Convergence, Clusters and Economic Performance[*]

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Abstract

This paper evaluates the role of regional cluster composition in the economic performance of regional industries, clusters and regions. Except in narrow circumstances, the traditional distinction between industry specialization and regional diversity is misplaced, failing to capture the linkages among related industries or the importance of spillovers from proximate regions. Building on Porter's (1990, 2001) concept of clusters, we offer a systematic evaluation of the relationship between regional cluster composition and the employment and patent growth of regions, clusters and industries. Our approach allows us to separately disentangle the impact of convergence from agglomeration. The cluster framework suggests three key spillovers influencing economic performance: within cluster, across related clusters, and across common clusters in neighboring regions. Using newly available data from the US Cluster Mapping Project, the empirical analysis exploits a rich panel dataset at the industry-cluster-region level between 1990 and 2003. We specify growth models that simultaneously accommodate convergence and agglomeration effects. The convergence effects will dominate at the narrowest level (e.g., industry level), the agglomeration forces are tested above that level of analysis (e.g., clusters and related clusters). To address the potential endogeneity between regional cluster composition and subsequent economic performance, we include detailed controls for the attributes of industries, clusters, regions and neighboring regions. We document several robust findings. First, for narrow units of analysis, we observe convergence (e.g., industry-region growth is declining in the initial level of industry-region development). After controlling for this convergence effect, we document several specific implications of cluster-driven agglomeration: (a) industries participating in a strong cluster are associated with higher employment and patenting growth, (b) industry and cluster level growth increase with the presence of related clusters in the region, and (c) industry and cluster level growth increase with the presence of strong similar clusters in adjacent regions. Finally, relative strength in a region's leading clusters (i.e., those highly over-represented in the region) contribute to the employment and patenting growth of other traded and local clusters within that region. Overall, these findings suggest the presence of cluster-driven agglomeration effects and highlight the role of regional clusters in economic performance.

Keywords: industry clusters, dynamic economies of agglomeration, inter-regional spillovers.

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1. Introduction

Significant variation in regional economic growth is a striking feature of the US economy. For example, using the Bureau of Economic Analysis Economic Areas (EAs) as the unit of analysis, Porter (2003) documents striking cross-EA differences in employment and wage growth during the 1990s, even when one conditions on the initial level of EA employment and wages. Numerous theories have been proposed to explain why some regions achieve significantly higher growth rates than others, with particular emphasis on the role of initial conditions, the potential for innovation and knowledge spillovers, and the composition of economic activity (*among* others, Porter, 1990; Glaeser, et al, 1992; Barro and Sala-i-Martin, 1995; Fujita, Venables, and Krugman, 1999). Notably, policymakers and researchers have focused intensely on areas such as Silicon Valley, which seem to have achieved strong economic performance through the presence of innovation-oriented clusters of interdependent companies and industries (Porter, 1990, 1998; Saxenian, 1994; Swann, 1998; Bresnahan and Gambardella, 2004). However, few studies systematically examine the empirical impact of industrial composition and clusters on regional economic performance and growth (Glaeser, et al, 1992; Henderson, et al, 1995; Feldman and Audretsch, 1999; Porter, 2003).

Two central, yet potentially competing, economic forces must be accounted for: convergence and agglomeration. Convergence arises when, as the result of diminishing returns, the potential for growth is declining in the level of economic activity (Barro and Sala-i-Martin, 1992). While many studies of convergence focus on diminishing returns at the regional level, (Barro and Sala-i-Martin, 1995), convergence may also arise at more fine-grained levels of analysis, such as the region-industry level (Henderson, 1995; Dumais, et al, 2002). A central implication of convergence at the region-industry level is that the region-industry growth rate (in terms of employment or productivity) will be declining in the initial level of region-industry employment or productivity. Agglomeration exerts a converse force on regional evolution. In the presence of agglomeration economies, the potential for growth is *increasing* in the level of economic activity (Glaeser, et al, 1992), with the potential for increased inequality over time in the distribution of regional economic activity (Dumais, et al, 2002). Of course, several different types of agglomeration effects may be at play, including localization (increasing returns to activities within an industry or closely related set of industries) and urbanization (increasing returns to diversity at the regional level). From an empirical perspective, distinguishing the relative importance and differential impact of convergence and agglomeration has been problematic: for example, if both convergence and agglomeration effects are present, the coefficient on the initial level of economic activity in a growth equation will reflect the balancing of these two effects, and therefore will not identify either effects in isolation (Henderson, 1995).

This paper moves beyond this impasse by identifying the impact of industrial agglomeration effects while simultaneously accounting for the impact of convergence. To do so, we suggest that the traditional distinction between isolated industries and aggregate regional economic activity is misplaced, failing to capture the linkages among related industries or the importance of spillovers from proximate regions. Building on Porter's (1990, 1998, 2001) concept of industrial clusters, we investigate the role of the co-location of related industries in regional economic growth. The cluster framework suggests three key spillovers forces influencing economic performance: within cluster, across clusters related by technology, skills, or other linkages ("cluster overlap"), and across common clusters in neighboring regions.

Our key insight is that, while convergence may occur at the industry level (or at a relatively narrow level of industrial aggregation), agglomeration forces may be salient across related industries within a regional cluster, across related clusters within a region or in neighboring clusters. Sharing common technologies, knowledge inputs and cluster-specific institutions, cluster-level agglomeration effects may contribute to economic growth at the region-industry level, even while convergence constrains growth at the region-industry level. Using rich data on the patterns of cluster development within regional economies, we offer a systematic evaluation of this conditional convergence pattern by examining the influence of regional cluster composition on industry-level, cluster-level and regional performance in terms of employment and patent growth.

The empirical analysis uses a detailed panel dataset at the region-cluster-industry level between 1990 and 2003. This panel has been assembled by the U.S. Cluster Mapping Project, based on County Business Patterns data. The regional units are 177 Economic Areas (EAs) in the contiguous United States. Using Porter's (2003) cluster classification, we examine the 41 clusters in the traded portion of the economy.[1] For every cluster (e.g., automotive or financial services), we look at the pattern of employment and patenting in every economic area. "Strong" cluster are those clusters that are over-represented in a region (in terms of employment or patenting). The cluster composition of a regional economy measures the specialization of the region across a set of strong clusters, and also the connections among them.

We specify growth models at the industry, cluster and region levels that simultaneously accommodate convergence and agglomeration effects. The main identification challenge is to eliminate the bias from omitted variables that impact both cluster composition and subsequent economic performance. We address this problem in two ways: by carefully selecting measures of cluster composition and by including detailed controls for the attributes of clusters, regions, and neighboring regions. In particular, we not only employ observable region and cluster attributes, but also experiment with the use of region, industry-year and cluster-year fixed effects.

Our findings provide support for the simultaneous yet distinct influences of cluster-driven agglomeration and convergence. At the industry level, we find that industries over-represented in a region grow at a slower pace. At the same time, consistent with studies that find that inter-industry technology linkages have a positive influence in the productivity and innovative capacity of industries (Scherer, 1982; Feldman and Audretsch, 1999), we find that industries participating in strong clusters outperform industries located in regions with weak clusters. This result supports the existence of within cluster spillovers and suggests that the cluster is a key economic unit to measure the impact of agglomeration.

A region's mix of related clusters also matters for the employment and patent growth of the region, individual clusters and their participating industries. For example, the biopharmaceuticals cluster in the Raleigh-Durham-Cary region (North Carolina) benefits from the diversity of interconnected clusters in that region, such as medical devices, education and knowledge creation, and chemicals. In other words, while cluster employment levels may display mean reversion in cluster employment growth, economies of agglomeration may be more salient in the set of related clusters.

[1] The traded clusters are those that sell products and services across regions and often to other countries.

This paper also explores the attributes of neighboring regions, specifically their cluster composition. In doing so, we introduce new hypotheses. We test whether industry-level and cluster-level growth is positively associated with the specialization of adjacent regions in the cluster. For instance, automotive clusters in Detroit and in neighboring economic areas have established different types of beneficial interdependencies. Our results suggest that inter-regional spillovers matter for both cluster and industry performance growth.

Finally at the region-level, we find that a region's leading clusters contribute to the employment and patenting growth of other traded and local clusters in the region. In other words, while there may be convergence forces at the cluster and region levels, the set of strong clusters in the region and the connections among them generate external benefits for other activities in the region.

The theoretical propositions carry some policy recommendations regarding which industries should be mobilized in a region. If important externalities take place across related industries within a cluster and across related clusters, policy makers should promote those activities that have a great degree of overlap with the region's strong clusters, rather than picking high-wage clusters (Porter, 2003; Cortright, 2006). Furthermore, if inter-regional spillovers matter for economic performance, regional development policies should take into account the neighbors' cluster strengths.

The paper is organized as follows. The next section defines the concept of clusters and justifies the importance of this unit of economic activity. Section 3 explains the regional unit of analysis and the relevance of inter-regional spillovers. The main hypotheses on the relationship between cluster-level, industry-level and regional performance growth and cluster composition are discussed in Section 4. Section 5 presents the empirical framework. The data is explained in Section 6, and Section 7 discusses the main empirical findings.

2. Cluster vs. Industry as an Economic Unit

We are interested in identifying dynamic externalities that influence the employment and patenting growth of industries, clusters and ultimately regions. From a theoretical perspective, agglomeration externalities may arise from the specialization of a region in particular industries sharing common inputs or knowledge (i.e., localization economies), or from the ability to exploit the diversity of industries across a region (i.e., urbanization economies).[2] However, empirical identification of these effects has been hampered because of the strong impact of convergence (mean reversion) on regional growth patterns (Barro and Sala-i-Martin 1992, 1995). As a result, the prior empirical literature has focused on identifying the balance of these two economic forces, or identifying alternative empirical implications. For example, Dumais et al (2002) focus not on convergence versus agglomeration per se, but on whether the *distribution* of industrial activity across regions is stable or diverging over time.

In contrast, Porter's (1990, 2003) cluster framework suggests that the industry may not be the best unit of analysis because of the important externalities that take place across related industries within a cluster. Since the late 1980s, there has been an increasing interest in the role of regional clusters in the process of regional economic growth, and the impact of cluster attributes on the advantage realized by firms within cluster-rich regions and nations (Porter, 1990). In geographically concentrated clusters, industries share common technologies, skills, knowledge, inputs, and institutions. These cluster-driven agglomeration forces may help industry-level growth. Along with detailed case studies of individual clusters, quantitative analysis of clusters has tended to focus on the self-reinforcing nature of clusters, and the role of complementarities among different cluster attributes. Indeed, previous work finds that technology linkages among related industries are an important driver of the innovation capacity of individual industries and their participating firms (Scherer, 1982; Feldman and Audresch, 1999).

The cluster framework suggests three key spillovers forces influencing economic performance: within cluster, across clusters related by technology, skills, or other linkages, and across common clusters in neighboring regions. Economies of

[2]Among those papers that study localization and urbanization economies together, some support positive and stronger within-industry spillovers (Rosenthal and Strange, 2003; Henderson, 2003). Other studies find that industry specialization has a negative effect on industry performance, and regional diversity matters the most (Glaeser, et al, 1992; Feldman and Audretsch, 1999). A few studies suggest that the relative impact of industry specialization depends on the type of industry, with more mature industries benefiting more from specialization and new industries benefiting more from diversity (Henderson, et al., 1995; Duranton and Puga, 2001).For further analysis on the respective influence of regional specialization and diversity see Glaeser, et al., (1992); Bostic, Gans, and Stern (1997), Feldman and Audretsch (1999), and Rosenthal and Strange's (2004) review, among others.

agglomeration multiply when we recognize these channels, especially in the presence of convergence effects. In particular, taking inter-industry linkages into account is crucial to identifying dynamic economies of agglomeration in the employment and patenting growth of regions, their clusters, and individual industries.

In our model convergence and agglomeration effects coexist. The convergence effects will be more salient at the more micro unit, and the regional cluster composition will help capture relevant agglomeration forces. In particular, while convergence effects in industry employment growth may occur at the industry level, we identify key agglomeration forces at a more aggregated level: the cluster, the clusters of related activities, and the neighboring clusters. We expect that industries located in regions with high presence of related industries and with neighbor regions that specialize in the cluster may grow faster. Similarly, in cluster growth, we test for agglomerations taking place in the set of related clusters and in neighbors. Finally, in region growth, we expect that the specialization in clusters and the connections among them should lead to higher regional growth than mere diversity across industries because relevant spillovers may occur within clusters and related clusters.

Cluster definitions. To identify the boundaries of clusters and the relationships between particular clusters, we use the systematic methodology developed by Porter (2001, 2003). Little effort has been made until quite recently to group industries into clusters, because the industry has been the dominant unit of analysis. There are notable exceptions. Ellison and Glaeser (1997) study the coagglomeration of related manufacturing industries, analyzing the correlations in the location choices of plants. They find that industries with stronger upstream-downstream ties tend to have greater coagglomeration. Interestingly, they also find pairs of industries with high input-output linkages that experience low co-agglomeration patterns. Recently, Ellison, Glaeser and Kerr (2007) test various mechanisms that may induce co-agglomeration, and conclude that input-output linkages are the most relevant factor followed by labor pooling.[3] Feldman and Audretsch (1999) group those manufacturing industries that have a common science and technological

[3] Faser and Bergman (2000) also use Imput-Output Tables to group industries into clusters.

base, using the *Yale Survey of R&D Managers.*[4] Their results suggest that an industry's level of innovative output is positively related to the presence of related industries in the region. Finally, other studies define linkages between industry activities in terms of their technological and/or market proximity (Scherer, 1982; Jaffe, Trajtemberg and Henderson, 1993; Bloom, Schankerman and Van Reenen, 2005; Hausman and Klinger, 2006).

Porter (2001, 2003) groups 879 4-digit SIC industries used in the County Business Patterns data into 41 traded clusters (e.g., automotive), 16 local clusters (e.g., retail clothing), and 10 natural-resource dependent clusters (e.g., metal mining). These three types of clusters have very different patterns of spatial competition and locational drivers. In the paper we focus on the traded clusters, which accumulate 590 industries that sell products and services across regions and often to other countries. Traded clusters are especially meaningful to explore inter-cluster and inter-region spillovers.[5]

The main criterion to define the traded clusters is the locational correlation of employment of four-digit SIC industries across regions (States, MSAs and EAs). The employment co-location will capture input-output, technology, skills and other linkages that occur among manufacturing and service industries.[6] In order to eliminate spurious correlation two additional methods are used: the detailed list of products included in each industry, and the measured input-output linkages between industries. Using these criteria, industries are grouped into clusters and subclusters, the latter being subgroups of industries within the cluster whose locational correlations with each other were higher than with remaining industries. Once clusters are defined, employment, wages and patents are grouped by cluster and region.

[4] This Survey assesses the relevance of key academic disciplines for a product category. Industries with similar rankings for the importance of the different academic disciplines are grouped together.

[5] In 2003, traded clusters accounted for about 30% of total US employment. Despite their relative small employment size, they are largely responsible for the growth of local clusters and they have much higher wages and productivity.

[6] The cluster definitions are based on 1996 County Business Patterns (CBP) data, using the state as the main regional unit. The co-location patterns are robust to using earlier years of data and smaller regional units (Porter 2003, pp. 562-563). The process of grouping industries into clusters is very complex and non perfect. The main limitations in the cluster mapping process are discussed in detail in Porter (2003). We are in the process of revisiting the cluster definitions using unsuppressed census data and longer time series.

Using this method, clusters often contain service and manufacturing industries as well as industries from different parts of the SIC system.[7] Individual industries can be part of more than one cluster. In order to eliminate double counting, the U.S. Cluster Mapping Project defines *broad* and *narrow* clusters. Narrow cluster definitions assign each industry to the single cluster with which it has the strongest locational correlation. In this paper the narrow cluster concept is the economic unit. Broad cluster definitions, which include all the industries significantly correlated with a cluster, are used to compute the degree of overlap between pairs of clusters (Section 6.2).

In the data, multiple regions are usually specialized in a given cluster (e.g., automotive). The clusters that are highly over-represented in a region (referred in the paper as "strong clusters") are not necessarily the national leading clusters based on employment levels. For example, in automotive, leading clusters nationally in terms of employment are located in Detroit-Warren-Flint (MI), Cleveland-Akron-Elyria (OH), and Indianapolis-Anderson-Columbus (IN), among other regions. However, smaller automotive clusters with high cluster strength are present in other regions, such as in Louisville-Elizabethtown-Scottsburg (KY-IN) and Lexington-Fayette-Frankfort-Richmond (KY) (Table A4 and Figure A1.1 in the Appendix).

3. Inter-Regional Spillovers

Theoretical work on city and neighboring city formation suggest that neighboring regions can be important to explain own-region industry composition and growth (Fujita, Krugman and Venables, 1999).[8] In contrast, studies of regions tend to focus on fixed regional units isolated from other regions. Notable exceptions are those studies that explore the extent to which economies of agglomeration attenuate with distance, pioneered by Ciccone and Hall (1996). They take into account neighboring counties agglomeration indicators, and find that counties with high employment density have a

[7] The number of 2-digit SIC codes represented in a cluster is on average 5.57, and even the average number of 1-digit SIC codes is 2.37. Table A2 illustrates the definition of the automotive cluster.

[8] For a review of the location theory, see Neary (2001), Fujita and Thisse (2002), Baldwin, et al., (2003), and Henderson (2004).

positive impact on the state-level labor productivity.[9] In a dynamic setting, Dobkins and Ioannides (2001) find that large cities favor the development of adjacent cities. Additionally, in the literature on regional endogenous growth, we find some very interesting studies that test for externalities from human capital or GDP distance to neighbors (Benhabib and Spiegel, 1994; Pede, Florax and de Groot, 2006).

Regional studies tend to define the geographic unit based on political boundaries, such as states, MSAs, and counties. We utilize a different exogenously defined region, the Economic Areas as defined by the Bureau of Economic Analysis (Section 6.2). EAs, which number 179, are continuous regional units that cover all the United States. While they are extensively used by the federal government and in the private sector, this regional unit has had little use in the regional economics literature. The EAs better reflect the relevant regional markets. They map naturally into counties and, in contrast to the MSAs, they include both rural and urban areas. Porter, et al., (2004) find that the same clusters often span urban and proximate rural areas. Furthermore, the EAs are especially relevant to study clusters since they tend to spread over larger geographic units than individual industries.

The data indicates that adjacent economic areas tend to specialize in the same or in related clusters. The specialization of a region in a cluster is significantly and positively correlated to the average specialization of neighbors in the same cluster and in related clusters (correlation coefficients of .50 and .23, respectively; Table 2). For example, Figure A shows that the strong automotive clusters tend to locate in EAs nearby Detroit. This suggests that agglomeration effects extend beyond the economic areas' borders. This co-location of the same cluster in nearby regions may be driven by several related mechanisms, such as input-output linkages between neighboring clusters; human capital composition; a national leading cluster generating clusters in nearby regions; and large cities contributing to the development and growth of nearby cities. We abstract from identifying the mechanism that generate the inter-regional spillovers, instead focusing on the impact of neighboring regions' cluster composition on the economic performance of individual industries, clusters and regions.

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[9] Other interesting empirical studies on static spillovers that attenuate with distance include, among others, Viladecans-Marsal (2004), which analyzes labor concentration of manufacturing sectors in Spain; and Rosenthal and Strange (2003), which studies the influence of localization economies on birth of firms.

4. Empirical Hypotheses

In this section we explain the hypotheses that underlie the relationship between regional cluster composition and the employment and patenting growth of industries, clusters and regions. First, we explain the coexistence of convergence and agglomeration forces, and how convergence forces may be more salient in narrower economic units. In the second part of this section, we discuss that if convergence effects happen first at the more micro level, agglomeration forces are more likely to be salient at more aggregated level. For instance, industry employment growth in a region may experience mean reversion in industry employment levels, while agglomeration forces may be larger in the set of related industries within a cluster.

4.1 Convergence and Agglomeration Forces Coexist

Our first hypothesis is that convergence and agglomeration have simultaneous influences in industry, cluster and regional growth. Prior agglomeration studies have emphasized agglomeration forces that occur within industries, within clusters, and in large regions. At the same time, the literature on regional growth patterns emphasizes the key role for a convergence effect (mean reversion) (Barro and Sala-i-Martin 1991, 1995). Indeed, a number of prior studies find that convergence effects in industry employment levels may be sufficiently large to compensate the localization economies that take place within industries (Henderson, et al., 1995; Dumais, et al., 2002). We extend this type of analysis by both considering the simultaneous influence of convergence and agglomeration and extending this analysis to cluster-level growth:

> **Hypothesis 1a:** Industry-region employment growth is negatively (positively) related to the initial industry-region employment-level under convergence (agglomeration effects).
>
> **Hypothesis 1b:** Cluster-region employment growth is negatively (positively) related to the initial cluster-region employment-level under convergence (agglomeration effects).
>
> **Hypothesis 1c:** Regional employment growth is negatively (positively) related to the initial regional employment-level under convergence (agglomeration effects).

In other words, industry-level, cluster-level, and region-level performance in the initial period may have a positive/negative effect on their own performance growth depending on the relative salience of agglomeration and convergence forces. The industry and cluster level convergence effects (Hypotheses 1a and 1b) mean that there are decreasing marginal effects that counteract the externalities that occur within large industries and clusters. For example, competition (including the potential for expropriation), product cycle effects (mature versus new industries) and congestion costs (price of local inputs, such as labor, housing, and transportation). The agglomeration and convergence forces may have a distinct effect in different firms participating in the industry (incumbents versus new entrants). There are also differences across industries, clusters and regions in the extent to which convergence or agglomeration forces dominate.[10] For most of the analysis, we do not explore the sources of these differences, and we simply control for industry, cluster and region heterogeneity using fixed effects.

4.2 Cluster-Driven Agglomeration Externalities

After controlling for convergence effects that may dominate at more micro level, we will now explain cluster-driven agglomeration forces. Specifically, we explore three spillover forces: within-cluster, across related clusters and across common clusters in neighboring regions. Before describing the hypotheses, we should clarify the concept of cluster specialization and the overall regional cluster composition. Cluster specialization indicates the extent to which a cluster is over-represented in a region (e.g., Automotive in Detroit).[11] In the paper, clusters with high cluster specialization are referred as "strong clusters." Regional cluster strength is defined as the share of regional traded employment in the set of strong clusters, taking into account the connections among them (e.g., the Detroit-Warren-Flint (MI) region has a high cluster strength resulting from the specialization in automotive-related clusters).

Our key insight is that while the convergence effect will be more likely to be salient in the narrowest economic unit, agglomeration forces across regional economic units (e.g., across industries within a cluster) may have a separate impact on regional growth. In other words, the cluster environment may condition the underlying convergence effect at the industry level:

> **Hypothesis 2:** Industries participating in strong clusters may outperform industries located in regions with low presence of related industries.

[10] For instance, Dumais, et al., (2002) find that the least concentrated industries have much stronger mean reversion. Similarly, Henderson (1995) finds that convergence is slower for mature industries, which seem to benefit more from MAR externalities than new industries.

[11] The specialization of a region in a cluster is measured by the employment location quotient (share of regional employment in the cluster relative to the share of U.S. employment in the national cluster).

While convergence effects may prevail at the industry level, industries participating in strong cluster may improve employment and patenting faster than the same industry in a region that does not specialize in the cluster. There are several rationales for this hypothesis. A cluster with a larger presence in a region should benefit from greater agglomeration economies, including large pools of skilled employees, specialized suppliers, sophisticated buyers, localized competition, related industries, and supporting institutions such as educational programs, trade groups, and quality organizations (Porter 1990, 1998; Swann 1998; Feldman and Audretsch, 1999). This will result in higher levels of innovation and employment in industries that participate in the cluster. Additionally, industries located in strong clusters may exceed the performance of their counterparts in other locations because they have a greater ability to respond against demand fluctuations and technological shocks than industries in weak clusters. Furthermore, strong clusters in a region can attract new firms in industries that support the activities of the cluster.

This basic insight – convergence at the narrow unit of analysis, agglomeration at a more aggregate level – applies to other levels of aggregation. For example, while there may be convergence in cluster-level growth, clusters and their participating industries might grow faster in regions that specialize in key related clusters. For instance, Biopharmaceuticals in Raleigh-Durham-Cary (NC) benefit from the presence of interconnected clusters in the region, such as medical devices, education and knowledge creation, and chemicals.[12] This benefit of diversity has extensive roots in the regional economics literature: diversity may serve to lower risk by reducing the impact of individual industry-level shocks, or knowledge spillovers may operate across industries and clusters that may at first seem distant from a marketing or technology perspective (Jacobs 1969; Glaeser, et al., 1992):

> **Hypothesis 3:** Clusters and their participating industries may grow faster in regions specializing in related clusters than in regions without supporting clusters.

[12] It is very difficult to draw the boundaries of a cluster because the same industry may participate in different clusters. Using Porter's (2003) broad cluster definitions we are able to approximate the connections between particular clusters and test for inter-cluster spillovers (see Section 6).

Finally, clusters and industries that are co-located in nearby regions may benefit from inter-regional spillovers. For instance, the aerospace vehicles and defense clusters in the neighboring regions of Tucson (AZ) Los Angeles-Long Beach-Riverside (CA) and Phoenix-Mesa-Scottsdale (AZ) seem to benefit from inter-regional spillovers. As well, there could be asymmetry in the type and the extent of inter-regional spillovers among neighbors. For example, leading national clusters in terms of employment scale may be more successful in promoting the same cluster in nearby regions:

> **Hypothesis 4:** Cluster and industry growth in a region may be enhanced by the presence of strong clusters in neighboring regions specializing in the same cluster.

4.3 The Impact of Cluster-Driven Agglomeration on Regional Growth

While there is convergence at cluster-level and region-level growth, the set of strong clusters in a region and the connections among clusters may contribute to regional performance by inducing growth in other local and traded clusters. Strong clusters might have a limited effect on regional performance if clusters become more specialized in a region at the expenses of other clusters. We suggest that strong clusters and their connections might generate important productivity and innovation gains that facilitate the growth of other traded and local clusters in the region.[13]

For instance, the economic area of Las Vegas-Paradise-Pahrump (NV) is highly specialized in hospitality and tourism, entertainment, and heavy construction service clusters (which account for around 70% of total traded employment), and these inter-connected clusters have facilitated a high employment and patent growth in the region.

Porter (2003) suggests that regional prosperity may be driven by the relative performance of the clusters that are over-represented in the region. The ability of a region to perform well in whichever clusters with meaningful position seems more important for regional economic performance than the region's efforts to specialize in nationally high-wage clusters. Specifically, he finds that, on average, about 75% of the wage difference between a region's overall wage and the national wage can be attributed to whether the region has higher or lower wages for its particular clusters than the national average for

[13] At the country level, previous work finds that countries with strong cluster environment tend to be more innovative (Porter and Stern, 2003), and their companies are more likely to prioritize innovation-oriented strategies versus low-cost strategies (Delgado, 2005).

those clusters ("the level effect"), while 25% of the wage difference is explained by the region's composition of nationally high (low) wage clusters ("the mix effect").[14] In other words, it matters whether a region has an IT cluster, but it matters much more if the region is competitive in IT. Even in regions that specialize in high-wage clusters, such as the New York and Boston economic areas, regional wages appear to be driven by their ability to outperform the same clusters in other locations:

> **Hypothesis 5:** The presence of strong clusters in a region and the connections among clusters may enhance the economic performance at the regional level.

Drawing on hypothesis 3, we expect that the connections among the top clusters in the region, may also improve regional performance. In other words, regions with top clusters that are related to each other may be associated with higher growth. For instance, this is the case of the Las Vegas-Paradise-Pahrump (NV) region. Similarly, regions with top clusters with high overlap with other traded clusters may experience higher growth. Regions with positioning in enabling clusters such as Analytical instruments and Chemicals (versus in clusters with lower overlap like Tobacco and Textiles) may be better able to generate linkages with other clusters in the region and in neighbors. For instance, the leading clusters in Austin-Round Rock (TX) include analytical instruments, IT, business services, and biopharmaceuticals; each cluster having a relatively high cluster overlap with other traded clusters.

5. Model

We specify industry, cluster and region level models, where performance is measured by employment and patent growth. We start with the industry-level model, which facilitates the understanding of the main agglomeration forces that occur within clusters and across related clusters in the region and in the neighbors; this draws out preliminary implications for the cluster and regional analysis.

The U.S. economy was experiencing important economic changes in the mid-nineties, especially, the increased productivity in the IT sector (Bosworth and Triplett, 2001, 2004; Stiroh, 2002). Hence, we are going to specify a two-period growth model

[14] This result referred to the wages of the EAs in 2000, and we find similar results using 2003 data. See Porter (2003, pp. 577) for details on this wage decomposition.

(1990-1996 and 1997-2003), and the cluster composition variables are specified in 1990 and 1997, respectively.

Two-Period Industry Growth Model. The industry growth model tests the convergence effects that may dominate at the industry-level, and the agglomeration forces that may occur within clusters, across related clusters and in neighboring regions. The core econometric specification is:

$$\ln\left(\frac{\text{Employ}_{\text{icrt}}}{\text{Employ}_{\text{icrt}_0}}\right) = \delta_0 + \delta_1 \ln(\text{Industry Spec}^{\text{employ}}_{\text{icrt}_0}) + \delta_2 \ln(\text{Reg Employ}_{\text{rt}_0}) +$$

$$\beta_1 \text{Cluster Spec}^{\substack{\text{employ} \\ \text{outside i}}}_{\text{icrt}_0} + \beta_2 \ln(\text{Strong Related Clusters}_{\text{crt}_0}) +$$

$$\beta_3 \ln(\text{Cluster Spec in Neighbors}_{\text{crt}_0}) + \alpha_{\text{it}} + \alpha_{\text{r}} + \varepsilon_{\text{icrt}_0}. \quad (1)$$

The dependent variable is the employment growth of industry *i* in cluster *c* at region *r* over the period *t* (1990-1996 and 1997-2003); and the explanatory variables are specified at t_0 (1990 and 1997, respectively).

In an industry growth model it is very difficult to separate the convergence effect from economies of localization that occur at the industry level. In order to disentangle both effects, some studies include in the model the industry's employment level as well as the specialization of the region in the industry. However, including both variables in the specification induce interpretation and identification problems. Building on Combes (2000b), we specify a model that includes the region specialization in the industry and the employment size of the region, which will capture the convergence or agglomeration effects that exist at the industry and region levels.

While convergence effects may be more salient at the industry level, the agglomeration forces are identified at a more aggregated level: the cluster, the clusters of related activities, and the neighboring clusters. We want to test whether industries co-located with related industries perform better than industries in regions with weak clusters. Drawing on Feldman and Audretsch (1999), the presence of the related industries in a region is measured by the employment location quotient of the other industries that constitute the cluster (Cluster Specialization). In addition, we test for the agglomeration effects that may take place across the set of related clusters and in neighboring clusters. We measure inter-cluster linkages using the specialization of the region in the set of related clusters (Strong Related Clusters); and we explore inter-regional spillovers utilizing the specialization of neighboring regions in the cluster. For instance, for each regional industry, like pharmaceutical preparations (SIC-2834) in the biopharmaceutical cluster in Raleigh-Durham-Cary (NC) , we look at the employment specialization of the region in the industry; the employment specialization of the region in biopharmaceuticals (excluding industry SIC-2834); the presence in the region of related clusters (such as medical devices, chemical products, and education and knowledge creation); and the adjacent regions' specialization in biopharmaceuticals.[15]

Finally, industry-level attributes, such as industry demand shocks, national size and life cycle may influence the extent of convergence and externalities. In the model we control for industry and region heterogeneity using industry-year and region dummies. Note that conditioning on the employment size of the region and on industry-year fixed effects, the coefficient of industry specialization variable can be interpreted as the employment-level of the industry in the region. Similarly, the cluster specialization coefficient is the same than the cluster employment-level. The current specification is preferred because it better separates the effect of regional employment size from changes in industry and cluster specialization.[16]

Two-Period Cluster Growth Model. The goal is to study the relationship between a cluster's innovation and employment growth and the cluster composition in the region. This model allows for agglomeration effects that operate in the set of related clusters and in neighboring clusters. The econometric specification for cluster employment growth is as follows:

$$\ln\left(\frac{\text{Employ}_{crt}}{\text{Employ}_{crt_0}}\right) = \delta_0 + \delta_1 \ln(\text{Cluster Spec}^{\text{employ}}_{crt_0}) + \delta_2 \ln(\text{Reg Employ}_{rt_0}) +$$
$$\beta_1 \ln(\text{Strong Related Clusters}_{crt_0}) + \beta_2 \ln(\text{Cluster Spec in Neighbors}_{crt_0}) +$$
$$\lambda X_{rt} + \alpha_{ct} + \alpha_r + \varepsilon_{crt_0}. \quad (2)$$

The dependent variable is the employment growth of cluster *c* at region *r* over the period *t* (1990-1996 and 1997-2003); and the explanatory variables are specified at t_0 (1990 and

[15] These variables are based on employment location quotients. See Section 6 for a detailed explanation of the variables.

[16] As explained in Combes (2000b), if local industry employment is held constant an increase in regional employment will induce a simultaneous decline in the specialization of the region in the industry, and regional size variable will be capturing localization economies.

1997, respectively). Similarly to the industry-level model, the cluster-level model includes the region specialization in the cluster and the employment size of the region, to capture the convergence or agglomeration effects that dominate at the cluster and region levels.

How to interpret the cluster specialization variable? The specialization of a region in a particular cluster might improve relative to the other clusters in the region (e.g., the biopharmaceutical cluster in Raleigh-Durham-Cary is improving its positioning in the region) and/or relative to the same cluster in other locations (e.g., biopharmaceuticals in Raleigh-Durham-Cary versus in Philadelphia). In the model we include cluster-year and region fixed effects and, consequently, the changes in the dependent and explanatory variables are relative to the national cluster and the average regional cluster.

Conditioning on employment cluster specialization, we are going to explore cluster composition variables that may contribute to cluster growth. Similarly to the industry-level model, we explore inter-cluster linkages using the specialization of the region in the set of related clusters (strength of related clusters), and inter-regional spillovers by including the specialization of neighboring regions in the cluster. In addition, we include other cluster-level attributes that may influence within-cluster spillovers forces, such as the extent of patenting in the cluster (patent specialization).[17]

Cluster and region heterogeneity may influence the relationship between cluster performance and the cluster composition of the region. In the model we include cluster-time fixed effects to control for national cluster shocks (α_{ct}). Alternatively, we take into account observable cluster-specific attributes, such as a cluster's degree of overlap with the other clusters, the size of the national cluster, and the high-tech cluster or service-oriented characteristics of the cluster. The model also controls for regional heterogeneity by using region fixed effects (α_{r}) or region specific attributes; and by including key time-varying attributes of the region (X_{rt}), such as patenting in the region and in neighbors, and patenting by universities.

[17] The extent of competition may also influence the employment growth of a cluster. The possibilities to explore the role of competition are limited because we do not know the distribution of employment across establishments. We could use establishment-based location quotient to proxy for competition, but this proxy has limitations in terms of its interpretation and high correlation with the employment-based specialization variables.

In the paper, we are also interested in explaining industry-level and cluster-level patenting growth. The innovation growth model will be parallel to equations (1) and (2) (using patent-based versus employment-based variables), so that it is easier to compare the impact of cluster composition on alternative performance variables. The comparison of patent and employment growth might shed light on the different types of externalities that impact employment creation versus innovation capacity.

Two-Period Region Growth Model. We want to test whether the set of strong clusters in a region may contribute to the employment and patent growth of other traded and local clusters in the region. To test this relationship, we regress the performance growth of the region outside the top clusters on the attributes of the top regional clusters, using a balanced panel of 177 contiguous EAs over the periods 1990-1996 and 1997-2003:

$$\ln\left(\frac{\text{Employ}_{rt}}{\text{Employ}_{rt_0}}\right)^{\substack{\text{Outside}\\ \text{Top clusters}}} = \delta_0 + \delta_1 \ln(\text{Reg Employ}_{rt_0}^{\substack{\text{Outside}\\ \text{Top clusters}}}) + \\ + \beta \text{Cluster Strength}_{rt_0} + \lambda X_{rt}^{\text{Top Clusters}} + R_r + \alpha_t + \varepsilon_{rt_0}. \quad (3)$$

The key explanatory variable is the regional cluster strength, which is measured by the share of regional traded employment in the set of top clusters, taking into account the connections among them (see Section 6.2). We also control for national demand shocks affecting the region top clusters, and the high-tech or service-oriented characteristics of the top clusters ($X_{rt}^{\text{Top Clusters}}$) because a region's type of cluster specialization in the initial period might be highly correlated to subsequent technological and demand shocks in the region, affecting regional performance growth and cluster composition. Finally, the econometric model takes into account the initial employment and patenting outside the top clusters, and controls for region heterogeneity using census region dummies (R_r).

5.2 Estimation Problems

Having controlled for industry, cluster and region heterogeneity, we still face the problem that a cluster's growth could impact the cluster composition of the region. In the two-period growth model, a cluster's performance growth in the first period (1990-1996) will positively influence the cluster employment in 1996. To address this problem, we select a one-year gap between the performance growth in the first and second periods (1990-1996 and 1997-2003). In addition, for robustness we estimate a 1990-2003 growth model as well as the two-period growth model.

Serial correlation. The error terms might be serially correlated because of persistent regional and cluster shocks. The econometric model addresses serial correlation in several ways. First, the standard errors are clustered by region in the cluster model and by region-cluster in the industry model, allowing for autocorrelation within each group. Second, we use industry-year, cluster-year and region fixed effects. Third, we include in the model the attributes of a region's leading clusters in the initial period.

Spatial dependence. Since nearby regions tend to specialize in the same type of clusters, there might be spatial dependence of the performance and unobserved attributes of a region and its neighbors.[18] We take into account the potential spatial dependence by including attributes of the neighboring regions and their clusters. As an extension, we will estimate a spatial lag and a spatial error regression model by maximum likelihood (Anselin, 1988; Anselin and Hudak, 1992).

6. Data Section

The core dataset is the annual County Business Patterns (CBP) data on establishments, employment and wages by county at the four-digit SIC level, over the period 1990-to-2003. Porter's U.S. Cluster Mapping Project matches the CBP data to patent data from the US Patent and Trademark Office and CHI Research.[19] Porter's (2001, 2003) defines *broad* and *narrow* clusters. Broad cluster definitions include all the industries that are related, while narrow cluster definitions assign each industry to the single cluster with which it has the strongest locational correlation. In this paper, we use the narrow cluster definitions to group employment and patents by cluster and region.

[18] For instance spatial dependence in performance exists if the growth of neighboring clusters influences own-cluster growth. Similar human capital composition in neighboring regions may induce spatial dependence in the error terms.

[19] The patent data is allocated to SIC codes using the algorithm developed by Silverman (1999).

6.1 The Geographic Unit: Economic Areas

In this paper the regional unit is the Economic Areas (EAs) as defined by the Bureau of Economic Analysis. The BEA's economic areas define the relevant regional markets surrounding metropolitan or micropolitan statistical areas. In the analysis we focus on 177 EAs, excluding Alaska and Hawaii since they have no adjacent regions.[20]

The EAs are in general larger than the MSAs, since they incorporate rural areas and might contain multiple MSAs, and normally smaller than the states. Most EAs are portions of a state, but over 19% of EAs are significantly spread over multiple states, among them the regions with the largest employment. The fact that many EAs cross the state borders reveals that state heterogeneity in tax systems and other factors does not eliminate the co-location of firms and workers in nearby states.

Neighboring Regions. In this paper, a region's neighbors are defined as all the adjacent regions. The data analysis reveals that specialized clusters tend to co-locate in nearby regions (Figure A).

6.2 Definition of the Variables

In what follows, we define industry and cluster specialization and cluster overlap. Having identified the strong clusters in a region and their attributes, we then define a region's cluster strength. Finally, we explain the controls that are used to account for regional and cluster heterogeneity (Table 1).

6.2.1 Cluster Specialization and Cluster Overlap

In this paper, the specialization of the region in a cluster is measured by the employment location quotient (LQ), which is the share of regional employment in the cluster as compared to the share of US total employment in the national cluster: $\text{Cluster Spec}_{rc} = \dfrac{\text{employ}_{rc} / \text{employ}_{r}}{\text{employ}_{USc} / \text{employ}_{US}}$, where *r* and *c* indicate the region and the cluster, respectively. In the paper, clusters with high cluster specialization are referred as "strong clusters."

[20] Detailed definition of the EAs can be found at http://www.bea.gov/bea/regional/data.htm.

While LQ has been widely used to measure industry specialization, it has limitations that are often ignored. The LQ tends to be significantly smaller in large regions and large clusters. Large clusters, such as business and financial services (fast-growing clusters), tend to be less concentrated and have a significantly smaller LQ.[21] To address the bias in LQ, in the econometric model we control for the size of the region, the cluster and the industry. In addition, when choosing a region's strong clusters we look at the distribution of LQ across regions for each cluster type and year. For instance, for automotive in 1997, the regional clusters are ranked according to their LQ. We then define as strong clusters those with the top 20% LQ (Table A4).

Having controlled for cluster heterogeneity to identify the set of strong clusters in the region, we are still concerned about small regions with very low employment that manage to hit the location quotient threshold. To correct these cases, the high LQ criterion is complemented with a minimum threshold for the share of national cluster employment (SHR) and the number of establishments.[22] All the clusters in a region that satisfy these three criteria constitute the region's top clusters (REG TOP CLUSTERS, Table 1).[23]

Cluster Overlap. We use the broad-cluster definitions to measure the linkages among clusters. Each cluster has a set of uniquely assigned industries (narrow industries) and a set of industries shared with other clusters (broad industries). For instance, a total of thirty-three SIC industries are grouped into the automotive broad-cluster, and fifteen of these industries are uniquely assigned to the narrow-cluster (Table A2 in the Appendix).

A cluster's narrow industries are often other clusters' broad industries. In the analysis, the clusters related to cluster *c* are those that have in common at least 1 of cluster c's narrow industries. In the case of automotive, the six related clusters are

[21] For instance, the 15% strongest business service clusters have an average LQ of 1.34; while in a very small cluster, such as footwear, the average LQ of the strongest clusters is around 8.

[22] The minimum SHR and establishment thresholds are selected by cluster and year, using the share and establishment values that correspond to the 20th percentile. We have also experimented with the 10th percentile, and the results change only trivially.

[23] Note that using these criteria all regions have at least one strong cluster. Some regions may have numerous strong clusters (e.g., Joplin, MO and San Diego-Carlsbad-San Marcos, CA) while others may have only one (Lewiston, ID-WA and Pueblo, CO).

production technology, metal manufacturing, heavy machinery, motor driven products, furniture, and aerospace engines (see Table A3).[24]

Having identified the set of clusters related to cluster *c*, we then measure the degree of overlap between each pair of clusters (*c*, *j*) using the average proportion of narrow industries that are shared in both directions ($\omega o_{c,j}$, which takes values 0-to-1). For example, automotive has 5 industries (out of 15) in common with production technology, and production technology shares 7 industries (out of 23) with automotives; the degree of overlap between these two clusters is then $\omega o_{c,j} = .32$.[25]

A cluster's overall overlap with its related clusters is the sum of the linkages with each of them ($WO_c = \sum_{j \in C_c^*}^{C^*} \omega o_{c,j}$; referred as CLUSTER OVERLAP). Clusters with higher overlap with other traded clusters include analytical instruments and communications equipment, among others; while clusters with few connections to other clusters include tobacco and footwear. On average, high-tech clusters, and to lesser extent large clusters, tend to have more linkages with other clusters (see Table A1).

6.2.2 *Regional Cluster Strength*

Previous work on regional growth focuses on the agglomeration forces that take place in regional diversity (i.e., looking at the distribution of employment across industries). Among the regional diversity indicators, the most sophisticated one is the Ellison & Glaeser index (1997) that controls for the size of the industry and the size of the region as well as for the distribution of employment across plants in the industry. In this paper we want to test for agglomeration forces within clusters and across related clusters. Thus, we are going to focus on cluster composition indicators that take into account the set of strong clusters in a region and the connections among them.

Strong Related Clusters. We expect that diversity in the form of the presence of related clusters in a region should be associated with better industry, cluster and regional growth (Hypothesis 3). The strength of the clusters related to cluster *c* is defined by their

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[24] This concept of related clusters is conservative since we count industry linkages in only one direction, but the overlapping clusters selected with this method are the most relevant ones for the given cluster.

[25] The pair of clusters with the highest overlap is biopharmaceuticals and medical devices ($\omega o_{c,j} = .81$).

location quotient ($\text{STRONG RELATED CLUSTERS}^{\text{wo}}_{\text{r,c}}$). This variable indicates to what extent the clusters linked to cluster *c* are over-represented in the region in terms of employment or patents. Since we know the degree of overlap between a pair of clusters ($\omega o_{c,j}$), we weigh more the related clusters that have stronger industry linkages with the cluster of interest:[26]

$$\text{STRONG RELATED CLUSTERS}^{\text{wo}}_{\text{r,c}}(\text{Employ}) = \frac{\sum_{j \in C^*_c}^{C^*} (\omega o_{c,j} * \text{employ}_{r,j})}{\sum_{j \in C^*_c}^{C^*} (\omega o_{c,j} * \text{employ}_{US,j})} * \frac{\text{employ}_{US}}{\text{employ}_r},$$

where C^*_c is the set of clusters overlapped to cluster *c*.

Regional Cluster Strength. In the region growth model, we define regional cluster strength ($\text{CLUSTER STRENGTH}_{\text{Employ}}$) as the share of regional traded employment (patents) contained in the set of strong clusters in the region. This variable captures within-cluster benefits of having an array of clusters highly over-represented in the region. Regional cluster strength will be large if there are a few strong clusters that account for most of the regional traded employment (e.g., automotive related clusters in Detroit-Warren-Flint, MI), and specially if there are numerous strong clusters (e.g., South Bend-Mishawaka, IN-MI).[27]

To assess the benefits from having strong and inter-related clusters, we weigh strong clusters by their overlap with each other ($\text{CLUSTER STRENGTH}^{\text{WOS}}$). Alternatively, to measure the benefits from having strong clusters with high cluster overlap with other traded clusters, we weigh strong clusters by their overall cluster overlap ($\text{CLUSTER STRENGTH}^{\text{WO}}$):

$$\underset{\text{(Weighted by overlap among top clusters)}}{\text{CLUSTER STRENGTH}^{\text{WOS}}_{\text{Employ}}} = \frac{\sum_{c \in \text{Top Cluster}_r} (1 + \text{WOS}_c) * \text{employ}_{r,c}}{\text{Traded Reg Employ}_r}; \quad \text{WOS}_c = \sum_{\substack{j \in \text{Top Cluster}_r \\ c \neq j}} \omega o_{c,j}.$$

[26] For instance, when we measure the presence of automotive related clusters in a region we weigh more metal manufacturing than furniture clusters.
[27] Section 6.1 explains how we identified the set of strong clusters in a region (REG TOP CLUSTER).

$$\underset{\text{(Weighted by cluster overlap)}}{\text{CLUSTER STRENGTH}^{\text{WO}}_{\text{Employ}}} = \frac{\sum\limits_{c \in \text{Top Cluster}_r} \text{WO}_c * \text{employ}_{r,c}}{\text{Traded Reg Employ}_r};\ \text{WO}_c = \sum_{j \in C^*_c}^{C^*} \omega o_{c,j}\ .$$

The alternative variables of cluster strength in the region are highly correlated, but there are interesting differences since they are capturing different aspects of the linkages across clusters. For example, Las Vegas-Paradise-Pahrump (NV) has a high cluster strength un-weighted and weighted by the industry linkages among the strong clusters (raking top 2 and top 20 across the 177 regions). However, this region has low cluster strength weighted by cluster overlap because the top clusters (hospitality and tourism, entertainment, and heavy construction services) have low overlap with other clusters.

6.2.3 Control Variables

The econometric models include detailed controls for the economic and technological sophistication of a region and its clusters. In contrast with prior work, we take into account key observable attributes of clusters and regions, and alternatively we use region and cluster fixed effects. In this section we explain the main controls.

Cluster-specific attributes. The cluster models account for crucial cluster attributes, such as the national cluster size (LARGE CLUSTER), a cluster's industry overlap with other clusters (CLUSTER OVERLAP), manufacturing versus service-oriented cluster (MANUFACT), and high-tech manufacturing cluster (HIGH-TECH).

Manufacturing cluster dummy (MANUFACT). This variable is equal to 1 for those clusters with over 65% of their industries in manufacturing activities (Table A1). It is important to distinguish manufacturing-intensive from service-oriented clusters because during the period of analysis manufacturing clusters experienced an overall decline in employment of over 21%; while traded service clusters improved their employment over 30%. Manufacturing clusters that have suffered a great reduction in their 1990-2003 employment growth include footwear, apparel, aerospace vehicles, and communications equipment, among others. Some of these clusters have experienced a relative high growth of real wages, such as footwear and communications equipment, suggesting that the decline in employment might be the result of international outsourcing of less advanced activities.

High-tech cluster dummy (HIGHT-TECH). Clusters classified as high-tech include aerospace engines, aerospace vehicles and defense, analytical instruments, communications equipment, information technology, medical devices, and biopharmaceuticals. Most of these clusters tend to have a larger employment size (lower cluster specialization); and they are "enabling" clusters since they have numerous input-output linkages with other industries.

Attributes of the top clusters in a region. Regions that specialize in advanced clusters versus in traditional manufacturing activities may experience distinct technological and demand shocks. To address this, we focus on the attributes of a region's top clusters, which are the clusters with the highest LQ relative to other clusters in their class. The key attributes of the region's top clusters are their average employment/patent growth outside the region and the number of them that are high-tech or service-oriented clusters.

Region-specific attributes. We use 6 Census-region dummies (West Pacific, West Mountain, Midwest, South Central, Northeast, and South Atlantic). Census-region dummies are important because these broad areas experienced different regional growth and specialize in different types of clusters. For example, the Northeast area is specialized in clusters that have been growing nationally, such as business services, education and knowledge creation, medical devices and biopharmaceutical clusters; in contrast, examples of strong clusters in the South Atlantic region are textiles, apparel and furniture.

7.1 Results for Industry Performance Growth

The industry-level model explains industry employment and patenting growth over the periods 1990-1996 and 1997-2003, using an industry-cluster-region balanced panel (Tables 3 and 4). In the employment growth model we condition on industries that have some employment in both periods, and in the patent growth model we additionally condition on industries that have some inflow of patents in both periods.[28, 29]

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[28] In the empirical analysis we focus on industries and clusters that have some positive employment. Note that industries that go from zero to some small positive employment may simply reflect measurement error. Specifically, with the implementation of the NAICS code in the 2003 data some industries go from non-

The industry employment growth model indicates that there is a convergence effect in industry employment specialization. Similarly, industry patenting growth is negatively influenced by the initial number of patents generated in the industry (models 3.1 and 4.1). While convergence forces dominate at the industry level, we also find cluster-driven agglomeration forces that influence industry employment and patenting growth.[30] We find that an industry's employment and, to a lower extent, patent growth is positively associated with the presence in the region of other industries that constitute the cluster (i.e., the coefficient of cluster specialization outside the industry is positive and highly significant). This finding supports the existence of within-cluster spillovers. Furthermore, industry employment and patent growth is positively associated with the presence of related clusters in the region. Finally, industry-level growth improves with the specialization of neighboring regions in the whole cluster and, to a lower extent, with their specialization in the individual industry.

The main results hold when we estimate a 1990-2003 growth model (models 3-5 and 4-5). Our findings only change trivially when we drop very small, noisy regional clusters.[31] Further analysis need to be done, exploring alternative indicators of the cluster composition of the region and neighbors.[32]

7.2 Results for Cluster Performance Growth

In this section, we explore the relationship between cluster growth and the cluster composition in the region and in neighboring regions. The cluster-level model explains a cluster's employment and patent growth over the periods 1990-1996 and 1997-2003, using a balanced panel of regional clusters (Tables 5 and 6).

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existing in 1997 to having some positive employment in 2003. For robustness, we plan to address the potential selection issues by estimating a Heckman two-stage model.

[29] In the current empirical analysis patenting is an inflow variable (i.e., new patents in year t in the industry-region). Since patents generated in the industry-region in year t may be subject to high fluctuations, we are planning to use a moving average of the patents generated in a three/two year window.

[30] The results reported in this Section focus on estimates that are at least significant at 10%; and when interpreting the magnitude of the coefficients, we always refer to the standardized coefficients.

[31] Certain amount of cluster employment in a region is actually the local activity of clusters based elsewhere (e.g. sales offices). In the sensitivity analysis, for every cluster we drop those regional clusters with a share of cluster employment in the bottom 20% of the cluster distribution.

[32] Since the industry is a smaller economic unit, the proper regional unit may be smaller than the EAs.

We first specify a model where we control for cluster and region heterogeneity using some basic observable cluster attributes and dummies for 6 broad Census areas (models 5.1 and 6.1). We then focus on our core specification, where we include cluster-year and economic areas fixed effects, looking at the factors that improve a cluster's performance growth above the national cluster and above the average regional cluster.

We find that, while cluster specialization in a region display mean reversion, patent and employment growth of a cluster is positively influenced by the presence of strong related clusters in the region and by the specialization of neighboring regions in the cluster.[33]

Convergence effect at the cluster level. The cluster growth models show that convergence forces dominate at the cluster level. We find that clusters with higher employment levels (relative to other clusters in the region and to the same cluster in other locations) tend to experience lower employment growth. Similarly, clusters with higher patenting experience lower patenting growth. The convergence effect seems especially larger in the patent model.

At the cluster-level, there are cluster attributes that attenuate the convergence forces. Specifically, conditional on the initial employment specialization of a cluster, the extent of patenting in the cluster has a positive effect on own employment growth. Similarly, conditional on patent specialization, the employment specialization of a cluster contribute to its patenting growth (Models 5-4 and 6-4).

We also find convergence at the region level. Clusters in regions with small employment (patent) size tend to increase their employment (patent) faster. Interestingly, clusters located in large employment regions generate patents at a significant faster pace, perhaps reflecting urbanization economies (Table 6).

Strong related clusters. Clusters are not isolated units. They share industries with other clusters, developing inter-cluster linkages. We find that clusters in regions with high presence of related clusters are associated with higher performance growth (Hypothesis 3). Strong related clusters based on employment is more important for a

[33] These results don't change after including additional controls, such as neighbors' overall innovativeness, attributes of the top clusters in the region, and university patenting in the region. Additionally, our findings only change trivially when we drop the 5% smallest and largest regions, or after excluding very small regional clusters. The main results also hold when we estimate a 1990-2003 growth model.

cluster's employment growth, while strong related clusters based on patents is more relevant for the growth in patents of the cluster.

The positive effect of the presence of related clusters is larger when they are weighted by the degree of industry overlap with the cluster of interest (versus un-weighted). This finding supports that the degree of cluster overlap is an important attribute of clusters. More generally, models 5-1 and 6-1 show that clusters with higher industry overlap with the rest of clusters (CLUSTER OVERLAP_c) experience higher employment and patent growth.

Inter-regional spillovers. The results support that inter-regional spillovers matter for cluster performance growth. We find that a cluster's employment and patent growth benefits from interdependencies with the same cluster in nearby regions. The inter-regional spillovers are higher when neighbors specialize in the same cluster than when neighbors specialize in related clusters. There is asymmetry in the attributes of neighboring clusters that matter the most for employment versus patent growth. In the employment growth model the key factor is the employment specialization of the neighboring clusters, while in the innovation growth model what matters the most is the patent specialization of the neighboring clusters.

7.3 Results for Regional Performance Growth

In this section we study the role of a region's top clusters in the patenting and employment growth of other traded and local clusters in the region. For every region we identify the top clusters in terms of employment specialization (REG TOP CLUSTERS, Table1). We then look at how the presence of the top clusters impact the innovation and employment growth of the region outside the top clusters. We use a panel of 177 U.S. economic areas (EAs) over the periods 1990-1996 and 1997-2003 (Table 7).[34] The results are robust to estimating spatial lag and spatial error regression models by maximum likelihood. The main conclusions are also valid when we estimate a 1990-2003 growth model.[35]

[34] In Table 7 the top clusters in a region are those with the top 20% LQ as compared to the same cluster in other regions. In the sensitivity analysis, we relax the concept of strong cluster and consider the top-four clusters in every region, and the main findings hold.

[35] The significant time variations in the dependent and explanatory variables in the two periods of analysis suggest that our model might be more appropriate than a 1990-to-2003 growth model. Patents and wages

Regional performance growth outside top clusters. The results suggest that regions with high cluster strength (i.e., the region's top clusters have a high share of total traded employment or traded patents) seem to be associated with greater employment and patent growth outside the top clusters. Table 7 shows that the various measures of regional cluster strength matter for the employment and patenting growth of non top clusters.[36] The un-weighted cluster strength variable seems to have a larger impact on employment growth (Models 7.1).[37] In the patent growth model, the cluster strength variable with the higher impact is the one weighted by cluster overlap. Even after conditioning on the high-tech attributes of the top clusters, we find that regions that specialize in clusters with many industry linkages seem to facilitate cross-fertilization of ideas, contributing to improve the innovation capacity of other local and traded clusters in the region (model 7.6).

8. Conclusion and Extensions

In this paper we emphasize that key agglomeration forces in industry, cluster, and region growth may operate above the more traditional distinction between industry specialization and regional diversity. Having controlled for region, cluster and industry heterogeneity, we find important externalities that take place within-clusters, across related clusters and across common clusters in neighboring regions.

Our findings suggest that the cluster unit is important to understand the coexistence of convergence and agglomeration effects in industry, cluster and region growth. While convergence forces seem to dominate at the more micro level, the regional cluster composition help capture relevant agglomeration forces. Specifically, industry employment growth in a region experiences mean reversion in industry employment levels, and agglomeration forces are more salient in the set of related industries within a

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grew significantly faster during 1997-2003, while the growth of employment declined sharply during this period. In the robustness analysis, we drop the 5% smallest and largest EAs, and the main results hold.

[36] The coefficients of the regional cluster strength variables are not very sensitive to the inclusion in the model of attributes of the top clusters, such as their growth outside the region, and the high-tech or service-oriented characteristics of the cluster.

[37] Alternatively, we use patent-based regional cluster strength variables to explain employment growth outside the top clusters (i.e., the explanatory variables used in the patent growth models 7.4-7.6). We find that employment growth is positively associated with the innovativeness of the set of top clusters in the region. Similarly, patent growth in the region is influenced by the employment presence of the top clusters.

cluster. Industries participating in a strong cluster are associated with higher employment and patent growth. This finding supports the existence of within-cluster spillovers.

While stronger clusters experience slower growth, clusters and their participating industries grow faster in regions that specialize in related clusters. Interestingly, strong related clusters based on employment is more important for employment growth, while strong related clusters based on patents is more relevant for patent growth.

The linkages among common clusters in neighboring regions also seem to contribute to the patent and employment growth of regional clusters and their industries. The inter-regional spillovers are higher when neighbors specialize in the same cluster than when neighbors specialize in related clusters.

Finally, a region's top clusters and the connections among them contribute to the employment and patenting growth of other traded and local clusters in the region. An interesting extension of the regional model will be to examine the relationship between region economic performance and the cluster mix of neighbors.

Overall, our findings imply that regional clusters play a central role in the performance of regional economies, but more research is needed in this area. We plan to improve the analysis of cluster performance by exploring the interactions of strong clusters with key attributes of the region and the cluster, such as human capital in the region and in the cluster, and the high-tech and service-oriented characteristics of the cluster.

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Table 1: Variables' Definitions and Descriptive Statistics

Variables	Definition	Industry* N=90,886	Cluster N=12,988	Region N=354
		Mean (Std Dev)		
ΔEMPLOYMENT	Employment growth $\log(employ_t/employ_{t0})$	.04 (.94)	.05 (.67)	.10 (.08)
ΔPATENTS	Patent growth	.22 (1.12)	.27 (1.06)	.26 (.38)
ΔEMPLOYMENT (Outside Top Clusters)	Employment growth excluding strong clusters			.12 (.09)
ΔPATENTS (Outside Top Clusters)	Patent growth excluding strong clusters			.25 (.39)
Log INDUSTRY SPEC (Employ)	Employment Location Quotient $LQ = \frac{employ_{ric}/employ_r}{employ_{USic}/employ_{US}}$	-.17 (1.38)		
Log CLUSTER SPEC (Employ)	Cluster employment LQ	-.21** (1.12)	-.43 (1.24)	
Log STRONG RELATED CLUSTERS (Employ)	Related clusters' employment LQ (weighted by cluster overlap)	-.04 (.60)	-.13 (.75)	
Log CLUSTER SPEC in NEIGHBOR (Employ)	Neighboring (adjacent) clusters' average employment LQ	-.01 (.71)	-.16 (.91)	
Log INDUSTRY SPEC (Patent)	Industry patent LQ	-.22 (1.02)		
Log CLUSTER SPEC (Patent)	Cluster patent LQ	-.60** (2.17)	-.22 (1.00)	
Log STRONG RELATED CLUSTERS (Patent)	Related clusters' patent LQ (weighted by cluster overlap)	-.03 (.42)	-.07 (.53)	
Log CLUSTER SPEC in NEIGHBOR (Patent)	Neighboring clusters' average patent LQ	.05 (.47)	.01 (.55)	
REG TOP CLUSTERS (Employ)	A region's # of clusters with top 20% LQ within their cluster class			7.11 (2.01)
CLUSTER STRENGTH (Employ)	Share of regional traded employ in the region's top clusters			.46 (.15)
CLUSTER STRENGTH^{WOS} (Employ)	Cluster strength weighted by the overlap among top clusters			.61 (.27)
CLUSTER STRENGTH^{WO} (Employ)	Cluster strength weighted by cluster overlap			.39 (.22)
CLUSTER STRENGTH (Patent)	Share of regional traded patents in the region's top clusters			.25 (.18)
CLUSTER STRENGTH^{WOS} (Patent)	Share of regional traded patents in the region's top clusters			.40 (.40)
CLUSTER STRENGTH^{WO} (Patent)	Cluster strength weighted by cluster overlap			.38 (.39)
Log REG EMPLOY	Regional employment			12.43 (1.20)
Log REG PATENTS	Regional utility patents inflow			4.29 (1.68)
Cluster Specific Attributes				
HIGH-TECH$_c$	Dummy equal to 1 if high-tech manufacturing cluster		.15 (.36)	
MANUFACTURING$_c$	Dummy equal to 1 if manufacturing oriented cluster		.73 (.44)	
CLUSTER OVERLAP$_c$	Industry overlap of a cluster with the related traded clusters		.93 (.77)	
LARGE CLUSTER$_c$	Dummy equal to 1 if large national cluster		.53 (.50)	

*In the industry-level patent growth model the sample is 72,994. ** Cluster Specialization outside the industry.

Table 2 Cluster-Level Specialization and Diversity: Correlation Table (N=12,988)

		V_1	V_2	V_3	V_4	V_5	V_6	V_7
CLUSTER SPEC $_{\text{Employ}}$	V_1	1.0						
CLUSTER SPEC $_{\text{Patent}}$	V_2	.23	1.0					
STRONG RELATED CLUSTERS $_{\text{Employ}}$	V_3	.27	.16	1.0				
STRONG RELATED CLUSTERS $_{\text{Patent}}$	V_4	.15	.39	.30	1.0			
CLUSTER SPEC in NEIGHBOR $_{\text{Employ}}$	V_5	.50	.17	.24	.11	1.0		
CLUSTER SPEC in NEIGHBOR $_{\text{Patent}}$	V_6	.21	.31	.11	.21	.34	1.0	
STRONG RELATED CLUSTERS in NEIGHBOR $_{\text{Employ}}$	V_7	.23	.12	.56	.22	.31	.20	1.0

Note: All correlations are significant at 5% level. All the variables are in log.

Table 3: Industry Growth in Employment (N=90,886)

	INDUSTRY EMPLOYMENT GROWTH$_{\text{rict}}$				
	Two-Periods Model N=90,886				1990-2003 N=45,443
	1	2	3	4	5
INDUSTRY SPEC$_{\text{Employ}}$	**-.272**	**-.290**	**-.295**	**-.299**	**-.438**
	(.003)	**(.003)**	**(.003)**	**(.003)**	**(.005)**
CLUSTER SPEC$_{\text{Employ}}$ (Outside the industry)		**.086**	**.074**	**.056**	**.076**
		(.004)	**(.004)**	**(.004)**	**(.006)**
STRONG RELATED CLUSTERS$_{\text{Employ}}$			**.089**	**.079**	**.108**
			(.006)	**(.006)**	**(.010)**
CLUSTER SPEC in NEIGHBORS$_{\text{Employ}}$				**.070**	**.078**
				(.006)	**(.009)**
REG EMPLOY$_{\text{rt}}$	**-.912**	**-.928**	**-.931**	**-.930**	
	(.065)	**(.065)**	**(.066)**	**(.070)**	
Intercept	**12.020**	**12.275**	**12.323**	**12.300**	**.378**
	(.851)	**(.864)**	**(.862)**	**(.856)**	**(.117)**
R-Squared	**.269**	**.277**	**.279**	**.281**	**.435**

Note: Bold and Bold-Italic numbers refer to coefficients significant at 1% and 5% levels, respectively. Robust standard errors clustered by economic area and industry cluster. All models include industry-year and EA fixed effects. The variables are in logs and all the cluster composition variables are location quotients. The sample is a balanced panel (industries with zero employment in a region in 1990 or 1997 are dropped).

Table 4: Industry Growth in Patenting (N=72,994)

	INDUSTRY PATENT GROWTH $_{\text{rict}}$				
	Two-Periods Model N=72,994				1990-2003 N=36,497
	1	2	3	4	5
INDUSTRY SPEC$_{\text{Patent, rict}}$	**-.664**	**-.671**	**-.687**	**-.691**	**-.742**
	(.008)	**(.008)**	**(.008)**	**(.008)**	**(.009)**
CLUSTER SPEC$_{\text{Patent, rict}}$ (Outside the industry)		**.025**	**.018**	**.016**	**.015**
		(.003)	**(.003)**	**(.003)**	**(.003)**
STRONG RELATED CLUSTERS $_{\text{Patent, rct}}$			**.236**	**.225**	**.211**
			(.015)	**(.015)**	**(.021)**
CLUSTER SPEC in NEIGHBORS $_{\text{Patent, rct}}$				**.136**	**.135**
				(.015)	**(.020)**
REG PATENTS$_{\text{rt}}$	**-.754**	**-.752**	**-.733**	**-.733**	
	(.036)	**(.034)**	**(.036)**	**(.036)**	
REG EMPLOY$_{\text{rt}}$	***.233***	***.216***	***.201***	***.187***	
	(.099)	***(.099)***	***(.099)***	***(.100)***	
Intercept	*-1.932*	-1.723	-1.520	-1.398	.171
	(1.074)	(1.067)	(1.050)	(1.058)	(.568)
R-Squared	**.410**	**.411**	**.417**	**.419**	**.519**

Notes: See notes in Table 3. Balanced industry-region panel that includes only those industries with some employment and patenting in 1990 and 1997.

Table 5: Cluster Employment Growth Model (over 1990-1996 & 1997-2003, N=12,988)

	EMPLOYMENT GROWTH $_{rct}$			
	Without Cluster & EA fes	Cluster*Year & EA fes		
	1	2	3	4
CLUSTER SPEC (employ)	**-.240**	**-.227**	**-.256**	**-.260**
	(.008)	**(.008)**	**(.008)**	**(.008)**
CLUSTER SPEC (patents)				**.030**
				(.007)
STRONG RELATED CLUSTERS (employ)	**.069**	**.076**	**.065**	**.062**
	(.011)	**(.010)**	**(.011)**	**(.011)**
CLUSTER SPEC in NEIGHBORS (employ)	**.098**		**.096**	**.095**
	(.010)		**(.010)**	**(.010)**
REG EMPLOY$_{rt}$		**-.899**	**-.906**	**-.907**
		(.109)	**(.107)**	**(.109)**
REG EMPLOY DENSITY$_{rt}$	***-.016***			
	(.007)			
HIGH-TECH$_{c}$	**-.135**			
	(.029)			
MANUFACTURING$_{c}$	**-.208**			
	(.012)			
CLUSTER OVERLAP$_{c}$	**.040**			
	(.011)			
LARGE CLUSTER$_{c}$	**-.040**			
	(.013)			
CLUSTER*YEAR Fes	**No**	**Sig.**	**Sig.**	**Sig.**
REGION (EAs) Fes	**No**	**Sig.**	**Sig.**	**Sig.**
CENSUS-REGION Fes	**Sig.**			
Year FE	**Sig.**			
Intercept	**.256**	**10.742**	**11.473**	**10.887**
	(.043)	**(1.359)**	**(1.332)**	**(1.358)**
R-Squared	**.177**	**.235**	**.246**	**.247**

Note: Bold and Bold-Italic numbers refer to coefficients significant at 1% and 5% levels, respectively. Robust standard errors clustered by economic area. All the variables are in logs and all the cluster composition variables are location quotients. We condition on region-clusters that have some positive employment in both 1990 and 1997. The Census-regions are West Pacific, West Mountain, Midwest, South Central, Northeast, and South Atlantic.

Table 6: Cluster Patent Growth Model (over 1990-1996 & 1997-2003, N=12,988)

	PATENT GROWTH $_{rct}$			
	Without Cluster & EA fes	Cluster*Year & EA fes		
	1	2	3	4
CLUSTER SPEC (patents)	**-.640**	**-.681**	**-.691**	**-.711**
	(.026)	**(.024)**	**(.024)**	**(.024)**
CLUSTER SPEC (employ)				**.099**
				(.008)
STRONG RELATED CLUSTERS (patents)	**.129**	**.132**	**.127**	**.113**
	(.036)	**(.037)**	**(.037)**	**(.035)**
CLUSTER SPEC in NEIGHBOR (Patents)	**.183**		**.131**	**.097**
	(.029)		**(.028)**	**(.028)**
REG PATENTS$_{rt}$	**-.082**	**-.888**	**-.893**	**-.892**
	(.032)	**(.097)**	**(.097)**	**(.097)**
REG EMPLOY$_{rt}$		**.776**	**.782**	**.751**
		(.308)	**(.309)**	**(.307)**
REG EMPLOY DENSITY$_{rt}$	**.138**			
	(.045)			
HIGH-TECH$_c$	***-.068***			
	(.027)			
MANUFACTURING$_c$	.016			
	(.020)			
CLUSTER OVERLAP$_c$	**.071**			
	(.014)			
LARGE CLUSTER$_c$	-.005			
	(.016)			
CLUSTER*YEAR Fes	**No**	**Sig.**	**Sig.**	**Sig.**
REGION (EAs) Fes	**No**	**Sig.**	**Sig.**	**Sig.**
CENSUS-REGION Fes	**Sig.**			
Year FE	**Sig.**			
Intercept	.067	-5.986	-6.032	-5.555
	(.099)	(3.770)	(3.781)	(3.748)
R-Squared	**.330**	**.440**	**.443**	**.454**

Note: Bold and Bold-Italic numbers refer to coefficients significant at 1% and 5% levels, respectively. Robust standard errors clustered by economic area. All the variables are in logs and all the cluster composition variables are location quotients.

Table 7 Regional Employment and Patent Growth Outside the Top Clusters in the Region (N=354)

	Region Employ Growth Outside Top Clusters			Region Patent Growth Outside Top Clusters		
	1	2	3	4	5	6
CLUSTER STRENGTH $_{Employ}$	**.141** (**.031**)					
CLUSTER STRENGTH$^{WOS}_{Employ}$ (weighted by overlap among top clusters)		**.069** (**.018**)				
CLUSTER STRENGTH$^{WO}_{Employ}$ (weighted by cluster overlap)			**.080** (**.023**)			
CLUSTER STRENGTH $_{Patents}$				**.319** (**.119**)		
CLUSTER STRENGTH$^{WOS}_{Patents}$ (weighted by overlap among top clusters)					***.129*** (***.051***)	
CLUSTER STRENGTH$^{WO}_{Patents}$ (weighted by cluster overlap)						**.195** (**.061**)
NATIONAL GROWTH of TOP CLUSTERS (Outside the region)$_{Employ}$	.062 (.043)	*.083* (*.045*)	*.088* (*.047*)			
NATIONAL GROWTH of TOP CLUSTERS (Outside the region)$_{Patents}$				**.970** (**.291**)	**.932** (**.298**)	**.748** (**.308**)
EMPLOY OUTSIDE TOP CLUSTERS	*-.021* (*.011*)	***-.024*** (***.011***)	***-.022*** (***.011***)	**.340** (**.080**)	**.338** (**.080**)	**.341** (**.075**)
PATENTS OUTSIDE TOP CLUSTERS	.010 (.008)	.011 (.008)	.009 (.008)	**-.291** (**.064**)	**-.289** (**.064**)	**-.297** (**.063**)
Intercept	**.303** (**.109**)	**.355** (**.105**)	**.352** (**.105**)	**-2.939** (**.687**)	**-2.898** (**.687**)	**-2.902** (**.678**)
R-Squared	**.432**	**.423**	**.409**	**.237**	**.233**	**.246**

Note: Bold, Bold-Italic and Italic numbers refer to coefficients significant at 1%, 5% and 10% levels, respectively. Robust standard errors clustered by economic area. All models include year fixed effect and Census-region fixed effects.

Appendix

Table A1: List of Traded Industrial Clusters (Cluster Overlap Rank)

Cluster Name	Cluster Overlap (Rank)	Cluster Name	Cluster Overlap (Rank)
Aerospace Engines*	**30**	Hospitality and Tourism**	**29**
Aerospace Vehicles and Defense*	**19**	Information Technology*	**3**
Analytical Instruments*	**1**	Jewelry and Precious Metals	**38**
Apparel	**31**	Leather Products	**21**
Automotive	**17**	Lighting and Electrical Equipment	**5**
Building Fixtures, Equipment and Services**	**11**	Construction Materials	**25**
Business Services	**13**	Medical Devices*	**6**
Chemical Products	**9**	Metal Manufacturing	**8**
Communications Equipment*	**2**	Motor Driven Products	**24**
Processed Food	**35**	Oil and Gas Products and Services**	**23**
Agricultural Products	**40**	Biopharmaceuticals*	**7**
Distribution Services**	**16**	Plastics	**12**
Education & Knowledge Creation**	**4**	Power Generation and Transmission	**26**
Entertainment**	**28**	Prefabricated Enclosures	**22**
Heavy Machinery	**15**	Production Technology	**10**
Financial Services**	**36**	Publishing and Printing	**18**
Fishing and Fishing Products	**34**	Sporting, Recreational and Children's Goods	**33**
Footwear	**39**	Textiles	**37**
Forest Products	**27**	Tobacco	**41**
Furniture	**14**	Transportation and Logistics**	**20**
Heavy Construction Services**	**32**		

Note: * These clusters are classified as high-tech. ** These clusters are service-oriented clusters. The Cluster Overlap Rank is equal to 1 for the cluster with the highest overlap with the other clusters.

Table A2: Automotive Cluster: Narrow Cluster Concept

Subclusters (8)	SIC	Label
Motor Vehicles	**3711**	**Motor vehicles and car bodies**
Automotive Parts	2396	Automotive and apparel trimmings
	3230	Products of purchased glass
	3592	Carburetors, pistons, rings, valves
	3714	Motor vehicle parts and accessories
	3824	Fluid meters and counting devices
Automotive Components	3052	Rubber and plastics hose and belting
	3061	Mechanical rubber goods
Forgings and Stampings	3322	Malleable iron foundries
	3465	Automotive stampings
Flat Glass	3210	Flat glass
Production Equipment	3544	Special dies, tools, jigs and fixtures
	3549	Metalworking machinery, n.e.c.
Small Vehicles and Trailers	3799	Transportation equipment, n.e.c.
Marine, Tank & Stationary Engines	3519	Internal combustion engines, n.e.c.

Table A3: Clusters Related to Automotive

Automotive Subclusters	SIC	Six Related Clusters
Motor Vehicles	3711	Production Technology
Automotive Parts	3592,3714	Metal Manufacturing
	3824	Production Technology
Automotive Components	3052	Furniture
	3061	Aerospace Engines
Forgings and Stampings	3322	Metal Manufacturing
	3465	Production Technology
Production Equipment	3544, 3549	Metal Manufacturing, Production Technology
Marine, Tank and Stationary Engines	3519	Heavy Machinery, Motor Driven Products

Note: The automotive cluster has a total of 14 industry links with 6 traded clusters.

Table A4: Strong Automotive Clusters in 1997

EA Name	LQ	SHR
High Cluster Specialization & Top 10% Share of National Cluster Employment		
Detroit-Warren-Flint, MI	7.43	19.36
Fort Wayne-Huntington-Auburn, IN	6.59	2.18
Toledo-Fremont, OH	6.50	2.63
Dayton-Springfield-Greenville, OH	6.15	3.32
Grand Rapids-Muskegon-Holland, MI	4.91	3.46
Indianapolis-Anderson-Columbus, IN	4.48	5.47
South Bend-Mishawaka, IN-MI	4.04	1.51
Nashville-Davidson—Murfreesboro—Columbia, TN	3.95	3.55
Cleveland-Akron-Elyria, OH	3.09	5.72
Columbus-Marion-Chillicothe, OH	2.22	2.04
Milwaukee-Racine-Waukesha, WI	1.89	1.89
St. Louis-St. Charles-Farmington, MO-IL	1.72	2.22
High Cluster Specialization & Low Share of National Cluster Employment		
Grand Forks, ND-MN	4.86	0.34
Traverse City, MI	3.75	0.31
La Crosse, WI-MN	3.54	0.31
Jonesboro, AR	3.47	0.31
Cape Girardeau-Jackson, MO-IL	3.18	0.28
Mason City, IA	3.06	0.18
Peoria-Canton, IL	3.01	0.98
Lexington-Fayette--Frankfort--Richmond, KY	2.94	1.22
Madison-Baraboo, WI	2.76	1.17
Kearney, NE	2.55	0.27
Knoxville-Sevierville-La Follette, TN	2.47	0.90
Erie, PA	2.43	0.43
Lincoln, NE	2.37	0.35
Evansville, IN-KY	2.35	0.65
Louisville-Elizabethtown-Scottsburg, KY-IN	2.25	1.29
Joplin, MO	2.17	0.26
Waterloo-Cedar Falls, IA	2.04	0.16
Asheville-Brevard, NC	2.04	0.39
Alpena, MI	1.95	0.13
Buffalo-Niagara-Cattaraugus, NY	1.89	1.02
Huntsville-Decatur, AL	1.85	0.62
Augusta-Richmond County, GA-SC	1.74	0.31
Rochester-Batavia-Seneca Falls, NY	1.73	0.93
Springfield, MO	1.70	0.46

Note: Automotive clusters with the top 20% LQ that satisfy the establishment and share criteria.

Figure A1: Location of strong regional clusters (1997)

High Cluster Specialization and Top 10% Share of National Cluster Employment

High Cluster Specialization (Top 20% Employment Location Quotient)

Top 10% Share of National Cluster Employment without Cluster Specialization

Fig. A1.1: Strong Automotive Clusters (See Table A4)

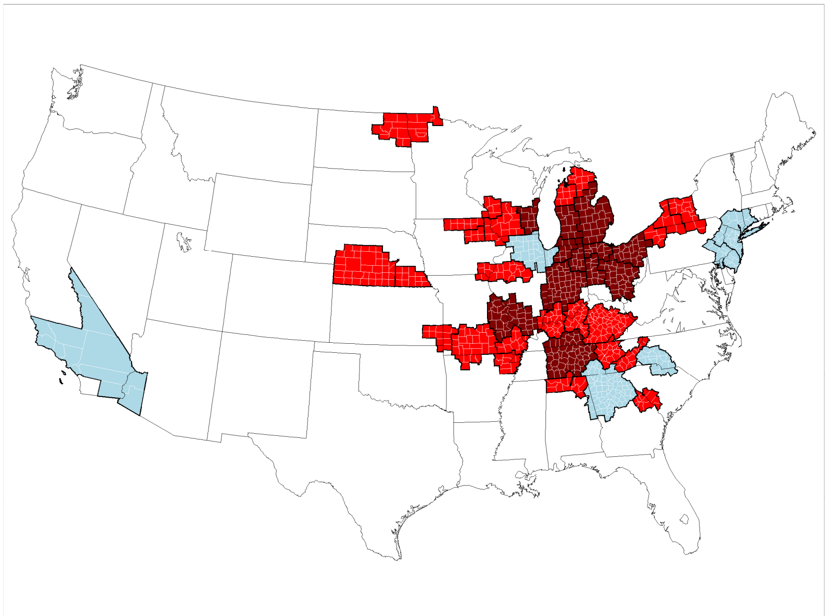

Fig. A1.2: Strong Financial Service Clusters