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Putting Sector Strategies to the Test:

Industry Clusters and Employment Outcomes in Washington State

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Abstract

This paper undertakes a comparative analysis of earnings and employment growth in clustered and non-clustered industries in Washington State for the years 2003 through 2009. Further investigation compares cluster effects on different regional levels within counties and Workforce Development Areas. Location Quotients (LQs) were the principal measure of assessing the agglomeration of industry clusters. To evaluate the relationships between LQ and wage and employment growth, four regression models were used. Results indicate that private firms within an industry cluster have a significantly lower employment growth rate, on average, than firms not in a cluster. It is noteworthy that the research detects no significant relationship between wage growth and whether firms are located in an industry cluster.

Executive Summary

As a result of the Workforce Development Act of 1998, which required states to align workforce and economic development strategies, the Washington Workforce Development Board employs industry clusters as one of twelve of its guiding principles. Washington's focus on industry clusters represents just one case in a growing movement to support industry clusters as a means to promote economic growth and employment outcomes both in the United States and internationally.

Focusing on industry clusters comes on the heels of theoretical works by Harvard economist Michael Porter and others that postulate a causal relationship between industry clusters and increased productivity. In the theory, increased productivity due to the spill-over effects of clusters will lead to higher output, employments growth, and wage growth. This theory remains contested, and this report offers an empirical examination of its tenets.

This study employed several fixed-effects regression models to test the relationship between industry clusters and employment outcomes, using data between 2003 and 2007. The models employed a limited definition of industry clusters, only using the readily available data for location quotients (a measure of the spatial concentration of industries). The first set of models looked at the relationship between industry clusters and employment and wage growth, defining clusters annually; while the second set (lagged models) look at the same relationships, defining clusters at a fixed point in time -- 2003. The results of both models cast doubt on popular theory.

The annual model found a significant positive relationship between employment growth and industry clusters, with employment growth 3 percent higher in clustered industries. However, it found no significant relationship between industry clusters and wage growth. Meanwhile, the lagged model also found no significant relationship between industry clusters and wage growth, but found a significant negative relationship between employment growth and industry clusters with clustered industries experience approximately a 3.9 percent lower employment growth rate. In the regression on raw employment numbers, clustered industries have an average employment that is approximately 558 employees higher than non-clustered. Using an industry fixed effects model, the results also indicate that the average real wage in clusters is approximately $4,435 higher than the average real wage in non-clustered industries.

Theoretically and empirically, a higher employment growth rate in annual model is unsurprising as spatially concentrated industries will default have more jobs. The negative employment growth rate in the second model may show some variation in the ability of clusters at different stages in their life-cycles to create jobs: newer clusters grow faster than older clusters. The real employment numbers show that overall clustered industries have more jobs, which is consistent with theory, but the results provide reasons for caution in assuming that promoting industry clusters will lead to job creation.

The lack of significant relationship between industry clusters and wage growth in both models provides reason to doubt the ability of industry clusters create high-wage jobs. It is important to note that the data used in this analysis runs through the recent recession, and while the models attempted to account for this factor, it may have influenced the model. The model also did not take into consideration the labor market conditions in Washington. A high supply of workers in key urban environments may depress wages in clustered regions.

This research raises many questions about the impact of industry clusters on employment outcomes in Washington, and lays the ground work for future studies using more robust statistical definitions of industry clusters.

Introduction

The Washington State Workforce Training and Education Coordinating Board (Workforce Board) contracted with the University of Oregon Master of Public Administration (MPA) capstone program to evaluate the Board's current strategy of supporting industry clusters as a way to promote robust economic activity within the State of Washington. The board oversees workforce development in the state; and its partner agencies, the Department of Commerce and the Economic Development Commission, oversee economic development. This capstone project evaluates the impact of the industry cluster strategy by asking whether employment and earnings have grown more quickly within clustered industries than within non-clustered industries in Washington State during the past decade.

Industry cluster strategies, like the one employed by the Workforce Board, rest on the idea that regions achieve a competitive advantage by specializing in the production of specific goods and services and preparing workers for jobs in those specialized industries. Although there are associated benefits of utilizing a cluster strategy, the merits of clustering remain disputed in both theoretical and empirical terms. This report uses quantitative data analysis to address the client's questions about the efficacy of clusters in promoting employment growth and higher wages. The two questions that guide the research are the following; 1) Is there a relationship between industry clusters and employment growth? and 2) Is there a relationship between industry clusters and earnings growth within those industries in each Workforce Development Area (WDA) and statewide?

This report proceeds to discuss the theory that underlies industry clusters while paying close attention to areas of debate. Subsequently, the report presents a myriad of industry cluster definitions along with a discussion of the varying empirical approaches to identifying clusters. The report then outlines the methods used in addressing the aforementioned research questions, highlights the findings from statistical analyses, and concludes with limitations and guidance for further research.

Industry Cluster Theory

Washington's strategy represents just one case in a growing movement to support industry clusters as a means to promote economic growth and employment both in the United

States and internationally. Clustering became popular in part as a result of the work of Michael Porter whose theories, along with those of his counterparts, hold that agglomeration may allow firms to benefit from various forms of market and non-market spillovers which, in turn, are thought to raise local endogenous innovation and productivity growth (Porter, 1990; Martin & Sunley, 1998; Krugman, 1997; Scott, 1998).

Porter's research grew out of a century's worth of work on the benefits of agglomeration and localization economies which Marshall initiated in the late nineteenth century (1890). Numerous authors have investigated the significance of clusters and localization economies. Steiner (1998) outlined the characteristics that he saw in common among all cluster theories. First, the theories assert that clusters are based on specialization resulting from a strong division of labor within the economy. Moreover, the result of this specialization leads to interdependence and cooperation among industrial actors which can take the form of inter-industry transactions between firms, knowledge exchanges between individuals and institutions, or linkages between public and semi-public institutions (Best, 1990). These linkages can be based on either formal contracts or social, cultural, and political ties. Second, specialization and interdependence are partly based on proximity in both economic and social space (Martin & Sunley, 1996; Oakey, Kipling & Wildgust, 2001). Proximity in economic space entails firms producing similar goods or services. Proximity in social space entails firms sharing similar cultural, political, and normative traits.

This combination of specialization and proximity may result in synergies that increase regional competitiveness, which, in turn, could lead to higher productivity, stabilization, and wealth creation for both the firm and the region (Martin & Sunley, 2003). Even within the context of a global economy, geographic space continues to be important to the success of industries. Lublinski (2003) and Saxenian (1996) talk about a location paradox in which economic activity still tends to be spatially concentrated even though improved information technologies and changes in the economy have made the transmission of financial capital, knowledge, and certain goods and services relatively unconstrained by geography.

Porter, however, remains the most well known theorist of clusters. Writing almost a century after Marshall, he argued that clusters consist of a geographic concentration of competitive firms in related industries that have a competitive advantage because they share certain components (Porter, 1997). Using success in international markets as an indicator of national competitiveness, Porter delineated four components of his concept of clusters that affect firm competitiveness and regional wealth. First, attitudes toward competition, the degree of local competition, attitudes toward market institutions, and other socio-historic factors affect firm competitiveness. Second, the basic resource endowments available within a geographic area affect firm competitiveness. Examples of endowment characteristics include the quantity, quality, and cost of human capital, information, and technological resources. Third, the nature of local and extra-local demand for domestic and foreign goods for industry or household consumption. Finally, the presence of related and supporting industries where competition among local intermediate suppliers resulted in lower prices affects firm competitiveness.

Porter illustrated his theory graphically with a "competitive diamond" (see Appendix A), which captures the driving forces of cluster development and positions clusters as the spatial manifestation of the diamond. The systemic nature of the diamond produces local concentration of the leading rival firms that magnify and intensify the interactions among multiple factors. Hence, according to Porter (1990, p. 157), "the process of clustering, and the intense interchange among industries in the cluster, also work best where the industries involved are geographically concentrated."

Porter's work has gained traction among policy makers because it focuses on the determinants of competitiveness for firms, localities, regions, and nations, and provides guidance on how to achieve specified policy outcomes. Porter's avowed aim is to inform companies, cities, regions, and nations how to compete on the world stage (Martin & Sunley, 2003). The lure of his cluster concept is that it sits well with the current preoccupation with microeconomic supply-side intervention-- and especially with the policy imperatives of raising productivity and innovation (Porter, 1996). For entities such as the Washington Workforce Board that promote higher wages and job creation, Porter's theory offers a readily adoptable strategy to increase productivity, and, in turn, to promote wage and job growth.

Additional authors have sought to hone Porter's theory, not directly questioning the underlying idea, but building on it as it applies to different regions and clusters. Two particular areas in this literature stand out as important for our analysis of industry clusters in Washington-- industry life cycles and applicability across geographic locations. Many authors have sought to explain why clustering does not produce the same benefits for all firms. Audretsch and Feldman (1996) use empirical research on clusters throughout the United States to examine the lifecycle of industries and explain the disparities in benefits. They argue that the generation of new economic knowledge tends to result in a greater propensity for innovative activity for a cluster during the early stages of the industry life cycle. However, Audretsch and Feldman (1996) further assert that innovative activity tends to be more highly dispersed during the mature and declining stages of the life cycle-- particularly after controlling the extent to which the location of production is geographically concentrated. Still others have questioned the application of an industry cluster policy to rural areas. Barkley and Henry (2002) found that clusters in rural areas can lead to positive outcomes but argued that creating the supporting institutions for industry clusters in such areas remains difficult. These two topics are relevant to this research since Washington's industry clusters are both old and new and rural and urban.

Industry Clusters and Employment Outcomes

Employment outcomes emerge from several attributes of clusters-- predominately higher productivity. Firms in clusters can lower production costs and obtain access to specialized goods and services more readily than other firms (Martin & Sunley, 2003). Alternatively stated, output is likely higher for a given dollar amount of input; that is, establishments are more productive. Higher productivity encourages additional firms to locate in the cluster or existing plants to expand, thereby increasing employment in the area and creating more competition for labor which, in turn, leads to higher wages (Gibbs & Bernat, 1997).

Other changes induced by the growth of industry clusters also have an impact on the local workforce. As employment density increases, the division of labor and specialization increases (Martin & Sunley, 2003). Jobs require more advanced or specialized knowledge and may become more task-specific. Skill levels, in turn, increase among the local workforce as more specialized workers become more proficient at their tasks. Workers also seek and secure jobs that match their particular specialized skills and abilities. This higher skill level and matching of skills should lead to higher average wages (Gibbs & Bernat, 1997). Scholars have studied the link between industry clusters and human capital creation. Florida (2002) points to the formation of a creative class within industry clusters while others (Glaeser, 2005; Donegan, Drucker, Goldstein, Lowe, and Malizia, 2008) suggest that rather than just creative class differences, traditional indicators of human capital (e.g., higher education levels and on-the-job training) within clusters are better explanations for productivity increases and regional growth.

Ease of information sharing in clusters also adds to higher productivity, and hence, greater employment outcomes. Sharing high-value information among workers and entrepreneurs makes good job-skill matches easier because workers are more aware of employment options and new skills; techniques then transfer among skilled workers at higher rates (Barley & Henry, 2002). Glaser and Mare (1994) illustrate that a faster rate of human capital growth in areas of concentrated economic activity is the key factor to explaining higher labor productivity and higher wages in clusters.

So-called spillover effects realize other productivity gains. Several positive externalities including knowledge spillovers, a ready local supply of non-traded inputs, a skilled local labor pool, and great levels of entrepreneurship have been associated with several positive externalities associated with clusters (Barkley, 2001). Spillover effects are also associated with higher innovation performance, product innovation, and patent production (Iammarino & McCann, 2006; Gilbert, McDougall, & Audretsch, 2007). Spillover effects are often considered a determining factor when drawing the boundaries of a particular industry cluster (Porter, 2000).

The Industry Cluster Debate

Numerous observers discuss the various shortcomings of cluster strategies. Barkley and Henry (2002) "acknowledge the benefits associated with developed industry clusters; however, question whether this is a realistic industrialization strategy for many regions," (p. 2). That is, one region's successful practices in developing a cluster may be ineffective in another region with a different economic structure (Boschma, 2004). Stroper (1997) further notes that the promotion of industry clusters for certain regions will prove unproductive and costly because some regions are unable to attract relevant investments.

Barkley and Henry (2002) offer three reasons that many regions struggle to establish industry clusters. First, regions will have difficulties in "picking winners," that is, identifying clusters and firms that best fit their local economies. Many researchers are skeptical of the capacity of public officials to identify regional competitive advantage, select "good" industries and firms to target, or design programs to assist specific sectors (Barkley & Henry, 2002; Greene et al., 2007). Furthermore, "growth prospects change over time in response to market forces, and individual firms within an industry may exhibit employment and sales trends counter to that of the industry as a whole" (Barkley & Henry, 2002, p. 7).

Second, latecomers may not be competitive (Barkley & Henry, 2002) or, as implied by Camagni (2002), regions simply do not compete equally. Established clusters have a distinct competitive advantage over late imitators. They further assert that new clusters will only compete with existing industry concentrations if the starting positions are not too unequal, workers and firms can relocate rapidly, and localization economies are realized early. Without these certain conditions, the only way firms will be able to compete is by receiving significant public expenditures (Barkley & Henry, 2002). However, because industrial cluster development is sometimes accompanied by increases in local land rents, wages, congestion, and utility costs, new firms may eventually relocate away from the region (Audretsch & Feldman, 1996; Kuah, 2002; Kukalis, 2010).

Third, as mentioned above, supportive institutions are not easily established. Barkley and Henry (2002) note that communities have difficulty finding financial and political support to develop the institutional environment required to support the establishment and growth of industry clusters. Furthermore, many economists are not optimistic that appropriate institutional arrangements will emerge because cooperative behavior is limited by incomplete information, opportunistic behavior, and committed assets (Barkley & Henry, 2002). These researchers conclude that a consensus for promoting economic development occurs only when the total gains are expected to be very large, when the distribution of the benefits and costs is quite clear, and when the community can agree on helping those who might be harmed (Barkley & Henry, 2002).

Other researchers' criticisms regarding industry clusters are broader. Bristow (2005) argues that the concept of competitiveness is too narrow in its description of ways that firms lead regions in global competition and in securing prosperity for residents. The focus on regional competitiveness ignores the effects that national and global forces exert on regions, and it overlooks other means of achieving regional prosperity such as the cultivation of inter-regional networks and the development of enterprises serving local markets or social causes (Bristow, 2005). Finally, much of the work in the field of competitiveness downplays the non-tradable aspects of regional development including regional institutions largely because of measurement difficulties (Bristow, 2005).

Motoyama (2008) raises the notion of regional specialization as an additional limitation of cluster theory. He asserts that although Porter strongly discourages competition by doing the same thing, quite a few disagreements exist about whether the specialization of clusters is good for the region over the long term or good at all (Motoyama, 2008). In line with this assertion, Martin and Sunley (2003) propose that there is little evidence to suggest that regions based on specialization consistently have a higher rate of innovation and economic growth. Cortright and Mayer (2004) further note that the boom-and-bust cycles of many high-tech sectors are often based on specialization which often brings about a multitude of risks. Scott and Stroper (2003) suggest that new kinds of policy interventions based on the concept of regional economies as aggregates of physical and relational assets need to be better identified and refined. This gap exists because cluster development-enhancing synergies are subject to two main problems (Scott & Stroper, 2003). First, the supporting conditions for maximizing such positive externalities tend to be undersupplied due to the strong temptation for potential producers to free ride on other producers' investments in the regional resource pool. Second, even in the vital center of a regional economy functioning on the basis of untraded interdependencies, significant moral hazards can generate severe negative externalities if left on their own, such as the emergence of low-trust relations between manufacturers and subcontractors. Overall, numerous shortcomings are inherent with a cluster strategy; therefore, with respect to the advisability of adopting a clustering strategy, it is best to compare the associated costs and benefits.

Definitions and Classifications of Industry Clusters

Given the complexity of industry clusters as theory and policy, writers have proposed several definitions and classifications of industry clusters resulting in what Martin and Sunley (2003, p. 10) call "conceptual and empirical confusion." Industry cluster definitions have variously contained elements such as input-output or buyer-supplier linkages, geographic location, shared relationships with business and intermediary suppliers, and co-operative competitions (Feser & Bergman, 2000). Although Porter's definition is probably the most frequently referenced, several other authors, in accordance with their research methods, have constructed the following definitions (see Figure 1) based on their approach to identify industry clusters.

Figure 1: Definitions of Clusters

Author(s)	Definition
Porter, 1998, p. 197	"A cluster is a geographically proximate group of interconnected companies and related institutions in a specific market, linked by interdependencies in providing a related set of products and/or services."
Bergman, & Feser, 1999	An industry cluster "may be defined very generally as a group of business enterprises and non-business organizations for which membership within the group is an important element of each member firm's individual competitiveness."
Group of 26 academics, practitioners and policy analysts, cited in Rosenfeld, 1996, p. 7	"A geographically bounded concentration of interdependent businesses with active channels for business transactions, dialogue, and communications, and that collectively shares common opportunities and threats."
Rosenfeld, 1997, p. 4	"A 'cluster' is very simply used to represent concentrations of firms that are able to produce synergy because of their geographic proximity and interdependence, even though their scale of employment may not be pronounced or prominent."
Cortright, 2006	"A cluster consists of firms and related economic actors and institutions that draw productive advantage from their mutual proximity and connections."
Roelandt and den Hertag, 1999, p. 9	"Clusters can be characterized as networks of producers of strongly interdependent firms (including specialized suppliers) linked to each other in a value-adding production chain."
Swann and Prevezer, 1996, p. 139	"Clusters are here defined as groups of firms within one industry based in one geographical area."

The various methods that individuals have used to identify clusters, including location quotients, input-output analysis, factor analysis, case studies, and indexes of agglomeration such as Gini coefficients give rise to multiple definitions that can be classified as either top-down or bottom-up analyses. Top-down analyses tend to utilize quantitative and statistical data through a deductive approach while bottom-up analyses utilize qualitative data such as case studies in an inductive approach that more narrowly focuses on industries (Cortright, 2006). Thus top-down approaches use location quotients, location Gini coefficients, input-output data, and data on employment, wages, and patents; whereas, bottom-up approaches use genealogies, surveys, interviews, and case studies.

Each method has strengths and weaknesses for identifying clusters. For instance, "location quotients and Gini coefficients measure the concentration of a single industry, but an important feature of clustering is that they are frequently composed of firms in different industries linked by buyer-supplier connections" which is where input-output models are useful (Cortright, 2006,). However, the current input-output models are limited since they are often constructed on the national level and may miss local dynamics. It seems that both of these measures do not fully capture the extent of shared knowledge among firms in clusters; thus, the use of a single identification method may not fully capture an industry cluster. Instead, the use of multiple methods that combine quantitative and qualitative approaches could be beneficial.

Clusters that do not fit neatly within political or industrial boundaries complicate the definition of industry clusters (Martin & Sunley, 2003). City, regional, and national levels identify industry clusters. Similarly, political boundaries do not limit clusters and can span multiple cities, states, and nations. Individual industries, since clusters involve firms from multiple industries, do not easily identify industry clusters. For example, Feser and Bergman (2000) identified "35 primary industries and 23 secondary industries" in the vehicle manufacturing cluster. Similarly, Cortright (2006) noted that industry clusters are not easily identifiable by North American Industry Classification System (NAICS) codes since clusters are not always contained within a single industry classification.

The various linkages between firms and industries have complicated the capacity to define industry clusters. Martin and Sunley (2003) note that the linkages of firms "are both vertical (buying and selling chains), and horizontal (complementary products and services, the use of similar specialized inputs, technologies or institutions, and other linkages)." Similarly, Doeringer and Terka (1996) conceptualized clusters in terms of production channels that are "the chains of suppliers, manufacturers, and distributors that begin with basic inputs and end with the marketing of the final product."

To assist with identifying industry clusters, scholars have created taxonomies of clusters. These classifications have included dimensions of industry or business life cycle, competition or cooperation, size, and geographic scope. Enright (2000) identified five characterizations of clusters-- working clusters, latent clusters, potential clusters, policy driven clusters, and "wishful thinking" clusters. Martin and Sunley (2003) note, however, that these classification schemes have been criticized for "incorporating almost all firms in clusters of one type or another; and as such, become virtually meaningless." Overall, there is "no agreed method for identifying and mapping clusters, either in terms of the key variables that are measured or the procedures by which the geographical boundaries of clusters are determined." Bergman and Feser (1999) also state the following:

> "In application, defining an industry cluster can become exceptionally difficult, particularly as competing policy objectives come into play. On the one hand, both space and time are relevant dimensions, such that the basic characteristics of the policy-relevant cluster vary widely between applications. On the other hand, data and methodological constraints may partially dictate cluster definitions. The latter is not necessarily a limitation if recognized explicitly by the analyst and policy conclusions are determined accordingly. However, if clusters are defined one way and measured another, resulting policy conclusions will clearly be tenuous," (Chapter 2.2, no page number).

Simply put, definitions and classifications of industry clusters can have immense policy implications.

Empirical Approaches

Economic development scholars have offered several methodologies to identify industry clusters. These methodologies include Porter's regional approach, Feser's Benchmark Value Chain approach, and the Washington State Workforce Board approach. Specifically, these methods target incentives to support traded (export-oriented) industries (Porter, 1990), the use of the cluster methodology for regional analysis (Smith, 2003), and input-output models with location quotients for cluster measurement (Feser, 2005). The Washington State Workforce Board approach also requires using input-output models to define linkages in addition to using detailed industry data to define regional specialties and developing maps of industry clusters that are integral to analyzing clusters. The aforementioned hierarchical cluster analyses approaches are based on industry-by-occupation data and calculate proportions of total employment by occupations in each industry by using a dendrogram to indicate cluster membership (U.S. Department of Energy, 2005).

Sector Strategies

Washington is one of twelve states to adopt a sector-based strategy for purposes of workforce and economic development (Accelerating State Adoption of Sector Strategies, 2008). The state has significant experience implementing sector strategies that embody many approaches of which a cluster-based approach is a particular type (Workforce Board, 2008). Sector strategies begin with the notion that many sectors are crucial to the state's economic well being and that a number of sectors, not just the largest, requires attention from government. Moreover, instead of focusing on a single firm, a sector strategy involves government working with industry leaders to help an entire sector become competitive (Bowles, 2002).

Sector strategies require a deep understanding of the many challenges facing firms within a sector which means assigning staff to work continuously with a number of key players within a sector including business associations and other firm owners or executives (Accelerating State Adoption of Sector Strategies, 2008). Understanding the common problems and opportunities of firms in a given sector, governments can develop policies that address industry-wide obstacles to growth (Bowles, 2002). Governments can work closely with industry sectors to address challenges and prevent firm dislocation or closure.

Sector approaches do not necessarily mean that the state is picking winners. It means that the state or region is giving attention to important industries that have typically been overlooked by economic development officials (Bowles, 2002). Both state and regional workforce development agencies share the responsibility for supporting sectors. Sector approaches might entail helping industry leaders develop effective workforce training programs in conjunction with community colleges, offering financial incentives that encourage developers to create cluster buildings that benefit a number of firms in the same sector, or providing seed grants to help companies within a sector create a strong industry association (Bowles, 2002). The main rationale behind a sector approach is that these efforts will be driven by industry needs, and programs will be designed with the cooperation of people within and outside the industry.

Washington State Cluster Strategy

One of the driving factors behind Washington's cluster strategy was the Workforce Investment Act (WIA) of 1998, which was enacted to "consolidate, coordinate, and improve employment, training, literacy, and vocational rehabilitation programs" (Workforce Board, 1998). WIA required states to coordinate workforce investment and economic development policies. The State of Washington, in collaboration with economic and workforce alliances, has targeted industry cluster analysis as a primary method for economic and workforce development (Senate, 2009). Eight guiding principles form Washington's cluster approach. Primary concepts include evidence-based quantitative data methods that guide cluster identification, collaborative partnerships that use common source data and indexing, and a regional emphasis on strategic clusters (Workforce Board, 2010).

The Workforce Board coordinates seventeen programs administered by seven agencies aimed at promoting a high skill and high wage economy. The Workforce Board advises the legislature on state and local level cluster-based approaches (Senate, 2009). The state legislature and the Workforce Board, in accordance with the report *High Skills, High Wages 2008-2018,* develops a comprehensive plan to guide workforce development. The board submits an annual progress report to the state legislature in December. At the local level, Washington has twelve Workforce Development Councils (WDCs) that provide employment services and outreach and are responsible for developing specific plans tailored to regional demands.

In 2009, the Washington Legislature approved Substitute House Bill 1323 that establishes industry clusters "as the central organizing framework for economic development planning and service delivery among workforce and economic entities" (Senate, 2009). A 2011 Progress Report on SHB 1323 notes significant movement forward in coordinating partner agencies, businesses, and labor to advance cluster strategies. Additionally, as organizations begin compiling local and regional level economic data, much more is known about clusters as organizations. For example, the Washington Economic Development Commission was able to identify emerging innovation clusters that have the potential to attain the regional concentration associated with a cluster, and the commission is examining them for further development. Efforts have also been underway to identify and define other industry clusters.

Washington identifies clusters using quantitative analysis of economic and labor market data (Sommers, Beyers, & Wenzl, 2008). The Workforce Board uses location quotients and eleven other variables to identify strategic industry clusters. Sommers, Beyers, & Wenzl (2008) note that employment and the percent of middle and high-wage jobs most widely determine the strategic importance of clusters within the twelve Workforce Development Areas (WDAs). The resulting analysis details clusters as having a high concentration of employment compared to national employment averages in the same industry. Using sales and purchases, outputs, and earnings data, inter-industry ties can be found suggesting a level of competitive advantage leading to targetable strategic clusters (Sommers, Beyers, & Wenzl, 2008).

Washington continues to develop its cluster strategies through several pieces of legislation. SHB 1323, bills such as HB 1395, and Companion Senate Bill 5048 have clarified workforce and economic development terms to better coordinate cluster efforts across various agencies. Statute RCW 43.330.090(5) defines an industry cluster as "a geographic concentration of interconnected companies in a single industry, related businesses in other industries, including suppliers and customers, and associated institutions, including government and education" (Senate, 2010).

Methodology

Data Sources

To answer the research questions, the research team used the Quarterly Census of Employment and Wages (QCEW) for Washington State from the Bureau of Labor Statistics. The QCEW data provides employment and wage information identifiable by two to six-digit NAICS codes for national, state, county, and metropolitan statistical areas. This research specifically uses data on the county level at the four-digit level of aggregation. The data is available for years 1990 to 2010Q2, but this project uses only the private sector data from 2003 to 2009. However, data are not available for some small areas due to disclosure restrictions. In the dataset, wages represent the total compensation during the year and include such items as paid leave, stock options and contributions to 401(k), or other compensation plans. Other variables included are the number of establishments, average monthly employment, taxable wage, average weekly wage, and contributions.

The QCEW data was supplemented with demographic data from Census Bureau's American Community Survey and Washington Office of Financial Management. This includes data on population, race, gender, and per capita income which are included in the models as controls.

Data Limitations

Analyzing only seven years of data is one of the limitations since affects of the industry cluster generated may not be completely covered during this time period. Also, data in this time period are not available for some small areas due to disclosure restrictions. Thus, the QCEW data has a significant amount of missing observations which creates an insufficiency for the data analysis.

Individual level data was obtained by the capstone group for the state collected by the Washington State Employment Security Department. The wage records are identified by four-digit NAICS codes at the county level available for years 2003 to present. Compared to the QCEW dataset, the individual-level records provide the opportunity to measure changes in wages and earnings within industries while holding fixed the composition of workers in those industries. Similarly, this dataset allows for an analysis of the experiences of specific workers in clustered and non-clustered industries. However, due to transaction delay and some administrative obstacles, the group could not get access to that data resource before the print of this paper. Further analysis is ongoing.

Methodology and Hypotheses

This research bases its findings on quantitative research methods because this permits a flexible and iterative approach. This study uses a county fixed effects regression analysis to examine the relationship between industry clusters and employment and earnings growth. This method helps answer the principal research questions of whether there is a relationship between industry clusters and growth of employment and earnings within those industries at the county level. Furthermore, the following specific hypotheses to be tested are:

Hypothesis 1: Industries that are clustered (e.g. greater concentration of employment) experience higher annual employment growth than industries that are not clustered.

Hypothesis 2: Industries that are clustered (e.g. greater concentration of employment) experience higher annual wage growth than industries that are not clustered.

To test these hypotheses, two models are necessary. One model regresses annual employment log growth rates on the independent variables and the other regresses annual real wage log growth rates on the independent variables using 2003 as the index year. Additional models also regress the levels of employment and wage numbers on the explanatory variables.

$$(\text{Annual Employment Growth})_{it} = \beta 1(\text{Cluster})_{it} + \beta 2(\text{wage growth})_{it} + \beta 3(\text{percent white})_{it} + \beta 4(\text{percent male})_{it} + \beta 5(\text{population growth})_{it} + \beta 6(\text{per capita income})_{it} + \alpha_{it} + \varepsilon_{it}$$

$$(\text{Real Annual Earnings Growth})_{it} = \beta 1(\text{Cluster})_{it} + \beta 2(\text{percent white})_{it} + \beta 3(\text{percent male})_{it} + \beta 4(\text{population growth})_{it} + \beta 5(\text{per capita income})_{it} + \alpha_{it} + \varepsilon_{it}$$

where α_{it} embodies the county fixed effects for industry *i* at time period *t*.

The key independent variable is a binary variable which is coded as a 1 if the firm/industry is in a cluster in 2003 and 0 otherwise. To identify whether or not the industry is a cluster, one must compute location quotients (LQ) for each industry sector. Location quotients are a measure of an industry's concentration in a locale relative to the nation or state. Use of the LQ assumes uniform local consumption patterns and labor productivity across the nation or state (Munnich, 1999). The calculation results in a ratio (e.g., a LQ greater than one suggests that the supply of goods or services is greater than the local demand). Particularly, analysts are able to see the employment concentration of a clustered industry relative to the employment concentration of non-clustered industry by using the LQ. The LQ allows analysts to distinguish between non-basic industries, those solely dependent on local conditions, basic industries, and those influenced by non-local conditions (Klosterman, 1990).

Results

To identify clusters for this part of the analysis, the research team calculated location quotients for each industry in 2003, and used them as benchmarks to identify whether these industries are clusters in 2004 to 2009. For example, an industry in 2003 that has a location quotient greater than 1.00 is identified as a cluster and the cluster variable is marked as 1 for years 2003 to 2009; otherwise, the cluster variable was noted as 0. The cluster variable was also calculated yearly allowing the industries to be defined as a cluster in later years. However, identifying clusters yearly allows for the possibility of reverse causation as high employment growth in one year could make it more likely that the industry is a cluster the following year. The regression results for this second method are listed in Appendices F and G.

As previously noted, location quotients provide a good starting point since they capture key aspects of industry clusters, specifically the labor force concentration in an industry. However, location quotients are limited in their ability to define clusters, thus, it will be important to build upon the analysis to develop a more robust model. The Workforce Board can build upon these models using input-output data along with qualitative studies to better define clusters. This expansion specifically includes adding additional variables to capture the other aspects of clusters such as business and social relationships of firms in different industries.

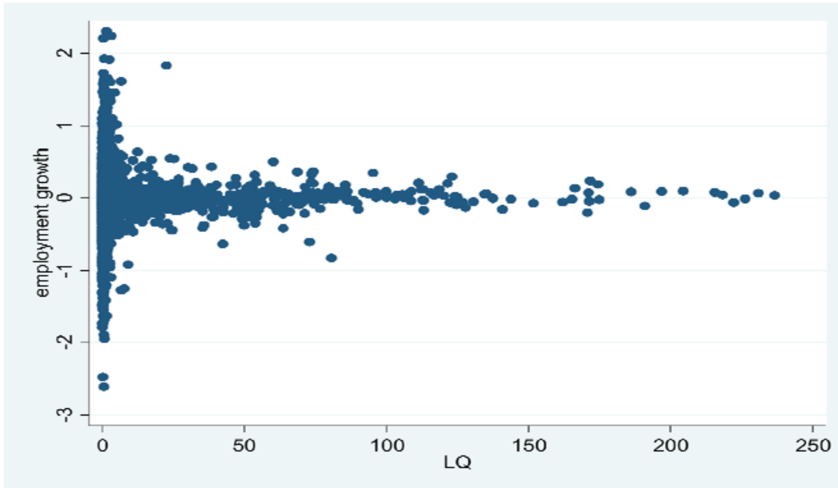
As previously mentioned, the analysis is conducted using the four-digit NAICS codes for private sectors in Washington State. Results for similar analyses were conducted using the more aggregated three-digit NAICS codes which are listed in the Appendices D and E. Similarly, the analyses and results for wage growth and employment growth were conducted separately for each workforce development area (WDA) and are listed in Appendices B and C.

Figure 2: Wage and Employment for Washington State

Year	Average Real Annual Wage (2003 dollars)	Average Real Wage Growth	Total State Private Employment	Average Employment Growth per Industry
2003	$38,673	-	2,157,934	-
2004	$38,338	-0.87%	2,196,183	1.77%
2005	$38,637	0.78%	2,264,776	3.12%
2006	$39,375	1.91%	2,345,531	3.57%
2007	$39,788	1.05%	2,416,994	3.05%
2008	$39,455	-0.84%	2,429,793	0.53%
2009	$39,811	0.90%	2,311,366	-4.87%

Figure 2 lists the average values of annual real wage growth, employment growth, and total private employment for the state. Additional descriptive statistics are listed in Appendices I and J. Figure 3 depicts the scatter plot of annual employment growth and location quotient, which shows neither an increasing nor decreasing trend. The graph also shows that the majority of industries have location quotients between 0 and 1. Similarly, the scatter plot depicting the relationship between annual average real wage growth and location growth shows a similar pattern.

Figure 3: Location Quotient and Annual Average Employment Growth



Finally, to help obtain an understanding of the relationship between clusters and annual employment and wage growth, the research team conducted a sets of pooled and fixed effects regressions. The first set of models regress annual real wage growth on the dummy cluster variable and various control variables; whereas, the second model regresses annual employment growth on the same variables. The models include a pooled ordinary least squares, county fixed effects, county and time fixed effects, and county and industry fixed effects. The model with the time fixed effects are not included as it they did not significantly change the coefficients. Additionally, for each model, the research team regressed the raw numbers of wages and employment on the cluster dummy variable and covariates to offer a different perspective of the relationships. For all of the models, robust standard errors are used to control for the presence of heteroscedasticity. The control variables include percent of the population that is white, percentage male, population growth, and per capita income. These variables are included since they are variables that theoretically affect employment growth and wage growth. Figure 4 lists the results for the wage growth models and Figure 5 list the results for the employment growth models logged annually.

Figure 4: Wage Growth Models (4-digit NAICS)

VARIABLES	(1) Pooled OLS	(2) County FE	(3) County FE w/ Industry FE	(4) Real Wage (in 2009 dollars)	(5) Real Wage w/ Industry FE
Cluster	-0.00289	-0.00260	-0.00189	-810.9***	4,435***
	(0.00192)	(0.00198)	(0.00247)	(289.9)	(209.0)
Percent white	-0.00593	2.804***	2.777***	78,288	53,375
	(0.0269)	(0.621)	(0.615)	(83,192)	(48,244)
Percent male	0.182	-33.07***	-32.24***	-798,722	-888,138
	(0.156)	(9.964)	(9.894)	(1.127e+06)	(672,506)
Population growth	0.143	0.527**	0.605**	11,289	12,240
	(0.111)	(0.250)	(0.256)	(31,854)	(19,257)
Per capita income (in 10,000)	-0.0020	0.047***	0.046***	2,600	2,610***
	(1.92e-07)	(1.27e-06)	(1.26e-06)	(0.165)	(0.0962)
Constant	-0.0741	14.15***	13.75***	353,918	414,845
	(0.0885)	(4.882)	(4.844)	(551,727)	(329,217)
Observations	15,176	15,176	15,178	15,570	15,572
R-squared	0.001	0.006	0.031	0.154	0.725

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 5: Employment Growth Models (4-Digit NAICS)

VARIABLES	(1) Pooled OLS	(2) County FE	(3) County FE w/ Industry FE	(4) Average Employment	(5) Average Employment w/ Industry FE
Cluster	-0.0386***	-0.0390***	-0.0415***	549.1***	558.6***
	(0.00322)	(0.00328)	(0.00414)	(34.16)	(45.48)
Wage growth	0.0654*	0.0620*	0.0458	-16.84	17.90
	(0.0346)	(0.0346)	(0.0330)	(122.5)	(104.3)
Percent white	-0.0724*	1.342	1.364	-11,135	-13,579
	(0.0415)	(0.912)	(0.900)	(13,203)	(11,090)
Percent male	-0.623**	-32.92**	-33.01**	-114,737	-103,587
	(0.265)	(15.04)	(14.82)	(153,241)	(132,919)
Population growth	0.809***	1.048**	0.998**	1,814	126.1
	(0.193)	(0.446)	(0.441)	(2,755)	(2,528)
Per capita income (in 10,000)	-0.0086***	0.0028	0.0012	0.0129	0.00479
	(2.94e-07)	(1.92e-06)	(1.89e-06)	(0.0227)	(0.0195)
Constant	0.433***	15.55**	15.59**	68,706	64,951
	(0.151)	(7.357)	(7.246)	(76,646)	(66,088)
Observations	15,176	15,176	15,178	15,176	15,178
R-squared	0.012	0.017	0.057	0.232	0.426

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The first four models in Figure 5 indicate that clustered industries experience a significantly lower employment growth compared to non-clustered industries. For instance, the county fixed effects model shows that clustered industries experience approximately a 3.9 percentage point lower employment growth rate. However, in the regression on raw employment numbers, clustered industries have an average employment that is approximately 558 employees higher than non-clustered industries. The results from Figure 4 indicate that there is not a significant relationship between wage growth and whether or not an industry is in a cluster. However, when the real annual average wage is regressed on the cluster variable and controls, the results indicate that the average real wage in clusters is approximately $810 less than the average real wage in non-clustered industries. When the real annual average wage with industry fixed effect is regressed on the cluster variable and controls, the results show that the average real wage in a cluster is approximately $4,435 higher than the average real wage in non-clustered industries.

Generally, industry cluster analysis represents a fresh framework for examining deep-rooted economic issues. Analysis of industry clusters is not a unilateral undertaking. If a single stakeholder initiates a study of clusters, even the most reliable data and most relevant applications will not lead to the widespread acceptance of the results. Industry clusters are not applicable to all settings. They must be studied and reassessed to truly reflect a region's competitive strengths. The results above help assess the impact of clusters in Washington State on employment and wage growth. Additionally, industry cluster analysis is not a final solution. As the deeply embedded networks that support diverse economies evolve and grow, the ability of workforce development, education, and economic development to effectively coordinate responses will influence the long-term impact resulting from the creation of new clusters and perhaps even the decline of mature clusters.

Discussion

The statistical analysis revealed a significant relationship between clustered industries and employment growth but found no significant relationship between clustered industries and wage growth. In fact, real wages with industry fixed effects in clustered industries were on average $4,435 higher than in non-clustered industries. The findings contradict the first set of assumptions of theory and this report's first hypothesis that clustered industries experience higher employment growth, but the raw data of real wages with industry fixed effect proved that clusters provide higher wages than non-clustered on average.

In line with mainstream theory, the research team would expect wages to increase with clustering. Productivity gains should lead more firms to locate in a cluster creating competition for workers and driving up wages. Also, as industries cluster, human capital increases from knowledge exchanges (among other factors) and so does specialization, increasing compensation for labor.

Negative employment growth may have resulted from the older clusters reaching saturation, or because clusters were hiring a less proportion of labor since they became more mature and labor productive. Several factors may explain why there was no significant relationship between clusters and wage growth. Employment growth may have resulted from the creation of low-wage, rather than high-wage jobs which would decrease wages on average. The report also did not look at competition for employment in clusters. A high supply of labor may have suppressed wages in key clustered regions affecting the results. The report controlled for per capita income, but broader macro-economic factors, specifically the recent depression and sluggish jobless recovery, may have also depressed earnings.

However, despite these possibilities, the results hold significance for the policies of the Workforce Board which specifically seeks to promote, not just employment growth, but also the growth of high-wage employment. If further studies reveal no significant correlation between industry clusters and wage growth, employment agencies would be wise to re-evaluate their workforce strategies.

Methodology and Analysis Limitations

Along with the myriad of industry clusters definitions, various methods are used to identify and study industry clusters. These methods include location quotient (LQ), input-output analysis, factor analysis, and case studies. As discussed in the methodology section, this study primarily uses the LQ method. The limitation in only using a LQ to identify a cluster is that an industry with a high LQ does not necessarily indicate that it is a cluster. In addition, we ignore dynamics of clusters by using LQ in 2003 as the benchmark for other years.

For the quantitative analysis, the group set up two linear regression models to specifically look at the relationship among LQ, wage growth, and employment growth. The two correlation models that analysts have set up are straightforward and reasonable for analyzing our research questions; however, studying industry clusters in Washington State through particular quantitative methods requires a relatively large sample size, and the logistical difficulties inherent in gathering a sufficiently large sample can potentially sabotage the study before it begins. Additionally, concern exists about the internal validity of our methods since numerous confounding variables must be taken into account in the two models. Inclusion of additional confounding variables, such as the age or size of different industry clusters, would dramatically improve the models. A thorough accounting of industries' age or size would provide additional information on industrial structure because, for example, a region specialized in agriculture experiences different growth patterns than a region specialized in high-tech enterprises (Dudensing R, 2008). A third limitation of our research method is that it is hard to accurately measure the employment situation and earnings in Washington because many people who live outside Washington may work in the state. Finally, industry clusters are not easily identified by NAICS codes since clusters "are not always contained within a single industry classification" (Cortright, 2006). Similarly, the data analysis will have to acknowledge the NAICS codes which were revised slightly in 2007 even though the majority of industries were not affected regarding content, code, or titles.

Furthermore, since QCEW dataset misses a portion of observations, the regression outcomes could not reflect the precise linear relationship between LQ and growth of employment and earning. We also included a limited amount of control variables for the regression models such as employees per establishment, population growth rate, gender, race, GDP, etc. However, other influential factors should be controlled but we did not include them due to the inaccessibility of data resources such as the age of the industry. As a result, the incomplete QCEW data and control variables may have biased our model analysis. For example, the calculated LQ's using QCEW data for some industries are exaggerated; and the linear relationships between LQ's and growth of wage and employment for some areas are also less persuasive.

Conclusion

Industry clustering has generated much attention during the last decade, yet the study of what constitutes an industry cluster is obscure since it encompasses many divergent theoretical and methodological approaches (Best, 1990; Fagan, 2000). The known approaches mentioned in this research used a quantitative approach to evaluate the attributes of industry clustering from various perspectives and levels. Attributes considered include regional GDP, firm level productivity, and wages, among others. The diamond model and benchmark value-chain approach provided comprehensive bases for the capstone project members to understand the nature of industry clusters, the process of their development, and the theories of assessing their effects.

The capstone project has conducted multidimensional assessments which not only compare the industry clustering effects on different regional levels but also compare the effects between clusters and non-clusters within the same region. The capstone project continues to use location quotient (LQ) as the major measure of assessing the agglomeration of industry clusters and unifies two regression models to evaluate the relationships between LQ and wage growth and employment growth on different regional levels.

This report studied the impact of industry clusters on wage and employment growth in Washington State. The Workforce Board has adopted industry clusters as a guiding principle in its work. Although industry cluster strategies are widely used in Washington and other states, the Workforce Board's approach to promoting cluster strategies is inconclusive. This conclusion follows many theoretical and empirical critiques among cluster experts. The results of this paper show a significant negative relationship between industry clusters and employment growth; but, no significant relationship is shown between clusters and wage growth thus adding further doubt and questions to the tenets of industry cluster theory.

This report employed a less than exhaustive quantitative model leaving ample room for expansion. Specifically, the use of individual level data would allow for a closer look at the difference between high-wage and low-wage positions and differences across occupations. To further appreciate the impact of clusters on employment and productivity, further studies could look at the impact of both social and human capital accumulation within specific clusters in Washington State focusing on knowledge spillover and inter-linkages. Further studies may also help explain geographic and life-cycle factors that play into cluster development. These factors could have effects on the employment and wage growth rates for clustered industries.

Clusters, according to our study, associate with negative employment growth, and do not promote the creation of high-wage jobs. Based on this fact, this study recommends that the Workforce Board further study what industry clusters increased and decreased their employment and wages during the past few years and the underlying reasons for this phenomenon and accordingly amend its policies to promote higher-wage employment.

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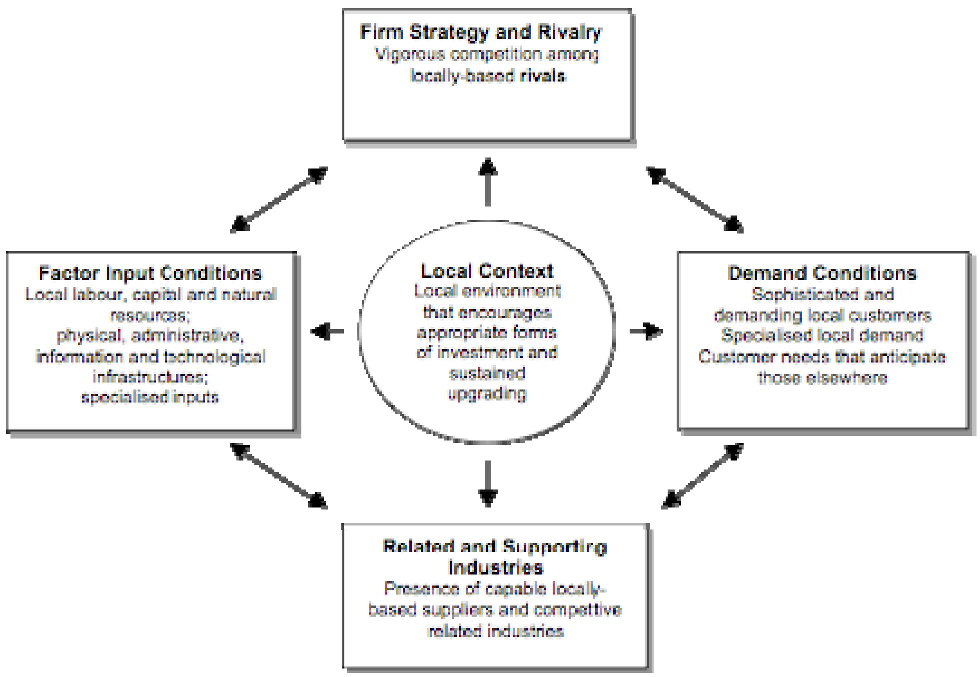
Appendix A

Porter's Competitive Diamond of Local Industrial Clustering
(Based on Porter, 1998, Ch 10).



Source:

Martin, R., & Sunley, P. (2003). Deconstructing Clusters: Chaotic Concept or Policy Panacea? Journal of Economic Geography, 3(1): 5-35.

Appendix B: WDA Employment Growth Models

	WDA Region					
VARIABLES	1	2	3	4	5	6
Cluster	-0.00728	-0.0281***	-0.0139**	-0.0640***	-0.0123	-0.0256**
	(0.00846)	(0.00566)	(0.00556)	(0.0121)	(0.00858)	(0.0110)
Wage growth	-0.00400	0.162**	0.0643	-0.0436	0.119	0.0266
	(0.0684)	(0.0717)	(0.0764)	(0.222)	(0.134)	(0.182)
Percent white	3.466***	2.970***	2.688***	9.046	-9.199	-20.55**
	(1.339)	(0.382)	(0.829)	(9.947)	(22.73)	(8.777)
Percent male	18.12	-11.99***	-10.53	520.6	-433.6	-1,517***
	(29.48)	(4.396)	(8.968)	(914.9)	(797.6)	(583.8)
Population growth	3.114*	1.858	3.400***	4.155	1.338	17.95***
	(1.776)	(1.151)	(1.054)	(4.675)	(7.646)	(5.461)
Per capita income	4.28e-07***	3.41e-07***	3.67e-07***	1.43e-06**	1.43e-06***	-2.10e-06
	(1.41e-07)	(8.79e-08)	(5.32e-08)	(5.93e-07)	(3.96e-07)	(1.29e-06)
Constant	-12.21	3.225	2.635	-268.4	222.8	771.0***
	(15.87)	(2.185)	(4.959)	(466.4)	(414.5)	(297.5)
Observations	1,640	2,417	2,375	1,038	1,446	1,036
R-squared	0.052	0.089	0.075	0.101	0.058	0.049

	WDA Region					
VARIABLES	7	8	9	10	11	12
Cluster	-0.0229***	-0.0127*	-0.0212**	-0.0138*	-0.0143	-0.0381***
	(0.00688)	(0.00655)	(0.00947)	(0.00765)	(0.0109)	(0.00990)
Wage growth	-0.0310	0.0726	0.316***	0.0587	0.197*	0.00237
	(0.0847)	(0.0809)	(0.0988)	(0.111)	(0.108)	(0.154)
Percent white	2.351**	0.505	-1.748	0.514	-1.563	6.064
	(1.194)	(1.057)	(2.296)	(0.524)	(1.143)	(4.376)
Percent male	-66.54*	1.310	-107.9*	-5.164	1.314	-198.7**
	(35.21)	(3.207)	(62.38)	(6.340)	(4.649)	(89.43)
Population growth	0.111	-0.0989	0.418	0.878	-0.786	6.785**
	(0.651)	(0.429)	(1.349)	(1.460)	(0.533)	(2.919)
Per capita income	2.98e-07***	4.82e-07***	6.49e-07***	2.45e-07***	1.13e-06***	9.13e-07
	(1.05e-07)	(7.52e-08)	(1.57e-07)	(4.99e-08)	(3.43e-07)	(8.16e-07)
Constant	30.91*	-1.156	55.40*	2.091	0.795	91.86**
	(18.44)	(1.829)	(32.86)	(3.417)	(2.200)	(45.97)
Observations	1,601	1,769	1,362	1,487	1,085	1,100
R-squared	0.058	0.026	0.060	0.028	0.039	0.065

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix C: WDA Wage Growth Models

	WDA Region					
VARIABLES	1	2	3	4	5	6
Cluster	0.00322	-0.000407	-0.00573	0.000866	-0.00607	-0.00822
	(0.00542)	(0.00335)	(0.00351)	(0.00582)	(0.00594)	(0.00625)
Percent white	1.447	0.671**	-0.0147	20.60***	20.80	-4.030
	(1.174)	(0.261)	(0.532)	(5.420)	(13.26)	(4.706)
Percent male	39.55	-1.825	15.39***	1,855***	715.8	-304.2
	(27.69)	(2.098)	(5.853)	(500.7)	(477.7)	(314.8)
Population growth	0.329	-0.263	2.849***	-5.813**	6.716*	4.834*
	(1.463)	(0.783)	(1.072)	(2.392)	(3.923)	(2.915)
Per capita income	-1.43e-07	-8.64e-08	-1.78e-07***	-1.07e-06***	-1.98e-09	-1.58e-06**
	(1.03e-07)	(5.81e-08)	(3.74e-08)	(2.79e-07)	(2.70e-07)	(6.94e-07)
Constant	-21.18	0.318	-7.624**	-946.3***	-372.2	154.6
	(14.90)	(1.100)	(3.173)	(255.2)	(248.0)	(160.4)
Observations	1,640	2,417	2,375	1,038	1,446	1,036
R-squared	0.014	0.006	0.020	0.025	0.005	0.007

	WDA Region					
VARIABLES	7	8	9	10	11	12
Cluster	0.00145	-0.00202	0.0131**	0.00359	-0.00656	0.00639
	(0.00517)	(0.00389)	(0.00539)	(0.00393)	(0.00535)	(0.00604)
Percent white	-0.235	0.400	1.014	-0.985***	-0.884	6.020**
	(1.081)	(0.585)	(1.066)	(0.283)	(0.577)	(2.414)
Percent male	-25.87	-1.167	10.98	3.891	1.535	-66.15
	(33.42)	(2.137)	(41.20)	(2.950)	(1.712)	(57.23)
Population growth	-0.348	-0.0521	0.116	0.147	-0.440	4.460**
	(0.486)	(0.112)	(0.795)	(0.953)	(0.557)	(1.963)
Per capita income	-2.10e-07***	-1.37e-07***	-6.35e-08	-1.99e-08	-5.50e-07***	-1.79e-06***
	(7.32e-08)	(4.89e-08)	(9.78e-08)	(2.57e-08)	(1.86e-07)	(5.43e-07)
Constant	13.10	0.244	-6.384	-1.050	0.107	26.91
	(17.44)	(1.228)	(21.28)	(1.583)	(0.700)	(29.09)
Observations	1,601	1,769	1,362	1,487	1,085	1,100
R-squared	0.006	0.008	0.005	0.020	0.018	0.014

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix D: Wage Growth Models (3-digit NAICS)

VARIABLES	(1) Pooled OLS	(2) County FE	(3) County FE w/ Industry FE	(4) Real Wage	(5) Real Wage w/ Industry FE
Cluster	-0.00283	-0.00245	0.000263	-1,064***	3,830***
	(0.00233)	(0.00243)	(0.00296)	(392.0)	(292.3)
Percent white	-0.0256	2.541***	2.568***	-32,628	15,849
	(0.0319)	(0.780)	(0.765)	(111,283)	(71,901)
Percent male	-0.0522	-22.01**	-21.98**	-699,786	-1.499e+06*
	(0.214)	(11.04)	(10.91)	(1.326e+06)	(820,324)
Population growth	0.298**	0.621**	0.630**	25,309	30,598
	(0.138)	(0.310)	(0.308)	(40,857)	(27,672)
Per capita income	-2.05e-07	3.35e-06**	3.44e-06**	0.206	0.288**
	(2.20e-07)	(1.51e-06)	(1.50e-06)	(0.193)	(0.122)
Constant	0.0574	8.774	8.724	409,722	756,940*
	(0.119)	(5.445)	(5.365)	(668,605)	(414,312)
Observations	8,653	8,653	8,654	9,108	9,109
R-squared	0.001	0.006	0.023	0.142	0.665

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix E: Employment Growth Models (3-Digit NAICS)

VARIABLES	(1) Pooled OLS	(2) County FE	(4) County FE w/ Industry FE	(5) Average Employment	(6) Average Employment w/ Industry FE
cluster	-0.0316***	-0.0313***	-0.0295***	1,168***	1,261***
	(0.00376)	(0.00387)	(0.00451)	(92.21)	(142.0)
Wage growth	0.0767*	0.0736*	0.0619	-100.7	-58.60
	(0.0447)	(0.0446)	(0.0442)	(331.7)	(244.7)
Percent white	-0.0665	1.221	1.190	-20,460	-17,298
	(0.0473)	(1.138)	(1.126)	(34,872)	(31,774)
Percent male	-0.433	-42.16**	-41.96**	-211,479	-192,169
	(0.306)	(18.01)	(17.90)	(363,639)	(339,822)
Population growth	0.785***	1.182**	1.192**	3,720	1,758
	(0.233)	(0.507)	(0.505)	(6,093)	(5,924)
Per capita income	-7.12e-07**	1.20e-06	1.02e-06	0.0280	0.0288
	(3.39e-07)	(2.45e-06)	(2.45e-06)	(0.0532)	(0.0493)
Constant	0.322*	20.38**	20.30**	126,425	113,504
	(0.173)	(8.767)	(8.706)	(190,115)	(176,571)
Observations	8,325	8,325	8,326	8,653	8,654
R-squared	0.012	0.019	0.057	0.302	0.416

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix F: Wage Growth Models (4-digit NAICS) (Clusters are identified year by year, which an industry is a cluster if its location quotient is greater than 1, and 0 otherwise.)

	(1)	(2)	(3)	(4)
VARIABLES	Pooled OLS	County Fixed Effects	County Fixed Effects w/ Time Fixed Effects	Real Wage (2009 dollars)
Cluster	0.00108	0.00139	0.00135	-903.2***
	(0.00193)	(0.00199)	(0.00199)	(285.9)
Percent white	-0.00165	3.047***	1.887***	553.8
	(0.0271)	(0.614)	(0.660)	(83,501)
Percent male	0.278*	-29.96***	-14.24	-269,888
	(0.155)	(9.839)	(12.00)	(1.127e+06)
Population growth	0.149	0.400	0.0175	-2,746
	(0.110)	(0.247)	(0.273)	(30,000)
Per capita income	-1.49e-07	5.00e-06***	3.36e-06**	0.201
	(1.95e-07)	(1.26e-06)	(1.60e-06)	(0.163)
Constant	-0.129	12.34**	5.443	158,367
	(0.0881)	(4.827)	(5.866)	(555,581)
Observations	16,351	16,351	16,351	17,666
R-squared	0.001	0.006	0.008	0.142
F-Test		0.0076	0.0000	

Appendix G: Employment Growth Models (4-digit NAICS) (Clusters are identified year by year, which an industry is a cluster if its location quotient is greater than 1, and 0 otherwise.)

	(1)	(2)	(3)	(4)
VARIABLES	Pooled OLS	County Fixed Effects	County Fixed Effects w/ Time Fixed Effects	Average Employment
Cluster	0.0187***	0.0205***	0.0205***	579.4***
	(0.00325)	(0.00333)	(0.00333)	(32.50)
Wage growth	0.0348	0.0305	0.0283	-38.59
	(0.0334)	(0.0334)	(0.0335)	(103.7)
Percent white	-0.0465	2.505***	1.491	-6,312
	(0.0410)	(0.919)	(1.003)	(12,387)
Percent male	-0.475*	-38.27***	-17.77	-79,291
	(0.265)	(14.70)	(17.29)	(140,083)
Population growth	0.879***	1.399***	0.935	1,324
	(0.197)	(0.499)	(0.571)	(2,489)
Per capita income	-7.72e-07***	2.06e-06	4.05e-06*	0.00974
	(2.92e-07)	(1.92e-06)	(2.43e-06)	(0.0210)
Constant	0.307**	17.13**	7.568	46,078
	(0.150)	(7.176)	(8.401)	(70,141)
Observations	16,350	16,350	16,350	16,350
R-squared	0.004	0.010	0.011	0.233
F-Test		0.0000	0.0001	

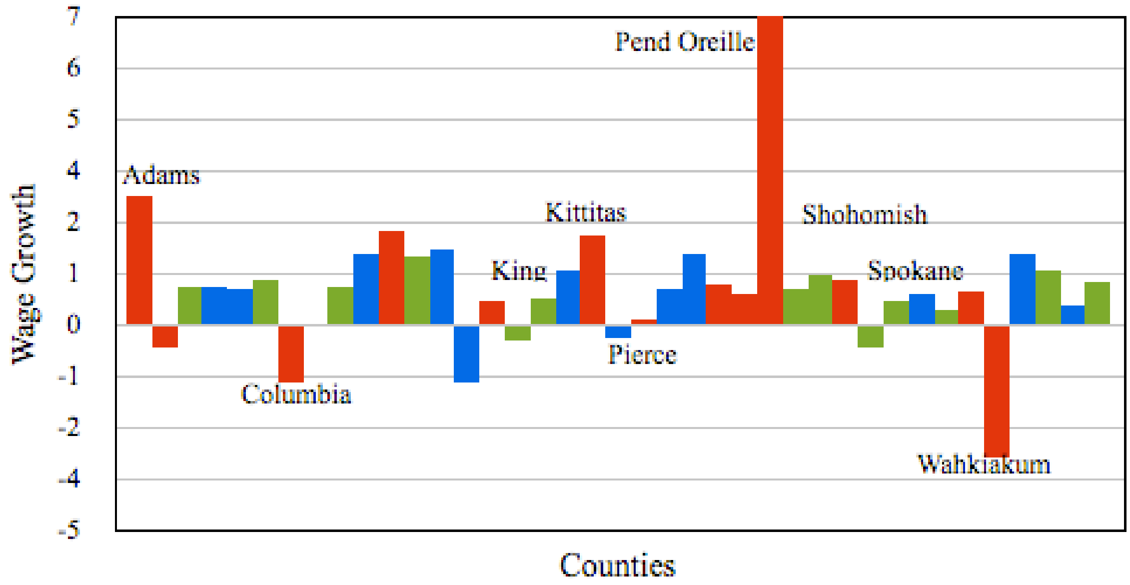
Appendix H: Top 5 clusters per WDA

WDA	Industry	Average LQ (years 2003 – 2009)
1. Clallam, Jefferson & Kitsap		
1	Timber Tract Operations	28.7
2	Animal Aquaculture	11
3	Fishing	9.2
4	Facilities Support Services	5.3
5	Ship and Boat Building	4.9
2. Grays Harbor, Lewis, Mason, Pacific & Thurston		
1	Fishing	70.1
2	Seafood Product Preparation and Packaging	35.9
3	Animal Aquaculture	34.4
4	Support Activities for Forestry	31.4
5	Logging	26.5
3. Island, San Juan, Whatcom & Skagit		
1	Seafood Product Preparation and Packaging	32.8
2	Animal Aquaculture	13.2
3	Fishing	9.6
4	Fruit and Tree Nut Farming	8.9
5	Ship and Boat Building	8.8
4. Snohomish		
1	Aerospace Product and Parts Manufacturing	33.4
2	Fishing	8.9
3	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	4.8
4	Sawmills and Wood Preservation	4.2
5	Ship and Boat Building	3.9

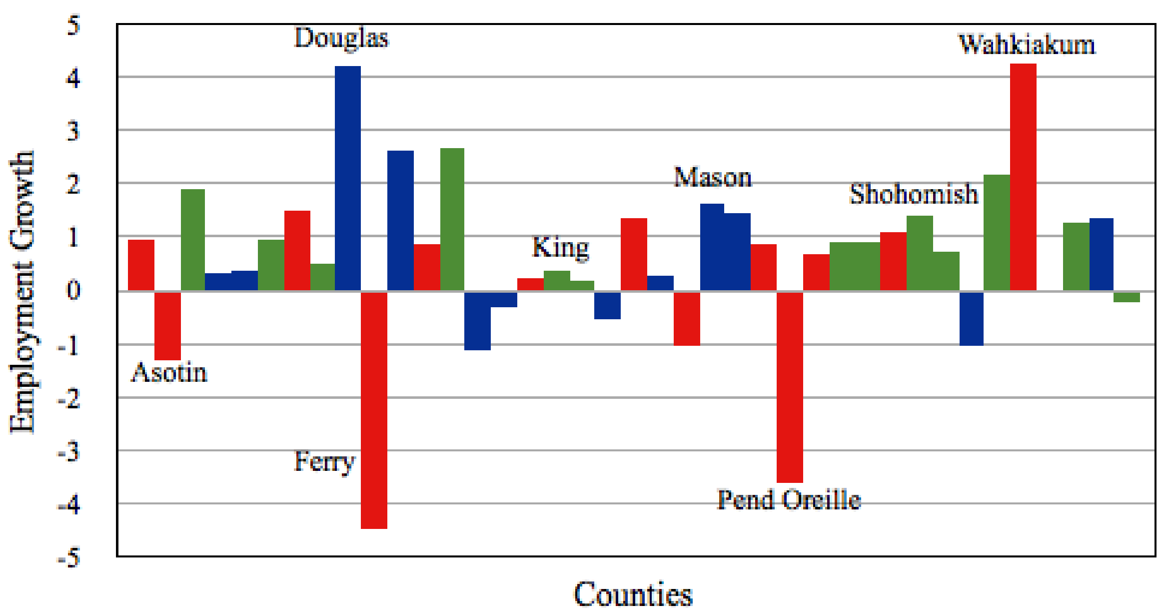
WDA		Industry	Average LQ (years 2003 – 2009)
5. King			
	1	Software Publishers	19.6
	2	Fishing	15.3
	3	Aerospace Product and Parts Manufacturing	10
	4	Seafood Product Preparation and Packaging	9.7
	5	Deep Sea, Coastal, and Great Lakes Water Transportation	8.7
6. Pierce			
	1	Fishing	12.1
	2	Support Activities for Water Transportation	7.7
	3	Lime and Gypsum Product Manufacturing	7.3
	4	Sawmills and Wood Preservation	5.0
	5	Seafood Product Preparation and Packaging	4.2
7. Clark, Cowlitz, Skamania & Wahkiakum			
	1	Pulp, Paper, and Paperboard Mills	17.0
	2	Sawmills and Wood Preservation	8.9
	3	Logging	7.5
	4	Support Activities for Forestry	6.1
	5	Gambling Industries	5.7
8. Adams, Chelan, Douglas, Grant & Okanogan			
	1	Fruit and Tree Nut Farming	124.1
	2	Fruit and Vegetable Preserving and Specialty Food Manufacturing	24.1
	3	Support Activities for Crop Production	20.5
	4	Other Crop Farming	19.9
	5	Oilseed and Grain Farming	17.7

WDA	Industry	Average LQ (years 2003 – 2009)
9. Kittitas, Yakima & Klickitat		
1	Fruit and Tree Nut Farming	84.5
2	Other Crop Farming	46.0
3	Support Activities for Crop Production	23.3
4	Cattle Ranching and Farming	13.0
5	Fruit and Vegetable Preserving and Specialty Food Manufacturing	11.6
10. Asotin, Columbia, Ferry, Garfield, Lincoln, Pend Orielle, Stevens, Walla Walla & Whitman		
1	Oilseed and Grain Farming	74.3
2	Rooming and Boarding Houses	37.0
3	Fruit and Tree Nut Farming	34.8
4	Sawmills and Wood Preservation	15.1
5	Support Activities for Forestry	11.1
11. Benton & Franklin		
1	Remediation and Other Waste Management Services	63.1
2	Fruit and Tree Nut Farming	41.4
3	Other Crop Farming	23.9
4	Fruit and Vegetable Preserving and Specialty Food Manufacturing	22.5
5	Vegetable and Melon Farming	16.0
12. Spokane		
1	Private Households	4.4
2	Medical and Diagnostic Laboratories	4.1
3	Communications Equipment Manufacturing	3.1
4	Community Care Facilities for the Elderly	2.7
5	Foundries	2.6

Appendix I: Average Real Wage Growth Rate by County (2004-2009)



Appendix J: Average Employment Growth Rate by County (2004-2009)



Population
0 - 30,000
30,001 - 74,000
74,001 >