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The Economic Performance of Regions

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PORTER M. E. (2003) The economic performance of regions, *Reg. Studies* **37**, 549–578. This paper examines the basic facts about the regional economic performance, the composition of regional economies and the role of clusters in the US economy over period of 1990 to 2000. The performance of regional economies varies markedly in terms of wage, wage growth, employment growth and patenting rate. Based on the distribution of economic activity across geography, we classify US industries into traded, local and resource-dependent. Traded industries account for only about one-third of employment but register much higher wages, far higher rates of innovation and influence local wages. We delineate clusters of traded industries using co-location patterns across US regions. The mix of clusters differs markedly across regions. The performance of regional economies is strongly influenced by the strength of local clusters and the vitality and plurality of innovation. Regional wage differences are dominated by the relative performance of the region in the clusters in which it has positions, with the particular mix of clusters secondary. A series of regional policy implications emerge from the findings.

Regional economic performance Clusters Competitiveness Industrial location

PORTER M. E. (2003) La performance économique des regions, *Reg. Studies* **37**, 549–578. Cet article cherche à examiner les principes fondamentaux de la performance économique régionale, de la structure des économies régionales, et du rôle des groupements dans l'économie des Etats-Unis de 1990 à 2000. La performance des économies régionales varie sensiblement du point de vue des salaires, de la croissance des salaires, de la hausse de l'emploi, et du nombre des brevets. A partir de la répartition de l'activité économique géographique, on classe les entreprises industrielles aux Etats-Unis sous les rubriques commerciale, locale, et dépendante des ressources. Les entreprises industrielles à vocation commerciale n'expliquent qu'un tiers de l'emploi mais laissent voir des salaires nettement plus élevés, des taux d'innovation bien plus importants, et influent sur les salaires locaux. Employant des distributions de localisations partagées à travers les Etats-Unis, on délimite des groupements d'entreprises industrielles à vocation commerciale. La structure des groupements varie sensiblement suivant la région. La performance des économies régionales est fortement influencé par la force des groupements locaux et par la vitalité et par la pluralité de l'innovation. Les écarts des salaires réels s'expliquent primordialement par la performance relative de la région quant aux groupements où elle est présente, la structure particulière des groupements n'étant que d'une importance secondaire. Il en résulte toute une série d'implications pour la politique.

Performance économique régionale Groupements
Compétitivité Localisation industrielle

PORTER M. E. (2000) Die wirtschaftliche Leistungskraft von Regionen, *Reg. Studies* **37**, 549–578. Dieser Beitrag analysiert Kerndaten regionaler Wirtschaftsräume in den Vereinigten Staaten, insbesondere ihre wirtschaftliche Leistungskraft, ihre Zusammensetzung und die Rolle regionaler Cluster. Die Regionen der Vereinigten Staaten unterschieden sich in den Jahren 1990 bis 2000 deutlich in ihrer wirtschaftlichen Leistungskraft gemessen an Lohnniveau und – wachstum, Beschäftigungsentwicklung, und Patentrate. Basierend auf der geographischen Konzentration öknomischer Aktitivtät klassifizieren wir Industriezweige als überregional ('traded'), lokal oder abhängig von der Präsenz von Naturschätzen. Cluster überregionaler Industrien beschäftigen nur circa ein Drittel aller Erwerbstätigen, verzeichnen aber überdurchschnittliche Löhne und signifikant höhere Innovationsraten als die Gesamtwirtschaft. Die relative Bedeutung einzelner Cluster innerhalb der Gruppe überregionaler Industrien unterscheidet sich deutlich im regionalen Vergleich. Der wirtschaftliche Erfolg einer Region wird stark von der relative Leistungskraft und Innovationsstärke der dort angesiedelten überregionalen Cluster beeinflusst. So hat das relative Lohnniveau in den überregionalen Clustern in einer Region einen dominanten Einfluss auf das regionale Lohnniveau, während die spezifische Identität dieser Cluster nur eine sekundäre Rolle spielt. Der Beitrag entwickelt aus dieser Analyse eine Reihe von Implikationen für die Wirtschaftspolitik.

Regionale Wirtschaftsleistung Cluster
Wettbewerbsfähigkeit Industriestandort

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Studies of competitiveness and economic development have tended to focus on the nation as the unit of analysis, and on national attributes and policies as the drivers. As regional scientists and economic geographers have long understood, however, there are substantial differences in economic performance across regions in virtually every nation. This suggests that many of the essential determinants of economic performance are to be found at the regional level.

There is a substantial theoretical literature on regional economic development, and numerous case studies have explored the influences on economic development and performance in particular regions. SCOTT, 2000, provides a comprehensive review of the economic geography literature over the past half century. FELDMAN, 2000; GLAESER, 2000; and HANSON, 2000, provide additional literature review. Despite this rich tradition, empirical studies of large samples of regions have been comparatively rare. A recent body of work has examined various hypotheses about regional performance in large samples of cities, most notably the respective influence of economic specialization and diversity.[1] In this paper, we aim to contribute to this empirical literature with a complementary approach. Using a newly assembled dataset covering every metropolitan area, economic area and state in the US, and new statistical methods to derive the composition of regional economies and the boundaries of clusters of linked industries, we seek to explore the basic facts about regional economies in the US. In particular, we explore the overall economic performance of regions, the composition of regional economies, and the role of clusters in composition and performance.

Our primary aim here is not to test a particular theory, but to examine facts and relationships that have been implicit or explicit in many theories.[2] How much do regions vary in wages, employment growth and patenting rates? How important is size or industry specialization in performance? Does the particular composition of industries in a region matter? What are the groups of industries that are linked in geographically concentrated clusters, and how does cluster position and mix relate to a region's performance. Those and many other questions are examined, employing basic statistical tests. In-depth analyses of particular hypotheses are the subject of other papers.[3]

The core dataset is the annual County Business Patterns (CBP) data, covering employment, establishments and wages by county at the four-digit SIC (Standard Industrial Classification) level.[4] The newer NAICS system offers some improvements because it is less aggregated, but the changes affect a modest number of industries. We utilize the SIC system in this analysis because of the availability of a decade of historical data. The CBP data excludes government and military employment but covers the great majority of the private sector, excluding only agricultural workers, railroad workers and household employment. To the CBP data we matched patent data from the US Patent and Trademark Office and CHI Research, which is allocated to SIC codes using an algorithm developed by Silverman (SILVERMAN, 1999). Patents are the best available measure of innovative activity across all regions, and we explore the patterns of patenting across geography and its relationship with industry location.[5] All our data covers the 1990 to 2000 time period.

The primary geographic unit used in the analysis is the Economic Area (EA) as defined by the Bureau of Economic Analysis. There are 172 EAs covering the entire US, which are generally smaller than states but larger than most metropolitan statistical areas or MSAs (see Appendix A). We utilize EAs, rather than MSAs which have been the focus of much of the statistical literature, because EAs cover the entire US, have stable definitions over time and, most importantly, better reflect true economic boundaries of regions because they capture the actual patterns of market exchange that often cross arbitrary MSA borders. We utilized states (51 including Washington, DC) as the geographic unit for some analyses due to less data suppression. All of the analyses here have been replicated using all three geographic units and, by and large, the results are similar.

The first section of this paper focuses on differences in overall regional economic performance in terms of wages, wage growth, employment growth, and patenting. The next section uses the actual patterns of industry employment across geography to decompose regional economies into traded, local, and resource-dependent industries, and we explore their respective roles in economic performance. We then employ statistical methods to derive clusters of traded industries that co-locate.[6] We explore the attributes, overlap, and distribution of clusters across the US economy and the relationship between the mix of clusters in a region and its performance. A final section provides a summary and conclusions.

DIFFERENCES IN REGIONAL ECONOMIC PERFORMANCE

A region's overall average wage[7] is perhaps the most basic measure of its economic performance and most associated with its standard of living. In 2000, the average wage in US EAs was $27,533. There is a striking variation in average wages among EAs, ranging from $19,228 in North Platte, NE-CO to $52,213 in San Francisco-Oakland-San Jose, CA (see Fig. 1).

The average EA experienced an $8,403 wage increase from 1990 to 2000, or about 44% of the 1990 average wage (a compound annual growth rate (CAGR) of 3·7%). However, wage growth also varied markedly across regions, with the CAGR over the 1990 to 2000 period ranging from 7·1% in Austin-

San Marcos, TX to 1·8% in Wheeling, WV-OH (see Fig. 2).

Regional wage inequality increased somewhat over the 1990–2000 period, with the wage GINI coefficient increasing from 0·0774 to 0·0940 over the period. However, wage growth was only weakly related to starting wage level (see Fig. 3). Hence, success or failure in growing wages in not determined by starting level but is affected by other influences that will be explored.

Another way of exploring the change in average regional wages over time is to group the EAs into wage deciles in 1990 and 2000 and examine the mobility between starting and ending decile groups (see Fig. 4).[8] Roughly half of the EAs (43·6%) remained in the same decile, 27·9% rose to a higher decile, and 28·5% fell to a lower decile, with no strong pattern related to starting level. Regions moving up two or more wage deciles included Fort Myers-Cape Coral (FL), Sioux City, Omaha, San Antonio, and Boise City, while regions moving down included Wheeling (WV-OH), Charleston (WV), Johnson City-Kingsport-Bristol (TN-VA), Erie (PA), and Champaign Urbana (IL).

Employment growth, another important attribute of economic performance, also varied markedly across regions, with employment CAGRs over the 1990–2000 period ranging from 6·49% for Austin-San Marcos to −0·08% for Syracuse. Employment growth had only a weak statistical relationship with starting employment size (see Fig. 5). Neither large nor small regions were more successful overall in growing employment in the 1990s. There was also no discernable relationship between employment growth and starting average wages (Fig. 6). There was a relatively weak but significant positive relationship between wage growth and employment growth (see Fig. 7). It appears that regions that were improving their economic fundamentals benefited both in terms of jobs and wages.

It is a common assertion in economic development circles that large regions that support diverse economies will be advantaged. Average wages do tend to be higher in larger regions measured by employment size, even after excluding the outliers New York and Los Angeles (see Fig. 8). However, the relationship between employment size and wage growth is much weaker (see Fig. 9). Once again, the data reveal that both large and small regions experienced success in growing wages; and both large and small regions experienced problems.

A third, more forward-looking measure of regional performance is patenting. While the patent system does not capture all innovative activity (e.g. in services, software, etc.), patenting is the best available and comparable measure of innovative activity across regions.[9] We mapped patents to regions by assigning each patent to the region in which the inventor resides. In the case of multiple inventors from different regions, patents were assigned fractionally to each region.

Patenting intensity, measured by patents per 100,000

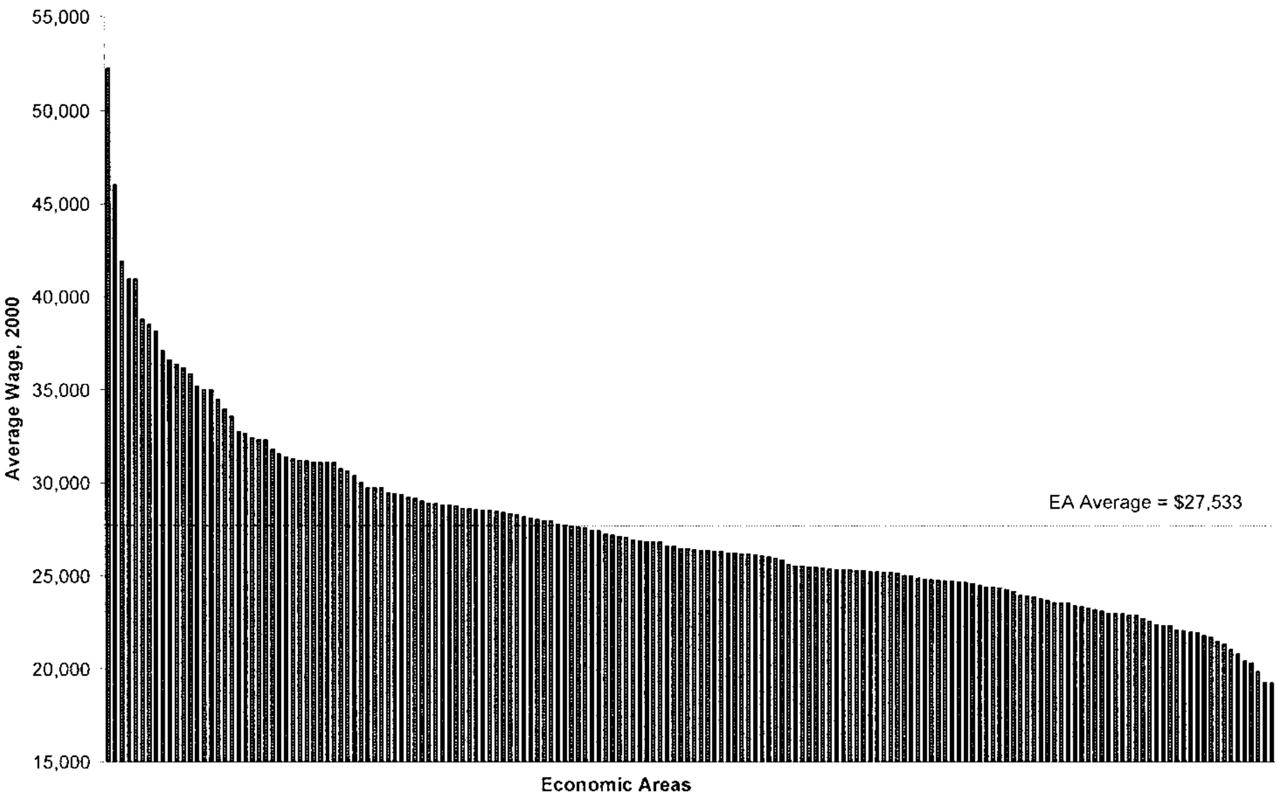

Fig. 1. Average wages by economic area, 2000

Sources: County Business Patterns; Cluster Mapping Project, Harvard Business School.

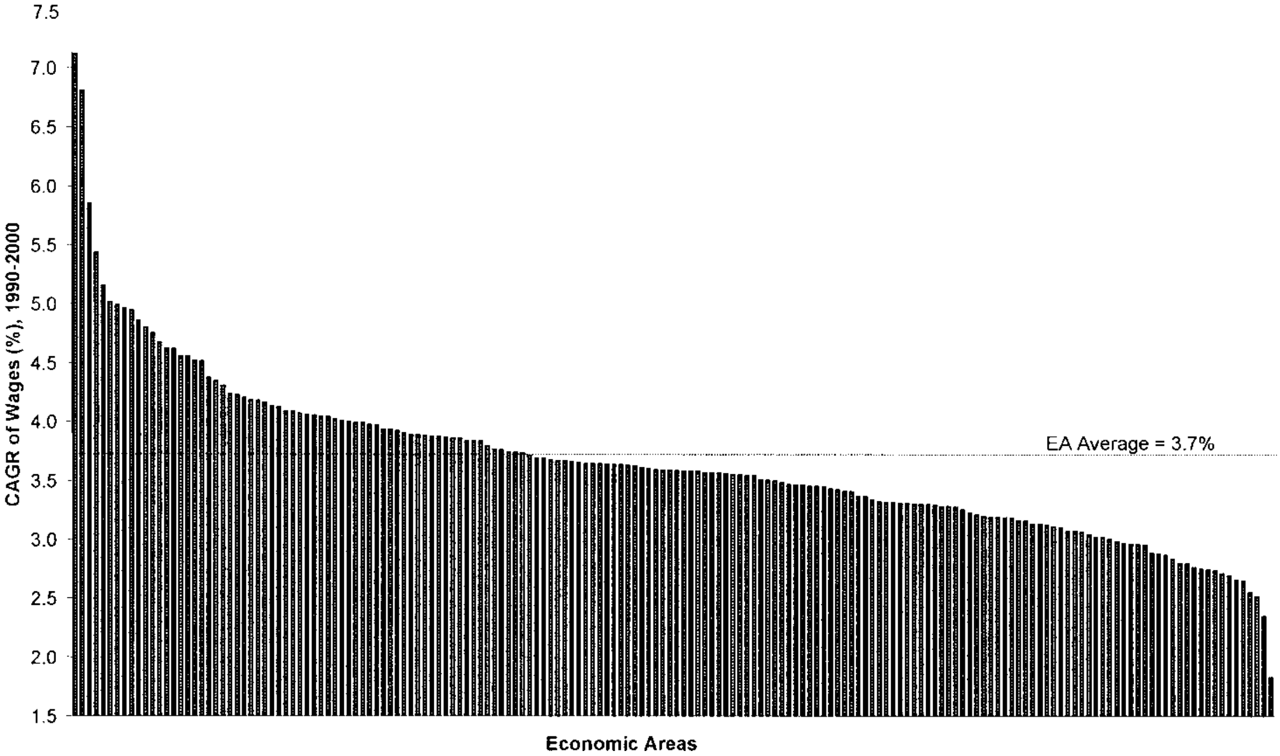

Fig. 2. Compound average wage growth by economic area, 1990–2000
Sources: County Business Patterns; Cluster Mapping Project, Harvard Business School.

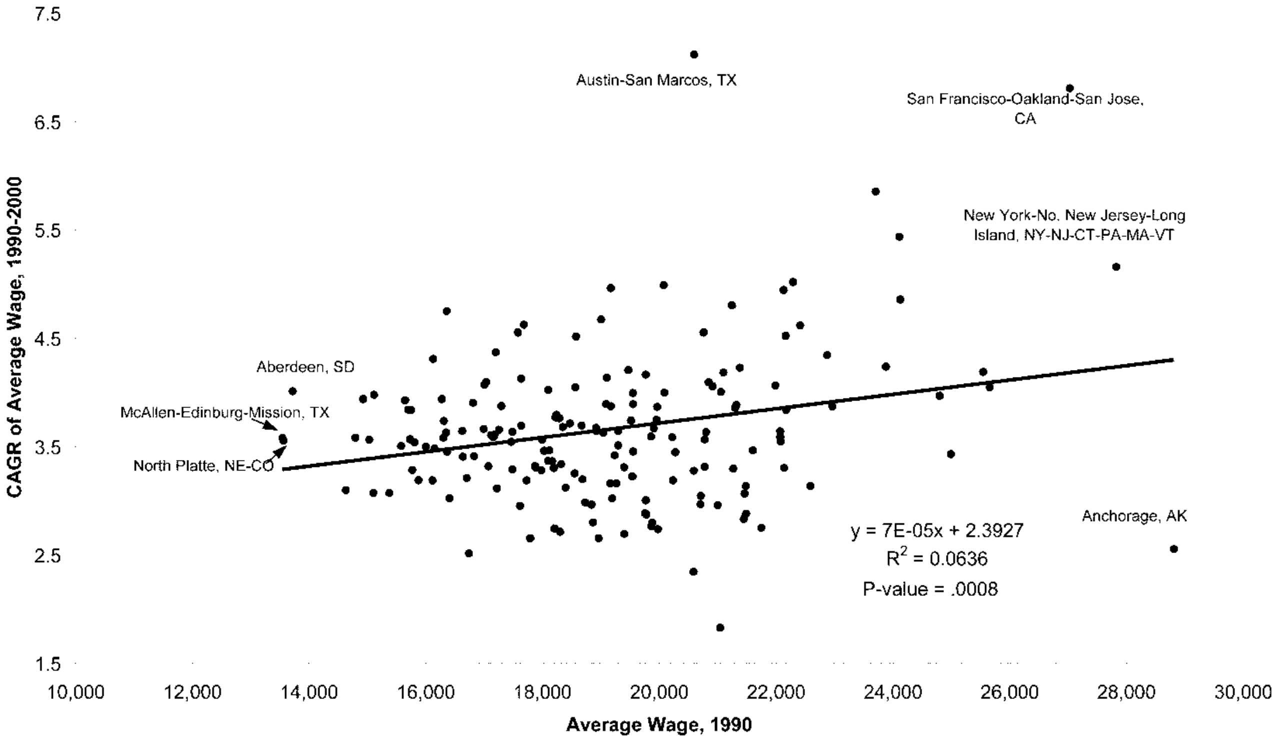

Fig. 3. Wage growth vs. starting average wage by economic areas, 1990–2000
Sources: County Business Patterns; Cluster Mapping Project, Harvard Business School.

		Ending Decile										
		1	2	3	4	5	6	7	8	9	10	Total
Starting Decile	1	15	3									18
	2	3	10	3	0	1						17
	3		3	7	4	2	1					17
	4		1	5	6	2	2	1				17
	5			2	5	3	6	0	1			17
	6				1	3	6	4	2	1		17
	7					5	2	3	6	1		17
	8				1	1	0	6	3	5	1	17
	9							3	5	7	2	17
	10									3	15	18
	Total	18	17	17	17	17	17	17	17	17	18	172

Fig. 4. *Changes in economic area wage deciles, 1990–2000*
Sources: County Business Patterns; Cluster Mapping Project, Harvard Business School.

inhabitants in 2000, ranges from essentially 0 patents per 100,000 inhabitants in Abilene, TX to over 250 in Boise City (see Fig. 10). The variation in patenting across regions far surpasses the variation of average wages and employment growth. Compound annual growth in patenting per capita from 1990 to 2000 also varied markedly, ranging from 28·2% in Boise City to –4·8% per year in Shreveport-Bossier City, LA-AR (see Fig. 11). There is no relationship between the starting level of patenting and patent growth over the 1990s. A scatter plot of patenting per capita vs. the size of a region is provided in Fig. 12. We utilized negative binomial regression to examine the relationship between patenting per capita and employment size, and find the coefficient of employment size to be statistically significant.

There was no statistical relationship between the rate of employment growth and starting patenting (see Fig. 13). However, a region's patenting intensity is strongly associated with average wages (see Fig. 14), with patenting intensity accounting for almost 30% of the variation across regions in average wage. High patenting signals more advanced products and processes and higher productivity that support a higher wage. Patenting intensity remains highly significant after controlling for regional size.

We would expect that the relationship between patenting and average wages to be affected by whether patenting is widespread or concentrated in a small number of firms or institutions. Patenting distributed among many inventors would yield greater spillovers across innovators and be associated with higher productivity in numerous fields.[10] Using Patent and Trademark Office data on patenting organizations, we computed a Herfindahl-Hirschman Index (HHI) of patentor concentration.[11] Increasing patentor HHI (higher concentration) is negatively related to average wages (see Fig. 15). Note that large regions will tend to have more patentors, tending to reduce patentor HHI. However, the concentration of patentors has a negative and significant relationship with average wages even after controlling for regional size. We explore some of these relationships in more detail in a related paper (see PORTER, 2003).

Given the differing challenges of urban and rural economic development, it is of interest to see how

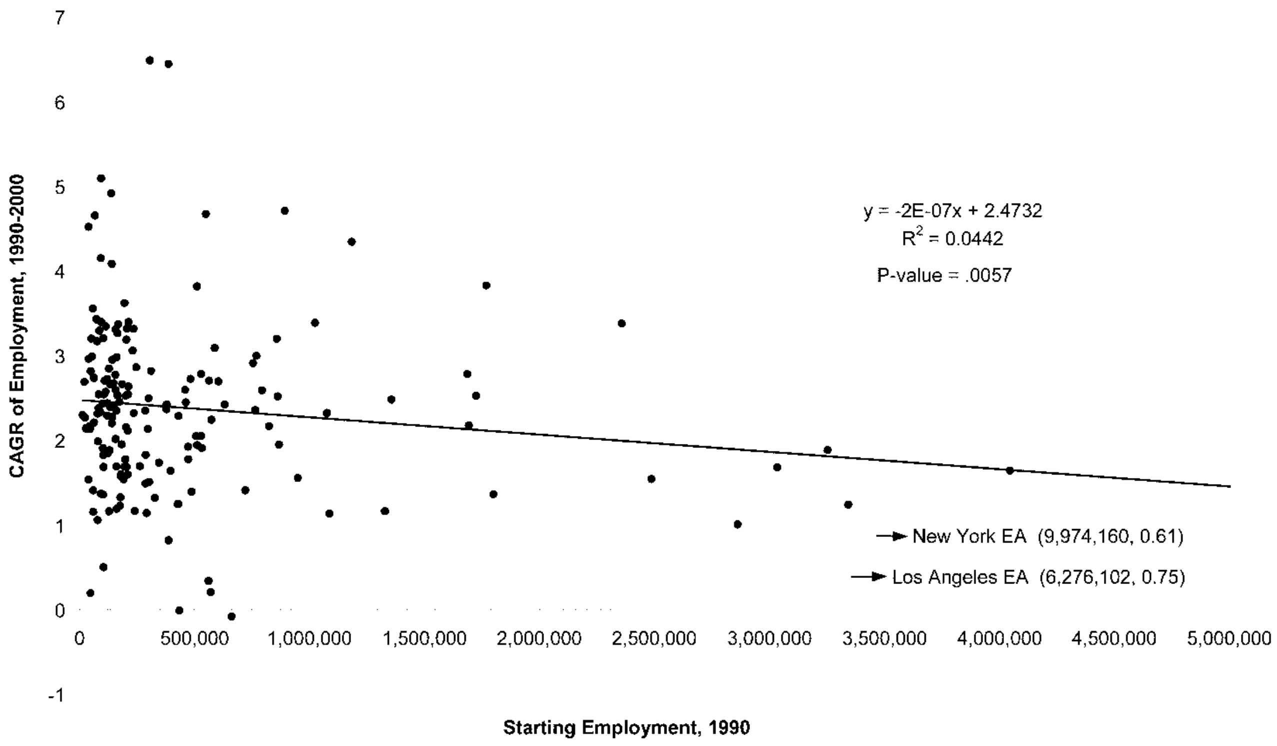

Fig. 5. *Employment growth vs. starting employment by economic area, 1990–2000*
Sources: County Business Patterns; Cluster Mapping Project, Harvard Business School.

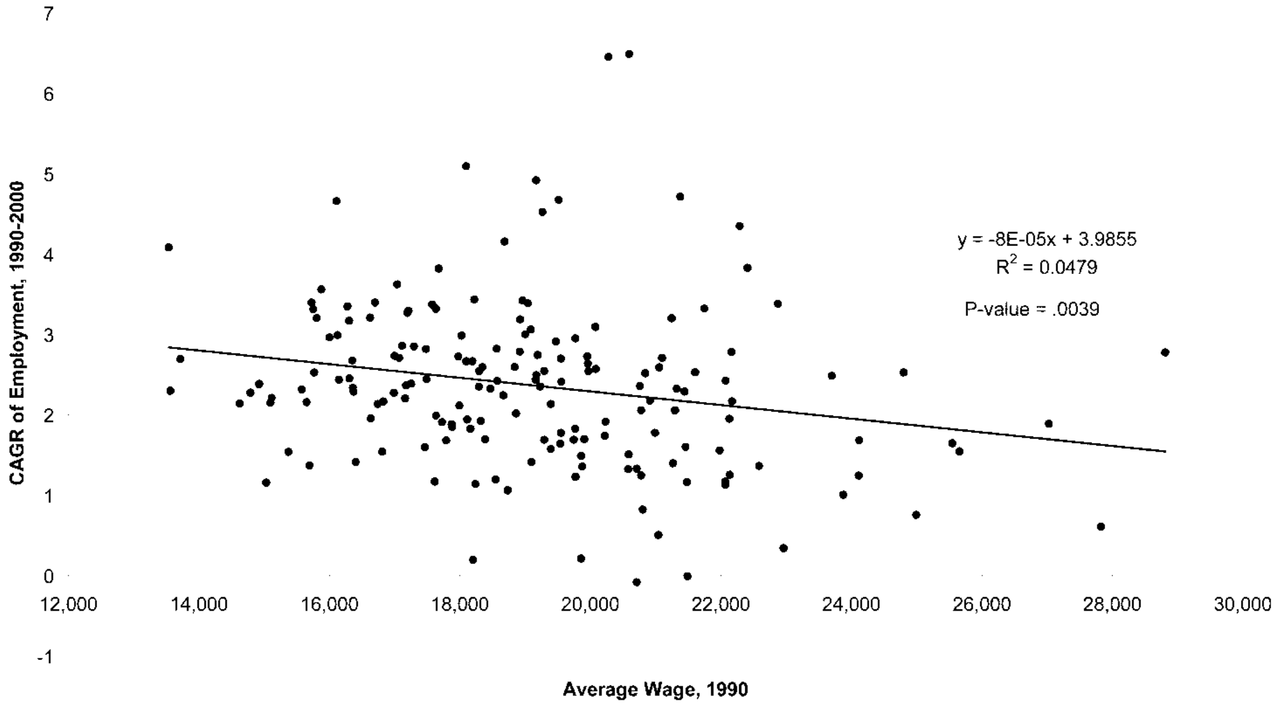

Fig. 6. Employment growth vs. starting average wage by economic area, 1990–2000

Sources: County Business Patterns; Cluster Mapping Project, Harvard Business School.

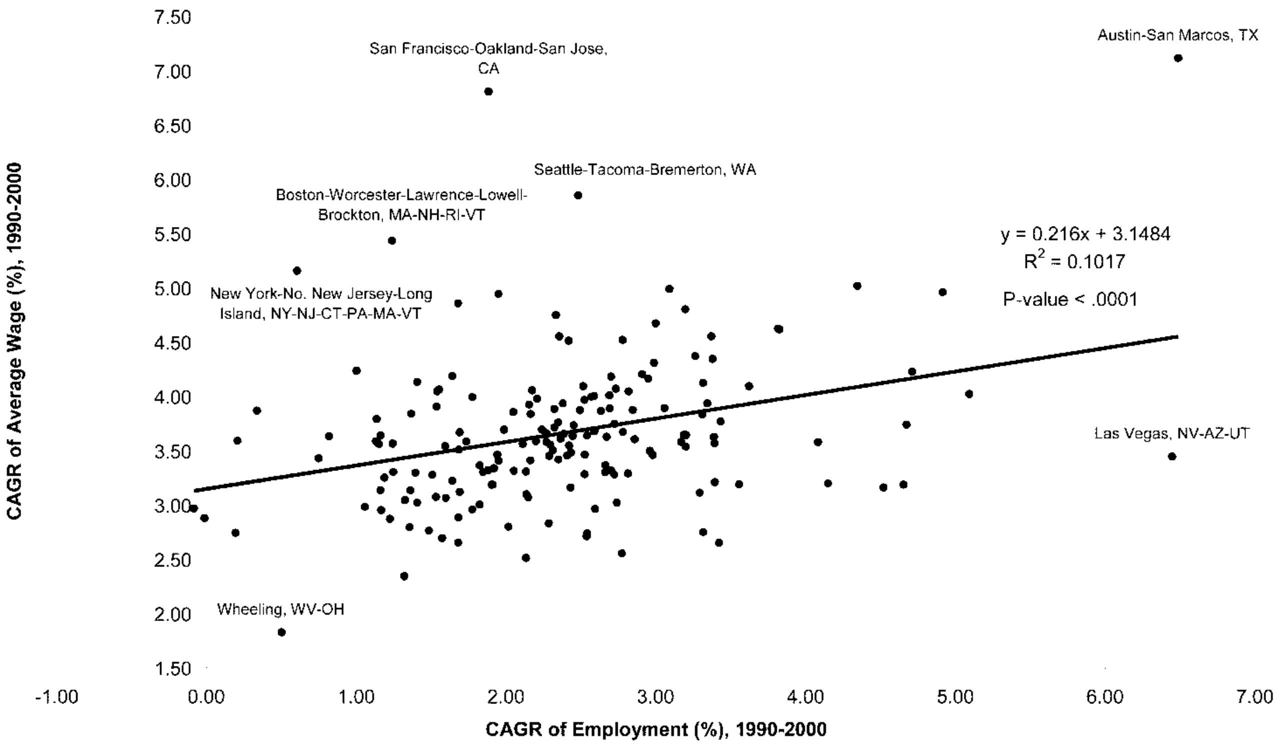

Fig. 7. Wage growth vs. employment growth by economic area, 1990–2000

Sources: County Business Patterns; Cluster Mapping Project, Harvard Business School.

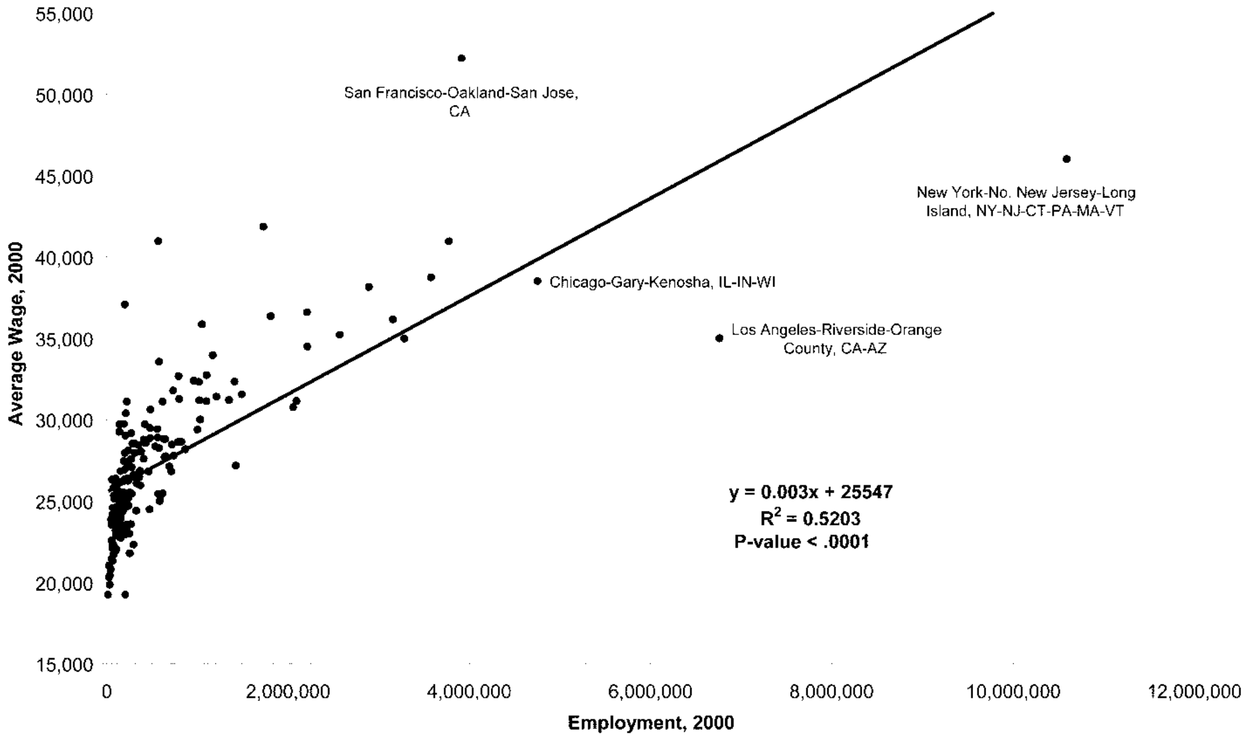

Fig. 8. Average wage vs. employment size by economic area, 2000

Note: Since the employment sizes of the Los Angeles and New York EAs are substantially larger than the size of the rest of the regions, we also examined the results after dropping these two observations. R^2 rises to 0.6145 and the coefficient of size remains positive but is somewhat higher.
Sources: County Business Patterns; Cluster Mapping Project, Harvard Business School.

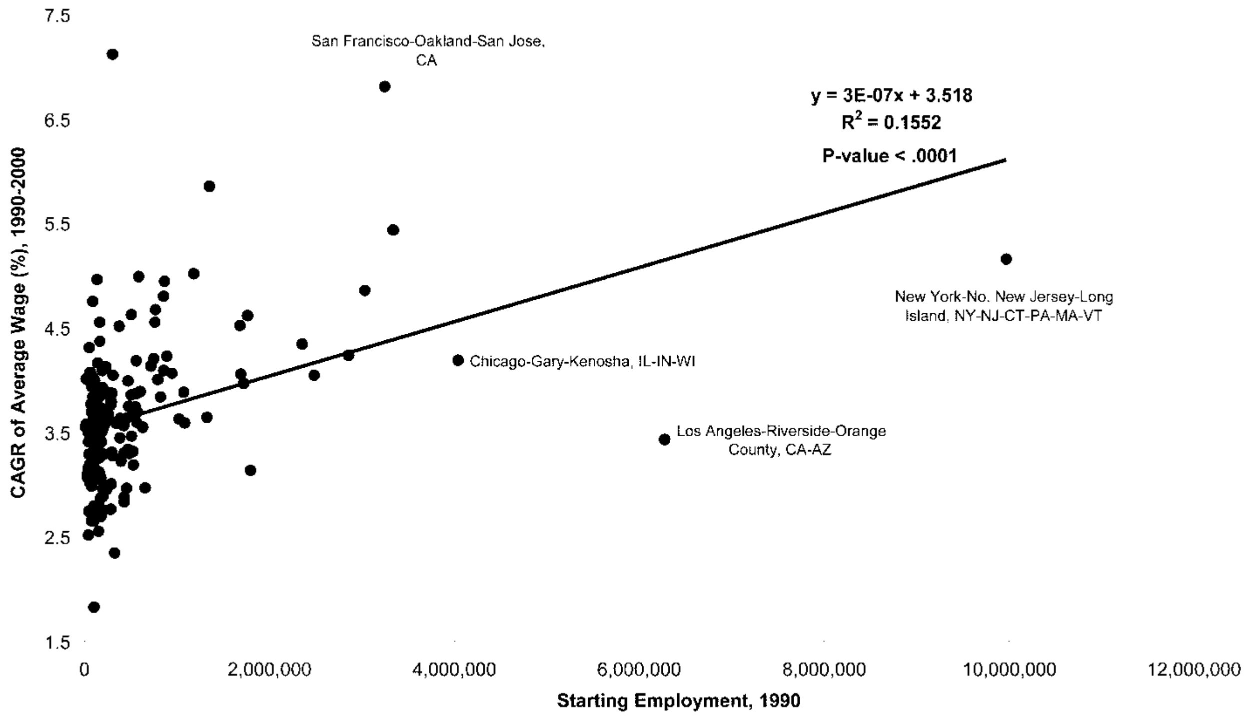

Fig. 9. Average wage growth vs. starting employment by economic area, 1990–2000

Note: Since the employment sizes of the Los Angeles and New York EAs are substantially larger than the size of the rest of the regions, we also examined the results after dropping these two observations. R^2 rises to 0.2379 and the coefficient is again moderately higher.
Sources: County Business Patterns; Cluster Mapping Project, Harvard Business School.

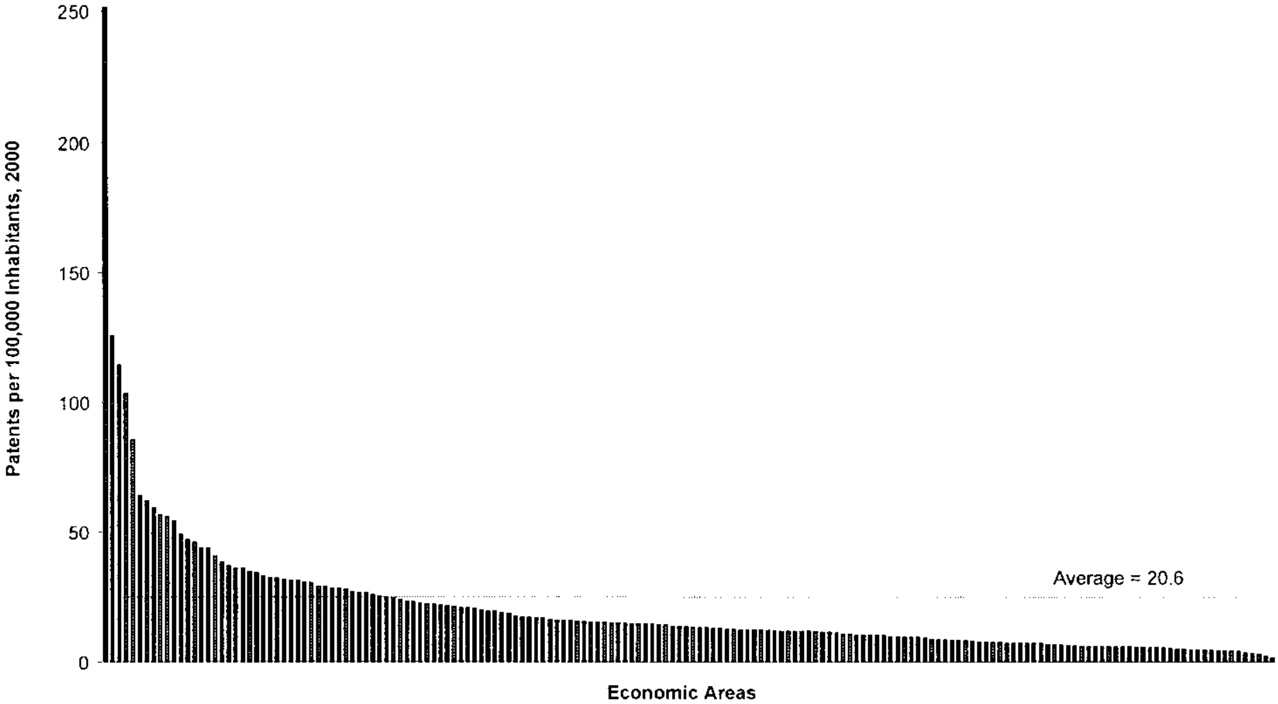

Fig. 10. *Patents per 100,000 inhabitants by economic area, 2000*
Sources: US Patent and Trademark Office; CHI Research; Cluster Mapping Project, Harvard Business School.

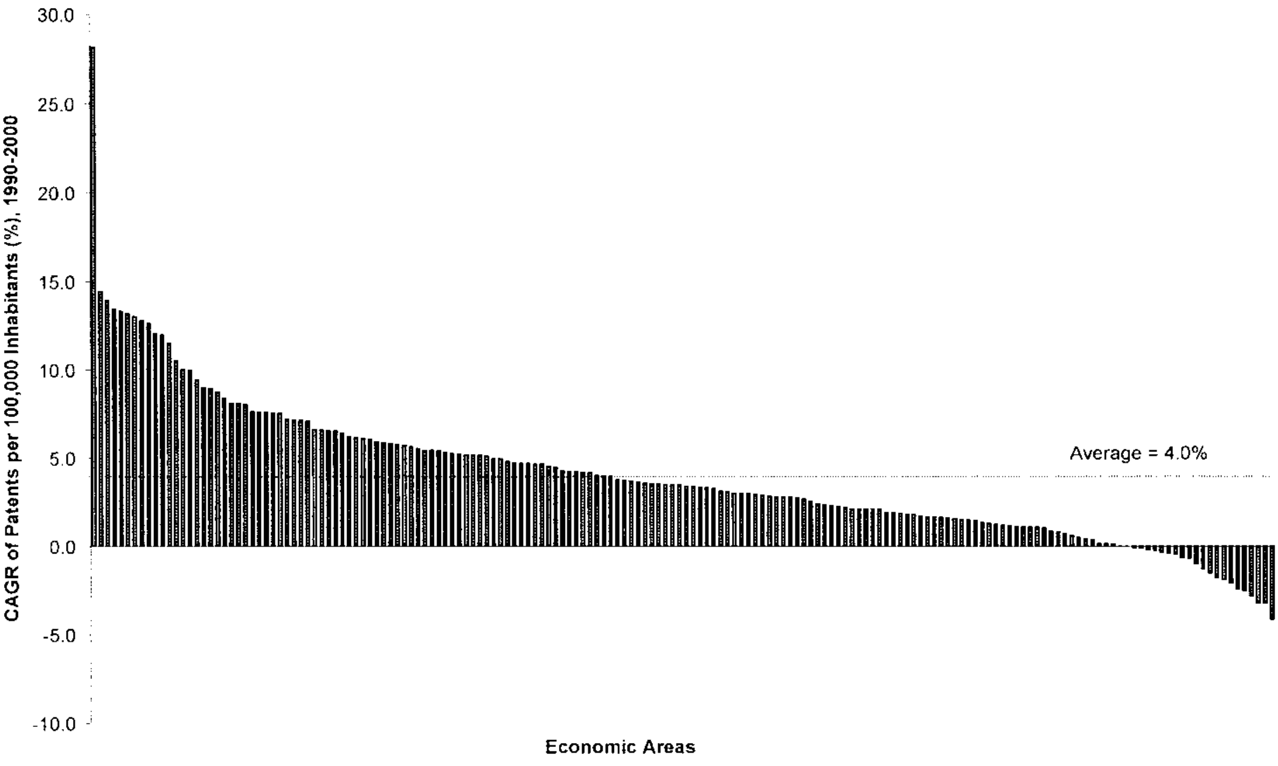

Fig. 11. *Growth in patents per 100,000 inhabitants by economic area, 1990–2000*
Sources: US Patent and Trademark Office; CHI Research; Cluster Mapping Project, Harvard Business School.

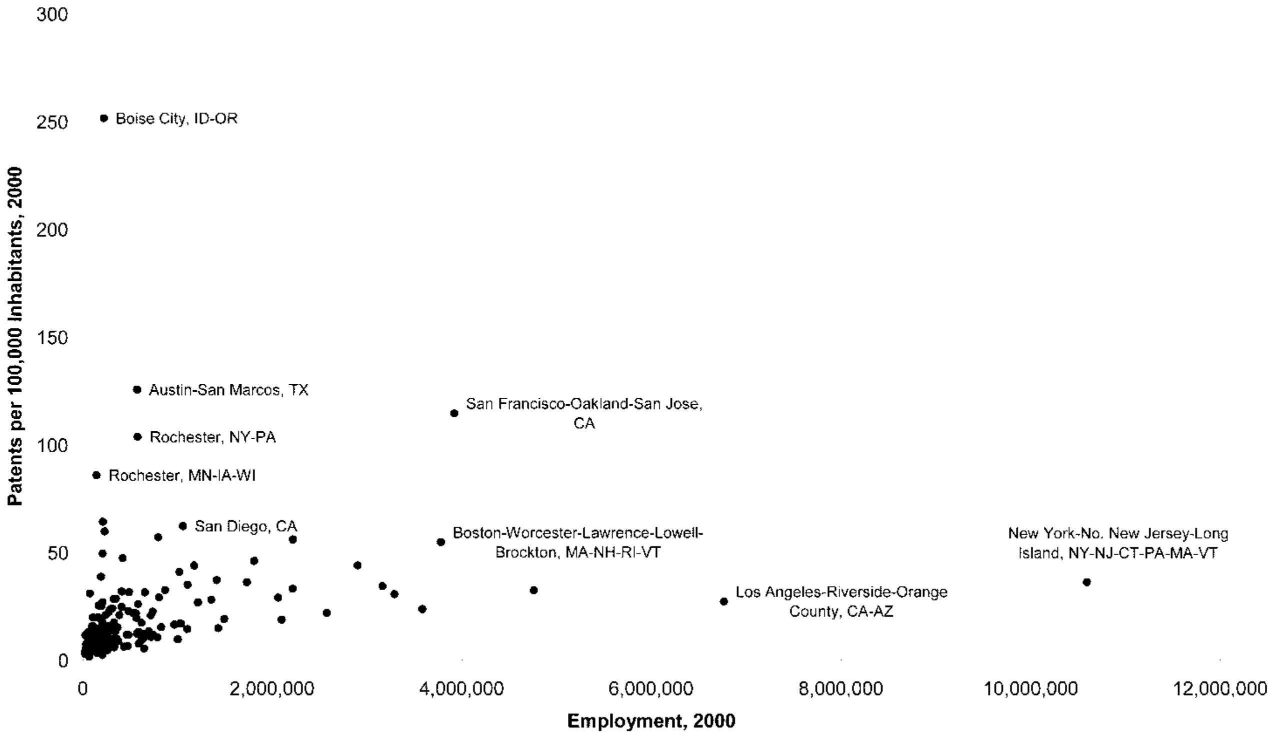

Fig. 12. Patents per 100,000 inhabitants vs. employment size by economic area, 2000

Sources: US Patent and Trademark Office; CHI Research; County Business Patterns; Cluster Mapping Project, Harvard Business School.

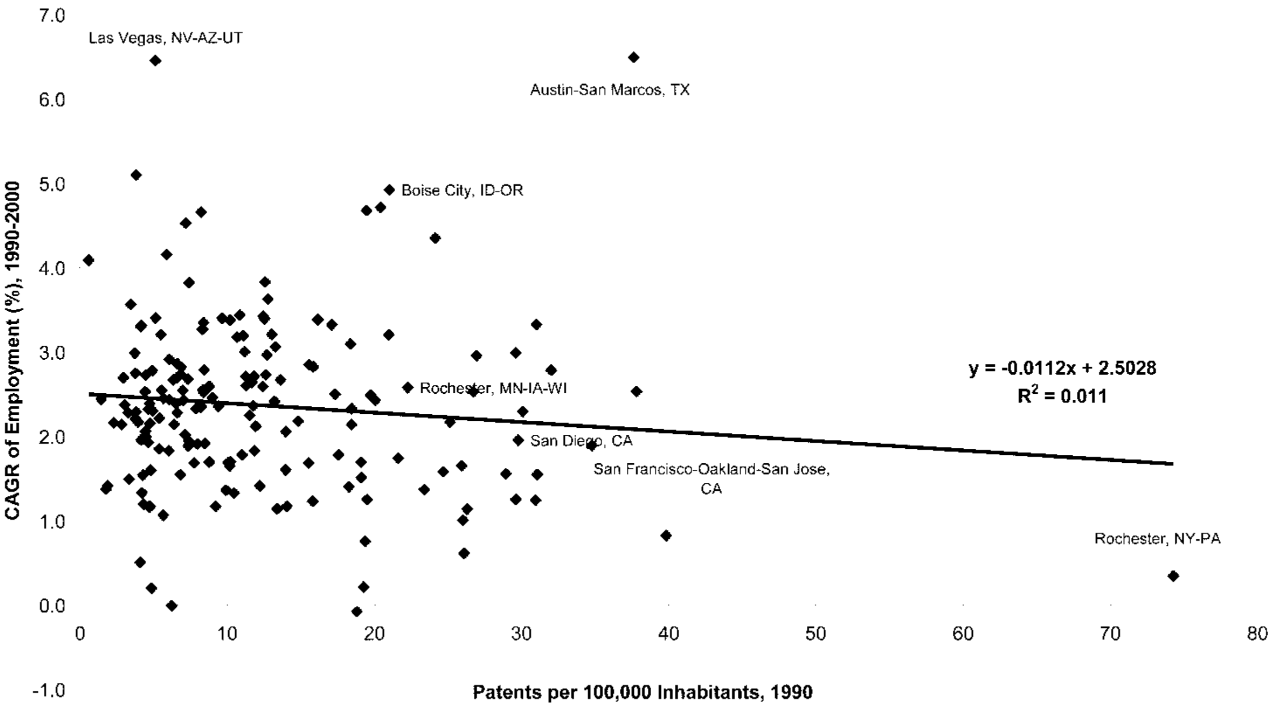

Fig. 13. Employment growth vs. starting patents per 100,000 inhabitants by economic area, 1990–2000

Sources: US Patent and Trademark Office; CHI Research; County Business Patterns; Cluster Mapping Project, Harvard Business School.

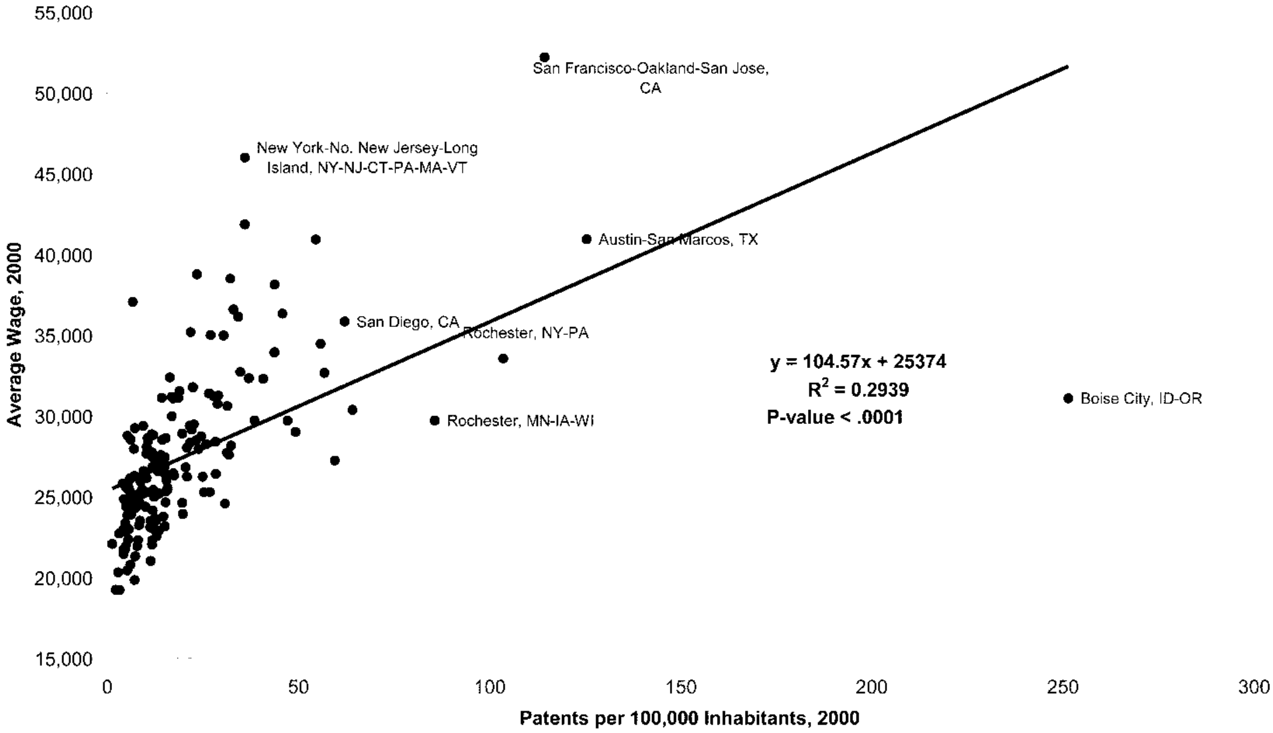

Fig. 14. Average wage vs. patents per 100,000 inhabitants by economic area, 2000

Sources: US Patent and Trademark Office; CHI Research; County Business Patterns; Cluster Mapping Project, Harvard Business School.

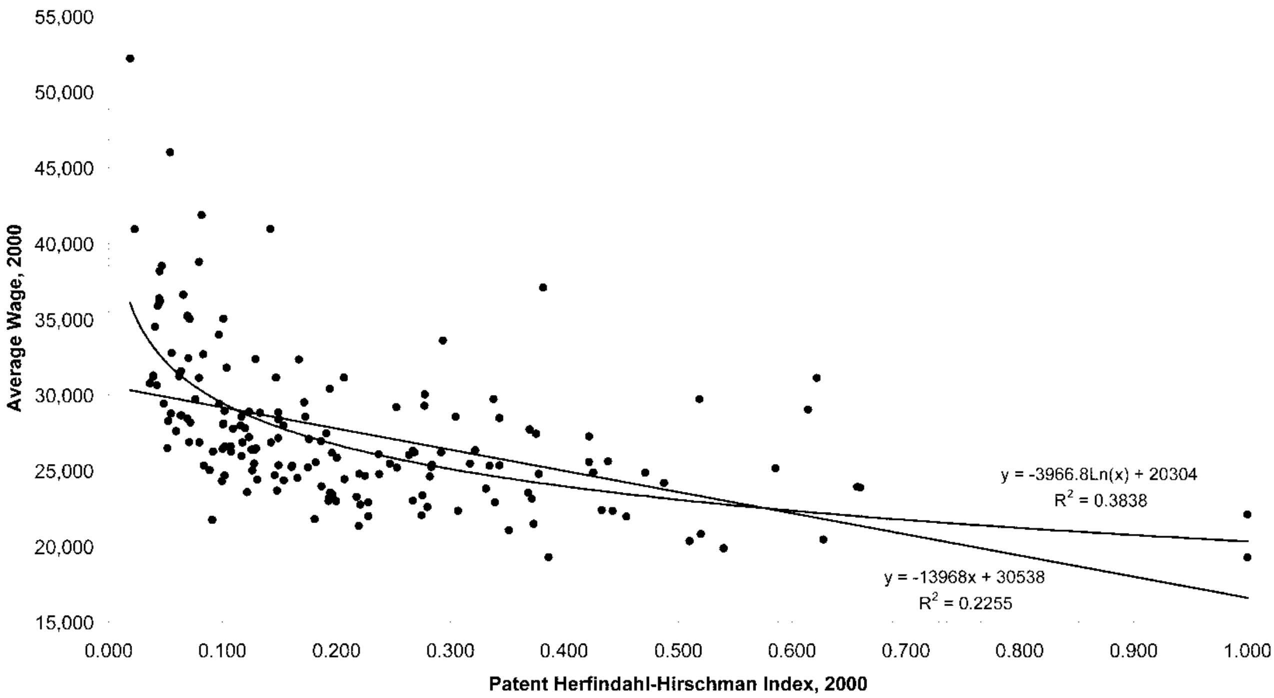

Fig. 15. Average wage vs. patent HHI by economic area, 2000

Sources: US Patent and Trademark Office; CHI Research; County Business Patterns; Cluster Mapping Project, Harvard Business School.

various measures of economic performance differ in urban versus rural areas. While a full analysis of this question is beyond the scope of this paper, we divided all US counties into those that are part of a metropolitan area (847) and those that are not (2,293). Metropolitan (urban) counties account for 80·4% of US population in 2000 and 85·6% of private employment in 2000. The average metropolitan county wage was $35,716 in 2000, far higher (49%) than the $24,004 average in non-metropolitan counties. The CAGR of wages over the 1990 to 2000 period in metropolitan counties was 4·82% versus 3·81% in non-metropolitan counties. However, the CAGR of employment between 1990 and 2000 in metropolitan counties was 2·19%, less than the 2·34% in non-metropolitan counties.

THE COMPOSITION OF REGIONAL ECONOMIES

To explore these marked differences in regional performance further, we examine the differing types of industries that constitute a regional economy. The distribution of economic activity by industry over geography reveals three different broad types of industries, with very different patterns of spatial competition and different drivers of locational behavior. Distinguishing them is essential in testing hypotheses about regional performance.

The first type of industry in regional economies is *local* industries. In these industries, employment that is evenly distributed across all regions – that is, employment is roughly proportional to regional population. Local industries provide goods and services primarily to the local market, or the region in which the employment is located.[12] Such industries compete in only a limited way with other regions. Most are services including local health services, most utilities, retailing and many types of construction. A few goods producing industries are revealed as local, including bottled and canned soft drinks, newspapers, concrete products and ready-mixed concrete.

A second type of industry is *resource dependent* industries. Employment in these industries is located primarily where the needed natural resources are found, but these industries compete with other domestic and international locations. Examples of such industries include uranium ore, logging, beet sugar, and freight transportation on the Great Lakes.

The third type of industries in regional economies is *traded* industries that are not resource dependent. These industries sell products and services across regions and often to other countries. They locate in a particular region based not on resources but on broader competitive considerations, and employment concentration varies markedly by region. Examples of traded industries include aircraft engines and engine parts, motion picture and videotape production, and automobile assembly.[13]

We utilize the actual distribution of employment by industry to separate industries into these three groups, using data for 1996.[14] The CBP data *understates* the true geographic concentration of traded industries by region because the employment related to the local sales, service, distribution and other support activities of traded industries based elsewhere are counted in the local region in which the employment appears, even though the primary and headquarters activities are based elsewhere. This might be termed the local portion of traded industries. We utilize three measures of the variation of industry employment across geography to separate industries: the share of national employment for all states with $LQ \geqslant 1$; the mean location quotient (LQ) for the top five states ranked by LQ; and the employment GINI coefficient.

After examining the pattern of employment across geography in many industries, cutoffs were established for each variable: employment in states with $LQ \geqslant 1$ of $\geqslant 50\%$ of total employment; mean LQ of the top five states $\geqslant 2$; and employment GINI of 0·3. The vast majority of the 879 industries in the SIC system were clearly traded or local based on all three criteria. For the industries that met two but not all three criteria, we examined the actual distribution of employment as well as the industry definitions. Of those 62 industries, 18 were categorized as traded and the rest as local. We also identified a number of industries that were traded based on all three criteria but were local based on the industry definition (mostly retailers). We classified all of those as local after examining the employment distribution.

This process resulted in 241 local industries out of 879. Of the 638 traded industries, 48 had locational distributions and industry definitions tied heavily to the location of resource endowments. Our designation of resource-dependent industries was conservative, and only industries clearly dominated by resource endowments were included. This left 590 non-resource dependent traded industries. Table 1 gives a further breakdown of these industries categorized into goods and services. While the cutoff points used in developing the classifications were arbitrary, modifying the cutoffs led to only minor changes in the results.

Local industries prove to account for by far the largest share of US private employment, or 67%, which is perhaps surprising in an era where geographic borders are seen as having limited economic significance.[15] Even in a global economy and in a nation (the US) with completely open internal borders, two-thirds of

Table 1. Mix of goods and services by industry type

	Traded	Local	Natural endowment dependent
Goods	441	7	37
Services	149	234	11

Table 2. Composition of the US economy by type of industry

	Traded industries	Local industries	Natural endowment dependent industries
Share of employment (%)	31·8	67·4	0·80
Employment growth, 1990–2000 (CAGR) (%)	1·7	2·8	−1·0
Average wage ($)	45,040	27,169	32,129
Relative wage	137·0	82·6	97·7
Wage growth, 1990–2000 (CAGR) (%)	5·0	3·6	1·9
Relative productivity	144·1	79·3	140·1
Patents per 10,000 employees	21·1	1·3	7·0
Number of SIC industries	590	241	48

Notes: 2000 data, except relative productivity which is 1997 data. Relative wage equals the average wage of the class relative to the overall average (average = 100). Relative productivity equals productivity of the class relative to overall average productivity (average = 100).

Source: Cluster Mapping Project, Institute for Strategy and Competitiveness, Harvard Business School.

employment is heavily tied to the local market. The ownership of the parent company in local industries may be based elsewhere, but almost all these jobs are inherently local. It should be noted that while the designation as a local industry always reflects the vast majority of industry employment, there are a relatively few cases where a small segment of a local industry is traded.[16] The disproportionate position of Delaware in commercial banks (SIC 6060), for example, reflects Delaware's role as the state of incorporation for many national companies. Our data do not account for these cases.

Traded industries account for about 32% of employment (see Table 2). Natural endowment dependent industries account for only about 1% of employment. In a highly advanced economy such as the US, industries heavily dependent on natural endowments have declined to a minor part of employment, unlike the case in many developing economies.

While local industries account for the majority of employment, however, traded industries are fundamental to prosperity.[17] The average traded industry wage is $45,040 in 2000 versus $27,169 for local industries. Traded industries also have higher wage growth, much higher productivity and much higher patenting rates (see Table 2).

We calculated average productivity by industry, defined as sales/receipts/shipments per employee, using data from the 1997 Economic Census. While the data is imperfect due to some data suppression and is only available for 1997, traded industries are revealed to have much higher productivity than local industries, consistent with their higher patenting rates and higher wages. Resource dependent industries fall in between.[18]

Traded industries, then, appear to heavily influence the relative prosperity of regions. Competitive success in traded industries creates demand for local industries serving commercial customers, while the higher wages paid by traded industries heavily influence local household demand.

The ratio of traded employment to total employment varies by EA, ranging from 18% in Sarasota-Bradenton, FL (a region with many retirees) to 47% in Hickory-Morganton, NC-TN in 2000 where the wood furniture cluster is located. A plot of total employment versus percentage of traded employment (Fig. 16) reveals no significant relationship, an interesting finding. Most regions tend to fall within a range of traded to total employment of between 26% and 37%, with smaller regions more likely to fall outside the range. This suggests that the presence of an unusually high or low proportion of traded employment may often be due to the misdefinition of true economic regions. Smaller regions, for example, may obtain local products and services from adjacent regions, reducing local employment share. Alternately, some regions may have large communities of retirees or higher proportions of individuals below working age, which can drive up the share of local employment.

There has been a meaningful shift in the composition of the US economy over the last decade, with the percentage of local employment rising from 64·9% in 1990 to 67·4% in 2000. Upon first reaction, this also appears contradictory to the globalization of competition. The rising proportion of local employment may be the result of several factors, including the higher productivity growth of traded industries and the fact that demand for local services tends to go up with prosperity (the 1990s were especially prosperous). An ageing population may also play a part. Also, the trend to greater outsourcing of services arbitrarily shifts the classification of some employment from manufacturing to services. Since many services are local, this boosts local share. Finally, overly broad industry definition may bury traded services in aggregates involving industries that are predominately local. For example, semiconductor chip design, which is traded and highly concentrated geographically, is part of 'engineering services', much of which is geographically dispersed.

The average level of local wages in a region is strongly associated with the average level of traded wages,[19] as shown in Fig. 17. On average, local wage is 66% of traded wage. Yet, the proportion of traded employment to total employment has a weak relationship with the regional average wage. This suggests that the average wage achieved in a region's traded industries tends to determine the local wage and hence drives the region's overall average wage. Hence the causality appears to go from traded wages to local wages, not vice versa.

In order to more precisely explore the role of a region's mix of traded versus local employment in regional average wage, we calculate a mix and level effect. The mix effect sets the average wage of traded

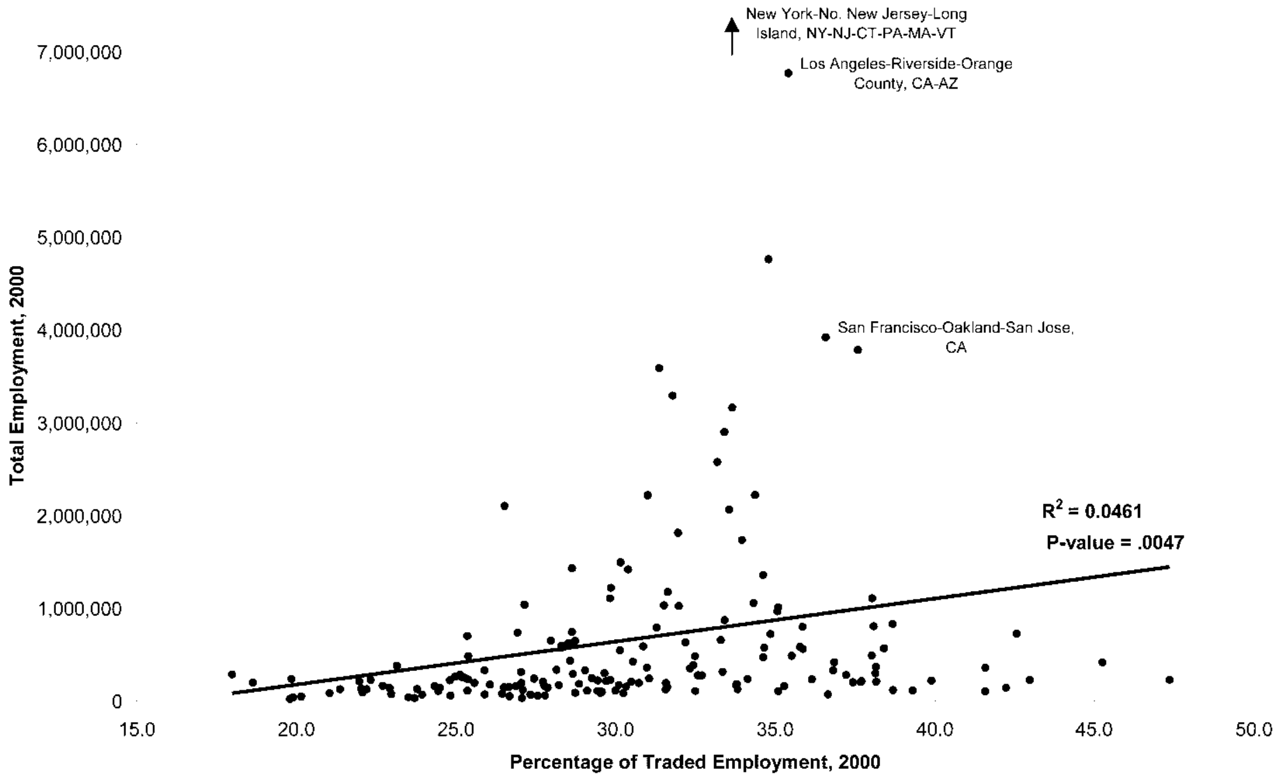

Fig. 16. Employment size vs. percentage of traded employment by economic area, 2000
Sources: County Business Patterns; Cluster Mapping Project, Harvard Business School.

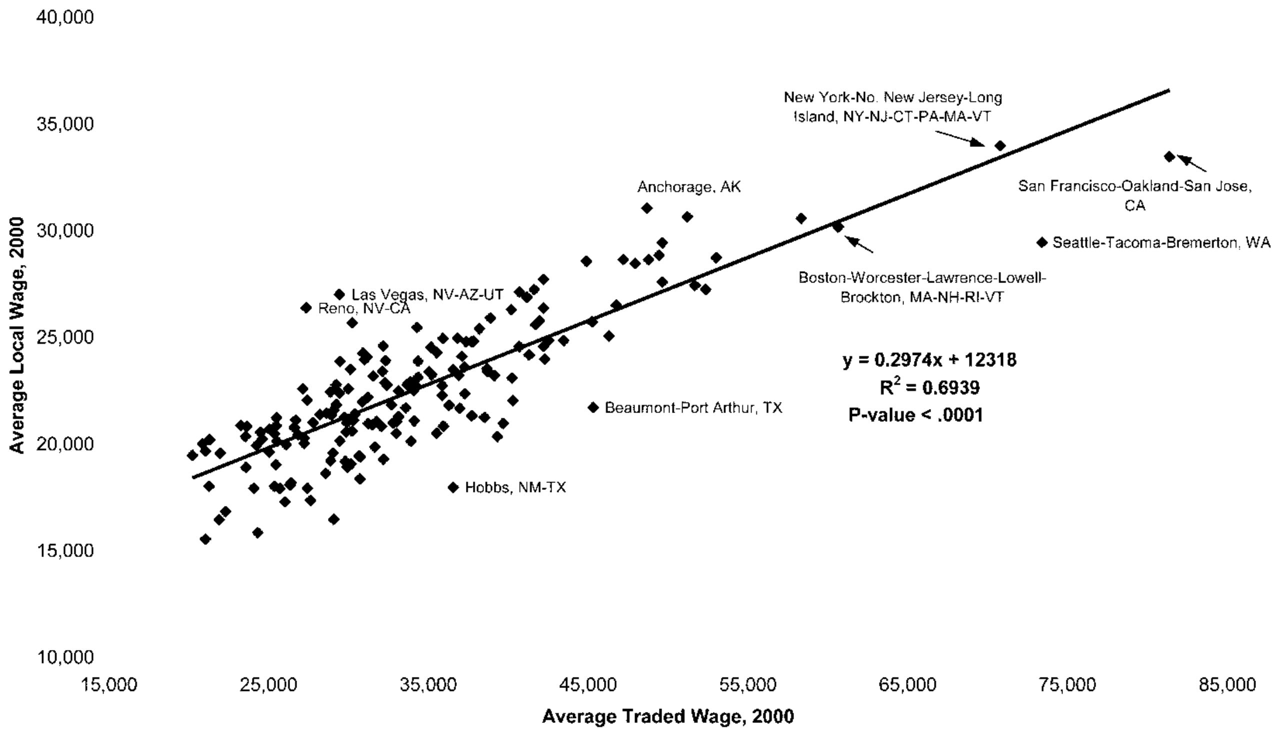

Fig. 17. Average local wages vs. average traded wage by economic area, 2000
Sources: County Business Patterns; Cluster Mapping Project, Harvard Business School.

and local industries at the national averages to isolate the effect of a region's traded–local employment mix on its average wage. The level effect measures the contribution to a region's average wage of the differences between its traded wage and local wages and the national averages weighted by the region's actual mix of traded and local employment. The level effect dominates, accounting for 79·4% of the variation in determining average wages across regions, while the mix effect accounts for just 20·6%. The key for a region, then, is to develop the conditions for supporting high wages in its traded industries, rather than attempting to grow the traded share of the economy.

Finally, we explored the differences in the composition of regional economies between urban and rural areas. Metropolitan counties and non-metropolitan counties prove to have similar shares of traded and local employment. Both traded and local wages are much lower in non-metropolitan areas, while the ratio of traded to local wages is moderately higher in metropolitan counties. Interestingly, the average wages for national endowment industries are nearly identical in urban and rural areas. Metropolitan counties account for a much lower proportion of natural endowment industries than non-metropolitan counties.

CLUSTERS OF TRADED INDUSTRIES

One of the most striking features of regional economies is the presence of clusters, or geographic concentrations of linked industries.[20] We define a cluster as a geographically proximate group of interconnected companies, suppliers, service providers and associated institutions in a particular field, linked by externalities of various types. Examples of clusters are financial services in New York (Wall Street), medical devices in Boston, and IT in Austin, Texas and Silicon Valley. Clusters are important because of the externalities that connect the constituent industries, such as common technologies, skills, knowledge and purchased inputs. Note that a given industry can be part of more than one cluster based on different patterns of externalities. Software, for example, is connected with other IT industries in terms of technology and demand, but also linked with medical devices because software is embedded in many types of devices and software development is crucial to medical device product development.

Recent academic and practitioner literature has placed increasing emphasis on industry clustering as a basic feature of regional and national economies, with an important influence on innovation, competitiveness and economic performance.[21]

The concept of clusters also bears on a debate in economic geography between the relative importance of regional specialization and diversity. This debate is framed predominantly in terms of individual industries. As characterized by Glaeser and colleagues (GLAESER *et al.*, 1992), the so-called MAR framework posits that regional performance will be driven by specialization in a few industries because specialized regions will advance more quickly down the earning curve.[22] Others, notably JACOBS, 1969, argue that regional diversity in a wide array of industries will spark creativity and innovation. We have been associated with MAR. Previous statistical tests, using MSAs as the unit of geography, have mixed results.[23]

The cluster perspective suggests that these hypotheses are too simple, and offers a third hypothesis in between the two extremes. The industry may not be the appropriate unit of analysis because of the externalities across related industries within clusters. The relevant knowledge spillovers that affect innovation and performance should be strongest within cluster and among related industries. Hence, specialization in clusters, not in industries *per se*, should lead to higher performance. Diversity of clusters in a region rather than diversity of industries may also be a more meaningful diversity measure (KETELHÖHN, 2002). A diverse array of overlapping clusters (see below) should be associated with better performance than a diversity of clusters that are unrelated.

A major constraint to the analysis of clusters has been the lack of a systematic approach to defining the industries that should be included in each cluster and the absence of consistent empirical data on cluster composition across a large sample of regional economies. Lack of large sample empirical data is understandable, since knowledge spillovers and other positive externalities are difficult if not impossible to measure directly.

We proceed indirectly, using the locational correlation of employment across traded industries to reveal externalities and define cluster boundaries. For example, if computer hardware employment is nearly always associated geographically with software employment, this provides a strong indication of locational linkages. Such a methodology exploits the unique characteristics of the US economy which is by far the largest economy in the world, in which virtually every industry and cluster in any economy is present, and which consists of a large number of distinct but interdependent regions. This approach is not feasible in most if not all other countries.

We utilized states as the base unit of geography for computing locational correlations for two reasons. First, states involve less data suppression in the CBP data than EAs. Second, starting with larger geographic regions mitigates the problem of artificially high locational employment correlation coefficients when employment in a given traded industry is small or zero in many regions. The use of small regions, then, can cause locational correlation across many industries to appear very high. The relevant geographic unit for a cluster varies by cluster and region. Clusters are often concentrated within a state and, conversely, clusters sometimes cross state lines. However, states are large enough and sufficiently diverse in economic landscape to reveal clusters. After defining clusters using states, we repeated the analysis using EAs. While the correlations were generally higher for EAs, the patterns were nearly identical to clusters defined using states.

Using CBP data for 1996, we identified pairs and then groups of tightly linked industries based on statistically significant locational correlations.[24] Standard clustering algorithms proved inadequate to revealing the multiple patterns of linkages across industries. To build up clusters, then, we proceeded pragmatically, beginning with small groups of obviously related industries and then tracing correlation patterns to others.

The major complexity arises because of spurious correlation, which can occur for several reasons. First, SIC industry definitions tend to be overly broad, hence two industries may be correlated overall though only a small portion of one industry involves the linked products or services. Second, the CBP data do not distinguish between employment in headquarters activities and that employment dispersed to serve local markets. This overstates true traded industry employment in many locations. Third, industries with a major presence in large employment states like California and New York can appear highly correlated with each other even though there is no economic relationship. Fourth, small industries can register small or zero employment in many locations, making them appear correlated. Finally, industries can register high locational correlation if they are part of different clusters that appear in some of the same larger states, either by chance or for historical reasons related to natural resources. The strong position in Michigan of both automotive industries and industries related to office and commercial furniture, for example, creates a statistical correlation between the two groups of industries even though they are located in different parts of the state and have little or no economic relationship with each other.

We employed a sequence of steps to eliminate spurious correlation. First, we used detailed four-digit SIC industry definitions and lists of products included in each industry, together with industry knowledge, to reveal the likely presence of logical externalities. Focused case studies were conducted in unfamiliar industries to better understand the possible externalities present. Second, where there were no apparent externalities, we utilized the National 1992 input–output (I-O) accounts from the Bureau of Economic Analysis to look for meaningful cross-industry flows.[25] Note that input–output links are just one of many forms of externalities or linkages between industries within a cluster, but have the advantage that systematic data is available even though industry definitions in the I-O tables are more aggregated than the four-digit SIC codes we employ. Where there was no logical externality *and* the I-O data revealed no meaningful product flows, a correlation pair was excluded as spurious. Through this sequence of steps, we eliminated those pairs of correlated industries where there was no apparent basis for linkages.

This process resulted in 41 traded clusters in the US economy, with an average of about 29 industries each.[26] Each cluster has a different geographic pattern of employment. Clusters often contain both manufacturing and service industries as well as industries from various parts of the SIC system. Clusters, then, represent a different way of dividing the economy than is embodied in conventional industrial classification systems that are based primarily on product type and similarities in production.

We expected overlap of industries across clusters, and such overlap was indeed present empirically. Total cluster employment including overlap is 204% of total traded employment in 2000. So that, on average, each industry is part of about two clusters. Fig. 18 provides a schematic representation of those clusters with substantial overlap. Some clusters are linked with several others, such as education and knowledge creation (significant overlap with eight other clusters) and analytic instruments (significant overlap with seven other clusters). Other clusters (e.g. textiles forest products, distribution services) are relatively independent.

The presence of overlapping industries across clusters leads to double counting of employment. In order to eliminate double counting for some analyses, we designated *broad* and *narrow* cluster definitions. Broad cluster definitions include all the industries included in a cluster. Narrow cluster definitions involve assigning each industry to the single cluster with which it has the strongest locational correlation. Here clusters are mutually exclusive.

We also subdivided each cluster into *subclusters*. Subclusters are subgroups of industries *within* the cluster whose locational correlations with each other were higher than with remaining industries. Subclusters are important because they can differ in sophistication, wage and patenting rates. Different regions often have differing concentrations in some subclusters relative to others.

Separate subclusters were defined for the set of industries included in the narrow cluster definition and those in the remaining industries. In most cases, subclusters were quite sharply delineated. In other cases, judgements based on detailed industry definitions were made or subclusters were designated with only one constituent industry. In all, there were 264 subclusters for narrowly defined clusters, or an average of 6·4 subclusters per cluster. There were a total of 550 subclusters for broadly defined clusters, or an average of 13·4 (see Appendix B).

Table 3 lists the 41 clusters together with some key parameters of each cluster using narrow cluster definitions. The clusters vary substantially in employment, average wages, employment growth and wage growth. The largest cluster is business services, which employed 4,667,320 in 2000. The average cluster

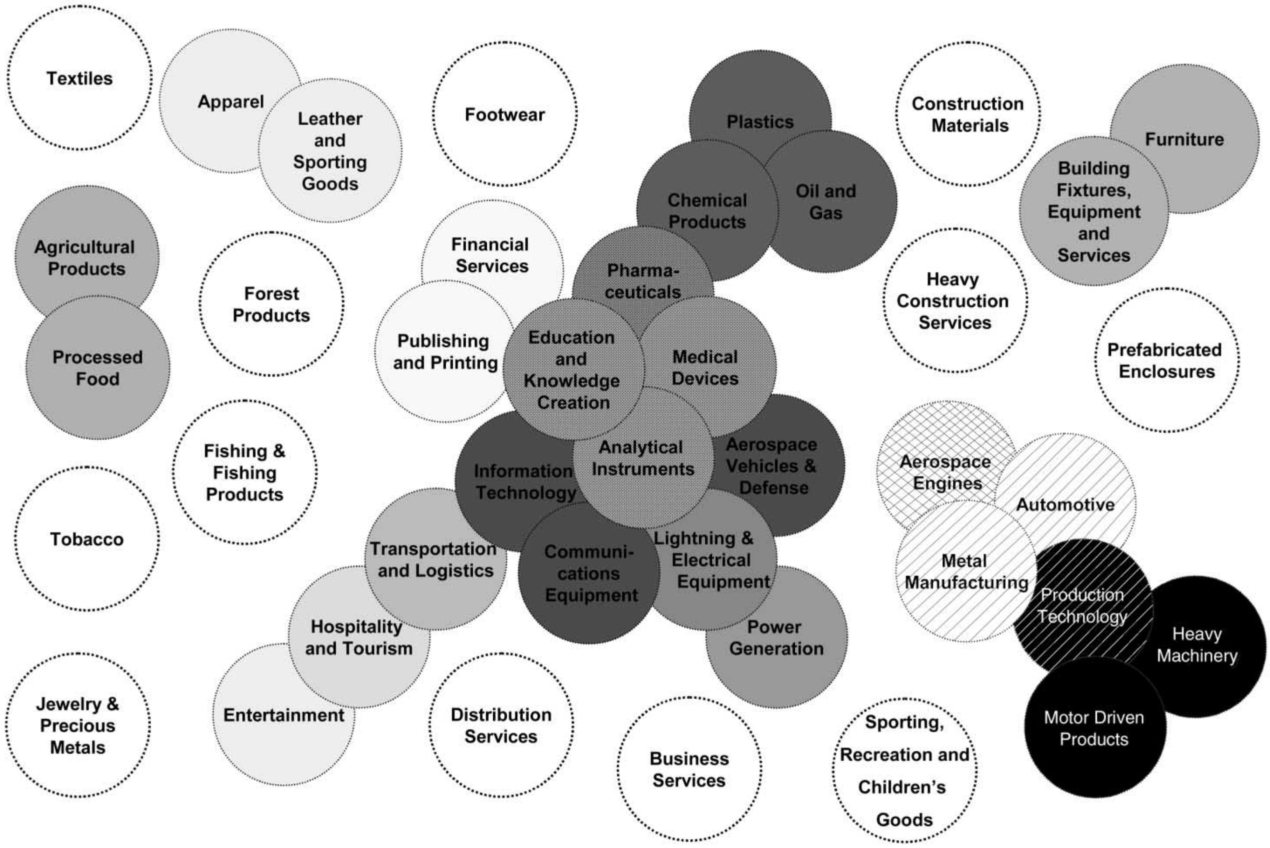

Fig. 18. *Schematic diagram of cluster overlap in the US economy*

Note: Clusters with overlapping borders or identical shading have at least 20% overlap (by number of industries) in both directions.

employed 854,352 workers. The smallest cluster, footwear, employed only 23,962 workers in 2000. Average cluster wages in 2000 ranged from $93,024 in information technology to $21,229 in hospitality and tourism (see Table 3).

Clusters normally designated as 'high-tech' – aerospace engines, aerospace vehicles and defence, analytical instruments, biopharmaceuticals, communication equipment, information technology and medical devices – account for just 8·9% of traded employment and 2·8% of total US private employment. The average high-tech cluster wage is $63,972 versus $43,183 for other clusters. The proportion of high-tech employment has a meaningful impact on a region's average wage, which explains 27·0% of the variation in regional average wages. However, high-tech share explains 12·5% of the variation in the average wage in *non*-high-tech clusters, and 14·4% of the variation of *local* wages. Hence success in high-tech clusters does not just raise wages directly, but signals an ability to compete productively and sustain higher wages elsewhere in the economy.

We found that regional high-tech share had no meaningful relationship with employment growth. Also, regions that are growing their high-tech share do not have higher wage *growth* in the region as a whole, nor is growth in high-tech share associated with higher wage growth in non-high-tech clusters.

Rather than focusing solely on developing 'high-tech' clusters, then, our data reveal that regions need to upgrade *all* the clusters that are present. This conclusion is verified by a statistical partitioning of the sources of regional wage differences to be discussed below.

A given cluster can register substantially different average wages in different regions, due to differences in its sophistication and productivity, patterns of unionization and cost of living. In the automotive cluster, for example, Michigan's 296,002 workers in 2000 earned an average wage of $58,799 versus $34,655 in California, $32,814 in Tennessee and less than $30,000 in Georgia and Alabama (see Table 4). Regional sophistication is revealed in part by the particular subclusters in which the region is strong.

Patenting rates also vary markedly by cluster (see Fig. 19). Measured by patenting per 10,000 employees, the communications equipment cluster has the highest patenting rate of 205 in 2000; the patenting rate in a number of service clusters is negligible in part due to the fact that patents are not the leading form of intellectual property protection in these clusters. The patenting intensity of a given cluster also varies substantially across regions, as shown for the biopharmaceuticals cluster (see

Table 3. Traded clusters in the US economy: narrow cluster definition

Cluster	Employment, 2000	CAGR of employment, 1990–2000	Job growth rank	Average wage, 2000 ($)	Wage rank	CAGR of average wage, 1990–2000	Wage growth rank
1 Business services	4,667,320	5·6	1	56,699	5	6·0	4
2 Financial services	3,242,151	2·4	12	74,237	2	7·8	2
3 Hospitality and tourism	2,565,077	2·5	10	21,229	41	4·4	11
4 Education and knowledge creation	2,246,974	3·4	4	33,453	29	5·0	8
5 Distribution services	1,962,523	3·3	5	51,110	10	5·4	5
6 Heavy construction services	1,883,271	3·1	7	37,123	21	3·0	36
7 Transportation and logistics	1,644,641	3·1	8	36,642	23	2·3	41
8 Metal manufacturing	1,412,368	0·4	19	38,052	20	3·0	34
9 Processed food	1,388,073	0·2	22	33,646	28	3·0	35
10 Automotive	1,386,153	1·6	15	45,941	15	3·3	29
11 Entertainment	1,057,193	5·1	2	38,668	19	4·2	14
12 Publishing and printing	983,152	−0·1	24	41,369	17	4·2	15
13 Plastics	874,482	1·9	13	34,328	27	3·1	32
14 Information technology	860,230	3·1	6	93,024	1	9·7	1
15 Analytical instruments	744,832	−1·6	35	53,247	9	4·8	9
16 Building fixtures, equipment and services	670,048	1·7	14	30,286	33	3·4	27
17 Production technology	665,382	0·3	20	40,452	18	3·5	25
18 Apparel	559,276	−5·1	39	21,444	40	3·9	17
19 Chemical products	438,967	−1·7	36	48,974	11	3·6	24
20 Communications equipment	425,332	−0·3	26	56,884	4	6·2	3
21 Heavy machinery	411,940	−0·4	30	36,987	22	2·9	37
22 Motor driven products	408,427	−0·4	28	35,601	25	3·1	33
23 Textiles	402,839	−3·3	37	28,962	35	3·7	23
24 Forest products	392,080	−0·4	27	42,222	16	2·7	38
25 Furniture	379,108	0·2	21	24,904	38	3·9	18
26 Medical devices	372,442	2·5	11	47,880	13	5·2	6
27 Oil and gas products and services	370,192	−1·2	33	53,734	7	4·4	12
28 Aerospace vehicles and defence	367,315	−6·3	40	56,118	6	3·8	20
29 Lighting and electrical equipment	329,723	−0·2	25	36,178	24	3·7	22
30 Prefabricated enclosures	317,080	2·6	9	32,206	30	2·6	39
31 Power generation and transmission	290,896	3·6	3	57,272	3	5·0	7
32 Agricultural products	265,260	0·1	23	29,405	34	3·3	30
33 Biopharmaceuticals	264,319	0·8	16	48,452	12	3·4	28
34 Construction materials	199,051	0·6	18	31,120	32	3·4	26
35 Leather products	133,253	−1·6	34	27,789	36	4·2	16
36 Jewellery and precious metals	126,621	−0·4	29	34,393	26	3·9	19
37 Sporting, recreational and children's goods	107,064	0·8	17	31,577	31	4·4	13
38 Aerospace engines	94,360	−4·2	38	53,277	8	3·8	21
39 Fishing and fishing products	51,222	−0·7	31	27,320	37	3·3	31
40 Tobacco	43,843	−1·0	32	47,703	14	2·6	40
41 Footwear	23,962	−9·3	41	22,323	39	4·7	10
Total traded employment	35,028,441						
Average cluster employment	854,352						
Standard deviation of cluster employment	967,019						

Fig. 20). This reflects differences in sophistication and subcluster mix by region. Also, cluster employment in regions without a strong cluster in that field tends to be dominated by the local activity of companies based elsewhere. Such activity, including sales and customer support, often does not involve R&D and innovation. Regions with small absolute employment and LQ $\leqslant 0{\cdot}5$ are areas where employment in a cluster is not usually a sign of competitive advantage.

Differences in cluster position across regions

Most states register some employment in many clusters, in part due to the reporting of local employment of companies based elsewhere. In most clusters, there is employment in at least 40 states and 160 (of 172) EAs. Footwear, the least represented cluster, has employment in just 24 states and 86 EAs in 2000.

About 83% of traded employment in the average EA is concentrated in its top 15 clusters in 2000, and 71% is concentrated in the top 10 clusters. This is modestly higher than the concentration of traded

Table 4. Automotive cluster employment and wages in 2000: selected states

State	Average wage, 2000 ($)	Employment, 2000	Share of national cluster employment (%)
Michigan	58,799	296,002	21·4
Ohio	49,160	182,687	13·2
Indiana	47,981	134,534	9·7
Illinois	42,125	57,728	4·2
Wisconsin	39,859	54,307	3·9
Pennsylvania	39,804	36,289	2·6
Minnesota	37,847	19,270	1·4
Kentucky	35,242	56,257	4·1
North Carolina	35,037	43,315	3·1
California	34,655	66,625	4·8
South Carolina	34,243	32,231	2·3
Tennessee	32,814	71,455	5·2
Missouri	30,508	44,601	3·2
Georgia	29,622	31,617	2·3
Alabama	28,935	16,357	1·2
US automotive cluster average	45,941	1,386,153	

employment by the top 10 and 15 clusters for the economy as a whole.

The mix of clusters, however, varies markedly across regions. Of the 41 clusters, 24 are the largest cluster for at least one EA in 2000, and 12 are the largest cluster for at least one state. The average standard deviation of employment rank of a given cluster in a region minus the US rank for that cluster is 7·3 for states and 8·5 for EAs. Business services, the largest cluster, is ranked number one in just 38 of 172 EAs and ranks as low as 19. Other examples are the information technology cluster whose rank ranges from 1 to 40; agricultural products 1 to 37; and plastics 3 to 38.[27]

Variation in regional specialization over time

To explore whether regions are becoming more or less specialized by cluster, we calculated GINI coefficient measuring the inequality of the *employment* distribution among the 41 traded clusters within states and EAs. The majority of states (35) had a positive change in the GINI coefficient over the 1990–2000 period signifying greater specialization, while 16 had a negative change. The corresponding figures for EAs are 72 and 100. State economies are tending to become more specialized by cluster, while EAs, which are smaller, are more mixed.[28]

Fig. 21 plots the change in employment GINI versus wage growth by state for the 1990 to 2000 period. States that are becoming more specialized have higher wage growth, with the proportion of explained variance 25·5% (the results are similar for EAs). This provides provocative though not definitive evidence that specialization of a region in an array of stronger traded clusters boosts regional performance.

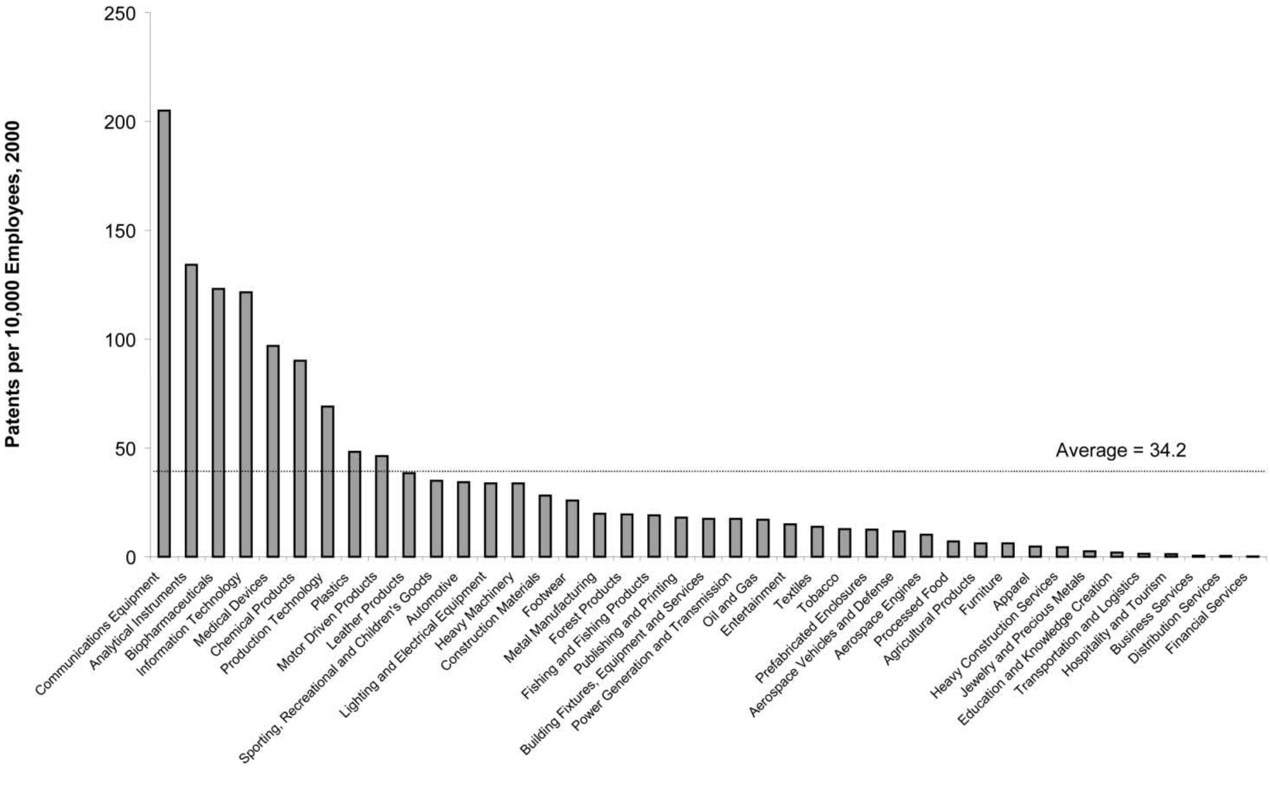

Fig. 19. US patents per 10,000 employees by traded cluster, 2000

Sources: US Patent and Trademark Office; CHI Research; Cluster Mapping Project, Harvard Business School.

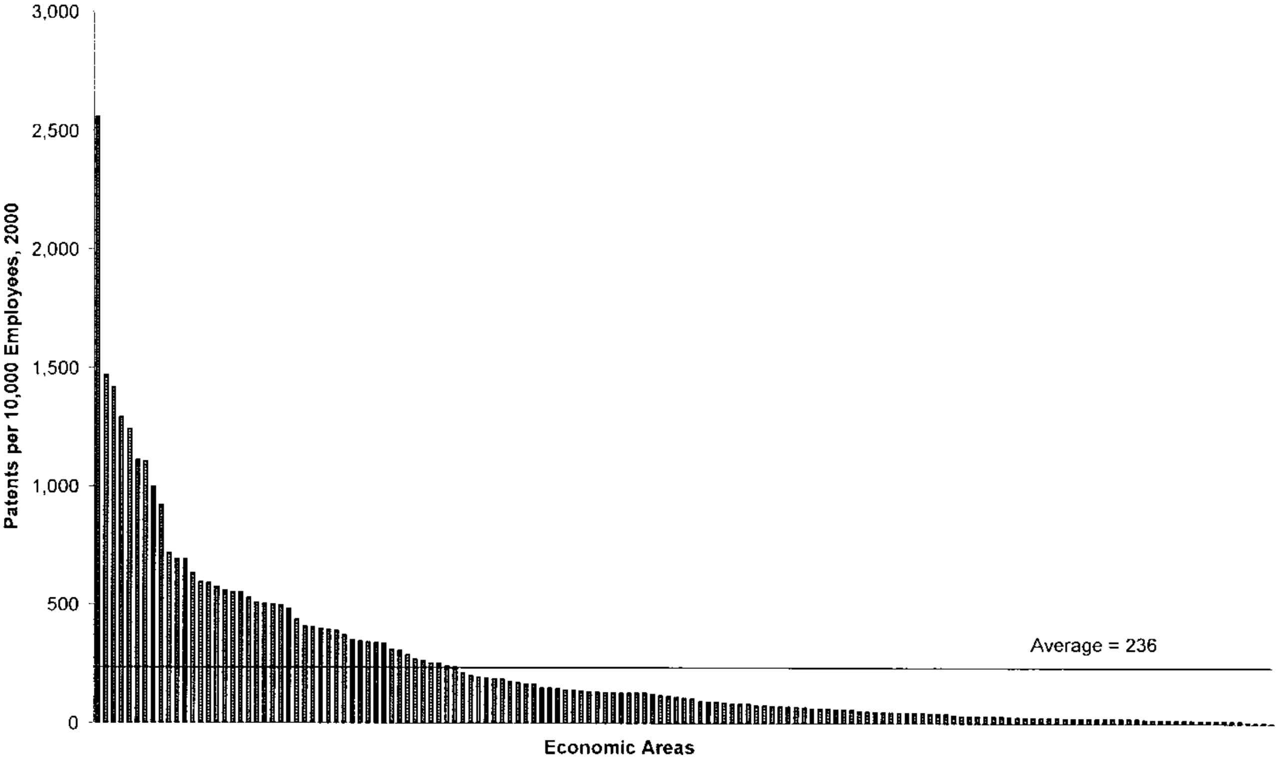

Fig. 20. Patents per 10,000 employees in the biopharmaceuticals cluster by economic area, 2000
Sources: US Patent and Trademark Office; CHI Research; Cluster Mapping Project, Harvard Business School.

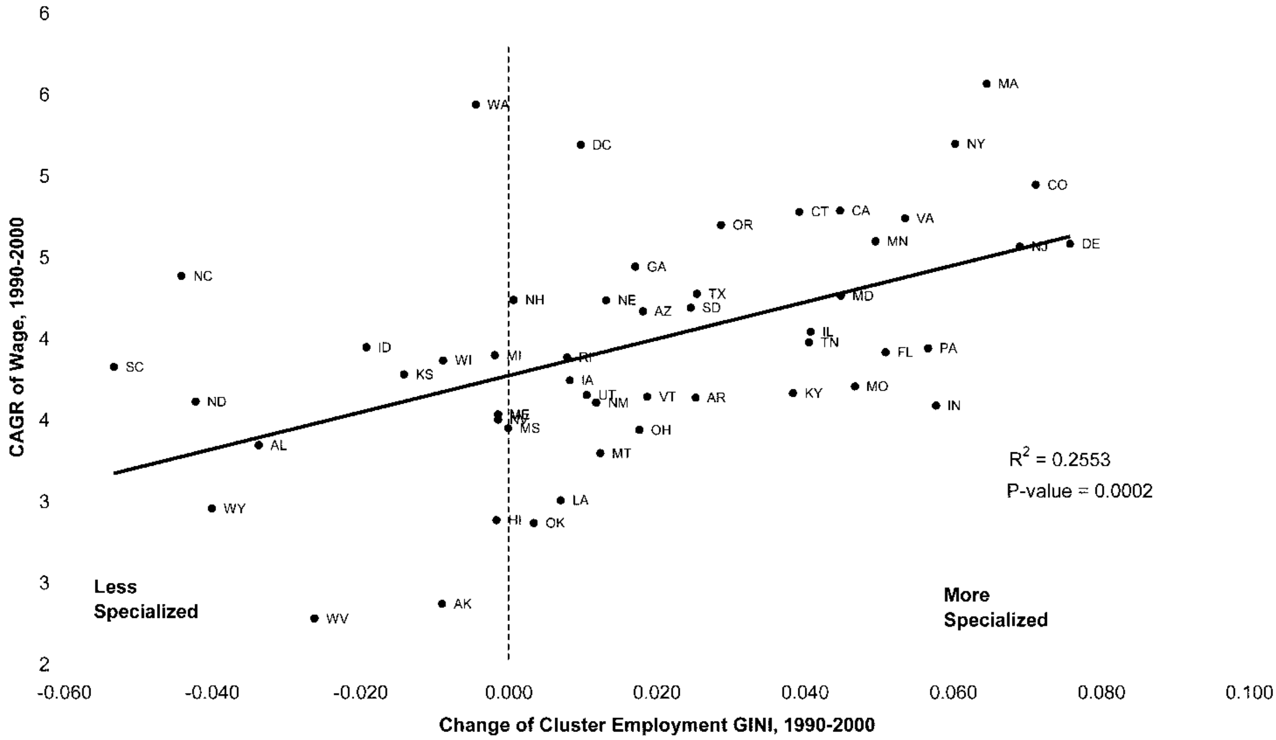

Fig. 21. Wage growth vs. change of cluster employment GINI by state, 1990–2000
Sources: County Business Patterns; Cluster Mapping Project, Harvard Business School.

Table 5. Variation in cluster concentration, 1990–2000

Strong cluster employment defined as LQ > = 0·8 → **Strong cluster employment defined as LQ > = 1** ↓	Concentrating in fewer regions	Dispersing across regions
Concentrating in few regions	Aerospace engines	Aerospace vehicles and defence
	Education and knowledge creation	Agricultural products
	Entertainment	Chemical products
	Fishing and fishing products	Footwear
	Metal manufacturing	Forest products
	Oil and gas products and services	Hospitality and tourism
	Production technology	Information technology
	Publishing and printing	Motor driven products
	Sporting, recreational and children's goods	Prefabricated enclosures
Dispersing across regions	Analytical instruments	Apparel
	Automotive	Biopharmaceuticals
	Financial services	Building fixtures, equipment and services
	Heavy construction services	Business services
	Haevy machinery	Communications equipment
	Jewellery and precious metals	Construction materials
	Leather products	Distribution services
	Plastics	Furniture
	Power generation and transmission	Lighting and electrical equipment
	Processed food	Medical devices
	Transportation and logistics	Textiles
		Tobacco

Variation in cluster concentration over time

To explore whether clusters themselves are becoming more or less concentrated in a few regions over time, we calculate the share of regions with strong employment in the cluster (LQ $\geqslant$ 0·8 or LQ $\geqslant$ 1·0 using narrow cluster definitions) to total US employment in the cluster.[29] We use these cutoffs, lower than in some investigations, because the presence of the downward bias in LQ due to the pervasive presence of local employment of cluster companies with headquarters located elsewhere. This means that most regions will have some employment in almost every cluster even though the region has no meaningful competitive position.

Clusters with a positive change in the proportion of employment in strong clusters from 1990 to 2000 are getting more concentrated. Those with a negative change are getting more dispersed. Since the use of a single cut-off value for LQ is sensitive to small changes on the margin (e.g. a change of LQ from 0·99 to 1·0 can shift strong cluster employment share), we explored a range of cut-off values. As shown in Table 5, nine clusters are becoming more concentrated using both cutoffs, while 12 clusters are getting more dispersed using both cutoffs. The balance show different trends for each cutoff, suggesting a shifting distribution of cluster positions across regions.

Explaining regional wage differences: cluster mix vs. relative wage level

Since the average wage varies by traded cluster, we explored the relative contribution to the regional average traded wage of the mix of clusters versus the relative level of wages achieved for given clusters.[30] The level of wages for a given cluster can also vary across regions due to differences in sophistication, productivity and subcluster structure. The cluster mix effect is the sum of the differences in each cluster's employment share versus the national average times the cluster's national average wage. The level effect is the sum of the difference between the region's cluster wage and the national average cluster wage times the region's employment in the cluster (see Appendix C).

The Las Vegas EA provides a striking demonstration of the two effects. Competing disproportionately in the cluster with the lowest average wage, hospitality and tourism, Las Vegas is ranked 171 out of 172 regions on the cluster mix effect. However, Las Vegas significantly outperforms the national average in hospitality and tourism cluster average wage, contributing to a high level effect for the region (ranked tenth nationally).

On average, the level effect accounts for 75·7% of the variation in average wages across regions, versus 24·3% for the cluster mix effect. The reason is that mix differences do not account for large enough shifts in employment to move a region's average wage relative to the impact of overperformance or underperformance in terms of wages in each cluster. A region's ability to compete in its array of clusters with higher productivity (e.g. better product quality, more advanced service delivery) has the decisive influence on the region's prosperity. This finding carries important implications of economic development. Many regional economic development initiatives focus heavily on shifting the mix to more 'desirable' clusters. An equally if not more important policy focus is to upgrade the productivity of *all* the clusters in which the region has a meaningful position.

The cluster mix and level effects for all EAs are plotted in Fig. 22. Many of the level effects are negative because a few large regions have a higher average wage than the US average – the median level effect is −\$13,387. The average mix effect is also negative (−\$3,622) because large regions tend to have a higher proportion of higher average wage clusters.

We can apply the same approach to examine the components of the large difference in wages between metropolitan and non-metropolitan counties. Traded share of employment is not a major influence. The overwhelming majority (82·3%) of the metro–non-metro differences is due to lower relative wage levels in traded and local industries, not the share of each. Hence, the imperative for non-metropolitan counties is to develop the conditions for supporting

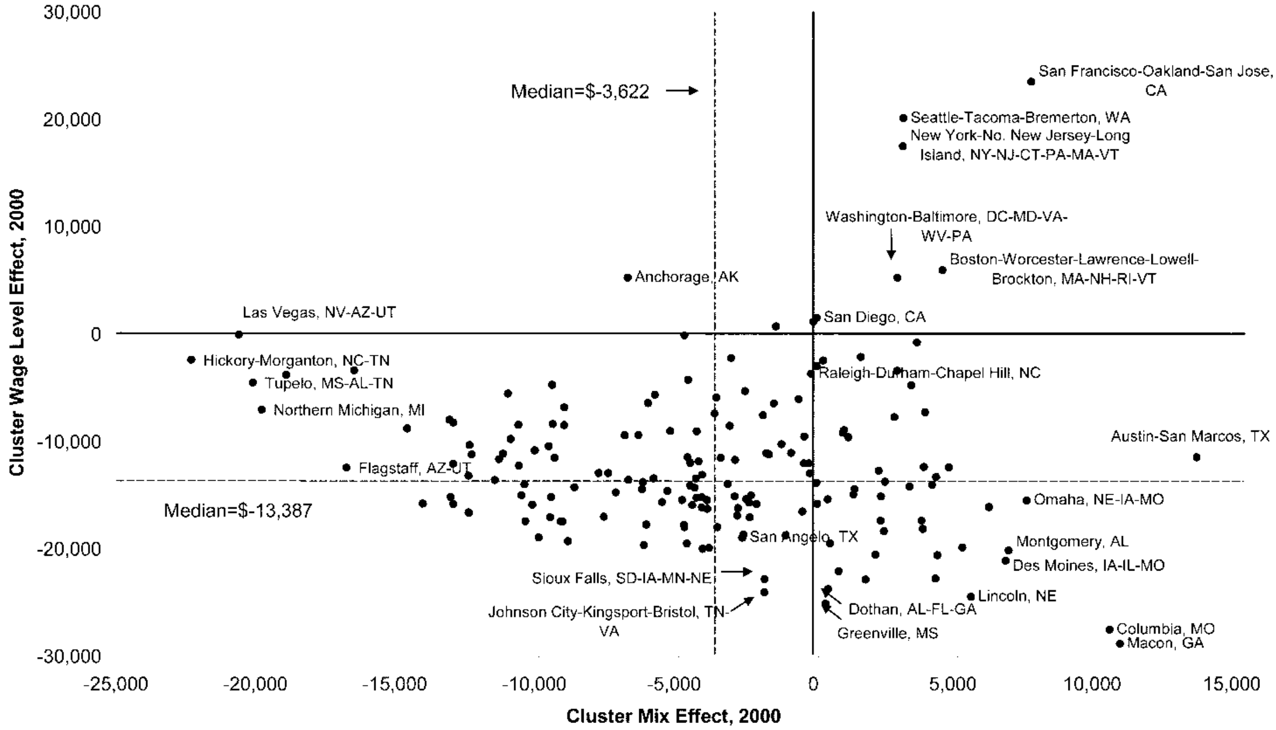

Fig. 22. Cluster wage level effect vs. cluster mix effect by economic area, 2000

Sources: County Business Patterns; Cluster Mapping Project, Harvard Business School.

high wages in their traded industries. Metropolitan and non-metropolitan counties have substantially different traded cluster composition, and skewed toward lower wage clusters. The cluster mix effect accounts for 52·3% of the difference in average traded wages between metropolitan and non-metropolitan counties, while the level effect accounts for 47·7%. For non-metropolitan counties, then, shifting the mix to more 'desirable' clusters is of about equal priority to raising the relative level of the wages of the clusters they have positions in.

The importance of leading clusters and regional performance

It is widely believed by practitioners and some economic development thinkers that reliance on a few clusters is dangerous for regional economic development because it exposes a region to shocks and business cycles. Many regions, then, set a goal of diversifying the clusters present. Fig. 23 reveals that this hypothesis is not borne out by the data, at least in its simplest form. There is no clear relationship between the importance of the leading clusters (measured by the employment of the top three clusters as a percentage of total traded employment), and average wages. The same is true of wage growth, employment growth and patenting. The results are nearly identical using the top five clusters.

Cluster strength and regional wages

We constructed several measures of the strength of a region's array of clusters, measured by the proportion of traded employment accounted for by strong clusters ($LQ \geqslant 0{\cdot}8$ or $LQ \geqslant 1{\cdot}0$) using both narrow and broad cluster definitions. The use of broad cluster definitions to measure cluster strength gives weight to the industries that overlap within a region's clusters, and measure crudely the extent of potential cross-cluster spillovers. The proportion of strong clusters in the economy should be positively related to productivity and hence average wages.

All four measures of cluster strength have a positive and mostly statistically significant relationship with average wages as well as other measures of regional performance metrics. Interestingly, cluster strength measured using broad cluster definitions has a stronger and markedly more significant positive relationship with regional wages, shown in Fig. 24.

Regional patenting rates by cluster

Patenting rates should increase with the size and depth of clusters due to more vigorous competition and greater spillovers among firms and institutions in the region.[31] We utilize the proportion of traded employment in strong clusters ($LQ \geqslant 0{\cdot}8$) using broad cluster definitions as an overall measure of the strength and depth of clusters since it measures not only strength within each cluster but also the extent of overlap among a region's clusters and hence spillovers among them. Fig. 25 reveals a positive and significant relationship between the patenting rate and the share of traded employment in strong clusters using negative binomial regression.

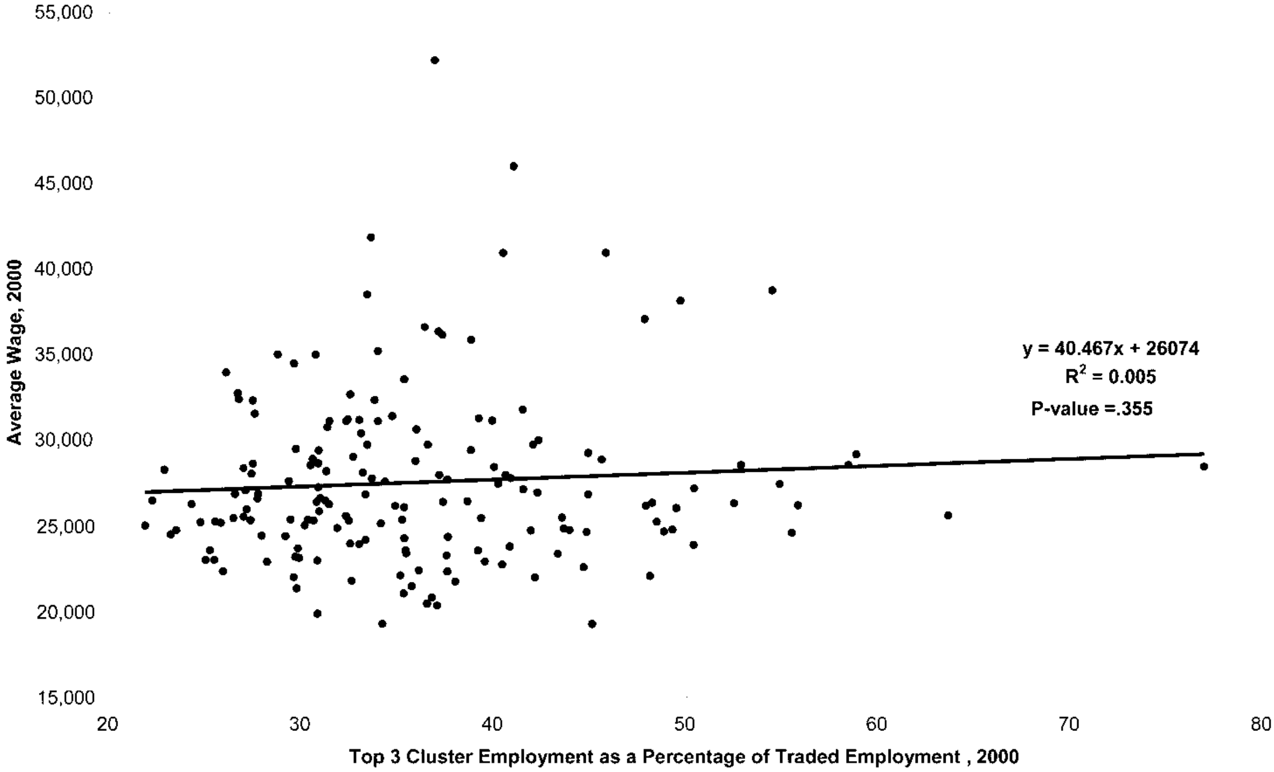

Fig. 23. Average wages vs. the importance of leading clusters by economic area, 2000
Sources: County Business Patterns; Cluster Mapping Project, Harvard Business School.

Fig. 24. Average wage vs. share of traded employment in strong clusters,[1] 2000
Note: 1. Broad cluster definitions.
Sources: US Patent and Trademark Office; CHI Research; County Business Patterns; Cluster Mapping Project, Harvard Business School.

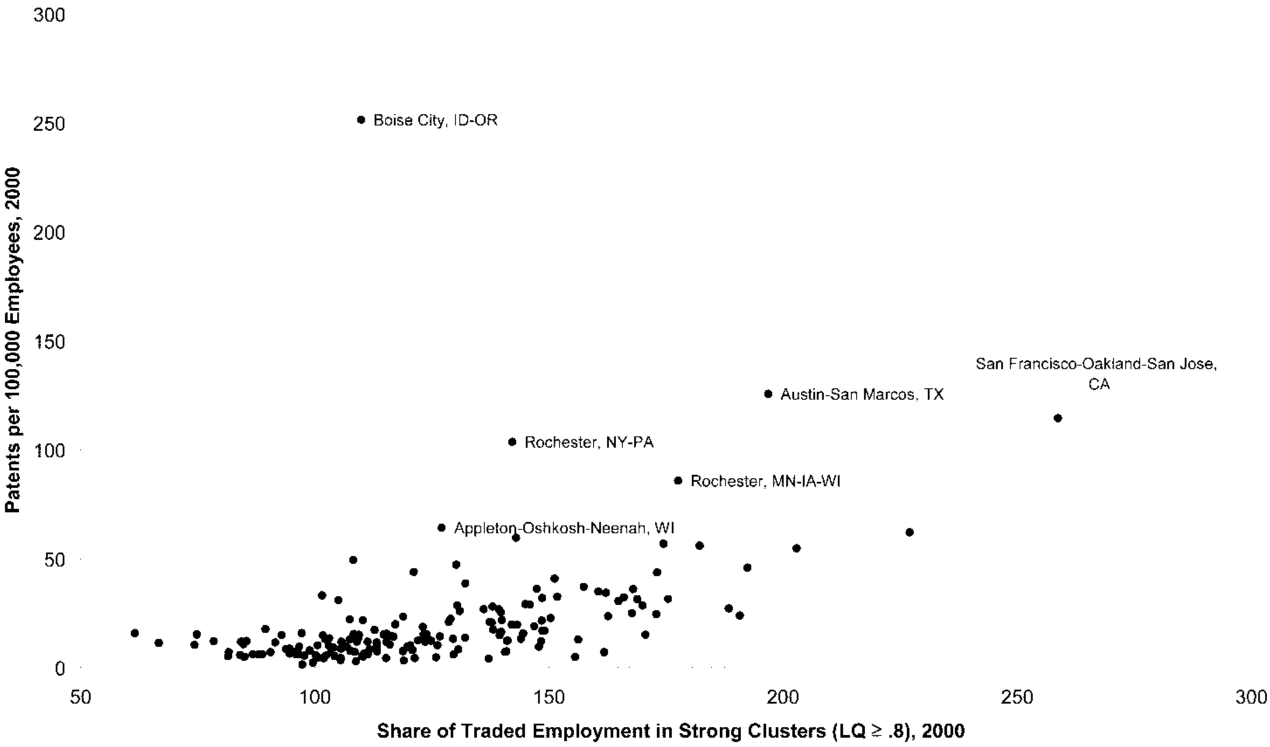

Fig. 25. *Patents per 100,000 inhabitants vs. share of traded employment in strong clusters,*[1] *2000*

Note: 1. Broad cluster definitions.

Sources: US Patent and Trademark Office; CHI Research; County Business Patterns; Cluster Mapping Project, Harvard Business School.

SUMMARY AND CONCLUSIONS

This paper reveals the striking importance of regional economies to the overall performance of nations, using the data from the US economy. The performance of regional economies varies markedly in terms of wages, wage growth, employment growth and patenting. National performance, then, is a composite of very different levels of regional performance. Regional economies differ moderately in their proportion of traded, resource-dependent and local industries, and differ markedly in the mix of clusters present. Regional economic performance is strongly influenced by the traded clusters which appear to shape wages in local industries. Relative wages in traded industries drive regional wage differences, dominating the influence of differences in the proportion of traded employment. Regional economic performance is strongly affected by the strength of clusters and the vitality and plurality of innovation. Regional performance differences are dominated by relative wage levels in the array of clusters that are present in a region, rather than the particular mix of clusters itself.

Our findings suggest that regional analysis must become far more central to research and policy formulation in competitiveness and economic development. Our results reveal the need for much of economic policy to be decentralized to the regional level. Since many of the essential determinants of economic performance appear to reside in regions, national policies will be necessary but not sufficient. The importance of regions may explain why countries with greater economic decentralization, such as Germany and the US, have been historically successful. It may also explain why countries such as India and China are making notable economic progress in particular states or provinces relative to others.

Our findings highlight the need for regional economic development policies to be particularly attuned to traded clusters, because these not only support higher wages but also appear to drive local employment and especially local wages. Regions should focus on upgrading the productivity of all clusters in which they have a meaningful position, rather than attempting to migrate to more 'desirable' clusters. Also, the importance of building innovative capacity at the regional level is strongly revealed, as is the benefits of diversifying the companies and institutions that generate innovative output.

Acknowledgements – This paper has benefited greatly from sustained research over a multi-year period by Daniel Vasquez, Elisabeth deFontenay, and especially Weifeng Weng in assembling the dataset, statistically deriving the composition of regional economies, defining clusters and performing the numerous analyses contained here. We are grateful to the Harvard Business School and Sloan Foundation for supporting the Cluster Mapping Project from which the paper is drawn, and to the editors and anonymous referees for helpful comments.

NOTES

1. See especially GLAESER *et al.*, 1992; HENDERSON *et al.*, 1995; HARRISON *et al.*, 1996; BAPTISTA *et al.*, 1998; FELDMAN *et al.*, 1999; HENDERSON, 1999; and KETELHÖHN, 2002.
2. There is some empirical literature on regional performance. The work of BORTS and STEIN, 1964, is one of the earliest and best-known efforts to test neoclassical explanations of regional growth disparities.
3. For example, see PORTER, 2003, for further statistical findings on regional differences in wages, wage growth and patenting.
4. CBP data is suppressed if the disclosure would compromise the data for a particular company. CBP data is made available at the county, state and US level. Economic area and metropolitan statistical area data are built up from the county file, which has the most data suppression problems. The state file has fewer suppression problems, mostly at cluster level. The national data is virtually free of suppression. When data is suppressed, a range is reported for the employment data. We utilize the mid-point in the range in our data. For payroll data, no information is provided when data is suppressed. Employment figures are therefore less affected than wage data.
5. The US Patent and Trademark office requires inventors to list their home address. CHI Research assigns patents to counties based on the county in which the inventor's residence is located. We would prefer attributing the patent to the work address, but this information is not available. In practice, the difference due to the use of home versus work addresses is quite small. Using EAs as the unit of analysis largely alleviates the problem since almost all of the commuting is within EAs.
6. Co-location of industries does not guarantee interaction or spillovers, but consistent co-location across many regions creates a strong presumption that such interactions are present.
7. Both full-time and part-time employees are reported in CBP. Since there is no reason to expect major differences in the mix of full-time and part-time workers across regions, there should be little bias introduced in examining the key relationships. However, reported wage differences across clusters may be affected, especially in the hospitality and tourism cluster.
8. For each year, EAs are sorted in descending order by average wage, then grouped into deciles. All decile groups contain 17 EAs, except for the first and last, which contain 18. The decile group with the lowest wages is marked as group 1, and the one with the highest wage is group 10.
9. Discussions of the relative merits of using patents as a proxy for innovative activity can be found in GRILICHES, 1984, 1990; JAFFE, 1986; DOSI *et al.*, 1990; and TRAJTENBERG, 1990. Some have used occupational data to explore patterns on innovation, but such data is only available for regions as a whole and, unlike patents, cannot be assigned to individual industries. Also, output oriented measures of innovation such as patenting offer advantages over input measures.
10. This is an implication of the theory of clusters, which is discussed in PORTER, 1998.
11. Patents filed by individuals unaffiliated with a specific organization are excluded in the patentor analysis.
12. Such industries have been termed residentiary – see VINING, 1946; NORTH, 1955.
13. Such industries have been termed export industries, although the definition of these varies from industries that export internationally to industries that export across regions. We define traded industries statistically using locational patterns. The export-based theory can be dated to INNIS, 1920. See ARMSTRONG and TAYLOR, 1985; LEICHENKO and COULSON, 1999; and LEICHENKO, 2000; for comprehensive reviews. Past studies have examined broadly defined sectors or manufacturing as a whole. Our focus is on the cluster and industry level.
14. The categorization is highly stable from year to year.
15. VINING, 1946, finds that employment in residentiary industries was about 55% of a state's total employment. Our figure is higher, which is consistent with the somewhat faster employment growth in local industries for the decade of the 1990s for possible reasons discussed in the paper.
16. This is a case of overly aggregated industry definitions, which will be discussed further below.
17. There was a debate on the relative importance of export and residentiary industries between North and Tiebout in the 1950s. NORTH, 1955, 1956, states that regional growth 'is closely tied to the success of its exports and may take place either as a result of the improved position of existing exports relative to competing areas or as a result of the development of new exports. . . . 'Since residentiary industry depends on income within the region, the expansion of such activity must have been induced by the increased income of the region's inhabitants.' On the other hand, TIEBOUT, 1956, argues that there is no reason to assume that exports are the sole or even the most important factor in regional growth, and 'in terms if causation, the nature of the residentiary industries will be a key factor in any possible development'. Our findings support North's view.
18. Data on productivity by industry at the individual region level is significantly affected by data suppression, especially for EAs and MSAs. We did not make use of this data in most of the analysis herein.
19. Data suppression is more common for industry level wage data than for employment data. Also, where wage data is suppressed no information is given, while for counties where employment is suppressed a range of employment is reported. We calculated a likelihood ratio test to explore whether data suppression caused a bias in the relationship between traded and local wages. The test examined whether the coefficients of the relationship between traded and local wages was the same in the sample of half of EAs with less suppression at the industry level versus the entire EA sample. The null hypothesis, i.e. no difference, cannot be rejected – an indication that wage data suppression does not introduce a major bias in the results.
20. It is well known that industries are often geographically concentrated in certain regions. The level of the concentration and the reasons for the persistence of industrial concentration are explored in ENRIGHT, 1990; KRUGMAN, 1991; DUMAIS *et al.*, 1997; ELLISON *et al.*, 1997, KIM, 1998; and ELLISON *et al.*, 1999.
21. There is a growing literature on clusters; see PORTER, 1998, for a brief survey.

22. Marshall, 1920; Arrow, 1962; and Romer, 1986.
23. There is a related hypothesis about the role of competition. MAR sees competition as bad because it reduces the rate of progress down the learning curve. Porter, 1990, argues that competition is good because it stimulates innovation and dynamism; Jacobs, 1969, is associated with this view although there is no explicit discussion of competition in her book. Previous results, again using industries and MSAs as units of analysis, support the positive role of competition.
24. This analysis was based on 1996, the most recent year then available. Replicating the analysis using more recent years revealed no material differences.
25. Application of the input–output method can be found in Tiebout, 1956; Miernyk, 1965; Nevin *et al.*, 1966; Yan, 1969; Richardson, 1972; Lewis and McNicoll, 1978; Pullen and Proops, 1983; and others. See Armstrong and Taylor, 1985, for the summary on the input–output approach.
26. Amended clusters have been defined using NAICS data which prove to be very similar in composition but include a moderate number of additional industries. We do not utilize NAICS clusters here due to lack of historical data.
27. The standard deviation of relative rank fell modestly between 1990 and 2000.
28. We also calculated the time trend of the employment GINI: $GINI = \alpha + \beta * t$, where t represents the year and ranges from 1990 to 2000. If the time coefficient is positive, this indicates that the state is becoming more specialized and vice versa. The findings were similar to the results for simple changes in GINI. More than half (32) of the states have a positive coefficient, and the rest have a negative coefficient. For EAs, 72 (of 172) have a positive coefficient. Most of the trend coefficients are statistically significant.
29. An LQ cutoff for cluster strength of $\geqslant 1{\cdot}0$ means that the cluster's employment in the region is equal to or greater than the region's share of total national employment. We also employ a somewhat lower cutoff ($\geqslant 0{\cdot}8$) to capture clusters with a substantial position in the region that from list – please add may fall just below LQ of 1.
30. The notion of cluster mix vs. relative wage level is similar in concept to shift-share analysis, which was originally proposed by Dunn, 1960, and has many applications in regional studies.
31. See Jaffe *et al.*, 1993.

APPENDIX A: US ECONOMIC AREAS

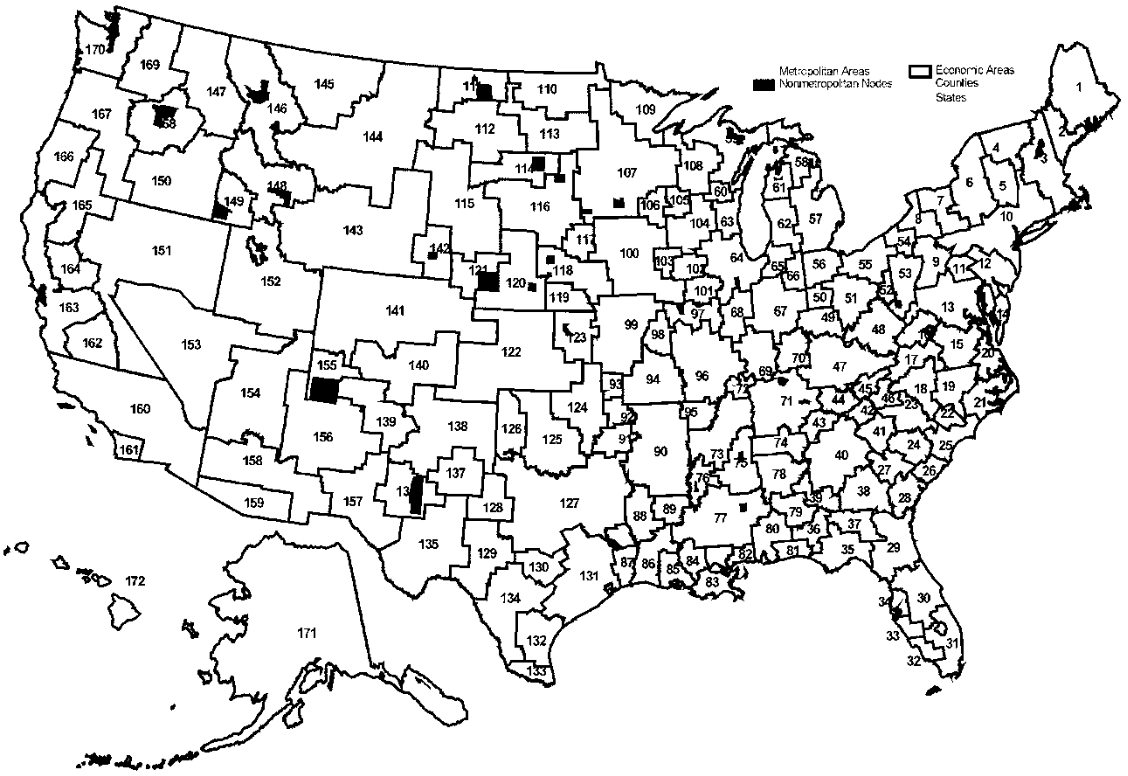

Fig. A1. *US economic areas: BEA economic areas and component economic nodes*[1]

Notes: 1. Established as of February 1995. Metropolitan areas are the MSAs defined by the Office of Management and Budget as of December 1997.

Source: Prepared by Regional Economic Analysis Division, Economics and Statistics Administration, Bureau of Economic Analysis, US Department of Commerce.

APPENDIX B: LIST OF TRADED CLUSTERS AND SUBCLUSTERS

Table B1. *List of traded clusters and subclusters*

Aerospace engines
Aircraft engines
Precision metal products
Engine and other instruments
Parts and components
Foundries
Parts processing
Nonferrous processing
Machine tools
Aircraft and parts

Aerospace vehicles and defence
Aircraft
Missiles and space vehicles
Defence equipment
Distribution and wholesaling
Metallic parts
Electronic parts
Instruments
Semiconductors and computers
Related equipment
Communications equipment
Software and computer services
Research

Agricultural products
Farm management and related services
Soil preparation services
Irrigation systems
Packaging
Fertilizers
Agricultural products
Wine and brandy
Cigars
Milling and refining
Product distribution and wholesaling
Malt beverages
Related processed foods
Related ingredients
Animal health products
Fish products
Agricultural chemicals
Supplies distribution and wholesaling
Related financial services
Transportation and logistic services
Marine transportation services
Bulk packaging
Packaging and packaging machinery
Related services

Analytical instruments
Laboratory instruments
Optical instruments
Process instruments
Search and navigation equipment
Electronic components
Distribution and wholesaling
Electronic parts
Other parts
Medical equipment
Related process equipment
Related equipment
Computer and software services
Research organizations

Apparel
Men's clothing
Women's and children's clothing
Hosiery and other garments
Accessories
Knitting and finishing mills
Gloves
Hats
Other accessories
Related garments
Outwear

Automotive
Motor vehicles assembly
Automotive parts
Automotive components
Forgings and stampings
Flat glass
Production equipment
Small vehicles and trailers
Marine, tank and stationary engines
Related parts
Motors and generators
Related vehicles
Metal processing
Machine tools
Related process machinery
Industrial trucks and tractors
Die-castings

Biopharmaceuticals
Biopharmaceutical products
Health and beauty products
Containers
Drug and related wholesaling
Biological products
Specialty chemicals
Packaging
Instruments and laboratory apparatus
Diagnostics
Surgical instruments and supplies
Dental instruments and supplies
Medical equipment
Ophthalmic goods
Patent owners and lessors
Research organizations

Building fixtures, equipment and services
Plumbing products
Drapery hardware
Fabricated materials
Heating and lighting
Furniture and fittings
Clay and vitreous products
Floor coverings
Steam and air-conditioning
Stone and tile work
Wood cabinets, fixtures and other products
Concrete, gypsum and other building products
Distribution and wholesaling
Plating and polishing
Lighting products
Ceramic tile
Elevators and moving stairways
Related electrical products
Furnishings
Other vitreous products
Mobile and motor homes
Related parts
Construction materials
Hardware
Millwork
Related fixtures
Steel work

Business services
Management consulting
Online information services
Computer services
Computer programming
Photocopying
Marketing related services
Professional organizations and services
Engineering services
Laundry services
Facilities support services
Freight arrangement
Surveying services
Media related services
Catalog and mail-order
Insurance

Chemical products
Intermediate chemicals and gases
Packaged chemical products
Other processed chemicals
Refractories
Leather tanning and finishing
Ammunition
Special packaging
Treated garments
Hydrocarbons
Petrochemicals
Plastics, resins and products
Pharmaceuticals
Diagnostics and biological products
Related consumer products
Other packaging
Processing instruments

Communications equipment
Communications equipment
Electrical and electronic components
Specialty office machines
Communications services
Related services
Distribution and wholesaling
Wiring, coils and transformers
Semiconductor and optical devices
Software and computer services
Metal processing
Cabinets
Power transmission equipment
Storage batteries
Computer equipment
Household audio and video equipment
Guided missiles and space vehicles
Search and navigation equipment
Related instruments
Research institutions

Construction materials
Tile, brick and glass
Plumbing fixtures
Wood products
Cut and crushed stone
Gum and wood chemicals
Rubber products
Adhesives and sealants
Insulation and roofing
Plastic sheet
Synthetic rubber
Steel pipe and tubes
Flooring and veneer
Sand and gravel
Concrete block and brick
Other wood products

Distribution services
Merchandise wholesaling
Apparel and accessories wholesaling
Catalogue and mail-order
Food products wholesaling
Farm material and supplies wholesaling
Transportation vehicle and equipment distribution
Special warehousing and storage
Jewellery and precious stones wholesaling
Construction machinery wholesaling

Education and knowledge creation
Educational institutions
Research organizations
Educational facilities
Patent owners and lessors
Supplies
Research related instruments
Pharmaceuticals
Publishing
Printing
Communications services
Marketing and information services
Online information services
Computer services
Prepackaged software
Computer and software wholesaling and services
Computer equipment

Entertainment
Video production and distribution
Recorded products
Entertainment equipment
Entertainment related services
Entertainment venues
Distribution and wholesaling
Marketing and promotional service
Related attractions
News syndicates
Audio and video equipment

Financial services
Depository institutions
Securities brokers, dealers and exchanges
Insurance products
Health plans
Risk capital providers
Investment funds
Real estate investment trusts
Passenger car leasing
Information providers
Computer and communication services
Printing services
Patent owners and lessors
Marketing related services
Research organizations

Fishing and fishing products
Fish products
Fishing and hunting
Processed seafoods
Seafood distribution and wholesaling

Footwear
Footwear
Speciality footwear
Footwear parts
Other leather goods
Related materials

Forest products
Paper products
Paper mills
Paper industries machinery
Prefabricated wood buildings
Wood partitions and fixtures
Paperboard and boxes
Process equipment
Hoists and cranes
Paper related machinery and instruments
Stationery products
Brooms and brushes

Furniture
Furniture
Wood materials and products
Furnishings
Tableware and kitchenware
Furniture related parts
Metal household furniture
Office furniture
Mattresses and bedsprings
Related household fixtures
Mobile homes
Other wood products
Power tools
Woodworking machinery
Millwork

Heavy construction services
Final construction
Subcontractors
Primary construction materials
Ceramic tiles
Equipment distribution and wholesaling
Fabricated metal structures and piping
Explosives
Transportation services
Chemical and related products
Glass and clay
Related equipment and components
Elevators and moving stairways
Related services
Tiling and glazing

Heavy machinery
Construction machinery
Farm machinery
Railroad equipment and rental
Mining machinery
Machinery components
Valves and pipe fittings
Hoists and cranes
Forgings, castings and metal parts
Engines
Related parts
Compressors and fans
Tires and inner tubes

Hospitality and tourism
Tourism attractions
Tourism related services
Water passenger transportation
Accommodations and related services
Boat related services
Ground transportation
Other local transportation
Related professional services
Other attractions
Air services
Vehicle distribution and wholesaling
Facilities support services

Information technology
Computers
Electronic components and assemblies
Peripherals
Software
Communications services
Distribution and wholesaling
Other electronic components and parts
Recording media services
Online information services
Computer services
Instruments
Communications equipment
Research organizations

Jewellery and precious metals
Jewellery and precious metal products
Costume jewellery
Cutlery
Collectibles
Distribution and wholesaling
Precious metal related financial services

Leather products
Leather products
Fur goods
Coated fabrics
Related products
Accessories
Women's footwear
Men's clothing
Women's clothing and accessories

Lighting and electrical equipment
Lighting fixtures
Electric lamps
Batteries
Switchgear
Electrical parts
Metal parts
Related electrical equipment
Instruments to measure electricity
Electric services
Glass and ceramics products
Wire
Related electronic parts
Other lighting equipment

Medical devices
Surgical instruments and supplies
Dental instruments and supplies
Ophthalmic goods
Medical equipment
Diagnostic substances
Biological products
Laboratory apparatus
Electronic components
Plastic parts
Metal parts
Software
Online information services
Precision instruments
Computer equipment
Pharmaceutical products
Research organizations

Metal manufacturing
Fabricated metal products
Metal alloys
Primary metal products
Precision metal products
Fasteners
Wire and springs
Metal processing
Iron and steel mills and foundries
Nonferrous mills and foundries
Metal furniture
Environmental controls
Pumps
Saw blades and handsaws
General industrial machinery
Laundry and cleaning equipment
Metal armaments
Measuring and dispensing pumps
Tools, dies and fixtures
Paints and allied products
Lubricating oils and greases
Abrasive products
Metalworking machinery and components
Related metal processing
Industrial furnaces and ovens
Automotive parts and equipment
Hoists and cranes
Related metal products
Motorcycles and bicycles

Motor driven products
Motors and generators
Batteries
Motorized equipment
Refrigeration and heating equipment
Appliances
Specialized pumps
Specialized machinery
Tires and inner tubes
Marine, tank and stationary engines
Motorcycles and bicycles
Metal processing
Related appliances
Hoists and cranes
Printing trades machinery
Elevators and moving stairways
Air and gas compressors
Power transmission, motors and pumps
Control devices

Oil and gas products and services
Oil and gas machinery
Hydrocarbons
Oil and gas exploration and drilling
Oil pipelines
Petroleum processing
Oil and gas trading
Water freight transportation services
Forgings and fittings
Turbines and turbine generators
Lubricating oils
Intermediate chemicals
Plastics and related materials
Barrels and drums
Other transportation services

Plastics
Plastic materials and resins
Plastic products
Paints and allied products
Synthetic rubber
Plastics distribution and wholesaling
Organic chemicals
Alkalies and chlorine
Inorganic chemicals
Related plastic products
Hydrocarbons
Petroleum processing
Surface active agents
Adhesives and sealants
Process equipment

Power generation and transmission
Electric services
Turbines and turbine generators
Transformers
Porcelain, carbon and graphite components
Electronic capacitors
Electrical apparatus and instruments
Motors, generators and electric fans
Switchgear, controls and components

Prefabricated enclosures
Recreational vehicles and parts
Mobile homes
Trucks and trailers
Caskets
Elevators and moving stairways
Office furniture
Household refrigerators and freezers
Aluminum processing
Non-ferrous processing, except aluminum
Aluminum forging and other processing
Steel springs
Railroad equipment
Other furniture and cabinets

Processed food
Milk and frozen desserts
Baked packaged foods
Coffee
Processed dairy and related products
Meat and related products and services
Flour
Specialty foods and ingredients
Milling
Candy and chocolate
Malt beverages
Paper containers and boxes
Metal and glass containers
Food products machinery
Distribution and wholesaling
Packaging materials
Bulk packaging

Production technology
Machine tools and accessories
Process equipment sub-systems and components
Hoists and cranes
Process machinery
Industrial patterns
Fabricated plate work
Industrial trucks and tractors
Ball and roller bearings
Production machinery and components
Blast furnaces and steel mills
Household appliances
Abrasive products
Metal heat treating
Process equipment
Vehicle and heavy stamping
Construction machinery
Casting, forgings and metal alloys

Publishing and printing
Publishing
News syndicates
Signs and advertising specialties
Photographic services
Photographic equipment and supplies
Radio, TV, publisher representatives
Printing services
Printing inputs
Paper products
Speciality paper products
Inked paper and ribbons
Office equipment and supplies
Marketing related services
Printing-related machinery
Online information services
Computer services
Research organizations
Research facilities

Sporting, recreational and children's goods
Sporting and athletic goods
Games, toys, and children's vehicles
Motorcycles and bicycles
Dolls and stuffed toys
Fabricated metal products
Toys and hobby goods wholesaling
Metal processing

Textiles
Fabric mills
Speciality fabric mills
Speciality fabric processing
Textile machinery
Yarn and thread mills
Carpets and rugs
Wool mills
Fibres
Finishing plants

Speciality apparel components	Tobacco processing	Airports
Women's and children's underwear	Specialty packaging	Bus terminals
Tyre cord and fabrics		Passenger transportation
Process chemicals	*Transportation and logistics*	Communication equipment and services
Coated fabrics	Air transportation	Rental of railroad cars
Home furnishings	Bus transportation	Computer services and equipment
	Marine transportation	
Tobacco	Ship building	
Cigarettes	Transportation arrangement and warehousing	
Other tobacco products	Trucking terminal	

APPENDIX C: MIX AND LEVEL EFFECT ON REGIONAL AVERAGE TRADED WAGE

Variable definitions

$RITA$ = regional employment in cluster i
$RITA_i^{Pr}$ = predicted employment in cluster i (see below)
$TRITA$ = total regional traded employment
$RITD_i$ = regional wage of cluster i
$NITD_i$ = national wage of cluster i
$TNITD$ = national traded wage

The predicted employment in cluster i is defined as:

$$RITA_i^{Pr} = NITA_i * \left(\frac{TRITA}{TNITA}\right)$$

with the term in parentheses being the region's share of traded employment.

National-level variables are aggregated from the regional CBP files, not taken from the US CBP file, in order to ensure that the wage and level effects add up to the actual difference between the region's average wage and the overall average wage. For the same reason, the employment variables contain only non-flagged employment

Cluster mix effect

$$\frac{\sum_{i=1}^{41} [(RITA_i - RITA_i^{Pr}) * (NITD_i - TNITD)]}{TRITA}$$

Level effect

$$\frac{\sum_{i=1}^{41} [(RITA_i * (RITD_i - NITD_i)]}{TRITA}$$

Discussion

The cluster mix and level effects add up to the actual difference between a region's average wage and the national average wage. The cluster mix component represents the portion of this wage difference that can be explained by the region's particular employment distribution across clusters. For instance, a region with above average employment in a nationally high-wage cluster will raise its average wage.

The level effect measures the portion of the wage difference that can be attributed to the region's having higher or lower wages for particular clusters than the national average for those clusters.

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