

Product Life-Cycles and the Geographic Diffusion of Industries*

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Abstract

We examine the geographic diffusion of industries and occupations. Using decennial census microdata from 1980 to 2000, we show that high-skilled types of work have diffused less rapidly than low-skilled work, within and across industries. We also use data on industries' use of new occupations and the share of revenue from new products to show that while industries that have experienced recent technological changes are more concentrated, the rate of geographical diffusion is unrelated to recent innovativeness. We interpret these results in the context of recent theoretical work linking product life-cycles and relative factor prices to the geographic diffusion of industries.

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1 Introduction

We examine changes in the geographic concentration of industries and occupations over time. First, we document important variation, across both industries and occupations, in changes in concentration patterns. While many industries and occupations have deconcentrated—or diffused—across locations over 1980–2000, we observe increased concentration for certain services and for some high-skilled occupations.

A compelling hypothesis is that changes in the concentration pattern of industries over time are governed by the product life-cycle. Recent theoretical models emphasizing this relationship include Duranton and Puga (2001) and Desmet and Rossi-Hansberg (2009). A shared feature of these models is that young firms tolerate high congestion costs in order to take advantage of some kind of dynamic external benefit, in the form of the creation of a new technology or the refinement of a production process. Then, having realized said benefit, these firms disperse to low-cost locations. Changes in the geographic concentration of industries or occupations over time are thus the result of changes in the dynamic value of congested locations over a firm’s or industry’s life-cycle.

This mechanism is part of a larger literature in urban economics on the various sources of agglomeration economies (see Duranton and Puga (2004) and Rosenthal and Strange (2004) for reviews.) Specifically, one aim of this literature is to assess the relative importance different types of agglomeration economies. In this paper, we attempt to evaluate the empirical importance of the product life-cycle mechanism versus other (dynamic and static) sources of agglomeration economies. The rest of the paper proceeds as follows. In Section 2, we motivate our work by discussing potential theoretical mechanisms for the diffusion of industries and occupations. Next, we document important differences across industries and occupations in spatial employment growth patterns over 1980–2000. We find that manufacturing employment diffused more rapidly across U.S. regions than services employment. Within industries, low-skilled occupations diffused more rapidly than high-skilled occupations. In Section 5, we relate the diffusion patterns of industries and occupations to information on the life-cycle stage of these industries. We observe only weak correlation between diffusion and these measures of recent technological change. While the product life-cycle model may have significant explanatory power in certain instances, the empirical case is weak across all industries. We then offer alternative explanations and tentative conclusions.

2 Motivation

What causes economic activity—specifically, industries or establishments producing similar output—to geographically disperse or gather over time? To help fix ideas, consider a standard (static)

problem of a firm deciding where to locate a production plant. Suppose that plant-level production follows

$$y = \alpha_g \cdot f(\mathbf{x}, \omega) \cdot \sigma(\mathbf{X}_g). \quad (1)$$

Here, y is plant-level output, α_g is an location-specific productivity parameter, \mathbf{x} is a vector of factors used as inputs by the plant, ω is the technology chosen by the plant, and f is a decreasing-returns-to-scale production function. Further, we allow for local aggregate economies of scale (net of congestion costs), which are some function σ of total economic (or perhaps total sectoral) activity \mathbf{X}_g in the plant's location. Thus the firms solves

$$\max_{\mathbf{x}, \omega, g} p_g \cdot \alpha_g \cdot f(\mathbf{x}, \omega) \cdot \sigma(\mathbf{X}_g) - \mathbf{x} \cdot w_g \quad (2)$$

where p_g is the mill price of y in location g and w_g is a vector of local factor prices. The plant's optimal location, $g^*(\alpha_g, w_g, p_g, \sigma(\mathbf{X}_g))$, depends on relative factor and output prices and static agglomeration economies across locations. Changes in these decisions over time might be caused by changes in any of the parameters of the optimal-choice function—the location-specific productivity parameters, relative prices, or agglomeration economies.

Thus, even in a model without explicit dynamics, the geographic concentration of industries might increase or decline in response to changes in relative factor or output prices or changes in degree of local aggregate economies of scale. (A recent version of this argument can be found in Beaudry, Doms, and Lewis (2006)). Changes in relative factor supplies, the movement of factors across locations, changes in the scale or composition of local economic activity, or changes in technologies to exploit agglomeration economies or reduce congestion costs are all examples of mechanisms which might affect changes over time in industry concentration in this model.

Alternatively, a model that explicitly incorporates dynamics can allow additional mechanisms to explain the diffusion of industries. Examples of this approach include Duranton and Puga (2001) [DP] and Desmet and Rossi-Hansberg (2009) [DR]. Changes in the dynamic benefits and costs of agglomeration over firms' life-cycles can determine changes in location decisions over time. In the DP model, young firms tolerate high factor prices in dense cities in order to better innovate, that is, discover a better technology ω which can then be used in lower-cost locations as the firm ages. (The DR model is similar but their interpretation frames the dynamic benefit as reduced-form TFP improvements rather than process discovery.)

Suppose that the available set of technologies used by the plant in time period t can depend on the density of economic activity in period $t - 1$, so that $\omega_t = \omega^*(\dots, \omega_{t-1}, \mathbf{X}_{g,t-1})$. Here $\omega^*(\dots)$ incorporates a reduced-form function describing dynamic externalities that may be associated with

knowledge spillovers and innovation. That is, there may be some situations where the firm can improve TFP in t by choosing a dense location in $t - 1$. Now, in contrast to the static problem, the plant's decision is a sequence of factor, technology, and location choices, that depends on the relative strength of potential inter-temporal benefits in ω , in addition to the static mechanisms (changes in relative factor and output prices and static agglomeration economies) described above. In particular, DR posit that the dynamic benefits to geographic concentration are large for young industries but small for mature industries. If we accept this assumption, that firms in mature industries will not benefit from dynamic externalities, then these plants will locate wherever factors are cheap, output prices are high, or (net) static agglomeration economies are valuable. Changes over time will thus reflect changes in these conditions over time. In contrast, firms in young industries (that is, those industries that can benefit from future technological improvements related to density) may choose congested places early on in order to take advantage of improved productivity in subsequent periods. Thus, we may observe changes in the geographic distribution of these firms over time (that is, deconcentration or diffusion) even in the absence of changes in relative prices over time. If this mechanism is empirically important, these industries diffuse as they exhaust their life-cycle-related dynamic agglomeration benefits.

Thus, one can predict changes in the spatial concentration of industries driven by the product life-cycle, even in the absence of changes in relative factor prices across locations. In the following sections, we attempt to evaluate the empirical relevance of this mechanism. First, we replicate the results of Desmet and Rossi-Hansberg (2009) using different data and show that manufacturing, a mature sector, has diffused more rapidly than services, a young sector, over our sample period. Then, we exploit the complementarity between recent technological change and skilled workers to motivate a second set of results—unskilled work has diffused more rapidly than high-skilled work. This result is still consistent with life-cycle driven changes in spatial concentration, if high-skilled work is a complement to, or used in the production of, recent new technologies. Finally, we use a number of measures of recent technological adaptation by industries, and test whether there is a strong statistical relationship between these measures and the geographic diffusion of industries.

3 Data on industries and skilled work, 1980–2000

We use data on workers from the decennial censuses 1980–2000, drawn from the Integrated Public-Use Microdata Series (Ruggles *et al.*, 2010). From the IPUMS, we use information on workers' education, wages, occupations, industries, and location via time-consistent public-use microdata areas, or CONSPUMAS. Our sample is similar to the time period examined by Desmet and Rossi-

Hansberg (2009). One advantage of the household data is that there is less suppression of data in smaller industry–location cells than in the establishment data. (However, there are only about one-sixth the amount of CONSPUMAS—543—as there are counties.) Another important reason for using the IPUMS, rather than public-use establishment data, is that the household data allow us to compute employment for detailed occupation–industry–location cells across the entire country. (Cross-tabulations of similar detail are generally unavailable from other public-use sources.) Following Carlino and Chatterjee (2002) and Desmet and Rossi-Hansberg (2009), we use only the continental U.S., excluding Alaska and Hawaii.

A further technical issue is that time-consistent CONSPUMAS give information on place of residence, rather than place of work. To address this, we aggregate some CONSPUMAS to metropolitan area boundaries. This increases the likelihood that individuals work in the location in which they live.¹ In the rest of the paper, we refer to these geographic aggregates as “regions” or “locations.” As needed, we then aggregate individual-level data in the IPUMS to the occupation, industry and modified-CONSPUMA levels.

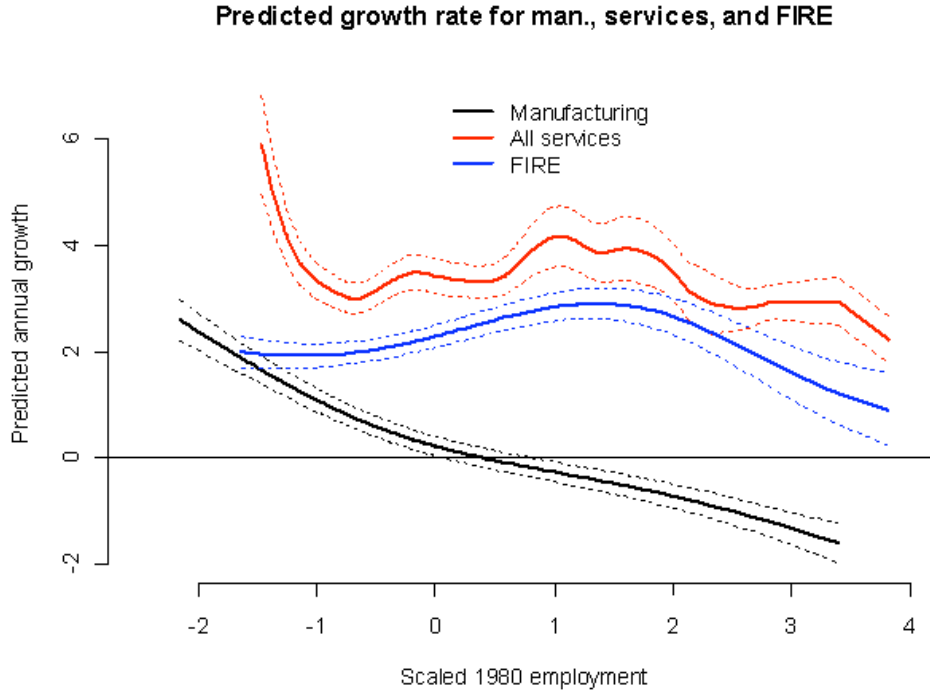
4 The diffusion patterns of industries and skilled workers

In this section, we show important differences across industries and occupations in spatial employment growth patterns over 1980–2000. In particular, certain types of industries and occupations have experienced marked deconcentration or diffusion, while others have experienced increased concentration over time. Our analysis in this section examines the scale dependence of growth, that is, for a given level of initial employment in a particular industry–region, occupation–region, or industry–occupation–region cell, what is the expected growth rate in employment over the subsequent decades? In this way we can assess diffusion or concentration trends in a non-parametric way: industries or occupations that are rapidly deconcentrating should see the fastest employment growth in regions that have low initial employment. (By extension, diffusing industries should see little, or declining, employment growth in existing centers.) In contrast, industries or occupations that are rapidly concentrating over time should see fast employment growth in regions that have high levels of initial employment.

For example, the scale dependence of employment growth is markedly different in manufacturing than in services. Regions with low levels of manufacturing employment in 1980 experienced the highest rates of growth in manufacturing employment 1980–2000. In contrast, services employment grew fastest in regions with relatively high initial levels of service employment. In short,

¹We assign CONSPUMAS to metropolitan areas based on area; the metro that makes up the largest share of each CONSPUMAS area claims that CONSPUMA, so long as the share is 30% or higher.

Figure 1: Predicted employment growth rates by initial employment levels, 1980–2000



Notes: This graph shows predicted values from three separate regressions using sector–region-level employment data aggregated from the IPUMS. For each sector, we perform a nonparametric regression of the annualized growth rate in sectoral employment, 1980–2000, on the logarithm of initial sectoral employment in 1980.

manufacturing employment diffused more rapidly across U.S. regions than services employment.

Further, we document differences across occupations and within industries in spatial growth patterns over the same period. For both the manufacturing and especially the services sector, high-skilled occupations experienced relatively rapid employment growth in areas with high initial levels of high-skilled occupational employment. In contrast, low-skilled occupations experienced rapid employment growth in regions with low initial levels of low-skilled occupational employment. In other words, within industries, low-skilled work diffused more rapidly than high-skilled work.

Figure 1 shows fitted lines from nonparametric regressions of the annualized growth rate of employment, 1980–2000, on the log initial employment level in 1980. (Dashed lines show 95% confidence intervals.) Variation along the x -axis comes from differences across regions (our modified CONSPUMAS) and sectors in the logarithm of initial sectoral employment. Each line shows the results of a separate nonparametric regression. (For display purposes, we cope with differences in the ranges of initial employment levels across sectors by rescaling the x -axis according to z -score of

the logarithm of the initial employment level. Thus each curve can be drawn over a similar range.)

The results shown in Figure 1 suggest that manufacturing employment diffused more rapidly across regions than services employment. Over this period, regions with low initial levels of manufacturing employment experienced the fastest employment growth. In contrast, regions with high initial levels of manufacturing employment lost employment over the same period.

Services exhibit a markedly different pattern. Regions with low levels of services employment, like those with low levels of manufacturing employment, experienced rapid employment growth. However, in contrast to existing manufacturing centers, regions with high initial concentrations of services employment also saw rapid growth in services employment. This can be seen in Figure 1 in the upward-sloping portion of the services curve and the local maximum near a scaled initial log employment of 1. This pattern is particularly pronounced for the finance, insurance, and real estate (FIRE) sector; for this sector, the fastest-growing regions had above-median initial employment levels. While manufacturing employment diffused across regions, our evidence suggests that services employment became more concentrated in regions already having medium to high levels of service employment.

These results both quantitatively and qualitatively match those shown for manufacturing and services in Desmet and Rossi-Hansberg (2009). Notably, they use establishment data (rather than household data) and choose counties (rather than metropolitan areas and public-use microdata areas) as the basic geographic unit of analysis. This close match is therefore somewhat surprising, since their observation of growth in the left tail of initial employment (see Figure 1 in their paper) may have been partly driven by the diffusion of economic activity from central to suburban areas within metropolitan areas.

We next consider the differences in the rate of geographic diffusion of skilled and unskilled occupations within industries. That is, given changes in the spatial distribution of an industry over time, do high-skilled types of activities diffuse more or less quickly than low-skilled types of activities?²

In order to evaluate the relative rates of geographic diffusion of different kinds of activities, we use census data on the national labor force to allocate occupations into skill quintiles. Occupations are allocated to quintiles based on the percent of workers in each (time-consistent) occupation that have college degrees or greater in 1980 and the distribution of employment across occupations in 1980.³ Using these occupational quintiles, we compute annualized employment growth rates

²Though it is less than precise, we sometimes use the term “activities” and the groupings of occupations we define interchangeably.

³Using hourly wages from 1980, 1990, or 2000, or using average educational attainment from any census year to allocate occupations into skill groups produces similar results.

for each triple (skill quintile, industry, region). Thus, an example of a typical comparison made possible might be growth in high-skilled work in services in the Philadelphia metropolitan area, versus growth in low-skilled work in manufacturing in Cleveland.

In Figure 2, Panel A, we show predicted employment growth rates of occupation–regions in manufacturing. As in Figure 1, the black line shows that regions with high initial levels of manufacturing employment experienced negative employment growth over 1980–2000.

Notably, there is evidence of significant variation in the scale dependence of employment growth, according to the skill intensity of work performed. For jobs in the first (lowest) skill quintile of occupations, the changes in geographic concentration over 1980–2000 mirror those of manufacturing at large—regions with low initial levels of low-skilled manufacturing employment experienced the fastest employment growth. However, for jobs in the fifth (highest) skill quintile of occupations, we observe a pattern that is qualitatively similar to the pattern for overall services employment, that is, increasing geographic concentration over time can be seen in the range where the relationship between growth and initial scale is upward-sloping. While strong employment growth in regions with little initial high-skilled employment indicates strong dispersion forces for this skill group, Panel A does suggest that jobs performing the highest-skilled activities diffused more slowly than other jobs in manufacturing.

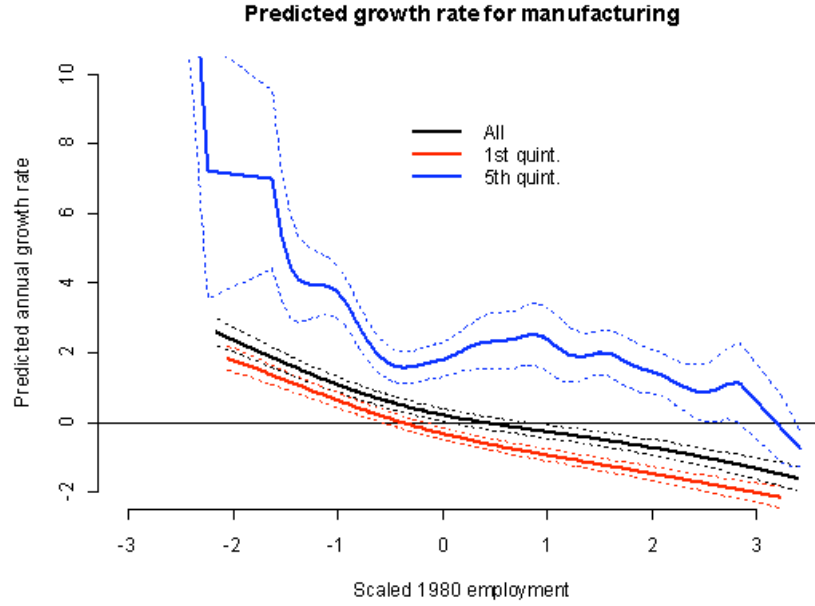
Panel B of Figure 2 shows that similar differences exist in the scale dependence of growth between high- and low-skilled occupations in services. Again, the black line reproduces the relationship between growth and initial scale for services from Figure 1. Notably, the highest-skilled occupations within services exhibit increasing concentration in regions with medium to high initial levels of employment, whereas the lowest-skilled occupations exhibit increased dispersion. In sum, for both the manufacturing and services sectors, we find that high-skilled types of work have diffused less rapidly over 1980–2000 than low-skilled types of work.

In Figure 3, we show similar results for finance, insurance and real estate (FIRE). Panel A shows results that are similar to those for services at large and manufacturing: high-skilled work has diffused less rapidly than low-skilled work. In Panel B, we use the results in Panel A to calculate the marginal effects of initial scale on subsequent employment growth; the marginal effects shown are positive when the curves in Panel A are upward-sloping. In this panel, we can interpret the relative rates of geographic diffusion among different skill-intensity groups of jobs by examining the vertical distance between the top and bottom quintile curves. Over nearly the entire range of initial scale, employment diffuses more slowly (concentrates more rapidly) for the highest-skilled occupations than for the lowest-skilled occupations.

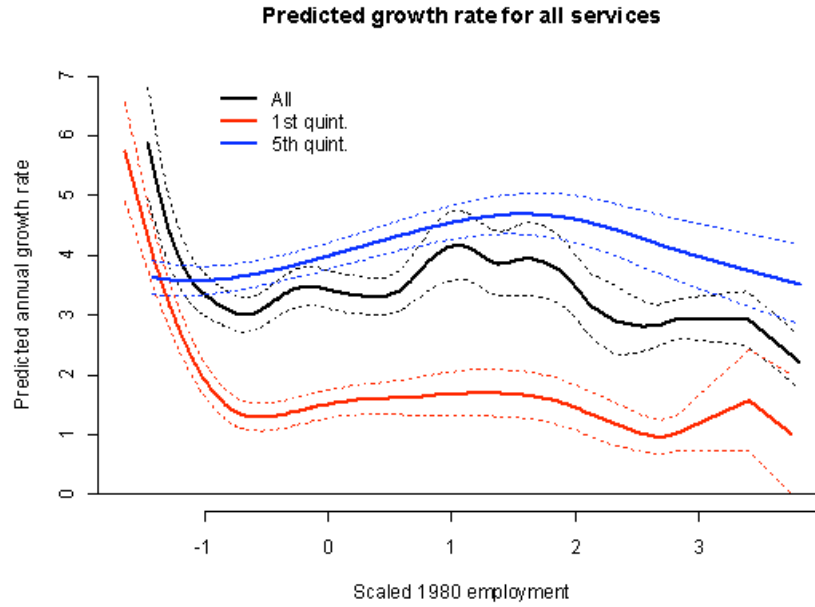
In sum, we present several findings. Manufacturing employment diffused more rapidly over

Figure 2: Predicted skill-group employment growth rates by initial employment levels, 1980–2000

Panel A. Manufacturing



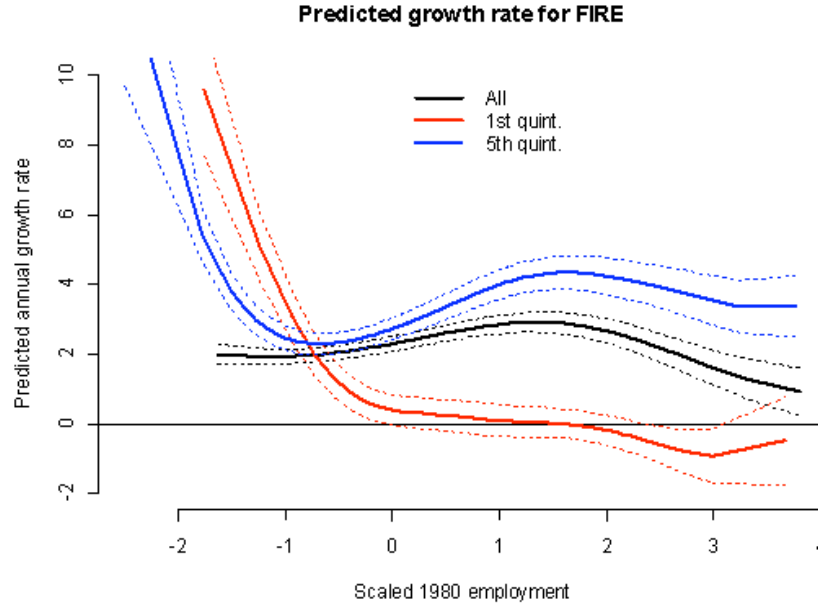
Panel B. Services



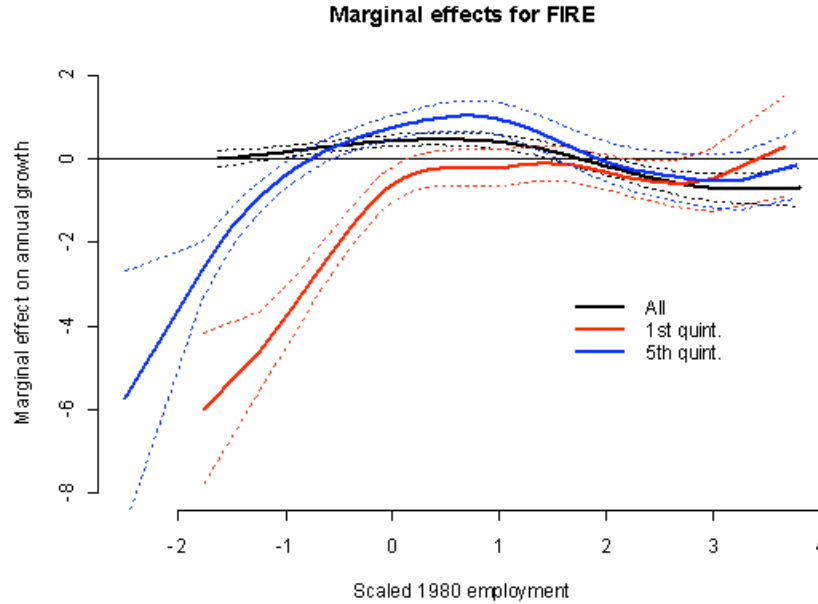
Notes: This graph shows predicted values from three separate regressions using skill-group–sector–region-level employment data aggregated from the IPUMS. For each skill-group–sector, we perform a nonparametric regression of the annualized growth rate in sectoral employment, 1980–2000, on the logarithm of initial skill-group–sector employment in 1980.

Figure 3: Predicted skill-group employment growth rates by initial employment levels, 1980–2000

Panel A. Finance, insurance and real estate (FIRE)



Panel B. Marginal effects of scale on growth for FIRE



Notes: These graphs show predicted values from separate regressions using skill-group–sector–region-level employment data aggregated from the IPUMS. For each skill-group–sector, we perform a nonparametric regression of the annualized growth rate in sectoral employment, 1980–2000, on the logarithm of initial skill-group–sector employment in 1980.

1980–2000 across U.S. regions than services employment. Notably, we also show that low-skilled occupations diffused more rapidly than high-skilled occupations. To the extent that manufacturing is a more-mature sector than services and that high-skilled occupations are more complementary to new technologies than low-skilled occupations, these results are consistent with a mechanism featuring product or industry life-cycles. Next, we examine these patterns in greater detail, and consider whether they provide robust evidence of the relationship between product life-cycles and the spatial evolution of industries.

5 Changes in concentration indexes and measures of the product life-cycle

5.1 Changes in concentration indexes

In this section, we examine industry-level trends in diffusion and how those trends relate to recent technological change experienced by an industry. This provides a further test of the hypothesis that the product life-cycle explains the diffusion of industries. In this paper, an industry is a 3-digit 1990 Census industry, which is comparable to a 3-digit NAICS industry.

In order to estimate regressions relating diffusion to the product cycle, we examine continuous measures of diffusion at the industry level. Following Carlino and Chatterjee (2002), we use changes in inequality indexes to measure diffusion; we use both the Theil and Gini inequality indexes. In addition, we use the Herfindahl concentration index. Each of these measures the extent to which employment density within an industry or skill-quintile-industry differs across regions. When an industry diffuses, the indexes for that industry fall. We use three indexes since the indexes have varying benefits and drawbacks.

We calculate these indexes separately for each industry. We also calculate the indexes by industry for 1st and 5th skill quintiles. In the following definitions, the industry and skill quintile subscripts are suppressed.

The Theil index was used by Carlino and Chatterjee (2002) to measure the diffusion of employment across metropolitan areas. We assume that, within each region, employment is uniformly distributed. With this assumption, the Theil index is defined as $T = \frac{1}{L} \left[\sum_{i=0}^N L_i \frac{v-e_i}{\frac{1}{2}(v+e_i)} \right]$ where L is the total land area in the continental US, N is the number of regions, L_i is the land area of region i , v is the mean skill-quintile–industry employment density across regions, and e_i is the observed density of region i .⁴

⁴We use this formula for percent difference rather than the log of a ratio because some region-industry-skill combinations have zero employment.

Table 1: Changes in the geographic concentration of industries and skilled work, 1980–2000

	Theil	Gini	Herfindahl
Mean % change, 1980–2000	-3.681	-3.416	-20.216
Difference between top and bottom skill quintiles	2.292	2.642	5.615

Notes: This table shows means across 209 census-defined industries. The top row shows mean percentage changes between 1980 and 2000 in each of three indexes of geographic concentration. The bottom row shows mean differences in percentage changes between the top and bottom skill quintiles. All reported values are statistically significant at the 99% level of confidence.

The Gini index is perhaps the most commonly used inequality index. We use Deaton’s (1997) formulation of the Gini index: $G = \frac{N+1}{N-1} - \frac{2}{N(N-1)v} \sum_{i=0}^N P_i e_i$ where P_i is the skill-quintile-industry employment density rank of region i and N, v , and e_i are the same as in the Theil index.

The last index we use is the Herfindahl concentration index (Hirschman 1964).⁵ While the other indexes measure spatial inequality broadly, the Herfindahl index is best suited to measuring whether an industry is highly concentrated. It is less sensitive than the other indexes to changes in concentration when an industry is not highly concentrated. The Herfindahl index is defined as: $H = \sum_{i=0}^N s_i^2$ where s_i is region i ’s share of total employment in the skill-quintile–industry combination.

Table 1 shows that the graphical results in the prior section hold when looking at the industry-level indexes. The first row shows the mean across industries in the percent change from 1980 to 2000 in each of the indexes. These results confirm that, overall, employment diffused over these decades. On average, the Theil and Gini indexes declined about 3.5 percent and the Herfindahl index declined 20 percent. The larger change in the Herfindahl index is due to the fact that most industries started with low values of the index, so small absolute changes yield large percentage changes.

The second row of Table 1 shows that, averaging across industries, the top skill quintile diffused more slowly than the bottom skill quintile. The average percent difference between the skill quintiles in the percent change in the indexes from 1980 to 2000 is about 2.5 percent for the Theil and Gini indexes and 5.6 percent for the Herfindahl index. Given the similarity between these results and

⁵We recognize that Hirschman was the first to develop this index, but we follow convention and use the more common name of the index.

the graphical results in the prior section, we are confident that the percent change in the indexes is a good proxy for employment diffusion.

5.2 Geographic diffusion and recent technological change

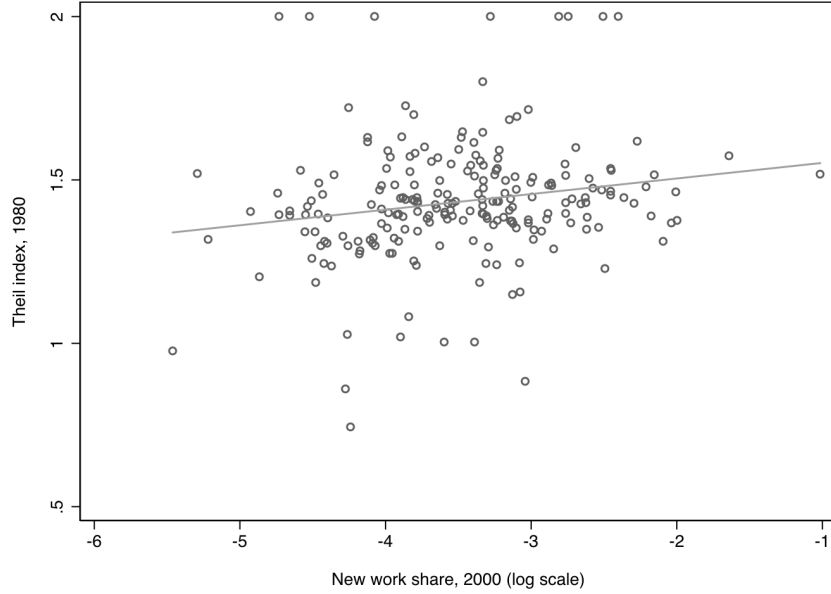
The results presented above show appreciable differences within industries in the dynamic location choices of high- and low-skilled jobs. Over our sample period 1980–2000, high-skilled occupations became increasingly concentrated in regions that already contained agglomerations of high-skilled work, whereas low-skilled occupations increasingly dispersed to locations without existing concentrations of low-skilled work. As a first pass, these facts seem broadly consistent with a product life-cycle story of geographic diffusion. If high-skilled work is used in, or a complement to, innovation and research, then we would expect these activities to diffuse more slowly to low-cost locations versus low-skilled work. However, as noted above, these facts may be consistent with other mechanisms: alternatively, variation in factor prices or even changes in static agglomeration economies might be responsible for the patterns observed so far.

We examine the relationship between the diffusion of industries and various measures of recent technology adoption by industries. In doing so, we attempt to more directly test the link between the adoption of new technologies and changes in the geographic distribution of industries and skilled work within industries.

We use three types of measures of recent technological change experienced by industries. The first type of measure is based on industries’ use of jobs requiring new combinations of activities or techniques that have emerged in the labor market in response to new information or new production technologies. These types of “new work” were first identified by Lin (2009), who uses revisions to occupation classification systems to identify newly-created categories of jobs between 1965 and 2000. We use three cohorts of new work: occupations that were new classifications in 1977, those that were new in 1991, and those that were new in 2000. Since some time may elapse from the time of invention before firms and industries can adapt to new technologies, using three cohorts of new work allows us to flexibly identify which industries between 1980–2000 have experienced recent technological changes.

By matching these new occupations to employment information in the decennial IPUMS, we can thus observe variation in industries’ use of new work in 1980, 1990, and 2000. For example, the 1980 new work variable may be better at measuring industries that innovated heavily in the 1960s and 1970s. Alternatively, the 2000 new work variable may be better at measuring industries that continued to innovate and adapt to new technologies during the period where we measure spatial employment growth. We might expect these industries, with high utilization of new work in 2000,

Figure 4: Industry concentration in 1980 and new work in 2000



to have diffused far more slowly than other industries over 1980–2000.

The second type of measure we use is based on industries’ introduction of new products. We use data from Xiang (2004) to classify industries based on the revenue share attributed to new goods in 1987. These new products appear in the 1987 Standard Industrial Classification (SIC) but not the 1972 SIC; we use industry revenues from 1992. The new goods data provides us with an alternative measure of recent technological changes experienced by industries. The third type of measure we use is patent count data by industry over the period 1970–2000. (The results using new products and patents are in the “to-do” pile.)

Figure 4 shows the positive correlation between geographic concentration and technological adaptation across industries. Industries that were more concentrated in 1980, as measured by the Theil index, also saw greater subsequent adoption of new work in 2000. While this result is consistent with a story featuring innovation and experimentation in dense areas, industries may be spatially concentrated for many alternative reasons—for example, the spatial distribution of inputs or customers, or the presence of static agglomeration benefits like labor pooling.

To more directly test for the relationship between spatial concentration and product life-cycles, we perform the following estimation.

$$\Delta C_i^{80,00} = \nu N_i^{80,00} + \mathbf{X}_i \beta + \epsilon_i \quad (3)$$

Here, $\Delta C_i^{80,00}$ is the 1980–2000 percent change in the geographic concentration index (Theil, Gini, or Herfindahl) for industry i . The regressors include a measure of technological adaptation in industry i between 1980 and 2000, sector effects, and the initial concentration index value in 1980. The main parameter of interest is ν , the coefficient on new work (or products or patents); variation in N_i comes from differences across industries in the adoption of jobs in new occupations, the introduction of new products, or the production of new patents. The aim here is not causal identification. Rather, we are interested in testing whether or not, conditioned on sector and initial spatial concentration, industries that experienced more recent technological changes also experienced less geographic diffusion.

Columns 1–3 in Table 2 display results from a series of such regressions. Each cell contains an estimate of $\hat{\nu}$ and the R^2 value from a separate regression of the (percent) change 1980–2000 in the geographic concentration index (columns) on a measure of new work (rows). A negative coefficient suggests that industries that adopted more new work saw greater diffusion over 1980–2000. The evidence is mixed. Few coefficients are statistically significant and the models have little explanatory power. In particular, partial- R^2 values for new work variables are generally low. Even in the case where the reported estimate is statistically significant, this suggests that the case for a relationship between technological adaptation and spatial diffusion is at best weak. (The Herfindahl index is more sensitive to changes in spatial concentration at low levels, which accounts for the larger magnitude of the estimates in column 3.) In only a few cases do we observe a statistically significant relationship: industries that had adopted more new work by around 1980 seem to have diffused more quickly than other industries over 1980–2000. This could be consistent with the product life-cycle hypothesis: if industries that experienced rapid technological change in the decades prior to 1980 were now “mature,” we would expect them to diffuse faster than younger or even more mature industries. However, the low precision of our estimates cautions against a strong interpretation here. Further, other measures of recent technological change do not appear to be strongly related to changes in spatial concentration.

One possible explanation for these results is that our measures of recent technological change are inadequate for testing for the use of new technologies. Lin (2009) shows that the new work measures are strongly correlated to measures of patenting and total factor productivity growth across industries. In addition, results are similar when we use other measures such as new products or patents instead of new work (this exercise to be completed).

In columns 4–6, we extend our analysis to consider changes in the difference in geographic concentration indexes between high-skilled jobs and low-skilled jobs. As in Table 1, we compute spatial concentration index for skill quintiles within industries, then summarize the 1980–2000

Table 2: Changes in the geographic concentration of industries and innovativeness, 1980–2000

		(1)	(2)	(3)	(4)	(5)	(6)
		Percent change, 1980–2000			Difference, top & bottom skill quintiles		
	mean (s.d.)	Theil	Gini	Herf.	Theil	Gini	Herf.
New work share in 2000	0.039 (0.036)	-0.91 (8.41)	6.11 (11.75)	-3.38 (52.04)	26.55 (17.00)	12.44 (15.11)	65.09 (63.72)
R^2		0.215	0.135	0.183	0.092	0.149	0.110
New work share in 1990	0.014 (0.015)	10.39 (10.65)	-3.00 (14.87)	26.31 (65.63)	2.35 (21.71)	-26.26 (19.06)	46.83 (80.53)
R^2		0.218	0.134	0.184	0.081	0.154	0.107
New work share in 1980	0.079 (0.029)	-5.19 (10.44)	-22.88 (14.56)	-136.44* (63.89)	7.04 (21.25)	-21.26 (18.80)	-151.33 (78.61)
R^2		0.216	0.144	0.202	0.081	0.152	0.122
Log(new work share in 2000)		-0.20 (0.47)	0.02 (0.65)	-3.68 (2.87)	1.20 (0.95)	0.67 (0.84)	3.91 (3.52)
R^2		0.215	0.134	0.190	0.088	0.149	0.111
Log(new work share in 1990)		0.16 (0.67)	-0.45 (0.94)	-5.66 (4.11)	0.06 (1.37)	-1.13 (1.20)	3.52 (5.07)
R^2		0.215	0.135	0.191	0.081	0.150	0.108
Log(new work share in 1980)		-0.83 (0.65)	-2.02* (0.90)	-11.85** (3.91)	1.28 (1.32)	-0.29 (1.17)	-8.62 (4.88)
R^2		0.221	0.155	0.220	0.085	0.146	0.120

Notes: Each cell displays an estimated coefficient from a separate regression of the percentage change in industries' geographic concentration index on a measure of industry innovativeness. Each regression includes as regressors sector dummies and the initial concentration level in 1980. $N = 209$ industries. Robust standard errors in parentheses; **—significant at the 99% level; *—significant at the 95% level; †—significant at the 90% level.

changes the difference between the top and bottom skill quintiles. A positive reported coefficient on new work suggests that industries that experienced more technological change also experienced greater differences in the rates of diffusion between high- and low-skilled work. In other words, in these innovative industries, low-skilled types of jobs diffused much faster than high-skilled types of jobs.

None of the coefficient estimates reported in columns 4–6 are statistically significant. Echoing the first set of regressions, we find no evidence of any systematic correlation between technological adaptation and the pattern of change in the spatial concentration of industries.

While there is strong evidence of differential patterns of diffusion between low- and high-skilled work, changes in the concentration patterns of industries seem at best weakly related to measures of recent technological change. These results suggest several preliminary conclusions. While the product life-cycle model may have significant explanatory power in certain cases, it seems unlikely to be a strong candidate explanation across industries for changes in geographic concentration patterns. A strong alternative explanation may be differences in the availability of high-skilled and low-skilled labor across locations. This explanation is appealing in the sense that it might be consistent with our results on differential rates of diffusion across skill groups. In future work, we hope to evaluate hypotheses related to differences in the availability of factors across locations.

6 Conclusions

We find that manufacturing employment diffused more rapidly across U.S. regions than services employment. Within industries, low-skilled occupations diffused more rapidly than high-skilled occupations. To the extent that manufacturing is a mature sector and there is complementarity between recent technological change and skilled workers, these results seem consistent with dynamic benefits to concentration and the life-cycle of products or industries. However, we find little correlation between measures of recent technological changes experienced by industries and geographic diffusion. We suggest that changes in statics, like factor prices or other agglomeration economies, may be more empirically relevant than product life-cycles in explaining the diffusion of industries over our sample period.

In future work, we hope to consider a longer sample period, the diffusion of industries abroad, and the relationship between changes in relative factor supplies and geographical diffusion of industries and occupations. We also hope to separately address changes in other sources of agglomeration economies, and other technological changes within industries that might affect productivity, establishment sizes, and location choice.

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