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NBER WORKING PAPER SERIES

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Working Paper 20375
http://www.nber.org/papers/w20375

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2014

This project has been funded by a grant from the Economic Development Administration of the U.S. Department of Commerce. We received financial support from Harvard Business School. We thank Bill Simpson, Xiang Ao, Rich Bryden, and Sam Zyontz for their invaluable assistance with the analysis. We also acknowledge the insightful comments of two anonymous reviewers, Harald Bathelt, Ed Feser, Frank Neffke, Juan Alcacer, Bill Kerr, Fiona Murray, Christian Ketels, James Delaney, Brandon Stewart, Muhammed Yildirim, Ram Mudambi, Sergiy Protsiv, Jorge Guzman, Sarah Jane Maxted and the participants in the Industry Studies Association Conference, NBER Productivity Seminar, Temple University Seminar, and the Symposium on the Use of Innovative Datasets for Regional Economic Research at George Washington University. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

At least one co-author has disclosed a financial relationship of potential relevance for this research. Further information is available online at http://www.nber.org/papers/w20375.ack

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NBER Working Paper No. 20375
August 2014
JEL No. R0,R1

ABSTRACT

Clusters are geographic concentrations of industries related by knowledge, skills, inputs, demand, and/or other linkages. A growing body of empirical literature has shown the positive impact of clusters on regional and industry performance, including job creation, patenting, and new business formation. There is an increasing need for cluster-based data to support research, facilitate comparisons of clusters across regions, and support policymakers and practitioners in defining regional strategies. This paper develops a novel clustering algorithm that systematically generates and assesses sets of cluster definitions (i.e., groups of closely related industries). We implement the algorithm using 2009 data for U.S. industries (6-digit NAICS), and propose a new set of benchmark cluster definitions that incorporates measures of inter-industry linkages based on co-location patterns, input-output links, and similarities in labor occupations. We also illustrate the algorithm's ability to compare alternative sets of cluster definitions by evaluating our new set against existing sets in the literature. We find that our proposed set outperforms other methods in capturing a wide range of inter-industry linkages, including grouping industries within the same 3-digit NAICS.

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1. Introduction

There is an increasing need for useful data tools to measure the cluster composition of regions, and support regional policy development as well as business strategy. The goal of this paper is to address this need by providing a rigorous methodology for generating and assessing sets of cluster definitions – groups of industries closely related by skill, technology, supply, demand, and/or other linkages. Our approach is novel by comparing the quality of alternative sets of cluster definitions and also by capturing multiple types of inter-industry linkages. We implement this clustering algorithm to create a new set of U.S. Benchmark Cluster Definitions (BCD), capturing a broad range of inter-industry linkages.

Clusters are geographic concentrations of related industries and associated institutions. The agglomeration of related economic activity is a central feature of economic geography (Marshall, 1920; Porter, 1990; Krugman, 1991; Ellison and Glaeser, 1997). Marshall (1920) highlighted three distinct drivers of agglomeration: input-output linkages, labor market pooling, and knowledge spillovers, which are associated with cost or productivity advantages to firms. Over time, an extensive literature has broadened the set of agglomeration drivers, including local demand conditions, specialized institutions, the organizational structure of regional business, and social networks (Porter, 1990, 1998; Saxenian, 1994; Storper, 1995; Markusen, 1996; Sorenson and Audia, 2000; among others). Thus, clusters contain a mix of industries related by various linkages (knowledge, skills, inputs, demand, and others) and supportive institutions.

The bulk of the cluster literature has been based on detailed case studies (Marshall, 1920; Porter, 1990, 1998; Swann, 1992; Saxenian, 1994). Over time, attention has begun to shift to larger-scale, quantitative studies across regions and industries (Porter, 2003; Feser, 2005). Using particular cluster definitions, studies have shown that the presence of related economic activity matters for regional and industry performance, including job creation, patenting, and new business formation (see among others, Feldman and Audretsch, 1999; Porter, 2003; Feser, Renski, and Goldstein, 2008; Glaeser and Kerr, 2009; Delgado, Porter, and Stern, 2010, 2014; Neffke, Henning, and Boschma, 2011).[1] This evidence has informed key questions of both research and policy interest: the size of cluster effects, which mechanisms are most important in driving agglomeration, and how clusters diversify and grow in a region. Based on different

[1] See Rosenthal and Strange (2004) and Cortright (2006) for a review of economies of agglomeration studies.

definitions of clusters, covering different portions of the economy ranging from high technological intensity industries to manufacturing to all industries defined in the industrial classification system, existing research has generated a range of results on these issues. However, the lack of a comprehensive methodology, and a way to compare alternative sets of cluster definitions, makes it difficult to reconcile key findings. This paper addresses this issue by developing a novel clustering algorithm to generate, assess and compare alternative sets of cluster definitions.

Cluster definitions are groups of industries related by skill, technology, supply, demand, and/or other linkages. This paper focuses on regionally comparable cluster definitions (i.e., the industries that constitute a cluster (e.g., Biopharmaceuticals) are the same for all regions). Inter-industry linkages are identified through the co-location patterns of industries across regions, or with a range of national data available across industries. The identified linkages are used to group industries into a set of defined clusters, allowing clusters to be compared across regions.

To generate a set of cluster definitions, we use clustering analysis – numerical methods for the classification of similar objects into groups (Everitt et al., 2011; Grimmer and King, 2011). Our algorithm generates many different cluster configurations, *C*s, through a clustering function that utilizes a particular measure of the relatedness between any two industries and well-specified parameter choices (e.g., the number of groups). Each configuration is composed of mutually exclusive groups of related industries (i.e., clusters). The algorithm then provides scores that assess the quality of each *C* (i.e., its ability to capture meaningful inter-industry linkages within clusters). This allows us to identify the configuration, C^*, that best captures certain types of inter-industry links. Because an algorithm cannot perfectly substitute for expert judgment, the methodology concludes with an expert assessment and adjustment of individual clusters in C^* to determine a final set of cluster definitions, C^{**}.

Our paper contributes to the literature on clusters and economies of agglomeration in several ways. First, the clustering algorithm allows us to compare the quality of alternative sets of clusters using a common approach that generates objective scores (i.e., most clustering methods do not provide scores to help compare across groupings (Everitt et al., 2011; Grimmer and King, 2011)). We can assess cluster configurations that are generated using different inter-industry linkage measures. For example, we can evaluate *C*s generated using pairwise industry co-location patterns to those based on input-output or other measures. We can also compare

existing sets of cluster definitions. The ability to score sets of clusters can help identify the appropriate sets for addressing particular research and policy questions.

Our scoring approach utilizes a basic clustering principle: creating groupings so that industries within a cluster are more related to each other than to industries in other clusters based on various measures of inter-industry linkages. The score for a given C depends on how well it captures various types of industry linkages. However, what constitutes a useful set of cluster definitions may change depending on the particular research and policy question. Some studies may be interested in a particular type of industry link (e.g., labor occupational links), making sets of cluster definitions that perform better in that link more useful.

Second, our algorithm allows for experimentation with multiple inter-industry linkage measures used in the economies of agglomeration literature, including input-output linkages, occupational linkages, the co-location patterns of industries, and combinations among them. We can then examine the cluster configurations generated based on these different measures. The methodology can incorporate additional inter-industry linkage measures as they become available (e.g., a measure that specifically captures knowledge linkages), and score their resulting cluster sets.

Third, although generating cluster definitions will require expert judgment for some individual clusters, our algorithm is transparent. In the last stage of the algorithm, there is room for expert judgment to correct for inevitable anomalies that arise due to data imperfections and industry definitions. For example, in a given C^*, there could be industry outliers that do not seem to belong to their assigned cluster. These can be reallocated to their "next best" cluster using a score that assesses the relatedness of the particular industry with another cluster, using a transparent process. Users can assess how adjustments (re-allocations of industries, combining or dividing clusters) impact cluster scores.

Another important contribution of this paper is that we implement our method to generate a new set of benchmark cluster definitions for the U.S. (BCD or C^{**}), which captures a wide array of inter-industry linkages. The U.S.-based empirical analysis focuses on grouping 778 6-digit NAICS industries in manufacturing and services in 2009, and uses County Business Patterns (CBP), the Benchmark Input-Output Account of the United States, and Occupational Employment Statistics (OES) datasets to define multiple industry relatedness measures.

The proposed BCD is generated using inter-industry measures of co-location patterns of employment and the number of establishments, input-output links, and labor occupation links, and contains 51 clusters. We examine the relative performance of the BCD and three existing sets of (mutually exclusive) cluster definitions: industries within the same 3-digit NAICS, Porter (2003), and Feser (2005). Grouping industries within the same 3-digit NAICS scores poorly in capturing multiple inter-industry linkages, which is perhaps not surprising since the industrial classification system groups industries based on the similarities of their products/services, not on their inter-industry complementarities. Moreover, manufacturing and service industries belong to different parts of the NAICS, so that products and services are definitionally unrelated. Numerous empirical studies on economies of agglomeration have relied solely on industry codes to define inter-industry relatedness, potentially limiting their ability to capture a broad array of relevant industry linkages.

Our benchmark set scores higher in capturing a broader range of inter-industry linkages than the three other prominent sets of cluster definitions. The BCD also scores better or the same as the other sets in input-output linkages and shared labor occupations.

While the analysis is based on U.S. data, our clustering methodology can be implemented in other large and integrated economies with sufficient data availability. At present, however, U.S. data offers several advantages. Comparably large and diversified economic areas like the EU have heterogeneous data accessibility across countries, and current and past barriers to trade across locations can limit economies of agglomeration. Smaller economies (like the Nordics) have access to rich data, but their relative small size leads to specialization in a narrow range of industries.

Our benchmark cluster definitions offer a useful tool for research and policy on regional economic development. They allow the comparison of clusters across locations and over time by mapping the defined clusters into regional units and measuring the specialization patterns of regions in the clusters. Using the BCD, the U.S. Cluster Mapping Project has created a detailed regional cluster dataset that facilitates comparisons across regions and across clusters on numerous dimensions.[2] For example, the Boston, MA and San Diego, CA Economic Areas have high employment specialization in Biopharmaceuticals, but the size and breadth of the cluster is

[2] The U.S. Cluster Mapping website (http://clustermapping.us/) is supported by the U.S. Economic Development Administration, U.S. Department of Commerce.

lower in San Diego, which lacks specialization in biological products (except in-vitro diagnostic substances). The Project also includes data on the business environment and cluster institutions to inform research and policy. This data tool can be used in combination with cluster methods that focus on examining region-specific links among firms, individuals, and supportive institutions in clusters to shed light on the mechanisms at play in particular regional clusters.

The rest of the paper is organized as follows: Section 2 reviews the literature on industry cluster definitions. Section 3 describes our clustering algorithm. In Section 4, we discuss our main findings regarding the generation and assessment of cluster configurations, and Section 5 proposes a set of benchmark cluster definitions. In Section 6 we compare the BCD to existing sets of cluster definitions in the literature, and discuss some research and policy applications. Section 7 concludes.

2. Defining Industry Clusters

There are various types of economies of agglomeration identified in the literature, including input-output linkages, labor market pooling, knowledge spillovers, sophisticated local demand, specialized institutions, and the organizational structure of business and social networks (Marshall, 1920; Porter, 1990, 1998; Swann, 1992; Saxenian, 1994; Storper, 1995; Markusen, 1996; among others). These economies of agglomeration manifest themselves in clusters – geographic concentrations of related industries and associated institutions. Within regional clusters, firms and associated institutions (i.e., trade organizations, universities, and local government) can operate more efficiently and innovate faster due to sharing common technologies, infrastructure, pools of knowledge and skills, inputs, and responding to demanding local customers.

To implement cluster research and policy, however, we need to measure the boundaries of clusters: What set of related economic activity and institutions constitutes a cluster? Two main approaches to defining clusters have developed over the last 20 years: clusters based on inter-industry linkages inferred from multi-region analysis (which we refer to as *comparable cluster definitions*) and cluster definitions based on observed linkages among industries or firms in a single region (which we refer to as *region-specific cluster definitions*). Many empirically derived cluster definitions have been generated by researchers and practitioners over the years based on both approaches (see Cortright (2006) and Feser et al., (2009) for a review). The goal of this

paper is to develop a novel methodology to generate and assess sets of comparable cluster definitions. We next explain both approaches to define clusters and the contribution of our clustering method to the literature.

2.1 Comparable Cluster Definitions

A set of comparable cluster definitions allocates individual industries to specific clusters (e.g., Biopharmaceuticals), allowing clusters to be compared across locations. The defined clusters are mapped into regional units to measure the cluster specialization of regions. We can then compare particular clusters across regions, as well as the overall cluster composition of regions. Regional cluster strength reflects specialization in an array of related industries, not specialization in a narrowly defined single industry (Porter, 1998, 2003; Feldman and Audretsch, 1999; Delgado et al., 2014). Thus, regional cluster strength is conceptually similar to the notion of "related variety" introduced by Frenken et al. (2007). For example, a regional cluster with a high breadth of industries will capture related variety.

There are two types of inter-industry relatedness measures that have been developed in the literature (see Section 3.1 for a detailed explanation). Some studies use national-level data to capture particular inter-industry linkages, including knowledge links based on co-patenting (see e.g., Scherer, 1982; Koo, 2005a; Glaeser and Kerr, 2009); input and output links (see e.g., Feser and Bergman, 2000; Feser, 2005); skill links (see e.g., Koo, 2005b; Glaeser and Kerr, 2009; Neffke and Henning, 2013); and product similarity as defined by the industry classification system (e.g., same 3-digit NAICS). Still other studies define measures based on the co-location patterns of industries across many regions to capture various types of linkages (Ellison and Glaeser, 1997; Porter, 2003; Ellison et al., 2010). Only a few studies use the inter-industry relatedness measures to then define clusters of related industries. We next discuss the main existing sets of cluster definitions.

Knowledge Clusters. Studies of knowledge clusters focus on a selected set of U.S. manufacturing industries with high technological intensity. For example, Feldman and Audretsch (1999) group industries that have a common science and technological base, using the Yale Survey of R&D Managers. This survey assesses the relevance of key academic disciplines for a product category. Industries with similar rankings of the importance of different academic disciplines are grouped into six mutually exclusive clusters. Alternatively, Koo (2005b) groups

manufacturing industries into seven mutually exclusive knowledge-based clusters using principal component factor analysis on an inter-industry patent-citation flow matrix.

Input-Output Clusters. Feser and Bergman (2000) define a set of U.S. manufacturing clusters using input-output links based on the Benchmark Input-Output Accounts of the United States. They group input-output classification codes (IO codes) into 23 clusters using principal component factor analysis on an inter-industry input-output link matrix. The factor analysis method tends to create highly uneven clusters, with a large number of IO codes grouped into a few clusters. To address this issue, Feser (2005) develops a new methodology based on hierarchical clustering on an input-output link matrix for manufacturing and service activities. This transparent method creates a set of 45 mutually exclusive clusters. Overlapping clusters are then created in a second stage by identifying secondary IO codes highly related to the primary codes within a cluster. For each cluster, the method provides scores of the fit of each IO code within its cluster. The IO codes are then matched to 2002 NAICS codes to create a final set of clusters of related industries.

Co-Location-Based Clusters. Porter (2003) examines the co-location patterns of narrowly defined industries in both service and manufacturing to define clusters, following the principle that co-location reveals the presence of linkages across industries. The methodology first distinguishes traded and local industries. Local industries are those that serve primarily the local markets (e.g., retail), whose employment is evenly distributed across regions in proportion to regional population. Traded industries are those that are more geographically concentrated and produce goods and services that are sold across regions and countries. The set of traded industries excludes natural-resource-based industries, whose location is tied to local resource availability (e.g., mining).

To measure the relatedness between a pair of traded industries (4-digit SIC), Porter (2003) computes the pairwise correlation of industry employment across states using 1996 data. This measure of co-location patterns is referred to as the "locational correlation" of employment (*LC-Employment*) and could capture various types of inter-industry linkages. Porter (2003) uses an iterative approach to define clusters rather than a clustering function approach. A set of 41 narrow (mutually exclusive) clusters are created using an iterative process to identify pairs and then groups of industries highly linked based on statistically significant locational correlations. In a second stage, a set of broad (overlapping) clusters is created by including other industries

that have a high locational correlation with the core industries within the narrow cluster. While the cluster definitions are mainly based on the empirical patterns of employment co-location among industries, the Benchmark Input-Output Account of the United States and industry definitions are used to correct the placement of industries with high co-location but low economic relatedness. These cluster definitions have proven very useful in the empirical analysis of the role of clusters on regional performance (see e.g., Porter, 2003; Delgado, Porter, and Stern, 2010, 2014).

2.2 Region-Specific Cluster Definitions

Comparable cluster definitions can capture most economic activities and are necessary for studies that aim to examine clusters across regions. However, one limitation of any multi-region cluster approach is that it may overlook specific inter-industry linkages that may exist in particular regional clusters. These idiosyncratic regional linkages are the focus of the region-specific cluster definitions. This approach focuses on a single region to measure industry and/or firm interdependencies and define the region's clusters. Such studies vary in their industry coverage, types of economic units (industry, technology classes, or firms), types of regional units (administrative or non-administrative), and methods.

A small set of papers defines region-specific clusters for a large set of economic activities. Some of these studies identify specific "driver" industries in which a region has a competitive advantage. Then they use region-specific inter-industry linkages, such as regional input-output models, to define the clusters around the driver industries (Hill and Brennan, 2000). Other studies focus on identifying the (non-administrative) geographic boundaries of a given cluster. To do so, they examine the spatial density of businesses for particular industries (Duranton and Overman, 2005) or the spatial density of patents for particular technology classes (e.g., Kerr and Kominers, 2010; Alcacer and Zhao, 2013). The goal is to identify locations with a high density of economic activity in a particular field that will facilitate inter-firm connections and externalities.

The bulk of region-specific cluster definitions are qualitative and based on case studies that tend to focus on particular clusters (see e.g., Bresnahan and Gambardella (2004); Cortright, 2010; Porter and Ramirez-Vallejo, 2013), for example, the Athletic and Outdoor cluster in Portland (Cortright, 2010). These studies rely on existing cluster organizations, industry

directories, and other primary data collection to identify clusters. They offer rich details on the firms and institutions within particular defined clusters, but may be less appropriate for comparing clusters across regions.

The conceptual limitation to region-specific approaches to define clusters is that such definitions are based on observed linkages among existing economic activities in a region (Bathelt, Malmberg, and Maskell, 2004; Maskell and Malmberg, 2007; Feser et al., 2009; Bathelt and Li, 2013). Activities that are not present in a region (e.g., industries, technology classes, and labor occupations that are not present) are classified as unrelated to the other activities in the region. However, such non-present activities could be related to the activities in the region, but historical factors, market imperfections or other factors may have prevented their development. Region-specific cluster definitions could thus be too narrow (or myopic) in terms of the linkages captured because they abstract from the linkages that may be present in other locations. Thus, region-specific cluster definitions could be complemented by comparable cluster definitions derived from patterns across multiple regions.

This paper creates a new cluster methodology that systematically generates comparable cluster definitions based on multiple types of inter-industry linkages. This approach provides scores that assess the ability of each set of definitions to capture high inter-industry linkages within individual clusters. For example, we can compare the Feser (2005) and Porter (2003) sets of cluster definitions as well as other sets.

We implement the algorithm and propose a new set of U.S. Benchmark Cluster Definitions (BCD) that captures a wide variety of inter-industry linkages. This set can be updated over time as new data (e.g., new industry definitions) becomes available.

3. The Clustering Algorithm

In order to derive clusters of industries, we use cluster analysis, or numerical methods to classify similar objects (cities, people, genes, industries, etc.) into groups (Everitt et al., 2011). In contrast to network analysis, where each object is related to any other object,[3] cluster analysis

[3] For example, some papers focus on defining the "product space" – the network of relatedness between products. Hidalgo et al. (2007) define the product space for exported goods. Other studies focus on specific dimensions of the product space, such as the technology, knowledge, or market space (Jaffe, Trajtenberg, and Henderson, 1993; Neffke et al., 2011; Bloom et al., 2012).

creates groups (termed clusters) in such a way that objects in the same cluster are more similar among themselves than to those in other clusters.

Defining clusters of related industries involves a number of key choices that can be parameterized in a clustering algorithm. The algorithm includes criteria for scoring alternative cluster configurations. Once the most promising configuration is identified, the algorithm addresses outlier industries to develop a final set of cluster definitions.

The clustering algorithm is designed to define mutually exclusive clusters, where each industry is uniquely assigned to one cluster. The methodology also allows the measurement of relatedness between any pair of (mutually exclusive) clusters and the creation of overlapping clusters (with individual industries shared by multiple clusters).

Drawing on Porter (2003), our method first distinguishes between traded industries (geographically concentrated) and local industries (geographically dispersed). There are 1,088 6-digit NAICS-2007 industries in the 2009 CBP data (excluding farming and some government activity). We identify 778 traded industries using the specialization and concentration patterns of each industry across U.S. regions. In 2009, the traded industries account for 36% of total U.S. employment, 50.5% of payroll, and more than 90% of patenting activity.[4]

The analysis focuses on grouping the 778 traded industries in service and manufacturing into non-overlapping groups. We refer to each cluster configuration as C and its individual clusters as c. There are five inter-related steps to create and assess each configuration C: (1) define a similarity matrix M_{ij} that captures the relatedness between any two industries; (2) make broad parameter choices β; (3) use a clustering function to create a configuration C based on the similarity matrix and parameter choices ($C=F(M_{ij}, \beta)$); (4) calculate performance scores for each C and identify the most promising configuration C^*; and (5) assess and correct the individual clusters in C^* to determine the finalized set of cluster definitions C^{**}. Each of these clustering algorithm steps is explained in detail below.[5]

3.1 Step 1: Similarity Matrix

The first step to group related industries into clusters is to define the degree to which each pair of industries is related. A similarity matrix M_{ij} provides the relatedness between any pair of

[4] The complete description of the traded and local categorization can be found on the U.S. Cluster Mapping website.
[5] All the steps of the algorithm were implemented using STATA software.

industries *i* and *j*. The matrix is based on the choice of indicator and the similarity measure. Indicators used in the literature include employment, number of establishments, measures of buyer-supplier linkages, and measures of shared labor requirements. The choice of a similarity measure allows the user to decide how the distance between two industries *i* and *j* should be measured (e.g., correlation coefficient, Euclidean, Jaccard index, or user-defined measures).

There are many alternative similarity matrices. Our analysis focuses on the inter-industry relatedness measures most frequently used in the field of regional studies to capture economies of agglomeration. The similarity matrices can be divided into three types. First, there are M_{ij} that exploit co-location patterns across many regions to capture various types of inter-industry linkages. This group includes the locational correlation of employment developed by Porter (2003) and the Ellison and Glaeser (1997) coagglomeration index. Second, there are M_{ij} that focus on national-level inter-industry linkages, including measures based on national input and output tables (see Feser and Bergman, 2000; Feser, 2005; Ellison, Glaeser, and Kerr, 2010) and on labor occupation links (Glaeser and Kerr, 2009). Third, we create multidimensional matrices that use a combination of these matrices. In what follows, we explain each of these similarity matrices as well as additional industry linkages we do not directly measure.

Pairwise Industry Co-location Patterns. Before we explain the co-location similarity matrices used in our analysis, we need to clarify the regional unit used for these measures and the source of the underlying data. There are two spatial approaches to measure the co-location patterns of industries across regions: using discrete spatial units like states (Ellison and Glaeser, 1997; Porter, 2003; Ellison, Glaeser, and Kerr, 2010) and using continuous spatial units that are based on the density of businesses (Duranton and Overman, 2005). Discrete spatial units that capture relevant regional markets offer a reasonable starting point for understanding co-location patterns. The differences between discrete and continuous co-location measures in their ability to capture inter-industry externalities can be tested. For example, Ellison, Glaeser, and Kerr (2010) show that their co-agglomeration index based on states and an approximation of the continuous co-agglomeration metric developed by Duranton and Overman (2005) both capture similar inter-industry Marshallian effects (input-output, skill, and knowledge links). Using continuous spatial measures is beyond the scope of this paper due to data limitations.

We use meaningful administrative regional units: Economic Areas (EAs) as defined by the Bureau of Economic Analysis (BEA). EAs represent 179 relevant regional markets that cover

the entirety of the continental United States (Johnson and Kort, 2004). The underlying employment and count of establishments of an EA-industry is sourced from the County Business Patterns (CBP) 2009 data.[6]

Locational Correlation (*LC*). Porter (2003) examines the employment co-location patterns of pairs of industries to capture inter-industry linkages of various types (e.g., technology, skills, supply, or demand links). He defines the locational correlation of employment (*LC-Employment*) of a pair of industries as the correlation coefficient between employment in industry *i* and employment in industry *j* in a region *r*:

$$LC\text{-}Employment_{ij} = Correlation(Employment_{ir}, Employment_{jr}) \quad (1).$$

Similarly, we also define an alternative locational correlation based on the count of establishments in a region-industry:

$$LC\text{-}Establishments_{ij} = Correlation(Establishments_{ir}, Establishments_{jr}) \quad (2).$$

Economies of agglomeration channels include firms as well as employees. The presence of numerous establishments can facilitate inter-firm interactions that result in spillovers (Glaeser and Kerr, 2009). Thus, the co-location patterns of count of establishments could help capture inter-industry linkages that are facilitated by the number of businesses.

The correlation coefficient is a well-known distance measure for continuous data used in clustering analysis (Everitt et al., 2011). The LC measures can be implemented for very granular industry definitions, and its scale is easy to interpret, with values between -1 and 1. Positive and large values suggest that there are relevant economic interdependencies between a pair of industries. For example, if the location of employment (count of establishments) in electronic computers and software is highly correlated, it would suggest that both industries are linked. While the *LC* measures tend to capture relevant linkages, it is possible that in some cases industries with high co-location may have little economic relatedness but instead capture shared natural resources. As we discuss further below, this does not limit the usefulness of co-location measures.

LC also could be sensitive to the size of the regions (Porter, 2003). For example, for pairs of industries with employment concentrated in large regions (i.e., with many pairs of zero

[6] The CBP data is made available at the county, state, and U.S. level. Economic Area data is built up from the county file. CBP data uses cell suppression in certain geography-industries with a small presence of firms. When employment data is suppressed, a range is reported. We utilize the midpoint in the range in our data.

activity across regions), the *LC* could be biased. We limit this problem by using EAs versus using smaller regional units (like counties) that do not fully capture the regional market. We also implement several sensitivities to EA size that suggest this problem is limited.[7] In our data, the average *LC-Employment* and *LC-Establishments* of a pair of industries are 0.30 and 0.52, respectively (Table 2).

The Coagglomeration Index (*COI*). This index developed by Ellison and Glaeser (1997) captures whether two industries are more co-located than expected if their employment is distributed randomly. We use the revised version of the *COI* in Ellison, Glaeser, and Kerr (2010):

$$\mathrm{COI}_{ij} = \sum_{r}(s_{ri} - x_r) * (s_{rj} - x_r) \Big/ (1 - \sum_{r} x_r^2) \qquad (3);$$

where s_{ri} is the share of industry i's employment in region r; and x_r measures the aggregate size of region r, which they model as the mean employment share in the region across industries. A value of zero or negative for *COI* would suggest no externalities-driven co-agglomeration. The higher the positive value of the *COI*, the greater is the potential for externalities between two industries, but it is not easy to assess whether particular positive values are large or small.

Ellison et al. (2010) compute the *COI* for pairs of manufacturing industries (3-digit SIC codes) and use states as the main regional unit. They find that each of the three Marshallian effects (input-output, skill, and knowledge links) matter for the co-agglomeration of a pair of industries. However, shared natural advantages (e.g., coastal access) also matter for the co-agglomeration, but this effect is less important than the cumulative effect of the Marshallian factors. Their findings suggest that co-location captures not only meaningful economic interdependencies and externalities between industries, but also some natural advantages.

We extend the Ellison, Glaeser, and Kerr (2010) analysis, and compute the *COI* for 6-digit NAICS manufacturing and service industries, using EAs as the regional unit. The mean of this variable is around zero with a standard deviation of 0.010; and the values range from a minimum of -0.05 to a maximum of 0.37 (Table 2). These values are very similar to those obtained in Ellison et al. (2010) for 3-digit SIC manufacturing industries and with a state as the regional unit. In our data, the *COI* is skewed, with 90% of the distribution below 0.01.

[7] We compute alternative LC matrices by dropping the 10 smallest and 10 largest EAs, and these LC matrices are highly correlated to our baseline measures based on all EAs.

National-Level Inter-Industry Links. We explain the next two similarity matrices that are based on national-level data: input-output and labor occupation links. Because these measures do not consider location patterns, they may capture industry interdependencies that are not geographically bounded.

Input-Output Links (*IO*). Measures based on the Benchmark Input-Output Accounts of the United States are widely used to capture supplier and buyer flows between industries (see Feser, 2005; Ellison, Glaeser, and Kerr, 2010; Alcacer and Chung, 2012). Following Ellison et al. (2010), we construct a symmetric *IO* link between any pair of industries *i*,*j* based on the maximum of all unidirectional input and output links:

$$\mathrm{IO}_{ij} = \mathrm{Max}\{\mathrm{input}_{i\rightarrow \mathrm{j}}, \mathrm{input}_{i\leftarrow \mathrm{j}}, \mathrm{output}_{i\rightarrow \mathrm{j}}, \mathrm{output}_{i\leftarrow j}\} \qquad (4).$$

The $input_{i\rightarrow j}$ link is the share of industry *i*'s total value of inputs that comes from industry *j*, and the $output_{i\rightarrow j}$ link is the share of industry *i*'s total value of outputs that goes to industry *j*.[8] The IO_{ij} link takes a minimum value of zero if the two industries do not buy from or sell to each other, and a maximum value of 1 if any of the two industries buy or sell exclusively from or to the other.

To compute this variable, we use the 2002 Benchmark Input-Output Account of the United States developed by the BEA. The average of this variable is 0.02 (Table 2). Most pairwise industrial combinations have a small *IO* link (also documented at Ellison et al., 2010), making the distribution over all pairwise combinations skewed to the right. In our sample, 90% of the distribution of this variable is below 0.06. Overall, input-output tables are more detailed for manufacturing than service industries, and so may better capture links among manufacturing industries.[9]

In the sensitivity analysis, we also compute a more conservative *IO* link score that takes the average (versus maximum) of the unidirectional input and output links, correcting downwards the score for pairs of industries with large asymmetries in their links. The average

[8] To properly capture the strength of the input-output links between two industries, we compute these percentages excluding final consumption and value-added commodity codes.

[9] In the underlying input-output data, many manufacturing industries are only available at the 4/5-digit NAICS level, and many service industries at the 2/3-digit NAICS level. The following activities are aggregated at the 2-digit NAICS level: Construction (23 NAICS), Wholesale trade (42 NAICS), Retail trade (44 and 45 NAICS), and Management of Companies and Enterprises (55 NAICS). This higher level of aggregation may induce some measurement error in the links among the corresponding 6-digit NAICS industries (e.g., we have to assume that any 6-digit industries within Wholesale trade have the same input-output links with other 6-digit industries).

and maximum pairwise *IO* links are highly correlated, and our findings are robust to using these alternative measures.[10]

Labor Occupation Links (Occ). Labor occupations have been used to measure the extent to which industries share similar skills (Koo, 2005a; Glaeser and Kerr, 2009). We use the Occupational Employment Statistics (OES) Survey of the Bureau of Labor Statistics (BLS; 2009 data). The OES data provides 792 non-governmental occupations and information on the prevalence of these occupations for each industry (i.e., for each occupation (e.g., computer programmers); it provides the percentage of that occupation in the total occupational employment of the industry). Using this data and following Glaeser and Kerr (2009), we compute the pairwise correlation between the occupation composition of any two industries:

$$Occ_{ij} = Correlation(Occupation_i, Occupation_j) \qquad (5);$$

where $Occupation_i$ is a vector with the percentage of each of the 792 occupations in the total occupational employment of industry *i*. A limitation of this measure is that occupation data is aggregated at the 4-digit NAICS level (i.e., industries with the same 4-digit NAICS will have the maximum occupational link by construction).[11] The average labor occupation correlation in our sample is 0.18.[12]

Multidimensional Similarity Matrices. We also create combinations of the unidimensional similarity matrices described above. Creating multidimensional similarity matrices begins with understanding the relationship between the unidimensional matrices. Looking at the correlations in Table 3, *LC-Employment* is highly correlated with *LC-Establishments* (correlation of 0.77) and with the coagglomeration index (correlation of 0.36). These high correlations are robust to the size of the industry and to manufacturing and service industries. *IO* links have a modest positive correlation with the other measures. We also explore a matrix that captures product similarity as defined by the industry code (NAICS-3). This matrix is equal to 1 for pairs of industries with the same 3-digit NAICS code (and 0 otherwise), and

[10] Other papers use measures of indirect input-output links that capture the extent to which a pair of industries have meaningful suppliers and buyers in common (see Feser, 2005).

[11] We are using 7-digit Standard Occupational Classification (SOC) and 4-digit NAICS data because of better coverage. The data can be accessed at http://www.bls.gov/oes/oes_dl.htm.

[12] Another way to measure skill links between industries is to examine the actual flow of employment using matched employer-employee data for the workforce of a country. See Neffke and Henning (2013) inter-industry skill-relatedness analysis for the Swedish economy.

relates very poorly with all similarity matrices except with occupational linkages (correlation of 0.45).

By using a multidimensional similarity matrix, we can better capture more types of inter-industry links (e.g., demand, supply, skills, knowledge, and others), and we can overcome some of the data limitations of the unidimensional matrices (see Table A1 in the Appendix for the definitions of all M_{ij} used). For example, we compute an M_{ij} that we call $LC\text{-}IO\text{-}Occ_{ij}$, which is the average of four (standardized) individual matrices: $LC\text{-}Employment_{ij}$, $LC\text{-}Establishments_{ij}$, IO_{ij}, and Occ_{ij}.[13] The multidimensional *LC-IO-Occ* has a high and statistically significant correlation with each of the individual matrices (Table 3). This suggests that a pair of highly linked industries based on one particular measure (e.g., *IO*) will also tend to be meaningfully related based on the multidimensional similarity matrix. Thus, *LC-IO-Occ* seems to better capture various inter-industry links.

Through our algorithm, we can compare how well cluster configurations derived from different similarity matrices perform given the validation scores developed in Step 4 below. We can then assess which matrices seem to result in cluster configurations that capture the broadest range of inter-industry links (see Section 4).

Similarity Matrices and Alternative Agglomeration Mechanisms. While we explore a particular set of relevant inter-industry measures, there are specific agglomeration mechanisms that we do not measure explicitly, such as knowledge linkages and social linkages.

Prior studies that focus on aggregated industries in manufacturing examine inter-industry knowledge linkages using patent citation patterns (e.g., Koo, 2005b; Ellison, Glaeser, and Kerr, 2010). We cannot create inter-industry patenting linkages due to data limitations.[14] However, knowledge linkages may be partly captured by our industry linkage measures. For example, co-location patterns of industries could capture some knowledge links as shown by Ellison, Glaeser, and Kerr (2010). Two industries may co-locate across regions because they share knowledge, and proximity facilitates the flow of knowledge. Similarly, if two industries share labor occupations, knowledge linkages could flow more easily.

We also do not measure social linkages of firms and individuals, which are important to define regional clusters. The inter-industry economic links captured by our measures can

[13] We standardize the unidimensional matrices since their scale and/or distribution are different (see Table 2).
[14] We use narrowly defined industries (6-digit NAICS), making the bridge to patent classes noisy. Additionally, many service industries have low patent intensity.

facilitate opportunities for inter-firm interactions. For example, firms operating in industries that share labor requirements or other inputs are more likely to interact and develop socioeconomic links.

If measures of inter-industry knowledge linkages or social linkages become available, they could be incorporated into our clustering algorithm. We could compare them against other similarity matrices, and assess how cluster configurations that are generated using the new matrices perform in the validation scores defined in Step 4 below.

More broadly, the nature and intensity of knowledge and socioeconomic linkages can vary significantly across regional clusters. Studies of the network among firms, individuals, and associated institutions will be especially informative as to the mechanisms at work in specific clusters (Sorenson and Audia, 2000; Rosenthal and Strange, 2003; Feldman, Francis, and Bercovitz, 2005; Bathelt, Malmberg, and Maskell, 2004; Storper and Venables, 2004; Lorenzen and Mudambi, 2013).

3.2 Step 2: Broad Parameter Choices

The parameter choices (β) required as inputs to the clustering functions include setting the initial number of clusters (i.e., number of groups), determining how the underlying data should be normalized, and determining the starting values for the clustering function.

An important parameter choice in clustering analysis is the initial number of clusters (*numc*). There are 41 clusters in Porter (2003) and 45 input-output based clusters in Feser (2005). Current methods to identify the "optimal" number of clusters in clustering analysis are very inconclusive (Everitt et al., 2011). Therefore, we explore values for the number of clusters between 30 and 60. Overall, too few or too many groups could result in less useful cluster definitions. Too few clusters could result in large clusters that include industries that are not very related; and too many clusters could result in clusters that are not meaningfully different from each other. Using Step 4 in the cluster algorithm (described below), it is possible to compare the quality of different configurations based on differences in the initial number of clusters.

The other two parameter choices refer to the starting values and the type of normalization of the underlying data for the clustering functions. The starting values were chosen at random. The underlying data was either untransformed (raw) or row-standardized (rst). These two parameter choices are relevant only for partition-clustering functions: *kmeans* and *kmedians*. The

normalization of the data can be important for these two clustering functions since it could result in a better centroid for each individual cluster.[15]

3.3 Step 3: Clustering Function

Clustering functions are designed to find the greatest relatedness among industries within each cluster. There are several clustering functions F(•) for grouping industries into clusters (see Everitt et al., 2011; Grimmer and King, 2011). Each function creates a new grouping *C* based on the similarity matrix and parameter choices: $C = F(M_{ij}, \beta)$. Our analysis uses the main cluster functions for continuous data: the *hierarchical* function (with Ward's linkage) and centroid-based clustering functions (*kmean* and *kmedian*).[16]

Only hierarchical functions allow the user to import a particular similarity matrix. In contrast, *kmean* and *kmedian* functions require the underlying raw data to directly compute the similarity matrix (and centroids). Thus, for similarity matrices that require additional manipulation of the underlying data (e.g., *IO* or *COI*), we can only use the hierarchical function.

Example of Steps 1 to 3 of the Clustering Algorithm. To illustrate Steps 1 to 3 of our algorithm, we replicate a set of cluster definitions that we already know, namely the 3-digit NAICS groupings. We define the similarity matrix $NAICS\text{-}3_{ij}$ as a symmetric binary matrix where pairs of industries within the same 3-digit NAICS code are assigned a value of 1 (and a value of 0 otherwise). Then, we set the broad parameters (β) so that there are 66 clusters just as there are 66 different 3-digit NAICS codes for our 778 industries. Finally, we run the hierarchical clustering function using the *NAICS-3* matrix and 66 clusters. As expected, we find that the resulting grouping *C* is indeed equal to the NAICS-3 groupings, validating the clustering algorithm.

3.4 Step 4: Performance Scores for Each C

Given the number of possible similarity matrices, parameters, and clustering functions that could be chosen, the number of alternative cluster configurations is quite large. By combining the choices described above in Steps 1 to 3 in different ways, we have generated 713

[15] The centroid of a cluster is the mean industry employment (for *kmean*) and the median industry employment (for *kmedian*). These centroids could be biased towards larger regional industries. To limit this problem, we allow for row-standardization of the region-industry employment/establishment data.

[16] We also tried hierarchical clustering with average linkages, but the resulting individual clusters were very uneven. See Grimmer and King (2011) for a new clustering approach that combines multiple clustering functions.

different *C*s. For example, choosing the *LC-Employment* similarity matrix, 40 clusters, raw underlying data, and the *kmean* clustering function will result in one configuration C_1. Alternatively, choosing the *IO* links similarity matrix, 35 clusters, and the hierarchical clustering function will result in a different configuration C_2 (see Table 1 for examples of *C*s).

Without some way to evaluate the relative quality of all these *C*s, it is very hard to find the most useful sets of definitions that incorporate a broad range of inter-industry linkages. The cluster analysis literature often lacks satisfactory methods for evaluating different categorization schemes (Grimmer and King, 2011). In contrast, our approach provides a score for each configuration *C*. In order to generate these scores, we must first address the question, *What makes a good set of cluster definitions?*

In our analysis, the primary criterion for a good set of cluster definitions is that industries within a particular cluster (e.g., the Automotive cluster) should be more closely related among themselves than to industries in other clusters. In other words, individual clusters should be meaningfully different from each other, and individual industries should fit well within their own cluster. Our score approach assesses this by using alternative measures of inter-industry linkages that we use for creating validation sub-scores (e.g., sub-scores based on input-output links). Our view is that a useful set of clusters will capture various types of industry linkages, including demand, supply, skills, and others (Marshall, 1920; Porter, 1998). Thus, we develop an overall validation score (VS) for each *C* that combines sub-scores based on alternative industry measures.

A secondary criterion is that the configurations should be robust. We would prefer cluster definitions that are similar to other well-performing cluster definitions generated by the algorithm, since this would suggest that they are more robust. We develop Overlap Scores (OS) to capture the overlap of each *C* to other configurations.

Those *C*s with the highest ranked validation scores are then subject to the robustness criteria to select the better configurations. The configuration that does relatively well in all criteria is the C^* selected to undergo further assessment in Step 5. In the remainder of this section, we explain the validation and overlap scores.

Validation Scores. We develop validation scores that capture the extent to which individual clusters and industries have high Within Cluster Relatedness (WCR) relative to Between Cluster Relatedness (BCR) with other clusters. The validation scores assess the quality

of a cluster configuration *C* along two dimensions. The first score, *VS-Cluster*, captures whether *individual clusters* in *C* are meaningfully different from each other. The second score, *VS-Industry*, assesses the fit of *individual industries* within their own cluster. The two scores are related, but capture different information. For example, in cluster configurations with many clusters, industries could fit very well in a cluster, but the individual clusters may not be very different from each other. Alternatively, in other cluster configurations with a few large clusters, individual clusters may be meaningfully different, but numerous industries may fit better in other clusters.

At the cluster level, we define WCR_c as the average relatedness between pairs of industries within a cluster, while BCR_c is the average relatedness between industries in cluster *c* and those in another cluster. For example, consider two clusters in *C*: cluster c_1 with industries a_1, a_2 and cluster c_2 with industries b_1, b_2; and a similarity matrix M_{ij} (e.g., *LC-Employment*) that may be different from the one used to generate *C*. Then, the WCR of focal cluster c_1 is $WCR_{c_1} = M_{a_1a_2}$, and the BCR of c_1 and c_2 is $BCR_{c_1,c_2} = Avg(M_{a_1b_1}, M_{a_1b_2}, M_{a_2b_1}, M_{a_2b_2})$.

For each focal cluster *c* in *C*, we compute its BCR with every other cluster and examine the resulting distribution to compute two cut-off values – the average and the 95th percentile values ($AvgBCR_c$ and $Pctile95BCR_c$). For example, if there are 47 clusters in *C*, for each focal cluster *c* we then have 46 different BCR_c values, and we compute the average and the 95th percentile of the BCR_c values. We can then assess whether a cluster's WCR_c is higher than these two threshold values.

Once we define WCR_c, $AvgBCR_c$, and $Pctile95BCR_c$ for each cluster in *C*, we compute a validation score that captures the percent of *clusters* with high WCR_c (*VS-Cluster)*. This score is made up of two broad sub-scores that we average. The first calculates the percent of clusters in *C* with WCR_c higher than $AvgBCR_c$ (*VS-Cluster Avg*) based on a particular similarity matrix M_{ij}. The second sub-score is similar but more restrictive; it calculates the percent of clusters in *C* with WCR_c higher than $Pctile95BCR_c$ (*VS-Cluster Pctile95*):

$$\text{VS-Cluster Avg}\ {}^{M}_{C} = (100/N_c) * \sum_c I[WCR_c(M_{ij}) > AvgBCR_c(M_{ij})] \quad (6a)$$

$$\text{VS-Cluster Pctile95}\ {}^{M}_{C} = (100/N_c) * \sum_c I[WCR_c(M_{ij}) > Pctile95BCR_c(M_{ij})] \quad (6b);$$

where N_c is the number of clusters in *C* and *I* is an indicator function equal to 1 if for a given cluster *c* $WCR_c > AvgBCR_c$ in (6a) or $WCR_c > Pctile95BCR_c$ in (6b). We then average these two

sub-scores to compute VS-Cluster^{M}. For example, for C^* the *VS-Cluster*$^{LC\text{-}Emp}$ score is 67.0%, meaning that approximately 31 (of 47) clusters have relatively high WCR_c based on *LC-Employment* (Table 5).

We compute (6a) and (6b) based on four different M_{ij} (*LC-Employment*, *LC-Establishments*, *IO*, and *Occ*). Note that the similarity matrices we use here are not dependent on the similarity matrix used to create *C*. This allows us to calculate validation scores that can be consistently compared regardless of the underlying measures used to generate *Cs*. This results in eight sub-scores that we then average to generate the main validation score.[17] A score of 100 indicates that all the individual clusters in *C* contain industries that are highly related based on multiple linkages. For example, for C^* the *VS-Cluster* is 81.6% (Table 5), while the average of this variable across all *Cs* is 73.9% (Table 4).

So far, we have computed a validation score that examines individual clusters. We then compute a validation score based on the fit of individual industries within their own cluster (*VS-Industry*). For a given industry *i*, we want it to be more related to the industries within its own cluster than to industries outside its cluster.[18] Similar to our calculation of *VS-Cluster*, we measure the percent of industries with WCR_{ic} higher than their average BCR_i (*VS-Industry Avg*) and higher than the 95th percentile of BCR_i (*VS-Industry Pctile95*) based on various similarity matrices.

$$\text{VS-Industry Avg}_{C}^{M}=(100/N_i)*\sum_{i} I[WCR_{ic}(M_{ij}) > \text{AvgBCR}_i(M_{ij})] \quad (7a)$$

$$\text{VS-Industry Pctile95}_{C}^{M}=(100/N_i)*\sum_{i} I[WCR_{ic}(M_{ij}) > \text{Pctile95BCR}_i(M_{ij})] \quad (7b);$$

where N_i is the number of industries in *C*. We compute (7a) and (7b) based on four different M_{ij} (*LC-Employment*, *LC-Establishments*, *IO*, and *Occ*), resulting in eight sub-scores that we then average to generate the validation score *VS-Industry*.

The overall validation score *VS* of a cluster configuration is computed as the average of the *VS-Cluster* and *VS-Industry* scores. Those *C*s with highly ranked scores for both *VS-Cluster*

[17] We do not include validation sub-scores based on *COI* to compute our main validation scores because *COI* and *LC-Employment* will capture similar industry interdependencies.

[18] The industry WCR_{ic} score is the average pairwise relatedness between the focal industry and the other industries within the cluster; while industry BCR is the average relatedness between the focal industry and industries in a different cluster. Using the example above, if we consider focal industry a_1 in cluster c_1, then its $WCR_{a1c}=M_{a1,a2}$ and the BCR of a_1 with industries in cluster c_2 is $BCR_{a1,\,c2}=\text{Avg}(M_{a1,b1,}\ M_{a1,b2})$.

and *VS-Industry* are the most promising configurations (the "candidates" C^*s). The final candidate C^* is the configuration with the maximum *VS* score. For example, Table 5 illustrates the validation scores and sub-scores for the candidate configuration C^*.

Overlap Scores. The candidate C^*s are subject to the robustness criteria. We develop scores that capture the robustness of a particular *C* by comparing the industry overlap between the clusters in *C* and the clusters in other candidate configurations. To compare a configuration C_1 to another C_2, for each individual cluster *c* in C_1, we find a matching cluster *b* in C_2 (i.e., the cluster *b* that has the highest industry overlap with *c*). Specifically, we compute the overlap between a pair of clusters *c*, *b* using the geometric mean of the industry overlap in each direction:

$$overlap_{c,b} = 100 \cdot (Shared\ Industries_{c,b} / \sqrt{Industries_c \cdot Industries_b}).$$

Where *Shared Industries* is the number of industries in common in *b* and *c*; and *Industries* are the number of industries in each cluster. The maximum overlap of a pair of matched clusters is 100. Then we define the overlap score of C_1 to C_2 as the average industry overlap across C_1's clusters: $Overlap\ Score_{C_1-C_2} = \frac{1}{N_c}\sum_{c \in C_1} overlap_{c,b}$ Similarly, we compute the average overlap of C_1 with all other candidate configurations ($Overlap\ Score_{\ C\text{-}Candidates}$). For example, on average the proposed candidate C^* has an industry overlap of 77.6% with other relevant candidates, indicating that these alternative *C*s tend to provide, on average, similar groupings of industries (Table 7).

The configuration that does relatively well in the validation score (and overlap score) is the C^* selected to undergo further assessment in Step 5. Generally, the higher the validation scores, the better the C^*. However, there could be anomalies within individual clusters that would require some assessment and reallocation of individual industries to obtain the finalized set of cluster definitions C^{**}.

3.5 Step 5: Assessing Individual Clusters of Candidate C^*

Because clustering analysis cannot perfectly substitute for expert judgment, the methodology concludes with a systematic correction of anomalies and characterization of the individual clusters in C^*, resulting in a finalized set of cluster definitions. Although Steps 1 to 4 systematically assign industries to clusters, the resulting *C*s can be improved. Limitations in the underlying data may create spurious industry relatedness that will place some industries into

clusters where they are not the best fit. Some clusters may contain conceptually distinct groups that may have not been separated because of the choice of initial number of groups (*numc* parameter); and other clusters may be better off combined. Step 5 allows us to examine the clusters in C^* to assess whether there are industry outliers that are better placed into different clusters and whether to combine or break individual clusters to improve the coherence of the clusters. We can use our score approach to inform these expert-driven choices. Users can assess how certain changes impact the WCR scores of individual clusters and the validation scores of the cluster configuration relative to the initial values.

We define two types of possible outlier industries: *systematic* and *marginal* outliers. Systematic outlier industries are those with a low overall WCR_{ic} score (based on the average of standardized sub-scores for $WCR^{LC\text{-}Emp}$, $WCR^{LC\text{-}Est}$, WCR^{IO}, and WCR^{Occ}).[19] Systematic outliers are identified and corrected with a simple sub-process. They are identified based on two criteria: the industry WCR is low relative to other clusters (i.e., WCR_{ic} is below the 75th percentile value of BCR_i); or WCR is low relative to other industries in the same cluster (i.e., WCR_{ic} is two standard deviations below the average WCR_{ic}). Then the systematic outliers are reassigned to the cluster where their WCR is highest. This sub-process is iterated several times until there are no systematic outliers.

Marginal outlier industries are those industries that, even with a high WCR_{ic}, could be conceptually better in another cluster. These outliers are often the result of limitations in the underlying data.[20] For example, *Men's and Boy's Clothing Manufacturing* industries (NAICS 315221-31525) are in the Printing Services cluster for C^*, but they likely best belong to an Apparel cluster. Identifying these marginal outliers requires examining each cluster and analyzing the main product/service lines of the industries based on the detailed definitions offered by the NAICS system. The outliers are reallocated to their "next best" cluster using the

[19] The WCR score is based on these four sub-scores to have a more robust score that captures multiple inter-industry linkages within the cluster.

[20] In a few cases, the input-output link between two industries may be overestimated due to the level of aggregation of underlying data and/or due to our symmetric measure of *IO* links. For example, R&D industries (NAICS 541700) appear very highly linked to Water Transportation (NAICS 483000) industries because Water Transportation supplies a large percentage of its output to R&D industries. This induces the R&D industries to be grouped with Water Transportation if input-output links are considered in the similarity matrix. For industries where the underlying input-output data is highly aggregated and for industries with very high input-output links in the cluster, we check that these industries also fit well in their cluster based on the other measures (*LC* and *Occ*).

WCR_i scores. Reallocated marginal outliers can be easily tracked and documented so that the process is transparent.

Once we correct industry outliers, we then examine whether some individual clusters should be combined or partitioned. If two individual clusters have very high BCR and they do not seem conceptually different, they could be combined. In contrast, some individual clusters could be partitioned if we find clear conceptual and relatedness differences among certain sub-groups of industries in a cluster. Because of these corrections, the initial number of clusters (*numc*) and the number of clusters in the finalized set of cluster definitions may differ.

After all five steps in the cluster algorithm are complete, we are able to recommend a final set of benchmark cluster definitions C^{**} (the BCD). We explain the main findings and the proposed new cluster definitions in the next Sections.

4. Generating and Assessing Cluster Configurations

We apply the clustering algorithm to generate 713 different cluster configurations that group 778 6-digit NAICS industries using 2009 U.S. data. These configurations are based on 13 different similarity matrices (M_{ij}) and the parameter and clustering function choices discussed in the prior section ($C=F(M_{ij}, \beta)$). As illustrated in Table 1, some *C*s are generated using unidimensional matrices (e.g., *LC-Emp*) and others using multidimensional matrices (e.g., *LC-IO-Occ*). We then generate the validation scores for each configuration to assess their relative quality. In this section, we use the scores to compare *C*s generated using different similarity matrices. We then explain the properties of the proposed candidate C^* that will be subject to assessment and adjustments of individual clusters in the last step of the algorithm to obtain the BCD.

Validation Scores by Choice of Similarity Matrix. Through our algorithm, we can compare how well the configurations derived from different similarity matrices perform in the validation scores. We can then assess which similarity matrices seem to result in cluster configurations that capture the broadest range of inter-industry linkages and potential externalities (e.g., demand, supply, skills, knowledge, and others).

We use our score function to compare *C*s generated by either a unidimensional similarity matrix (*LC-Emp*, *LC-Est*, *COI*, *IO*, *Occ*) or the multidimensional *LC-IO-Occ* matrix. Each of these matrices can be used to create a number of different *C*s by changing the type of clustering

function and/or the parameter choices. For example, there are 31 *C*s generated using a hierarchical function, M_{ij}=*LC-IO-Occ*, and 31 different values for the number of clusters (*numc*). We then assess the average quality of *C*s generated with the same similarity matrix. The analysis is shown in Table 6, which reports the mean validation score (VS) and the mean validation sub-scores ($VS^{LC\text{-}Emp}$, $VS^{LC\text{-}Est}$, VS^{IO}, and VS^{Occ}) by similarity matrix.

If we want to capture various inter-industry linkages within clusters, then *C*s with higher overall validation scores will be preferred. We find that *C*s generated with the *LC-IO-Occ* matrix have, on average, statistically significant higher VS scores than other *C*s generated based on unidimensional matrices. For example, the mean VS of *C*s(*LC-IO-Occ*) is 76, and the next best mean VS is 71 for *C*s(*LC-Est*) (Table 6). This difference in the means is statistically significant at 1%.[21] The matrix $LC\text{-}IO\text{-}Occ_{ij}$ seems to generate meaningful sets of cluster definitions that capture a broad set of industry interdependencies. One of the *C*s generated with this matrix is the proposed candidate C^*, which is the basis for our final set of cluster definitions.

We can also examine how other model choices influence the validation scores. While we cannot estimate the optimal number of groups (*numc*) for a good set of cluster definitions, we can evaluate whether some *numc* values result in higher validation scores. For example, we find that validation scores for *C*s with 40-to-49 clusters are higher than the validation scores for configurations that have either fewer (30-to-39) or more (50-60) clusters. This type of analysis can help users identify good parameter values for their clustering models.

Choosing the Candidate Configuration C^*. The choice of C^* depends primarily on the validation scores. Those configurations with highly ranked scores for both *VS-Cluster* and *VS-Industry* (i.e., top-40 rankings in both scores across the 713 *C*s) are the candidates, C^*s. There are 24 candidates (see Table 7). Then the configuration with the maximum overall validation score *VS* is the proposed candidate C^*. The C^* is generated using a hierarchical clustering function with 47 clusters and the multidimensional similarity matrix *LC-IO-Occ*. This configuration has the highest validation score across all the *C*s, with a score of 77.7% (see Table 5 for all the scores and sub-scores for C^*).

[21] Some studies may be interested in the sets of clusters that best capture a particular measure. Cluster configurations that are generated based exclusively on one particular measure tend to have better sub-scores in that particular measure. That is the case for *C*s generated using *LC-Emp*, *LC-Est*, or *Occ*, but not for *C*s generated based on *IO*. Using *C*s(*Occ*) as an example, in Table 6 these *C*s have a mean validation sub-score VS^{Occ} higher than that of *C*s(*LC-IO-Occ*) (99 versus 95); but do significantly worse than *C*s(*LC-IO-Occ*) in the other sub-scores.

For sensitivity, we assess the robustness of the candidate C^* by comparing its overlap to the other 23 promising configurations. Table 7 shows that on average C^* has a high overlap of 77.6% with these other *C*s, indicating that they tend to provide very similar groupings of industries. The configuration C^* will be subject to assessment and improvement of individual clusters in Step 5 to derive C^{**}.

5. Proposed Set of Benchmark Cluster Definitions C^{**}

Our methodology concludes with an assessment and correction of the individual clusters in C^* to derive the finalized set of cluster definitions. We explain this process here, present a summary overview of the BCD, and illustrate a few selected clusters. A detailed overview of the cluster definitions, with a description of each cluster, associated industry NAICS codes, summary calculations of the fit of each industry within its cluster, and a full explanation of the process to get to these clusters, is available in the supplemental online Technical Appendix.[22]

The proposed set of cluster definitions C^{**} has 51 clusters (see Table 8). In this set, 7 industries are systematic outliers and 125 industries are marginal outliers that were re-allocated into other clusters.[23] While we started with 47 clusters in C^*, our final set of definitions has 51 clusters because we partitioned and combined some clusters to improve the coherence and usefulness of the cluster definitions. These modifications had a trivial effect on the VS score, which is 78% in C^{**} and C^* (see Tables 5 and 10).

There are four cases where the algorithm divided industries into two clusters, but we created a single combined cluster because they had high Between Cluster Relatedness and seemed conceptually similar. Specifically, we combined the following pairs of clusters into an individual cluster: two textile clusters, two financial services clusters, two food clusters, and two upstream metal manufacturing clusters.

We also partitioned the original clusters in seven cases: six individual clusters were each partitioned into two clusters, and one cluster was partitioned into three. These partitions are

[22] The cluster definitions and the Technical Appendix are available at the U.S. Cluster Mapping website (http://clustermapping.us).

[23] The correction of marginal outlier industries may not improve the overall VS score since some industries are moved to clusters with lower WCR_i than the original cluster. Most industries are moved to clusters with high relative WCR_i scores. Specifically, around 40% of industries are re-allocated into a new cluster where they have a WCR_{ic} rank of 1 (best fit out of 51 clusters). A list of the marginal industries and their original and destination clusters can be accessed at the online Technical Appendix.

supported by sensitivity analysis, and the new clusters have better properties (WCR_c) than their original larger cluster. We separated Downstream Chemical Products from Biopharmaceuticals as supported by the underlying data and expert opinion. By doing this, we create narrower clusters that focus on different markets. Similarly, we separated the Downstream Metal Products cluster from the original Production Technology cluster, Leather and Related Products from the original Apparel cluster, and Coal Mining from Electric Power Generation and Transmission; the Mining cluster was partitioned into Metal Mining and Nonmetal Mining clusters. One partition happened systematically when we slightly increased the parameter value for the number of initial clusters (all else being equal): the Performing Arts cluster was separated from the original Marketing, Design, and Publishing. Finally, the original Lighting and Electrical Equipment cluster was partitioned into three clusters: the focal Lighting and Electrical Equipment, Medical Devices, and Recreational and Small Electronic clusters. While these clusters share skills, they are distinct groups. We explain these three clusters below.

After this process of assessment and correction of individual clusters, we finalize the characterization of clusters in C^{**} with the creation of names and conceptual subcategories (termed "subclusters") to help describe the content of each cluster. These subclusters are based mainly on industry definitions.

Table 8 offers a summary overview of the clusters in C^{**} (the BCD), with information by cluster on the number of industries, the average WCR score, and sub-scores. All the individual clusters have a high WCR score, but there is variation across clusters with Tobacco, Music and Sound Recording, and Jewelry and Precious Metals having the highest scores. Most clusters have an average WCR score greater than the maximum BCR score (i.e., WCR Rank of one).

Cluster Examples. We illustrate the BCD with number of clusters that differ in the types of industries included (e.g., different 3-digit NAICS) and in the types of corrections undertaken in Step 5 to provide additional insights into the cluster definitions.

Aerospace Vehicles and Defense Cluster (Table 9.1). This cluster includes establishments that manufacture aircraft, space vehicles, guided missiles, and related parts. It was systematically generated by Steps 1 to 3 of our algorithm, and contains seven industries in two different 3-digit NAICS (336 and 334). These industries can be categorized into three sub-clusters: Aircraft, Missiles and Space Vehicles, and Search and Navigation Equipment. All the industries fit best in this cluster as compared to being placed in any of the remaining 50 clusters (i.e., the rank for

each industry based on WCR_{ic} score equals 1). The industry with the highest WCR score is Aircraft Manufacturing (NAICS 315999), suggesting that this is a focal activity with relevant links to the other industries within the cluster. As an example of the cluster's distribution over U.S. regions, Figure 1 shows the Economic Areas that are highly specialized in this cluster, including, among many others, Seattle-Tacoma-Olympia, WA; Wichita-Winfield, KS; and Dallas-Fort Worth, TX.

Oil and Gas Production and Transportation Cluster (Table 9.2). This cluster includes firms involved in locating, extracting, refining, and transporting oil and gas. It contains 12 industries in six different 3-digit NAICS. The focal industry here is Petroleum Refineries (NAICS 324110). The mix of manufacturing and service industries in this cluster (and in other ten clusters) contrasts with the measurement of related economic activity used in other papers. For example, Frenken et al. (2007) develop a meaningful conceptual distinction of regional diversity in related economic activity versus diversity in unrelated economic activity. They classify industries in service and manufacturing as unrelated, which may not be the case for some clusters.[24]

Insurance Services Cluster (Table 9.3). The firms in this cluster provide a range of insurance products as well as insurance support services. It contains eight service industries and is one of three clusters that is exactly equivalent to a 3-digit NAICS group (524). Insurance-related services (e.g., Claims Adjusting, NAICS 524291; All Other Insurance Related Activities, NAICS 524298) is a focal part of the cluster, supporting a broad range of insurance types.

Medical Devices; Lighting and Electrical Equipment; and Recreational and Small Electric Goods Clusters (Tables 9.4–9.6). The algorithm originally grouped all three clusters into one large cluster. Using expert judgment, we separated the overall cluster into three based primarily on the NAICS definitions. We checked that the WCR_c of each of the new clusters improved or changed minimally relative to the score of the initial larger cluster, and that their WCR_c rank is 1 (Table 8).[25] We also examined the geographic concentration of the three cluster

[24] Frenken et al. (2007) define *related* variety in a region by examining the diversity of industries within a given two-digit industry class (i.e., entropy at the five-digit level industries within each two-digit industry class); and find that related diversity enhances regional employment growth.

[25] Specifically, in the initial C^* with 47 groups (and after correcting the industry outliers), the WCR_c of the original cluster was 1.5, while each of the WCR_c of the partitioned clusters was 1.7 for Lighting and Electrical Equipment, 2.3 for Medical Devices, and 1.5 for Recreational and Small Electric Goods.

categories across EA regions as an additional criterion, and concluded that they have different geographic concentration patterns.

As suggested by their descriptions, the three clusters are conceptually different. The Medical Devices cluster (Table 9.4) consists of firms that manufacture different medical devices and supplies. It has five industries representing two 3-digit NAICS codes (333 and 339). Firms in the Lighting and Electrical Equipment cluster (Table 9.5) are not involved in manufacturing medical devices, but do manufacture other electrical equipment and electronic components. It is a larger cluster, consisting of 15 industries representing one 3-digit NAICS code (335). Finally, firms in the Recreational and Small Electric Goods cluster (Table 9.6) are related to those in the Lighting and Electrical Equipment cluster, but the focus is different. These establishments manufacture end-use products for recreational, decorative, and office purposes. There are 15 industries that represent five different 3-digit NAICS codes.

6. Comparison of our C^{**} and Existing Sets of Cluster Definitions

Using the clustering algorithm, we can assess the relative performance of our proposed set of benchmark cluster definitions C^{**} and other existing sets of cluster definitions: NAICS-3, Porter (2003), and Feser (2005). We use the mutually exclusive sets of cluster definitions offered by Porter (2003) and Feser (2005) since the differences are more readily apparent when each industry is assigned to one cluster, and their overlapping clusters rely on having well-defined mutually exclusive clusters. Before providing the details of the comparisons, it is important to clarify that the number of industries and the number of groups are different across the four sets. Our C^{**} includes 778 industries and 51 clusters, NAICS-3 grouping includes 778 industries and 66 clusters, Porter's (2003) set includes 685 industries and 41 traded clusters, and Feser's (2005) set includes 910 industries and 44 clusters (excluding farming and a few other industries due to data limitations).[26]

The validation scores for the selected sets of cluster definitions are presented in Table 10. Our analysis shows that a definition based on grouping industries with the same 3-digit NAICS code performs relatively poorly when trying to capture a broad set of industry interdependencies. The overall validation score of NAICS-3 is the lowest (58) not only among the existing sets, but

[26] One of the clusters in Feser's (2005) set is Farming, which is excluded from the CBP data; therefore, we focus the analysis on the other 44 clusters and 910 industries (out of 969 industries) that we can bridge into 2007 NAICS codes and CBP data. The larger number of industries in Feser (2005) is in part due to the inclusion of local health services.

also among all the cluster configurations (*C*s) generated by the algorithm. The NAICS-3 groupings do poorly in most sub-scores except for occupational linkages. The low validation scores are perhaps not surprising, since the industry code system groups industries based on similarities in products or services, not based on broader inter-industry complementarities. This suggests that many studies that classify industries from different parts of the industry code as unrelated may fail to capture relevant inter-industry linkages.

In Table 10, we find that C^{**} scores better in capturing a broad set of industry interdependencies than any of the other sets of clusters. C^{**} receives the highest validation score (and highest *VS-Cluster* and *VS-Industry* scores) with a *VS* value of 78 as compared to 73 for Porter (2003), 69 for Feser (2005), and 58 for NAICS-3. Furthermore, the validation score of C^{**} ranks second across the 713 *C*s generated by the algorithm. C^{**} also seems to perform well in particular inter-industry measures. Specifically, C^{**} scores better or the same as the three other sets in the validation sub-scores for pairwise industry co-location of the number of establishments ($VS^{LC\text{-}Est}$), input-output links (VS^{IO}), and shared labor occupations (VS^{Occ}). Porter (2003) set scores highest in the validation sub-score for pairwise industry co-location of employment ($VS^{LC\text{-}Emp}$), but with little difference from the C^{**} score (67 versus 66). The Feser (2005) set does relatively worse than C^{**} in the *LC* and *IO* sub-scores. The lower validation sub-score for *IO* links could be due to the fact that Feser's (2005) set of clusters uses a particular *indirect IO* link measure that is different from the one used in this paper (i.e., his measure captures the percent of meaningful suppliers and buyers in common for a pair of industries rather than the direct selling and buying to and from each other). Overall, these findings suggest that the clusters in our proposed set of benchmark cluster definitions contain industries that are meaningfully related, and may facilitate externalities of various types.

We can also analyze the industry overlap between the clusters in C^{**} and the clusters in the other three sets of cluster definitions to evaluate whether different clustering methods tend to generate similar clusters. In each case, we examine the overlap for the sub-set of industries in common with C^{**}. For example, $C^{**}$and NAICS-3 definitions have 778 industries in common, which belong to 51 clusters in C^{**} and 66 clusters in NAICS-3. We then assess if the industries are grouped in similar clusters using our overlap score (see Section 3.4). We compute the overlap score in each direction (i.e., C^{**} to NAICS-3 and NAICS-3 to C^{**}) and then take the average in both directions. The findings are presented in Table 11. The average industry overlap is 61%

between C^{**} and NAICS-3, which means that on average a pair of clusters shares 61% of their industries. Only three clusters are identical in both sets (100% overlap): Environmental Services (NAICS-562); Insurance Services (NAICS-524; Table 9.3); and Paper and Packaging (NAICS-322).[27] Similarly, the average cluster overlap is 57% between C^{**} and Porter's (2003) set, and 54% between $C^{**}$and Feser's (2005) set. While there is overlap between sets, the scores indicate that the clusters in the BCD are meaningfully different from those in the other existing sets.

6.1 Research and Policy Applications for the BCD

What constitutes a good set of cluster definitions depends on the particular research or policy question. We implement our clustering algorithm to offer a set of benchmark cluster definitions that captures numerous inter-industry linkages and could facilitate externalities of various types (e.g., skills, supply, demand, and others).

For research questions that focus on a particular type of inter-industry link (e.g., occupational links and potential labor market pooling benefits), groupings that better capture that specific link may be preferred. For example, if the policy goal is to promote training and skills that could be shared by industries with similar labor needs, cluster configurations that best capture occupational links will be useful.

However, if the goal is to promote multiple complementarities across industries, we believe our BCD may be more useful. Industries within our cluster categories are highly related based on a mix of various links. Some industries in a cluster may have strong skill links, while other industries may be closely related by *IO*, technology, and/or other types of links. Policies that focus on improving a specific link for a sub-set of industries within the cluster (e.g., training and skills shared by some industries) can facilitate complementarities of many types among all industries in the cluster.

We believe our proposed BCD is particularly important for studying the economic development of regions. We map the finalized set of cluster definitions into different regional units (Metropolitan Statistical Areas (MSAs), Economic Areas (EAs), and States) over time, creating a regional cluster dataset that allows for a systematic comparison of the cluster composition of regions using different metrics (e.g., employment, specialization, wages, and number of establishments). For example, Figure 1 shows the top regional Aerospace Vehicles

[27] The number of different 3-digit NAICS in a cluster in C^{**} is on average 2.7.

and Defense clusters across Economic Areas in 2010. This database is publicly available at the U.S. Cluster Mapping website.

For a particular cluster category, we can assess its presence in a region and examine what industries are under-represented (or non-existing) in the region as compared to the national cluster or as compared to similar clusters in other regions. These comparisons can then be the focus of key research and policy actions. To design policies that help a regional cluster, we need to examine why certain industries are under-represented or under-performing. Several explanations are plausible: the lack of skills, inputs, technology, sophisticated demand, and/or institutions for collaboration. Other methods that focus on examining region-specific links among firms and individuals in clusters could complement our benchmark cluster definitions and offer important insights into the mechanism at play in a particular regional cluster.

The ability to compare a cluster across regions can also facilitate the evaluation of regional cluster policies (Feldman et al. 2012). For example, we could identify a few regional clusters that look very similar in a base year in terms of various cluster attributes (size, specialization, number of firms, industry composition, etc.), but where one cluster is the target of a relevant investment (say a private-public grant) and the others are not. We can then assess if over time we observe differences in the composition and performance of the treated regional cluster relative to the others. In addition, researchers can use our clustering method and the BCD-based database to examine relevant questions on the role of clusters in the performance of regions and firms.

7. Conclusion

In order to compete more effectively, regions need to understand their cluster strengths as compared to those of other regions. To make this comparison, a set of regionally comparable cluster definitions that marks the industry boundaries of each cluster is necessary. This paper responds to this need by providing a clustering methodology to generate and assess sets of cluster definitions. In our algorithm, each cluster configuration is generated by a clustering function that uses as inputs a particular inter-industry similarity matrix and well-specified parameter choices. The clustering algorithm provides scores that assess the quality of each configuration. This allows us to identify the candidate configuration that best captures multiple types of inter-industry links. The methodology concludes with a correction of anomalies of the

individual clusters in the most promising configuration to determine our finalized set of cluster definitions.

Using U.S. data, we implement the clustering algorithm to generate a transparent set of benchmark cluster definitions that captures many inter-industry interdependencies. The proposed definitions use measures of inter-industry linkages based on the co-location patterns of employment and establishments, input-output linkages, and shared labor occupations. The BCD contains 51 clusters that can be mapped consistently into U.S. regions to create a regional cluster database.

With an updateable algorithm for defining and assessing alternative cluster definitions, a number of extensions are possible. First, we can add additional inter-industry similarity matrices as they become available (e.g., specific measures of knowledge linkages or labor flows among industries) to generate improved cluster definitions.

Second, while the analysis here focuses on mutually exclusive clusters, the methodology also provides scores of the relatedness between any pair of clusters and between any industry and any cluster. These scores are based on various inter-industry linkage measures. Thus, we can assess which mutually exclusive clusters are meaningfully related (e.g., industries in the Financial Services cluster and in the Insurance Services cluster are highly related). We can also develop overlapping cluster definitions by adding secondary industries that are highly related to the industries that constitute each (mutually exclusive) cluster (Porter, 2003; Feser, 2005). Defining measures of the relatedness among clusters is important since economies of agglomeration arise across related clusters as well as within individual clusters (Delgado, Porter, and Stern, 2014).

Third, our clustering method can be applied to other countries using their specific data. Defining clusters is best undertaken using data from large and diverse economies with numerous highly integrated regions. Since the U.S. is a large and diverse economy, the U.S. benchmark cluster definitions are a good starting point, especially for economies that lack the data needed to implement the clustering methodology. However, there are some limitations on using the BCD in other economies that are weighted toward economic activities that are less prevalent in the United States (e.g., ship building) or that are not well captured by U.S. data (e.g., farming). They may also be less useful in countries with a lower level of technological development, but here, our definitions offer important insights into how clusters could form with reduced internal

barriers to trade and technological improvements. Finally, the BCD will be especially useful for countries with an industry code schema similar in detail to the one in the United States (e.g., Mexico and Canada). It can also be applied with higher aggregation to a large set of countries through matching the U.S. NAICS code to the U.N. International Standard Industrial Classification (ISIC). Definitions based on ISIC would facilitate an examination of the trade and foreign direct investment links of clusters across countries (e.g., Bathelt and Li, 2013; Delgado, Kyle, and McGahan, 2013).

A fourth extension is the further examination of local industries (e.g., retail industries, hospitals) and their linkages with traded regional clusters. Our clustering analysis excludes local industries because they do not geographically concentrate, but rather focus on serving a region's population. Also, within a region certain local industries (e.g., local business services, retail activities) can geographically concentrate, which has implications for policy.

Fifth, the algorithm can be used to track the evolution of the industry boundaries of clusters over time. For example, while IT and analytical instruments industries are highly related today, they may have been less complementary a decade or two ago. The emergence and evolution of clusters have not been widely studied due to lack of data (Swann, 1998; Porter, 1998; Bathelt and Boggs, 2003; Klepper, 2010). However, an understanding of cluster emergence and relatedness could have wide-ranging implications for forward-looking regional strategy.

Another area for future research is the development of methods to adapt cluster definitions to specific regions (i.e., the industry boundaries of a cluster can sometimes vary by region). For example, regional input-output tables could be used to measure region-specific buyer-supplier linkages in clusters.

Finally, our benchmark cluster definitions can be mapped into continuous spatial units as well as administrative units (e.g., MSAs, EAs, and States). We could then analyze the micro-geography of clusters within (and across) jurisdictions (e.g., Duranton and Overman, 2005; Kerr and Kominers, 2010; Alcacer and Zhao, 2013). For example, in a particular Economic Area (e.g., Los Angeles, CA), we could assess whether a cluster category is geographically separated in distant parts within the region or whether the whole cluster is closely co-located. Understanding the micro-geography of clusters can help inform policies to facilitate the connectivity of firms and supportive institutions within clusters.

The BCD, combined with other available data sources, can be used to greatly inform economic development. For example, using the BCD and other data sources, the U.S. Cluster Mapping Project has created a regional cluster dataset together with multiple regional performance and business environment indicators (e.g., employment, specialization, wages, and number of establishments). The Project provides a powerful tool for researchers and policymakers, and offers a new interactive tool for practitioners and firms looking to identify opportunities in regions and design cluster-based regional economic development policies. The tool also maps the cluster composition of regions to encourage connections previously not identified.

7. References

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Table 1: Examples of Cluster Configurations Generated

Similarity Matrix M_{ij}	Parameter Choices β		Clustering Function	No. of *C*s
	No. Clusters (numc)	Data	C=F(M_{ij}, β)	
LC-Employment$_{ij}$	30-60	Raw	Hierarchical-Ward's	31
		Raw/Std	Kmean	62
		Raw/Std	Kmedian	62
LC-Establishments$_{ij}$	30-60	Raw	Hierarchical-Ward's	31
		Raw/Std	Kmean	62
		Raw/Std	Kmedian	62
Labor Occupation (Occ$_{ij}$)	30-60	Raw	Hierarchical-Ward's	31
		Raw	Kmean	31
		Raw	Kmedian	31
Input-Output (IO$_{ij}$)	30-60	Raw	Hierarchical-Ward's	31
Coagglomeration Index	30-60	Raw	Hierarchical-Ward's	31
LC_IO_Occ$_{ij}$*	30-60	Raw	Hierarchical-Ward's	31

*This M_{ij} is an average of the (standardized) LC-Employment, LC-Establishments, IO, and Occ matrices. See Table A1 for a list of all the similarity matrices used. The Hierarchical function uses Ward's linkages.

Table 2: Descriptive Statistics for Similarity Matrices (778 industries (6-digit NAICS-2007 codes), 2009 data; N=604,506)

Similarity Matrices M_{ij}	Mean	Std Dev	Min	Max	Median	Pctile90
LC-Employment (LC-Emp$_{ij}$)	0.296	0.232	-0.176	0.993	0.263	0.631
LC-Establishments (LC-Est$_{ij}$)	0.519	0.259	-0.174	0.998	0.555	0.840
Input-Output (IO$_{ij}$)	0.017	0.045	0	1	0.001	0.064
Labor Occupation (Occ$_{ij}$)	0.183	0.202	-0.013	1	0.113	0.450
Coagglomeration Index (COI$_{ij}$)	-0.000	0.010	-0.051	0.372	-0.000	0.007
LC-IO-Occ$_{ij}$*	-0.002	0.646	-1.438	6.716	-0.037	0.801

Notes: An observation is any pair of industries (ij, i≠j). *LC-IO-Occ$_{ij}$ is an average of the (standardized) LC-Employment, LC-Establishments, IO, and Occ.

Table 3: Correlation between Similarity Matrices (778 industries (6-digit NAICS-2007 codes), 2009 data; N=604,506)

	LC-Emp	LC-Est	IO	Occ	COI	NAICS-3
LC-Employment	1.00					
LC-Establishments	0.77	1.00				
Input-Output	0.16	0.13	1.00			
Labor Occupation	0.03	0.10	0.13	1.00		
Coagglomeration Index	0.36	0.17	0.07	0.15	1.00	
NAICS-3*	0.05	0.05	0.09	0.45	0.09	1.00
LC-IO-Occ$_{ij}$	0.76	0.78	0.55	0.49	0.29	0.25

Notes: An observation is any pair of industries (ij, i≠j). All coefficients are significant at 1% level. All variables are based on 2009 data except for IO, which is based on 2002 data. *NAICS-3 matrix is equal to 1 for a pair of industries with the same 3-digit NAICS code (and 0 otherwise).

Table 4: Descriptive Statistics: Validation Scores for Cluster Configurations (No. of *C*s=713)

Validation Scores	Description	Mean	Std Dev	Min	Max	Pctile90
VS-Cluster	% of clusters with high WCR_c (Average of *VS-Cluster* sub-scores)	73.9	4.8	63.5	83.9	80.4
VS-Industry	% of industries with high WCR_{ic} (Average of *VS-Industry* sub-scores)	66.3	3.1	56.9	74.2	70.2
VS	Average *VS-Cluster* and *VS-Industry*	70.1	3.5	63.4	77.7	74.5
Sub-scores based on individual similarity matrix (LC-Emp, LC-Est, IO, or Occ)						
$VS\text{-}Cluster^{LC\text{-}Emp}$	% of clusters with high $WCR^{LC\text{-}Emp}$	76.7	14.9	50.0	100.0	96.9
$VS\text{-}Cluster^{LC\text{-}Est}$	% of clusters with high $WCR^{LC\text{-}Est}$	71.4	11.0	50.0	96.7	89.5
$VS\text{-}Cluster^{IO}$	% of clusters with high WCR^{IO}	68.3	15.9	41.7	98.3	94.1
$VS\text{-}Cluster^{Occ}$	% of clusters with high WCR^{Occ}	79.3	18.2	47.3	100.00	100.0
$VS\text{-}Industry^{LC\text{-}Emp}$	% of industries with high $WCR^{LC\text{-}Emp}$	70.6	16.0	45.9	97.8	92.9
$VS\text{-}Industry^{LC\text{-}Est}$	% of industries with high $WCR^{LC\text{-}Est}$	68.9	13.4	45.6	95.2	88.7
$VS\text{-}Industry^{IO}$	% of industries with high WCR^{IO}	54.9	12.1	40.3	80.4	75.7
$VS\text{-}Industry^{Occ}$	% of industries with high WCR^{Occ}	70.8	19.1	46.5	99.8	98.3

Notes: For each *C*, *VS-Cluster* is the average of the sub-scores ($VS\text{-}Cluster^{LC\text{-}Emp}$, $VS\ Cluster^{LC\text{-}Est}$, $VS\text{-}Cluster^{IO}$, $VS\text{-}Cluster^{Occ}$); and similarly *VS-Industry* is the average of the VS-Industry sub-scores. See Table 5 for an illustration of the scores and sub-scores using a particular *C*.

Table 5: Validation Scores (sub-scores) for Selected Cluster Configuration C^* (778 industries)

	C^* **=Hierarchical (LC-IO-Occ, 47 clusters)**		
Validation Sub-scores	**VS-Cluster** % Clusters with high WCR_c	**VS-Industry** % Industries with high WCR_{ic}	**VS** (Avg VS-Cluster, VS-Industry)
$VS^{LC\text{-}Emp}$ (Avg)	**67.0**	**61.7**	**64.4**
WCR>AvgBCR	93.6	90.7	92.2
WCR>Pctile95BCR	40.4	32.6	36.5
$VS^{LC\text{-}Est}$ (Avg)	**68.1**	**62.3**	**65.2**
WCR>AvgBCR	89.4	91.0	90.2
WCR>Pctile95BCR	46.8	33.5	40.2
VS^{IO} (Avg)	**92.6**	**78.0**	**85.3**
WCR>AvgBCR	97.9	89.7	93.8
WCR>Pctile95BCR	87.2	66.3	76.8
VS^{Occ} (Avg)	**98.9**	**92.8**	**95.9**
WCR>AvgBCR	100.0	98.7	99.4
WCR>Pctile95BCR	97.9	86.9	92.4
Validation Scores	**81.6**	**73.7**	**77.7**
Rank (1=best)	**14**	**4**	**1**

Notes: We compute to what extent individual clusters and industries in *C* have Within Cluster Relatedness (WCR) greater than a Between Cluster Relatedness (BCR) cut-off value based on particular similarity matrices M_{ij}. We then average these sub-scores into the Validation Scores: $VS=Avg(VS^{LC\text{-}Emp}, VS^{LC\text{-}Est}, VS^{IO}, VS^{Occ})$. The Validation Score Rankings are computed across 713 sets of cluster definitions.

Table 6: Mean of Validation Score (and sub-scores) by Selected Similarity Matrices (M_{ij})

M_{ij}	No. *Cs*(M_{ij})	Validation Score VS (Avg sub-scores)	Validation Sub-scores $VS^{LC\text{-}Emp}$	$VS^{LC\text{-}Est}$	VS^{IO}	VS^{Occ}
LC-IO-Occ	31	76	62	64	84	95
LC-Emp	155	67	94	70	50	54
LC-Est	155	71	79	89	53	63
IO	31	70	56	59	85	82
Occ	93	67	55	55	58	99
COI	31	65	89	70	50	53

Notes: Validation scores and sub-scores take value [0,100]. The differences in the means of the validation scores and sub-scores of *Cs*(*LC-IO-Occ*) versus *Cs*(M_{ij}) are all statistically significant at 1% level, except for the sub-score VS^{IO} of *Cs*(*LC-IO-Occ*) and *Cs*(*IO*) (84 and 85).

Table 7: Candidate Cluster Configurations C^*s (Top-40 Rankings in both VS-Cluster and VS-Industry)

	Model Choices			**Validation Scores**						**Overlap Score**
				VS-Cluster		VS-Industry		VS		$OS_{C\text{-}Candidates}$
C^*s	M_{ij}	Numc	Function	Rank	Score	Rank	Score	Rank	Score	Score
C*	**LC-IO-Occ**	**47**	**Hiw**	**14**	**81.6**	**4**	**73.7**	**1**	**77.7**	**77.6**
C_2	LC-IO-Occ	56	Hiw	12	81.7	8	73.3	2	77.5	75.5
C_3	LC-IO-Occ	48	Hiw	9	81.8	10	73.3	3	77.5	77.7
C_4	LC-IO-Occ	55	Hiw	15	81.6	9	73.3	4	77.5	75.9
C_5	LC-IO-Occ	53	Hiw	7	82.1	17	72.8	5	77.4	76.8
C_6	LC-IO-Occ	49	Hiw	8	81.9	12	72.9	6	77.4	77.6
C_7	LC-IO-Occ	54	Hiw	11	81.7	11	73.0	7	77.4	76.4
C_8	LC-IO-Occ	42	Hiw	39	81.0	6	73.7	8	77.3	77.0
C_9	LC-IO-Occ	59	Hiw	17	81.6	13	72.8	11	77.2	73.6
C_{10}	LC-IO-Occ	57	Hiw	16	81.6	16	72.8	12	77.2	74.9
C_{11}	LC-IO-Occ	58	Hiw	21	81.5	14	72.8	14	77.1	74.3
C_{12}	LC-Est	43	Hiw	13	81.7	23	72.5	15	77.1	39.5
C_{13}	LC	41	Hiw	3	82.6	40	71.3	18	77.0	43.7
C_{14}	LC-IO-Occ	50	Hiw	19	81.5	27	72.3	19	76.9	77.3
C_{15}	LC-IO-Occ	60	Hiw	27	81.3	21	72.6	20	76.9	73.0
C_{16}	LC-IO-Occ	52	Hiw	20	81.5	29	72.3	21	76.9	77.1
C_{17}	LC-IO-Occ	51	Hiw	26	81.4	28	72.3	22	76.8	77.1
C_{18}	COI-IO-Occ	44	Hiw	38	81.0	18	72.7	23	76.8	68.3
C_{19}	LC	42	Hiw	6	82.1	31	71.4	24	76.8	43.4
C_{20}	COI-IO-Occ	42	Hiw	39	81.0	19	72.6	25	76.8	67.7
C_{21}	LC-Est	41	Hiw	36	81.1	26	72.3	26	76.7	39.9
C_{22}	LC	44	Hiw	18	81.5	34	71.4	30	76.5	42.9
C_{23}	LC	43	Hiw	25	81.4	32	71.4	31	76.4	43.0
C_{24}	IO-Occ	44	Hiw	27	81.3	34	71.4	32	76.3	69.7

Notes: Rank is across the 713 *C*s. Overlap $Score_{C\text{-}Candidates}$ is the average cluster overlap between the focal *C* and the 23 other sets of definitions. *Hiw* refers to the Hierarchical-Ward's clustering function.

Table 8: Overview of Proposed Set of Benchmark Cluster Definitions *C***

Cluster Name	No. Industries	% Traded Employ	WCR Rank	WCR Score	$WCR^{LC\text{-}Emp}$ [-1,1]	$WCR^{LC\text{-}Est}$ [-1,1]	WCR^{IO} [0,1]	WCR^{Occ} [-1,1]
Aerospace Vehicles and Defense	7	1.3%	**1**	**1.93**	0.20	0.63	0.15	0.87
Agricultural Inputs and Services	9	0.2%	**1**	**1.14**	0.35	0.53	0.10	0.46
Apparel	21	0.4%	**1**	**2.28**	0.45	0.74	0.11	1.00
Automotive	26	1.9%	**1**	**2.27**	0.31	0.62	0.22	0.65
Biopharmaceuticals	4	0.6%	**1**	**3.35**	0.59	0.76	0.23	1.00
Business Services	33	24.2%	**1**	**1.17**	0.66	0.83	0.04	0.25
Coal Mining	4	0.2%	**2**	**2.30**	0.44	0.53	0.22	0.62
Communications Equipment and Services	8	1.3%	**1**	**2.37**	0.47	0.79	0.23	0.41
Construction Products and Services	20	1.8%	**1**	**1.81**	0.39	0.61	0.21	0.29
Distribution and Electronic Commerce	62	13.0%	**1**	**2.19**	0.67	0.82	0.12	0.63
Downstream Chemical Products	13	0.6%	**1**	**1.30**	0.39	0.69	0.04	0.71
Downstream Metal Products	16	1.0%	**1**	**1.05**	0.28	0.58	0.02	0.82
Education and Knowledge Creation	15	6.8%	**1**	**1.34**	0.70	0.85	0.03	0.38
Electric Power Generation and Transmission	5	0.3%	**2**	**0.90**	0.30	0.31	0.00	1.00
Environmental Services	7	0.2%	**1**	**2.81**	0.57	0.78	0.22	0.67
Financial Services	26	4.9%	**1**	**2.04**	0.54	0.71	0.16	0.51
Fishing and Fishing Products	5	0.1%	**1**	**3.40**	0.48	0.63	0.28	1.00
Food Processing and Manufacturing	47	2.2%	**1**	**0.82**	0.26	0.46	0.03	0.72
Footwear	6	0.0%	**1**	**5.22**	0.09	0.31	0.72	0.75
Forestry	4	0.2%	**1**	**3.47**	0.59	0.66	0.36	0.51
Furniture	12	0.9%	**1**	**1.43**	0.34	0.76	0.03	0.83
Hospitality and Tourism	31	7.0%	**5**	**0.45**	0.50	0.60	0.01	0.21
Information Technology and Analytical Instrument	27	2.6%	**1**	**1.32**	0.43	0.78	0.03	0.69
Insurance Services	8	3.8%	**1**	**4.35**	0.59	0.82	0.39	0.91
Jewelry and Precious Metals	4	0.1%	**1**	**5.49**	0.53	0.79	0.55	1.00
Leather and Related Products	6	0.1%	**2**	**1.32**	0.35	0.75	0.01	0.86
Lighting and Electrical Equipment	15	0.8%	**1**	**1.49**	0.36	0.75	0.02	0.94
Livestock Processing	5	1.2%	**1**	**1.66**	0.34	0.56	0.14	0.65
Marketing, Design, and Publishing	22	2.9%	**1**	**1.68**	0.76	0.90	0.04	0.48
Medical Devices	5	0.7%	**1**	**2.12**	0.52	0.89	0.07	0.87
Metal Mining	8	0.1%	**1**	**0.60**	0.09	0.23	0.05	0.81
Metalworking Technology	17	1.2%	**1**	**1.43**	0.62	0.82	0.02	0.59
Music and Sound Recording	5	0.1%	**1**	**6.19**	0.85	0.94	0.57	1.00
Nonmetal Mining	13	0.2%	**1**	**0.63**	0.13	0.19	0.03	0.89
Oil and Gas Production and Transportation	12	1.3%	**1**	**1.47**	0.61	0.64	0.10	0.36
Paper and Packaging	20	0.9%	**1**	**1.62**	0.28	0.52	0.08	0.97
Performing Arts	8	0.7%	**1**	**1.84**	0.65	0.86	0.10	0.42
Plastics	15	1.6%	**1**	**2.04**	0.49	0.76	0.10	0.82
Printing Services	13	1.3%	**1**	**2.54**	0.54	0.87	0.15	0.78
Production Technology and Heavy Machinery	41	2.3%	**1**	**1.08**	0.29	0.59	0.01	0.89
Recreational and Small Electric Goods	15	0.5%	**1**	**1.30**	0.32	0.74	0.01	0.90
Textile Manufacturing	23	0.5%	**1**	**1.20**	0.35	0.52	0.10	0.49
Tobacco	3	0.0%	**1**	**7.53**	0.09	0.35	1.00	1.00
Trailers, Motor Homes, and Appliances	9	0.3%	**1**	**0.52**	0.08	0.26	0.01	0.90
Transportation and Logistics	17	3.8%	**1**	**1.14**	0.42	0.76	0.10	0.22
Upstream Chemical Products	12	0.4%	**1**	**1.24**	0.12	0.32	0.09	0.95
Upstream Metal Manufacturing	26	0.9%	**1**	**0.97**	0.25	0.50	0.04	0.76
Video Production and Distribution	6	0.5%	**1**	**3.13**	0.69	0.83	0.23	0.69
Vulcanized and Fired Materials	17	0.6%	**1**	**0.94**	0.26	0.53	0.02	0.78
Water Transportation	12	0.7%	**1**	**1.73**	0.37	0.69	0.16	0.45
Wood Products	13	0.9%	**1**	**1.71**	0.36	0.54	0.10	0.87
Average				**2.07**	0.42	0.65	0.15	0.71

Notes: WCR is the average of the (standardized) $WCR^{LC\text{-}Emp}$, $WCR^{LC\text{-}Est}$, WCR^{IO}, and WCR^{Occ}.

Table 9.1: Aerospace Vehicles and Defense Cluster

Description: Establishments in this cluster manufacture aircraft, space vehicles, guided missiles, and related parts. It also contains firms that manufacture the necessary search and navigation equipment used by these products.

NAICS	NAICS Name	Subcluster Name	Within Cluster Relatedness (WCR_{ic})	
			Rank (1=best)	Score
336411	Aircraft Mfg	Aircraft	1	3.53
336412	Aircraft Engine & Engine Parts Mfg	Aircraft	1	1.65
336413	Other Aircraft Parts & Auxiliary Equipment Mfg	Aircraft	1	2.22
336414	Guided Missile & Space Vehicle Mfg	Missiles & Space Vehicles	1	1.47
336415	Guided Missile & Space Vehicle Propulsion Unit & Propulsion Unit Parts Mfg	Missiles & Space Vehicles	1	1.89
336419	Other Guided Missile & Space Vehicle Parts & Auxiliary Equipment Mfg	Missiles & Space Vehicles	1	0.99
334511	Search, Detection, Navigation, Guidance, Aeronautical, & Nautical System & Instrument Mfg	Search & Navigation Equipment	1	1.77

Table 9.2: Oil and Gas Production and Transportation Cluster

Description: This cluster includes firms involved in locating, extracting, refining, & transporting oil & gas. This includes companies that manufacture the equipment necessary to extract oil & gas, as well as companies that provide support services for oil & gas operations & pipeline transport.

NAICS	NAICS Name	Subcluster Name	Within Cluster Relatedness (WCR_{ic})	
			Rank (1=best)	Score
324110	Petroleum Refineries	Petroleum Processing	1	2.58
324199	All Other Petroleum & Coal Products Mfg	Petroleum Processing	1	0.83
213112	Support Activities for Oil & Gas Operations	Support Activities for Oil & Gas Operations	1	2.17
541360	Geophysical Surveying & Mapping Services	Support Activities for Oil & Gas Operations	1	0.79
213111	Drilling Oil & Gas Wells	Drilling Wells	1	0.94
211111	Crude Petroleum & Natural Gas Extraction	Oil & Gas Extraction	1	2.47
211112	Natural Gas Liquid Extraction	Oil & Gas Extraction	1	2.17
333132	Oil & Gas Field Machinery & Equipment Mfg	Oil & Gas Machinery	1	1.15
486110	Pipeline Transportation of Crude Oil	Pipeline Transportation	1	1.29
486210	Pipeline Transportation of Natural Gas	Pipeline Transportation	1	1.10
486910	Pipeline Transportation of Refined Petroleum Products	Pipeline Transportation	2	1.11
486990	All Other Pipeline Transportation	Pipeline Transportation	1	1.09

Table 9.3: Insurance Services Cluster

Description: This cluster consists of firms providing a range of insurance types, as well as support services such as reinsurance and claims adjustment.

NAICS	NAICS Name	Subcluster Name	Within Cluster Relatedness (WCR_{ic})	
			Rank (1=best)	Score
524291	Claims Adjusting	Insurance Related Services	1	6.17
524298	All Other Insurance Related Activities	Insurance Related Services	1	6.20
524113	Direct Life Insurance Carriers	Insurance Carriers	1	3.93
524114	Direct Health & Medical Insurance Carriers	Insurance Carriers	1	3.92
524126	Direct Property & Casualty Insurance Carriers	Insurance Carriers	1	3.92
524127	Direct Title Insurance Carriers	Insurance Carriers	1	3.55
524128	Other Direct Insurance Carriers	Insurance Carriers	1	3.32
524130	Reinsurance Carriers	Reinsurance Carriers	1	3.76

Table 9.4: Medical Devices Cluster

Description: Establishments in this cluster primarily manufacture surgical, dental, & optical instruments & supplies.

NAICS	NAICS Name	Subcluster Name	Within Cluster Relatedness (WCR_{ic})	
			Rank (1=best)	Score
333314*	Optical Instrument & Lens Mfg	Optical Instruments & Ophthalmic Goods	1	1.98
339115	Ophthalmic Goods Mfg	Optical Instruments & Ophthalmic Goods	1	2.48
339112	Surgical & Medical Instrument Mfg	Surgical & Dental Instruments & Supplies	1	2.19
339113	Surgical Appliance & Supplies Mfg	Surgical & Dental Instruments & Supplies	1	2.34
339114	Dental Equipment & Supplies Mfg	Surgical & Dental Instruments & Supplies	1	1.61

Note: *Marginal industry outliers reallocated from other cluster (see online Technical Appendix).

Table 9.5: Lighting and Electrical Equipment Cluster

Description: This cluster contains firms involved in the manufacture of electrical equipment & electronic components. The companies in this cluster manufacture wire for communications, wiring devices, fiber-optic cables, switchboards, lighting fixtures, motors, transformers, & related products.

NAICS	NAICS Name	Subcluster Name	Within Cluster Relatedness (WCR_{ic})	
			Rank (1=best)	Score
335110	Electric Lamp Bulb & Part Mfg	Lighting Fixtures & Parts	1	1.34
335121	Residential Electric Lighting Fixture Mfg	Lighting Fixtures & Parts	1	1.77
335122	Commercial, Industrial, & Institutional Electric Lighting Fixture Mfg	Lighting Fixtures & Parts	1	1.77
335129	Other Lighting Equipment Mfg	Lighting Fixtures & Parts	1	1.68
335311	Power, Distribution, & Specialty Transformer Mfg	Electrical Equipment	1	1.62
335312	Motor & Generator Mfg	Electrical Equipment	1	1.30
335313	Switchgear & Switchboard Apparatus Mfg	Electrical Equipment	1	1.48
335314	Relay & Industrial Control Mfg	Electrical Equipment	1	1.64
335921	Fiber Optic Cable Mfg	Electrical Components	1	1.39
335929	Other Communication & Energy Wire Mfg	Electrical Components	1	1.61
335931	Current-Carrying Wiring Device Mfg	Electrical Components	1	1.67
335932	Noncurrent-Carrying Wiring Device Mfg	Electrical Components	1	1.23
335991	Carbon & Graphite Product Mfg	Electrical Components	1	1.15
335999*	All Other Miscellaneous Electrical Equipment & Component Mfg	Electrical Components	1	1.65
335911	Storage Battery Mfg	Storage Batteries	1	1.00

Note: *Marginal industry outliers reallocated from other clusters (see online Technical Appendix).

Table 9.6: Recreational and Small Electric Goods Cluster

Description: This cluster contains establishments that manufacture end-use products for recreational & decorative purposes. These products include games, toys, bicycles, motorcycles, musical instruments, sporting goods, art supplies, office supplies, shades, & home accessories. This cluster also incorporates firms that produce small, simple electric goods like hairdryers, fans, & office machinery.

NAICS	NAICS Name	Subcluster Name	Within Cluster Relatedness (WCR_{ic})	
			Rank (1=best)	Score
337920	Blind & Shade Mfg	Recreational & Decorative Goods	3	1.37
339992	Musical Instrument Mfg	Recreational & Decorative Goods	3	1.60
339993	Fastener, Button, Needle, & Pin Mfg	Recreational & Decorative Goods	3	1.37
339999	All Other Miscellaneous Mfg	Recreational & Decorative Goods	1	1.58
339931	Doll & Stuffed Toy Mfg	Games, Toys, & Children's Vehicles	2	1.17
339932	Game, Toy, & Children's Vehicle Mfg	Games, Toys, & Children's Vehicles	1	1.44
336991*	Motorcycle, Bicycle, & Parts Mfg	Motorcycles & Bicycles	1	0.94
339920	Sporting & Athletic Goods Mfg	Sporting & Athletic Goods	3	1.25
333313	Office Machinery Mfg	Office Supplies	4	1.00
333315*	Photographic & Photocopying Equipment Mfg	Office Supplies	3	1.35
339941	Pen & Mechanical Pencil Mfg	Office Supplies	2	1.43
339942	Lead Pencil & Art Good Mfg	Office Supplies	1	1.50
339943	Marking Device Mfg	Office Supplies	1	1.61
339944	Carbon Paper & Inked Ribbon Mfg	Office Supplies	1	1.11
335211*	Electric Housewares & Household Fan Mfg	Electric Housewares	1	0.78

Note: *Marginal industry outliers reallocated from other clusters (see online Technical Appendix).

Table 10: Validation Scores (sub-scores) for Selected Sets of Cluster Definitions

	BCD (C^{**}) 51 clusters, 778 industries			3-digit NAICS 66 clusters, 778 industries			Porter (2003) 41 clusters, 685 industries			Feser (2005) 44 clusters, 910 industries		
	VS Cluster	VS Industry	VS*	VS Cluster	VS Industry	VS	VS Cluster	VS Industry	VS	VS Cluster	VS Industry	VS
VS Scores	82	73	78	56	59	58	77	69	73	70	67	69
VS Rank	9	7	2	717	710	717	261	146	200	541	258	429
VS Sub-scores												
$VS^{LC\text{-}Emp}$	70	63	66	49	46	47	68	66	67	48	59	53
$VS^{LC\text{-}Est}$	73	64	68	51	49	50	67	63	65	61	58	59
VS^{IO}	87	74	81	39	44	42	77	68	73	72	61	67
VS^{Occ}	98	93	95	88	97	92	94	80	87	99	92	95

Notes: *VS is the average of VS-Cluster and VS-Industry. The VS rankings are computed across the 713 *C*s and the 4 sets included in the table (1=best, 717=worst). Each set of clusters contains mutually exclusive groups.

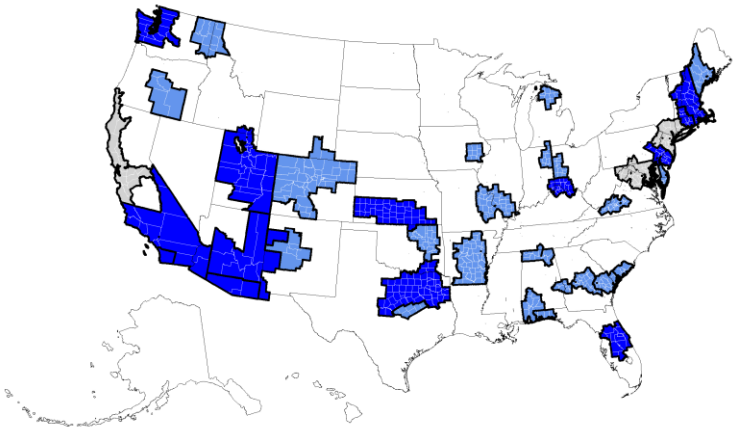
Table 11: Overlap between C^{**} and Other Sets of Cluster Definitions

Overlap Score	C^{**} and 3-digit NAICS	C^{**} and Porter (2003)	C^{**} and Feser (2005)
$C^{**} \rightarrow C$	66%	55%	54%
$C^{**} \leftarrow C$	56%	58%	54%
$C^{**} \leftrightarrow C$ (Average)	61%	57%	54%
Industries in C^{**} and C	778	671	734
No. clusters in C^{**}, C	51, 66	47, 41	49, 44

Note: We compute the overlap score for the sub-set of industries in common with C^{**}.

Figure 1: Top Regional Aerospace Vehicles and Defense Clusters in 2010 (Economic Areas; C^{**})

EAs with Top Employment Specialization and Share of U.S. Cluster
EAs with Top Employment Specialization
EAs with Top Employment Share



Notes: Economic Areas (EAs) with **Top Employment Specialization** in a cluster meet these criteria: Location Quotient (LQ) of Cluster Employment must be greater than 75th percentile when measured across all EAs with non-zero employment in the cluster. Secondary criteria to differentiate marginal cases: LQ of Cluster Employment greater than 1.0, Share of National Cluster Employment greater than 25th percentile, Share of National Cluster Establishments greater than 25th percentile. EAs with **Top Employment Share** in a cluster meet this criterion: Share of National Cluster Employment must be greater than 90th percentile when measured across all EAs with non-zero employment in the cluster. EAs with **Top Employment Specialization and Share** meet all of the above criteria.

Appendix A

Table A1: Similarity Matrices Used to Generate Sets of Cluster Definitions *C*s

Similarity Matrix	No. of *C*s	Type of M_{ij}	Definition
LC-Emp	155	Unidimensional	Locational Correlation of employment [-1, 1]
LC-Est	155	Unidimensional	Locational Correlation of establishments [-1, 1]
IO	31	Unidimensional	Input-Output link [0, 1]
Occ	93	Unidimensional	Labor Occupation link [-1, 1]
COI	31	Unidimensional	Coagglomeration Index
LC-IO-Occ	31	Multidimensional	Average of (standardized) LC-Emp, LC-Est, IO, Occ
COI-IO-Occ	31	Multidimensional	Average of (standardized) COI, IO, Occ
LC	31	Multidimensional	Average of LC-Emp, LC-Est
IO-Occ	31	Multidimensional	Average of (standardized) IO, Occ
LC-Emp-IO	31	Multidimensional	Average of (standardized) LC-Emp, IO
LC-Est-IO	31	Multidimensional	Average of (standardized) LC-Est, IO
LC-Emp-Occ	31	Multidimensional	Average of LC-Emp, Occ
LC-Est-Occ	31	Multidimensional	Average of LC-Est, Occ

An online Technical Appendix, with a detailed cluster-by-cluster overview of the proposed set of benchmark cluster definitions (C^{**}), may be accessed here.