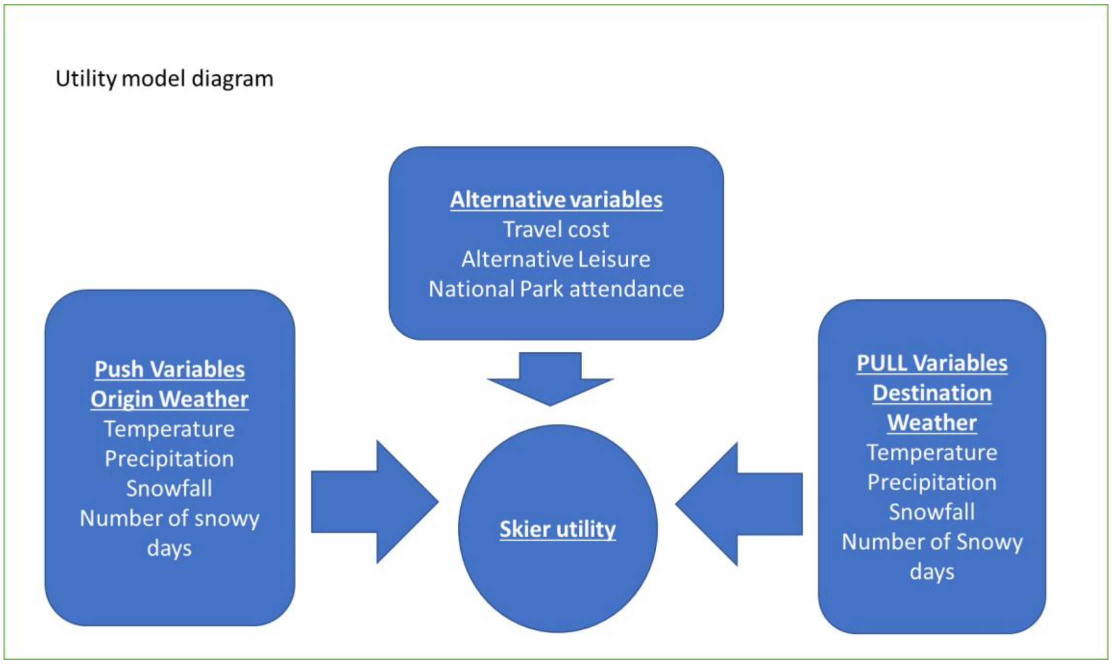


Figure 3.1 Utility Model Diagram

### 3.8 Utility Model: Destination Weather Variables

Destination weather significantly influences the quality and availability of a ski trip. Cold temperatures and ample snowfall are essential for a positive skiing experience. Skiers prefer freshly fallen snow, and warm, dry weather can make the terrain undesirable and dangerous. High temperatures may lead to freeze-thaw cycles, resulting in icy ski runs. More snow and colder temperatures are associated with increased skier visits.

The same weather variables that enhance skiing quality also expand the spatial and temporal availability of skiing. Snowfall provides more available trails and terrain, while cold temperatures extend the ski season. Access to ski areas increases, making skiing more enticing. Research by Goldsmith et al. (2001) supports the positive relationship between snowfall and skier visits.

The relationship between temperature and utility likely forms an upside-down "U" shape, with the peak around 32 degrees Fahrenheit. Temperatures above freezing reduce quality and availability, while extreme cold does not significantly improve skiing quality. Snowfall's impact on utility follows a logistic curve, with diminishing returns as snowfall increases.

### 3.9 Utility Model: Origin Weather Variables

Origin weather's impact on skier utility is complex. Origin weather serves as a push factor, influencing skiers' choices based on their local weather. Short distances between origin and destination correlate with stronger relationships between these weather variables. Origin weather's objective signaling ability weakens as distances increase, leading to primarily subjective effects on utility. Changes in origin weather shift the opportunity cost of destination ski trips by introducing competition from local leisure activities.

Cold origin weather could increase the demand for destination ski trips, making them more appealing. A longer, colder winter at the origin maintains the availability of alternative leisure activities, increasing the desirability of a ski trip. The experience of cold weather at home reduces the cost of destination ski trips in terms of gear, adjustments, and mindset.

The subjective impact of origin weather variables on utility is more significant when objective signaling is limited. The opportunity cost of alternative leisure activities plays a pivotal role in determining the impact of origin weather. To explore this, national park attendance and employment data were considered, indicating that origin behaviors change based on weather variables.

The relationship between origin weather and destination utility is likely monotonically decreasing, with more warm days indicating more leisure alternatives. The direction of this relationship is influenced by local leisure activities, priming the demand for destination ski trips as poor weather conditions persist.

### 3.10 Utility Model: Alternative Variables

Alternative variables, aside from weather, encompass geographic characteristics of origin and destination, the number of ski areas at each destination, the availability of season ski passes spanning different regions, and various socioeconomic factors. These factors exert a substantial influence on skier utility.

Fixed geographic factors, such as the area and distance between origin and destination, may pose as barriers to participation, reducing utility. The number of ski areas in a destination can enhance utility by offering more access and diverse terrain, influencing decisions made by skiers from the origin. Moreover, the presence of local ski areas at the origin can create a complementary effect between origin and destination ski trips, establishing a path dependency. Socioeconomic elements, encompassing personal income, price, and earning per capita, play a pivotal role in determining skiers' affordability of trips. Skiing is akin to a luxury good, featuring a positive income-demand relationship. Changes in price and income levels impact ski trip demand similarly to the price and income effects typical of luxury goods.

In summary, the utility model explores the multifaceted relationship between weather, origin, and alternative variables, shedding light on how these factors shape the decisions of skiers when planning destination ski trips.

### 3.11 Data and Methods

The presented model aims to investigate whether push and pull weather variables can elucidate national-level skier demand trends, thereby providing insights into the potential impacts of forecasted climate change on the ski industry. Building upon the findings of Hamilton et al., which identified snow coverage and air temperature at both origin and destination as key indicators of ski demand, this study utilizes NOAA weather data to capture these push and pull factors comprehensively.

The dependent variable in this study is derived from skier visitation data provided by the National Ski Area Association (NSAA), while weather variables are sourced from NOAA weather stations. Destination weather variables are aggregated based on stations sharing a FIPS code with a ski area and are averaged per region. Additionally, weighted averages, considering elevation, were explored, albeit yielding minimal variation in results. These variables encompass average, minimum, and maximum temperatures, as well as total snowfall, averaged monthly over the typical six-month ski season period from November to April.

To gauge the impact of weather on potential skiers, origin weather data is collected from NOAA weather stations across the entire region. Weighted by population at the census block level, these data reflect the weather's influence on the broader populace. Notably, the approach to weighting origin and destination weather produces differing results, particularly in terms of average temperatures and snowfall, with the destination method yielding colder and snowier conditions.

Origin weather variables encompass average temperature, snowfall, precipitation, days of snowfall, days below 32 degrees Fahrenheit, and days exceeding 70 degrees. This broader array of variables aims to capture a wider range of subjective weather effects, allowing for a comprehensive examination of weather-skier demand dynamics.

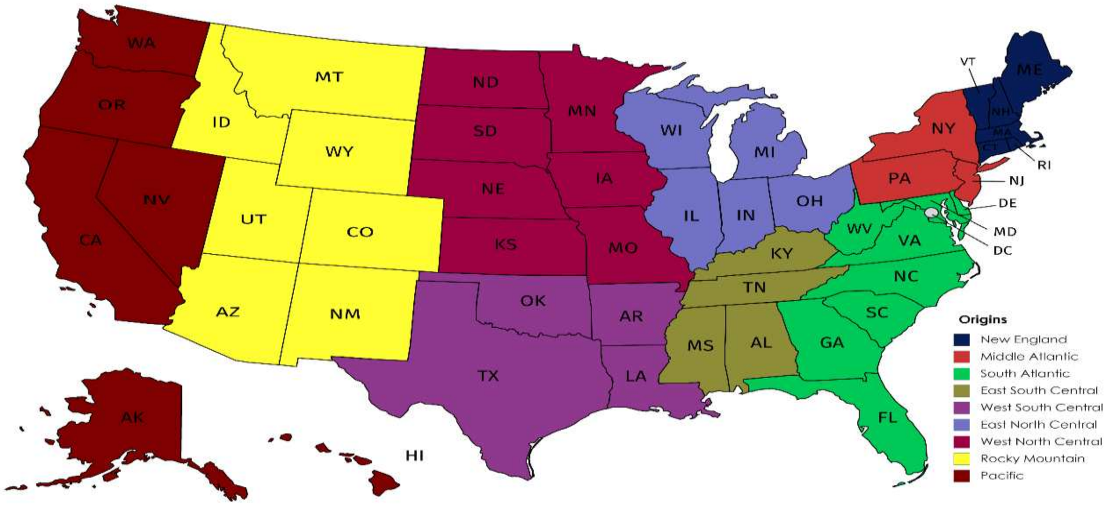
The skier behavior data utilized in this study is sourced from the National Ski Area Association (NSAA), a prominent organization offering industry services and overseeing safety and behavioral trends for ski areas across the United States. Representing over 90 percent of the ski industry within the country, the NSAA graciously provided seasonal attendance data per region, collected from its extensive membership network.

The NSAA's dataset categorizes total visits per destination based on skier origins, allowing for the grouping of nine origins and five destinations into unique pairs over the course of 13 seasons, spanning from the 2001-02 season to the 2013-14 season. Notably, one of the nine origins—comprising Texas, Oklahoma, Arkansas, and Louisiana—lacked any known ski areas, rendering it a unique case and necessitating its exclusion from the dataset. Consequently, the model operates with eight origins and five destinations, yielding a total of 520 observations when treated as a pooled model or as a panel dataset featuring 40 distinct origin-destination pairs. Additionally, maps illustrating both origin and destination distributions are provided below for reference in figure 3.2 and 3.3 respectively.

Travel costs between each origin-destination pair were sourced from the Federal Aviation Administration (FAA). Leveraging data on passenger traffic at airports, the FAA facilitated the assignment of the most frequented airports to both origin and destination points. Additionally, data on passenger volumes and associated travel expenses for each pair were acquired, enabling the calculation of average travel costs for each unique panel throughout the ski season.

In addition to weather variables, several other factors potentially influencing ski trip demand were examined. These variables, although not statistically significant in the models, offer insights into factors affecting skier demand beyond weather conditions. They encompass changes in per capita income per region sourced from the Bureau of Labor Statistics (BLS),

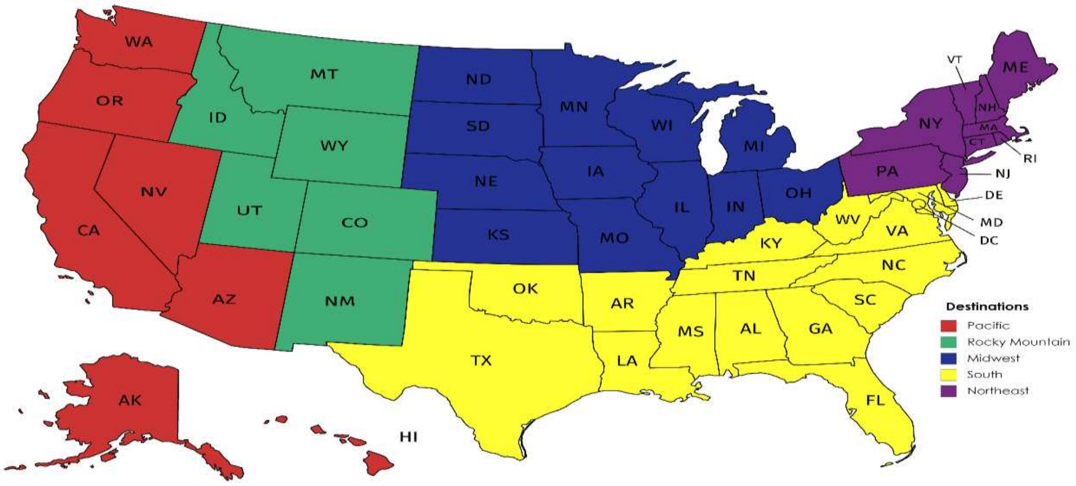
## Skier Origins Regions



Created with mapchart.net ©

Figure 3.2 Skier Origins Regions

## Skier Destination Regions



Created with mapchart.net ©

Figure 3.3 Skier Destination Regions

attendance at national parks, and data from the Quarterly Census of Employment and Wages (QCEW) pertaining to employment and wages in accommodation and entertainment sectors. Detailed summaries of all variables are provided in the summary statistics presented in Appendix A.

Further exploration of the dataset involved analyzing the correlation structure among variables. A correlation matrix, included in Appendix B, revealed significant insights guiding variable selection in the Model. Strong correlations among destination weather variables necessitated the selection of a single variable to avoid multicollinearity. Similarly, while origin weather variables exhibited weaker correlations compared to destination variables, the limited number of observations per panel constrained variable selection to mitigate multicollinearity risks. Although weaker, the relationships between origin and destination weather variables were scrutinized for collinearity using Variance Inflation Factor (VIF) tests, the results of which are available in Appendix C.

$$Y_{it} = BX_{it} + a_i + U_{it}$$

Where: $Y_{it}$ is the dependent variable observed for individual $i$ at $t$ time.

$B_1$ is the matrix of coefficients.

$X_{it}$ is the time variant independent variable.

$a_i$ is the unobserved time-invariant individual effect.

$U_{it}$ is the error term.

$i$ represents the unique pairings of origin and destination

$t$ represents each of the 13 seasons.

The fixed effect model (FEM) emerged as the most suitable among alternative specifications, outperforming both pooled Ordinary Least Squares (OLS) and Random Effects (RE) models. A Wald test conducted on the pooled OLS model revealed joint significance of origin-destination pairs (F(39, 477) = 972.20, p = 0.000), rendering the pooled OLS inappropriate. Consequently, a panel regression model was deemed more appropriate, with the choice between FEM and REM contingent upon a Hausman test. However, the rejection of the null hypothesis in the Hausman test (Chi2(3) = 10.75, p = 0.0132) favored the FEM as the superior fit.

This outcome aligns with expectations, considering the regional disparities inherent in unique origin-destination pairs, which likely exert substantial influence on ski trip likelihood. The FEM specification, while effective, imposes limitations on fixed explanatory variables, grouping them under fixed effects and precluding their individual identification in the model. All model specifications and test statistics are provided in the appendices.

Subsequently, the FEM specification underwent heteroskedasticity testing using a modified Wald test, revealing its presence (chi2(40) = 64465.61, p = 0.000). Consequently, robust standard errors were incorporated into the model to mitigate time-dependent variance in the error term. While this transformation attenuated the significance of some weather variables, those directly indicative of snowfall in origin or destination regions remained significant at a P-value of 10%. Thus, the model retains its capability to assess both push and pull factors influencing ski trip demand.

Furthermore, the fixed effect robust panel model underwent unit root testing to confirm stationarity. Levin-Lin-Chu and Breitung unit-root tests, alongside a Dickey Fuller test, collectively rejected the presence of unit roots, affirming that seasonal shifts in skier visits did not yield time-variant fluctuations in future visits across panel observations.

In summary, the limited 13 seasonal observations precluded exhaustive examinations of lagged variables, typically more discernible in longer-term models. Prior investigations with more extensive datasets (Shih et al., 2008; Hamilton, 2007; Scott et al., 2007) benefited from greater observations, enabling the inclusion of lagged variables without significant sample size reduction. Attempts to incorporate seasonal differences in variables, albeit reducing the model from 520 to 480 observations, further compromised its efficacy. Despite this, a model utilizing seasonal skier visit differences is provided in Appendix D, where push and pull weather variables remain significant, albeit with R-squared values below 1%.

Given the model's focus on exogenous weather impacts on behavior, endogeneity concerns commonly found in consumer behavior models are less relevant. Previous studies by Shih et al. (2008), Scott et al. (2007), and Ridderstaat et al. (2014) have established the independence of weather and behavior within these models. Although preliminary exploration of instrumental variables was undertaken, it failed to yield meaningful linkages between weather and skier behavior.

### 3.12 Results and Discussion: Origin Push Effects

The initial six findings presented in Table 3.1 illustrate the outcomes of panel regressions involving diverse origin weather variables, offering insights into the push effects originating from weather conditions. Notably, among the origin weather variables, statistical significance is observed primarily in the number of days with snowfall, total snowfall amount, average origin weather, and extreme high temperature days. It is worth noting that due to the broad geographical scope of the data, the p-values for the number of snowfall days and snowfall amount in the origin are marginally above the conventional significance threshold at 0.076 and 0.075, respectively. While conventional regression analysis might typically disregard results at the 10% significance level, similar findings have been employed in other travel models to support both push and pull effects (Ridderstaat et al., 2014; Chen et al., 2017; Shih et al., 2009). Furthermore, previous studies by Hamilton et al. (2007) and Shih et al. (2009), which utilized daily data and encompassed more localized areas, have utilized the 10% significance level. Hence, in alignment with these precedents, this study acknowledges the potential impact of origin winter weather, particularly snowfall and snowfall days, in driving increased skier visits at destinations.

The push effect was also presented by the occurrence of unseasonably warm weather indicated by extreme high temperature days and by origin average temperature. Extreme high temperature days and origin average temperature were significant and had negative coefficients at the 5% and 10% levels, respectively. The two origin temperature results support the view that warmer origin weather reduces the preference for destination ski trips, making them less appealing as temperatures rise. This result supports the push effect hypothesis that origin weather shifts the preference for ski trips but is counter to what most travel models have described where travels are pushed from one kind of weather to a destination with a different climate.

The remaining variables, including wider descriptions of temperature and precipitation were not found to be significant.  With regards to precipitation, if an origin experiences above average rainfall this would not likely create many new alternative outdoor leisure activities meaning that there is no substitution effect that is possible with warm weather. Rain would in either of these descriptions neither encourage of discourage skier visits allowing the non-significant results fit within the leisure alternatives described in the utility model. The other option is that these nonsignificant origin weather variables may not be noteworthy for potential skiers and thus have no significance on the decision to participate in a ski trip. Either way these weather variables do not offer any further clarification of how skier visits are motivated.

The first four models described in Table 3.1 also offer evidence of the pull effect with the inclusion of the destination snowfall variable. Each of the models include destination snowfall and average travel cost which are significant at the 1% level. Destination snowfall has a positive coefficient that would indicate the presence of a pull factor for weather that would increase the availability of ski terrain and of improved quality for those participating in a ski trip. The average travel cost has a negative coefficient and meets the expectation that travel costs presents a barrier for skiing. Using the first regression results from Table 3.1 for examination the destination snowfall and average travel cost are tested individually (F( 2, 39) = 3.29 and P = 0.0479) and jointly (F( 1, 39) = 5.59 P = 0.0232) and each have significance at the 5% level. These results confirm that skier behavior and expectations are positively influenced by the quality of the destination and deterred by travel cost. These results are similar across the other models that used varying origin weather variables. The pull effects are further discussed in the following sections, but it is noteworthy to demonstrate that both push and pull effects are present across several push variables.

To establish what impact origin snowfall, snowy days, origin average temperature and the measure of extreme high temperature has on skier demand a marginal elasticity response was performed. This allows for the impact of push factors on skier visits to be discussed in terms of the responsiveness between the dependent and independent variables of the model. Table 3.2 describes the elasticities of the origin variable impact on the number of destination ski trips and

Table 3.1: Push Models

| Column1 | Column2 | Column3 | Column4 | Column5 | Column6 | Column7 |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Variables | Destination | Destination | Destination | Destination | Destination | Destination |
| | | | | | | |
| Dsnowfall | 0.000213** | 0.000206** | 0.000205** | 0.000244** | 0.000271** | 0.000243** |
| | (8.03e-05) | (8.16e-05) | (8.10e-05) | (9.61e-05) | (0.000115) | (9.24e-05) |
| Avgtravelcost | -0.00105** | -0.00125** | -0.00124** | -0.00118** | -0.00101*** | -0.00101*** |
| | (0.000489) | (0.000528) | (0.000527) | (0.000516) | (0.000366) | (0.000333) |
| oextreme_max_temp | -0.0331** | | | | | |
| | (0.0157) | | | | | |
| oworigin_snowfall_days | | 0.0345* | | | | |
| | | (0.0190) | | | | |
| owtotal_snowfall | | | 0.000345* | | | |
| | | | (0.000189) | | | |
| owtotal_precip | | | | 1.42e-05 | | |
| | | | | (0.000181) | | |
| wdx32 | | | | | -0.00211 | |
| | | | | | (0.00298) | |
| wdx70 | | | | | | -0.00128 |
| | | | | | | (0.00351) |
| Constant | 1.965*** | 1.248*** | 1.255*** | 1.299*** | 1.311*** | 1.328*** |
| | (0.307) | (0.0606) | (0.0583) | (0.0940) | (0.0479) | (0.0981) |
| | | | | | | |
| Observations | 520 | 520 | 520 | 520 | 520 | 520 |
| R-squared | 0.073 | 0.071 | 0.072 | 0.055 | 0.072 | 0.057 |
| Number of trip | 40 | 40 | 40 | 40 | 40 | 40 |
| Robust standard errors in parentheses | | | | | | |
| *** p<0.01, ** p<0.05, * p<0.1 | | | | | | |

Table 3.2: Push Variable Elasticity Responses of Skier Visits

| Variables | eY/eX | Std. Error | Z | P\|>\| | 95% Conf. Interval | |
|---|---|---|---|---|---|---|
| owtotal_snowfall | 0.05754 | 0.030267 | 1.9 | 0.057 | -0.00178 | 0.116861 |
| oworigin_snowfall_days | 0.063037 | 0.033337 | 1.89 | 0.059 | -0.0023 | 0.128378 |
| oavg_temp F | -0.08329 | 0.045812 | -1.82 | 0.069 | -0.17308 | 0.006501 |
| Oextreme_max_temp F | -0.52561 | 0.259107 | -2.03 | 0.043 | -1.03345 | -0.01777 |

demonstrates that all these variables are inelastic and have only a minor effect. For example, a 1% increase in origin snowfall results in 0.057% increase in skier visits, and similarly a 1% increase in origin snowfall days results in 0.063% increase in skier visits. If origin snowfall was to increase one standard deviation from the mean total of 225 inches to 431 inches more than 70,000 more skier visits would occur between that origin and another destination ceteris paribus. It is also worth noting that the gains in skier visits only describes the behavior between one origin and destination pair, but each origin has five destinations making the origin snowfall capable of motivating skier visits across the whole country. If one origin region had a big snow year, multiple ski destinations could get a boost instead of the impact being purely located in the origin.

The extreme maximum temperature variable has the strongest elasticity among the significant push weather variables and is significant at the 5% level. The extreme maximum temperature avoids this regional interpretation as every region will have outlier weather and these can often be a focal point for last-minute leisure trips that present alternatives to ski trips. The impact of extreme temperature days on skier visits can be interpreted as a 1% increase in extreme maximum temperature reduces skier visits by 0.52%. With the mean extreme maximum temperature of 67.8° F one standard deviation increase would result in a new extreme max of 73°F and per this model would reduce skier visits by 114,000 visits given that all other independent variables are at their mean values. Given the record setting weather that several regions are experiencing the relationship between extreme origin temperature and skier visits should not be overlooked.

To provide a more substantive analysis, consider how the Rocky Mountain region would be affected if each origin experienced either a higher extreme temperature or decline in snowfall. Instead of using the mean across each panel the following example uses the mean destination snowfall for the Rocky Mountain destination and the mean values of average travel cost between the origin and the Rocky Mountain destination. Each of the eight origins has their own mean total snowfall and origin specific standard deviation. Table 3.3 provides the origin impact of less snowfall in each origin and its impact on the skier visits to the Rocky Mountain destination.

Table 3.3: Impact of Lower Weighted Origin Snowfall on Rocky Mountain Skier Visits

| | Weighted Origin Snowfall | | Skier Visits (in millions) | | | |
|---|---|---|---|---|---|---|
| | Mean | Standard Deviation | Before | After | Difference | Percent change |
| New England | 390.565 | 144.809 | 1.368 | 1.318 | -0.050 | -3.66% |
| Middle Atlantic | 465.409 | 160.109 | 1.418 | 1.363 | -0.055 | -3.90% |
| East North Central | 390.363 | 102.080 | 1.437 | 1.402 | -0.035 | -2.45% |
| West North Central | 319.822 | 101.467 | 1.426 | 1.391 | -0.035 | -2.46% |
| South Atlantic | 47.123 | 35.551 | 1.256 | 1.244 | -0.012 | -0.98% |
| East South Central | 69.261 | 41.330 | 1.248 | 1.234 | -0.014 | -1.14% |
| Rocky Mountain | 107.663 | 23.288 | 1.336 | 1.328 | -0.008 | -0.60% |
| Pacific | 14.882 | 5.272 | 1.364 | 1.362 | -0.002 | -0.13% |
| Total | | | 10.852 | 10.640 | -0.212 | -1.95% |

This results in 212,000 fewer skier visits or a 1.95% decline in total attendance. Given that the average person will spend $100 per day on a ski vacation according to a 2012-13 survey conducted by the NSAA, this analysis equates to a loss of over $20 million of revenue. Additionally, the survey does not consider community spillover effects like lodging, additional travel costs etc. and so there would likely be a greater loss to the ski community. Doing a similar analysis for Rocky Mountain skier visits using origin extreme temperatures based on origin specific mean temperature and standard deviation results in a decline of more than 254,000 skier visits or more than a 2.34% decline in skier visits. Table 3.4 provides a breakdown of the calculations for each Rocky Mountain origin prediction. One to two percent drop in attendance may not seem like a substantial difference but when it is explained only by fluctuation of origin weather and result in tens of millions of dollars of revenue it should be concerning for the ski industry.

Table 3.4: Impact of Higher Origin Extreme Temperature on Rocky Mountain Skier Visits

| | Origin Extreme Temperature | | Skier Visits (in millions) | | | |
|---|---|---|---|---|---|---|
| | Mean | Standard Deviation | Before | After | Difference | Percent Change |
| New England | 63.130 | 2.044 | 1.436 | 1.394 | -0.042 | -2.91% |
| Middle Atlantic | 76.929 | 1.400 | 1.379 | 1.337 | -0.042 | -3.02% |
| East North Central | 65.665 | 2.258 | 1.463 | 1.425 | -0.038 | -2.57% |
| West North Central | 65.816 | 1.287 | 1.407 | 1.365 | -0.042 | -2.99% |
| South Atlantic | 61.438 | 2.268 | 1.125 | 1.101 | -0.024 | -2.14% |
| East South Central | 64.500 | 0.927 | 1.143 | 1.117 | -0.026 | -2.26% |
| Rocky Mountain | 78.641 | 1.305 | 1.411 | 1.387 | -0.024 | -1.68% |
| Pacific | 66.773 | 2.282 | 1.486 | 1.469 | -0.017 | -1.15% |
| Total | | | 10.849 | 10.596 | -0.254 | -2.34% |

The analysis of the push factor of origin weather variables has shown that colder weather primes skiers to demand further ski trips. This observation would demonstrate winter weather generates a complimentary effect for skier visits. This is dissimilar to the warm weather destinations discussed in the literature review where every instance described tourism motivated to leave one climate for another type of climate. Additionally, the origin weather does not indicate the quality of the destination. We can speculate that there is a subjective influence on skier demand based on the climate they reside in, which fits within the tourism demand seen in other tourism research that focused on push factors. The nuances of cold weather providing a complimentary weather effect on skier demand offers one more unique characteristic for tourism demand.

### 3.13 Results and Discussion: Destination Pull Effects

Based on the output from Table 3.5 there are several models that support the pull effect of destination weather. Each model uses a different pull weather variable in combination with average travel cost, and origin average temperature. Snowfall in the destination provides a strong positive impact on skier visits while higher temperatures described by either destination average temperature and destination maximum temperature have negative coefficients. More snowfall generated greater skier visits and higher temperatures reduce visits meets the expected outcome from this model. Snowfall and maximum temperature are significant at the 5% level and average temperature is significant at a 1% level. This meets the expected outcome that each pull factor is connected to the objective quality of the experience and further increases the accessibility of ski terrain and the ski season. It is also worth noting that the last pull model used minimum temperate was found to have no significance possibly indicating that cold weather is a sufficient

Table 3.5: Pull Factor Models

| Variables | Destination | Destination | Destination | Destination |
|---|---|---|---|---|
| | | | | |
| Dsnowfall | 0.000210** | | | |
| | (0.0000842) | | | |
| avgtravelcost | -0.00116** | -0.00111** | -0.00143** | -0.00136** |
| | (0.00051) | (0.00048) | (0.00058) | (0.00054) |
| oavg_temp | -0.0224* | -0.0289** | -0.0219** | -0.0203* |
| | (0.0112) | (0.0135) | (0.0103) | (0.0105) |
| Dmintemp | | -0.00459 | | |
| | | (0.00301) | | |
| Dmaxtemp | | | -0.0187** | |
| | | | (0.00693) | |
| Davgtemp | | | | -0.0155*** |
| | | | | (0.00538) |
| | | | | |
| Constant | 1.419*** | 1.591*** | 2.715*** | 2.074*** |
| | (0.0648) | (0.108) | (0.513) | (0.256) |
| | | | | |
| Observations | 520 | 520 | 520 | 520 |
| R-squared | 0.065 | 0.035 | 0.053 | 0.046 |
| Number of trip | 40 | 40 | 40 | 40 |
| Robust standard errors in parentheses | | | | |
| *** p<0.01, ** p<0.05, * p<0.1 | | | | |

condition for skiing to occur but does not have a meaningful impact on utility unless it is above freezing which is not the case in this data set.

The explanatory power of the model is on the weaker side, with R-squared results for the overall providing less than a 0.1 result. This is due to the model explaining skier behavior using mostly weather variables, when there are likely many other factors that contribute to this decision. Because the observations are on an annual basis and the regions are so large there was relatively few additionally variables that could be used. Furthermore, since each panel is made from only 13 season it does limit the ability to apply a wider combination of variables at once. Despite this, other travel models have used models with low power to explain many weather phenomena. For example, Ridderstaat et al. (2014) provided models that ranged from adjusted R-squared of 0.05 to 0.07 to explain push and pull weather effects monthly observations. Provided that is has been used in the literature by others (Ridderstaat et al. 2014 and Chen et al. 2017) the results of this model can also be used to support evidence of pull effects.

Upon scrutinizing each of the pull models, it becomes apparent that snowfall at the destination serves as a marginally stronger predictor of skier visits compared to temperature metrics. This assertion is based on the comparison of R-squared values, where destination snowfall yields a coefficient of determination of 0.065, surpassing the values of 0.053 and below observed in the remaining models. While this disparity may seem subtle, the slight increase in explanatory power aligns with the ethos of ski culture, which predominantly emphasizes season total snowfall over temperature measurements. Snowfall exerts a pulling force on skiers towards a location, whereas temperature dictates the maintenance and quality of the snowfall, thus serving as a tangential indicator of destination ski experience quality. Notably, maximum temperature also influences pull models, presumably by impacting perceptions of season duration, ski condition, and terrain accessibility. This was evident in 2011 in California, where a significant temperature rise led to muddy terrains, an unusually early end to the season, and diminished ski attendance in the Western region compared to historical averages. Considering the nuanced distinctions between snowfall and temperature across the pull models, it appears that snowfall subtly reflects skier behavior in response to quality, while temperature offers a broader depiction of accessibility. Both variables are indispensable for assessing the impacts of climate change on the ski industry.

The outcomes of the pull effects echo findings from case studies by Hamilton et al. and Shih et al., highlighting the influence of snowfall and colder weather at destinations on increased skier attendance. Noteworthy differences lie in the present model's utilization of aggregated spatial regions spanning multiple states and solely relying on annual attendance data. Confirming the presence of pull effects using national data that encapsulate skiers' behavior across state boundaries unequivocally underscores the influence of winter weather on interregional travel decisions. Essentially, this model underscores the dependence of skier behavior on destination weather and underscores how such behavior will respond to climate change-induced shifts, underscoring the imperative for further research.

Another component of Hamilton et al. (2007) pull effect of snowfall was that it was stronger than push effect of snowfall for the surrounding urban centers. Their results indicated that snowfall in the destination was correlated with higher skier visits than when the same snowfall occurred in the origin. This comparison provides a distinction between snowfall either at the origin or at the destination shaped the decision to ski. Origin snowfall provides a signal of destination quality when origin and destination are located closely together, and origin snowfall could also prime the desire to ski. This was the case in the Hamilton et al. case study of the east coast ski areas, the difference that this model offers in the comparison of push and pull of snowfall is that there is no signal offered by the origin snowfall for destination quality. Instead, this model's origin snowfall could isolate the priming effect. To make a similar claim this model cannot compare model coefficients of origin and destination snowfall variables as the snowfall is measured using different techniques. Recall from the data section that the origin is weighted by population and only weather stations that share a FIPS code with a ski area are used in the destination snow measure. For this reason, the two measures of snow in either origin and destination are not measuring the same thing. Instead to offer an equivalent comparison an elasticity response function similar to the one preformed in Table 3.2 is presented for the significant pull variables. The elasticity response of skier visits to destination snowfall has a value of 0.09 in Table 3.2 compared to the origin snowfall response of 0.057 as seen in Table 3.6. The greater responsiveness of snowfall at the destination confirms that the pull effect is also greater at this national level. This kind of comparison also provides an opportunity for future work to consider how responsive a push snowfall effect would differ based on distance between origin and destination.

Table 3.6: Push variable Elasticity Responses

| | eY/eX | Std. Error | Z | P\|>\| | 95% Conf. Interval | |
|---|---|---|---|---|---|---|
| Dsnowfall | 0.090519 | 0.035745 | 2.53 | 0.011 | 0.020461 | 0.160577 |
| Dmaxtemp | -0.8982 | 0.343548 | -2.61 | 0.009 | -1.57154 | -0.22486 |
| Davgtemp | -0.40937 | 0.145924 | -2.81 | 0.005 | -0.69538 | -0.12337 |

Temperature at the destination emerges as a critical determinant for ski areas, particularly elucidated through the elasticity response function outlined in Table 3.6. The temperature specific elasticities presented here exhibit a more pronounced response compared to snowfall. Notably, the elasticity response for maximum temperature stands at -0.89, while for average temperature, it registers at -0.409. This outcome is intuitive, considering that a degree variance in temperature would exert a greater influence on the quality of skiing conditions and terrain accessibility compared to a similar percentage change in snowfall. Temperature metrics offer valuable insights into a ski area's operational capabilities and its allure in attracting skier visits. In the absence of sufficiently low temperatures, snowfall would be adversely affected, thereby limiting the potential for enhanced ski experiences. From the perspective of the utility model, it can be inferred that temperature metrics provide a more nuanced understanding of accessibility rather than the quality of the skiing experience. Consequently, destination temperature measures serve as excellent indicators of ski area viability at a regional level.

Comparing pull effects in terms of total skier visits can be generalized across all panels of the model, with destinations on the West Coast and in the Rocky Mountains garnering the most interest from skiers. Notable West Coast ski areas include resorts such as Squaw Valley, Kirkwood, and Mt. Hood, while the Rockies boast destinations like Jackson Hole, Vail, and Sun Valley, which are likely on the radar of serious skiing enthusiasts nationwide. However, even these premier locations are subject to the vagaries of winter weather, as evidenced by this model. Tables 8 and 9 present origin-specific means for average temperatures and average travel costs to both the Rockies and the West Coast. For instance, utilizing the Midwest's average temperature from the dataset and the corresponding travel costs between the Midwest and either the West Coast or Rocky Mountains enables the determination of skier trip numbers. This analysis reveals that a decline in destination snowfall by 169 inches translates to a reduction of 28,000 visitors or 2.69% for the Rocky Mountain destination (Table 3.7). Similarly, a 202-inch reduction in snowfall for West Coast ski areas results in an overall decrease of 340,000 visitors or 3.4% in skier visits (Table 3.7). These findings underscore the profound significance of snowfall even for premier destinations like those in the Rockies and West Coast.

Table 3.7: Impact of Lower Snowfall in the Rocky Mountains and West Coast

| | Destination Snowfall | | Skier Visits (in millions) | | | |
|---|---|---|---|---|---|---|
| | Mean | Standard Deviation | Before | After | Difference | Percent Dhange |
| Rocky Mountains | 792.785 | 169.424 | 10.854 | 10.569 | -0.285 | -2.63% |
| West Coast | 561.496 | 202.136 | 10.005 | 9.665 | -0.340 | -3.40% |

The results of higher temperature at both the Rocky Mountain destination and West Coast ski areas show in Table 3.8 reveal a similar impact on skier visits as decreased snowfall. As discussed earlier, high temperature is devastating for the industry as it can severely impact snowfall limiting both quality and access to ski areas. When the maximum temperature rose one standard deviation in the Rockies to 59.2°F, there was a decline in skier visits by 188,000 or 1.71%. Similarly, for the West Coast, if extreme maximum temperatures rose to 61°F the model estimates 189,000 fewer visits or a 1.86% decline in skier visits. The expectation is that sudden increases in maximum temperature are increasingly likely under the climate change predictions and being able to quantify these climate change impacts on skier behavior offers one more example of the cost of climate change.

Table 3.8: Impact of Extreme Maximum Temperature in the Rocky Mountains and West Coast

| | Destination Maximum Temperature | | Skier visits (in millions) | | | |
|---|---|---|---|---|---|---|
| | Mean | Standard Deviation | Before | After | difference | Percent change |
| Rocky Mountains | 58.035 | 1.258 | 10.999 | 10.811 | -0.188 | -1.71% |
| West Coast | 59.803 | 1.267 | 10.166 | 9.977 | -0.189 | -1.86% |

To further support the seriousness that pull weather effects have on these premier ski areas we also need to consider the financial burden ski communities would face as climate change predicts higher average temperatures. Given the estimates of skier expenditures offered by NSAA the snowfall model would predict a reduction in revenue by upwards of $28 million for the Rockies and $34 million for the West Coast. In terms of the impact of temperature the predicted model would reduce ski area revenue by over $18 million at both the Rocky Mountain region and the West Coast. These estimates do not include the lodging and travel costs, all of which are taxable revenue to support the isolated mountain communities.

This model has presented evidence of the pull effect of several different destination weather variables. The responsiveness that skier's exhibit when faced varying conditions between season has real impact on skier visits. This model has also demonstrated that the impact of regional climate change, where one region experiences warmer or dry winter conditions can and will impact the decision of skiers to both travel to or from the affected area. The cross-regional climate change behavior observed in this model provides one more concern for the ski industry and for the travel industry in general, as the impact of climate change are economically realized.

### 3.14 Conclusions and Next Steps

The interplay between weather conditions, acting as both push and pull factors, significantly influences the total number of seasonal skier visits. This analysis reveals that snowfall levels throughout the season wield considerable predictive power, with shifts in skier visits numbering in the thousands between various origin and destination pairs. Likewise, slight temperature variations from the norm, whether at the skiers' starting point or their intended destination, lead to fluctuations in total visits across vast ski regions spanning multiple states.

Were these impacts confined to a select few ski areas, the financial strain would be considerable for all but the largest resorts.

Future investigations necessitate more detailed and localized data for micro-regional insights. While obtaining such data poses challenges due to inter-ski area competition, alternative avenues exist. Ski resorts, for instance, collect customer information, including home addresses, through season pass sales. By tracking origin weather alongside on-site ski conditions, future investigations could enhance the accuracy of daily data on push and pull weather effects, sidestepping reliance on skier population assumptions.

However, this model faces a limitation regarding the timeframe for studying the long-term implications of skier responses to climate change. Over the next century, as projected by the IPCC, travel behaviors are poised to evolve in response to climate shifts. Short-term disruptions, such as those experienced during pandemics, reveal vulnerabilities beyond the scope of our current model. Nevertheless, this research underscores the presence of cross-regional weather variables that exert influence on skier participation.

Considering a hypothetical scenario of linear climate change progression to a 2-degree Celsius increase within the first year, our model forecasts a decrease of over 17 thousand total skier visits across the US, equating to a mere 0.034% of the nationwide mean total skier visits in this sample. While seemingly minor for the industry, persistent declines over subsequent years, as projected by the IPCC, would compel the ski industry to acknowledge the dual threat posed to both slopes and surrounding communities.

# CONCLUSION

The research presented in this dissertation has demonstrated how spatial details further our understanding of regional economic activities. In chapter 1, spatial characteristics refine the differences between communities and allows the markets that connect them to explain behaviors obscured otherwise. In chapter 2, preserving spatial details in our models provides nuanced insights that cannot be produced by higher level of aggregation. In chapter 3, the distinction between origin and destination weather reveals that ski travel decision are shaped by push and pull weather effects, expanding the scope of how climate change will affect the ski industry. These chapters proved that place matters and deeps our understanding of how spatial detail should be applied to regional economic research.

In Chapter 1, the spatial characteristics represented in the separate regions and the market structures that connect rural, urban, and interface regions demonstrate a unique insight into effects of urban population growth. This contributes to a literature that has focused on how urban growth and rural water transfer affect the rural region. To provide greater insight about the rural region this research introduced numerous model advancements including regional specific sectors, an endogenous water market that response to urban population growth, and an interregional intermediate input market that refines linkages between regions. This study demonstrates that higher costs of water driven by urban growth can negatively impact the industries and households of urban’s neighboring regions. This impact is visible through various factor markets in addition to the water market that links the three regions. The addition of the interregional intermediate input market further demonstrated that urban growth resulted in higher cost of production for urban's neighboring regions. Adjusting the markets that connect urban to its neighbors reduces the costs associated with urban growth. However, in any of the various alternative models presented in this chapter, rural agriculture declined, and the reduction of urban growth is not offset by the rural and interface regions.

In chapter 2, two models with different aggregated structures are built using the same data and compared across identical simulations to determine how their structures alters their output. This research reveals how a multi-regional structure in a CGE model provides greater insight for regional research. The literature has relied on justifying the MRCGE's benefits by adjust both data and aggregation to create improved accuracy. Isolating the benefit of the disaggregated component of the MRCGE demonstrates that the models that foster greater spatial detail can explain wider regional behaviors that contribute to changes in the net output of the model. This model reveals nuanced understanding of regionally specific households and industries that were not seen in the more aggregated single region model. These unique outcomes drive slight variations in the net output of the model, showing how regionally specific characteristics in small rural communities can shape the behaviors of labor markets outside of their borders. The unique regional output of the disaggregated CGE model demonstrate the benefits of this structure and what can be lost in the analysis when they are not utilized.

In chapter 3, the skier behavior model explains how the spatial characteristics of skier's origin and destination weather variables shape their demand for ski visits. This model confirms that greater snowfall in a destination contributes to more skier visits, providing a national model that confirms similar conclusions of regional ski area studies. Additionally, origin weather shapes expectations, contributing to changes in skier visitations. When origins had greater snowfall there was greater skier visitations from that regions to other ski areas across the country.

Evidence of the push and pull weather variables for winter destinations coincides with similar behavior seen for warm weather destinations. The cross-regional skier visits behaviors described in this chapter reveal how shifting weather patterns can impact the ski industry since skiers are susceptible not just to the weather of their destination but also to the weather of their backyard.

Across each of the three chapters of this dissertation different spatial characteristics have offered greater insight into how markets behave. Having uniquely identified regions allows these spatial characteristics to enrich our understanding of these communities. Additionally, the variations between regions, whether it be the allocation of water, the distribution of labor, or the temperatures experienced, have the capacity to shape behaviors. When spatial characteristics are represented in models, they expose underlying behaviors, thus improving the accuracy of the results. This research proves that the effort of utilizing spatial features in models is worthwhile.

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## Appendix A: Skier Variable Summary

| Variable Summary | | | | | |
|---|---|---|---|---|---|
| Variable | Obs | Mean | Std. Dev. | Min | Max |
| | | | | | |
| destination | 520 | 1.297759 | 2.296808 | 0 | 10.0551 |
| dsnowfall | 520 | 568.6157 | 315.8482 | 32.37778 | 1266.37 |
| davgtemp | 520 | 33.50772 | 4.611983 | 22.24338 | 43.57652 |
| dmintemp | 520 | 6.585047 | 6.66876 | -7.99031 | 17.5642 |
| dmaxtemp | 520 | 61.38405 | 4.616459 | 53.57547 | 74.85833 |
| wdx32 | 520 | 21.04786 | 21.70294 | 0.489614 | 138.1907 |
| wdx70 | 520 | 35.40585 | 30.35895 | 2.870414 | 111.0368 |
| oavg_temp | 520 | 4.40257 | 4.296894 | -1.96341 | 13.98079 |
| oextreme_max_temp | 520 | 19.92313 | 3.455884 | 14.72702 | 27.43082 |
| oworigin_snowfall_days | 520 | 2.467429 | 2.019529 | 0.09499 | 7.322865 |
| owtotal_snowfall | 520 | 225.636 | 195.4847 | 7.475175 | 681.8666 |
| owtotal_snowfall | 520 | 225.636 | 195.4847 | 7.475175 | 681.8666 |
| avgtravelcost | 520 | 122.4319 | 43.75836 | 37.80611 | 265.988 |
| Note that variables beginning with “o” represent origin and “d” represent destination | | | | | |

## Appendix B: Skier Correlation Table

| Correlation Table | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | dsnow | dsnowfall | dmintemp | dmaxtemp | davgtemp | oextreme_min_temp | oextreme_max_temp | oworigin_snowfall_days | owtotal_precip | owtotal_snowfall | dx32 | dx70 | wdx32 | wdx70 | oorigin_snowfall_days | ototal_precip | ototal_snowfall | oavg_temp |
| dsnow | 1 | | | | | | | | | | | | | | | | | |
| dsnowfall | 0.82 | 1 | | | | | | | | | | | | | | | | |
| dmintemp | -0.71 | -0.66 | 1 | | | | | | | | | | | | | | | |
| dmaxtemp | -0.58 | -0.8 | 0.62 | 1 | | | | | | | | | | | | | | |
| davgtemp | -0.81 | -0.78 | 0.91 | 0.81 | 1 | | | | | | | | | | | | | |
| oextreme_min_temp | -0.06 | -0.05 | 0.08 | 0.02 | 0.06 | 1 | | | | | | | | | | | | |
| oextreme_max_temp | -0.04 | -0.04 | 0.02 | 0.06 | 0.04 | 0.76 | 1 | | | | | | | | | | | |
| oworigin_snowfall_days | 0.1 | 0.08 | -0.08 | -0.07 | -0.09 | -0.71 | -0.59 | 1 | | | | | | | | | | |
| owtotal_precip | 0.04 | 0.04 | -0.03 | -0.05 | -0.04 | 0.32 | 0.25 | 0.16 | 1 | | | | | | | | | |
| owtotal_snowfall | 0.1 | 0.08 | -0.07 | -0.08 | -0.09 | -0.67 | -0.6 | 0.98 | 0.21 | 1 | | | | | | | | |
| dx32 | 0.1 | 0.08 | -0.09 | -0.07 | -0.09 | -0.87 | -0.86 | 0.79 | -0.21 | 0.76 | 1 | | | | | | | |
| dx70 | -0.03 | -0.02 | 0.02 | 0.02 | 0.03 | 0.84 | 0.92 | -0.71 | 0.14 | -0.71 | -0.8 | 1 | | | | | | |
| wdx32 | 0.1 | 0.09 | -0.11 | -0.09 | -0.11 | -0.62 | -0.51 | 0.67 | 0.04 | 0.65 | 0.74 | -0.5 | 1 | | | | | |
| wdx70 | 0 | 0 | 0 | 0 | 0 | 0.76 | 0.73 | -0.78 | -0.14 | -0.77 | -0.8 | 0.9 | -0.55 | 1 | | | | |
| oorigin_snowfall_days | 0.1 | 0.09 | -0.07 | -0.05 | -0.08 | -0.65 | -0.87 | 0.72 | 0.01 | 0.74 | 0.83 | -0.8 | 0.49 | -0.7 | 1 | | | |
| ototal_precip | 0.03 | 0.03 | -0.02 | -0.03 | -0.03 | 0.54 | 0.34 | -0.08 | 0.92 | -0.02 | -0.4 | 0.31 | -0.17 | 0.06 | -0.08 | 1 | | |
| ototal_snowfall | 0.09 | 0.08 | -0.07 | -0.06 | -0.07 | -0.59 | -0.83 | 0.68 | 0.1 | 0.74 | 0.77 | -0.8 | 0.46 | -0.67 | 0.98 | 0.01 | 1 | |
| oavg_temp | -0.06 | -0.05 | 0.05 | 0.04 | 0.06 | 0.94 | 0.91 | -0.74 | 0.27 | -0.72 | -0.9 | 0.96 | -0.63 | 0.84 | -0.81 | 0.45 | -0.76 | 1 |

# Appendix C: Auxiliary Model Specification Table

| Auxiliary Model Specification Table | | | | |
|---|---|---|---|---|
| Model Description | REM | FEM | FEM Robust | Alternative FEM Robust |
| Variables | Destination | Destination | Destination | Destination |
| | | | | |
| dsnowfall | 0.000207*** | 0.000205*** | 0.000205** | 0.000205** |
| | (-5.11E-05) | (-5.08E-05) | (-8.10E-05) | (-7.89E-05) |
| avgtravelcost | -0.00135** | -0.00124** | -0.00124** | |
| | (-0.00056) | (-0.00056) | (-0.00053) | |
| Different.avgtravelcost | | | | -0.000727* |
| | | | | (0.000414) |
| owtotal_snowfall | 0.000345*** | 0.000345*** | 0.000345* | 0.000314* |
| | (-0.00012) | (-0.00012) | (-0.00019) | (-0.00018) |
| Constant | 1.268*** | 1.255*** | 1.255*** | 1.113*** |
| | (-0.34) | (-0.0746) | (-0.0583) | (-0.07) |
| | | | | |
| Observations | 520 | 520 | 520 | 480 |
| R-squared | 0.0956 | 0.072 | 0.072 | 0.076 |
| Number of trip | 40 | 40 | 40 | 40 |
| Standard errors in parentheses | | | | |

# Appendix D: Skier Auxiliary Regression Results

Auxiliary regression results

| | -1 | -2 | -3 | -4 | -5 | -6 | -7 | -8 | -9 | -10 |
|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | destination | destination | destination | destination | destination | destination | destination | destination | destination | destination |
| | | | | | | | | | | |
| avgtravelcost | -0.00116** | -0.00111** | -0.00143** | -0.00136** | -0.00105** | -0.00125** | -0.00124** | -0.00118** | -0.00101*** | -0.00101*** |
| | -0.000513 | -0.000478 | -0.000583 | -0.000538 | -0.000489 | -0.000528 | -0.000527 | -0.000516 | -0.000366 | -0.000333 |
| oavg_temp | -0.0224* | -0.0289** | -0.0219** | -0.0203* | | | | | | |
| | -0.0112 | -0.0135 | -0.0103 | -0.0105 | | | | | | |
| dsnowfall | 0.000210** | | | | 0.000213** | 0.000206** | 0.000205** | 0.000244** | 0.000271** | 0.000243** |
| | -8.42E-05 | | | | -8.03E-05 | -8.16E-05 | -8.10E-05 | -9.61E-05 | -0.000115 | -9.24E-05 |
| dmintemp | | -0.00459 | | | | | | | | |
| | | -0.00301 | | | | | | | | |
| dmaxtemp | | | -0.0187** | | | | | | | |
| | | | -0.00693 | | | | | | | |
| davgtemp | | | | -0.0155*** | | | | | | |
| | | | | -0.00538 | | | | | | |
| oextreme_max_temp | | | | | -0.0331** | | | | | |
| | | | | | -0.0157 | | | | | |
| oworigin_snowfall_days | | | | | | 0.0345* | | | | |
| | | | | | | -0.019 | | | | |
| owtotal_snowfall | | | | | | | 0.000345* | | | |
| | | | | | | | -0.000189 | | | |
| owtotal_precip | | | | | | | | 1.42E-05 | | |
| | | | | | | | | -0.000181 | | |
| wdx32 | | | | | | | | | -0.00211 | |
| | | | | | | | | | -0.00298 | |
| wdx70 | | | | | | | | | | -0.00128 |
| | | | | | | | | | | -0.00351 |
| Constant | 1.419*** | 1.591*** | 2.715*** | 2.074*** | 1.965*** | 1.248*** | 1.255*** | 1.299*** | 1.311*** | 1.328*** |
| | -0.0648 | -0.108 | -0.513 | -0.256 | -0.307 | -0.0606 | -0.0583 | -0.094 | -0.0479 | -0.0981 |
| | | | | | | | | | | |
| Observations | 520 | 520 | 520 | 520 | 520 | 520 | 520 | 520 | 520 | 520 |
| R-squared | 0.065 | 0.035 | 0.053 | 0.046 | 0.073 | 0.071 | 0.072 | 0.055 | 0.072 | 0.057 |
| Number of trip | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 |
| rho | 0.989 | 0.989 | 0.989 | 0.989 | 0.989 | 0.989 | 0.989 | 0.989 | 0.989 | 0.989 |
| r2_b | 0.108 | 0.0675 | 0.11 | 0.0896 | 0.116 | 0.113 | 0.12 | 0.178 | 0.127 | 0.13 |
| r2_o | 0.0918 | 0.0634 | 0.0985 | 0.0808 | 0.101 | 0.0846 | 0.0882 | 0.117 | 0.0846 | 0.092 |
| r2_w | 0.0651 | 0.0353 | 0.0532 | 0.0458 | 0.0734 | 0.071 | 0.0724 | 0.0552 | 0.0721 | 0.0566 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1