

APPLYING AN ECONOMIC BASE ANALYSIS TO COUNTIES IN THE ROCKY MOUNTAIN WEST:
FINDING A TYPOLOGY AND ILLUMINATING SOCIOECONOMIC PATTERNS

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Ethan O. Mansfield

Major Professor: Phillip Watson, Ph.D.

Committee Members: Tammi Laninga, Ph.D., Paul Lewin, Ph.D.

Department Administrator: Jaap Vos, Ph.D.

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Authorization to Submit Thesis

This thesis of Ethan Mansfield, submitted for the degree of Master of Science with a Major in Bioregional Planning and Community Design and titled "APPLYING AN ECONOMIC BASE ANALYSIS TO COUNTIES IN THE ROCKY MOUNTAIN WEST: FINDING A TYPOLOGY AND ILLUMINATING SOCIOECONOMIC PATTERNS," has been reviewed in final form. Permission, as indicated by the signatures and dates below, is now granted to submit final copies to the College of Graduate Studies for approval.

Major Professor: _____ Date: _____
Phillip Watson, Ph.D.

Committee
Members: _____ Date: _____
Tammi Laninga, Ph.D.

_____ Date: _____
Paul Lewin, Ph.D.

Department
Administrator: _____ Date: _____
Jaap Vos, Ph.D.

Abstract

Major shifts in the economic, social and demographic structure of the American West have taken place over the last 50 years. These changes have roots in three broad categories—the increasing concern for environmental quality, changes in technological innovation, and changing macroeconomic conditions. Several studies have used economic base theory to better understand the economic structure of western counties that emerged from the restructuring that occurred during the second half of the twentieth century. This study aims to more comprehensively capture the array of sources that contribute to a county's economic base and to better understand this restructuring in the Rocky Mountain West (RMW) over the most recent recession by using a Social Accounting Matrix (SAM). A typology is created based on the SAM outputs which is then used to detect socioeconomic patterns across groups and to assess the economic shifts as a result of the Great Recession.

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Dedication

This thesis is dedicated to everyone with whom I have had an impassioned conversation about the American West, its history or its future; and to the western towns and landscapes themselves, without which there would be no reason to undertake this research effort in the first place.

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Chapter 1: Introduction

1.1 Introduction

Major shifts in the economic, social and demographic structure of the American West have taken place over the last 50 years. Generally, the inception of these changes occurred in the post-WWII era and gained steam throughout the 1960s and 1970s, culminating in transformations that occurred in the late 1970s, 1980s and 1990s. The changes experienced by the American West have roots in three broad categories—the increasing concern for environmental quality, changes in technological innovation, and changing macroeconomic conditions. They have been well-documented in the literature (Power 1996, Nelson and Beyers 1998, Booth 1999, Ohman 1999, Shumway and Otterstrom 2001, Smutny 2002, Winkler et al. 2007). Several of these studies have used economic base theory to better understand the economic structure of the “New West” that emerged from the restructuring that occurred during the second half of the twentieth century (Nelson and Beyers 1998, Vias and Mulligan 1999, Beyers and Lindahl 1996, Mulligan 1987). This study aims to more comprehensively capture the array of sources that contribute to a county’s economic base and to better understand this restructuring in the Rocky Mountain West (RMW) over the most recent recession by using a Social Accounting Matrix (SAM) for each RMW county.

Economic base theory conceptualizes the economic composition of the region in a way that allows the researcher to pinpoint where economic activity originates within the region’s economy (Tiebout 1962, Schaffer et al. 2004). Economic base theory separates the economy into two broad sectors, basic and non-basic. Basic or primary industries export goods and services by bringing income into the local economy from outside the local economy. It is important to recognize that an economic base can be any avenue by which exogenous income is brought into a community. Traditionally, these sources of income in the West were mining, timber harvesting, agriculture, and

other extractive pursuits. With new technological developments and the rise of a knowledge economy, “sales of ‘invisible’ products such as newspaper articles, architectural designs, or computer code can and do generate basic income for a community in the same way that grain, cattle and timber do” (Nelson and Beyers 1998, 300). Income flowing into the region through households in the form of transfer payments is another important source of economic activity, especially in the West (Mulligan 1987, Nelson and Beyers 1998, Nelson 1999, Vias and Mulligan 1999). Retail and consumer services contribute to the economic base via tourism (Power 1996, Ohman 1999).

While economic base theory has informed the economic analysis of western counties in the past, there has apparently not been a study that examines the economic base of the entire RMW across all exogenous sources of growth. Exogenous sources of growth include not only private sectors and government, but also extra-regional household income. Previous economic base studies have examined either specific sectors of the economy such as the role of tourism or producer services (eg. Beyers 1991), non-labor income or transfer payments versus earnings income (eg. Mulligan 1987, Nelson and Beyers 1998), or singular or very few geographic regions (eg. Waters et al. 1999, Watson and Beleiciks 2009). Additionally, the primary economic dependency typology produced by the USDA Economic Research Service and used in many economic studies (eg. Vias 1999, Shumway and Otterstrom 2001) only implicitly uses the most rudimentary base estimation in the creation of their typology. The measure is one-dimensional in that it does very little to take into account the similarity or differences of sectors beyond the “dominant” sector. This study, by contrast, uses a Social Accounting Matrix for 215 Rocky Mountain Region counties to establish a comprehensive economic typology grounded in economic base theory.

After establishing this typology, the study addresses three objectives. First, it examines the clusters against 18 socioeconomic variables to see how economic structure influences or is

influenced by these variables. This typology then is compared with a typology developed using gross employment shares to assess how base employment differs from gross employment across the study area. This base typology is more analytically rigorous than the USDA's current typology of economic dependence in that it uses economic base analysis across all industries and institutions to create a comprehensive snapshot of the counties' economic structure. Finally, the base typology is used to determine the change of county-level economic structure across the Rocky Mountain West from 2008-2012, a time period corresponding with the Great Recession.

1.2 The Rocky Mountain West

The Rocky Mountain West (RMW) is a five state, 216 county region defined by the Bureau of Economic Analysis (BEA) as the Rocky Mountain region. It includes Colorado, Montana, Idaho, Utah, and Wyoming. The region covers 511,309 square miles and was home to more than 11.2 million people in 2012 (Census 2012). Mean household income in the region was just over \$101,000 in 2012 and total personal income (TPI) was \$452.4 billion (BEA 2012). From 1970 to 2011, its population grew 120 percent, while the US population grew just under 53 percent. Only Montana grew at a rate slower than the nation. Employment in the region closely mirrors the trend in population, but saw a much larger increase, 198 percent, while the US employment increased by 93 percent. Employment growth across all RMW states was greater than the nation as a whole. The increase in TPI mirrors population and employment growth, but this increase was larger still than population growth and employment growth. From 1970 to 2011, total personal income increased fourfold, while the US grew 169 percent. Again, only the growth of TPI in Montana was slower than national TPI growth during that time.

The development of the RMW from the mid-1800s until the late 1960s was characterized by resource extraction (Baden 1997, Nash 1999, Power 1996, Winkler et al. 2007). The zeitgeist of

resource extraction was entrenched in two ways. First, technological and economic realities demanded extraction or use of natural resources. High transportation costs, raw material input-intensive manufacturing processes occurring in distant markets, weak economies of scale and relatively low labor productivity dictated that western communities existed solely to extract resources from the land or to support that extraction (Baden 1997). The second driver of the entrenchment was institutional. The federal government facilitated the initial extraction by pouring endless funding into the recovery of raw materials (Nash 1999). From the early twentieth century until 1968, the federal government subsidized the settlement of the west through the construction of dams (Nash 1999). Dams irrigated the west, providing crops and people with a scarce resource necessary for development. Wartime demand for raw materials stimulated western extractive economic growth, especially in mining (Nash 1999). Federal policies such as the General Mining Law (1872), the Desert Land Act (1877), Reclamation Act (1902), and the Stock Raising Homestead Act (1916) firmly indicated that the West was to be mined, irrigated and grazed by opening land to settlement and keeping costs of extraction well below market rates (Baden 1997).

Several factors explain the shift from the primacy of traditional, extractive economic bases to the dominance of non-traditional economic bases such as services and non-labor income in the West. First, a concern for environmental quality became apparent by the 1960s and early 1970s. Second, by removing time, energy and resource constraints, new technological innovations allowed these environmental quality values to be expressed in a way that altered the demand for the goods and services flowing from Western economies. Finally, a changing macroeconomic climate that saw the decline of traditional extractive bases created a void in the economic structure to accommodate these changing demands.

Beginning in the 1960s, citizens' environmental values began to change, evidenced by a slew of environmental regulation in the late 1960s and early 1970s. The passage of the Clean Air Act

(1963, with amendments in 1967, 1970, 1977, and 1990), the Clean Water Act (1972), and the National Environmental Protection Act (NEPA, 1970) all reflected the growing concern for the quality, rather than quantity of growth (Nash 1999). Additionally, dams in the American West had begun to come under fire for their negative environmental consequences, such as blocking anadromous fish migration and flooding scenic canyons, as well as inhibiting other biophysical processes (Nash 1999). As environmental values changed and locations for building became scarcer, cost-benefit analyses undertaken by dam building agencies often yielded costs that were higher than benefits. Thus, the last major federal water project, Central Arizona Project, was authorized in 1968 (Nash 1999).

Simultaneously, technological change facilitated the development of an American West where many—though certainly not all—regional economies were no longer reliant on traditional extractive bases (Baden 1997). First, transportation of both “stuff” and ideas was completely revolutionized by the invention of the microchip (Nash 1999) and air travel (Rasker et al. 2009). The subsequent development of the telecommunications industry as well as the proliferation of rural airports has almost completely removed the geographic constraints that characterized previous methods of communication and transportation. The removal of geographic constraints also allows for an expression of preference for environmental quality that was previously unattainable. In other words, the removal of geographic barriers allowed people to “vote with their feet” in a way that was impossible before. Second, these new technologies have enabled a production function that relies less on raw materials and more on how those raw materials are configured. Romer’s (1990) endogenous growth theory formally acknowledges the importance of knowledge as the central input to production in the new economy. Now, human capital plays a pivotal role in the production process, especially in rural communities that are able to attract human capital with amenities. The ability to attract high levels of human capital has been found to be a primary source of county-level

growth through the 1990s and into the 2000s (Patridge et al. 2008, Wu and Gopinath 2008). In sum, Baden (1997, 117) explains, “By allowing environmental quality to coexist with economic prosperity, these technologies are fundamentally altering the nature of the West’s political economy. Power is shifting from those who own and move ‘stuff’ to those who manipulate symbols.”

Taken together, concern for environmental quality and concurrent removal of geographic barriers due to technological change has given rise to amenity migration, whereby people are drawn to a location because it offers a pleasant climate, nice scenery, or recreation opportunities (Deller et al. 2001, McGrannahan 1999, Rudzitis 1999). McGrannahan (1999) developed a natural amenities index comprised of six climactic and geographic variables and showed that people were generally attracted to warm winters, lots of winter sun, a temperate climate, low summer humidity, topographic variation (i.e. mountain and canyons), and large areas of water. More than 72 percent of recreation counties, determined by Beale and Johnson (1998), and 63 percent of retirement counties (Cook and Mizer 1994), scored in the top quartile of the natural amenity index. Rudzitis (1999) used survey methods to examine the importance of amenities in making location decisions. He found that 72 percent of respondents selected scenery as an important “pull” factor in their decision to move. Sixty-two percent identified pace of life, 65 percent identified environmental quality and 59 percent identified outdoor recreation as important “pull” factors, while only 30 percent identified employment opportunity as an important “pull” factor.

Recently, spatially explicit techniques have been used to elucidate spatial differences in the economic development of regions. Deller et al. (2001) extended research on natural amenities by including firms that capitalize on natural amenities (i.e. ski areas, guide services) and grouping variables into different amenity classes. They developed variables for climate, recreational infrastructure, land amenities, water amenities and winter amenities, and found that all of them contributed significantly to at least one measure of population, employment or income growth, and

in many cases, more than one. Using geographically weighted regression, Partridge et al. (2008) found that, across the nonmetropolitan United States, different natural amenity measures affect employment growth differently in different places. For example, in some places, long winters were negatively associated with growth, while in other places, like those known for winter recreation, the same variable was positively correlated with growth. A growing body of literature supports the conclusion that people migrate to areas with high levels of natural amenities.

Because environmental quality appears to draw people to communities to work, recreate or retire, it would follow that land that is protected in order to preserve its natural character would draw people and income into a region. Lorah and Southwick (2003) found that counties with protected federal land—wilderness, national parks, national monuments and roadless areas—did indeed experience higher growth rates than those without protected land. Population, employment and income growth were all found to be positively correlated with the presence of protected land. Rasker et al. (2013) went beyond examining the correlation between growth and protected lands and found that, holding all other variables constant, an increase of 10,000 acres of protected land would see per capita incomes that were \$436 higher than the original level. Booth (1999) found that that a one percent increase in national park land within a county is responsible for a 6-8 percent increase in income for that county. However, he did not note this same effect from wilderness areas. Protected lands make a difference in the economic development of the West.

Another implication of amenity migration is that the location decisions of people are sometimes based upon quality of life factors above prospects for employment. Studies have demonstrated that, in fact, jobs do follow people rather than people following jobs. Vias (1999) used regional adjustment models to identify that jobs follow people into the Rocky Mountain region. Quality of life concerns, particularly regarding natural amenities, were found to play a major role in employment growth by stimulating migration into the region. Wu and Gopinath (2008, 404) support

this finding, noting that “because amenities attract human capital, which attracts firms, locations with better amenities also have higher demand for labor,” but that this is instigated by the existence of human capital. Deller et al. (2001) also support the conclusion that high amenity levels lead to employment growth.

Natural Amenities are not the only factor that affects the development of the RMW. Another factor, pulling, in some ways, in the opposite direction of the natural amenity pull, is the accessibility of markets. Rasker (2009, 19) notes, “on one hand, the vast distances between towns and cities of the West are a challenge to economic development. On the other hand, the amenities of the public lands that create those vast distances are an asset that attracts and retains people and business.” Despite the loosening of geographic constraints via technology, the ease of access to markets and level of remoteness of a county play a significant role in county-level growth. Booth (1999) measured remoteness by distance to a metro center and the number of interstates. He noted that, in addition to amenities, remoteness is a primary determinant of county-level growth. In an earlier study, Carlino and Mills (1987) also found that the number of interstate freeways have significant positive effects on population and economic growth. Partridge et al. (2008) and Wu and Gopinath (2008) concur that remoteness is a major barrier to economic development. Rasker et al. (2009) divides Western counties into metro, non-metro with an airport, and non-metro. He finds that an airport in a non-metro county reduces many of the remoteness factors that may lead to slower growth. Taken together, advances in telecommunication and air travel have significantly reduced, but not entirely eliminated the difficulty in accessing markets and economic hubs from remote locations.

Finally, changing macroeconomic conditions have had serious implications for the decline of the extractive industries and the rise of new forms of growth that were poised to take off between the 1970s and 1980s. Perhaps nothing affected the economic climate of the West more than the

energy boom in the 1970s and its subsequent collapse in 1985. The OPEC embargo in 1973 and Presidents Nixon, Ford and Carter's domestic energy initiatives, such Project Energy Independence in 1973, the Strategic Oil Reserve in 1975, the Synfuels Act of 1976 and the Energy Security Act of 1980, stimulated incredible domestic demand for coal, oil and gas (Nash 1999). From 1973 to 1982, the value of US oil reserves increased ten-fold (Nash 1999). The West had never, to that point, experienced a boom of such magnitude (Martson 1989). However, the end of the OPEC embargo, the realization that the new environmental regulation of the 1970s and intensive resource extraction were not necessarily compatible policy goals, and the deregulation of energy prices in the Regan administration, caused an even bigger bust in the West (Martson 1989, Nash 1999). This, combined with global trade liberalization (Gosnell and Abrams 2011) and changing technologies that were less resource intensive (Martson 1989), led the West into a recession from which the extractive industries in many western counties never recovered. This opened the door for other avenues of economic growth.

The reemergence of some rural economies in the 1990s was credited to an entirely different type of economic growth. Shumway and Otterstrom (2001) defined a set of "New West" counties using a cluster analysis on the USDA ERS economic typology (Cook and Mizer 1994), McGrannahan's (1999) natural amenity index, and Beale and Johnson's (1998) recreation index. "New West" counties had higher natural amenities, more dependence on recreation and experienced less employment in extractive economic activities. Shumway and Otterstrom (2001) found that population and income became increasingly concentrated in "New West" counties from 1950 to 1999. Winkler et al. (2007) used factor analysis on eight variables to define the "New West-ness" of western Census Defined Places and then applied Local Indicators of Spatial Association (LISA) to determine the extent of spatial clustering across the Rocky Mountain region. "New West-ness" was found to include high levels of in-migration, a high percentage of 4-year college graduates, many

seasonal or second homes, high levels of gross employment in finance, investment, real estate, and tourism-related industries, low levels of extractive employment, and high property values. Winkler et al. (2007) found that significant spatial autocorrelation did exist and that “New West” counties tended to exist near high-amenity areas, specifically near national parks, national monuments or national forests. In many areas of the RMW, specifically those with lower amenity values, communities with decidedly non-“New West” characteristics existed in abundance. Winkler et al. (2007) and Shumway and Otterstrom (2001) demonstrate the diversity of social, demographic and economic structure present across the Rocky Mountain West.

1.3 Typologies

A typology is a classification of individual observations or units into a set of categories that are useful for a particular purpose (Blunden et al. 1998). Typologies are used to distinguish meaningful groups within large, diverse datasets (Cook and Mizer 1994). Because of the diversity of county economic types in the RMW, much of the research on the region uses some sort of classification system either as a final product or to aid in further analysis (eg. Mulligan 1987, Nelson and Beyers 1999, Ohman 1999, Rasker et al. 2009, Shumway and Otterstrom 2001, USDA ERS 2009, Winkler et al. 2007). Most of these studies have used cluster analysis or factor analysis to define classes with groups of similar variables. For example, Nelson and Beyers (1999) clustered Western counties based on five income variables and used ANOVA to establish that the type of income flowing into a county was related to per capita income growth, population change, migration and employment rate. Winkler et al. (2007) used factor analysis on variables previously found in the literature to define “New West” places to classify Census Designated Places on a “New West” continuum. They then showed that these places exhibited significant spatial autocorrelation. Typologies have been widely used to distinguish differences and similarities within diverse datasets.

One of the more widely used economic development typologies is the USDA Economic Research Service's (ERS) Economic Dependence Typology (USDA ERS 2009). The ERS economic typology classifies counties into one of six mutually exclusive economic types: farming-dependent, mining-dependent, manufacturing-dependent, federal/state government-dependent, services-dependent, and nonspecialized. Each of these categories is determined based on a share of gross county income cut-off rule of one standard deviation above the mean for non-metro counties. Non-metro counties were used to reflect the motivation of the typology—to aid in forecasting rural “conditions, trends and program needs” (USDA ERS 2009). The typology is still applied to metro counties. For example, if the non-metro mean agriculture income share is 11 percent, and the standard deviation is 4 percent, then an agriculture-dependent county would be any county that has an agriculture income share of 15 percent or more. If a county is over the threshold in two or more categories, the sector with the largest number of percentage points above the mean takes precedence. One exception is services, which were not allowed to take precedence over any other sector. Another exception is agriculture, which takes precedence over all other sectors.

The USDA typology has been utilized in several studies of the RMW. Shumway and Otterstrom (2001) employed the typology as a variable in a cluster analysis to create a “New West” typology of their own. Vias (1999) used the USDA typology in a regression analysis showing the impact of county economic structure on economic and population growth. Additionally, USDA studies on rural trends use the ERS typology when it is necessary to distinguish counties based on economic dependence (eg. Beale and Johnson 1998).

The motivation behind the ERS typology is to describe regional “economic characteristics” (USDA ERS 2009). This is somewhat vague, so it seems helpful to provide a more definitive objective, such as using the typology to describe sources of economic activity. This is what the questions “What do people in this county do?” or “How does this county make money?” strive to answer. The

ERS typology has three shortcomings when answering these questions. First, it uses gross rather than base measures of economic activity. Defining the largest gross sector may or may not truly reflect the largest source of economic activity in that county. Ada County, Idaho is one example. Despite the computer and electronics manufacturing industry employing only four percent of Ada County's workforce, the industry was responsible for supporting nearly 16 percent of all employment in the county in 2008. This might be easily overlooked if using gross employment scores, but is captured if measuring base employment. Next, because it uses gross employment, the ERS typology misses the important role that extra-regional income plays in defining the economy of some counties. For example, Waters et al. (1999) found that over 20 percent of Oregon's employment is a result of extra-regional transfers—money flowing into Oregon through the institution of households, rather than through export of industrial production. Watson and Beleiciks (2009) found that, for two small towns on the West Coast, extra-regional transfers were responsible for over seven percent of total employment in each town. Because of these two factors, a researcher using gross measures could potentially miss important competitive advantages that are present in a county. In the Ada County example, using gross measures completely misses the competitive advantage that Ada County has in semiconductor manufacturing.

Finally, even if base theory was used, the typology is based upon one variable. For example, Agricultural counties are based on having an Agriculture score above 15 percent and nothing else. Service counties are Service counties solely because they meet their 45 percent threshold and have more percentage points above the cutoff than any other variable above their threshold. This might be acceptable generally, but if other industry groupings are vastly different in the composition of their employment share, it might lead to incorrect conclusions about the county's economic structure. For example, Cheyenne County, Colorado and Jackson County, Colorado both have a 24 percent share of gross employment in Agriculture, but the other components of their economies

differ substantially. Cheyenne County has five percentage points more mining employment (six percent versus one percent), 16 percentage points more government employment (34 percent versus 18 percent), eight percentage points less employment in Retail, Tourism and Hospitality Services (15 percent versus 23 percent) and seven percentage points less employment in Forestry (one percent versus eight percent). Both counties would be characterized as Agricultural counties in the ERS typology, but not accounting for the other differences may make it difficult to see the full economic picture.

The following typology uses base employment data from 2008 for 215 counties within a 5 state region in the RMW. Cluster analysis was used to define six clusters based on 13 industry and household groupings and then compare these clusters to the 2008 gross employment and the 2012 base employment for each county. Not only is this typology more well-grounded in economic theory, it has been created so as to better capture the current economic bases of rural America, particularly in the RMW.

1.4 Economic Base Theory

Gross measurements may generally describe economic conditions in a region, but they often yield misleading results in terms of the economic contribution of an industry or institution to a local economy. Instead, economic base measures are better suited to this task. Economic base theory has its roots in land use, urban, and regional planning, when it was developed to aid in the creation of the Regional Plan of New York (Isserman 2001). It conceptualizes the economic composition of the region in a way that allows the researcher to pinpoint where economic activity originates within the region's economy (Tiebout 1962, Nelson and Beyers 1998, Schaffer et al. 2004). Economic base theory separates the economy into two broad sectors, basic and non-basic. Basic or primary industries export goods and services, bringing income into the local economy from outside

the local economy. In much of the West, mining and agriculture are traditional basic activities (Power 1996, Shumway and Otterstrom 2001, Winkler et al. 2007). Non-basic or support industries grow up in support of the basic industries. These industries do not bring new income into the economy, rather they recirculate the income that was created by the basic industries, serving local markets (Nelson and Beyers 1998, Schaffer et al. 2004, Tiebout 1962). In the West, traditional support industries include bars, restaurants, and professional services such as lawyers and accountants. It is important to note that in reality, no industry is fully basic or fully non-basic. For example, bars and coffee shops can bring money into a region if they sell a beer or coffee to someone from outside of the region. On the other hand, a farmer might sell wheat to the local baker, thus eliminating the need for that baker to purchase wheat outside of the region. An economic base analysis pinpoints and measures the sources of economic activity within the region, showing what truly drives local economic growth.

Base employment is composed of direct, indirect and induced components (Watson and Beleiciks 2009). The direct component is the number of jobs that are generated by export activity directly. The indirect component includes the local employment dedicated to the inputs used to create the export good. Finally, the induced component is the employment generated by the consumer spending of wages created by the export activity. In Ada County for example, 16 percent of employment is dependent upon the computer and other electronics manufacturing industry due to the high indirect and induced effects that exist within the industry. A reduction of 200 workers in this industry will have far-reaching implications throughout the economy. The direct effect is that 200 jobs will be lost. Indirectly, a downsizing of economic activity will create less demand for intermediate inputs, which includes everything from other electrical components produced locally to local accountants, lawyers and healthcare. Finally, the induced effect will be on consumer spending within the economy. Fewer hamburgers and less beer will be purchased at the brewpubs

in Boise, which may negatively impact the sales of breweries and the local meat producers. Overall, fewer dollars will be spent within the local economy. It is clear that the economy of Ada County depends on the export of computer and other electronic goods. In fact, using economic base analysis, it is evident that 16 percent of all employment in Ada County is dependent upon the industry. Therefore, the level of base employment, that is, export driven employment, within a region also measures the level of dependency of that region on the industry (Watson and Beleiciks 2009).

Economic Base Theory has frequently been applied by economic development practitioners in the development an “export enhancement” growth strategy. This strategy boils down to the logic pinpointing the sources of regional growth and enhancing those sectors. Kilkenny and Partridge (2009) criticize the application of economic base theory in this way, finding that development outcomes, such as employment growth and income growth, are not enhanced by increasing a county’s employment share in traditional economic base sectors, especially in rural regions. They posit that increasing employment in an export-sector may lead to decreasing employment in local non-basic establishments, forcing a leakage of what would have been local consumption into other counties. In this case, the supply of labor is not completely elastic, as is assumed in input-output models. In many rural communities, labor is limited and, when a new export-oriented firm enters the county, it crowds out non-export firms that meet local demands. Their point is well-taken and points to the potential danger of focusing only on export enhancement.

While the model employed in this study does not account directly for any economic leakages or the extent to which income in a community is recirculated throughout the economy, it should not be forgotten that this recirculation can play an important role in a region’s economic growth. Import substitution, or substituting local purchases for those made outside of a region, has been acknowledged as a potential economic driver in and of itself, given that the local region has a

comparative advantage in producing the good or service that is being substituted (Cooke and Watson 2011). Although the model in this study does not explicitly address the import substitution question, it is still useful in determining the origin of economic activity within a region at a specific point in time.

In this study, an economic base is defined as any income that enters a county exogenously. To define export sectors, Kilkenny and Partridge (2009) use a crude estimation method that assigns “export sector” status to manufacturing, mining and farm sectors. Therefore, this study avoids the question of assigning economic bases to industries that, Kilkenny and Partridge (2009) note, are often either declining or slow-growing, traditionally economic bases. One of the strengths of the model employed in this study is that it accounts for the ability for all sectors to contribute to the economic base, minimizing the need to assign “export activities” to sectors that traditionally did drive export activity, but may or may not do so now.

Modeling the Economic Base in the RMW

Studies of the economic base of the new Rocky Mountain West (RMW) economy indicate that traditional economic bases are being supplanted by new sources of growth (Power 1996, Nelson and Beyers 1998, Vias and Mulligan 1999, Beyers and Lindahl 1996, Mulligan 1987). Traditionally, sources of income in the West were mining, timber harvesting, agriculture, and other extractive pursuits. With new technological developments and the rise of a knowledge economy discussed above, “sales of ‘invisible’ products such as newspaper articles, architectural designs, or computer code can and do generate basic income for a community in the same way that grain, cattle and timber do” (Nelson and Beyers 1998, 300). Nelson and Beyers (1998) and Vias and Mulligan (1999) have attributed county-level employment and population growth to increasing non-labor income in the West. Beyers and Lindahl (1996) showed that in rural America, some producer

services that the authors call “Lone Eagles” (for a sole proprietor) or “High Fliers” (for a firm with multiple employees) who locate in a place primarily for quality of life reasons, export between 70 and 85 percent of their services. Of course, retail and consumer services contribute to the economic base via tourism (Ohman 1999, Power 1996). Thus, new economic bases in the RMW include non-labor income such as transfer payments through retirees, investment income or government support like welfare or food stamps; extra-regional income from commuters; footloose jobs in services and manufacturing; and recreation, tourism and retail trade.

It is important to note that although the RMW has seen significant growth stemming from economic and demographic change throughout the past several decades, many communities are experiencing just the opposite—economic stagnation and decline (Smutny 2002). This reinforces the point elucidated by nearly all research conducted on the West that there is significant spatial diversity, in terms of economic structure, demographic change and social, cultural and economic well-being.

The diversity of economic structures present in the RMW is difficult to capture if only one segment or base of the regional economy is examined. For example, looking at the economic contribution of non-labor, farm-income and non-farm income is useful but it is incomplete if a researcher wants to paint a picture of the region’s economic structure and compare these regions to one another. In the same way, using base analysis to show the increasing share of service exports in many economies is useful, but it is unable to provide the researcher with an economy-wide snapshot of service exports’ relationship to, for example, non-labor income.

Studies that analyze multiple counties across multiple states have generally relied upon publicly available employment and income data and have used base estimation techniques such as location quotients or the assumption method to determine the base contribution of the subject of

analysis (USDA ERS 2009). Survey data and Input-Output techniques have largely been ignored in this field due to their inability to capture and integrate exactly what researchers wanted to study, the contribution of extra-regional institutional transfers to a region's economic base. It has been found, however, that understanding the extra-regional component is important to understanding the regional economy. For example, Mulligan (1987) found, using survey data from Arizona communities, that unless transfer payments were included in economic base analysis, the relative contribution of industries to the economic base was consistently overstated. Additionally, he found that transfer payments affected the level of non-basic employment in much the same way that basic industries do. This characteristic was also acknowledged by Weber et al. (1999). Weber et al. (1999) used a Social Accounting Matrix (SAM) to circumnavigate this issue to find the base contribution of extra-regional income in Oregon's economy.

Social Accounting Matrices

The SAM is a more sophisticated subset of I-O analysis. It is a step above traditional I-O analysis in its ability to take into account the circular flow of economic resources into and out of a region (Waters et al 1999, Watson and Beleiciks 2009). Production and consumption accounts balance across the model, allowing for a complete characterization of the linkages across exogenous and endogenous industrial and institutional purchases. A simplified example SAM is shown in Table 1.1, adapted from Waters et al. (1999).

Table 1.1: Example Social Accounting Matrix

Column demands element from corresponding Row. Row supplies element to Column	Endogenous Accounts				Exogenous Accounts				TOTAL
	Industries	Factors of Production	Households		Federal Government	State/Local Government	Enterprises (Corporations), Capital, and Inventory Additions/Deletions	Foreign and Domestic Trade	
Industries	Intermediate Inputs		Household Demand		Federal Government Demand	State/Local Government Demand	Gross Business Investment	Export Demand	Total Industry Output
Factors of Production	Payments to Land, Labor and Capital								Total Factor Receipts
Households		Factor Payments to Households (Wages, Interest and Rent)			Federal Transfer Payments to Households	State and Local Transfer Payments to Households	Dividends to Households; Financial Returns from Capital outside Region		Total Household Income
Exogenous Accounts	Federal, State/Local Indirect Business Taxes; Imports	Federal, State/Local Factor Taxes	State/Local and Federal Government Taxes; Imports		Imports	Imports	Imports		Total Exogenous Accounts Receipts
TOTAL	Total Industry Outlays	Total Factor Payments	Total Household Payments		Total Exogenous Accounts Payments				

There are five primary elements of a SAM (Watson and Beleiciks 2009):

- Production activities use commodities and factors of production as inputs to produce commodities. In the SAM, **industries** produce commodities by way of production activities.
- Commodities are produced by production activities, used as **intermediate inputs** by production activities, and consumed by institutional **demand**. In the SAM each industry produces a suite of commodities given by a fixed production function. Commodities are produced locally and are also imported and exported into and out of the region.
- **Factors of production** are land, labor and capital, which are not commodities but are used as inputs (i.e. they “sell to”) an **industry’s** production process. Factors of production are the Value-Added or Gross Regional Product of the economy. In a SAM analysis, all factors are owned by households and thus, the **payments to factors of production** are distributed to households as income.
- Institutions are **households, governments** and investments that consume commodities receive **payments from factors of production**, levy **taxes** and provide services.
- **Exogenous accounts** are the imports and exports into and out of the region. This includes commodities, income and investment flowing into or out of the region.

The columns of the SAM represent the expenditures to the associated rows, which represent receipts. Due to the assumptions of market clearance and income balance, industry expenditures and receipts balance (Watson and Beleiciks 2009). The assumptions of the SAM include constant returns to scale, no supply constraints, a fixed commodity input structure, a fixed commodity output structure, a fixed commodity technology structure, and static prices (Olson 2013). While these assumptions may or may not hold in a long-run, large-scale economic impact analysis, they are

generally reasonable when using the model to ascertain the economic base at a particular moment in time or the change from one time period to another with the introduction of a shock.

Note that the model is treating industries, factors of production and households as endogenous and State/Local Government, Federal Government, Capital, Enterprises, and Trade as exogenous. What to include as exogenous and endogenous depends on the scale and scope of analysis. In this study, State/Local Government is treated as exogenous because at the county level there are typically more financial flows to/from the state government—always exogenous to a county—relative to the county or municipal governments.¹

In the SAM, the economic impact of an institution or industry can be assessed according to the Leontief Inverse, given by the equation:

$$X = (I - S)^{-1}Y \text{ (eq. 1.1)}$$

X is an $nx1$ matrix of total output by industry. I is an nxn identity matrix with a diagonal value of 1 and all other values 0, which is the matrix form of 1. S is an nxn matrix of expenditure coefficients for the endogenous regional SAM accounts, or the endogenous shares matrix. The sum of each column of S is the industry's share of total industry output produced from endogenous commodities and factors of production. Y is an $nx1$ matrix of exogenous demand.

The SAM includes institutional, as well as industry, transfers. In this way, the role that exogenous payments to local factors of production play in the regional economy can be assessed, thus capturing all components of the economic base.

¹ In Waters et al.'s (1999) analysis of Oregon State, for example, State/Local Government was treated endogenously because the economic flows between endogenous factors and State/Local Government do not leave the study area.

An issue arises when assessing the contribution of multiple industries and institutions simultaneously. When assessed across an economy, the impact of a given industry or institution is overstated because their indirect and induced effects are, in many instances, double counted (Watson et al. 2015). In this scenario, the sum of the impacts is greater than the total economic output of the economy, an impossibility that arises from double-counting. To avoid this double counting and capture the basic contribution of industries and institutions across a regional economy, a modified Leontief equation is used:

$$\mathbf{TX} = (\mathbf{I} - \mathbf{S})^{-1}\mathbf{TY} \text{ (eq. 1.2)}$$

\mathbf{TY} is an $n \times n$ matrix of diagonalized exogenous demands. Diagonalizing the exogenous demands allows the process of multiplying \mathbf{TY} with $(\mathbf{I} - \mathbf{A})^{-1}$ and facilitates the creation of the basic shares matrix that would not be attainable using \mathbf{Y} , the $n \times 1$ exogenous demands matrix from eq. 1. Thus, \mathbf{TX} is made possible – and double counting the contribution of various industries to a region’s economic base is avoided – by creating the diagonalized matrix of exogenous demands and using matrix multiplication. \mathbf{TX} is an $n \times n$ matrix of total base shares, the dependency matrix. The sum of each column of \mathbf{TX} is the basic contribution of each industry and endogenous institution to the regional economy. The basic share is the dependency score for each industry and endogenous institution in each county. The sum of each *industry* row is the gross industrial output, or \mathbf{X} , the $n \times 1$ matrix seen in eq. 1. *The sum of the industry row totals equals the sum of the endogenous industry and institution column totals.* Thus, a situation where the sum of the parts is larger than the whole is eliminated.

It is important to recognize that an economic base can be any avenue by which exogenous income is brought into a community. For example, some influential past studies on the significance of non-labor income (Vias and Mulligan 1999, Kendall and Pigozzi 1994), treat this source of income

as separate from a community's economic base. While these studies acknowledge the fact that non-labor income is an important job creator in certain communities, they spend time differentiating it from basic income. In the most straightforward sense, non-labor income, if it flows from outside of the region into the region, is just another economic base.

It is useful to break the sources of economic activity into three types, expanding the traditional conception of the economic base theory's two sources. In this conception, labor may be a) commuting or receiving non-labor income that enters the local economy in a transfer payment, rent or dividends, b) employed in an industry that is primarily non-basic, deepening the indirect and induced components of the base multiplier or c) employed in an industry that is primarily basic, increasing the direct component of the base multiplier. If an individual demands a pristine environment or high levels of recreation, he or she will be likely to move to an area that possesses these attributes. Therefore, the economic base of some communities has moved away from extractive uses in some counties as "footloose" firms, non-labor income or tourist attractions establish themselves as primary bases, reflecting the most valuable use of the land—in this case, for conservation and/or recreation activities. The transformation from an economy based on extractive activities to one based on tourism, non-labor income or services has occurred, to varying degrees, in many communities across the West and this transition is expected to be expressed in the results of the study.

Chapter 2. Methods

2.1 IMPLAN Data

County-level employment and input-output data to run the SAM model were extracted from the 2008 and 2012 IMPLAN database.

IMPLAN provides an adequate employment dataset by compiling data from the Bureau of Labor Statistics Quarterly Census of Employment and Wages (BLS QCEW) and supplementing these data with County Business Patterns (CBP) data provided by the Census Bureau and Regional Economic Information Systems (REIS) data provided by the Bureau of Economic Analysis (BEA). Since the QCEW only counts covered employment, IMPLAN used CPB and BEA to include non-covered employment. By supplementing QCEW employment data with CPB and REIS data, IMPLAN is able to fill gaps in undisclosed data, ordinarily a common problem with county level employment data. Value-added data is estimated using the same sources as employment data, with the exception of QCEW, which has no value-added data. The QCEW and REIS provide wage and income data while CBP is used to estimate these data when they are undisclosed.

Institutional data for households, government, inventory, capital and import/exports is found using the BEA's National Income and Product Accounts (NIPA), the BEA's Benchmark I-O accounts, and various industrial surveys (eg. National Agricultural Statistics Service Surveys or Annual Survey of Manufacturers). Most output data is from the BEA's Annual Industry Accounts and the Annual Survey of Manufacturers. Retail data come from the U.S. Census Bureau's Annual Census of Retail Trade. Other sectors use information from various sector-specific surveys and censuses. For estimating I-O coefficients and trade flows, IMPLAN uses a doubly-constrained gravity model given by Lindall et al (2006). The Trade Flows Model uses IMPLAN's county-level commodity supply and demand estimates—gathered using NIPA, BEA I-O accounts data, and various industry surveys—

a county-to-county distance by transportation mode dataset provided by Oak Ridge National Laboratory, and the Commodity Flows Survey ton-miles by commodity data. The model is closed in the sense that all sources of supply and demand are accounted for, so that domestic imports and exports “cancel out”. IMPLANs Regional Production Coefficients (RPCs, I-O coefficients) are created using this model. The RPC is the proportion of local supply that satisfies local demand.

2.2 Variable Creation

IMPLAN data was used to create the SAM from which base and gross employment shares for 215 counties in the RMW were derived. The Automated Social Accounting Matrix (ASAM) program developed by Braak et al. (2011) was applied to find the gross and base shares for 215 of 216 counties in the study area. This program automates the application of the expanded Leontief Inverse equation (eq.2). The data was compiled for two time periods, 2008 and 2012. Data from Washington County, Colorado, was not available in 2012, so the county was dropped from the analysis. For the 2008 and 2012 base shares, a matrix of 215 counties with 95 variables, which included 86 industries aggregated at the 3-digit NAICS level and 9 household categories sorted by household income, was constructed. The variables were employment dependency scores (base employment shares) for each of the 95 industries or household categories. For the 2008 gross employment shares, a matrix of the 215 counties with 86 industries aggregated at the 3-digit NAICS level was constructed. The variables were simply gross employment for each industry. There is no gross employment through the institution of households.

2.3 Grouping Industries

In order to draw useful conclusions about a county’s economic structure, and because clustering algorithms perform better with fewer variables (Kaufman and Rousseeuw 1990), the 86 industries and 9 household levels were aggregated into 13 industry groups or sectors. The sectors

were Agriculture; Forestry; Mining; Government; Low-Tech Manufacturing; High-Tech Manufacturing; Retail, Hospitality and Tourism; Other Services; Transportation and Utilities; Low-Middle- and High-income household's extra-regional transfers; and Construction. The gross aggregation process excluded household transfers because they are not responsible to any gross employment. Table 2.1 shows the assignment of 3-digit NAICS codes into their respective groups. Each and every industry and household level was placed into a group. The sum of the dependency scores for the industries/households within the group was taken to find the dependency score for the group. Therefore, the dependency scores across all groups for one county sum to one.

Table 2.1 Industry Grouping Scheme

Agriculture	Forestry	Mining	Government	low-tech manufacturing	high-tech manufacturing	Retail, Hospitality, Tourism or Recreation Services
111 Crop Farming	113 Forestry & Logging	211 Oil and Gas	92 Government & non NAICS	313 Textile Mills	325 Chemical Manufacturing	441 Motor veh & parts dealers
112 Livestock	115 Ag & Forestry Svcs*	212 Mining		314 Textile Products	333 Machinery Mfg	442 Furniture & home furnishings
114 Fishing- Hunting & Trapping	321 Wood Products	213 Mining services		316 Leather & Allied	334 Computer & oth electron	443 Electronics & appliances stores
115 Ag & Forestry Svcs*		324 Petroleum & coal prod		322 Paper Manufacturing	335 Electrical eqpt & appliances	444 Bldg materials & garden dealers
311 Food products		327 Nonmetal mineral prod		323 Printing & Related	336 Transportation eqpmt	445 Food & beverage stores
312 Beverage & Tobacco				326 Plastics & rubber prod		446 Health & personal care stores
				331 Primary metal mfg		447 Gasoline stations
				332 Fabricated metal prod		448 Clothing & accessories stores
Other Services				337 Furniture & related prod		451 Sports- hobby- book & music stores
454 Non-store retailers				339 Miscellaneous mfg		452 General merch stores
511 Publishing industries	Transportation and Utilities	Low-Income HH	Middle-Income HH		Construction	453 Misc retailers
512 Motion picture & sound recording	221 Utilities	Households LTI0k	Households 35-50k		485 Transit & ground passengers	
515 Broadcasting	42 Wholesale Trade	Households 10-15k	Households 50-75k	High-Income HH	487 Sightseeing transportation	
516 Internet publishing and broadcasting	481 Air transportation	Households 15-25k	Households 75-100k	Households 100-150k	531 Real estate	
517 Telecommunications	482 Rail Transportation	Households 25-35k		Households 150k+	532 Rental & leasing svcs	
518 Internet & data process svcs	483 Water transportation				562 Waste mgmt & remediation svcs	
519 Other information services	484 Truck transportation				711 Museums & similar	
521 Monetary authorities	486 Pipeline transportation				712 Performing arts & spectator sports	
522 Credit intermediation & related	492 Couriers & messengers				713 Amusement- gambling & recreation	
523 Securities & other financial	493 Warehousing & storage				721 Accommodations	
524 Insurance carriers & related					722 Food svcs & drinking places	
525 Funds- trusts & other finan					811 Repair & maintenance	
533 Lessor of nonfinance intang assets					812 Personal & laundry svcs	
541 Professional- scientific & tech svcs					814 Private households	
551 Management of companies						
561 Admin support svcs						
611 Educational svcs						
621 Ambulatory health care						
622 Hospitals						
623 Nursing & residential care						
624 Social assistance						
813 Religious- grantmaking- & similar orgs						

*allocated depending on which industry --either forestry or agriculture and livestock-- contributes more to base employment in the county

The goal of the aggregation process was to produce groupings that generally reflect economic activity of a similar type or that progresses toward a similar end product. Thus, the aggregation was based on the concept of industrial clusters (Porter 1990). Porter defines clusters as “geographic concentrations of interconnected companies, specialized suppliers, service providers, firms in related industries, and associated institutions (e.g., universities, standards agencies, trade associations) in a particular field that compete but also cooperate” (Porter 2000, 20). Clusters develop as a result of economic agglomeration within the regional economy. One important characteristic of a cluster is the supply chain linkages that develop within the cluster. A simple example is a lumber processing facility locating in a region with extensive forestry and logging. Transportation of logs is more costly than transportation of lumber, so mills tend to be located nearby the source of extraction. This is the case with many extractive industries. Services and manufacturing can experience clustering as well. Silicon Valley and Hollywood are examples of clusters in computer components manufacturing/software development and screen entertainment respectively.

It is difficult to ignore the role that clusters play in a regional economy. For example, when performing a base analysis of Twin Falls County, Idaho, the comparative advantage that the county has in agricultural production would be underestimated if the food products manufacturing industry and the livestock and crop farming industries had been separated. Food product manufacturing provides 7 percent of economic base employment while livestock and crop farming together provide 7 percent. By combining these into one group called agriculture, some detail within the regional economy is sacrificed (i.e. Twin Falls County must be examined specifically to find out exactly how much employment is devoted to raising dairy cows), but explanatory power is gained because these industries are inextricably linked. A food products industry exists in Twin Falls County because of the livestock and crop farming industries and vice versa. Thus, when the livestock industry but not the

food products industry is included in an agriculture cluster, the farmer who milks the cow is included, but not the worker who pasteurizes the milk. And while the pasteurization could not exist without the milk itself, the process adds significant value that might be missed were it not included the agricultural group. While this process is not an exercise in cluster mapping per se, using an aggregation process informed by Porter's theory of business clusters should capture some of the agglomeration effects and input-output linkages that are lost in the USDA ERS typology.

The Retail, Hospitality and Tourism (RHT) sector consists of industries that generally require the business transaction to physically occur within the region. For example, not only were the traditional tourism services such as Amusement, Gambling and Recreation and Accommodations included, but so were hospitality, retail and support services for these industries such as retail outlets, Rental and Leasing Services, and Repair and Maintenance services. In short, any industry whose base contribution might be derived from people coming from outside of the region to spend money in the region was included in the RHT sector.

The Other Services group consists mainly of firms whose base contributions are likely derived from services being sold outside of the region or that have no relation to retail, hospitality or tourism activities. Examples include Professional, Scientific and Technical Services, which might include a cartography firm that makes a map for a client outside of the firm's county, and Non-store Retailers like Amazon.com, who sell goods and services using the internet or catalog.

The Low-Tech and High-Tech Manufacturing groupings are differentiated using the Organization for Economic Co-operation and Development (OECD) definition of high-tech and low-tech manufacturing sectors (OECD 2011). This is based on the Research and Development (R&D) intensity, found by taking the R&D expenditure in the industry and dividing it by industry value added, taking the R&D expenditure and dividing it by production, and then comparing the two

scores. Industries that score high in each are high-tech manufacturers, industries that score lower in each are low-tech manufacturers.

Breaking the households into income groups serves as a proxy for the type of exogenous payment being made to them. Across all income groups, commuter income is one part of household payments. For low-income households, extra-regional income are comprised mainly of welfare payments, food stamps, and other government transfer payments. For high-income households, these payments primarily consist of investment, rental, or retirement income. Mid-income households will most likely consist of a mix of commuting income and various sources of non-labor income.

2.4 Cluster Analysis

A Partition Around Medoids (PAM) clustering algorithm was applied to the dependency scores for each group to cluster the counties with similar economic base structures. The PAM is a partitional algorithm similar to k-means, in that each breaks n observations into k groups and attempts to minimize error between points within each group. The primary difference is that PAM selects actual data points from within the dataset to use as medoids, the most central point in each cluster, while k-means creates centroids, artificially created points that represent the average center of each cluster (Kaufman and Rousseeuw 1990). Creating medoids is useful for this analysis to find the “representative county” within each cluster. This can be used for further qualitative or quantitative analysis.²

² For a qualitative study that follows a cluster analysis on county-level income types see Beyers and Nelson. 2000. Contemporary Development Forces: New insights from rapidly growing communities, *Journal of Rural Studies* pp. 459-474

The PAM algorithm is given by the problem:

$$F(x) = \text{minimize } \sum_{i=1}^n \sum_{j=1}^n d(i,j)z_{i,j} \text{ (eq. 2.1)}$$

Where $d(i,j)$ is the measure of dissimilarity between points i and j , and $z_{i,j}$ is a variable that ensures i and j are members of the same cluster (Kaufman and Rousseeuw 1990). Therefore, the objective of the algorithm is to minimize the dissimilarity of observations within each cluster. The algorithm proceeds in two steps. In the build phase, k number of observations are selected as medoids, the dissimilarity matrix is calculated, and the remaining observations are assigned to the closest medoid. In the swap phase, selected medoids are exchanged with remaining observations until the lowest average dissimilarity within each cluster is reached. In this way, the algorithm solves the problem by grouping the most similar counties into clusters.

Besides the ability to use an observation from the dataset as the cluster's central point, the PAM algorithm's primary advantage over k-means is that it is less sensitive to outliers because PAM uses a medoid rather than a centroid center and because it uses a dissimilarity matrix rather than a Euclidean distance matrix (Singh and Chauhan 2011). Because of the diversity of economic drivers in the RMW, and judging by the high Coefficient of Variation, outliers in the analysis were expected and confirmed.

An average silhouette index was used to specify the number of clusters, k , between 6 and 8. This range of k was chosen to meet the needs of the study—too many k and the results became difficult to interpret, too few and they do not provide the level of detail required. The silhouette index is a measure of the strength of cluster membership, given by:

$$s(i) = \frac{b(i)-a(i)}{\max\{a(i),b(i)\}} \text{ (eq. 2.2)}$$

Where, for each data point i , $b(i)$ is the lowest average dissimilarity of i to any other cluster but its own. The cluster with the next lowest average dissimilarity is the “neighboring cluster,” the cluster with the next best fit. $A(i)$ is the average dissimilarity of i to all other points in the same cluster. The silhouette index ranges from -1 to 1, with values less than zero indicating that the data point might be more appropriately included in the neighboring cluster. Values greater than 0 indicate the proper membership and values of 0 indicate points on the border between to clusters. The silhouette widths of individual counties can also indicate a lot about the structure of the county. Silhouettes show the relative strength of a county’s position within its cluster. A high silhouette width for a particular county indicates that the county is archetypical of that cluster. On the other hand, a county with a negative value indicates that the county is not in the proper cluster. A $k=6$ was selected based on average silhouette values.

To examine whether the economic type of a county had any bearing on variables that were not used in the cluster analysis, an Analysis of Variance (ANOVA) was performed on 18 socioeconomic and demographic variables. Thus, it was possible to determine if there were significant differences ($p<.05$) between the county clusters for each of the 18 variables. These variables were selected from the literature because they have been shown to have some influence on the economic development trajectory within the county. The variable list, their sources, and a brief description of the variable (if necessary) are provided in Table 2.2.

Table 2.2 Variable Table for Variables used in ANOVA		
Variable	Description	Source
Population2010	Population by county in 2010	U.S. Census Bureau, 2010 Census
Population Density 2010	County Population in 2010 per square mile	U.S. Census Bureau, 2010 Census
Net Migration (2000-2010)	Estimated net migration per 100 people in a county between 2000 and 2010	Winkler, Richelle, Kenneth M. Johnson, Cheng Cheng, Jim Beaudoin, Paul R. Voss, and Katherine J. Curtis. Age-Specific Net Migration Estimates for US Counties, 1950-2010. Applied Population Laboratory, University of Wisconsin- Madison, 2013. Web. < http://www.netmigration.wisc.edu/ >
Net Migration Rate; 60+ y/o	Estimated net migration of individuals over 60 years old per 100 people in a county between 2000 and 2010	Winkler, Richelle, Kenneth M. Johnson, Cheng Cheng, Jim Beaudoin, Paul R. Voss, and Katherine J. Curtis. Age-Specific Net Migration Estimates for US Counties, 1950-2010. Applied Population Laboratory, University of Wisconsin- Madison, 2013. Web. < http://www.netmigration.wisc.edu/ >
Net Migration Rate; 15-29 y/o	Estimated net migration of individuals between 15 and 29 years old per 100 people in a county between 2000 and 2010	Winkler, Richelle, Kenneth M. Johnson, Cheng Cheng, Jim Beaudoin, Paul R. Voss, and Katherine J. Curtis. Age-Specific Net Migration Estimates for US Counties, 1950-2010. Applied Population Laboratory, University of Wisconsin- Madison, 2013. Web. < http://www.netmigration.wisc.edu/ >
Median Age 2010	Median age in a county in 2010	U.S. Census Bureau, 2010 Census
Pct. 4-year Degree07-11	Percent of individuals over 25 years old with a 4-year degree	U.S. Census Bureau, American Community Survey 5-year estimates
Social Capital Index09	This index measures the per capita level of organizations and variables that contribute to strengthening social ties within communities. For more information about the chosen variables, see http://aeese.psu.edu/nercd/economic-development/for-researchers/poverty-issues/big-boxes/wal-mart-and-social-capital/social-capital/data-dictionary-of-variables	Rupasingha, Anil and Stephan J. Goetz, "US County-Level Social Capital Data, 1990-2005." The Northeast Regional Center for Rural Development, Penn State University, University Park, PA, 2008.
Pct. Creative Class07-11	This group of occupations was compiled by the USDA Economic Research Service. Occupations defined O*NET, a program of the Employment and Training Administration within the Bureau of Labor Statistics that had high levels of "thinking creatively" were found. "Thinking creatively" involves "developing, designing, or creating new applications, ideas, relationships, systems, or products, including artistic contributions." See http://www.ers.usda.gov/data-products/creative-class-county-codes/documentation.aspx#identifying for more information regarding the creative class.	USDA ERS; U.S. Census Bureau; American Community Survey 5-year estimates
Pct. Protected Land2012	This variable was calculated using the USGS Protected Areas Database of the United States. All management levels were considered. Two protection classifications were chosen: Class 1: "An area having permanent protection from conversion of natural land cover and a mandated management plan in operation to maintain a natural state within which disturbance events (of natural type, frequency, intensity, and legacy) are allowed to proceed without interference or are mimicked through management." Class 2: "An area having permanent protection from conversion of natural land cover and a mandated management plan in operation to maintain a primarily natural state, but which may receive uses or management practices that degrade the quality of existing natural communities, including suppression of natural disturbance." For more information, see http://gapanalysis.usgs.gov/wp-content/uploads/2013/10/PADUS_Standards_Oct2013_USGSreview.pdf	USGS Gap Analysis Program, Protected Areas Database of the United States (PADUS) version 1.3, 2012
Natural Amenity Scale		Natural Amenities Drive Rural Population Change. David McGranahan. USDA ERS Agricultural Economic Report No. (AER-781) 27, October 1999
Airport/Remoteness05	Rasker et al. (2009) proposed this classification to represent one measure of remoteness. A county is scored as either 1, 2 or 3: 1. Metro Counties remain the same as the OMB taxonomy--counties that fall within an Metropolitan Statistical Area. 2. Connected Counties are "non-metro counties with population centers within a one-hour drive of the nearest major airport with daily passenger service" 3. Isolated Counties are non-metro counties at least a one hour drive from the nearest major airport.	Rasker, R. P.H. Gude; J.A. Gude, J. van den Noort, 2009. The Economic Importance of Air Travel in High-Amenity Rural Areas. <i>Journal of Rural Studies</i> 25(2009); 343-353.
Urban Influence Code2003	Urban Influence Codes form a classification scheme that distinguishes metropolitan counties by population size of their metro area, and nonmetropolitan counties by size of the largest city or town and proximity to metro and micropolitan areas. The standard Office of Management and Budget (OMB) metro and nonmetro categories have been subdivided into two metro and 10 nonmetro categories, resulting in a 12-part county classification.	USDA ERS, Urban Influence Codes
GRP/Capita08	This is the Gross Regional Product per capita of a county estimated by IMPLAN. For more information on estimation techniques see http://www.implan.com/index.php?option=com_content&view=article&id=349&Itemid=1745	IMPLAN
Pct. Poverty08	Percent of individuals living at or below the poverty level in 2008	U.S. Census Bureau, Small Area Income and Poverty Estimates
Unemployment2008	Percent of the county labor force unemployed in 2008	Bureau of Labor Statistics, Local Area Unemployment Statistics
Unemployment CV 2000-2012	The coefficient of variation is the ratio of the standard deviation to the mean. For the unemployment CV 2000-2012, we found the annual average unemployment rate for each year and calculated the standard deviation as a share of the mean. This is a measure of employment stability.	$C_V = \sigma / \mu$ where σ is the standard deviation and μ is the mean of average annual unemployment
ShannonWeaver Diversity Index08	This is a measure of the economic diversity of a county. A diversity score of 1 indicates that employment is evenly distributed throughout all sectors. A diversity score of zero indicated that employment is completely concentrated in only one sector. Employment is calculated at the 3-digit NAICS level	$D = - \sum_{i=1}^n E_i \ln E_i$ where E_i is the share of employment in industry i and n is the number of industries in the economy. Employment is from IMPLAN dataset.

A post-hoc Tukey's Honest Significant Difference test (Tukey's HSD) was then used to further tease out the clusters between which there were significant differences.

2.5 Comparing 2008 Base to 2008 Gross Employment Data

A minimum average distance function was applied to answer the question, "how do the results of the analysis change if gross rather than base employment scores were used?" To compare the 2008 Base clusters to the 2008 Gross data, a minimum average distance function applied to the remaining counties' gross scores to classify each county into one of the clusters defined by the gross scores of the medoids. Thus, each county was classified into a cluster where the average distance to that cluster's medoid was minimized.

The silhouette index and neighboring cluster information for each county was used to develop a four-case scale to capture the magnitude of classification difference if using the gross instead of the base measurements. The first case occurs when the silhouette index is negative for a county and the gross share classification places the county in the neighboring cluster. This means that the county is poorly classified to begin with, and so it is no surprise if the gross share causes the county to be classified in the next-best cluster. The next three cases are instances of misclassification. In the next case, classification by gross share places the county in the adjacent cluster but the silhouette index less than one standard deviation above zero. In this case, the county is misclassified, but is close to being in the adjacent cluster. The third case, places the county in the adjacent cluster, but the silhouette index is greater than one standard deviation above the mean, so the misclassification is more significant. Finally, the last case misclassifies the county into a non-adjacent cluster. In this case the use of the gross share is severely misleading.

In addition to gross share classification, the gross data was standardized around the mean for each of the 10 industry groups to detect outliers, defined here as differences of more than two standard deviations above or below the mean. This allows each variable to be examined individually, rather than using what amounts to 10-dimensional space to find the changing of cluster membership. For example, several of the counties that experience significant differences between gross and base shares might not actually change cluster membership as a result of these differences. However, it is useful to examine them nonetheless.

Recognizing that the gross shares might yield an inaccurate depiction of a counties economic activity is important for reasons discussed above. Using these methods, it is possible to determine where misclassification occurs when relying upon gross shares to provide information about the economic activity taking place within a county.

2.6 Examining Change from 2008 to 2012

The recession that began in late 2007 had significant effects on the economy of the RMW. In 2008, employment reached an all-time high of 6,902,805 in the 5 state region; by 2010 it had dropped 4 percent to 6,652,976, the largest decrease since the Great Depression. Personal income suffered a similar fate (BLS QCEW, BEA REIS). Across the RMW, retail sales and construction were responsible for most of the decrease in employment (BEA REIS). However, the impacts were not shared evenly across the RMW. The change in the base share of each industry sector is calculated to see how it has changed over the recession. While an increased share does not necessarily mean growth, it does mean that other industry group shares declined relative to these groups.

To examine the change in dependency scores from 2008 to 2012, the two methods outlined above were used with some minor specifications. First, when addressing the change in cluster membership, rather than using the base scores from the 2012 dataset as medoids around which to

classify new data, the 2008 base share medoid less the economy-wide average base score change was used. This is the 2008 dependency score adjusted for area-wide change. Each of the changes was assigned a case, given by the definition above. Instead of a reclassification representing the misclassification that might occur if gross shares rather than base shares had been used, *the reclassification of 2012 base data shows where changes in a sector's base share were significant enough to cause a change in cluster membership. In other words, this analysis shows whether or not the county's cluster membership changed between 2008 and 2012 and if it did change, to which cluster did it change?*

Finally, as in the base to gross comparison, an outlier analysis was performed to distinguish significant changes by each group variable.

Chapter 3. Results and Discussion

This chapter will outline the results obtained by applying the methods discussed above. First, the descriptive statistics of the industry groupings are provided. Then, the outcomes of the PAM clustering algorithm are discussed. Socioeconomic variables that were not used in the cluster analysis are examined using an ANOVA and Tukey's HSD test. Then, the outcome of the gross employment to base employment comparison scores are examined. Finally, the economic base change from 2008 to 2012 is discussed.

Table 3.1 Industry Group Descriptive Statistics - RMW Counties 2008													
Statistic	Ag	For	Mine	Gov	LT_Man	HT_Man	Ret_Hos_Tour	OthServ	Tans_Util	LowHH	MidHH	HighHH	Con
Mean	0.143	0.016	0.051	0.186	0.019	0.018	0.186	0.140	0.046	0.044	0.041	0.012	0.099
Standard Error	0.009	0.002	0.005	0.005	0.002	0.002	0.007	0.006	0.002	0.002	0.002	0.001	0.004
Median	0.104	0.003	0.019	0.168	0.010	0.006	0.162	0.121	0.038	0.042	0.039	0.009	0.088
Standard Deviation	0.127	0.034	0.074	0.077	0.023	0.032	0.105	0.092	0.034	0.026	0.024	0.015	0.060
Sample Variance	0.016	0.001	0.005	0.006	0.001	0.001	0.011	0.009	0.001	0.001	0.001	0.000	0.004
Kurtosis	0.148	14.175	6.520	2.009	18.115	29.135	9.269	25.091	3.808	-0.177	0.331	48.621	0.576
Skewness	0.972	3.548	2.426	1.194	3.319	4.526	2.358	3.629	1.674	0.421	0.536	5.617	0.863
Range	0.560	0.244	0.401	0.493	0.199	0.290	0.851	0.924	0.200	0.132	0.128	0.166	0.311
Minimum	0.000	0.000	0.000	0.019	0.000	0.000	0.015	0.005	0.002	0.000	0.000	0.000	0.000
Maximum	0.560	0.244	0.401	0.512	0.199	0.290	0.866	0.929	0.202	0.132	0.128	0.166	0.311
Max County	Gooding, ID	Benewah, ID	Campbell, WY	Elmore, ID	NezPerce, ID	Caribou, ID	Gilpin, CO	Butte, ID	Platte, WY	Lincoln, MT	Park, CO	Douglas, CO	Teton, ID
SD/Mean	0.884	2.220	1.432	0.415	1.245	1.808	0.564	0.662	0.743	0.593	0.588	1.275	0.605

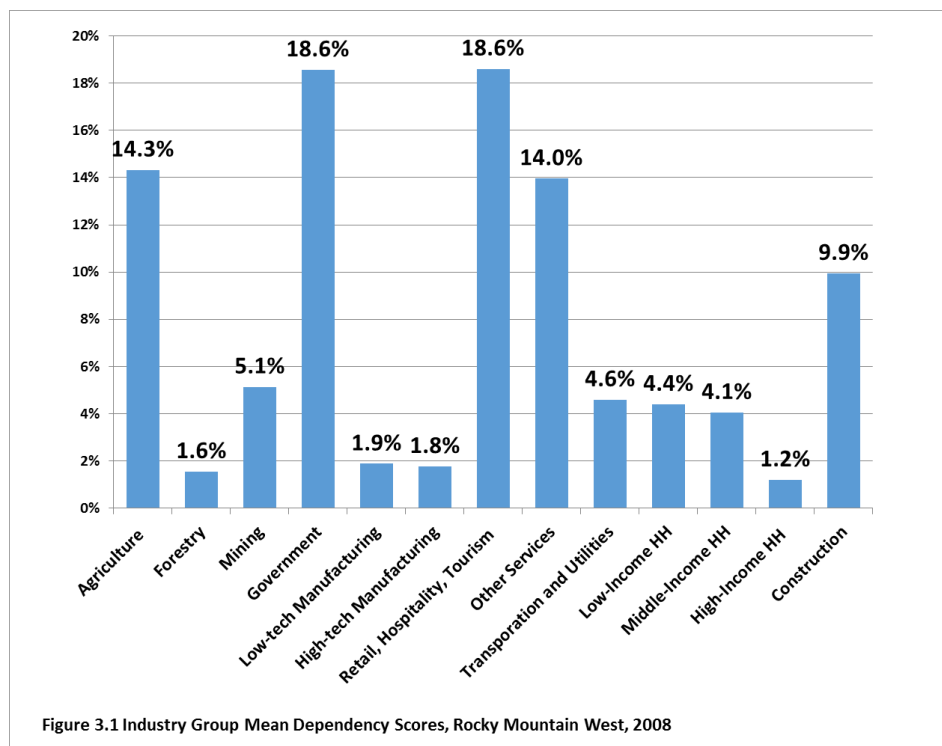


Table 3.1 and Figure 3.1 show the descriptive statistics for each industry grouping. The relatively high coefficient of variation (ratio of standard deviation to the mean) in nearly every group indicates that there are an extremely diverse set of economic drivers throughout the RMW.

It is no surprise that Agriculture plays an important role in many RMW economies, given its historic importance in the economic development of the RMW. Agriculture's average contribution is lower than that of the Retail, Hospitality and Tourism (RHT) group, however, which is tied for the highest mean share and has the second highest median share after government. RHT also has the second lowest coefficient of variation (CV), suggesting that it plays at least some role in the economic base of even the least retail and tourism oriented counties. Ironically, given the strong anti-government sentiment throughout much of the west, Government is the largest contributor to the base of RMW counties on average. This is in keeping with the thesis of Nash (1999) and Baden (1997) that government employment drives much of the economic activity in Rocky Mountain West counties. This is to be expected considering that over half of the land area of the West is publicly owned and nearly 46 percent is managed by the federal government (U.S. Geological Survey 2012). The contribution of Government is also the least variable across RMW counties. Also to be expected given previous studies (Nelson and Beyers 1998, Vias and Mulligan 1999) is the contribution of extra-regional payments to households to the economic base of RMW counties. The mean contribution of extra-regional payments across all income levels is 10 percent. Interestingly, while these payments to low- and middle-income households contribute similar amounts and have a similar coefficient of variation, the share of payments to high-income households are less on average and more variable across counties. Construction contributes nearly 10 percent to the economic base of RMW counties on average. Forestry, Mining and Manufacturing all have relatively lower average base contributions but are the most variable groups—that is, some counties

specialize significantly in these sectors while others have virtually no economic activity in them at all.

	Ag	For	Mine	Gov	LT_Man	HT_Man	Ret_Hos_Tour	OthServ	Trans_Util	LowHH	MidHH	HighHH	Con
Ag	1.000												
For	-0.048	1.000											
Mine	-0.176	-0.088	1.000										
Gov	-0.042	0.088	-0.122	1.000									
LT_Man	-0.281	0.049	-0.123	-0.122	1.000								
HT_Man	-0.136	-0.055	-0.081	-0.120	0.273	1.000							
Ret_Hos_Tour	-0.339	-0.122	-0.183	-0.257	-0.078	-0.169	1.000						
OthServ	-0.235	-0.201	-0.247	-0.241	0.175	0.139	-0.075	1.000					
Trans_Util	0.028	-0.139	0.184	0.000	0.039	0.011	-0.269	-0.045	1.000				
LowHH	0.002	0.203	-0.037	0.156	0.057	-0.045	-0.319	-0.270	-0.074	1.000			
MidHH	-0.178	0.097	-0.087	0.043	0.106	0.008	-0.224	-0.195	-0.116	0.761	1.000		
HighHH	-0.269	-0.081	-0.130	-0.180	0.055	0.027	0.092	0.075	-0.193	0.106	0.541	1.000	
Con	-0.551	0.027	0.122	-0.202	0.098	0.017	0.185	-0.125	-0.128	-0.022	0.215	0.285	1.000

Table 3.2 shows the correlation matrix for the group variables in 2008. Interestingly, Agriculture shows a weak negative correlation to every other group except Low-Income Household payments and Transportation and Utilities. It is most strongly inversely related to Construction and RHT Services. Forestry is weakly correlated with payments to low-income households. Mining is weakly opposed to RHT and Other Services, and weakly correlated with Transportation and Utilities and Construction. Government is weakly negatively correlated with Construction, RHT and Other Services and weakly positively correlated with payments to Low-Income Households. Relative to other correlations, Low-Tech and High-Tech Manufacturing display very little correlation to other variables, with the exception of a weak negative correlation between Low-Tech Manufacturing and Agriculture. There is a strong correlation between payments to Low- and Mid-Income Households, and a relatively strong correlation between payments to Mid- and High-Income Households. However, the correlation between payments to Low- and High- Income Households is relatively weak. In sum, the most interesting findings here are that *RHT and Agriculture both display a negative correlation, in some cases a relatively strong one, to every other industry group except two.* For Agriculture, these two are payments to Low-Income Households and Transportation and

Utilities, which have little to no correlation to agriculture. For RHT, they are payments to High-Income Households, which has little correlation to RHT, and Construction, which has a weak positive correlation to RHT. These correlations should be expressed in the results of the cluster analysis.

3.1 Cluster Results

Table 3.3 and Figure 3.2 show the summary statistics of the cluster analysis performed on the thirteen 2008 dependency scores for the 215 counties in the RMW. Each industry group has widely divergent dependency scores in each county, thus, each cluster represents a distinct economic structure present in the RMW.

Cluster	Statistic	Ag	For	Mine	Gov	LT_Man	HT_Man	Ret_Hos_Tour	OthServ	Trans_Util	LowHH	MidHH	HighHH	Con
1	Mean	4.5%	0.9%	2.8%	16.3%	3.7%	3.6%	18.0%	25.2%	4.8%	3.9%	3.8%	1.6%	10.9%
	SD	3.6%	1.7%	3.1%	6.4%	3.5%	4.3%	5.2%	13.1%	3.0%	2.6%	2.3%	2.5%	4.9%
	Medoid	2.2%	0.1%	1.6%	18.8%	4.1%	3.4%	19.5%	25.0%	4.9%	4.8%	4.2%	1.3%	10.2%
	SD/Mean	0.81	1.87	1.13	0.39	0.94	1.18	0.29	0.52	0.62	0.67	0.59	1.58	0.45
	Count	43	Avg.Silhouette					0.15	Medoid Name					Pueblo, CO
2	Mean	8.6%	4.2%	4.1%	27.5%	1.5%	1.1%	14.7%	10.0%	3.6%	6.1%	5.6%	1.4%	11.8%
	SD	4.4%	6.0%	4.7%	9.0%	1.2%	1.2%	5.0%	3.7%	3.3%	2.5%	2.4%	1.0%	5.7%
	Medoid	9.8%	3.2%	3.2%	27.0%	0.8%	1.7%	13.7%	8.9%	2.7%	7.8%	6.4%	1.7%	13.0%
	SD/Mean	0.51	1.42	1.15	0.33	0.82	1.19	0.34	0.37	0.92	0.42	0.43	0.75	0.48
	Count	39	Avg.Silhouette					0.09	Medoid Name					Montezuma, CO
3	Mean	2.9%	0.6%	3.9%	13.1%	1.5%	0.4%	40.1%	12.1%	1.7%	2.9%	3.5%	2.1%	15.3%
	SD	2.8%	0.8%	4.6%	4.3%	1.4%	0.5%	12.3%	5.4%	1.3%	1.6%	2.1%	1.8%	6.8%
	Medoid	1.9%	0.4%	3.6%	13.2%	1.6%	0.0%	40.2%	12.4%	0.3%	1.9%	1.9%	2.3%	20.3%
	SD/Mean	0.97	1.35	1.19	0.33	0.97	1.12	0.31	0.45	0.76	0.55	0.61	0.87	0.44
	Count	27	Avg.Silhouette					0.31	Medoid Name					SanMiguel, CO
4	Mean	37.2%	0.7%	2.0%	15.5%	0.7%	1.1%	14.7%	11.5%	4.4%	4.2%	3.2%	0.8%	4.0%
	SD	6.5%	1.8%	2.0%	4.0%	1.0%	1.6%	5.3%	5.6%	2.8%	2.4%	1.9%	1.0%	2.3%
	Medoid	37.4%	0.5%	4.3%	15.1%	0.0%	5.3%	13.8%	12.5%	2.8%	3.0%	2.8%	0.9%	1.7%
	SD/Mean	0.18	2.41	0.98	0.26	1.42	1.44	0.36	0.48	0.64	0.59	0.58	1.25	0.56
	Count	35	Avg.Silhouette					0.31	Medoid Name					GoldenValley, MT
5	Mean	19.7%	1.5%	3.5%	20.1%	1.7%	2.1%	15.6%	12.6%	5.8%	4.7%	4.2%	0.8%	7.6%
	SD	4.6%	2.9%	3.8%	5.5%	2.2%	4.3%	5.2%	4.6%	3.5%	2.7%	2.6%	0.7%	3.8%
	Medoid	17.2%	0.7%	2.9%	21.4%	1.0%	3.4%	15.2%	15.1%	6.3%	5.5%	4.8%	1.0%	5.5%
	SD/Mean	0.23	1.98	1.07	0.27	1.24	2.01	0.34	0.37	0.61	0.56	0.61	0.82	0.50
	Count	51	Avg.Silhouette					0.16	Medoid Name					Logan, CO
6	Mean	8.7%	0.5%	22.9%	15.2%	1.5%	1.1%	13.3%	8.0%	7.3%	4.0%	3.4%	0.6%	13.5%
	SD	6.5%	0.5%	8.3%	3.8%	1.5%	1.5%	3.8%	2.7%	3.4%	2.0%	1.8%	0.5%	5.7%
	Medoid	9.8%	0.3%	24.3%	15.9%	0.9%	1.7%	7.5%	4.6%	12.5%	5.1%	2.7%	0.6%	14.1%
	SD/Mean	0.75	1.16	0.36	0.25	0.97	1.31	0.28	0.34	0.47	0.51	0.52	0.77	0.42
	Count	20	Avg.Silhouette					0.3	Medoid Name					Duchesne, UT

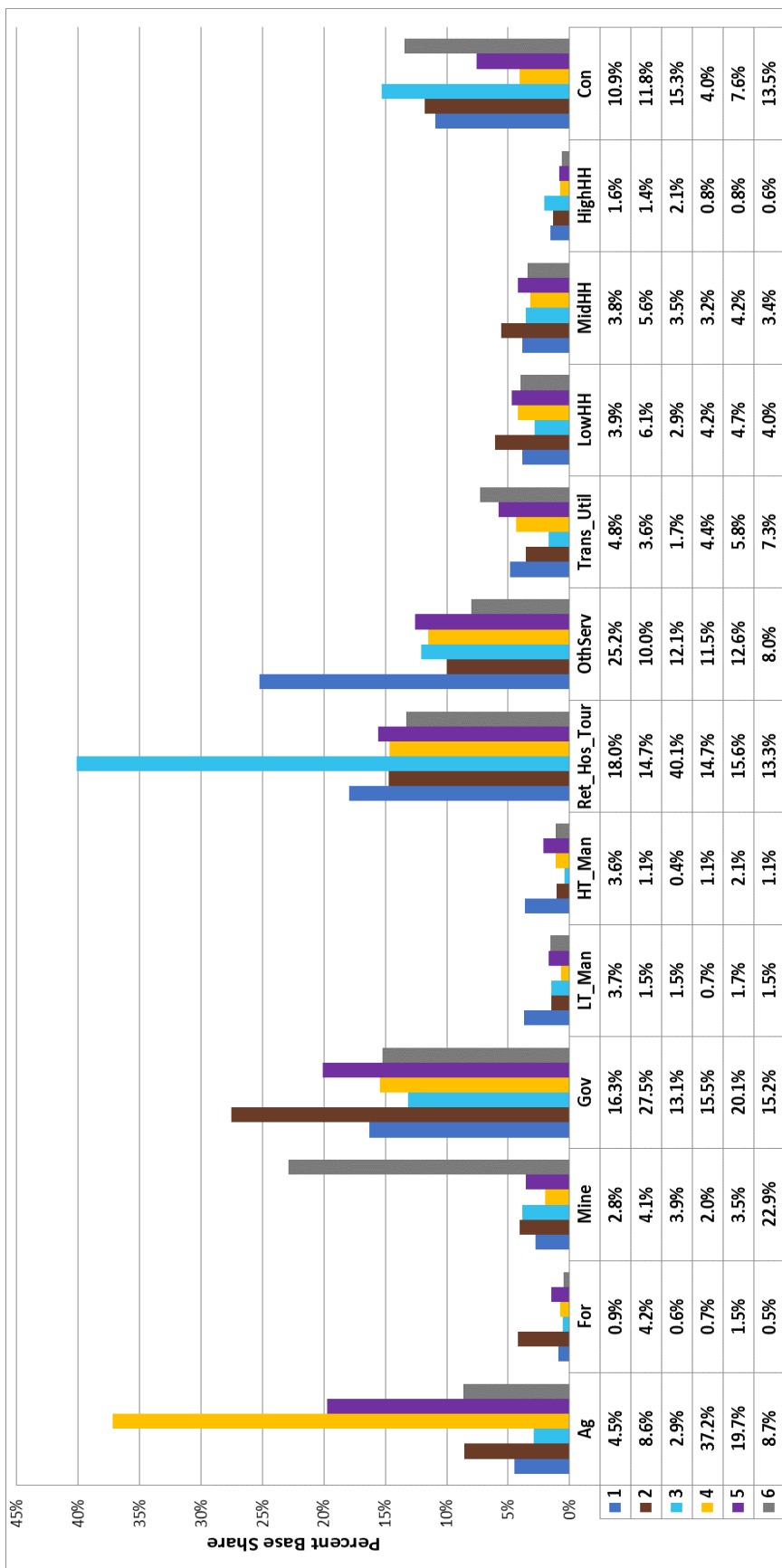
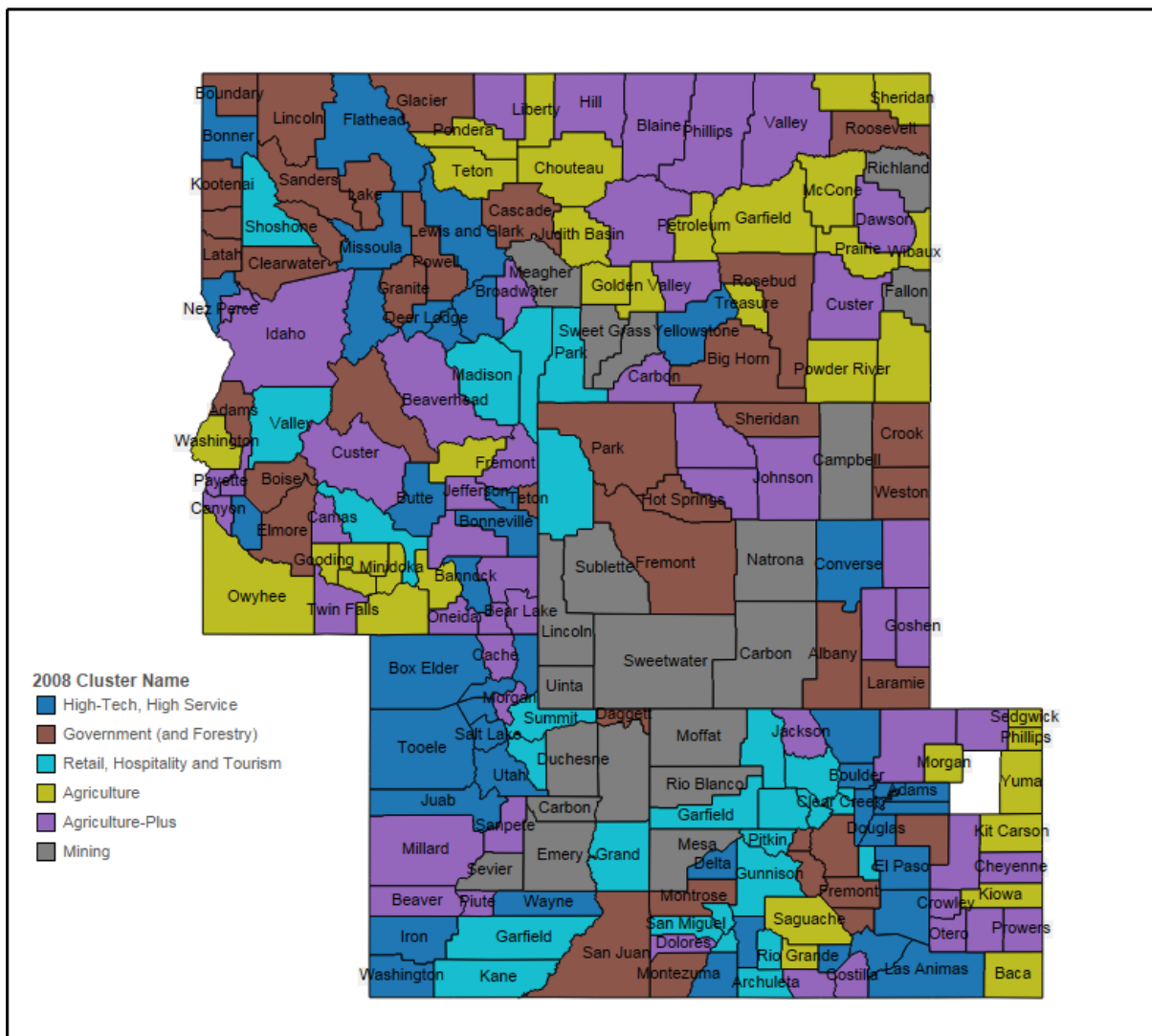


Figure 3.2 Industry Group Means by Cluster -- 2008 RMW

Within each sector, the blue cell represents the maximum base score and the red cell represents the minimum base score. With the exception of cluster five, it is clear that each cluster has distinct base shares in specific industry groups that set them apart from the other clusters. The average silhouette indicates how tightly the cluster is grouped. The smaller the minimum average distance between all counties in the cluster, the higher the average silhouette.

Map 3.1 shows the geographic distribution of the county types across the RMW.

**Map 3.1 Base Employment Clusters
Rocky Mountain West
2008**



Cluster 1—High-Tech, High-Service Cluster

Cluster 1, the High-Tech, High-Service cluster, contains 43 counties and has the highest base share of Other Services, with over 25 percent, and both Low-Tech and High-Tech Manufacturing, with just under 4 percent each, of all clusters. It has a below average share of Agriculture, Forestry, Mining, Government and payments to Low-Income Households. It has an above average base share of payments to High-Income Households and Construction. The average silhouette width of Cluster 1 is 0.15, the second lowest of all counties. Recall that cluster membership is stronger or more distinct as the average silhouette index for that cluster increases. Thus, 0.15 indicates the cluster membership is relatively weakly defined. However, it is clear that the high base share in Other Services, lower than average share of Government, lower than average Agriculture and average share of RHT all define this cluster given the relatively low coefficients of variation in those industry groups. Given this, these counties are likely to be located primarily in metropolitan areas with healthy manufacturing sectors and developed service sectors that are not specific to retail or tourism.

Indeed, the medoid of this cluster is Pueblo County, Colorado, home to Pueblo, a city of over 106,000 people. Beside the medoid, the most representative counties of this cluster include Jefferson County, Colorado, which contains the suburbs east of Denver such as Lakewood and Arvada; Utah County, Utah, home to cities south of Salt Lake like Orem and Provo; Denver County, Colorado, which contains central Denver; and Salt Lake County, Utah, home of Salt Lake City.

Cluster 2—Government (and Forestry) Cluster

Cluster 2, the Government (and Forestry) cluster, contains 39 counties and has the highest share of Government, Forestry, and payments to Low-Income and Mid-Income Households of all clusters. It has an above average base share in Construction and a slightly above average base share

of payments to High-Income Households. It has a lower than average base share of Agriculture, Transportation and Utilities, RHT, and Other Services. This cluster is the most loosely defined, with an average silhouette of only 0.09, but it is primarily characterized by its high base share of Government. While it contains the counties that have a high base share of Forestry employment, specializing in timber production is clearly not a prerequisite to be a member of this cluster given the high coefficient of variation in this industry group. Rather, it is a high share of Government combined with payments to Low- and Mid-Income Households that define the cluster. Given this, these counties might have higher levels of public lands (high base share of Government) but may not have developed the cachet that some high-profile recreational tourist destinations have (relatively low share of RHT). Based on McGrannahan (1999), Rudzitis (1999) and Deller et al. (2001), these counties should have lower scores on the natural amenity index.

The medoid of Cluster 2 is Montezuma County, Colorado, which contains several gateway communities to Mesa Verde National Park. The other counties that are representative of this cluster are Lake County, Colorado, encompassing Leadville and the Mt. Massive Wilderness Area; Fremont County, Colorado, bordering Pueblo County to the West; Latah County, Idaho, home to the University of Idaho; and Fremont County, Wyoming, encompassing Lander, Riverton and most of the Wind River Indian Reservation.

Cluster 3—Retail, Hospitality and Tourism Cluster

Cluster 3, the Retail, Hospitality and Tourism cluster (RHT), contains 27 counties and is defined almost exclusively by the highest base share of RHT of all clusters—on average, 40 percent of all economic activity can be attributed to employment in the RHT sector. Additionally, this cluster is tied for the most well-defined cluster based on average silhouette width. In keeping with the results of the correlation matrix, this cluster has the highest base share of Construction and the highest

share of payments to high-income households than any other cluster. Also in keeping with the findings in the correlation matrix, this cluster also has the lowest mean Agriculture, Forestry, Government, Transportation and Utilities, High-Tech Manufacturing and payments to Low Income Households of all clusters. It also has a below average score in payments to Mid-Income Households. Interestingly, this cluster is defined by having either very high or very low scores in each industry group.

The medoid of this cluster is San Miguel, Colorado, whose capital seat is Telluride. The other representative counties are Grand County, Utah, home to Moab and several national parks; Eagle County, which is west of Denver on I-70 and home to Vail and Beaver Creek Ski Areas; Pitkin County, Colorado, directly west of Eagle County and home to Aspen Resort; and Teton County, home of Jackson Hole and Grand Teton National Park. This cluster of counties is unique in that most are associated with well-known outdoor recreation hotspots like Moab, Utah; Sun Valley, Idaho; Steamboat Springs, Colorado; and Bozeman, Montana. Each county in this cluster has built its fortunes on this cachet and, as evidenced by the tightness of the cluster, has exploited its comparative advantage its scenic beauty.

Cluster 4—Agriculture Cluster

In many ways, the Agriculture cluster, comprised of 35 counties, exhibits the polar opposite economic characteristics of Cluster 3. For example, while Cluster 3 had the lowest Agriculture score, Cluster 4 has by far the highest, at over 37 percent. There was also little variance among the county scores of Agriculture, suggesting a tightly clustered group of counties with a specialization in Agriculture. It is also tied with Cluster 3 as the most well-defined cluster, with an average silhouette width of .31. Cluster 4 has the lowest score in Mining, Construction, Low-Tech Manufacturing and

payments to Mid-and High-Income Counties. This cluster also has a lower than average score in Government and Other Services, which, interestingly, is also the case for Cluster 3.

The medoid for Cluster 4 is Golden Valley County, Montana, a large county by area with a small population—884 in 2010—located in central Montana northwest of Billings. The most representative counties other than the medoid include Chouteau County, Montana, located northeast of Great Falls on the Plains in north-central Montana; Garfield County, Montana, located on the plains due east of Great Falls; McCone County, Montana, located directly east of Garfield County; and Minidoka County, Idaho, which lies on the Snake River Plain in south-central Idaho.

Cluster 5—Agriculture-Plus Cluster

Cluster 5, the Agriculture-Plus cluster, contains 51 counties and is somewhat of a mixed bag with above average values for Agriculture, Forestry and Government and lower than average values for Mining, RHT and construction. It has the second highest score in Other Services, but is still below the average, indicating the specialization of that industry group within the High-service, High-tech counties and nowhere else. It is unsurprising then, that this cluster is also somewhat ill-defined, as suggested by the average silhouette value of .15. Overall, this cluster appears to be a catchall for counties that maintain a dependence on agriculture but are also dependent on one or more industry groups that are not expressed in the counties specialized solely in Agriculture. In this sense, they could be called unspecialized or diverse; however, given the low coefficient of variation, it is clear that Agriculture still occupies a substantial base share in each of these counties' economies. Therefore, it might be better called the "Ag-plus" county, in that each county relies on Agriculture plus another—or several other—economic bases.

The medoid for this cluster is Logan County, Colorado, a county with just under 23,000 people located in the northeastern corner of Colorado on the Great Plains. The other representative

counties beside the medoid are Franklin County, Idaho, on the border with Utah in southeastern Idaho; Musselshell County, Montana, in central Montana north of Billings; Camas County, Idaho, in south-central Idaho where the Rocky Mountains meet the Snake River Plain; and Prowers County, Colorado on the far eastern side of the state in the plains.

Cluster 6—Mining Cluster

Finally, Cluster 6 is distinctly represented by counties that are highly Mining-dependent. In keeping with the results of the correlation matrix, this cluster also has the highest share of Transportation and Utilities and the second-highest share of Construction after Cluster 3. It has the lowest share of RHT and Other Services. Both this cluster's dependencies and its low base share of other industry groups have low variability amongst counties across the cluster, making it a distinctly Mining cluster with a low share of services or other sectors.

The medoid for this cluster is Duchesne County, Utah, a county with just under 19,000 people located in northeastern Utah just south of the Uinta Mountains. The counties most representative of this cluster are Uintah County, Utah, immediately east of Duchesne County; Sublette County, Wyoming, in the west-central part of Wyoming on the west side of the Wind River Mountains; Sweetwater County, Wyoming, the county immediately south of Sublette County, and Campbell County, Wyoming, located in the northeast corner of the state.

3.2 ANOVA and Tukey's HSD Results

Tables 3.4 and 3.5 show a comparison of socioeconomic and demographic variables that were not used in defining the clusters and a table that indicates which variables are significantly different between clusters. For example, Table 8 can be read, "cluster 1's population in 2010 is significantly different from clusters 2, 3, 4, 5 and 6." Similarly, clusters 2-6 can be read that their 2010 population is significantly different from cluster 1.

Cluster	Population 2010	Population Density 2010	Net Migration per 100 (2000-2010)	Net Migration Rate; 60+ y/o	Net Migration Rate; 15-29 y/o
1	176703	297	10.7	11.6	6.5
2	23206	13	8.4	9.9	-9.4
3	19633	14	11.4	3.5	5.4
4	6658	5	0.7	3.9	-29.4
5	21822	17	5.8	9.2	-18.6
6	26480	8	10.3	4.3	-10.6
Cluster	Median Age	Pct. 4-year Degree07-11	Social Capital Index09	Pct. Creative Class07-11	
1	36.7	29.5	-0.14	24.9	
2	41.6	22.6	0.39	19.8	
3	41.7	37.1	1.53	28.5	
4	43.1	16.8	1.37	13.3	
5	40.2	18.6	0.33	17.3	
6	37.4	18.6	0.26	18.1	
Cluster	Pct. Protected Land2012	Natural Amenity Scale	Airport/Remoteness05	Urban Influence Code2003	GRP/Capita08
1	9.8	3.18	1.69	4.49	\$43,591
2	7.7	2.93	2.36	7.05	\$28,768
3	21.3	5.05	2.26	7.96	\$51,194
4	3.7	0.90	2.77	9.31	\$36,250
5	5.0	2.13	2.51	8.25	\$32,539
6	7.0	2.85	2.60	8.70	\$57,960
Cluster	Pct. Poverty08	Unemployment2008	Unemployment CV 2000-2012	ShannonWeaver Diversity Index08	
1	12.2	4.4	0.31	0.725	
2	14.7	5.7	0.28	0.701	
3	8.9	4.4	0.36	0.706	
4	14.8	3.9	0.21	0.682	
5	15.0	4.3	0.26	0.684	
6	9.9	3.1	0.32	0.699	

Cluster	Population2010	Population Density 2010	Net Migration per 100 (2000-2010)	Net Migration Rate; 60+ y/o	Net Migration Rate; 15-29 y/o
1	2, 3, 4, 5, 6	2, 3, 4, 5, 6	4	3, 4 (adj. p<.1)	4, 5
2	1	1	4		4
3	1	1	4	1 (adj. p<.1)	4, 5
4	1	1	1, 2, 3, 6	1 (adj. p<.1)	1, 2, 3
5	1	1	--		1, 3
6	1	1	4		--
Cluster	Median Age 2010	Pct. 4-year Degree07-11	Social Capital Index09	Pct. Creative Class07-11	
1	2, 3, 4	2, 3, 4, 5, 6	3, 4	2, 3, 4, 5, 6	
2	1	1, 3, 4	--	1, 3	
3	1	1, 2, 4, 5, 6	1	1, 2, 4, 5, 6	
4	1, 6	1, 2, 3	1, 5, 6	1, 3, 5, 6	
5	--	1, 3	4	1, 3, 4	
6	4	1, 3	4	1, 3, 4	
Cluster	Pct. Protected Land2012	Natural Amenity Scale	Airport/Remoteness05	Urban Influence Code2003	GRP/Capita08
1	3	3, 4	1, 2, 3, 4, 5, 6	2, 3, 4, 5, 6	2
2	3	3, 4	1	1, 4	1, 3, 6
3	1, 2, 4, 5	1, 2, 4, 5, 6	1	1	2, 5
4	3	1, 2, 3, 5, 6	1	1, 2	6
5	3	3, 4	1	1	3, 6
6	--	3, 4	1	1	2, 4, 5
Cluster	Pct. Poverty08	Unemployment2008	Unemployment CV 2000-2012	ShannonWeaver Diversity Index08	
1	--	2, 6	4, 5	--	
2	3, 6	1, 3, 4, 5, 6	3, 4	--	
3	2, 4, 5	2, 6	2, 4, 5	--	
4	3, 6	2	1, 2, 3, 6	--	
5	3, 6	2, 6	1, 3, 6	--	
6	4, 5	1, 2, 3, 5	4, 5	--	

Cluster 1—High-Tech, High-Service Cluster

This group of counties has a greater population, population density, lowest “remoteness” as measured by access to airports, and most urban counties, all characteristics of counties with major cities. Additionally, the migration rate of those between the ages of 15 and 29 in this group is higher than any other group—and this group is the only cluster other than the Retail, Hospitality and Tourism cluster that showed a positive 15-29 year old migration rate over the decade. This positive rate is significantly different from the Agriculture and Agriculture-plus counties. The High-Tech, High-Service counties also have the lowest median age of all counties, significantly lower than the Agriculture, Government (and Forestry), and Retail, Hospitality and Tourism clusters. Both the percent of the population that holds a 4-year degree and the share of employment in the “creative class” is significantly higher than all other county groups except for Retail, Hospitality and Tourism, but significantly lower than that group. Despite having a high share of college grads and creative class members, these counties have a lower social capital index than all other county groups, likely due to the large populations, and thus, low per capita social capital infrastructure. Finally, while the GRP per capita is higher than all county groups except Retail, Tourism and Hospitality, it is only significantly higher than the Government (and Forestry) group. Given all this, it might seem intuitive that these counties would be more economically diverse than the other county groups; however, the Shannon Weaver diversity index is not statistically different from all other county groups. While the index is higher than all other groups—indicating more diversity—this difference is not statistically significant.

Cluster 2—Government (and Forestry) Cluster

Counties in this cluster generally score somewhere between the High-Tech, High-Service counties and the counties in the Agriculture group. They are typically rural, but less rural than the

Agriculture group. The population and population density of these counties are significantly less than the population and population density of the High-Tech, High-Service counties, but still more than the Agriculture counties. These counties stood out in two variables—they had significantly higher unemployment throughout 2008 than any other group and they had significantly lower GRP per capita in 2008 than the High-Tech, High-Service; Retail, Hospitality and Tourism; and Mining groups.

Cluster 3—Retail, Hospitality and Tourism Cluster

The Retail, Hospitality and Tourism cluster is characterized by a high natural amenity scale score, a large percentage of protected land, a high percentage of 4-year degree holders and members of the creative class, and a relatively high GRP per capita. While these counties are rural, they are less rural than counties in the Agriculture, Agriculture-plus and Mining clusters, although not significantly so. The net migration rate of 15-29 year olds is higher only in the High-Tech, High-Service cluster, and is significantly greater than the rate in the Agriculture and Agriculture-plus categories. While the GRP per capita is the second highest of the six clusters, it is only significantly higher than the Government (and Forestry) and the Agriculture-plus clusters.

Cluster 4—Agriculture Cluster

Agricultural counties are the most remote, have the lowest population and population density, lowest net migration rate, and lowest natural amenity score of any county cluster. The rate of migration among the 15-29 year old age group was almost twice as low as any other cluster, with the Ag-plus cluster receiving the next-lowest marks. The rate of 4 year degrees holders in the Agriculture cluster is the lowest of any cluster, which is reflected in the clusters low creative class score. The cluster has high social capital, though, indicative of its stability. It also has the smallest percentage of protected land of any of the clusters. Its GRP sits in the middle of the pack, well lower

than the urban, tourism and mining counties but above the government and forestry and agriculture-plus counties. Agricultural counties, however, saw a lower unemployment rate than most county clusters and perhaps most interestingly, the most stable rates of any cluster between 2000 and 2012, perhaps indicating that this cluster was less affected by the recession than any other.

Cluster 5—Agriculture-Plus Cluster

As socioeconomic indicators go, Ag-plus counties' variables often fall logically between the Agriculture cluster and the other clusters. Net migration and 15-29 net migration is low, but not as low as the Agriculture cluster, the rate of 4-year degrees and the creative class is in a similar position. The 2008 poverty rate is the highest of any cluster, 0.2 points higher than the Agriculture cluster, which is the second-highest. Interestingly, 2008 GRP/capita is about \$4,000 less than Agriculture counties, but still \$4,000 above the Government/Forestry cluster. Ag-plus counties are remote, but not as remote as Agriculture or Mining counties. While Ag-plus ranks significantly higher on the natural amenity scale than the Agriculture cluster, it is lower than the other clusters and significantly lower than the RHT cluster.

Cluster 6—Mining Cluster

The Mining cluster is characterized by a low 2008 unemployment rate, the highest 2008 GRP/capita of any cluster, and remoteness. It is clear that these counties are generally experiencing economic success based upon extractive activity. While the 4-year degree rate and social capital index is relatively low in these counties, economic activity is generating wealth based on extractive uses. Stability, measured by the year to year variation in unemployment rates, is relatively low. Likely, this is due to the volatility of raw material markets, which dictate economic activity in these counties. Like RHT counties, these counties are wealthy but their economies are volatile. Unlike RHT

counties, the instability is caused by raw material markets, whereas the RHT counties likely fluctuate based on the success of the construction and services sectors, as well as payments to households.

Conclusions of ANOVA and Tukey's HSD

Of specific interest is the result that suggest the polarizing forces of the RHT and Agriculture clusters (clusters 3 and 4) suggested by not only the ANOVA and Tukey's HSD tests, but also the correlation coefficients. Although both are similarly remote and have low populations, RHT counties register significantly higher than all counties in the natural amenity scale while Agriculture counties register significantly lower. McGranahan (1999) and others suggest that this is a driving force for development of amenity migration, which draws a subset of mobile people into certain counties. This analysis supports this hypothesis and shows that net migration as well as net 15-29 year-old migration from 2000 to 2010 was significantly higher in RHT counties than Agriculture counties, which experienced a net migration per 100 people near zero and a negative net migration of young people. RHT was one of only two clusters to experience a positive net migration of 15-29 year-olds over the decade, the other being the High-Tech, High Service cluster (cluster 1).

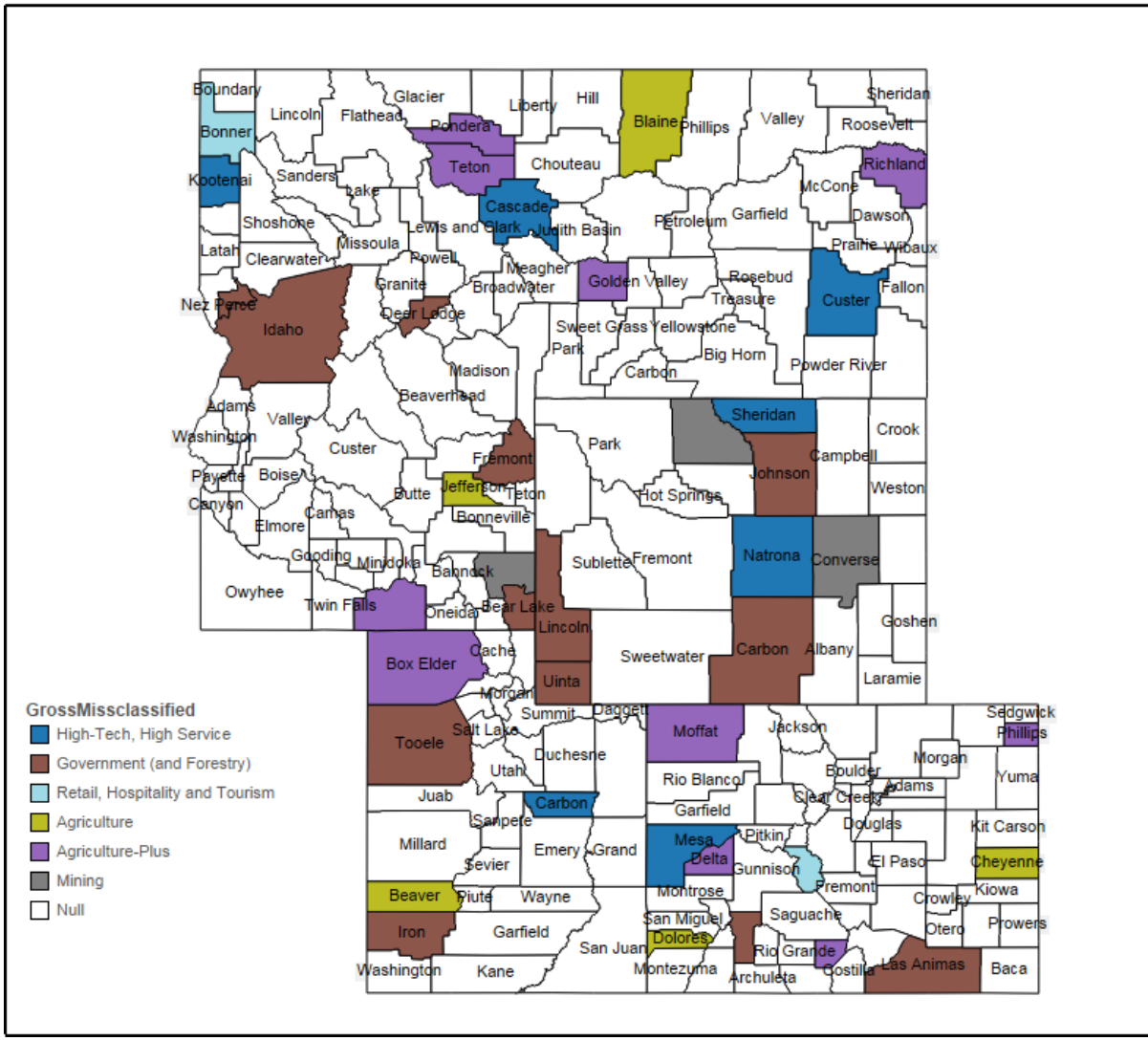
The RHT and Agriculture clusters are on opposite ends of the spectrum on other variables as well. The percent of people that hold a 4-year degree is highest in RHT counties and lowest in Agriculture. The same is true of the number of people employed in creative class occupations. The percent of land in a county that is protected is exponentially higher in the RHT cluster, reflecting the recognition by policy-makers that this source of natural capital is a major source of wealth creation in these counties. The GRP per capita is highest in the RHT cluster, while Agriculture's falls in the middle of the six clusters. Finally, in support of Deller (2010) and Reeder and Brown (2005), who find little evidence that recreation and tourism activities have a downward effect on the poverty rate,

this study finds that RHT counties actually have the lowest poverty rate of any cluster, while Agriculture and Ag-Plus counties have the two highest rates.

3.3 2008 Gross to Base Employment Comparisons Results

Map 3.2 indicates the counties that the analysis indicated were misclassified or potentially misclassified when the gross employment shares and base employment shares were compared. The map is colored with the gross employment classification.

**Map 3.2 Gross-Base Difference and Gross Misclassification
Rocky Mountain West
2008**



Two examples of misclassifications are Bonner County in Northern Idaho and Mesa County in Western Colorado. By using gross employment instead of base employment share, Bonner County was misclassified as a Retail, Hospitality and Tourism county. In 2008, however, Bonner County's Retail, Hospitality and Tourism sector had a 19 point spread between gross and base employment, with gross employment in that sector making up nearly 35 percent of total employment in the county. When considering the dependency score, however, that share was only 16 percent, indicating that using the gross employment share led to a substantial overrepresentation of the Retail, Hospitality and Tourism sector as an economic driver in Bonner County. Using base employment, Bonner County was classified as a High-Tech, High-Service county, due to its strong base contributions from High-Tech manufacturing and Other Services.

On the other hand, Mesa County, in far western Colorado was misclassified as a High-Tech, High-Service county while the base analysis placed it firmly in the group of Mining counties. The reason for the misclassification is that, when using gross instead of base employment, mining is nine points below its real economic impact in the county. In reality, mining drives over 14 percent of all employment in the county. Had gross employment been used, the importance of mining's activity would have been measured only by its direct employment, which was closer to 5 percent of total employment in Mesa County.

Not only do these two examples serve to show that a county's economic drivers may be misconstrued when looking only at gross employment, they also show that it is important to have a defensible definition of industry clusters that elucidate the differences between tourism activity and service activity that may or may not be related to tourism. If all of the services had been lumped together in this analysis, both of these counties' real economic drivers may have been misunderstood.

Table 3.6 shows the results of the comparison between the gross employment and base employment for counties that had a gross-base difference of more than two standard deviations from the average difference. In other words, for a given group, the table shows the counties that are the most misclassified by using gross employment over base employment. By using gross employment, these counties' economies are likely the most misrepresented. The shaded counties are instances where gross employment is significantly higher than the base and the unshaded counties are instances where the gross employment is significantly lower than the base. For example, Agriculture in Lewis County, Idaho contributed nine percentage points more in economic activity within the county than the gross employment measures indicate. Counties listed in bold type are listed more than once in the table.

The mean difference for each group is the region-wide average difference between the gross and base employment shares. The max standard deviations from the mean is the number of standard deviations away from the mean that the most different county—listed first—exhibited. Not surprisingly, the extraction-dependent sectors of Agriculture, Forestry and Mining were severely underrepresented as economic drivers when using gross employment in 39 different counties. Additionally, manufacturing, while still playing a relatively small role overall by either measure, was underrepresented when using gross employment. This underscores the reason that the USDA-ERS Typology uses a higher cut-off point to define service-dependent economies and a relatively lower employment and earnings cut-off to define these extractive clusters. However, using a base employment rather than gross employment as a measure on which to group counties should produce a more robust typology since it is grounded in economic theory and economy-wide clustering, not simply a cut-off for a specific economic sector.

Table 3.6 Counties >2 Standard Deviations from Mean Gross-Base Difference

	Ag	For	Mine	Gov	LT_Man	HT_Man	Ret_Hos_Tour	OthServ	Trans_Util	Con
Mean Gross-Base Difference	-1.77%	-0.31%	-1.98%	-0.31%	-0.56%	-0.81%	9.08%	7.76%	0.58%	-2.01%
SD of Difference	2.3%	0.7%	2.9%	1.6%	1.1%	1.7%	4.7%	4.6%	1.2%	2.0%
Max SD from Mean	4.1	5.9	5.5	4.1	10.7	7.2	2.8	2.8	5.6	4.2
Counties	Lewis, ID Gooding, ID Morgan, CO Minidoka, ID McCone, MT Garfield, MT Payette, ID Pondera, MT Chouteau, MT Cache, UT Washington, ID Yuma, CO	Clearwater, ID Boundary, ID Benewah, ID Bonner, ID Lincoln, MT Flathead, MT Mineral, MT Payette, ID Granite, MT Broadwater, MT Lewis, ID Sanders, MT Latah, ID RioGrande, CO Idaho, ID	Campbell, WY Sublette, WY Natrona, WY Uintah, UT Sweetwater, WY Richland, MT Duchesne, UT Mesa, CO Carbon, UT Yellowstone, MT Carbon, WY HotSprings, WY	Latah, ID ElPaso, CO Cascade, MT LewisandClark, MT Davis, UT Laramie, WY Petroleum, MT Mineral, CO Caribou, ID Lincoln, MT Carbon, WY Roosevelt, MT Costilla, CO	NezPerce, ID SaltLake, UT Cache, UT Weber, UT Gallatin, MT	Caribou, ID Ada, ID Boulder, CO Larimer, CO SilverBow, MT SaltLake, UT Weber, UT Cache, UT	Gilpin, CO Douglas, CO Boulder, CO Pitkin, CO Bonner, ID Lincoln, MT Yellowstone, MT	Mesa, CO SilverBow, MT Flathead, MT Butte, ID Mineral, CO Lincoln, MT Yellowstone, MT	Platte, WY Lewis, ID Dawson, MT Minidoka, ID Rosebud, MT Hill, MT Payette, ID NezPerce, ID Gooding, ID Caribou, ID	Routt, CO Teton, ID Blaine, ID Flathead, MT Kootenai, ID Gallatin, MT Mesa, CO Lincoln, WY Washington, UT

Listed largest SD to smallest
Indicates Gross > Base Emp
Bold indicates multiple listings

Table 3.7 shows the number of counties that are misclassified by using gross employment over base employment to cluster counties. A total of 32 counties, almost 15 percent, were misclassified when using gross employment. Of these, half were misclassified but close to being classified correctly (Case 2.1). Another 16 were completely misclassified by using gross employment instead of base employment to capture economic activity (Case 2.2). Finally, eight counties may or may not have been misclassified—the silhouette index for those counties was negative when clustered using base employment, making it possible that these counties were misclassified in the first place (1.1).

	Count	Percent	Case
Possibly Misclassified using Gross Employment	8	3.7%	1.1
Misclassified using Gross Employment	16	7.4%	2.1
	9	4.2%	2.2
	7	3.3%	2.3

3.4 2008 Base Share to 2012 Base Share Comparison Results

Many counties in the RMW experienced a significant structural economic shift throughout—and likely as a result of—the Great Recession. The dependency scores for the sectors hardest hit by the recession—construction and RHT—reflect the employment change experienced over the recession (see Figure 3.3).

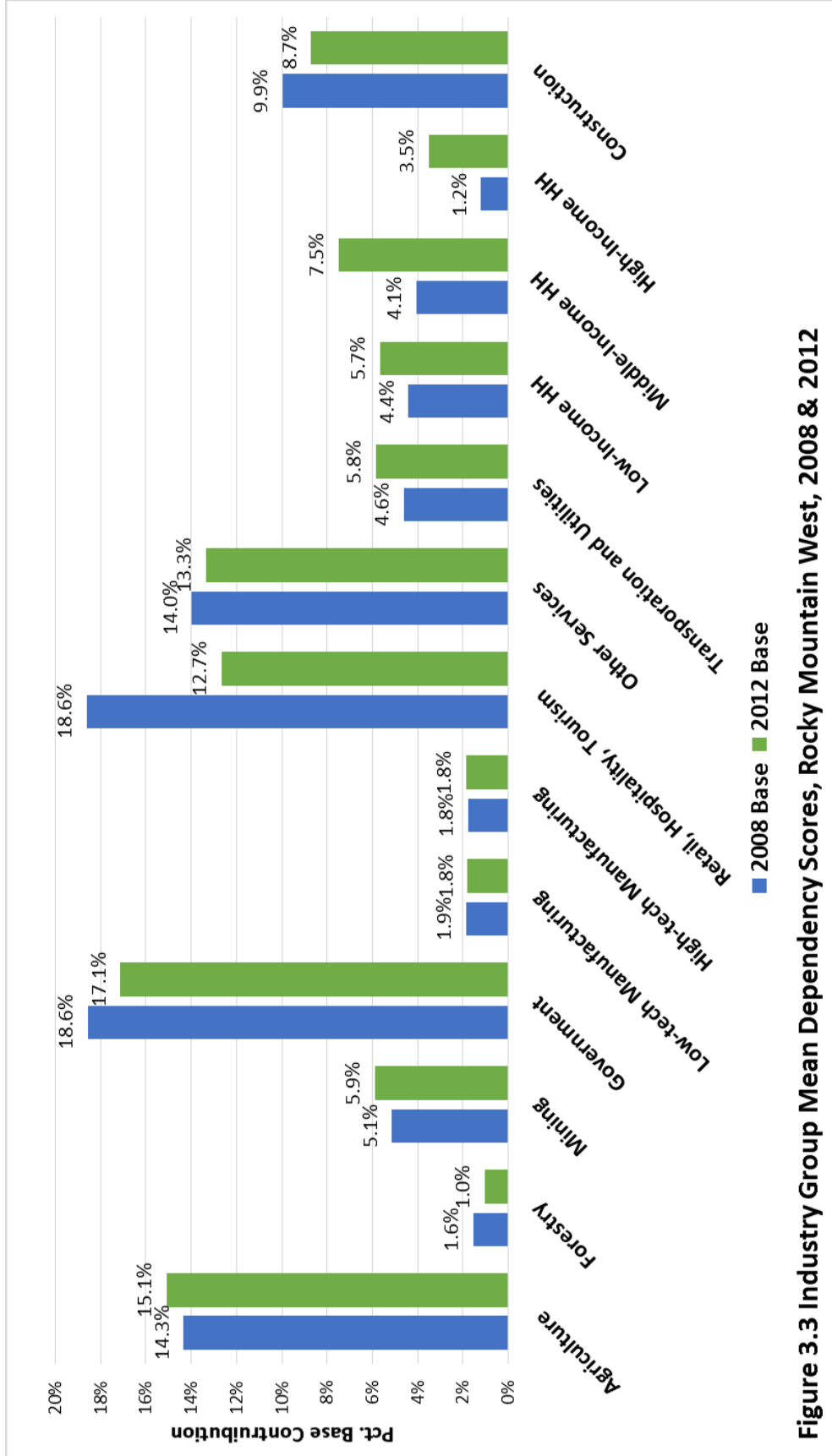


Figure 3.3 Industry Group Mean Dependency Scores, Rocky Mountain West, 2008 & 2012

RHT's base contribution decreased a full 6 points between 2008 and 2012, from 18.6 percent to 12.6 percent. Construction, the sector whose fallout as a result of the recession has been oft-discussed, decreased 1.2 points from 9.9 percent to 8.7 percent. Along with RHT and Construction, Government decreased by a point and a half. Other Services lost 0.6 points and Forestry half a point. The base share for Agriculture increased seven-tenths of a point and mining eight-tenths between 2008 and 2012, taking up some of the space that RHT, Government and Construction created. It was extra-regional transfers, however, that made up the lion's share of the difference lost in RHT, Construction, Government, Other Services and Forestry—a full 7 point increase for all income levels between 2008 and 2012.

Almost across the board, extra-regional payments to households made up a larger share of basic employment in 2012 than in 2008. This is curious, as it seems intuitive that a decrease in wealth would decrease the share of base contribution by transfer payments, especially from investment income and dividends. Falling importance of non-labor income was portended by Beyers and Nelson (2000) who questioned whether or not the rising importance of non-labor income was just as susceptible to a major shock as the mining industry was in the collapse of the early 1980s. However, these findings indicate that just the opposite has happened. Despite the enormous loss of collective wealth, most counties in the RMW in 2012 actually saw a higher share of basic employment contribution from households of all income levels. In other words, wages and proprietor income made up less of the basic share in 2012, the difference made up by payments to households. What's more, while the shares from all income levels increased in the Rocky Mountain West, the ratio of the basic contribution of low- to mid- and high- income transfer payments actually became less equal in 2012 than in 2008.

Two possible explanations exist for these phenomena. One explanation is that the recession's negative effect on employment was experienced more severely in various industries,

rather than in the decline in non-labor income. Second, increasing unemployment and stagnating wages through the recession increased unemployment benefits payments, social security, food stamps and Medicaid spending (Moffitt 2013). These payments flow to many households across the Rocky Mountain West. At the same time, mid- and high-income HH experienced larger increases. This could be due to one of several factors: a) increasing inter-county commuting may increase the payments to the commuting household—that is, more people not living where they work or b) investment income to mid- and/or high-income households has increased compared to industrial economic activity.

Table 3.8 shows the change from 2008 to 2012 by sector and outlier counties. The mean change is the average percentage point change within that sector. The counties listed under each sector were the sectors that experienced the most change from 2008 to 2012—at least two standard deviations from the average change. The counties in grey are counties that had a higher base share of that industry group in 2008 than in 2012. For example, in the mining sector, all counties but one that experienced a change of more than two standard deviations recorded positive growth in mining's base contribution from 2008 to 2012. Mining activity in Meagher County, Montana, however, declined by over 27 percentage points throughout that same period. The fact that on average, mining gained only less than a point over the four year period, but had several counties experience double-digit growth in the industry group's contribution to their economic bases, illustrates the geographic concentration of the mining boom and highlights the need for a more geographically fine-grained analysis of economic change in the Rocky Mountain West to truly understand that boom.

Table 3.8 Counties >2 Standard Deviations from Mean 2012-2008 Difference

	Ag	For	Mine	Gov	LT_Man	HT_Man	Ret_Hos_Tour	OthServ	Trans_Util	LowHH	MidHH	HighHH	Con
Mean	0.7%	-0.4%	0.8%	-1.5%	-0.1%	0.1%	-6.0%	-0.6%	1.2%	1.3%	3.4%	2.3%	-1.2%
SD	3.9%	1.5%	4.3%	4.4%	1.3%	1.7%	6.1%	5.6%	2.8%	2.1%	2.9%	1.9%	4.1%
Max SD from Mean	4.19	6.31	8.34	6.89	4.65	9.64	3.34	4.37	6.79	3.38	2.90	4.38	3.39
Countries	Kiowa, CO	Lewis, ID	Meagher, MT	Bent, CO	Pueblo, CO	Camas, ID	Garfield, UT	Rich, UT	Wheatland, MT	Park, MT	Camas, ID	Douglas, CO	Teton, ID
	Carter, MT	Cleanwater, ID	Musselshell, MT	Dolores, CO	NezPerce, ID	SilverBow, MT	Gem, ID	Bent, CO	Daggett, UT	Canyon, ID	Washington, UT	Huerfano, CO	Blaine, ID
	Cheyenne, CO	Lincoln, MT	Fallon, MT	Cheyenne, CO	Toole, UT	Liberty, MT	Dolores, CO	ClearCreek, CO	Plute, UT	Roosevelt, MT	Wibaux, MT	Teton, WY	Hinsdale, CO
	Wibaux, MT	Benewah, ID	Toole, MT	Wibaux, MT	BoxElder, UT	Broomfield, CO	Rich, UT	Wayne, UT	Treasure, MT	Wibaux, MT	Park, MT	Blaine, ID	Juab, UT
	Beaver, UT	Granite, MT	Converse, WY	Sheridan, MT	JudithBasin, MT	Washington, ID	Summit, UT	Piute, UT	Hinsdale, CO	Jefferson, CO	Canyon, ID	Pueblo, CO	Routt, CO
	Baca, CO	Payette, ID	Garfield, UT	Wheatland, MT	BoxElder, UT	Blaine, ID	Summit, UT	Saguache, CO		Petroleum, MT	Teton, WY	Camas, ID	SanJuan, CO
	Jerome, ID	Saguache, CO	Sweetwater, WY	Sedwick, CO	Lincoln, MT	Lincoln, MT	Weston, WY	Daniels, MT		Wasatch, UT	Fremont, CO		Pitkin, CO
	Washington, ID	Sanders, MT	SilverBow, MT	Niobrara, WY	Benewah, ID	Sweetwater, WY	Wasatch, UT	Costilla, CO		Huerfano, CO	Dolores, CO		Carbon, WY
	Costilla, CO	RioGrande, CO	Moffat, CO	Saguache, CO	Madison, ID		JudithBasin, MT	Daggett, UT		Pueblo, CO	Otero, CO		RioBlanco, CO
	Yuma, CO	Powell, MT	Stillwater, MT	Daggett, UT	Fergus, MT		Delta, CO	Payette, ID				Summit, UT	Mineral, CO
	PowderRiver, MT	Idaho, ID		Crowley, CO	Jefferson, ID			Carter, MT				ClearCreek, CO	Archuleta, CO
	Daniels, MT	Boundary, ID						Mineral, CO				Costilla, CO	Eagle, CO
								Juab, UT				Petroleum, MT	Fallon, MT
													Montezuma, CO
													PowderRiver, MT
													Wibaux, MT

Listed largest SD to smallest

Indicates 2008 > 2012 Base Emp

Bold indicates multiple listings

Despite the fact that the basic share of the RHT sector lost six points from 2008 to 2012, six of the ten counties with greater than two standard deviation's change in RHT saw their base share of that sector increase. After Garfield, Utah, which experienced a 21 point decline in RHT through the recession, the next largest changes were in counties that have seen increases in RHT, indicating that although the recession severely impacted this sector, some counties, including tourism powerhouses of Summit County, Colorado and Blaine County, Idaho, remained tethered to their core industries and did not see a decline in their RHT base shares.

This figure also highlights the counties that experienced the largest changes to extra-regional payments to households. Counties that experienced large changes in their low- and mid-income households tended to follow the same upward direction as that group's region-wide change. The reason for these changes might be increased commuting activity (very possible in Canyon County, Idaho), increased transfer payments such as welfare, food stamps or Medicaid, or simply a decrease in industrial activity in the county, leading to an increased share of household's contribution, even if the actual contribution didn't change at all. Interestingly, given the relatively large region-wide increase, the counties that experienced major changes to the base contribution of high-income households were split on the direction of the change. For example, Blaine, Teton and Summit Counties—counties that rely heavily on the capitalization of natural amenities—all had significantly higher high-income household contributions in 2008 than in 2012. Montezuma, Huerfano, Dolores and Fremont—all relatively agriculturally dependent—experienced higher high-income household contributions in 2012 than in 2008.

Across the 215 counties in the study, 59 of them, or over 27 percent changed enough to move from one cluster type to another (see Table 3.9). Another 9 counties moved clusters but had a negative silhouette to begin with, so their original cluster membership is somewhat in doubt.

	Count	Percent	Case
Possible Change in Cluster	9	4.2%	1.1
Change in Cluster	19	8.8%	2.1
	20	9.3%	2.2
	20	9.3%	2.3

Table 3.10 shows the descriptive statistics of the new 2012 clusters. Recall that the medoid, or central point, for each cluster is no longer a county but a point in 13-dimensional “space” that represents the original medoid values from the 2008 clusters adjusted for the region-wide change that occurred between 2008 and 2012. The resulting cluster changes are cases where the minimized total distance changed from the original 2008 medoid to a different 2012 medoid. With the exception of a few cases, the minimum and maximum average base shares in each sector occur in the same cluster in 2012 as they did in the 2008 clusters. This is to be expected, as the “space” has changed only in that it has been adjusted for region-wide change. Therefore, the changes that do exist represent the structural changes within each cluster from 2008 to 2012.

Cluster	Statistic	Ag	For	Mine	Gov	LT_Man	HT_Man	Ret_Hos_Tour	OthServ	Trans_Util	LowHH	MidHH	HighHH	Con
1	Mean	2.8%	0.4%	2.6%	14.1%	3.3%	3.7%	12.2%	28.9%	4.8%	6.1%	7.6%	4.2%	9.2%
	SD	2.1%	0.9%	3.8%	6.6%	4.9%	4.7%	6.9%	15.5%	3.1%	2.5%	3.2%	2.5%	5.3%
	Median	2.3%	0.1%	0.9%	13.5%	2.2%	1.3%	9.3%	24.2%	3.9%	5.6%	8.3%	3.6%	8.0%
	SD/Mean	0.76	2.07	1.47	0.47	1.49	1.25	0.57	0.54	0.66	0.41	0.42	0.59	0.57
	Count	26	Net Change		-17									
2	Mean	7.6%	2.7%	3.7%	23.1%	2.0%	1.8%	11.2%	11.4%	4.2%	7.2%	9.8%	4.5%	10.8%
	SD	4.5%	4.3%	3.7%	9.2%	2.8%	2.2%	5.7%	3.7%	2.8%	2.1%	3.0%	1.9%	4.3%
	Median	7.7%	0.4%	2.3%	19.7%	0.9%	1.1%	9.5%	10.1%	3.6%	6.7%	9.8%	3.9%	10.9%
	SD/Mean	0.59	1.57	0.98	0.40	1.37	1.21	0.51	0.33	0.66	0.29	0.31	0.42	0.40
	Count	49	Net Change		10									
3	Mean	1.8%	0.3%	3.0%	10.5%	0.9%	0.4%	48.0%	11.5%	1.3%	3.7%	4.7%	2.9%	11.0%
	SD	1.6%	0.5%	4.0%	2.6%	1.2%	0.6%	12.4%	4.6%	1.0%	1.2%	1.8%	1.0%	5.4%
	Median	1.2%	0.1%	1.4%	10.6%	0.4%	0.1%	45.9%	12.1%	1.1%	4.0%	4.7%	2.8%	11.1%
	SD/Mean	0.90	1.46	1.34	0.25	1.30	1.65	0.26	0.40	0.72	0.32	0.38	0.35	0.49
	Count	14	Net Change		-13									
4	Mean	37.4%	0.6%	2.0%	14.9%	0.9%	1.0%	7.3%	10.7%	6.6%	4.7%	6.0%	2.6%	5.2%
	SD	7.9%	1.2%	2.3%	6.1%	1.5%	1.7%	3.3%	7.5%	4.6%	1.8%	2.6%	1.5%	3.0%
	Median	36.1%	0.2%	1.3%	13.9%	0.3%	0.2%	6.6%	8.0%	5.8%	4.4%	5.8%	2.3%	5.1%
	SD/Mean	0.21	1.81	1.18	0.41	1.56	1.76	0.45	0.70	0.70	0.37	0.44	0.59	0.57
	Count	44	Net Change		9									
5	Mean	16.7%	1.0%	2.2%	17.6%	2.1%	2.1%	11.5%	12.8%	7.5%	6.1%	8.5%	3.8%	8.3%
	SD	5.7%	2.5%	2.3%	6.1%	2.9%	3.6%	7.3%	4.9%	5.3%	2.0%	2.3%	1.8%	3.9%
	Median	16.0%	0.3%	1.5%	17.7%	1.0%	0.7%	8.9%	11.4%	5.2%	5.9%	8.6%	3.4%	8.0%
	SD/Mean	0.34	2.65	1.03	0.35	1.35	1.75	0.64	0.38	0.70	0.32	0.28	0.46	0.47
	Count	47	Net Change		-4									
6	Mean	9.2%	0.4%	22.4%	15.8%	1.4%	2.0%	9.4%	9.3%	7.5%	4.7%	5.7%	2.7%	9.4%
	SD	5.3%	1.0%	9.6%	4.8%	1.3%	5.3%	4.1%	3.6%	3.5%	1.9%	2.8%	1.6%	2.9%
	Median	8.2%	0.1%	21.3%	15.4%	0.9%	0.5%	8.1%	9.4%	7.0%	4.4%	5.5%	2.6%	9.7%
	SD/Mean	0.58	2.21	0.43	0.30	0.95	2.73	0.44	0.39	0.46	0.41	0.50	0.58	0.31
	Count	35	Net Change		15									

Figure 3.4 shows the change between cluster means in 2008 and in 2012 for each sector. Looking at these changes yields some interesting conclusions. Despite the fact that it gained just under a point region-wide from 2008 to 2012, every cluster but two saw a decrease in the Agricultural sector's base share. Mining saw the greatest increase, likely due to the fact that many Agriculture-Plus counties moved into the Mining cluster, bumping up the agriculture score. The Agriculture cluster saw a slight increase as well, while the remaining clusters experienced large declines in the base share of the agriculture sector. Interestingly, the Ag-Plus cluster saw the largest decline in the agriculture base share. This is likely due to many counties shifting from Ag-Plus to the Mining cluster, leaving an Ag-Plus cluster with less of the "Ag" and more of the "Plus" than in 2008. The forestry sector lost its base share in all clusters, but it lost the most, ironically, in the Government (and Forestry) cluster. The mining cluster complements the story told by the agriculture sector. Strangely, despite an eight-tenths point increase in mining's base share across

the region, it lost ground in every cluster except Agriculture, where there was no change. This indicates that the Mining cluster was diluted by the incoming Ag-Plus counties, who saw an increase in their mining share that was enough to bump them into the Mining cluster but significantly less than the high base share of mining that already existed in that cluster. Additionally, gains in the base share of mining must have been spread across the different county clusters, not concentrated in any one particular cluster. As might be expected due to the 1.5 point decline in government's base share region-wide, the base share of Government in every cluster but Mining declined. In this case, as in the case of the Forestry sector, the Government (and Forestry) cluster experienced the most decline. Given the number of counties that moved into this cluster from the High-Tech, High-Service, RHT and Ag-Plus clusters it is likely that here, again, is a case of counties moving because of a loss in the base share of a sector that defined them in another cluster and a smaller, less significant, gain—or no gain at all—in the Government or Forestry sectors. These same counties could explain the increase in both low- and high-tech manufacturing. Another explanation for this might be the growing base share of manufacturing in the original Government (and Forestry) cluster.

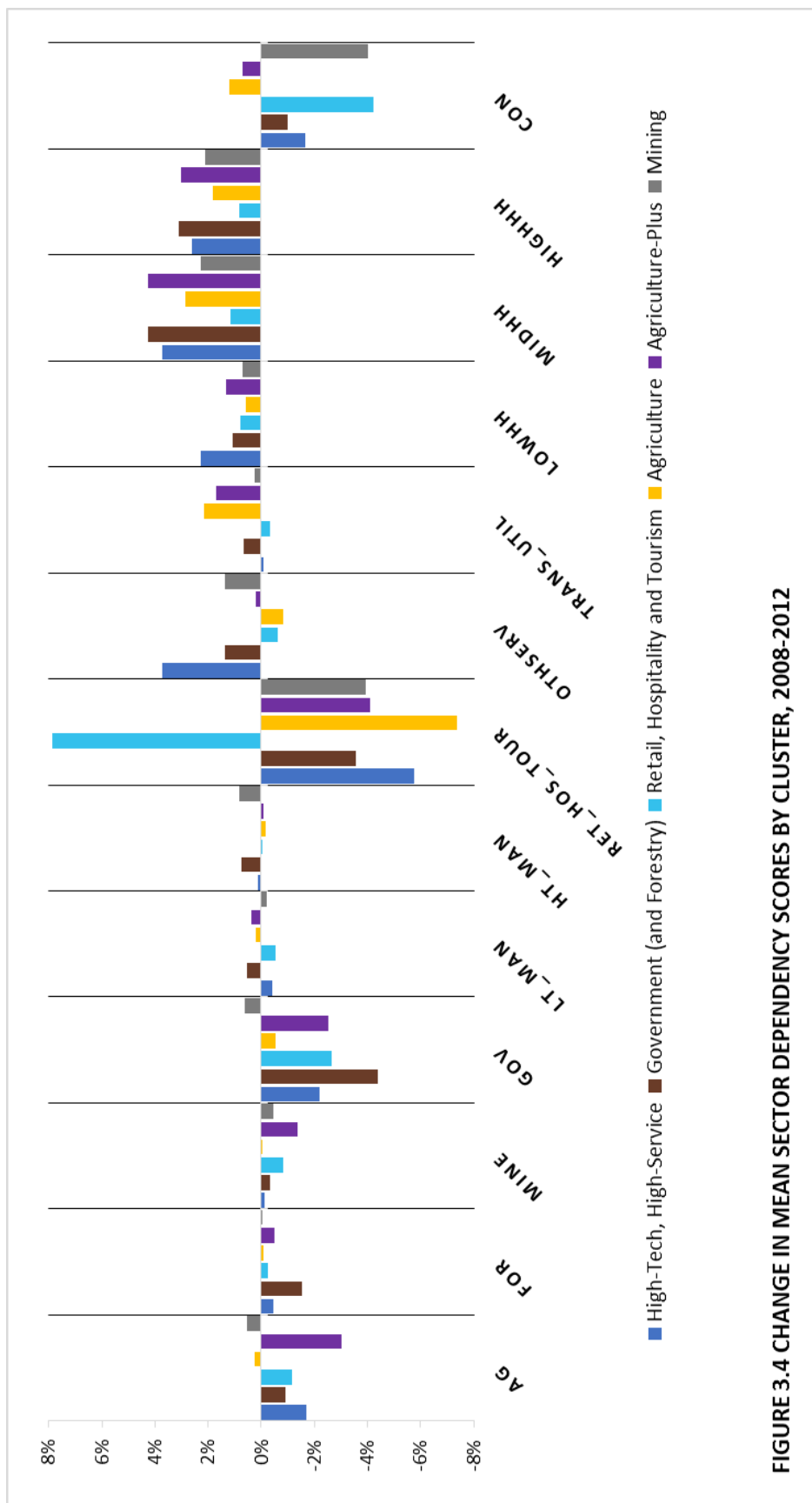
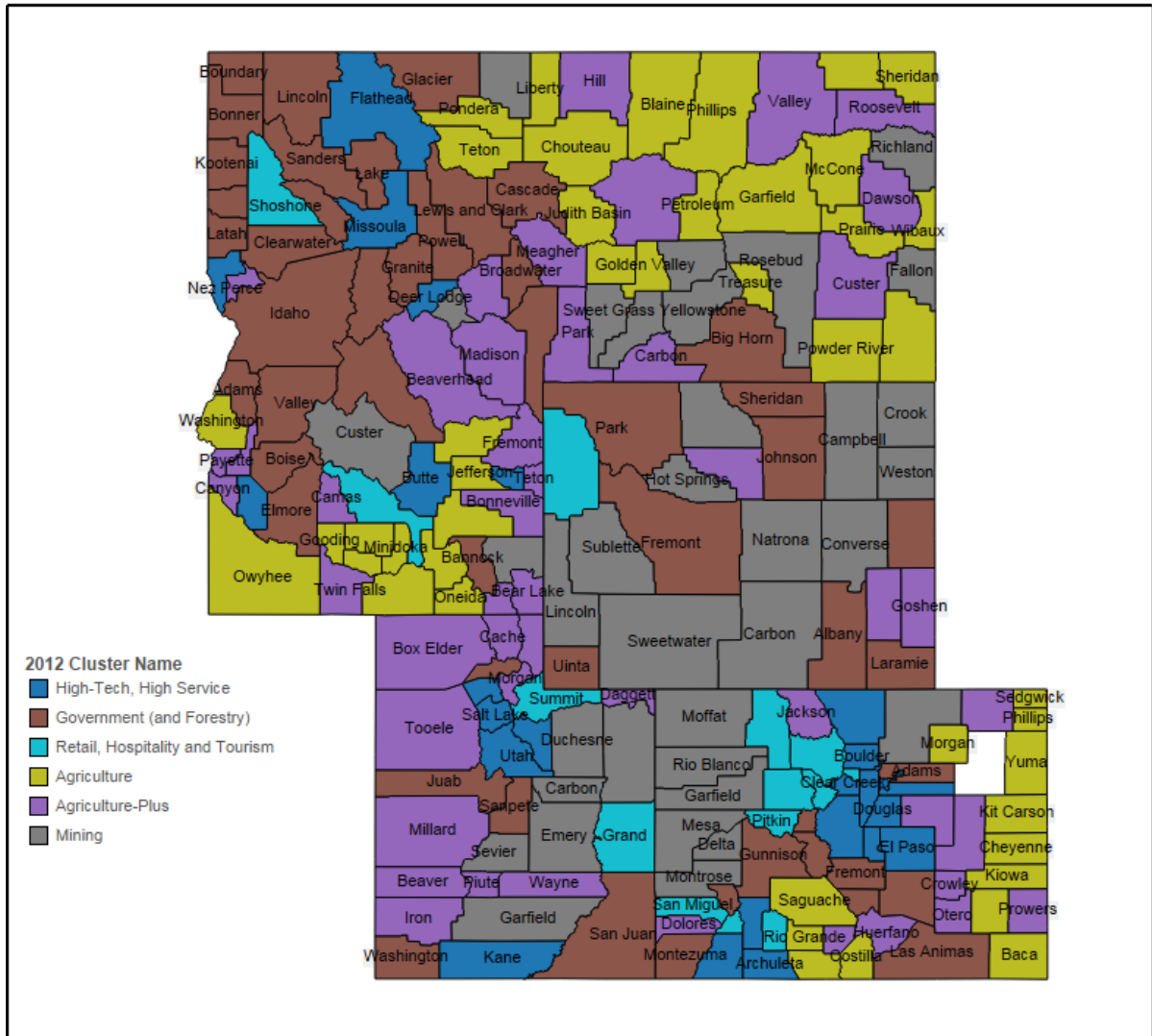


FIGURE 3.4 CHANGE IN MEAN SECTOR DEPENDENCY SCORES BY CLUSTER, 2008-2012

Map 3.3 shows the 2012 clusters and Map 3.4 shows the counties that changed cluster membership between 2008 and 2012. The color of the county represents the new 2012 classification for both maps. It is interesting to compare Map 1 and Map 4 to see the old and new clusters for the counties that changed. In all, 68 counties moved from one cluster to another.

**Map 3.3 Base Employment Classification
Rocky Mountain West
2012**



**Map 3.4 Base Employment Share and Cluster Classification Change
Rocky Mountain West
2008-2012**

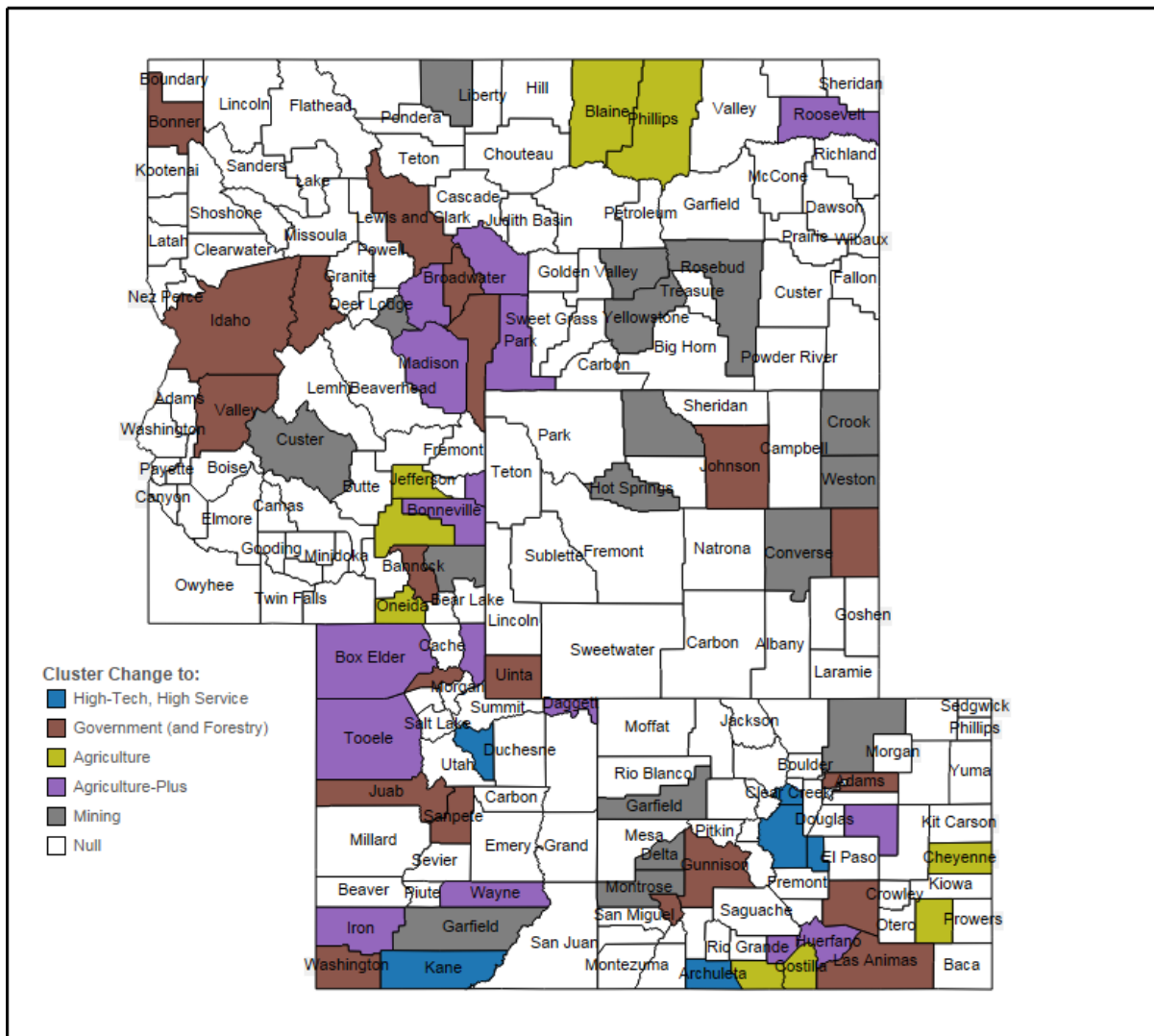
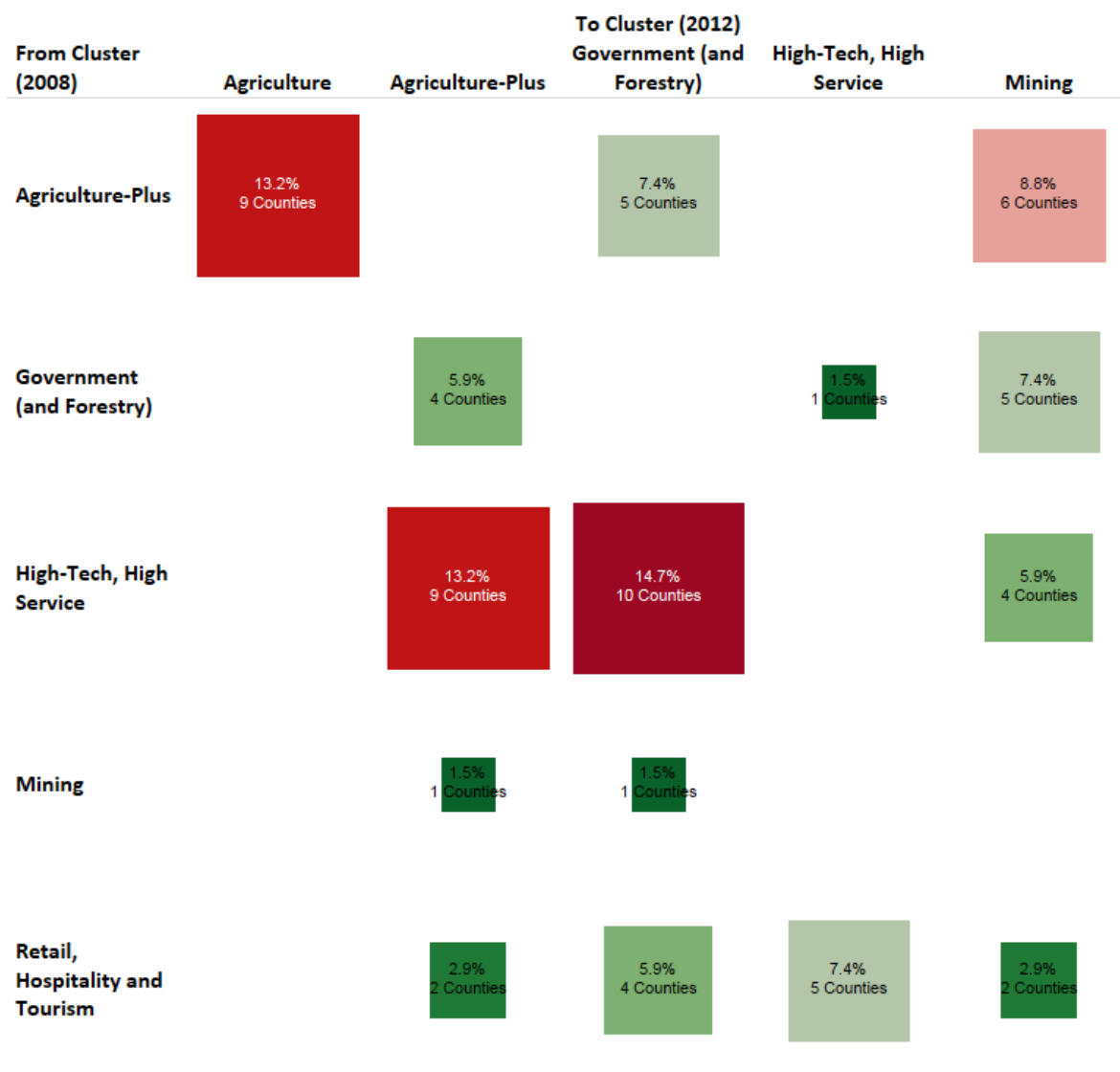


Figure 3.5 shows the movement of counties between clusters. Each row represents a cluster where counties have moved from and the columns represent the cluster that those counties have moved into. The three clusters with the counties that experienced the most structural economic change from 2008 to 2012 were the High-Tech, High-Service cluster, with 23 counties that changed cluster membership, the Ag-Plus cluster, with 20 counties that changed, and RHT counties, with 13 counties that changed.

Figure 3.5 Cluster Movement 2008-2012



The movement of counties through the recession can be summarized by a common progression ending, by various economic transitions, in a net gain for the Agriculture, Government (and Forestry) and Mining clusters. In general, Agriculture gained from the Ag-Plus cluster, Ag-Plus and Government (and Forestry) gained from the High-Tech, High-Service cluster, and Mining gained from a variety of counties that had at least some base share in mining before the recession.

It is surprising that RHT counties lost fewer than both the High-Tech, High-Service and Ag-Plus clusters, as it would make intuitive sense that the RHT cluster—the cluster whose primary drivers, RHT and construction, lost by far the most base share across the RMW through the recession—would be the cluster most affected by the changes to those sectors. In fact, those counties left in the RHT cluster in 2012 actually brought the average base score of the RHT sector *up*, suggesting that they were not affected negatively at all by the region-wide decline in the RHT sector, or, at the least, that other sectors lost more basic employment than the RHT sector in those counties of the recession. A comparison of the means of only the RHT cluster counties that remained in 2012 shows that the base share of RHT employment actually increased by a point from 2008 to 2012. Construction in these counties lost 4 points. The RHT counties that did move, however, saw their base share of RHT sector decline by a full ten points. Most of the RHT counties that did change clusters moved into either the High-Tech, High-Service cluster or the Government (and Forestry) cluster.

Another finding of interest is that, while few counties moved to the Agriculture cluster, the counties that did were exclusively Ag-Plus counties. This is most likely a product of these counties “Plus” component shifting during the recession, thus causing the county to become more “Ag”-like, which is discussed above. Over half the cases where Ag-Plus counties moved, though, the “Plus” component of the economy changed enough in one direction or another to shift the county into the Mining cluster or Government (and Forestry) cluster. This also might help explain why Government (and Forestry) counties lost base shares of both government and forestry, because the low share of those sectors in some of the Ag-Plus may have diluted the pre-recession average concentration.

Nine of the 16 counties that changed to Ag-Plus were High-Tech, High-Service counties. This is a reflection of a significant base decline in the RHT sector and to a lesser extent, other services in those counties. Not a single Agriculture county moved into another cluster, reflecting the stability of

that sector noted by many western scholars (Baden, 1997, Martson 1989, Winkler et al 2007, etc.). Additionally, only two mining counties moved away from mining and into another cluster, reflecting the increasing price of West Texas Crude Oil from 2008 to 2012. By the end of 2008, oil prices had sunk to near \$40/barrel from a high of over \$130/barrel in 2007. The price increased through 2012 at the same time as the housing market was in a free-fall. Thus, the general movement of non-agricultural counties towards mining is not surprising.

What all this shows is that the west has not bucked its boom and bust trend but has rather added another economic sector that is equally volatile to the mix in construction and RHT, elements of what some researchers call the “New West”. Martson (1989, 67) explained that “although no one planned it that way, ranching and irrigated agriculture were to be the steady part of the economy. Laid over this base was to be the unsteady part: the mining ... the drilling for oil and gas, and the construction of dams and coal-fired powerplants.” Martson’s commentary on the stability of the agricultural sector still rings true, however, the sector laid over the stable base changed. Like extractive activities, these new sources of growth tied to recreation and tourism still overlay the stability of an agricultural base that just keeps on keeping on. The exception are those counties that have capitalized on RHT to such an extent that, despite the gutting of the very sectors they were built upon, they maintain and even increase their specialization in those sectors. Further research should be conducted to see whether the wealth of these counties was impacted disproportionately to the rest of the west.

3.5 Policy Implications and Conclusions

This study introduces a typology that is useful for analyzing the primary sources of economic activity for 215 counties in the Rocky Mountain West. It improves upon earlier typologies by focusing on the base, rather than gross, employment, which provides a more accurate assessment

of economic activity. This analysis is helpful for policy makers in that it pinpoints competitive advantages among counties. While most economists and planners know that retail, hospitality, tourism and other services do not typically make up a region's economic base—and can often intuitively tell when they do—questions usually remain as to how much or how little a certain sector actually contributes. The method used in this study answers that question.

While an Automated Social Accounting Matrix (ASAM) developed by Braak et al. (2011) was used in this study, IMPLAN data will soon be available with built-in economic base measures, eliminating the need to manipulate IMPLAN data manually using a SAM. This will ease the calculation of base shares and make this type of analysis more feasible for economic development professionals.

This study introduced an industrial typology that broadly captures the sources of growth in western communities. It then used base shares of employment to pinpoint the sources of growth for each county. Then, a PAM algorithm that minimizes the difference of a suite of variables within groups of similar counties was applied to the county-level data. This algorithm was used to determine the misclassifications that might have arisen had gross rather than base employment been used to measure the sources of economic activity. Finally, these clusters were used to measure the change in base share between 2008 and 2012, immediately prior to—in most western economies—and somewhat after the Great Recession.

For the 2008 clusters, an ANOVA and Tukey's Honest Significance Difference tests was applied to tease out differences in socioeconomic variables between groups. The results from this analysis, as well as the correlation matrix used on the clustering variables, suggests that that the Agriculture and RHT clusters are generally the most polarizing across the RMW. In the correlation matrix, the RHT and Agriculture sectors displayed a negative correlation, in some cases relatively

strong, to every other industry group except two. For Agriculture, these two were payments to Low-Income Households and Transportation and Utilities, which have little to no correlation to agriculture. For RHT, they are payments to High-Income Households, which has little correlation to RHT, and Construction, which has a weak positive correlation to RHT. Not only do the base shares of sectors in these two clusters frequently repel each other, but the socioeconomic variables are also extremely polarized.

For both ANOVA and the post-hoc Tukey's HSD test, the assumption that each observation is independent must be made. While this study is not the first to assume this when comparing attributes across geography (Beyers and Nelson 2000, etc.), it must be noted that there is significant evidence (Booth 1999, Marcouiller et al. 2004, Partridge et al. 2008) that spatial autocorrelation does exist across geography. This study suggests spatial autocorrelation in the uneven nature of economic development based upon different competitive advantages held by each region. This is obvious when thinking about variables like the natural amenity index—some regions are simply more appealing than others, leading to potentially uneven growth patterns. While this spatial autocorrelation does not invalidate the findings of the ANOVA and Tukey's HSD, further research should be done to assess the influence that spatial autocorrelation plays in economic development and competitive advantage.

One thing that is not clear from this research is the extent to which the structural change impacted the well-being of people who live in the Rocky Mountain West. For example, individual county-level data of some RHT counties show that population growth completely reversed during the recession, moving from a strongly positive growth rate before the recession to a negative rate during the recession. Further research needs to address the impacts of these types of changes on communities. Additionally, what factors increase resiliency to these types of shocks. In this analysis, the most diverse, most "advanced" economies were the ones that experienced changes that forced

them out of their High-Tech, High-Service cluster. Critics of extractive industries often point to the boom-bust economic cycle that causes so much instability in counties that are reliant on these industries. This research has shown, however, that diversified high-service counties are not immune from booms and busts that afflicted frontier towns in the old west. This study has shown that the economic structure of these “new west” counties changed fundamentally over the course of the recession, not unlike changes that have been experienced by extraction-dependent counties during commodity booms and busts. Does this transition have the same negative impacts that boom-bust cycles had on extraction dependent communities? On the opposite side of the same coin, the most specialized counties did not lose any base share of the very sector, RHT, that was impacted the most through the recession. Despite the fact that their economic structure was largely unaffected, did they experience a net loss of economic activity, whether measured in lost jobs, GRP or wages, as the regional averages suggest?

Several questions arise from the increase in extra-regional payments to households across the RMW. Why did the Rocky Mountain West experience such an increase in these payments as a share of the economic base? Was it primarily commuting income, income supplement payments, investment income, retirement income or something else? How might the aging population and the retirement of baby boomers affect the share of payments? Regarding extra-regional transfers, it is important to identify whether the changes in the base share of certain sectors over time are due to the growth in that particular sector or the decline in other sectors.

Perhaps the biggest challenge moving forward is to identify the drivers responsible for the change in cluster membership by some counties. Why do some counties experience economic change while others do not? This research lays the groundwork for answering that question. It identifies counties that experienced real shifts in their economic bases. Further research should look at specific changes and identify the similarities and differences among counties that changed in

a certain way, using key concepts from the literature review presented earlier in this paper. As noted throughout the research, there are significant geographic differences across the RMW that have led to the development of economies that are specifically suited to certain geographies. Just as a biotic ecosystem is dependent upon abiotic factors, a regional economy is defined by geographic opportunities and limitations. Therefore, any further research in this area should be conducted with an eye towards spatial constraints and autocorrelations.

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