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Labor Pooling as a Source of Agglomeration
An Empirical Investigation

Henry G. Overman and Diego Puga

4.1 Introduction

Spatial concentrations of establishments and workers offer great productivity advantages. Many modern econometric studies have confirmed and quantified this important stylized fact. Estimates of the productivity increase from a doubling in the size of an agglomeration range between 2 and 8 percent, depending on the sector and details of the estimation procedure (see Rosenthal and Strange [2004] and Combes et al. [chapter 1 in this volume]).

Unfortunately, the literature has been far less successful at distinguishing between the different sources of urban increasing returns than at quantifying their overall magnitude. Specifically, while we have sound theoretical models providing microeconomic foundations for the economies of agglomeration, the different mechanisms are hard to distinguish empirically. The main difficulty arises from the "Marshallian equivalence" of these theories (see Duranton and Puga [2004]): they all predict an increase in productivity with spatial concentration but work through mechanisms that are hard to trace.

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This chapter focuses on a potential source of agglomeration economies to which Alfred Marshall (1890) devoted particular attention: labor market pooling. While there are various interpretations of labor market pooling as a source of agglomeration economies, Marshall emphasized that "a localized industry gains a great advantage from the fact that it offers a constant market for skill" (Marshall 1890, 271). In section 4.2, we use a simple model to clarify the microeconomic foundations of labor pooling as a source of agglomeration economies and to motivate our empirical analysis. The model is a version of the labor pooling model of Krugman (1991). We consider a series of sectors where establishments experience idiosyncratic shocks. Individual profits are convex in the establishment-specific shock, since each establishment responds to the shock by adjusting its levels of both production and employment. However, changes in the establishment's employment affect local wages, and the more isolated the establishment is from other establishments in the same sector or using similar workers, the greater the effect. If wages are higher when the establishment wants to expand production in response to a positive shock and lower when it wants to contract production in response to a negative shock, this limits the establishment's ability to adapt its employment level to good and bad times. Consequently, establishments that tend to experience substantial changes in their employment relative to other establishments using workers with similar skills will find it advantageous to locate in places where there is a large number of workers with such skills. As a result, the model predicts that sectors whose establishments experience more idiosyncratic volatility will be more spatially concentrated.[1]

To assess the importance of labor market pooling as a source of agglomeration economies empirically, we use establishment-level data from the United Kingdom's Annual Respondents Database (ARD), which underlies the Annual Census of Production. The data is described in section 4.3. We begin by constructing an establishment-level measure of idiosyncratic employment shocks by calculating the difference between the percentage change in the establishment's employment and the percentage change in the sector's employment. We then average this (in absolute value) across time and across establishments in the sector to obtain a sector-level measure of how much idiosyncratic volatility individual establishments in each sector face. We then check whether, consistent with the theory, sectors whose

1. Labor market pooling is not the only theoretical agglomeration mechanism operating through local labor markets. Larger markets also improve the chances of matching between firms and workers, as well as the average quality of matches (see Helsley and Strange [1990]). In addition, larger markets also encourage workers to focus on a narrower set of tasks and to acquire more specialized skills (see Baumgardner [1988], Becker and Murphy [1992], and Duranton [1998]). We focus just on labor pooling, whereby concentrations of employers using similar workers allow labor to move more easily from less-productive to more-productive firms. We maintain this specific focus because only by concentrating on the unique implications of a given agglomeration mechanism can we hope to identify it empirically.

establishments experience more idiosyncratic volatility are more spatially concentrated. We find that this is indeed the case, even after controlling for a range of other industry characteristics that include a novel measure of the importance of localized intermediate suppliers.

4.2 The Theoretical Advantages of Labor Pooling

In this section, we present a simple model of labor pooling. This helps clarify the microeconomic foundations of labor pooling as a source of agglomeration economies. It also allows us to derive an empirically testable prediction about how the importance of labor pooling will vary across sectors. The model is a multisector and multilocation version of the labor pooling model of Krugman (1991).

4.2.1 Setup

Consider a series of sectors indexed by $s = 1, \dots, S$. Each sector has a discrete number of production establishments distinguished by subindex $i = 1, \dots, N$ and a continuum of workers with skills specific to that sector. Establishments and workers are risk neutral. After choosing its location, each establishment receives a productivity shock ε_i. The shocks are uncorrelated across establishments and identically distributed over $[-\varepsilon, \varepsilon]$ with mean zero and variance σ_s. Establishments observe these shocks and decide how much labor to hire from the local labor pool in the sector. If establishment i chooses an employment level l_i, it has operating profits given by:

$$\pi_i = [\beta + \varepsilon_i]l_i - \frac{1}{2}\gamma[l_i]^2 - wl_i. \tag{1}$$

4.2.2 Wages

Following Krugman (1991), assume that each establishment takes the local wage as given. Thus, after shocks are realized, each establishment hires labor until its marginal value product equals the wage. This yields establishment i's labor demand:

$$l_i = \frac{\beta - w + \varepsilon_i}{\gamma}. \tag{2}$$

Denote by L the hours of labor effectively supplied in a given city and sector. Labor market clearing, together with equation (2), implies

$$L = \sum_{i=1}^{N} l_i = \frac{\beta - w + \sum_{i=1}^{N}\varepsilon_i}{\gamma}. \tag{3}$$

We can then solve for the market-clearing wage from equation (3):

$$w = \beta - \gamma\frac{L}{N} + \frac{1}{N}\sum_{i=1}^{N}\varepsilon_i. \tag{4}$$

Taking expectations yields the expected wage.[2]

(5) $$E(w) = \beta - \gamma\frac{L}{N}.$$

4.2.3 Profits

Substituting equation (2) into equation (1), this simplifies to:

(6) $$\pi_i = \frac{[\beta - w + \varepsilon_i]^2}{2\gamma}.$$

Note that establishment profits are a convex function of the idiosyncratic productivity shock, since the establishment adjusts its production level in response to the shock. Similarly, profits are convex in the wage.

Taking expectations of the profits in equation (6) yields:

(7) $$E(\pi_i) = \frac{[\beta - E(w)]^2 + \mathrm{var}[\varepsilon_i - w]}{2\gamma}.$$

Substituting equation (5) and $\mathrm{var}[\varepsilon_i - w] = \mathrm{var}[\varepsilon_i] + \mathrm{var}(w) - 2\mathrm{cov}[\varepsilon_i, w]$ into equation (7), this simplifies to:

(8) $$E(\pi_i) = \frac{\gamma}{2}\left(\frac{L}{N}\right)^2 + \frac{\mathrm{var}[\varepsilon_i] + \mathrm{var}(w) - 2\mathrm{cov}[\varepsilon_i, w]}{2\gamma}.$$

The first term of the right-hand side is what establishment profits would be in the absence of shocks. It increases as the ratio of workers to establishments L/N increases, because this lowers the expected wage. The second term captures the labor pooling effect. This shows that expected profits increase with the variance of the establishment-specific productivity shock, $\mathrm{var}[\varepsilon_i]$, and with the variance of the local wage, $\mathrm{var}(w)$, because of the convexity of profits previously discussed. However, they decrease with the covariance of the establishment-specific productivity shock and the local wage, $\mathrm{cov}[\varepsilon_i, w]$. The reason is that if the local wage is higher when an establishment wishes to expand production in response to a positive shock and lower when the establishment wishes to contract production in response to a negative shock, profits become less convex in the shock and fall in expectation. This is the key intuition of the model, which highlights the microeconomic foundations of labor pooling as a source of agglomeration: *establishments prefer locations where their productivity shocks get ironed out rather than heavily reflected in local wages.*

To simplify equation (8) further, we can use equations (4) and (5) to calculate $\mathrm{var}(w) = \sigma_s/N$ and $\mathrm{cov}[\varepsilon_i, w] = \sigma_s/N$. Substituting these and $\mathrm{var}[\varepsilon_i] = \sigma_s$ into equation (8) yields:

2. We assume that the support of the distribution of productivity shocks is not so large that the nonnegative employment constraint for some establishment might be binding under some realization of shocks. In particular, we assume that the restriction $\gamma/\varepsilon \geq [2(N - 1)]/L$ holds. This follows from $l_i > 0$ and equations (2) and (4) for a case where $\varepsilon_i = -\varepsilon$ and $\varepsilon_j = \varepsilon\ \forall j \neq i$.

$$(9) \qquad E(\pi) = \frac{\gamma}{2}\left(\frac{L}{N}\right)^2 + \left(1 - \frac{1}{N}\right)\frac{\sigma_s}{2\gamma},$$

where we have dropped subindex i, since expected profits are equal for all establishments in the same location and sector. The labor market pooling effect, as captured by the term $(1 - [1/N])(\sigma_s/2\gamma)$, is stronger when the σ_s in the sector is higher. Thus, *the benefits of labor pooling will be greater when the heterogeneity of establishment-specific shocks in the sector is larger.* This suggests that sectors with more heterogeneous shocks are more likely to be agglomerated. To show this more formally, we now explore two alternative definitions of an urban equilibrium in this model, both of which yield the same key testable prediction.

4.2.4 Equilibrium with Simultaneous Relocation by Firms and Workers

Following Ellison and Fudenberg (2003), let us first treat location and production in this model as a two-stage game. In the first stage, all establishments and workers (whose total number is exogenously given) simultaneously choose their location. In the second stage, each establishment receives its productivity shock ε_i. Since there is a continuum of workers, a relocation by an individual worker has no effect on wages or profits. Provided wages are equalized across locations, no worker has an incentive to relocate. From equation (5), this implies that the equilibrium ratio of workers to establishments L/N must be the same in all locations.

Establishments, unlike workers, are discrete, and this assumption is essential for there to be advantages from labor pooling. Thus, a relocation by an individual establishment alters wages and profits at both the origin and destination of the relocation. In equilibrium, it must be the case that an individual establishment cannot increase the expected profits of equation (9) by deviating and locating elsewhere. An establishment must consider two aspects in deciding whether such a deviation is profitable. First, starting from a situation where wages are equalized across locations, the establishment's relocation would decrease the ratio of workers to establishments in the destination location, making the labor market tighter in expectation and increasing the expected wage, which would reduce the establishment's expected profits. This labor market tightness effect operates through the first term on the right-hand side of equation (9). Second, if after the deviation, the destination has a larger number of establishments, the establishment's productivity shocks (that get translated into employment shocks) will not affect the local wage as much, allowing the establishment to adapt better to circumstances and obtain higher expected profits. This is the labor pooling effect previously discussed, summarized now by the second term on the right-hand side of equation (9).

Suppose that the S sectors differ only in terms of the variance of productivity shocks, σ_s. Then, the labor market tightness effect favoring establishment dispersion is equally strong across all sectors, but the labor market pooling effect is stronger when σ_s in the sector is higher. Thus, the balance of agglomeration and dispersion forces tips more easily in favor of agglomeration when σ_s is higher. In particular, if a location has fewer than $\sigma_s/[2(\gamma^2R^2 + \sigma_s)]$ times as many establishments as the largest agglomeration in the sector, all remaining establishments find it individually profitable to relocate to the largest agglomeration.[3] Thus, *sectors with more heterogeneous shocks are more likely to be agglomerated.* We will test this prediction empirically in section 4.4.

4.2.5 Equilibrium with Free Entry and an Agglomeration Wage Premium

The urban equilibrium we have just derived already captures the key prediction used next to check the empirical relevance of labor pooling as a source of agglomeration. However, while theoretically elegant, it also has some counterfactual predictions for cities. In particular, in equilibrium, workers capture none of the benefits of agglomeration, whereas in practice, larger cities and denser agglomerations are associated with a significant wage premium (see Glaeser and Maré [2001]; Wheaton and Lewis [2002]; and Combes, Duranton, and Gobillon [2008]).

To capture this wage premium, following Glaeser (2008), we now redefine an equilibrium of the model so that the number of establishments in each city is endogenously determined by free entry and exit, taking the size of local labor markets as given. We let the size of the labor pool differ across cities but keep it fixed for simplicity (although this can be justified through a heterogenous fixed housing stock). The equilibrium number of establishments in each city is then determined by free entry up to the point where a further increase in N would leave each establishment unable to cover the fixed cost of entry, denoted ϕ.[4] Substituting equation (9) into $E(\pi) = \phi$ and solving for N yields the equilibrium number of establishments in each city (ignoring integer constraints):

$$N = \frac{\sqrt{\sigma_s^2 + 4(2\gamma\phi - \sigma_s)\gamma^2 L^2} - \sigma_s}{2(2\gamma\phi - \sigma_s)}. \tag{10}$$

It follows from this expression that a city with a larger local labor market not only has more establishments but also a higher ratio of establishments to workers (or equivalently, a lower ratio of workers to establishments):

3. Stated differently, an equilibrium in this model is an allocation of workers and establishments across locations such that each location is either empty or has at least $\sigma_s/2(\gamma^2R^2 + \sigma_s)$ as many establishments as the location with most establishments, and the ratio R of workers to establishments is the same in all nonempty locations as in the aggregate economy. See Ellison and Fudenberg (2003) for details.

4. Note that by equation (9), we must have $\phi > \sigma_s/2\gamma$. Otherwise, entry would continue indefinitely without exhausting profits net of ϕ.

$$(11)\quad \frac{\partial(L/N)}{\partial L} = \frac{-2\sigma_s(2\gamma\phi-\sigma_s)}{\sqrt{\sigma_s^2+4(2\gamma\phi-\sigma_s)\gamma^2L^2}\,[\sqrt{\sigma_s^2+4(2\gamma\phi-\sigma_s)\gamma^2L^2}-\sigma_s]}$$
$$= \frac{-\sigma_s}{N\sqrt{\sigma_s^2+4(2\gamma\phi-\sigma_s)\gamma^2L^2}} < 0.$$

By equation (5), this creates a wage premium that offsets the advantages of greater labor pooling in larger markets and ensures that profits are exhausted everywhere:

$$(12)\quad \frac{\partial E(w)}{\partial L} = -\gamma\frac{\partial(L/N)}{\partial L} > 0.$$

The equilibrium with free entry, with its agglomeration wage premium, is quite different from the equilibrium with simultaneous relocation of a fixed number of establishments and workers. Still, the key prediction we wish to take to the data also holds. To see this, differentiate equation (10) with respect to σ_s to obtain:

$$(13)\quad \frac{\partial^2(L/N)}{\partial L\partial\sigma_s} = -\frac{1}{2\gamma^2L^2}\left\{1+\frac{\sigma_s[\sigma_s^2+2\gamma^2L^2(8\gamma\phi-3\sigma_s)]}{[\sigma_s^2+4(2\gamma\phi-\sigma_s)\gamma^2L^2]^{3/2}}\right\} < 0.$$

(The inequality $\phi > \sigma_s/2\gamma$ has been used to sign this derivative; see note 4.) This implies that cities with a larger local labor market attract a disproportionate number of establishments and that the effect is stronger when σ_s in the sector is higher. Thus, once again, *sectors with more heterogeneous shocks tend to be more agglomerated.*

4.3 Data

To examine the role of labor pooling, we will regress a measure of spatial concentration for each sector on a measure of the potential for labor pooling in the sector and a number of sectoral characteristics that are also likely to affect geographic concentration. The measure of geographic concentration and the pooling variable described next are calculated using exhaustive establishment-level data from the Annual Respondents Database (ARD), which underlies the Annual Census of Production in the United Kingdom. We use data from 1994 to 2003. The data set is collected by the Office for National Statistics (ONS) and covers all UK establishments (see Griffith [1999] and Duranton and Overman [2005] for a detailed description of this data).[5] For every establishment, we know its postcode, four-digit industrial classification, and employment. We restrict our attention to production

5. We use the terms establishment and plant interchangeably. Our description of the data is based closely on Duranton and Overman (2005).

establishments in manufacturing industries using the Standard Industrial Classification 92 (SIC 15000 to 36639) for the whole country except Northern Ireland. For the purposes of this exercise, we have plant data from the ARD for 1994 to 2003. We observe 557,595 plants at least once. On average, we observe each plant 4.16 times.

Since the labor pooling mechanism depends on establishments' ability to take more or less workers from the local labor pool without difficulty, we must work with geographical units that correspond as closely as possible to local labor markets. Thus, our geographical units of analysis are the UK travel to work areas (TTWA), 1998 classification. Similar to the labor market areas that the Bureau of Labor Statistics defines for the United States, these TTWA are defined on the basis of commuting patterns to capture local labor markets. Specifically, the boundaries are drawn such that of the resident economically active population, at least 75 percent work in the area, and of everyone working in the area, at least 75 percent live in the area. The classification is exhaustive, with 308 TTWA covering the whole of Great Britain. United Kingdom postcodes can be uniquely mapped to TTWA, so we are able to locate establishments in the ARD according to the TTWA classification. The number of plants per TTWA is rather skewed. There are 15,154 on average, while the median number is 4,545. There are fourteen TTWA with less than one hundred plants, although inclusion of the very large or the very small areas does not affect our results, so we include the whole sample in what follows. One slight complication involves the treatment of plants that move across TTWA or change sector. We treat these as a separate observation.[6]

Our controls for other industry characteristics come mainly from the ONS input-output (IO) tables, available annually from 1994 to 2003.[7] We complement these where necessary with Eurostat's detailed enterprise statistics for the United Kingdom and the ARD itself. We provide more details as we introduce these controls.

4.4 The Importance of Labor Pooling for Industry Concentration

The theoretical model of section 4.2 suggests that sectors whose establishments experience more heterogeneous employment shocks have greater potential to benefit from labor pooling and, to exploit this, will be more

6. Moves across TTWA should not actually happen, as plant identifiers are supposed to designate a unique physical entity. In reality, firms sometimes report under the same plant identifier when they have actually moved plants. This justifies our decision to treat these observations separately. The issue of changing SIC is more problematic, as these classifications are based on the most significant activity undertaken at a given plant and may change over time.

7. The UK input-output tables use a 77-industry classification. This is compatible with NACE (Nomenclature générale des Activités économiques dans les Communautés Européennes) Rev. 1 and corresponds roughly to NACE three digit. We map this to the 237 industries in the UK SIC 92 by assigning the same value to all four-digit industries under any given IO heading.

spatially concentrated. In this section, we consider this prediction empirically by regressing a measure of spatial concentration for each sector on a measure of the potential for labor pooling in the sector. Of course, other characteristics of industries may also affect the extent of concentration, and we will need to control for these. That is, we estimate:

$$C_s = \alpha + \rho P_s + \phi \mathbf{X}_s + \epsilon_s, \tag{14}$$

where C_s is a measure of spatial concentration for sector s, P_s is a measure of the potential for labor pooling in the sector, $\mathbf{X}_i$ is a vector of sector characteristics, α, ρ, and ϕ are parameters to be estimated, and ϵ_i is an identically and independently distributed error term.

This approach to investigating the significance of different motives for spatial concentration has been used before. (See Audretsch and Feldman [1996] and in particular Rosenthal and Strange [2001] to which our regressions are most directly related.) The main novelty of our analysis is that by measuring the heterogeneity of individual establishments' employment shocks in each sector, we are able to look explicitly at the potential for labor pooling of different sectors. In contrast, as discussed next, the existing literature has had to rely on fairly indirect proxies to capture any possible effect. We also offer an important refinement for measuring the importance of the sharing of intermediate input suppliers.

4.4.1 Measuring Each Sector's Potential for Labor Pooling

The argument that labor pooling, by allowing establishments to better adapt to idiosyncratic shocks, can be an important determinant of agglomeration is well known. However, data restrictions mean that previous studies have had to get at this effect indirectly by focusing, for example, on the extent to which workers in an industry are likely to have industry-specific skills. Rosenthal and Strange (2001), for example, use three measures of labor pooling: net labor productivity (the value of shipments less the value of purchased inputs, all divided by the number of workers in the industry), the ratio of management workers to production workers, and the percentage of an industry's workers with doctorates, master's degrees, and bachelor's degrees. These indirect measures are not ideal, because while sectors with a larger share of managers or high-skilled workers may agglomerate partly because of labor pooling, there are many other reasons why they may concentrate geographically. For instance, agglomerations of high-skilled workers may facilitate better matching between jobs and workers (see Helsley and Strange [1990]). Alternatively, large markets may also allow high-skilled workers to specialize in a narrower set of tasks and become more productive (see Baumgardner [1988], Becker and Murphy [1992], and Duranton [1998]), or they may help solve dual-career problems for high-skilled couples (see Costa and Kahn [2000]).

We wish to be able to isolate the role of labor pooling, as motivated by the theoretical argument of section 4.2, from other labor market considerations. The crucial point, as previously discussed, is that a labor pooling advantage only arises if whenever a plant expands employment, many other plants using similar workers are contracting and vice versa. That is, what matters is the plants' idiosyncratic need to alter employment. To capture this effect, we exploit the fact that we have a panel of plants over a long time period to construct a direct measure of the idiosyncratic nature of any given plant's employment adjustments. To measure the idiosyncratic shock to a plant in any given year, we calculate the difference between the percentage change in the plant's employment and the percentage change in the industry's employment (in absolute value). This will take a high value for plants that either expand employment when the rest of the industry is contracting or vice versa. Taking the difference between the plant's change and the industry's change is important, because there is no labor pooling advantage if whenever the plant expands employment, many other plants using similar workers also expand.[8] We then take the average of this variable across all years and across all plants in each sector. The resulting "pooling" measure captures how much idiosyncratic volatility is faced by individual establishments in each sector.

4.4.2 Measuring Each Sector's Spatial Concentration

There are a variety of statistics that can be used to measure the extent of spatial concentration. We adopt the widely used index proposed by Ellison and Glaeser (1997). This measures the amount of clustering in a sector over and beyond that which we would expect to find based on randomness alone. It has the advantage of being comparable across sectors and controlling for both the overall geographic concentration of employment and for the "lumpiness" of employment. This lumpiness arises because industrial concentration means plants are of different sizes. This is a problem when trying to measure spatial concentration, because even random distributions of plants across spatial units can give rise to some places having more employment than others (if they happen, by chance, to get a particularly large plant). Because the Ellison-Glaeser index controls for industrial concentration of the industry, it corrects for this problem. Let s_a be the share of sector's employment that is in area a and x_a be the share of total manufacturing employment that is in area a. Then, the Ellison-Glaeser index of geographical concentration is defined as:

$$C_s \equiv \frac{G_s - (1 - \sum_a x_a^2)H_s}{(1 - \sum_a x_a^2)(1 - H_s)}, \tag{15}$$

8. We are assuming that plants in the same industry use similar workers so that the plant's industry is the appropriate reference group. When we turn to our results, we will also consider the opposite extreme, where the appropriate reference group is manufacturing as a whole.

where G_s is a raw localization index equal to

$$G_s \equiv \sum_a (s_a - x_a)^2, \tag{16}$$

and

$$H_s \equiv \sum_i z_i^2 \tag{17}$$

is the Herfindahl index of the sector's plant size distribution, with z_i denoting plant i's share of sector s's employment. Ellison and Glaeser (1997) show that if plants are randomly distributed across locations with probabilities given by x_a, then the expected value of this measure is zero. A positive value of the index indicates a level of spatial concentration over and above what one would expect by chance.

4.4.3 Results

Although we have panel data for the Ellison-Glaeser index and some of the explanatory variables, preliminary regressions exploiting the panel dimension of the data did not perform well. Perhaps this is unsurprising, as location patterns change only slowly, while some of the industry characteristics (e.g., research and development [R&D] expenditure per worker) can show a considerable amount of year-on-year variation. Furthermore, for the labor pooling measure, it is necessary to take into account plant-level employment shocks relative to the sector for a number of years. Given both these considerations, we choose to average variables over time. Specifically, we split the time period in half and regress the average Ellison-Glaeser index for the six years from 1998 to 2003 on the average of the industry characteristics from 1992 to 1997. This specification has a rather nice economic interpretation whereby plants are able to observe industry characteristics before making their location decisions, so we would actually expect some lag from characteristics to outcomes. It also helps to partially address concerns about the endogeneity of some of the industry characteristics.

Figure 4.1 shows what happens when we plot (time-averaged) values of the Ellison and Glaeser index against our (lagged time-averaged) measure of the importance of labor market pooling.[9] A regression of the Ellison and Glaeser index on a constant and our measure of labor market pooling gives a coefficient on labor pooling of 0.1, significant at the 4 percent level. The upward-sloping line in figure 4.1 plots the predicted values from this regression. Overall, the figure provides preliminary evidence in favor of the importance of labor market pooling in explaining geographic concentration. Of course, many other industry characteristics may be correlated with both

9. The plot and our econometric results drop one four-digit sector—1725: other textile weaving—which is a large outlier in terms of our measure of labor market pooling (it takes a value over three times the next highest value and over 12 standard deviations away from the mean). Dropping this outlier does not affect our regression results but does affect the significance of the univariate correlation coefficient we report in the text.

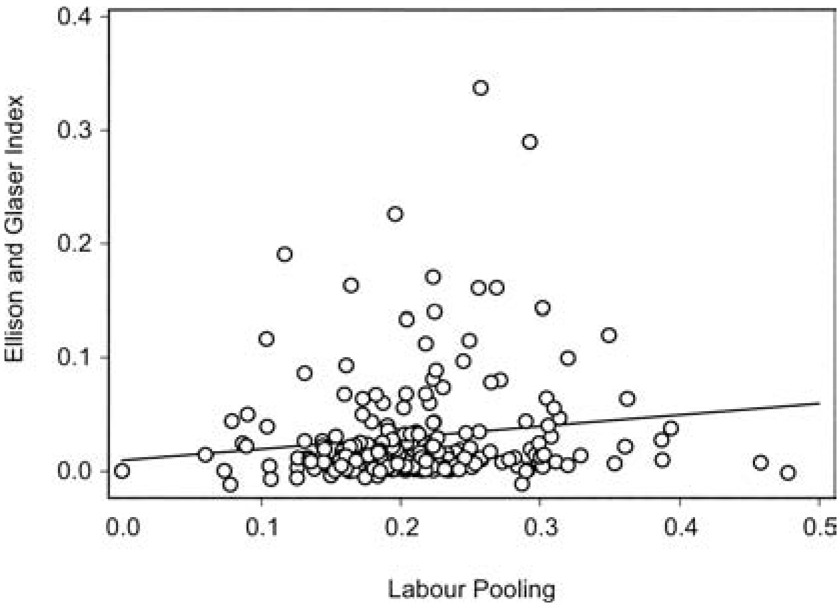

Fig. 4.1 Ellison and Glaeser geographic concentration index against potential for labor pooling

geographic concentration and our measure of labor market pooling, and we will need to control for these to reach a more robust conclusion on the role of labor market pooling.

Before turning to our results, we now briefly consider each of the industry characteristics for which we are able to control. The control variables for our first specification broadly follow Rosenthal and Strange (2001). We briefly motivate all of them but refer the reader to Rosenthal and Strange (2001) for a more detailed discussion.

The availability of natural resources may differ across regions. If natural resources are very spatially concentrated, then we would expect industries that use them intensively to be very spatially concentrated. Of course, if natural resources are very dispersed, then the opposite effect could hold, and industries that use these resources intensively may be dispersed. As we do not have independent information on the distribution of resources, we capture the effect of natural resources on geographic concentration by looking at each industry's primary inputs (from agriculture, forestry, fishing, mining, and quarrying) as a share of total inputs. As the preceding discussion makes clear, we do not have a strong prior on whether the impact will be positive or negative. Industries also differ in the intensity with which they use water and energy. As the price of water and energy may differ across regions, the intensity with which industries use these two inputs may affect their spatial distribution.[10] We capture reliance on water using "collection, purification and distribution of water" (IO 87) as a share of total inputs from the ONS input-output tables. Eurostat's detailed enterprise statistics provide data on the value of energy products purchased at the SIC four-digit level, which we normalize by total inputs to provide a proxy for reliance on energy. We expect the coefficients on these two variables to be positive and significant if price variations across regions are large enough to affect plant location and insignificant otherwise.

Turning to agglomeration forces, we start by following Rosenthal and Strange (2001) and using the purchase of goods and services as a share of inputs to capture the importance of vertical linkages. These are calculated using the input coefficients on manufacturing (IO 8–84) and nonmanufacturing industries (IO 107–115, 118–123), respectively, from the ONS input-output tables. The basic idea is that industries that buy or sell a lot from other plants may have an incentive to cluster near those plants. If the degree to which an industry buys goods and services as inputs captures this effect, then we should expect the coefficient on these two variables to be positive. As emphasized in models of new economic geography, the level of transport costs for an industry will be crucial in determining whether agglomeration forces outweigh dispersion forces leading to the spatial clustering of the industry. We use transport services (IO 93–97) as a share of inputs to capture the impact of transport costs on industry spatial concentration, again using data from the ONS input-output tables. As Rosenthal and Strange (2001) argue, this measure is not ideal, as it is most likely endogenous. Unfortunately, for the United Kingdom, alternative data are not available in the time period that we consider. Finally, we use the share of R&D expenditure in value added to capture the possible role of technological externalities and knowledge spillovers in driving the spatial concentration of high-tech industries. These are calculated on the basis of Eurostat's detailed enterprise statistics for the United Kingdom.[11]

Results from a regression of the Ellison-Glaeser index (averaged over the years 1998 to 2003) on these industry characteristics (averaged over the years 1992 to 1997) are given in column (1) of table 4.1. The main result of interest is the relationship between each sector's potential for labor pooling and the spatial concentration in the sector. As predicted, the role of the labor pooling variable is positive and significant. Thus, industries where, on

10. The UK water industry is comprised of a number of privatized regional monopolies that have different pricing structures. Thus, we allow for the possibility that water usage may play a role in industrial concentration, although the existence of a national regulator is likely to restrict the importance of water in practice.

11. Preliminary data for all these variables were kindly provided by Roberto Picchizzolu, a PhD student in the department of geography and environment at the London School of Economics. The final version of our data continues to use the energy and R&D variables provided by Picchizzolu, but the remaining variables are based on the authors own calculations from the ONS input-output tables from 1992 to 2003.

Table 4.1 **Regression of localization and urbanization on industry characteristics**

	Ellison-Glaeser localization index				Urbanization
Dependent variable:	(1)	(2)	(3)	(4)	(5)
Pooling (plant to sector)	0.1167 (0.0535)**	0.1261 (0.0521)**		0.1261 (0.0523)**	0.0169 (0.0685)
Pooling (plant to United Kingdom)			0.0196 (0.0113)*		
Pooling (sector to United Kingdom)				0.0002 (0.0106)	0.0026 (0.0068)
Natural resources as share of inputs	–0.1656 (0.0493)***	–0.1782 (0.0571)***	–0.1689 (0.0566)***	–0.1782 (0.0572)***	–0.1496 (0.0708)**
Water as share of inputs	1.7106 (3.0794)	0.7851 (2.7732)	1.8663 (2.7124)	0.7898 (2.7105)	–1.1054 (3.1246)
Energy as share of inputs	–0.0748 (0.3603)	–0.3268 (0.3533)	–0.3615 (0.3472)	–0.3274 (0.346)	–0.7768 (0.3550)**
Goods as share of inputs	–0.1866 (0.0758)**	–0.2453 (0.0847)***	–0.2512 (0.0863)***	–0.2453 (0.0851)***	–0.1621 (0.0707)**
Services as share of inputs	–0.5701 (0.1628)***	–0.4079 (0.1580)**	–0.3803 (0.1546)**	–0.408 (0.1576)**	–0.1773 (0.1966)
Share of R&D expenditure in value added	–1.8371 (1.2614)	–2.0807 (1.2106)*	–2.2511 (1.2184)*	–2.0771 (1.2141)*	–3.3887 (1.1219)***
Transport costs as share of inputs	–0.4248 (0.1403)***	–0.4265 (0.1356)***	–0.4604 (0.1376)***	–0.4261 (0.1387)***	–0.2855 (0.1123)**
Own industry as share of inputs		0.095 (0.0285)***	0.0937 (0.0287)***	0.0949 (0.0285)***	0.0928 (0.0337)***
IO weighted EG index		0.5767 (0.2512)**	0.5422 (0.2541)**	0.5756 (0.2502)**	–0.155 (0.2172)
Constant	0.1501 (0.0459)***	0.1426 (0.0485)***	0.1666 (0.0501)***	0.1425 (0.0490)***	0.1438 (0.0454)***
R^2	0.09	0.14	0.13	0.14	0.13
Observations	235	235	235	235	235

Notes: Errors are robust to heteroscedasticity. The dependent variable for columns (1) through (4) is the Ellison and Glaeser (EG) index of localization or spatial concentration; for column (5), it is the percentage of industry in the three largest UK TTWA in terms of manufacturing employment (London, Manchester, and Birmingham).

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

average, plants face more idiosyncratic shocks relative to their industry are more spatially concentrated.

Turning to other determinants of spatial clustering, a high natural resource requirement actually causes industries to be less spatially concentrated than they otherwise would be. This may well reflect the fact that agricultural inputs tend to dominate for most industries where natural resource inputs are important, and at least in the United Kingdom, agricultural activity is reasonably dispersed across the country. Water and energy use have no significant effect on spatial concentration. As suggested previously, this is probably because price variations are not that large across UK regions. Ignoring for one moment the role of purchases of goods and services, we see that the share of R&D expenditure in value added does not have a significant effect. The final variable, transport costs, has a negative and significant effect on spatial concentration. As expected, industries with high transport costs are more dispersed.

Perhaps the biggest surprise are the negative and significant coefficients on the purchase of goods and services as a share of inputs. As we already discussed, if these variables are actually capturing vertical linkages, then we would expect them to have a positive significant effect on spatial concentration.[12] How then do we explain the negative coefficients? It may be that sharing intermediate suppliers is not an important motive for agglomeration, but other evidence suggests it is.[13] The answer, it turns out, is similar to that which explains the negative coefficient on natural resources. When an industry buys a lot from other industries, the effect on its concentration in turn will depend on whether those industries are spatially concentrated or dispersed. For instance, the meat processing industry is a large buyer of inputs from farms and from the plastic film industry. However, farms are very dispersed across the country, and so is the plastic film industry, since it supplies many other sectors located in different places, in addition to processing meat. Hence, the meat processing industry has no reason to concentrate spatially, even if it makes large intermediate purchases: it can easily find its inputs everywhere. For a sector to cluster to share intermediate suppliers, it must be the case that the sector not only makes large purchases of intermediates but also that those intermediates are supplied by industries that are themselves very spatially concentrated. Following this line of reasoning, to better capture the importance of vertical linkages for a particular industry, *s*, we calculate the input share weighted sum of the Ellison-Glaeser index across all industries from which industry *s* purchases intermediates. That is, we calculate:

$$V_s = \sum_{j \neq s} I_{sj} C_j, \tag{18}$$

where V_s is our new measure of vertical linkages, I_{sj} is the share of sector *j* in sector *s*'s intermediate inputs from other sectors, and C_s is the Ellison-Glaeser index of spatial concentration for sector *j*. Notice that for obvious reasons, we exclude industry *s*'s own Ellison-Glaeser index from this calculation. However, we would expect ceteris paribus industries that buy a large share of intermediate inputs from their own industry to be more spatially

12. Rosenthal and Strange (2001) find no significant effect for these variables.

13. Holmes (1999) looks at variations in intermediate input purchases within sectors across locations and finds a strong connection between spatial concentration and intermediate purchases.

concentrated. To capture this, we can include I_{ss}, the share of intermediates purchased from own industry, in the regression, in addition to the vertical linkages variable.

Column (2) in table 4.1 shows what happens when we include these two new variables. We see that both the own-industry inputs as a share of inputs and the input-output weighted Ellison-Glaeser index have a positive and significant impact on spatial concentration. Industries that buy a lot of intermediates from other plants in the same industry or that buy a lot of intermediates from other industries that are spatially concentrated are in turn more spatially concentrated. We see that the coefficients on goods purchased and services purchased remain negative and significant. That is, purchasing large amounts of inputs per se has a negative impact on spatial concentration. Finally, note that the coefficient on our main variable of interest, labor market pooling, remains positive and significant.

So far, we have assumed that the appropriate reference group for calculating our measure of labor pooling is the industry. An alternative would be to consider idiosyncratic shocks relative to manufacturing as a whole; that is, to use a measure of labor market pooling that is calculated as before, but this time using the sectoral average of the difference between the percentage change in the plant's employment and the percentage change in UK manufacturing employment (in absolute value). Column (3) of table 4.1 reports results when we use this alternative measure of labor market pooling. As can be seen, the coefficient on this alternative measure is positive and significant. Conceptually, we can think of this alternative measure (plants relative to UK manufacturing as a whole) as being disaggregated into two orthogonal components: plants relative to their industry ("plant to sector") and industries relative to the whole of UK manufacturing ("sector to United Kingdom").[14] From column (4) of table 4.1, we see that the finding of a significant coefficient on the pooling measure calculated using plants relative to UK manufacturing as a whole is purely driven by plants experiencing idiosyncratic shocks relative to their industry ("plant to sector"). Industries that tend to experience idiosyncratic results relative to manufacturing as a whole ("sector to United Kingdom") do not tend to be more geographically concentrated.

This raises the interesting question, however, of whether these industries are more likely to go to larger locations where they can benefit from labor market pooling *across* sectors rather than within their own sector. To consider this possibility, we can undertake a similar exercise, but this time using as our dependent variable a measure of the extent to which the industry is

14. Formally, this decomposition is not exact, but in practice, it holds to a close approximation. As a result, including all three measures does not make any sense, given that they are essentially colinear.

urbanized rather than geographically concentrated. To measure urbanization, we take the share of each industry in the three largest manufacturing cities in the United Kingdom (London, Manchester, and Birmingham).[15] The final column of table 4.1 shows the results when we regress this measure of urbanization on the two components of labor pooling (plant to sector and sector to United Kingdom) and other industry characteristics. We find no significant effect on urbanization of either measure. In results not reported here, we also find no effect if we simply use the combined measure based on plants relative to the whole of UK manufacturing.

Do our findings suggest that labor market pooling plays no role in explaining urbanization? We would argue not. The central problem, of course, is whether our measure is capturing the correct reference group when calculating the importance of idiosyncratic shocks. For localization, our measure is appropriate if workers move easily within four-digit sectors. This seems a reasonable assumption, and so we are able to identify an effect from our labor pooling measure on localization. However, for urbanization, our measure is only appropriate if workers move easily *across* sectors. This is unlikely to be the case, suggesting that our results could easily be explained by the use of an inappropriate reference group when considering urbanization rather than by there being no effect of labor market pooling. Unfortunately, making any progress on defining the appropriate reference group would require data on worker moves between industries. This data is not available from the Annual Respondents Database that we use in this chapter. Finally, we also note that we are only considering manufacturing sectors, and it is often argued that urbanization is more important for services than for manufacturing.

4.5 Conclusions

Since Alfred Marshall talked about labor pooling as a source of agglomeration, it has been the focus of much interest in the urban economics literature. Existing empirical studies tend to find that labor market issues play a key role in leading industries to cluster, but despite the interest in labor pooling, we have so far not had a direct test of whether ironing out plant-level shocks by drawing workers from a large local pool is at least in part an explanation of these labor market effects. In this chapter, we have developed a novel measure that captures precisely this aspect: we calculate the fluctuations in employment of individual establishments relative to their sector and average these across the sector and over time. Our results show

15. Our decision to rank cities in terms of manufacturing employment reflects the fact that the pooling mechanism relies on movements between plants, and such movements are less likely between services and manufacturing than within manufacturing.

that sectors whose establishments experience more idiosyncratic volatility are more spatially concentrated, even after controlling for a range of other industry characteristics.

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