RESEARCH & POLICY

INSIGHTS

Economic Competitiveness:
A Literature Review of Industry, Occupation and Skill Clusters, and Related Topics

Publication 115

April 2025

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Economic Clusters for the 21st Century

Disclaimer: This review of literature is prepared by Purdue Center for Regional Development using Federal funds under award # ED23RNA0G0174 from the Economic Development Administration, U.S. Department of Commerce. The statements, findings, conclusions, and recommendations are those of the author(s) and do not necessarily reflect the views of Economic Development Administration or the U.S. Department of Commerce.

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1.0) Introduction

This report presents a comprehensive review of the published research on industry clusters and related topics. The focus areas of this literature review were informed, in part, by a bibliometric analysis of the literature compiled by using the Web of Science (WoS) and SCOPUS (Elsevier's abstract and citation repository) databases. The co-authors of this report and the project team also discussed and refined the topics and subject areas for this literature review.

The review is divided into five sections. Section one is an introduction to the entire literature review document. Section two delves into the origins of the industry cluster concept, and specifically motivates on the development of Benchmark Industry Clusters in the U.S. The review covers technical aspects and methodological nuances of the previous cluster benchmarking efforts in the U.S. There have been five major efforts to define industry clusters and develop benchmarked cluster definitions in the past, since 2000. The section provides succinct descriptions of the previous research efforts.

Section three explores the economic geography of knowledge and innovation by reviewing literature from the U.S., and international contexts. The review concentrates on the development and dissemination of new knowledge and innovations related to the industry clusters. It delves into diffusion and sharing of codified versus tacit or explicit versus implicit knowledge within and between the industry clusters. This section introduces and explains terms, such as epistemic communities, local knowledge spillovers, etc. The section ends with several international case studies of industry clusters, and how clusters are considered to achieve regional economic development in other countries.

Section four explores occupations and skills clusters, and how they can add invaluable insights into human capital for public programs, private investments, and educational institutes within the regions. The review presents the need for new data sources and analytical methods to understand the linkages between occupations and skills, and crosswalks to the industries.

Section five, the final section, reviews the theories of social networks, social capital, and network analysis. The review looks at the role of networks and interactions and information flows in industry cluster development, and the role of network analysis in uncovering relationships.

The four areas of reviews explore the topic of regional competitiveness from different but important lenses, which include agglomeration and production of goods and services; human capital or occupations and skills present in the regions; discovery and dissemination of knowledge and innovation in regional economies; and the role of social networks and culture in regional economic competitiveness.

The review provides evidence that the expectations from industry cluster analysis have changed over the decades. During the late 1990s, 2000s, and 2010s, the purpose of industry cluster analysis was to identify competitive industry sectors for regions and develop economic development strategies to promote the competitive industry sectors. The emphasis was on metrics such as jobs growth, reducing unemployment rate, wages, etc. Whereas these metrics remain important, the industry cluster concept is embracing new paradigms such as resilience, ecosystems, and human capital development. For example, an overarching and integrated cluster is an entirely new lens to view economic resilience and competitiveness. The boundaries between traditional fields of economic, community, and workforce development have merged. For practitioners and researchers, occupation clusters are as important as the industry clusters. The advent of artificial intelligence (AI) and high technological areas have incited the importance and interest on skill development focusing on growing, attracting, and retaining talent in the region. There is an opportunity for further research on occupations and skills clusters, and interrelationships between industries, occupations, knowledge, skills, and networks. Similarly, social networks present significant opportunities for research in the areas of industry and occupation clusters, workforce development, and human capital. Another potential area of research is related to data applications including methods to identify detailed industry to industry transactions or flow data to facilitate research on economic networks.

2.0) What are industry clusters?

2.1) Origins of the industry clusters

Industry cluster is a commonly applied term in contemporary regional economic development practices in the U.S. Academic scholars have debated on the origins of the concept and concluded that the first reference on clustering of industries occurred in ***Principles of Economics*** authored by *Alfred Marshall* in the late 19th century. Marshall described how specialized industries developed and concentrated in particular locations, and how locally available natural and physical resources, human skills, and trade craftsmen prompted the development and growth of economic enterprises attracting supplementary and supporting industries in proximity to each other (Marshall, 1890). In many ways the concept of modern industrial clusters in the U.S., which are also known as industrial districts in Europe refer to the Marshallian principles of benefits from external and internal economies of scale, and agglomeration advantages (Kumar et al., 2017).

Kadokawa (2011) researched four Marshallian benefits nurturing the agglomeration of industries, which included knowledge spillover, skilled labor pool, supporting industries or suppliers, and input resources such as raw materials. In a survey of new industries in Japan, it was uncovered that proximity to related firms, headquarters, and research institutions; support from governments; land prices; co-location with other firms; and availability of water and amenities in the region mattered for new industrial plants (Kadokawa, 2011). The second set of significant variables included was proximity to raw materials and markets; business and logistics services; and labor availability and technical skills pointing to the importance of transportation and logistics services (Kadokawa, 2011). The third aspect was social and professional networks such as the variable on manager's personal ties in making the decision to locate in a specific region (Kadokawa, 2011). This research elucidated that in addition to location specific factors such as access to highways, firms considered Marshallian agglomeration benefits and industrial cluster characteristics in choosing a specific region within the country. The location decisions of firms could be divided into two hierarchical levels, regional and site-level locations. It was at a higher spatial level of regions that opportunities for industrial clustering guided the decisions for locating or creating new industrial plants, and site-specific factors guided the decision to locate in a specific place, such as an industrial park (Kadokawa, 2011).

A reference to agglomeration is incomplete without a discourse on "localization or clustering of similar industries" versus "urbanization or clustering of diverse industries," two noteworthy mechanisms of agglomeration explained by regional economists. There is an ongoing debate amongst scholars if the regions should strive for specialization of industries versus diversification and variety in industries. According to Cortright (2006), the findings from previous research have been mixed with some studies providing evidence in favor of specialization of industries, and some uncovering evidence in favor of diversification of industries.

Ellison and Glaeser (1997) put forth that the expectation of increasing returns is the primary motivation for an industrial plant to select a specific location. The authors consider two types of agglomerative forces causing the increasing returns, physical and intellectual spillovers, and natural advantages such as proximity to water resources (Ellison and Glaeser, 1997). Physical spillovers include transport cost externalities because firms agglomerate to take advantage of economies of scale and save transport costs and create labor demand to attract large numbers of labor force, which eventually results into a positive-feedback cycle as posited by Arthur (1990) and Krugman (1991)[1]. The focus of Krugman (1991) was on developing an explanatory but rigorous economic model of why manufacturing in the U.S. is concentrated in proximate geographies known as "core" with the remaining part of the country and the world known as "periphery" serving the industries located in the "core." While developing the "core-periphery" theory, Krugman (1991) was inspired by the "circular and cumulative causation" model by Myrdal (1957) and the "positive feedback" model by Arthur (1990). In simpler terms, Myrdal's and Arthur's frameworks postulate that specialization begets further specialization causing the rise in labor demand, attracting migrants, and eventually resulting into economic growth and development. An example of "positive feedback" is that the probability an industry may come in a region depends in part on the existing proportion of that industry (specialization) in the region (Arthur 1990). It is important to note that Myrdal (1957) attempted to provide an explanation of spatial inequities in regional economic development across nations leaning in favor of "divergence" or disequilibrium than "convergence" or equilibrium schools of thoughts. Sheppard (2017) described that "uneven geographical development" (p. 973) was considered by Myrdal as a norm than an exception.

The international trade and the new economic geography theory postulated by Krugman (1991) could explain why diverse countries are specializing and at the same time trading in similar products such as automobiles. However, scholars including Krugman have noted that the manufacturing patterns that inspired the development of the theory have been unravelling especially after the 1990s (Bruilhart, 2009). The manufacturing from the U.S. and Europe has been dispersing to the developing countries creating specializations in the "periphery" regions in contrast to the original core-periphery pattern assumptions (Bruilhart, 2009). However, after the COVID-19 pandemic, scholars are interested in the wisdom of Krugman's New Economic Geography (NEG) theory to explain spatial economic patterns accounting for frictions such as distances, border restrictions, tariffs, lockdowns, and the push and pull factors reshaping the agglomerations in developed and developing economies (Nijkamp et al., 2024).

As scholars in economics and geography attempted to theorize and explain patterns of economic development, a new framework emerged in 1990. In the wide-ranging discourse on means for economic growth and success, *The Competitive Advantage of Nations* by Michael Porter holds a significant milestone. In this treatise, Porter (1990) stated that "national prosperity is created and not inherited," and competition and innovation between industries are the ways to achieve competitive and comparative advantages. In this context, the role of government shall be to enable conditions for competition and innovation without interfering into operations of the firms and industrial processes (Porter 1990). With increased globalization and faster means of transportation and communication enabling movement from anywhere to anywhere, the dictum of "location, location, and location" should have faded away. However, Porter (1998) uncovered that contrary to losing importance, "locations" became even more important for success of businesses and industries. Porter (1998) found that competitive advantages were embedded in the select

[1] Paul Krugman developed the new international trade theory focusing on monopolistic competition and intra-industry trade in the world. For example, Sweden and the U.S. are both developed economies and produce different brands of automobiles to sell to each other. Consumers benefit from the variety of products in the market.

groups of interconnected firms that were highly specialized and competitive but located only in specific locations. These groups of interconnected firms were termed as "**clusters**" by Porter (1998). In fact, industry clusters were recognized as the building blocks of global value chains and competitiveness of the nations. In many ways "clusters" operationalized the concepts of agglomeration, cumulative causation, and positive feedback along with the capacity to explain the spatial disequilibrium and inequities observed between regional economies. It was almost a merger of strands of thinking happening around the contributions of Marshall, Myrdal, and Arthur. The introduction of the industry cluster concept in the late 1990s was a seminal contribution to academic research and professional practice of regional economic development in the U.S.

2.2) Defining benchmark industry clusters: Early and contemporary efforts in the U.S.

2.2.1) Early 2000s

The decades of research in economic geography had attempted to explain variations in economic development between regions. Whereas the national framework for economic competitiveness was available, the substantial regional-level differences in the economic growth and development could not be explained properly. In the early 2000s, Michael Porter investigated the role of industry cluster specializations in explaining the economic development and prosperity of the regions (Porter, 2003). It was established that national competitiveness relied on specializations in industry clusters, which were not universal across the nation, but were located in select regions. Porter (2003) used County Business Patterns (CBP)[2] data from 1990 to 2000 based on Standard Industry Classification (SIC) to identify definitions for 41 traded clusters in the U.S. Porter (2003) used co-location based on Pearson's correlation coefficients of SIC 4-digit employment at the state level to delineate definitions of industry clusters. After defining the clusters, the data were aggregated for the 172 Economic Areas (EAs)[3] developed by the Bureau of Economic Analysis (BEA). Porter (2003) explored average wages, employment, and compound annual growth rates of wages and employment to describe differences in economic performances between regions. However, the author could not find any substantial relationship between initial higher wages and growth rates in wages to explain employment levels or growth in employment and vice versa. After employment and wages, Porter (2003) investigated innovation by using patents and patent intensity[4] to explain economic performance of regions and study relationships with employment and average wages. The relationships between patent intensity and average wages and employment were found to be significant. The author commenced defining industry clusters by distinguishing between "**local**" (geographically dispersed) and "**traded**" or (geographically concentrated) types of industries in a regional economy. A third category of "resource dependent" industries such as logging, mining, etc., were also identified.

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[2] County Business Patterns (CBP) data exclude government and military employment. The CBP is mainly comprised of private sector employment excluding agricultural workers, railroad workers, household employment, self-employed, etc. At the county level, CBP data are highly suppressed.

[3] Economic Areas (EAs) were defined by the Bureau of Economic Analysis (BEA). These were delineation of the regional markets spanning the entire U.S. In 2004, BEA increased the number of EAs from 172 to 179 (Johnson and Kort 2004).

[4] Patents per 100,000 residents and patent per capita.

The local industries serving the local population accounted for nearly 67% of total employment, traded industries exporting to other regions and nations accounted for 32% of total employment, and resource dependent industries accounted for only 1% of the total employment (Porter, 2003). The traded industries exporting goods and services were unique to the regions, but local industries were present proportionately in every region (Porter, 2003). The author distinguished traded industry from local industry if location quotient (LQ)[5] was >= 1, industry employment was >=50% of total employment, mean LQ of the top five states was >=2, and employment GINI[6] coefficient was 0.3. In addition to employment patterns, the author also applied industry knowledge, industry definitions, and judgement to distinguish between local and traded industries. It is to be noted that the data were analyzed for U.S. states to account for data suppression issues in smaller geographies.

Whereas traded industries accounted for only one-third of employment on average in a region, it could explain average wages and employment growth in regions substantially, facilitating Porter (2003) to develop 41 traded cluster definitions for the first time in the U.S. Hence, Porter (2003) can be attributed to developing the first set of the **Locational Correlation (LC) or co-location-based** industry cluster definitions for the U.S. The author used an iterative approach to distinguish 41 narrowly defined, and to some extent mutually exclusive (partially overlapping) industry clusters based on statistically significant correlations of employment between traded industry sectors at the state level. National Input-Output (IO) table was further used to ensure that cluster definitions aligned with the interindustry linkages. In addition, judgment and knowledge of industries were used to exclude highly correlated but unrelated industry pairs from the cluster definitions (Porter, 2003).

The development of industry clusters and related research was a milestone in that it established that specializations in clusters and not in individual industries mattered for the regional economic performance and national competitiveness. Porter (2003) described industry clusters as “geographically proximate group of interconnected companies, suppliers, service providers and associated institutions in a particular field, linked by externalities of various types (p. 562).” For the first time, evidence was demonstrated that industries along with their suppliers and associated institutions constituted the relevant framework for regional economic development research, practice, and decision making.

During the same time period, U.S. researchers pursued another strand of thinking around developing industry cluster definitions. The exploration of this method in developing benchmark industry clusters for the U.S. can be attributed to Edward Feser and Edward Bergman. Feser and Bergman (2000) developed industry cluster definitions based on interindustry linkages, and hence explored a methodology more nuanced than the descriptive and qualitative approaches undertaken by scholars and practitioners in the previous decades. The authors derived manufacturing value chain clusters for U.S., by using the 1987 National Input Output (IO), 362 X 362 matrices data based on SIC, the older

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5 LQ is known as the Location Quotient. It is a ratio of employment share of an industry in a region with respect to the nation. $LQ = \frac{R_i}{R_n} \Big/ \frac{N_1}{N_n}$; where, R is employment in region, N is employment in nation, i is industry, and n is total. LQ >=1 is considered as the cutoff point for specialization or exporting in Economic Base Theory.

6 GINI is a measure of inequality. Higher values of GINI coefficient mean more inequality which shows that employment/income/wages are more concentrated in fewer regions.

industry classification system. The clusters were derived for both, manufacturing and nonmanufacturing industry sectors by using the intermediate purchases and sales between industries. It is to be noted that Bergman and Feser (1999) identified IO analysis as one of the key methods to define clusters in addition to the expert opinion, LQ, network analysis, and surveys. However, the origins of IO analysis for identifying clusters or meaningful groupings of industries can be traced back to Czamanski and Ablas (1979) and O'hUallachain (1984). While explaining the value of analyzing flows in identifying industry clusters, Czamanski and Ablas (1979) emphasized that IO based methods create "**aspatial clusters** (p. 62)," and the defined clusters were needed to be studied in spatial contexts. Scholars as early as 1970s identified the value of spatial analysis and mapping of industry clusters, especially in the context of industrial complexes.

The authors argued in favor of benchmark clusters explaining that such definitions and its applications in different regions can uncover unique industrial mixes and compositions in different regions within the same cluster. In so doing, benchmark clusters can reveal unique strengths and weaknesses of the regions including supply chain gaps and opportunities for economic development in the region (Feser and Bergman, 2000). The authors developed purchase and sales coefficients[7] by using the IO transaction values, ran correlations based on four coefficients, selected the largest coefficient, and ran Principal Component Analysis with Varimax rotation to derive factors or industry clusters. Based on the factor loadings, industry sectors with factor loadings of 0.6 or higher were considered as primary and remaining industry sectors were considered as secondary sectors of that cluster (Feser and Bergman 2000). The authors derived 28 industry clusters for manufacturing industries. However, when the data were expanded to include non-manufacturing sectors (478 X 362 matrices), only 18 large cluster definitions could be derived, which were not so intuitive. Feser and Bergman (2000) mentioned that non-manufacturing sectors such as services develop similar linkages to many types of industries, and hence cluster definitions may include technologically dissimilar industries making it difficult to interpret intuitively.

2.2.2) Mid 2000s

Feser (2005) was the first study of benchmarking industry clusters based on the North American Industry Classification System (NAICS), a major departure from previous studies which had used the old SIC industry classifications to develop the industry cluster definitions. Another departure was in the methodology of identifying value chain clusters where Feser (2005) used the National IO table and Ward's Hierarchical algorithm instead of the factor analysis used in previous research. The author made a case for ***Benchmarking Industry Cluster*** definitions where clusters are derived based on interindustry purchases and sales patterns followed by geographical analysis to assess if the constituent industry sectors of a cluster are present in the region. Hence, *Benchmarking Value Chains* at the national level provided a systematic basis for economic analysis at the regional level (Feser, 2005). The argument was that certain relationships between industries are revealed in the economic space and not geographical space, and interindustry transactions (purchases and sales) IO table at the national level is a rich source of information (Feser, 2005; Perroux, 1950). The research efforts on industry clusters during the early- and mid-2000s focused on

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7 $X_{ij} = \frac{a_{ij}}{P_j}; X_{ji} = \frac{a_{ji}}{P_i}; Y_{ij} = \frac{a_{ij}}{S_i}; Y_{ji} = \frac{a_{ji}}{S_j}$; where X are intermediate goods purchases and Y are intermediate goods sales. There are two coefficients based on purchases and two coefficients based on sales values.

uncovering interaction patterns in the economic and geographical spaces. It was only later that interactions in the social space or social networks were added to the research discourse on clusters. Section 5 of this literature review explores the topic of social networks and the role of networks in economic clusters.

Feser (2005) delved into explaining strengths and weaknesses of data reduction techniques such as factor analysis versus statistical clustering algorithms, where the earlier method produced overlapping but uneven clusters and the later method produced mutually exclusive and even clusters. Although, Feser (2005) stated explicitly that "mutually exclusive industry groupings or cluster definitions are theoretically indefensible (p. 5)." Each industry has a unique value chain comprised of purchases from upstream industries (suppliers) and sales to the downstream industries (customers). Theoretically, an industry cluster contains groupings of industry sectors that share similar and linked-value chains, and hence facilitating a cluster instead of a sector to be used as the unit of regional economic analysis (Feser, 2005). It should be noted that Feser (2005) built on the previous studies by Feser and Bergman (2000) and Feser and Renski (2000), which used the 1987 and 1992 National Benchmark IO tables, respectively.

The analysis commenced with a 489 x 489 interindustry transactions table obtained from the 1997 National IO accounts. The matrix was reduced to 463 x 463 after excluding service industries and government sectors. A specific set of industry sectors mostly purchasing and selling to itself and connected to very few industry sectors were termed as singletons[8] by Feser (2005). After excluding singletons, Ward's hierarchical clustering algorithm was run on a square linkage matrix of 437 x 437 sectors. The linkage[9] was developed based on the number of sectors common in purchasing or sales sectors between two industries i and j. Unlike, previous research where dollar values of flows mattered, here the emphasis was on presence or absence of sectors above a certain threshold[10] in purchasing or sales patterns between industries i and j. This eliminated the effect of outliers as evidenced in previous research. The Ward's algorithm resulted in 45 clusters or value chains of industries. Whereas, the clusters were mutually exclusive due to the nature of the algorithm, Feser (2005) explored the "fuzziness" by providing the basis[11] that an industry sector can be a member of more than one cluster based on the strength of the linkages. Feser (2005) developed another set of 15 technology-based industry clusters by using a reduced 111 x 111 sector matrix.

The National Benchmark Value Chain (VC) clusters by Feser (2005) was the first national template based on the NAICS system. The 45 clusters covered 64% of employment and 73% of payroll in 2004 in the U.S. The research formed the basis for further national and regional cluster analyses in the U.S. However, Feser (2005) cautioned that benchmarks were national templates and might not capture linkages unique to the region; however, at

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[8] NAICS 312120 (breweries) and 312140 (distilleries) are examples of singletons.

[9] $I_{ij}^{ss} = S_i \cap S_j$; $U_{ij}^{ss} = S_i \cup S_j$; $R_{ij}^{ss} = I_{ij}^{ss} / U_{ij}^{ss}$; Where measure R is a ratio of number of supply sectors common for industry i and j to the total number of supplying sectors for i and j. A similar measure was developed for buyer sectors for i and j. Further ratios were developed between common suppliers and total buyers and vice versa to show the secondary relationships.

[10] For the supplier linkage measure, the threshold was 0.02 or 2% and for the buyer linkage measure, it was 0.01 or 1%. For example, a sector was an important supplier if it supplied 2% or more of the total supplies to industry i or j.

[11] A sector having linkage metrics above a certain threshold to different clusters can be included as secondary member of the cluster. The results from Ward's algorithm provided clusters with primary industry sectors.

the same time such information could provide guidance on targeting industry sectors which could be co-located within the regional cluster.

Scholars have been interested in the socioeconomic conditions of rural regions since the beginning of the 20th century relying primarily on partially available data from the U.S. Decennial Census. The county geography was used substantially during and after the 1900 Decennial Census, however, it was only in 1990 and later that various census geographies were created for the entire U.S., encompassing rural areas including demographic and socioeconomic data for the rural regions (Kumar and Kim, 2019; U.S. Bureau of Census, 1994). The concepts of economic competitiveness and specialization of industries that emerged during the late 1990s were applied to metropolitan regions by practitioners despite earlier efforts by Porter (2003) to use the framework for EAs for the entire U.S. An advantage of benchmarked industry cluster definitions was that it could be used as a template to explore competitiveness of a region and compare competitiveness between regions. There was a need to extend the framework for industry clusters that could benefit regions comprised of both, urban and rural areas to facilitate regional development practices.

The ***Unlocking Rural Competitiveness: The Role of Regional Clusters*** project was commissioned to the Purdue Center for Regional Development (PCRD) in 2005. The objective was to explore a set of industry cluster definitions that were applicable to metropolitan regions including micropolitan and rural regions. The primary audiences included regions such as Economic Development Districts (EDDs), designated regions from the Economic Development Administration (EDA), that served mainly micropolitan and noncore counties, and select metropolitan counties in the U.S. The research project had the following broader research questions.

- What were the linkages between cluster structure, degree of rurality, and economic performances, and if cluster composition and specialization changed because of rurality and remoteness?
- How are industry clusters distributed over space and what is the interface between rural and metropolitan regions?
- What are the growth trajectories of counties that differ by industry clusters, rurality and distance to metropolitan areas?

This project defined a set of 17 industry clusters at the NAICS 6-digit level. The manufacturing sector[12] was further subdivided into six subclusters bringing the total number to 22 clusters. This project did not define a cluster for retail industries or local services as the focus was mainly on basic industries[13] or export-oriented businesses and industry sectors. Hoyt (1954) stated that basic industries within the Economic Base Theory (EBT) were primarily classified to identify population growth in cities with the premise that employment growth would cause growth in population. Later, EBT and basic industries were used for forecasting land use requirements and local and regional economic development

[12] The manufacturing sector was termed as supercluster in the project.

[13] In the Economic Base Theory, basic industries are those industry sectors that can export goods and services outside of the region. Hoyt (1954) considered proportion of employment in manufacturing, state and federal government, wholesale trade, transportation and tourists as starting points for basic industry analysis. Later the LQ method was used to identify basic industries.

policies. Cluster definitions were derived based on Benchmarked Value Chain Clusters by Feser (2005); Location Correlation or co-location-based industry clusters by Porter (2003); Location Quotient[14]; Shift-Share analysis[15]; industry clusters by Nolan (2003); and a review of previously published cluster definitions. Previous benchmarked industry clusters were used as starting points and then industry sectors were included or excluded based on current co-location patterns, competitive-shift values, and the current industry cluster definitions developed by researchers and practitioners. The preliminary cluster definitions and economic metrics were applied to a case study region, the Economic Growth Region 8 of Indiana, which contained both, nonmetropolitan and metropolitan counties. The feedback from regional decision makers, local economic development offices, and planners were used to refine the industry cluster definitions and economic metrics. The project in the study region also informed how to present competitiveness analysis to the regions and develop regional development strategies.

The project utilized a continuous measure of the **Index of Relative Rurality** (IRR) by using four variables of population, population density, extent of urbanized area, and distance to the nearest metropolitan area (Waldorf, 2006). Unlike discrete measures[16] from the Economic Research Service (ERS) and the Office of Management Bureau's (OMB) metropolitan and nonmetropolitan classification, the IRR was not based on thresholds of indicator values. The index varied from 0 to 1 with 0 being the most urban and 1 being the most rural counties. The IRR did not answer if a county was "urban or rural" but what was the extent or the degree of the rurality for the county (Waldorf, 2006). Metropolitan areas contain the core and outlying counties with counties located in the outskirts having rural areas. Hence, metropolitan areas are heterogenous mix of counties comprised of urban and rural parts (Waldorf, 2006). The IRR was expected to simplify the classification and hence, facilitating the study between industry cluster specializations and the rurality (PCRD, 2007; Waldorf, 2006).

The study revealed that certain types of industry clusters concentrated more toward rural areas whereas certain industry clusters were located more in urban areas. The scatter plots between IRR and the employment share of clusters revealed that business and financial services; printing and publishing; information technology and telecommunications; and biomedical/biotechnical were more urban centric (PCRD, 2007). At the same time, agribusiness, food processing and technology; mining; and forest and wood products clusters were more rural centric (PCRD, 2007). The project provided important insights into the spatial distribution of specialization of industry clusters through GIS mapping and spatial analysis. The project discovered that rural regions were not dependent on agriculture only,

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[14] Refer to Footnote 5.

[15] Shift-Share Analysis could parse employment growth or decline to three influences: The effect of national growth or decline on regional industry sector or cluster known as the **National Effect**; effect of the industry-level national trend on regional-level industry sector or cluster known as the **Industry Share**; and regional competitiveness effect on industry sector or cluster known as the **Regional Share** (PCRD, 2007). Despite declining trends at the national level, an industry cluster could increase its concentration or specialization at the regional level due to unique regional competitive and comparative advantages such as a skilled labor pool, the proximity to raw materials, established transportation linkages to national and global markets, and an established chain of different tiers of suppliers, etc.

[16] ERS has developed the Rural-Urban Continuum Codes (RUCC), which divides metropolitan counties into three types and nonmetropolitan counties into six types. ERS has used population size, degree of urbanization, and adjacency to a metropolitan area as criteria to classify counties. ERS has also developed the Urban Influence Codes (UIC) that classify a county into nine categories based on population size of metro area, size of the largest town or city, and proximity to metropolitan or micropolitan counties.

which was contrary to the common understanding. Regions had specializations in more than one industry cluster, and urban and/or rural parts contributed to the specializations of the industry clusters. The case study revealed that targeting a diverse group of specialized industry clusters was feasible and useful for regions. Hence, unlike the previous academic discourse on urbanization (heterogeneity) versus localization (specialization), an appropriate approach was targeting a mixed group of industry clusters.

2.2.3) Mid 2010s

The latest effort in defining Benchmarked Clusters for the U.S. is by Delgado, Porter and Stern (2015) in their publication, "*Defining Clusters of Related Industries.*" The authors classify cluster identification methods as IO linkages, co-location patterns and knowledge clusters. The authors summarized the previous efforts highlighting the nuances in methodologies. For example, Feser and Bergman (2000) used factor analysis of IO linkage matrix, which provided an uneven group of clusters with overlapping sectors. Feser (2005) improved the method by applying hierarchical clustering on the IO linkage matrix and derived a set of 45 mutually exclusive clusters. Porter (2003) explored industry clusters based on co-location patterns or location-correlation of employment to derive a set of 41 clusters of traded industries or sectors, which had the potential to export goods and services outside the regions, states, and the nation. Refer to Table 1 for details of the previous industry cluster projects in the U.S.

The algorithm developed by Delgado, Porter and Stern (2015) contained a similarity matrix between industry pairs. The authors extended the previous research on LC of employment by Porter (2003) to include both, LC of employment and establishments. Similarly, the Co-Agglomeration Index (COAI)[17] developed by Ellison and Glaeser (1997) and Ellison, Glaeser and Kerr (2010) was extended from SIC 3-digit to NAICS 6-digit by Delgado, Porter and Stern (2015). The authors mention that linkages based on the national IO table reveal interindustry purchasing and selling patterns that reveal economic linkages, but do not capture relationships based on geographical characteristics. The authors computed two types of IO linkages[18] based on the maximum and average values of four unidirectional relationships between industries i and j, and hence extended the previous research by Ellison, Glaeser and Kerr (2010) and Feser (2005). The authors also developed occupation links by using occupation or staffing patterns by industries data available from the Occupational Employment Statistics, Bureau of Labor Statistics (BLS). The pairwise correlation[19] of occupation distribution between two different industries revealed if those industries were linked through skills and occupational or labor requirements (Delgado, Porter and Stern, 2015). Hence, the authors extended previous studies by Koo (2005a) and Glaeser and Kerr (2009).

The standardized average of four similarity matrices, LC of employment and establishments, IO_{ij} and Occ_{ij}, were used in the clustering algorithm. The authors proposed a

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[17] COI was developed for Economic Areas (EAs). The formula is $COAI_{ij} = \sum_r (S_{ri} - X_r)(S_{rj} - X_r) / (1 - \sum_r X_r^2)$, where S_{ri} is the share of industry i employment in the region r and X_r is the mean share of employment in all industry sectors (Delgado, Porter and Stern 2015).

[18] $IO_{ij} = Max\{input_{i \to j}, input_{i \leftarrow j}, output_{i \to j}, output_{i \leftarrow j}\}$ (Delgado, Porter and Stern 2015).

[19] $Occ_{ij} = Correlation\ (Occupation_i, Occupation_j)$ (Delgado, Porter and Stern 2015)

method of clustering functions[20] and parameter choices to define groups of industry sectors into clusters by using hierarchical clustering with Ward's linkages and kmeans and kmedians centroid-based clustering functions (Delgado, Porter and Stern, 2015). The authors developed a validation method to compare different cluster configurations including within and between clustering interrelationships and overlapping scores. The algorithm and process created definitions for several clusters and in several cases splits or mergers were made after validation. Delgado, Porter and Stern (2015) developed a set of 51 mutually exclusive traded clusters for the U.S. This was the last effort in developing the Benchmarked Cluster Definition for the U.S. The authors developed a robust set of similarity matrices to explore different interrelationships between industries; however, Delgado, Porter and Stern (2015) mentioned that the cluster definitions did not include patent-citations (knowledge and technology) linkages and social linkages between firms and agents such as entrepreneurs. The benchmarked cluster data and resources were distributed through dedicated websites[21].

2.2.4) Knowledge-based industry clusters

There has been significant research and discussions on the mechanisms for knowledge spillovers; however, limited works have occurred in identifying interrelatedness between knowledge and industries. This is the reason for the lack of **knowledge-based industry clusters** in the U.S., irrespective of the pre- and post-2010 periods. Feldman and Audretsch (1999) identified six industry clusters based on commonalities of R&D activities in specific academic disciplines. Industry sectors within the cluster were engaged in research, innovation and product development from the same academic disciplines. While the industries within the cluster or group[22] shared the same knowledge and innovation research base, the geographic distribution and product development could be disparate (Feldman and Audretsch, 1999). This research extended the debate between diversification and specialization by finding evidence that variety in production promoted innovation and in turn triggered economic growth in the regions. The research by Feldman and Audretsch (1999) supported Jacobs' (1969) findings that knowledge spillovers among diverse industries promoted regional economic growth in contrast to the ***Marshall-Arrow-Romer (MAR)***[23] hypothesis on specialization of industries and spillovers within the firms causing economic growth in the regions. At the heart of this debate lies the two contrasting viewpoints. The first was on local specialization and concentration and knowledge spillover within the same group of industries as elucidated by the MAR hypothesis. The other view-point was that urbanization encouraged industrial variety and competitions causing knowledge spillovers between diverse industries as elucidated by Glaeser et al. (1992) and Jacobs (1969). Compared to the product innovation pursued by Feldman and Audretsch (1999); Koo (2005) utilized cited patents in manufacturing industries to derive knowledge-

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[20] $C = F(M_{ij}, \beta\ ); Where\ Mij\ is\ combined\ similarity\ matrix\ and\ \beta\ is\ the\ parameter\ choices.$ Note that clustering algorithm requires minimum number of clusters as inputs.

[21] https://www.isc.hbs.edu/about-michael-porter/affiliated-organizations-institutions/Pages/us-cluster-mapping-project.aspx; https://clustermapping.us/.

[22] The six groups were identified by using the Yale Survey of R&D Managers and Small Business Administration's Innovation Data Base.

[23] Marshall, Arrow and Romer (MAR) published their seminal works in 1890, 1962 and 1986, respectively. Together it is known as the MAR Model for specialization-based regional growth. According to MAR, regional growth happens because of industrial growth where the specialization or concentration of similar industries cause knowledge spillovers among firms within the same industry sector (Beaudry and Schiffauerova 2009).

based industry clusters. However, post-2005, new research on knowledge-based industry clusters has been limited.

2.2.5) Integrated industry clusters

It is evident that industry clusters have been explored by different researchers through different lenses, especially the methods to define the clusters. Vom Hofe and Chen (2006) found that the common understanding that industry clusters included a group of interrelated industry sectors, institutions, labor force, suppliers, and buyers have been consistent through the decades; however, scholars had employed different methodologies including IO, LQ, shift-share, and other methods. This resulted in different industry cluster definitions over the decades because of the lack of "rigorous microeconomic foundations" to identify industry clusters (Vom Hofe and Chen 2006). The lack of a microeconomic foundation might have led to different industry cluster definitions; however, it also provided an opportunity to explore various methodologies including quantitative and qualitative methods. Note that the benchmarked clusters reviewed in this section employed quantitative methods. However, a recent study on the most commonly used methods to identify industry clusters emphasized the role of qualitative analysis or interviews and expert focus groups to understand and define industry clusters (Komorowski 2020). Academicians and practitioners are discovering that the industry cluster framework has applications beyond the traditional economic development field.

In the past, industry cluster strategies and initiatives had focused solely on increasing competitiveness and regional economic growth, and in so doing ignored the critical aspects of distribution of the economic growth across the society. However, a recent effort by Wilkinson, Suchanic and McCarty (2024) initiated addressing this gap by exploring the development of integrated clusters. The authors used interviews of experts and case studies to analyze how industry cluster initiatives are addressing the issue of distribution in the U.S. The authors share some important lessons to develop the industry clusters, which include "starting with the committed leadership; planning and budgeting for engagement efforts; and building trust and business support systems that are time consuming but critical" (Wilkinson, Suchanic and McCarty, 2024).

2.3) Data limitations

It is evident that scholars have used a variety of public data sources to define and analyze industry clusters in the U.S. However, there have been challenges because of the lack of granularity and suppression in the publicly available data. The most commonly used data sources were the national IO table of industry flows from BEA; jobs and establishments data from CBP, U.S. Census Bureau; jobs and establishments data from the Quarterly Census of Employment and Wages (QCEW) from the Bureau of Labor Statistics (BLS); and Occupational Employment and Wage Statistics (OES) from the BLS. Refer to Table 1 for data sources used in various industry clusters benchmarking projects in the U.S.

Over the decades, these data sources changed substantially in terms of coverage, types of variables, etc. This makes the temporal analysis substantially challenging. For example, the benchmark IO tables from BEA are published every five years during the economic census period. The 2017 benchmark IO table shows intermediate industry transactions for a group of 402 industry sectors. At the same time NAICS classified 1,057 industry sectors at the 6-digit level in 2017. There is a scale mismatch between vital information on industry-to-industry flows and industry sector employment data. The annual IO table for 2022 provides intermediate industry transactions for only 72 industry sectors. Compared to 1,012 NAICS 6-digit industry sectors in 2022, the IO table from BEA is only marginally helpful in deciphering detailed industry-to-industry flows. The lack of granularity and the suppression in public data remain a challenge even after decades of public data availability.

The NAICS codes for industries decreased in numbers at the most granular 6-digit level for every economic census period. For example, there were 1,179 NAICS 6-digit codes during the 2002 Economic Census; however, the NAICS 6-digit codes decreased to 1,012 in the 2022 Economic Census. For CBP 2021 county-level data, 41% of manufacturing sector data were noted with high-noise[24] at the NAICS 6-digit level. For the NAICS 2-digit level, 19% of data were noted with the high-noise. The noise was added to the published numbers in the CBP data instead of suppression. For QCEW, 10% of data were suppressed in 2022 for manufacturing sectors at the NAICS 2-digit level. The suppression increased to 85% for counties at the NAICS 6-digit level. The BEA provides economic metrics for industry sectors at only NAICS 2-digit levels. For U.S. manufacturing, 11% of BEA data were suppressed for NAICS 2-digits at the county level.[25] The NAICS 2-digits provide only a broad overview of the industry sectors, and the 2-digit codes are not useful for developing industry cluster definitions. However, the NAICS 2-digit data can provide insights into the employment distribution in major industry sectors. Research on industry clusters requires detailed establishment, employment, and earnings data for industries, and the high suppression levels in public datasets pose significant challenges.

2.4) Conclusions

There have been five specific initiatives to develop benchmarked industry cluster definitions in the U.S. during the years 2000, 2003, 2005, 2007, and 2015, respectively. These research initiatives utilized a variety of data sources from BEA, BLS, and the Census to develop industry cluster definitions that could be applied to different regions. As elucidated by the term, “benchmark,” the cluster definitions provided a template for regional economic competitiveness analysis comparing peer, competitor, or aspirant regions. Over the decades, the data sources have become comprehensive; however, the challenges of data suppression and time lag remain. Previous research efforts have used a mix of qualitative and quantitative methodologies including a review of existing definitions of industry clusters, economic IO analysis, and various correlational measures. The scholars stated that production and spillovers of innovation such as patent-citations linkages data were sparse, and hence could not be used to inform cluster definitions. Similarly, suppression of economic data at the granular level of NAICS codes for sub-state geographies creates information gaps despite un-suppression methods utilized by

[24] The high-noise means that the original data have been changed by 5% or more to protect the confidentiality. https://www.census.gov/programs-surveys/cbp/technical-documentation/methodology.html#par_textimage_245304869.

[25] As of the preparation of this manuscript, BEA has discontinued county level industry employment and earnings data from December 2024.

researchers and proprietary data sources. These gaps and challenges inform future research directions.

Table 1: Features of the U.S. Benchmark Industry Cluster Projects

Serial Number	Year	Author	# of Clusters	Method	Data
1	2000	Edward Feser and Edward Bergman	28	Purchase and sales coefficients of IO transactions table and Factor Analysis	1987 National IO
2	2003	Michael Porter	41	Location-correlation of employment	County Business Patterns
3	2005	Edward Feser	45; 18	Purchase and sales coefficients of IO transactions table and Ward's Hierarchical Clustering algorithm	1997 National IO
4	2007	PCRD	22	Feser (2005), Porter (2003), Location Quotient, Nolan (2003), review of previously published clusters	Unsuppressed QCEW (Quarterly Census of Employment and Wages) data for Indiana; Suppressed QCEW data for other states
5	2015	Mercedes Delgado, Michael Porter and Scott Stern	51	Combined similarity matrices based on location correlation, IO, and occupations; hierarchical clustering; validation scores	2009 CBP data for EAs (Economic Areas); 2002 Benchmark IO Account for U.S.; 2009 OES (Occupational Employment and Wage Statistics) data from BLS

Serial Number	Year	Author	Geography	Remarks	Journal/Report	Funding Source
1	2000	Edward Feser and Edward Bergman	U.S.	Manufacturing industries	National Industry Cluster Templates: A Framework for Applied Regional Cluster Analysis (Feser and Bergman 2000)	State of North Carolina
2	2003	Michael Porter	U.S. States	Traded cluster, local cluster, and resource dependent cluster; overlapping cluster definitions	The Economic Performance of Regions (Porter, 2003)	EDA
3	2005	Edward Feser	U.S.	Value Chain clusters and technology-based industry clusters	Benchmarking Value Chain Clusters for Applied Regional Research (Feser 2005)	State of North Carolina, NSF[26]
4	2007	PCRD	U.S.	Overlapping cluster definitions based on NAICS 6-digit industry codes	Unlocking Rural Competitiveness: The Role of Regional Clusters (PCRD 2007)	EDA
5	2015	Mercedes Delgado, Michael Porter and Scott Stern	U.S.	Mutually exclusive clusters based on NAICS 6-digit industry codes. Traded and local clusters.	Defining Clusters of Related Industries (Delgado, Porter and Stern 2015).	EDA

[26] National Science Foundation

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3.0) Economic geography of knowledge and innovation: National and international contexts

There is substantial research on knowledge and innovation spillovers and diffusion processes in economics, geography, and planning as researchers have tried to understand mechanisms of economic growth. Knowledge production, knowledge transfer and diffusion, innovation production and spillovers, national and regional innovation systems, innovative milieux, etc., are a few terms coined by researchers to describe the processes in the knowledge and innovation space. Feldman (2000) has described the vast literature on knowledge and innovation in two categories—1) innovation as an output in production function using geography as the unit of analysis and other descriptors; and 2) innovation as one of the descriptors to explain differences in economic growth and productivity between regions. Innovation is entered as a dependent variable in the first category, and it is an independent variable in the second category of such studies. The geographical units are "regions" and not "local" or "national" that are intrinsic to both the categories of research to provide the spatial contexts (Feldman, 2000).

Schumpeter is credited with developing the concept and role of innovation in economic development identifying five types of innovations that included new products, new materials, new production processes, new markets, and new organizational forms (Ziemnowicz, 2013). Innovation, entrepreneurship, and "Creative Destruction" were central to Schumpeterian thinking of mechanisms for economic development (Ziemnowicz, 2013). Many scholars have also explored the role of agglomeration in enabling knowledge creation, diffusion, and innovation. Within agglomeration, especially the role of urbanization and the diversification of industries, institutions, employers, labor force, and residents have been explored in facilitating innovations and spillovers such as patents, citations, trademarks, technologies, and ideas (Jaffe, Trajtenberg and Henderson 1993; Jacobs, 1969; Feldman, 2000).

The geography of production has, in part, explained the geography of innovation as specialization and proximity of firms have facilitated knowledge spillovers. Yet researchers have also found that investments in the industry R&D, university research, and concentration of skilled workers were significant in explaining the innovation outputs (Audretsch and Feldman, 1996). Hence, the geographies of production, knowledge, and innovation have important spatial aspects requiring further research. In addition to agglomeration and specialization of factors of production, research has also revealed "culture" as an important determinant for innovation as revealed by Saxenian's insightful research on the technological success of Silicon Valley (Saxenian, 1996).

The knowledge development process is a continuum. An accepted general pathway is "information—knowledge—wisdom." Whereas the cost of transferring information over large distances has declined because of the progress in internet and data storage technologies, there are limitations on how knowledge can be transferred, especially through the mechanisms of spillovers and economic gains. This review of literature looks into the spatial and aspatial aspects of knowledge and innovation systems from the lens of agglomeration and regional development. It also includes international cases of industry clusters as different developmental pathways.

3.1) Knowledge and collective learning

The conversion of information to knowledge is a collective learning process. However, knowledge development and knowledge management are distinct processes. Effective knowledge management can be achieved through developing operational routines, standards, norms and social interactions and communications. The ability to manage this chain of processes determines the competency of the organizations. Knowledge management is directly connected to firms' competitiveness. In the industry cluster setting, strategic alliances, competition, and cooperation are actively pursued through knowledge sharing and resource integration activities. Joint efforts in Research and Development (R&D) and innovation in the industry clusters contribute to strengthening firms' international competitiveness (Lai et al., 2014). The knowledge transmission and collective learning are fostered by cultural, institutional, and geographical proximity. Network and dependencies might have significant effects on competitive performance of organizations (Keeble and Wilkinson, 1999). Here, the authors have defined two types of knowledge, which include codifiable and tacit knowledge. The codifiable knowledge is readily transferrable whereas the tacit knowledge is embedded within the context, therefore it is not readily transferrable (Keeble and Wilkinson, 1999).

3.2) Knowledge transfer and epistemic community

Lissoni (2001) discussed knowledge codification and innovation in clusters of small- and medium-sized enterprises (SMEs) in Italy. The case study of the top three sectors in Italy's Brescia's machinery industry showed dominance of. Industrial clusters are better in facilitating tacit knowledge production and the knowledge circulates within the **epistemic communities** or professionals and workers sharing similar occupations, training, knowledge, skills, and abilities. The epistemic communities are formed by professionals in a common enterprise who share the common professional language and vocational frameworks and extends beyond individual organizations (Loasby, 1998; Hakanson, 2005). Lissoni (2001) also discussed localized labor mobility and knowledge socialization as the main contributors to knowledge transfers, which included firms and establishments, workers, suppliers and even customers.

Breschi and Lissoni (2001) defined **localized knowledge spillovers (LKSs)** as a public good and a positive externality. It is tacit in nature and difficult to codify or transfer. Hence, LKS allows companies operating in spatial proximity to access key knowledge sources and innovations faster. Technical knowledge can be highly specific and dynamic, which can be acquired through practical experiences, but tacit exchange is still possible. The localized knowledge spillover econometrics have used knowledge production function, emphasizing impact of external R&D on a private firm's innovation capabilities. R&D and patents are used as core variables to measure an individual firm's innovation capabilities.

Industry clusters are the concentration of interlinked industries, and firms within the cluster can access tacit knowledge which can provide competitive advantages to those firms. The professionals in the cluster belong to the same or related epistemic communities (Loasby, 1998; Hakanson, 2005). These epistemic communities extend beyond individual organizations. For knowledge-based industries, socialization and vocational trainings lead to professional communities and networks with common codes, technical language, and understanding. In this epistemic community, both codified and tacit knowledge move easily.

Some epistemic communities are geographically concentrated like communities clustering around Silicon Valley, but long-distance communication and collaboration among firms allow development of epistemic communities beyond geographical boundaries (Hakanson,2005).

3.3) Knowledge management to innovation

3.3.1) Systemic support in knowledge management

Geographical or spatial proximity allows knowledge to circulate among local actors and informal contacts play key roles in transferring knowledge and information. Firms relocated into the industry cluster benefit from these positive externalities. For example, Morrison (2008) described the role of leader firms in furniture industries in southern Italy in shaping the district's learning processes. Leading firms in the industrial districts can build stronger capacity and access a larger set of external information and knowledge sources. They play a leading role in shaping industrial districts and are at the core of multi-level knowledge networks. For complex knowledge and transfer mechanisms, leader firms can develop strategies in implementing knowledge translation and codification function (Morrison, 2008). The leading firms play the role of knowledge gatekeepers who would identify external sources, absorb them, and then translate and disseminate external knowledge through local-level learning activities (Allen, 1977; Morrison, 2008). The concept of knowledge gatekeeper provides useful insights into the processes of learning and knowledge diffusion. Gatekeepers are a small community of individuals who are the core nodes of the information network and have informal linkages with external actors. Gatekeepers will search, transcode and share knowledge for the actors in the organization (Allen, 1977; Morrison, 2008).

Local business organizations and trade associations play important roles in organizing trade shows, industry conferences, social activities, etc. These events give valuable opportunities for participants to connect, exchange contacts, technical, and market information. Trade associations play a critical role in providing technical, financial, marketing, training, and other support services and representing employers in dealing with the government and organized labor (Keeble and Wilkinson, 1999).

Innovation should be understood as a cycle involving interactions between tacit and articulated knowledge (Keeble and Wilkinson, 1999; Lawson and Lorenz, 1996). The ability to share and use varied knowledge leads to the success of high-technology regions. For example, interactions between technology user and producer, multidisciplinary culture of a local university, links between large and small firms, etc., are channels of knowledge flows.

3.3.2) Innovation milieux and entrepreneurial activities

Innovation processes have been discussed by many scholars in relation to knowledge and competence. Innovative Milieux is the term adopted by European researchers to describe local clustering of highly innovative producers of high-technology products and services. To achieve continued success of innovative milieux, learning from external knowledge is essential (Keeble and Wilkinson, 1999). Industrial districts generate high levels of trust and encourage informal and tacit knowledge transfer. This leads to an industrial atmosphere, external economies, and savings in transaction costs. Synergies and innovative capacity are created by cooperative relations facilitating knowledge transfer. In this process, industrial districts become innovative milieux (Capello, 1999; Keeble and Wilkinson, 1999).

Lai et al. (2014) discussed the relationship between knowledge management of industrial cluster and innovation performance. Knowledge management is defined as an all-encompassing process which spans from knowledge creation, acquisition to dissemination, and storage. Innovation performance is measured by market performance and product performance. Empirical analysis based on survey questionnaires collected from the Taiwanese industrial clusters including science parks, export processing zones, and industrial zones supported the main hypotheses that firms can utilize resources more effectively in the industrial cluster environment and achieve higher competitiveness. Industrial clusters allow firms to manage more effective knowledge management and raise the level of innovation performance.

Hakanson (2005) outlined a model of cluster dynamics and key factors leading to the following outcome: Industrial cluster growth is derived from flows of the various factors such as growth of existing firms, high rate of new firm formation, positive environment for entrepreneurship, competitive technological advancement and innovation opportunities, and resource inflows through globalization (Hakanson, 2005). Cluster setting provides easy access and varied opportunities to both entrepreneurs and job seekers, and active formation of new firms and their accomplishments play an important role in continuation and growth of the cluster (Hakanson, 2005).

3.4) Industry cluster case studies

3.4.1) Manufacturing

Schmitz and Musyck (1994) discussed the role of formal institutions in four European industrial districts including the Third Italy, Baden-Wurttemberg in Southern Germany, West Jutland in Denmark, and South-West Flanders in Belgium. Institutions can help in new technology development, new market identification, skilled labor training, and raising capital. In these European industry district examples, local credit institutions, regional systems and regional governmental support played a critical role in fostering small-medium sized firms in the region. Vocational and technical training programs for both workers and entrepreneurs were widely used and fostered in these regions. Provision of local level training and apprenticeship, training programs for entrepreneurs and courses on technical and managerial issues were also provided. A dual system of vocational training and education was offered through vocational training colleges in the region. The Chamber of Commerce and Industry, professional associations, training and technology centers played a significant role in dual educational and training system. Regional governments played an important role in pursuing active innovation efforts. In addition, regional and local associations contributed to develop strategic policies to support industrial districts with small and medium sized firms (Schmitz and Musyck, 1994).

3.4.2) High-technology

Gray et al. (1996) called Seattle a hub-and-spoke industrial district where a region hosts one or more industries with one or a few dominant firms or nonprofit institutions. The case study examined Seattle’s three major high-technology industries including aerospace, software, and biotechnology. Boeing was the single most important hub for aerospace activities. The software hub was formed due to Boeing's internal needs. The biotechnology hub was formed independently. The three successful industry hubs generated agglomeration economies, enriched infrastructure, and strengthened resistance to disruptions in the region. Federal procurement, projects and subsidies were critical in the development of both aerospace and software hubs. The role of the University of Washington and Fred Hutchinson Cancer Research Center was significant in the development of the biotechnology hub in the areas of R&D and entrepreneurial opportunities.

3.4.3) Culture

Santagata (2002) defined culture as the capital asset accumulated by community reflecting tangible and intangible identity. Both material and non-material cultural-based goods are created through human creativity and intellectual activities during this distinctive process. In Europe, cultural markets provided major employment in the region. Industrial cultural districts initially started with many small and medium sized enterprises such as the Third Italy. Within industrial cultural districts, enterprises were benefiting from the low cost of use of the market due to positive externalities, tacit knowledge, high rate of innovation and easy networking. Two types of positive externalities from the creation of industrial cultural district were identified by Santagata (2002): 1) ***Atelier effect*** focusing on training local cultural professions and creating entrepreneurial opportunities, and 2) new product creation and differentiation through new product creation process.

Italy's museum cultural district is composed of a network of museums. The museum district impacts include increased demand for hotel and tourism services, boosting international reputation and positive externalities including network, consumption, time, and economy of scale. Metropolitan cultural districts are concentrated with buildings such as performing arts, museums, organizations producing cultural events, goods, and services. Many metropolitan cities are hosts to the metropolitan cultural districts. Art markets, performing arts, museums, cultural heritage sites, design-based goods can be chains of value creation. Culture and cultural districts hold an economic significance and help the regions thrive. It is to be noted that such districts represent a clustering of performing arts services, tourism-related activities, and creative occupations.

3.5) The international perspective on industry clusters

Whereas the Industry Cluster strategy lends itself to a local or regional perspective, they do not function in isolation. Globalization has shifted traditional business in many ways, including bringing in competition from abroad. Understanding how industry clusters operate in a global context provides further insights into the potentials of this strategy. In addition, when looking at the international literature, case studies of industry clusters in a variety of contexts become available. Through examining the common themes from the literature, one can better understand industry clusters and their applications.

3.5.1) Recurring characteristics from international case studies

The literature highlights a wide range of case studies of industry clusters across the globe. Previously, we discussed the history and definition of industry clusters. In this section we are going to review some of the common characteristics seen in the international literature on industry clusters. The Sinos Valley industry cluster case study brought forward several characteristics that are thematic across case studies (Schmitz, 1995). These include: 1) importance of place and proximity, 2) competitiveness within the cluster, 3) cooperation and collective action, and 4) culture within the cluster. The following sections will dive deeper into each of these themes, bringing in examples from the literature.

3.5.1.1) The importance of place and proximity

Place and proximity have been recurring discussion points throughout the literature. As stated in chapter two, geographic concentration is a key feature of industry clusters. But where the cluster is and the proximity of enterprises both have effects that are recurring topics of discussion in the literature. In Asheim and Isaksen (2002), three industry clusters in Norway are examined. These examples highlight how enterprises within an industry cluster leverage regional resources to be competitive at a global level. In addition, the Sinos Valley example (Schmitz, 1995) demonstrates how the proximity of firms leads to innovations resulting in new small and medium enterprises focused on specialized niches. In addition, with businesses being clustered together in close proximity, it allows them to cooperate on shared issues, so everyone benefits. The cooperation and collective action present in industry clusters is further explored in the next section.

3.5.1.2) Cooperation and collective action

Despite the competition among enterprises, cooperation for the common good is a theme across industry clusters. As mentioned previously, the Sinos Valley's Shoemaking industry cluster is a prime example of how collective action is not only a characteristic of industry clusters, but can also strengthen the cluster (Schmitz, 1995). To become globally competitive, the enterprises in Sinos Valley worked together to host industry events that brought foreign buyers to them. This exposure facilitated interest and business deals between Sinos Valley and the U.S. Other examples of cooperation within industry clusters include sharing resources to cultivate training opportunities to skill-up the workforce. This is further underscored by the findings of Asheim (1996) that interfirm collaboration is essential to facilitating learning networks.

3.5.1.3) Competitiveness within the cluster

When operating in a global context, competition is abundant. However, enterprises often focus on competition within their industry cluster. Buyers are looking to source products at the lowest cost possible, but when presented with competing bids from outside Sinos Valley, enterprises did not react. But once presented with a competitor's pricing from within the Sinos Valley, firms were quick to try and undercut one another.

3.5.1.4) Culture within the cluster

A unique culture develops within industry clusters. In fact, the industry becomes part of the identity of those involved. This is partly due to how small the world is within the cluster, as one can frequently run into the same people. For this reason, relationships often aren't just for economic gains. A level of trust is built that helps facilitate the collaboration mentioned previously.

3.5.2 Industry clusters as a road to development

When looking at industry clusters in an international context, a key discussion point is their role in development. The process of development is a well-studied topic with differing opinions and is no different when it comes to industry clusters. Industry clusters have been exemplified as a “high road” to development, but also criticized. In this section, we will explore arguments on both sides by taking a step back and defining what we mean by development. These definitions will then be discussed alongside the arguments for and against industry clusters to highlight the breadth and depth of the ongoing discussion.

In her book Theories and Practices of Development, Katie Willis presents three schools of thought on how development is defined: Economic, Modernity, and Human (Willis, 2011, ch. 1). Development as an economic process focuses on expanding economic activities, both buying and selling among individuals and enterprises. This is especially popular in capitalist societies as many assume “that with greater wealth come other benefits such as improved health, education, and quality of life” (Willis, 2011, p. 5). Interpreting development as becoming modern is less of an exact science, as what is modern or current is a goalpost constantly on the move. It is also subjective, changing based on cultural, economic, or political contexts. Finally, the human development perspective focuses on improving the quality of life for people. From health and well-being, to happiness and freedoms, this can include a range of topics. Regardless of what definition one can use, development is multifaceted, requiring examination of multiple factors. The following sections will examine the industry cluster strategy from these different perspectives.

3.5.2.1) Industry clusters as a road to economic development

With the many dimensions of development in mind, we can begin to examine the discussion around industry clusters as a tool for development. In the case study of Torreon’s Blue Jeans industry in Mexico as well as the Sinos Valley’s Shoemaking industry in Brazil, the researchers question the economic development for individuals and the workforce. A key piece of this discussion is the wages for workers within the cluster. While wages may be better within the industry cluster than workers could otherwise expect, the low wages are still criticized. As buyers push to lower the bottom line, the cuts ultimately come from workers’ wages. The insufficient wages still leave many workers trapped, and this is expected to continue as the current model depends on lowering the costs through lowering the wages. Without the lower costs, North American buyers could source these products closer to home or find someplace else to provide the cheap labor. Many workers dream of climbing the ladder within the cluster by starting their own businesses, but the Sinos Valley example demonstrates how this has become harder as time has progressed. And in the case of Torreon’s blue jean industry, U.S. contractors are documented as repeatedly returning to the same enterprises, making it hard for new ones to break in. Due to the low wages and limited upward mobility for workers, the economic development achieved from the industry cluster model becomes questionable for the individual or workforce in the context of the developing economies.

However, there have been several beneficial economic outcomes within the clusters. In the case of the Sinos Valley, the researchers examined the industry cluster over time which revealed the growth of several enterprises. In addition, many enterprises have been started over the decades in this cluster with varying lifespans. The geographic proximity and the expertise within the workforce have helped facilitate these start-ups and growth, leading to collaboration within the cluster as enterprises outsource aspects of production to specialty firms. For both Sinos Valley and Torreon, the clusters saw significant growth when foreign buyers started purchasing from within the cluster. In addition, while wages may be low, they are comparably higher than they would otherwise be outside of the cluster. Ultimately, there is significant economic development facilitated through the industry cluster model as it provides many opportunities for currency to exchange hands within the industry, as well as bringing in funds and resources from outside the country.

3.5.2.2) Industry clusters as a road to modernity

In terms of industry clusters as a tool for modernity, there are mixed arguments as well. Modernity goes hand in hand with innovation and upgrading. Upgrading has been defined as “the capacity of a firm to innovate to increase the value added of its products and processes” (Giuliani, Pietrobelli and Rabellotti, 2005). Much research has focused on how and why firms innovate within clusters, because upgrading and innovation impact a cluster’s ability to be globally competitive (Asheim, 1996). And many characteristics of industry clusters aid in innovation. In the examples in Norway (Asheim and Isaksen, 2002), the enterprises take advantage of local and regional education resources for upgrading. Similarly, in the Sinos Valley, the opportunities for collaboration between enterprises has led to the development of niche expertise for small and medium enterprises. By integrating their work into the production process, large enterprises have added additional value to their products (Schmitz, 1995). In the modern age, this innovation extends to technology. To keep up with one another, firms adopt new technologies and make improvements, leading to technical advances coming from within industry clusters.

However, the limitations foreign buyers impose can limit innovation. This is seen in the Torreon industry cluster, as U.S. buyers limit in what ways the enterprises can upgrade by insisting certain parts of the process be done in the U.S. versus in Torreon, Mexico. Further, a handful of the enterprises have a monopoly on the contracts from the U.S. and are gatekeepers for smaller enterprises. Without the prospect of more business, enterprises do not have the incentive to upgrade. These points underscore the conclusion of Giuliani, Pietrobelli and Rabellotti (2005) that “both the local and the global dimensions matter.”

3.5.2.3) Industry clusters as a road to human development

Human development is a broader topic, encompassing multiple areas such as health, economics, social capital, and more. Amartya Sen summarized it best by saying: “The process of economic development can be seen as a process of expanding the capabilities of people. Ultimately, the process of economic development has to be concerned with what people can or cannot do,” (Amartya Sen quoted In Wresch, 2009, p. 262). Hence to look at the industry cluster strategy as a tool for human development, we must ask what capabilities are expanded by people’s involvement in an industry? One well documented outcome is the educational opportunities within clusters. The shipbuilding, mechanical engineering and electronics industry clusters in Norway are an example of clusters that capitalize on the educational institutions in their regions to improve their workforce, products, and production (Asheim and Isaksen, 2002). In addition, many clusters such as the ones in the Sinos Valley demonstrate inter-firm collaboration to address common needs such as education (Schmitz, 1995). In addition, Schmitz (1995) takes it a step further in claiming a community and regional development component, as mentioned previously. The shared industry knowledge and experiences create social bonds and trust that may have benefits outside of business. Inter-firm collaboration also extends to collective action on community and governance issues. Expanding people’s social power is a key part of John

Friedman’s development framework: “development is a process that seeks the empowerment of the households and their individual members through their involvement in socially and politically relevant actions” (Friedmann quoted in Myer, 2011, p. 158).

Hence, if we begin to look at human development through John Friedman’s social power framework, we get a mixed picture. Friedmann identifies eight dimensions of social power: “social networks, information for self-development, surplus time, instruments of work and livelihood, social organization, knowledge and skills, defensible life space and financial resources” (Myers, 2011, p. 118). In the examples given in the previous paragraphs, we see industry clusters expand people's social power in the realms of social networks, information for self-development, social organization, and knowledge and skills. However, the remaining four present a mix of criticism and a need for further study. As mentioned in section 3.2.2.1 (economics), there has been much criticism of the wages and working conditions within industry clusters in ”developing” countries (Myers, 2011). Low wages can limit the financial resources and the required working hours needed to make a living wage can limit surplus time. In addition, section 3.2.2.2 (modernity) touches on innovation in technology, such as tools (instruments) for work (Myers, 2011). Industry clusters are hotbeds for innovation as the concentration of expertise leads to new niche firms.

In Torreon, the researchers highlighted how U.S. partners guarded parts of the industry value chain, specifically the marketing and product design. Arguably, these are the creative parts, and the gatekeeping stifles artistic growth and expression from those within the cluster. Further, by imposing U.S. culture in this way, we harken back to the argument from Willis (2011) that while some may see this as development, for others “it is associated with the eradication of cultural practices, the destruction of natural environments, and a decline in the quality of life.” (Willis, 2011, p. 3). If individuals in industry clusters outside the U.S. or Western Europe were involved in the creative process, such as the design of blue jeans in Torreon or shoes in Sinos Valley, what innovations could their unique cultural lenses bring to the products? This question is reminiscent of the points brought forth by Abhijit Banerjee and Esther Duflo, who assert that the “poor” have significant knowledge and reasons for why they do what they do (Myers, 2011, p. 39). Which, ironically, is the reason many buyers choose to import products from these clusters, because the enterprises there have a history in their craft that leads to expertise. This was well documented by Schmitz (1995) in the Sinos Valley.

3.5.2.4) Concluding remarks and areas for further study

As this section has demonstrated, the industry clusters strategy has many opportunities for development purposes. However, this strategy also comes with downsides. The reality is that further study is needed. Most literature on industry clusters focuses on the economic benefits for the firms or nation. However, more research needs to be focused on the individuals in these clusters, as well as the industry cluster’s impact on nearby residents. Particularly, it would be interesting to compare the Human Development Index of different industry clusters. Other measures of quality of life, spanning across economic, modern, and human development, should also be examined. Ultimately, differences in culture, geography, economics, and politics will make every industry cluster unique.

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4.0) Occupation and skills clusters

4.1) Occupation and skills clusters provide a different lens for regional analysis

Economic development researchers and practitioners commonly use industry cluster analysis—which examines interdependence and specialization within regional economies—to identify regional competitive advantage (Wolman and Hincapie, 2015). Many cluster analyses use interindustry buying and selling patterns to demonstrate the interdependence between firms and regions. However, this approach can prove limiting because these transactional relationships do not reflect other important types of interdependencies (Renski, Koo, and Feser, 2007). Most notably, these analyses do not always consider the contributions that area workers make to regional competitive advantage.

Recognizing the distinction between what businesses make and what workers do is an important step toward fully understanding a regional economy (Thompson and Thompson, 1987). The former relies on industry-based employment and wage data (i.e., NAICS[27]-based data), while the latter often requires occupational data (i.e., SOC[28]-based data) and these different perspectives can highlight different trends. For example, an approach that prioritizes" what workers do" shows that both Washington, D.C. and Charlotte—two metro areas not traditionally thought of as leading centers of innovation—nevertheless have relatively large concentrations of IT[29] workers because these workers support government and finance, respectively.

To understand our regional economies more fully, we must continue developing analytical methods and tools that provide insights about the geography of talent. Many industries are mobile, but talent is more place-based. Therefore, economic futures often rely on the regional workforce's inherent knowledge, skills, and abilities. Over the past 20 years, regional researchers have applied the cluster concept to occupations. This approach allows researchers to better understand the relationships, similarities, and dissimilarities among different types of work activities (Feser, 2003). Grouping occupations with similar characteristics (e.g., required education, experience, skills, common tasks) can show what regions do well and how they compare to other regions. These occupational approaches provide an important complementary lens for understanding regional competitive advantages.

This section will explore how researchers and practitioners use occupation and skill clusters to better understand the contributions that human capital makes toward regional competitive advantage. It begins by reviewing several notable efforts to operationalize occupational clusters and create a regional analytical framework. It then highlights the ways in which different stakeholder groups can use occupational cluster analysis to inform their economic and workforce development planning and activities. It concludes by identifying several opportunities to further develop occupational cluster analysis so that it can better meet the current and emerging needs for practitioners and researchers.

[27] North American Industry Classification System
[28] Standard Occupation Classification
[29] Information Technology

4.2) Demand remains for frameworks that explain regional workforce strengths

The need for economic development practitioners to understand their local workforce's relative strengths and weaknesses has never been greater. The capacity of local workers can dictate a region's economic opportunities available to them and where it fits within the broader economy. In an early attempt to understand the relative position of a regional workforce, Thompson and Thompson (1987) identified five distinct regional roles—entrepreneurship, central administration, R&D, precision operation, and routine operation. This framework highlighted the importance of a region's occupational mix in determining its future, because industry employment trends may not reveal the range of activities within a region. Firms in a single industry may locate production in one region and R&D in another, each of those activities require workers with different skills. The versatility and adaptability of the local skill base can also dictate the extent to which regions can take advantage of growth opportunities or manage "sunset occupations" lost to automation or globalization.

Feser (2003) created a conceptual framework to identify **knowledge-based occupational clusters** as a tool to help economic development researchers and practitioners identify the competitive advantages within their regional workforce. This framework relied heavily on two sources—the U.S. Bureau of Labor Statistics (BLS) and the O*Net[30] database. BLS' Occupational Employment and Wage Statistics (OEWS) provide data on occupational employment within a region, and the National Industry-Occupation staffing matrix shows occupational employment within a given industry. The O*Net database provides, among other things, information about the requisite knowledge, skills, education, and experience necessary for individual occupations. These data can be used to create occupational groups based on the relationships, similarities, and differences among occupations, as well as the relative importance of these requirements to those occupations.

Feser used Ward's hierarchical agglomerative clustering method to subsequently construct a set of 21 knowledge-based occupational clusters. These cluster definitions can inform descriptive and explanatory studies about the geography of human capital when used in conjunction with occupational employment data (e.g., growth, relative concentration, etc.). The subsequent analysis can be used to help economic development practitioners identify targets based on the region's workforce strengths or post-secondary institutions to develop programs that better meet regional skill needs.

4.2.1) Occupational cluster frameworks should align with regional priorities

Many subsequent efforts to operationalize occupational clusters have used similar data sources and methodologies (e.g., Koo, 2005; Nolan et al., 2011; Slaper, 2014), but these efforts often pursue different goals. For instance, Nolan et al (2011) prioritized more knowledge-intensive occupations when creating a framework that included 15 knowledge-based occupational clusters. These clusters consisted primarily of occupations that require extensive amounts of knowledge, preparation, and training (i.e., O*Net Job Zones 3 to 5).

[30] Occupational Information Network

This framework was based in the assumption that knowledge-driven occupations will cluster in places with greater innovation potential.

By contrast, Chrisinger, Fowler, and Garshick Kleit (2012) took a different approach by developing cluster definitions that include occupations more commonly found in lower-wage, locally serving industries. As a result, their 25 occupational clusters included areas such as personal healthcare and assistance, medical and social assistance, and hospitality and personal services, among others. These clusters provide more insight about many lower-wage occupations that are often filled by people in poverty or near poverty. This shows that to better align with user needs and priorities, researchers can adapt occupational cluster definitions to target different segments of the workforce.

Researchers can also try to appeal to a much broader audience. Slaper (2014) created a more comprehensive set of occupational cluster definitions that covers a relatively large portion of the overall workforce. This framework consists of 34 different occupational clusters and includes both knowledge-based clusters (that resemble other, previous efforts) and other clusters that include less-knowledge-intensive occupations. These additional clusters often include occupations that support more knowledge-intensive activities. For instance, many" financial, legal, and inspection services, support" occupations can be found in the same firms as occupations in the "Financial, Legal, and Real Estate" occupational cluster. This broader framework, therefore, captures more of the occupations in O*Net Job Zones 1 and 2 (which require relatively less education, training, and experience). However, Slaper did note that creating a workable set of occupational clusters often involves both art and science and the primary challenge is finding the proper level of aggregation. Ultimately, effective occupational cluster definitions possess both a level of aggregation that allows users to understand the primary occupational groups within a region, but at the same time are not so specific that they offer no generalizable knowledge.

Occupational cluster analysis, or occupationally focused research more generally, can make important contributions to regional research. Firms within industry clusters—particularly manufacturing-related clusters—often share similar production processes, technologies, and markets, and as a result they broadly hire workers with similar skill sets (Koo, 2005). In spite of this overlap between typical industry clusters and occupational clusters, there are many forms of interdependence that bind regional economic clusters; a shared labor pool might only represent one (Renski, Koo, and Feser, 2007).

As a result, there remains strong practical reasons to examine clusters from different perspectives. These different perspectives yield different insights that may reveal connections and potential opportunities that are not obvious. For instance, Markusen and Barbour (2003) noted that engineers in Southern California's aerospace industry also found opportunities in the sportswear industry, due to their knowledge of different materials. Similarly, the demand for woodworking skills allowed displaced furniture workers in North Carolina to find work in the state's boatbuilding industry. As a result, cluster initiatives—large scale investments and activities that grow and leverage the regional competitive advantage arising from a unique concentration of skills or activities—can change a region's economic trajectory. These initiatives, therefore, can help regional economies transition away from existing clusters that are losing their relative competitiveness, and instead build more competitive clusters that offer greater future growth potential (Donahue, Parilla, and McDearman, 2018).

4.3) Occupational cluster analysis has applications for multiple user groups

Workforce analysis—including, but not limited to analyzing occupational clusters—has become more essential to community and economic development (Nolan et al, 2011) and can inform the work of economic and workforce development practitioners, employers and corporate decision makers, and educational leaders. The responsibility for developing cluster definitions and performing the actual analysis often falls to scholars and consultants. As a result, scholars and consultants must not only understand each stakeholder group's information needs, but they must also effectively translate this information so that it can lead to actionable decisions. This section reviews how occupational cluster analysis can benefit different user groups.

4.3.1) Workforce research informs how regions promote themselves and build competitive advantage

Occupational cluster analysis can inform the central activities of economic development—business attraction, retention, and expansion. By understanding their region's intrinsic brain power, education, knowledge, and skills, economic developers can more effectively differentiate how they market their region (Slaper, 2014). Similarly, this analysis can help economic developers learn from, and benchmark themselves to other regions with a similar occupational mix.

Just as communities target specific industries, so too can they target specific high-growth or knowledge-intensive occupations or occupational clusters (Markusen, 2004). This kind of occupational targeting may include developing marketing messages or creating incentives tailored toward industries with a high concentration of specific occupational groups (e.g., engineers, artists, etc.). Ideally, the demand for these occupations would draw from a relatively broad group of industries. Given the relative mobility of labor and the growing prevalence of remote work, communities may also seek to directly market to individuals in those fields. Creating regional initiatives that strengthen and invest in local workforce competitiveness is also recognized as a key step in building sustainable regional economic advantage. Investments in training local workers are considered more effective than traditional business incentives because worker skills often remain, even if companies decide to relocate (Bartik, 2023). This information can also help shape how regional stakeholder groups determine and advocate for their economic development priorities and strategies.

Beyond economic development, workforce development practitioners can use this information to shape efforts to address regional challenges like declining industries. Kahlaf, Michaud, and Jolley (2021) used a form of occupational clustering to develop occupational transition maps that help connect workers in declining industries (e.g., North Carolina's tobacco manufacturing industry) to more promising career opportunities in growing industries. When faced with more immediate shocks (e.g., mass layoff events), this approach offers greater utility for local practitioners because it avoids timely and costly surveys. That said, Geel and Backes-Gellner (2011) found that workers were more likely to find flexibility moving between jobs within an occupational cluster than moving between jobs between clusters.

4.3.2) Occupational clusters can influence corporate site location decisions

Corporate decision makers can also use occupational cluster analysis to identify other labor markets that hire workers that require similar skills and experience. These other labor markets might serve as potential talent pools from which to draw workers, or they may represent competitors for in-demand workers and employers (White, 2020). Similarly, this analytical approach can inform corporate site location decisions because it can identify labor markets that possess the workers that companies need, not just those with similar types of firms. If employers offer remote work opportunities, this information can also help inform where they promote those opportunities.

By translating this information into products that employers can quickly digest and understand, analysts and researchers can increase their analysis' overall utility. This requires creating a language or framework that allows employers to convey their needs more effectively to educators and intermediaries (e.g., public workforce agencies, economic development organizations) (Nolan et al, 2011). Moreover, visual tools like occupational transition maps, can help illustrate how different industries may draw on a similar talent pool (Kahlaf, Michaud, and Jolley, 2021).

4.3.3) Occupational cluster analysis can shape educational programming decisions

Occupational cluster analysis is also directly relevant to secondary and post-secondary education providers. These institutions regularly receive employer feedback about their needs, but this information is often anecdotal. Although not specific enough to inform detailed course curriculum, this analysis can provide both short- and long-term insights about the regional economy's workforce needs. As a result, this information can help educational leaders more effectively do long-term planning, particularly for their programs that are designed to support specific regional strengths (Feser, 2003).

These analyses can further help educational institutions better understand the market demand for their programs. It can show which industries—and by extension, specific firms—hire workers to fill different occupations. This information can give education and training providers additional market intelligence so that they can more effectively market and promote their programs. Building program demand is critical for their feasibility and sustainability (Donahue, Parilla, and McDearman, 2018), particularly for programs that require significant capital investments to deliver.

4.4) New data resources and approaches can refine future occupational cluster analysis

As noted above, many established occupation clustering methods rely on established sources such as the BLS industry-occupation matrices and O*Net occupational skill profiles. Others incorporate additional data sources, such as the U.S. Census Bureau's Public Use Microdata Sample (PUMS), to further examine the relationship between industries and occupations (Currid and Stolarick, 2008; Lin, Stolarick, and Sheng, 2019). However, current occupational definitions can prove limiting. For example, they do not always keep pace with the changing labor market, as the Standard Occupational Classification (SOC) system only recently added key occupations like “Data Scientists.” Regardless, there remains an ongoing need to bolster the analytical tools and create new approaches so that practitioners and researchers can answer more specific and contemporary questions.

4.4.1) New tools and data sources can advance occupational research

Labor market information (LMI) has evolved dramatically over the past decade, and new LMI tools and resources can strengthen our ability to understand occupational and skills clusters. Most notably, several proprietary vendors offer tools that extract and code data elements (e.g., industries, locations, occupations, job titles, required education, skills, certifications, etc.) from online job advertisements. This information is gathered daily (hence “real-time LMI”), and therefore provides one advantage over more traditional sources of labor market information where months or years may pass between the time the data are collected and then subsequently published. These data tools also allow researchers to search for very detailed information about employers or skill requirements. However, users must entertain several caveats when using these data. Notably, not all industries make extensive use of online job advertisements, large firms are more likely to post online job advertisements than small firms, growing firms are overrepresented, and not all job advertisements are deduplicated (Hershbein and Kahn, 2018).

Despite these limitations, job postings data allow researchers to ask questions that more traditional sources of labor market information cannot answer. For instance, Bloom et al (2020) used these data to highlight the types of occupations and skills necessary to support emerging technology areas that the current NAICS system does not cover. They also allow researchers to refine their analysis by considering factors that make some labor markets unique or cause them to function differently. For example, White (2020) used online job postings data to show that the skills and qualifications sought by the expanding National Geospatial-Intelligence Agency (NGA) in St. Louis. Specifically, the job postings data showed that NGA needed workers with security clearances and/or government experience. This factor can significantly limit the potential labor pool to those workers who already possess these qualifications. Filling these positions, therefore, required drawing from St. Louis’s existing base of government contractors or attracting workers from other metro areas with similar defense-related workforce needs (e.g., Washington, D.C.; Huntsville, AL; Norfolk, VA; Colorado Springs, CO).

Whereas job postings data has become more prominent over the past 15 years, data reflecting the demand for industry recognized credentials, certifications, and licenses represents a new and emerging tool for advancing occupational analysis. These credentials better reflect the types of knowledge and skills that employers seek and how many regional workers possess those skills. Although it might be too soon to include this type of information into occupational clustering schemes, advances are also being made to gather information more systematically about industry recognized credentials, certifications, and licenses (Credential Engine, 2022). Regardless, this is an area just beginning to garner greater attention in workforce analysis. For instance, Renski (2018) used data from the Current Population Survey to show that manufacturing workers with credentials or licenses earn more than those without.

Creating detailed and comprehensive databases about credentials remains a work in progress, but they could potentially help distinguish some of the difference between higher and lower skilled jobs within occupations that do not typically require a 4-year degree. As with other data sources, these data come with some limitations. In addition to the current lack of a comprehensive data set, a recent study from the Georgetown Center on Education and the Workforce found that for 3 out of 10 middle-skill credentials there is little to no direct connection to a specific occupational cluster.

Although existing sources (e.g., O*Net, BLS OEWS) will remain important for occupational research, the information contained therein is not always the most current. For instance, the O*Net database is continuously updated, but it can take seven to eight years to completely refresh that database. As a result, there remains an ongoing need to find effective ways to use these data sources to complement and strengthen existing analytical approaches to occupational and skills clusters.

4.4.2) Bottom-up approaches can yield different insights about occupational clusters

Broad occupational clusters can show the geography of talent across the country, but local and regional efforts often focus more on the workforce needs of firms in specific supply chains (aircraft manufacturing) or market areas (e.g., renewable energy). Markusen's earlier work on occupational targeting, for instance, showed how this analytical approach could support the arts by building efforts around artistic occupations (e.g., musicians, dancers, actors), more so than performing arts establishments (e.g., symphonies, dance companies, theaters).

Nevertheless, more detailed analysis can lead to more actionable information. For instance, Forbes (2018) used many of the same sources described above (e.g., input-output tables, industry-occupation matrices, and occupational skill profiles) to examine the distribution of skills throughout the automotive supply chain, as well as across the different tiers of suppliers. She found that higher tier suppliers often had workers with greater and more sophisticated manufacturing skills than lower-tier suppliers. Moreover, these skill differentials hindered the ability of lower-tier suppliers to upgrade their processes which could limit the region's ability to expand these activities. Understanding these differences, therefore, can highlight areas that need greater focus and attention.

Broader occupational analysis can provide a top-down view on a region's relative workforce strengths, but regional actors often need more targeted occupational analysis. Rather than considering the regional workforce as a whole, analysts may instead start with an individual occupation and then begin to identify related and similar occupations. This information is already available for jobseekers and counselors. Not only is this information available through the O*Net database, but researchers at the Federal Reserve Bank of Philadelphia created an Occupational Mobility Explorer[31] that allows job seekers to look for occupations in their metro area that require similar knowledge and skills and will pay a higher wage (Demaria, Fee, and Wardrip, 2020).

This bottom-up approach can also prove useful for broader regional analysis. For example, Wong (2011) assigned occupations to the job titles provided in the credits of video

[31] https://www.philadelphiafed.org/surveys-and-data/community-development-data/occupational-mobility-explorer.

games as a way to understand the video game industry's workforce needs. Starting with these key occupations, analysts can begin to look at related occupations and then define an occupational cluster that serves this emerging industry. Once defined, researchers can then place this occupational cluster within the broader geographic distribution of talent and see the other markets that possess workers with similar skill sets.

4.4.3) Effective occupational cluster analysis must also consider regional differences

The industry-occupation staffing matrix is foundational to the development of occupational clusters, but researchers and practitioners must also recognize that these staffing patterns vary among regions (Barbour and Markusen, 2007; Slaper, 2014). Capturing these differences can prove challenging, as BLS only provides national staffing patterns data. State labor market information agencies produce industry and occupational employment projections that may better capture the state's economy. These projections may prove most useful when focusing on one state or region but are less useful for broader systematic analysis.

More qualitative research can help reveal regional differences and uncover the tacit knowledge (Gertler and Vinodrai, 2009; Henry and Pinch, 2000) and untraded independencies (Storper, 1997) that can make regional labor markets unique and competitive. It is these interdependencies—rather than simple co-location of similar firms—that makes and sustains meaningful clusters. Ultimately, occupational cluster analysis can reveal the geographic patterns of related work activities but understanding how those patterns arose can only come from additional qualitative research.

These clusters do not exist in a vacuum, and state and regional priorities and policies can greatly influence how they form and grow. For example, North Carolina built its biotechnology industry by investing in both its innovation ecosystem and workforce training. This enabled the state to develop competitive advantages in both research and biomanufacturing. As a result, North Carolina has created job opportunities for both highly educated workers and workers without a 4-year degree, thereby making progress toward achieving both its innovation and workforce development goals (Lowe and Wolf-Powers, 2018). By contrast, states like Pennsylvania—that have historically been leaders in the pharmaceutical industry—have focused their workforce efforts on training high-level scientists and technicians but have not captured the opportunities arising from building both the state's research and manufacturing activities. There is no one way to capture these regional differences but by combining quantitative and qualitative research we can more fully understand these regional workforce advantages and what makes them work.

4.5) Conclusions

Examining regional economies through an occupational lens effectively complements more widely used NAICS-based industry clusters approaches. Many occupational cluster schemes utilize the national industry-occupation staffing patterns and information drawn from the O*Net database, but these cluster definitions may vary because different user groups have different needs and priorities. For instance, occupational analysis that informs economic development targeting efforts will often emphasize higher wage jobs in export-oriented industries, but analysis that serves the public workforce system must include information on lower-wage occupations found in more locally serving industries. Moving forward, the incorporation of new labor market information tools and resources will bolster these frameworks. Emerging resources related to online job postings or industry recognized credentials will allow researchers to ask and answer more specific questions and provide more current information. The responsibility for incorporating these analytical tools and building more robust frameworks falls primarily on researchers, scholars, and consultants. For these resources to be useful, however, researchers must convey this information in ways that individual practitioners, employers, or educators can effectively use it to make more data-driven decisions (Kahlaf, Michaud, and Jolley, 2021).

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5.0) Social networks

5.1) Social network theory and evolution

The prominence of social networks and its theory have emerged strongly since 2000. Social network theory comprises a framework used to study relationships and interactions between individuals, groups, or organizations. It explores how these entities are connected through various types of ties, such as friendships, professional relationships, or communication channels. Some key concepts within social network theory and some of the chief scholars who have consistently advanced knowledge in this area include (some of whom are cited in this chapter, but not with their seminal work nor as a first author necessarily):

1. **Nodes**: These are the individual entities within the network, such as people, organizations, or even nations (Granovetter, 2005; Wellman, 2003).
2. **Edges (Ties)**: These represent the relationships or interactions between nodes. Edges can be directed (one-way) or undirected (bidirectional) (Burt, 1992; Granovetter, 2005; Wellman, 2003; Bidart, 2020, and Shalizi and Thomas, 2011).
3. **Network Structure**: Refers to the overall pattern of connections among nodes in the network. This includes how densely connected the network is, which nodes are central or peripheral, and whether there are clusters or cliques of nodes (Newman, 2006; Borgatti, 2003 and 2014).
4. **Centrality**: This measures the importance or influence of a node within a network. Nodes with high centrality might have more connections, control over information flow, or occupy strategic positions (Freeman, 1979; Bonacich, 1987; Burt, 1992; and Faust, 1997).
5. **Clustering**: Refers to the tendency for nodes to form clusters or groups where nodes within the same cluster are more densely connected to each other than to nodes outside the cluster (Newman, 2006; Girvan and Newman, 2002; and Bidart, 2020).
6. **Homophily**: The principle that individuals tend to associate with others who are similar to them in characteristics such as age, gender, ethnicity, or interests (Coleman, 1958; Lazarsfeld and Merton, 1954; and Jackson, 2021 and 2023).
7. **Structural Holes**: Refers to gaps between groups of nodes that, when bridged by certain nodes (often called brokers), can provide access to new information or resources (Burt, 1992; Krackhardt, 1999).
8. **Small World Phenomenon**: The observation that in many social networks, any two individuals are connected through a relatively short chain of intermediaries (Milgram, 1967; Strogatz and Watts 1998).

Social network theory remains primarily interdisciplinary and draws from sociology, mathematics, computer science, and organizational studies. It underpins a wide range of phenomena, from the spread of information and diseases to the dynamics of innovation and collaboration in organizations. An early attempt to elucidate the dynamic and the profuse effects of social networks comes from Malcolm Gladwell's The Tipping Point (2000). He refers to stickiness of networks needed to attract audience attention and engagement with content. Media that solicits deep audience engagement and aggregates attention (via its networks) to specific content in a centralized place has such stickiness (Jenkins et al., 2013). Markusen (1996) uses the term "sticky places" as those that attract and retain capital and labor, despite globalizing tendencies. Stickiness thus influences the retention of knowledge, relationships, innovations, a common pool of resources, and digital transformations to be developed and built via multiple media platforms in specific geographically defined locations with assets that foster the spread of media. Individuals in those areas use their social connections to attract, build, and preserve online reputations that matter greatly in the human capital and labor markets. Sometimes brief online interactions reflect and/or facilitate this stickiness. It should be noted, that stickiness relies on a network to not only support, but to affirm the posting. The entire network does not need to agree or validate the post, but it does require the approval of a set audience to exist.

Social network connections may also be predicted on professional expertise and trust. Thus, professional workforce survival (such as within an industrial cluster) hinges on managing reputation, knowledge of product or service, and leveraging the social capital accrued from the offline or online social networks. Fenwick (2012:601) cited McRobbie (2002), who argued that networks are temporary structures based on "fleeting social interaction," not development "through long term collective structure and are linked to personal association and goals of self-promotion and self-advancement" and thereby segregates large swathes of the overall workforce from each other.

Social networks show that relationships rely on people transmitting and sharing content, in addition to others further down the network responding to and possibly augmenting the content before sharing that content in turn (Swani et al., 2014; Ridgeway, 2013). This reciprocity strengthens business relationships, and behaviors along a network that are matched to become mutually beneficial over time (Quinton 2016). Because many professionals are connected via social media with their co-workers (Duggan et al., 2015; Schmidt et al., 2016), this matters significantly to their ability to relate to peers. These ideas will be further explored in this chapter.

5.2) Economic geography's relational turn

While social network theory continued to grow in the 2000s, a relational turn also occurred within the field of economic geography. It became concerned with how networks of firms and production systems vary from place to place. The relational turn sought to increase competitiveness by creating, accessing, and sharing knowledge. The research focused on knowledge sharing beyond global competitiveness; primarily, with how firms link with one another through knowledge networks can help explain the social organization of individuals.

Bathelt et al. (2005) maintain that their theories on the interrelationships of knowledge resources emphasize the important role of physical infrastructure to ensure competitiveness in a global market. They further assert that global linkages, rather than local connections, facilitate innovation at technology firms and global knowledge flows impact of relational proximities are nuanced and constitute a significant economic role in society (Tranos and Nijkamp, 2013). Tranos and Nijkamp (2013) outlined several types of proximity such as geographical, which does not always refer to physical distance. Proximity could also pertain to how a network is organized, and is therefore, relational in makeup. Rather, economic activities continue to be based in the physical sense, dependent on infrastructure, its geographic position and the organization of people in space. Former economic indicators predicated on industrial production are obsolete and should be replaced by a global space of flows, which provide an “information-friendly milieu” (Stock, 2011, p. 965). Whereas the significance of knowledge workers, network cities, and informational cities has been discussed at length, a composite definition has yet to be agreed upon in scholarly circles (Cruz-Porter, 2018).

A more theoretical stance on the importance of creating industrial clusters within particular regions and the ways that firms connect with one another in a multitude of complex ways provides a vital part of cluster economic theory. Barthelt and Glucker (2005) explored the ‘relational turn’ in economic geography by exploring the theoretical interactions between resources and how these relationships stimulate effective spatial, technological, and economic development. They identified the following: material resources (such as bundles of services), knowledge, power and social capital. Each variable works interdependently to influence the success of an economic development project. In terms of regional industries, within a cluster, Bathelt and Glucker (2005: 1553) assert that social relations are ”constantly being produced and reproduced through on-going communications between the actors…about which technologies to use, and the like.” They also define social capital on micro and macro levels, of which, the micro-level constitutes the most important aspect. This is in part because economic geography underpins their theories on how the interrelationships between resources emphasize the role of physical infrastructures and the different types of resources from a spatial perspective. In addition, these micro processes highlight the contextual, path-dependent, and contingent nature of economic action and interactions within networks. Bathelt et al. (2005) asserts that global linkages, rather than local connections, facilitate innovative performances of tech firms and are pivotal to their ability to innovate.

Overman, Rice and Venables (2008) applied their economic models to understand new economic geography linkages across regions – a concept dubbed “new regionalism.” They found that infrastructure investment or any supply side improvements produced a ”positive productivity shock.” This, in turn, impacts the earnings-employment relationships. In terms of technological infrastructure improvements, four relationships (earnings employment, cost of living and migration) determine the economic linkages between urban areas. The authors considered these linkages significant to understanding the impacts of policy decisions on neighboring cities and regions. It is unclear whether these findings can be applied on a smaller scale between specific industrial clusters. The implications of applying these theories on a micro-scale also remain unclear; however, they prefer the application of regional industrial clusters. The empirical evidence that connects industrial clustering with technology innovation in China has also been explored within economic geography.

5.3) Ties, homophily, and other characteristics of social networks

Social networks function by leveraging social connections within a structured framework (Cruz-Porter, 2018). Shalizi and Thomas (2011) pointed out that bonded ties form among individuals who are closely situated in a network and possess shared characteristics, exhibit similar behaviors, and experience analogous events. This raises the question: does this imply a contagion or influential phenomenon, or is it merely a result of the shared similarities among these connected individuals? They argue that various factors contribute to social contagion, including inspiration, imitation, persuasion, biological transmission (such as behaviors prompted by a virus), mutual enthusiasm for certain activities, latent homophily concerning unobserved traits, or an external common cause. Notably, Shalizi and Thomas (2011) observe that homophily and contagion resemble each other so closely that distinguishing between the two can be challenging, if not impossible. Whether one subscribes to the idea of social contagion or homophilic causation, the sphere of influence within social networks is limited to the connections and their relationships. Shalizi and Thomas (2011) propose that this phenomenon may not arise from social contagion, but rather from a series of behavioral choices. Does this effect provide an explanation for social structures, or is the cultural spread merely an adaptation to a newly emerging social framework? These researchers indicate that this dynamic occurs within a homophilic network—either latent or manifest - which creates homogeneous clusters that share specific values. Observationally, it is challenging to make this distinction; even mathematical modeling has struggled to clarify the differences (Shalizi and Thomas, 2011).

5.4) Social ties, types, and design

Connections between individuals are referred to as ties. These ties can also exist between nodes and come in various forms. Research in social network analysis has identified three types of ties that are pertinent to social media networks (Kane et al., 2014, p. 282).

Proximities: The shared physical or social spaces that provide opportunities for tie formation, such as living in the same city and working in the same office (Cruz-Porter, 2018). Proximity can also refer to the organization of a network, indicating its relational nature. The notion that the world is becoming smaller due to easily accessible relationships via smartphones overlooks the complexity of spatial interactions and oversimplifies the idea of place. Economic activities remain rooted in physical settings, relying on infrastructure, geographic location, and the spatial arrangement of people. Traditional economic measures based on industrial production have become outdated and should be replaced with a global framework of flows, which offers an "information-friendly environment" (Stock, 2011, p. 965). Although the roles of knowledge workers, networked cities, and informational cities have been extensively explored, a unified definition in academic discussions is still lacking.

Social relations: Persistent social connections between nodes, such as friends, colleagues, or bosses. On social media, they represent friends, connections, followers, and affects (likes or dislikes). Affects, in this case, affirm a relationship node and because it is not transitory, it sits in the social relation space.

Interactions: Brief and temporary engagements with another entity, such as conversing face-to-face, sharing a meal, or making a phone call.

All of these may be used to analyze industry clusters further at some point in the future.

5.5) Structure and relational flows

Social network structures facilitate movement between money, services, goods, knowledge, information, trust, norms and sentiments/perceptions. Moreover, the various types of ties—whether representing skills, users, relationships, or content—play a dynamic role in shaping network formation. Granovetter (2005) argues that social structure, represented through social networks, has a significant effect on economic outcomes for three key reasons: first, networks influence both the flow and the quality of knowledge; second, they serve as critical sources of rewards and punishments; and third, trust in others to act appropriately develops within the framework of a social network. The effects of relational proximities are complex and carry substantial economic implications for society (Tranos and Nijkamp, 2013). Knapp et al. (2014) emphasize the importance of relational ties, stating that they shape attitudes, intentions, and behaviors. Their findings suggest that the concepts of fellowship, identity, and psychological ownership are predictors of satisfaction. Nonetheless, the results indicate that identity might not be as crucial for members of the community as initially thought.

The experience of being part of an insider group conveys a sense of fellowship and integration, fostered by various practices and benefits that signal an individual's acceptance as a member. This membership fulfills a basic human desire for connectedness, independence, and influence over one's surroundings. Those who feel included are more likely to take on their responsibilities within the organization, nurturing a positive outlook towards the community, which reflects their emotional commitment. Such individuals are motivated to stay within the community and play an active role in its activities through "innovative behavior."

5.6) Social capital, innovation and networks

Social capital is intrinsically linked to the idea of networks, emphasizing the significance of relationships (Cruz-Porter, 2018). Bruni and Sugden (2000) contend that the strength of social capital correlates with the density of these networks, as trust, cooperation, and reciprocity enhance the well-being. Bourdieu (1988, p. 2480) defines social capital as "the sum of the actual or potential resources connected to the existence of a lasting network of somewhat institutionalized relationships characterized by mutual acquaintance and recognition." In essence, social capital embodies the obligations and connections that exist among group members. According to Coleman (1990), social capital is regarded as a public good, a collective resource that can be either actual or potential, while Putnam (2000) affirms the significance of relationships among individuals. They observed a notable social transition from nurturing neighborhood connections to focusing on networks primarily comprised of friends and family. Like networks, social capital fundamentally relies on trust and shared understanding. Castells (1996) pointed out that with the rise of a "network society," individuals tend to exchange "bridging social capital" for "bonding social capital" (Hampton and Gupta, 2008), illustrating a noteworthy shift in how social mobility is perceived. While human capital pertains to the inherent qualities and skills possessed by individuals, particularly within the context of the digital economy, social capital typically represents a less tangible resource created through interactions between at least two individuals (White and Green, 2011). Parnwell (2007) presents a conceptual framework for social capital where “associational” social capital emerges from networks, collaborations, interpersonal relationships, and collective endeavors. These collective actions might lead to cultural erosion, increased individualism, atomization, and materialism, while simultaneously diminishing bonding social capital, trust, social engagement, authority, and competitiveness.

For over a century, social network analysis has been employed within the social sciences to explore the relationships and connections among individuals and their chosen social groups. This approach revolves around networks as its foundational concept, consisting of a series of interconnected dyadic ties. The nodes within these networks can include individual actors, organizations, or elements within the network, with the types of connections characterized as social relationships, such as “friend” or “colleague.” Dyadic interactions refer to scenarios where a person “chats” or “promotes” to another. Moreover, a set of ties connects to create paths, which allow nodes to influence one another indirectly. Social network analysis suggests that a node’s position within a network structure establishes its opportunities and limitations. Kane et al. (2014, p. 277) point to researchers who have highlighted four key areas within social network studies. These areas include environmental shaping, which examines how the surrounding network affects its members; contagion, which refers to the transmission of resources that influences individuals within the network; structural capital, which focuses on how personal connections can either enable or limit opportunities; and resource access, which concerns how individuals can tap into and benefit from the resources available in the network. Castilla, Hwang, and Granovetter (2006, p. 219) point out that networks in Silicon Valley play a critical role in the labor market, influencing the dynamics of power and the generation of innovation.

According to Castilla et al. (2006), a social network is defined as “a set of nodes or actors (persons or organizations) linked by social relationships or ties of a specified type.” Trust among these connections is essential. In their research on social networks in Silicon Valley, they identify two types that impact trust between individuals: relational networks, which shape expectations based on past interactions, and structural networks, which allow individuals to establish connections while minimizing the risk of unethical behavior. Granovetter (2005, p. 36) suggests that “in most real labor markets, social networks play a key role” and characterizes these networks as a form of social capital. He notes that all social interactions involve the exchange of information (i.e., knowledge sharing), which can lead to asymmetric information distribution influenced significantly by social structures. Granovetter (2005) also connects the spread of innovation to social networks, noting that those who are "socially marginal" can more easily diverge from accepted practices since their actions are less constrained by the prevailing norms in closely knit networks. This project aims to explore knowledge-sharing behaviors among three distinct groups by assessing the actions, expectations, and norms of individuals within each cohort.

Granovetter (2005, p. 34) outlines four fundamental principles of social networks that impact economic outcomes. The first principle pertains to norms and network density, explaining that as commonly accepted behaviors become more entrenched, the social network becomes increasingly dense. Higher density facilitates more frequent trust and cohesion among nodes, shaping how information, ideas, and influence circulate. The second principle posits that individuals gain knowledge through their weak social ties, as strong ties often belong to similar social groups and share comparable information. Burt (1992, as noted by Granovetter, 2005) broadened the weak ties discussion by emphasizing how various components of networks should be leveraged to facilitate the flow of knowledge resources across different networks. The third principle highlights the significance of “structural holes," representing individuals in the network who serve as bridges between disparate groups.

Finally, the fourth principle is the interpenetration of economic and non-economic action, which focuses on how economic and non-economic activities are socially embedded. Granovetter (2005, p. 36) asserted that “in most real labor markets, social networks play a key role.” He calls these networks a form of social capital and states “social interactions inherently serve as conduits for transmitting information and sharing knowledge.” This process of knowledge exchange can often result in asymmetric communication, heavily influenced by the surrounding social structure. The variety of experiences within social networks is essential, as demonstrated by Reagans and Zuckerman (2001), who found that R&D teams comprised of diverse social networks achieved higher productivity compared to those connected to more homogenous groups. As noted by Granovetter (2005), weak ties within a network can support individuals by offering diverse connections that contribute to increased social capital. Holgate et al. (2012) examined the impact of social networks within ethnic minority London, UK neighborhoods in Lambeth and Hackney, where union membership had diminished. Their research revealed that these communities often failed to leverage bridging social capital, resulting in social networks that provided minimal job guidance or support. In fact, the study indicated that reliance on local connections typically limited employment opportunities within ethnic enclaves that largely consisted of familial ties. This insight emphasizes the significance of social networks in relation to employability.

More broadly, social networks serve as a representation of the capacity to forge and sustain social capital (Donald and Blay-Palmer, 2005). Ferrary and Granovetter (2009) discovered that tightly knit social ties cultivated tacit knowledge and fostered an "innovative milieu" for the technology sector in Silicon Valley. They describe Silicon Valley as an area marked by high clustering density, wherein various ties—ethnic, academic, friendly, and professional—play a critical role in knowledge creation (Ferrary and Granovetter, 2009, p. 334). The concepts of clustering density and relationship types are pertinent to industrial innovation. By applying complex network theory to analyze innovation dynamics in Silicon Valley, Ferrary and Granovetter (2009) concluded three key points: 1) Silicon Valley consists of a diverse and interconnected network of agents; 2) the interactions among these agents are multifaceted and self-organizing; and 3) this system is robust enough to resist technological disruptions.

5.7) Network effects, dynamism and behavior

A notable characteristic of social networks that has emerged in recent years is the concept of "buzz." As defined by the Oxford Living Dictionary (Anon, 2017), buzz refers to being "busy or moving quickly" as well as a "continuous sound." Together, these definitions capture the essence of the urban media landscape. Mould and Joel (2010) view buzz as a crucial concept in creative and cultural industries, particularly at the local scale. Bathelt et al. (2004, p. 38) define buzz as: “specific information and continuous updates of this information intended and unanticipated learning processes, in organized and accidental meetings ...refers to the network of communication and information linkages which develop within a cluster. This occurs in negotiations with local suppliers, in phone calls ...talking to neighbors … or when having lunch with other employees. The nature of buzz is spontaneous and fluid." Grabher (2002) identifies it as an intangible quality often recognized in hindsight. Social networks thrive on maximizing potential buzz, "noise" (Grabher, 2002), or "project ecologies" (Grabher, 2004) of trends. Mould and Joel (2010) contend that the dynamics of knowledge flows within the advertising sector spotlight the gatekeepers in a highly interconnected industry that embodies the characteristics of the Informational City. This is marked by the dominance of the space of flows over the space of places (Cruz-Porter, 2018). The term "space of flows" pertains to the system governing the exchange of information, capital, and power, which shapes the fundamental processes linking societies, economies, and states across various locales (Castells, 1993, p. 136). While Castells' theory lacks a modern example, it can be reasonably applied to several global cities characterized by industrial agglomerations, diverse populations, and skilled workforces interacting in a networked environment. According to Castells, the quintessential cities that define the knowledge economy are characterized by rich information flows that transcend mere geographical considerations, positioning the informational city as superior to the knowledge or creative city. Urban centers emerge as vital nodes within these spaces of flows, facilitating infrastructure development, cognitive networks, concentrated spatial arrangements, and digital links to similar hubs (Castells, 2001). In parallel, the implications of relational proximities are complex, yet they play a crucial economic role in regional and community development contexts (Tranos and Nijkamp, 2013).

Stock (2011) postulates that traditional economic indicators based on industrial output have become outdated, advocating for a new framework focused on a global space of flows that provides an "information-friendly milieu" (Stock, 2011, p. 965). Although the importance of knowledge workers, network cities, and informational cities has been thoroughly examined, an all-encompassing definition remains elusive among scholars. Both the concepts of knowledge society and information society exhibit several common traits: the significance of computers, mobile infrastructure, and communication technologies; the reliance of basic innovations on informational resources; the fundamental necessity of lifelong learning; the constant availability of information and content creation; and the central role of digital information and networks as facilitators. At the core of this assessment is the influence of networks on the dispersal of information, where interactions within a network signify nodal influence. For instance, the concept of network effects elucidates how messages with "pass-along value" and "spreadability" (Jenkins et al., 2013) circulate, prompting questions about their recipients and dissemination methods. Warner (2002) contrasts the media "public" with the traditional idea of an audience, suggesting that the "public" comprises an imagined connection among consumers. This notion crystallizes during moments of recognition when individuals acknowledge their personal stake in circulatory interactions.

5.8) Network agency

This section highlights some of the economic theories and findings regarding technological development and seeks to illuminate how they may influence economic development at a regional level. Literature regarding technology and economic development strongly favors the theory of clusters and the agglomeration of industrial resources. These concepts appear to fall under the precepts of new economic geography as characterized by Venables (2005). On his view, new economic geography integrates spatial economics and emphasizes the role of spatial clustering in generating specialized industrial activities (Venables, 2005). Several different concepts emerged from the literature gathered which suggest the prevalence, importance and need for innovative civic infrastructure with technological features to support sustainable economic growth. The following section will discuss some of the relational linkages between media (entertainment industries) and technological infrastructure clusters strategic to economic development.

Jensen (2011) examined the spatial and economic contributions of visual entertainment industries in Sydney and found that government agencies have a strong role in facilitating the siting of creative industry clusters. He distinguished two different types of clusters serving the entertainment field: general and specialized. The specialized media cluster in this case consists of videographers and video game designers, for example. The author did not give a precise or defined category. Jensen (2011) theorized that these clusters formed, in part, because of a shift in greater use of the internet for communications. In addition, Jensen (2011) found that local media productions contributed to the experience of urban places and reinforced the significance of Australian locations. The clustering of media industries ”exhibited both regional and local agglomeration forces” (Jensen, 2011, p. 27). Jensen (2011) also questioned whether the clustering models such as network or spatial accurately reflected the Australian entertainment industry. The author speculated that the driving locational factors for entertainment industries throughout the Sydney region were influenced by both regional (generalized) and more specialized cluster dynamics. Jensen (2011) touched on the idea of social networking in Sydney. He explained that networking in virtual settings is, particularly for people in the entertainment field, important because many of these people work alone and need to keep in touch with others in the field. In this sense, location temporarily becomes less important. However, the people needed to have met and networked with colleagues prior to working alone because these networks cannot form within an isolated bubble. The author stated that Sydney clusters “are relatively loose” primarily as the internet allows people to exchange files, video and communications via the internet. Broadband access was key to business dealings in media industries. (Jensen, 2011). Jensen’s findings suggested that the use of technology in these ways eliminates the need for geographic economic clusters. This theory has implications for geographic areas seeking to implement premium broadband services and encourage economic growth.

Cluster development, in Jensen’s opinion, remained ”embryonic and patchy” within digital industries in Sydney (Jensen, 2011, p. 28). The author also analyzed the relevant industrial infrastructure necessary to support digital industries. Jensen (2011) speculated that the convergence of major media conduits within specified districts (Pyrmont, Redfern and Australian Technology Park) may shift the concentration of businesses over the long term from the lower north shore to south of Sydney’s harbor. The creative ambience (urban villages with quality coffee) of particular places within the entertainment industry become central to their ability to connect with other people within their field. Jensen (2011) also noted that media industry strategies varied based on the place within Sydney: businesses located to the north of the CBD[32] (Lower North Shore) are more established than those in East Sydney. People working with the entertainment industries experienced intense

[32] Central Business District

pressure to become socially connected. This observation linked up to the importance of proximity, interactions and relations espoused by Stock (2011).

Environmental attributes that support spatial clustering of these industries remains obscure (Jensen, 2011). Jensen (2011) observed that the ambience that attracts successful businesses to a particular area also increases land costs/rentals and hastens to shift cluster patterns to the inner or middle west of the Sydney metro region. In short, the subjects stated that planning should promote the facilitation of networks and clusters rather than interfere with the market.

The concept of ”network power” and the ways that gateway locations manifest economic competitiveness are driven by the ”networks make possible the creation or the strengthening of interdependencies between places…it is through networks that territories form a system” (Offner, 2000). This notion refers to all the characteristics of social networks, particularly its ability to influence.

5.9) Role of networks in industrial clusters

Navarro, Gibaja et al. (2009) completed a detailed study on Regional Innovation Systems (RIS) in the European Union (EU) and identified eight important regional groups and policy recommendations. The authors developed 21 indicators based on relational factors such as economic outputs, technological inputs and outputs, agglomeration economies, and social filters. Their findings suggest that innovation-based policies may not be replicated across regions considering the differences in economies, social and locational contexts and knowledge creation environments. Along similar lines, Truffer (2008) believed that it is fundamental for economic geography to incorporate within the social study of technology.

Liebovitz (2003) analyzed the collaborative processes that supported the economic development of Canada’s Technology Triangle. The author highlighted the ”institutionalist” view of economic development which places a premium on local innovations. The author argued that institutions play a role in reinforcing norms, routines, trust between actors and collaborative efforts. It is suggested that the tech triangle thinks and acts like a region “against a history of parochialism where local identities have constituted an important geographical element” (Liebovitz, 2003, p. 2638). The author considers institutionalist perspectives on regional economic development to be inadequate because they neglect the process of institutional change, issues involving diverging opinions, and ”undertheorized notions of space and scale.” New regional transformations also became the focal point of an evaluation of the alternative hydrogen energy economy in the Teesside located in the UK (Hodson et al., 2006). In particular, he examined the interrelationships between governance and socio-technical innovations and the ways that institutions influenced economic transformations. He cited conflictual issues involving the need for regional competitiveness and the need to transform a ”historically embedded” disused industrial region into a center of innovation. The hydrogen economy project at Teesside represented a place that could only serve as a test site. Hodson et al. (2006) focused their paper on the struggle to transform the place into a center of innovation excellence despite a climate of obduracy. In doing so, the authors located several issues involving the new regionalist theories including: the role competitive pressures played in developing relationships; the role of producing a symbolic narrative based on interrelationships; the failure of the nation-state to communicate the narrative of a re-imagined Teesside; and the formulation of institutional decisions predicated on the “attractiveness” and ”competitiveness” of the region (Hodson, 2006).

5.10) Network interactions and clusters

In Chile, Giuliani (2013) found that regional clusters facilitate the formation of local inter-organizational networks, which act as conduits of (tacit and explicit) knowledge and innovation. Bell and Zaheer (2007) described the ways that social networks serve as a conduit for knowledge which is often rich, fine-grained and tacit – i.e., “capable of transmitting subtle cues” (Bell and Zaheer, 2007, p. 957). This section will give a precis on knowledge and how it flows within networks. Tacit knowledge consists of experience, competence, commitment, deed, cognitive, noncodified such as norms, and experiential – cannot be recorded or stored (Nonaka, 1994). It forms the basis of workplace socialization and is therefore pertinent to industrial clusters. On the other hand, explicit knowledge consists of objective, logical and technical information, easily transferable, documents, and records (Nonaka, 1994). This includes degrees, certificates, diplomas and trainings. This type of knowledge is more pertinent to institutional networks which sometimes cross over with industrial networks. Giuliani (2013), however, found that within the Chilean wine clusters the formation of knowledge networks at the micro-level display the following network characteristics and occurred with the following observations:

- **Cohesion effects**, which assume that knowledge network growth is characterized by greater cohesion and network closure among firms – a view that coincides with many cluster narratives, but which has not been tested empirically.
- **Status effects**, which suggest that more prominent firms in terms of their links, tend to reinforce this prominence through the formation of more ties over time, especially relevant in the resource-poor and uncertain contexts that frequently characterize developing/emerging countries.
- **Capability effect**, which refers to how heterogeneity in firm-level knowledge bases influences the formation of new knowledge ties (Giuliani 2013; 4-5).

These three effects are driven by various underlying motivations. Cohesion effects lead to more homogenous, egalitarian and dense networks. Status and capability effects are likely to promote fragmentation and hierarchy within the network structure (Giuliani, 2013). Capability refers primarily to the skills at the firm level and could be viewed from an occupational standpoint.

5.11) Conclusions

This section sought to bring together an overview of the theoretical work that underpins the concept of social networks so that it may be applied to the development of economic clusters. It is important to lay out the various concepts before delving into the implications of this research on industrial clusters. Industries and social networks display clustering characteristics, which are inherently relational. Social networks represent clusters of individual economic agents, their rationalities and strategies, and how these lead to specific practices of interactions.

5.12) References

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Publication 115 April 2025

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