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Time-Varying Agglomeration Externalities in UK Counties between 1841 and 1971

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Abstract
Using dynamic panel data methods on UK counties (1841-1971), we investigate long-term employment dynamics in seven distinct local industries. We study how industries benefit from specialised environments (MAR), diverse local economies (Jacobs') and large local markets (urbanization), and, in contrast to most other authors, test if the strength of MAR, Jacobs' and urbanization externalities changes over time. We find declining MAR and rising Jacobs' externalities since the mid-nineteenth century, questioning the adequacy of a static framework when studying agglomeration externalities.

Keywords: agglomeration; dynamic externalities; Jacobs' externalities; MAR externalities; urbanization externalities.
JEL classification: L60, N930, N940, R11

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1. Introduction

In the past two decades, there has been a rapid increase in research on agglomeration externalities, starting from two widely cited papers in the field: Glaeser et al. (1992) and Henderson et al. (1995). Analyses like the ones in these papers have been conducted on a large amount of databases covering a wide variety of regions, industries and time spans. The basic question, however, has remained more or less the same: do firms benefit more from a local specialisation in their own industry (localization externalities) or from a large variety of local industries (Jacobs' externalities)? Unfortunately, empirical evidence is as yet inconclusive

The methodology used in this literature has evolved since the groundbreaking work by Glaeser and his colleagues. As a result, over time, papers that study the same topic of agglomeration externalities seemingly quite different methodologies. In the first part of this paper we discuss eight well known papers in this strand of literature. Our main goal in this section is to show how the underlying logics behind the models used in the different approaches relate to one another. However, new approaches are added every year and we can only give a flavour of the variety and similarities in approaches. A full review of the literature is beyond the scope of this text.

Apart from a methodological discussion, we provide an overview of the empirical findings of the papers. Even in such a small subset of papers, this summary clearly shows the divergence in outcomes that characterizes the literature. The remainder of this text is concerned with the question whether the temporal dimension may have contributed to this uncertainty.

To the author's knowledge, up to this date, all empirical studies in the tradition of Glaeser et al. (1992) take agglomeration externalities to be constant over time. However, many factors that theoretically influence the strength of externalities, have changed. For example, the costs of travelling and communication have sharply declined over the decades. Also, the way production is distributed across between clients and suppliers in modern economies differs from the way this was done in the past. For these reasons, the influence of agglomeration externalities may very well have changed over the course of the past century or two. In this second part of the paper, we study whether this is indeed the case.

For our empirical analysis, we use a dataset on employment in 24 broad industries in 48 (standardized) counties in the United Kingdom. The sample starts in 1841 and observations are added every decade up to 1971, excluding the war year of 1941. To obtain precise estimates, data are pooled across all periods. Using dynamic panel data methods, we estimate the influence of past local specialisation and past local diversity on current local industry employment. Compared to the existing literature, the prime novelty in this paper is that agglomeration parameters are allowed to vary over time.

The outcomes on localization externalities turn out to be surprisingly robust across the investigated industries: all industries start out with a strong and positive influence of local specialisation. However, this positive effect diminishes significantly as time progresses. Urbanization, in contrast, exhibits negative congestion externalities in the early decades of the sample. These congestion effects, however, diminish over time. The effect of local diversity is less clear. Estimates are barely significant and, depending on the industry, range from strongly negative to strongly positive.

In section two, we discuss the selected papers on agglomeration externalities we mentioned above. Special attention is devoted to the justification of specific empirical estimation schemes and how the variety of economic models used in the different articles relate to one another. In section three, we develop the estimation methodology for the assessment of temporal variations in agglomeration externalities. Section four covers a description of the data on UK counties. Section five addresses the outcomes. Section six summarises the paper and indicates directions for further research.

2. Some approaches to the measurement of agglomeration externalities

Agglomeration economies or agglomeration externalities are benefits a firm derives from spatial concentration of economic activity in its vicinity. This section reviews the literature that assesses the strength of agglomeration externalities stemming from local diversity or local specialisation. The literature on this topic has been quite prolific, using a large variety of data sets and estimation techniques. As announced, an exhaustive overview is beyond the scope of this text. Instead, some well known papers are reviewed. The large variation in methods and data found is representative for the literature in this line of research. The goal of this section is to uncover how the different empirical strategies relate to one another.

As a starting point, agglomeration externalities are thought to influence the profitability of plants. This can be expressed in the following profit function of a plant:

$$(1) \qquad \pi_i = A(E_i) f(x_i, q(E_i)) - c(x_i, p(E_i))$$

Where π_i is the profit of plant *i*, $A(E_i)$ represents the level of technology, which depends on the local environment. E_i, $f(x_i, q(E_i))$ is the production function using inputs x_i valued at output prices $q(E_i)$. $c(x_i, p(E_i))$ are the production costs as a function of inputs and input prices, $p(E_i)$. Theoretically, agglomeration externalities can arise both from higher productivity and from cost savings. The latter is reflected in the fact that prices depend on the local environment. However, in empirical work, this is usually neglected and agglomeration externalities are modelled to operate solely through the productivity term, $A(E_i)$:

(2) $$\pi_i = A(E_i) f(x_i) - c(x_i)$$

If input prices are allowed to vary across locations, they sometimes enter the model explicitly, but not as a function of characteristics of the local environment:

(3) $$\pi_i = A(E_i) f(x_i) - c(x_i, p_i)$$

Equation (3) can be implemented in a regression analysis in several ways. The choice for a specific implementation depends largely on the data available and on the assumptions authors are willing to make.

For a start, it is informative to have a look at the paper by Henderson (2003). Henderson rewrites (3) as:

(4) $$\pi_i + c(x_i, p_i) = A(E_i) f(x_i)$$

The LHS of this equation measures output and the RHS describes how this output is generated. $f(x_i)$ is commonly assumed to be either Cobb-Douglas or translog, without any constraints on the parameters.[1] To estimate such an equation, input and output data at the plant level have to be available. Taking logs, the regression equation is linear in inputs and technology. Agglomeration externalities enter the equation through the technology term $A(E_i)$. The only assumption made is on the functional form of the production function. Given the level of inputs, the technology term measures how

[1] Henderson (2003) justifies these choices respectively as first order (log of Cobb-Douglas) and second order (translog) Taylor approximation of a log transformed production function of a general shape.

efficient these inputs are used in a plant. Parameter estimates for variables describing the local environment, therefore, show how different types and levels of agglomeration influence the efficiency of local plants.

The advantage of this method is that it imposes very little structure on the data. However, if firms are optimizing the use of their inputs, they should choose production levels that equate the marginal factor productivity (MFP) of each input to its price. Modelling firms as price-takers, this suggests a second set of equations, with one equation for each input. Feser (2002) therefore adds a set of MFP equations to the production function equation. This approach will in general lead to more efficient estimates, but comes at the cost of the extra assumption of optimal firm behaviour. Moreover, such estimates are only feasible if local factor prices are available.

Often, capital data are not available. Using output data and data on labour inputs, it is still possible to estimate the effect of externalities. However, if capital inputs and agglomeration indicators are correlated (e.g. if due to the high costs of labour in big cities, production is more capital intensive), it is hard to determine which part of the variation in labour productivity is due to variations in capital and which to varying agglomeration effects. A large part of the literature, however, does not only suffer from a lack of data on capital, but also from a lack of data on output. In these cases, authors usually only know the level of employment in an industry at a certain location. Moreover, data are often not available for individual plants, but are aggregated at the regional or city level. The production functions are therefore interpreted at the level of local industries, instead of at the level of plants, shifting the unit of analysis from the plant to the regional industry. In the formulas below, this is reflected in the subscript r (regional industry) or c (city-industry) instead of i (plant). A variety of strategies exists to use such data in the framework of equation (1), all based on an analysis of changes in employment over time.

One example is Glaeser et al. (1992). The authors abstract from capital inputs and arrive at a profit function of the following shape:

(5) $$\pi_c = A_c f(L_c) - L_c w$$

As the market for labour is assumed to be national, wages are taken to be equal across all spatial units. Furthermore, assuming that the level of labour input is chosen optimally, the marginal product of labour (MPL) must equal this national wage level. Now, if the equation MPL = wage is expressed in terms of growth factors, after rearranging terms we get:

(6) $$\frac{f'(L_{c,t})}{f'(L_{c,t-1})} = \frac{A_{c,t}}{A_{c,t-1}} - \frac{w_t}{w_{t-1}}$$

where $f'(L_{c,t})$ is the MPL: the first order derivative of the production function with respect to labour inputs.

Given that wages are fixed nationally, wage dynamics are assumed to be the same for all observations and their effects are therefore subsumed in the constant of a regression equation. If the production function is monotonously increasing in labour, this equation states that – keeping other inputs constant – in a city-industry, growth of labour inputs will mimic growth of productivity. The final step is now to let growth in productivity depend on variables that describe the local environment at the beginning of the period, i.e.: $\frac{A_{c,t}}{A_{c,t-1}} = g(E_{c,t-1})$. In this way, growth in employment is linked to start-of-period agglomeration measures.[2]

[2] It is interesting to note that this critically depends on the assumption that wages do not vary with labour demand in a region. If labour markets are not national, this assumption is hard to sustain. In this case wages would increase in cities confronted with a rise in demand for labour, weakening the link between employment growth and productivity growth. Another issue could arise from insufficient demand. Under perfect competition,

A similar approach is found in Henderson et al. (1995). However, Henderson and his colleagues do not specify their model in growth rates, but assume that $A_{c,t+1} = g(E_{c,t})$. In other words, productivity at $t=1$ depends on the local economic environment at $t=0$. Again, assuming monotonously increasing output, the MPL = wage equation leads to the conclusion that above average agglomeration externalities at $t=0$ result in higher than average employment at $t=1$.

A second strategy to measure agglomeration externalities when only employment data are available is to reason from the point of view of firm entry dynamics. Henderson (1997) uses a reduced form equation that is derived in Henderson (1994). In this model, a new actor is introduced, the entrepreneur. The main idea is that entrepreneurs only enter an industry in a city if they can earn profits above a certain minimum level. This minimum level rises with the number of entrepreneurs already in the market, reflecting the increasing difficulty to attract entrepreneurs out of existing activities. Actual profits in the industry are as in equation (2). Entry takes place as long as actual profits exceed the minimally demanded profit by entrepreneurs. As actual profits increase with better technology, the number of entrepreneurs in the market depends positively on agglomeration effects. Furthermore, all entrepreneurs choose the same profit maximizing employment as the existing entrepreneurs. As the number of active firms grows if technology improves, and labour input per plant remains the same or increases as well, regional employment in the industry will rise.

Another paper based on firm entry dynamics is the paper by Rosenthal and Strange (2003). These authors state that entry will occur if profit is positive. They then assume that entrepreneurs are heterogeneous and face the following profit function:

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any productivity gains will be reflected in lower prices, leading to increasing demand. However, if increases in productivity augment output faster than lower prices boost demand (i.e. if the price elasticity of demand is smaller than 1), the demand for labour could decrease. Both issues are discussed at length in Combes *et al.* (2004).

(7) $$\pi_i = A(E_i) f(x_i)(1+\varepsilon_i) - c(x_i)$$

where ε_i is a random draw from a distribution with zero mean that reflects the quality of the entrepreneur.

Assuming that inputs are chosen optimally, for each $A(E_i)$ there is a different minimum ε at which an entrepreneur would enter a local industry. Like in Henderson (1997), as the number of entrants rises with $A(E_i)$, so will local new establishment employment. Therefore, total entry employment in a region is positively correlated with the number of entrants.

Rosenthal and Strange, unlike Henderson, do use data on entry of firms to test their model. They argue that a higher probability of entry must be reflected in higher entry per square km. The advantage of this approach is that no optimality assumptions regarding firm behaviour are needed. Even if entrepreneurs are only satisficing instead of optimizing, entry per square km should be higher if agglomeration externalities are higher. Moreover, as new entrants have to set up an establishment, all costs can be considered variable and all inputs, including capital investment, can be chosen optimally. Unconstrained by existing productive assets, the chosen amount of labour (and the corresponding, yet unobserved, amount of capital) will more accurately reflect current agglomeration effects than employment for existing producers would.

A last paper that adds the number of firms into the model, is Combes et al. (2004). The authors build a model of Cournot competition, where each firm maximizes profit given a certain demand elasticity. Here, in contrast with the previous studies, demand is not considered inelastic. Because of this, prices, and therefore profits, will vary with the number of firms in a local market. Using this relation, Combes and his colleagues show how average plant scale (measured in terms of labour input) depends on the price elasticity of demand and the supply elasticity of labour. Moreover, the assumption that entry will occur until profits are equal to zero results in an equation that can be used to identify the number of active firms in a region. Through the profit function, this number of active firms depends on agglomeration externalities. The authors then estimate a system of equations, with number of firms and average employment per firm as dependent variables.

Although all models seek to locate agglomeration externalities in the technology term of the production function, data availability and willingness to make certain assumptions lead to a wide range of models. However, it is interesting to note that most papers that use only employment data, arrive at the same basic regression equation. The fact that most authors estimate a model with own industry employment as the dependent variable and the lag of own industry employment as a regressor, means that their models can be rearranged into growth models by subtracting the lag of own industry employment from both sides of the equation. From an estimation point of view, therefore, the models of Glaeser et al. (1992), Henderson et al. (1995), Henderson (1997), the new establishment employment equation of Rosenthal and Strange (2003) and the average employment equation in Combes et al. (2004) are the same or very similar. They can all be rewritten in the following general shape:[3]

(9) $$\ln(L_{r,t}) = \ln(A(E_{r,t-1}))$$

where $\ln(A(E_{r,t-1}))$ can be decomposed into a summation of various terms, one of which is the log of lagged own industry employment, $\ln(L_{r,t-1})$.

[3] There are small differences in the last two cases: Rosenthal and Strange take employment per square km and Combes and his co-authors take average employment per plant, but control for number of plants, complicating the rearrangement of terms.

It is therefore not surprising that the final paper in our review, Combes (2000) only provides us with a reduced form equation that fits the general shape of equation (9).

Where the models do differ, is in the specification of the agglomeration circumstances and the estimation techniques. Most articles take at least the following three different aspects of the local economic environment into consideration: specialisation, diversity and the size of the local economy.

Externalities arising from specialisation are often called localization externalities. A high degree of specialisation in an industry can benefit the industry through advantages of labour market pooling, local input-output linkages and intra-industry knowledge spillovers. Most authors focus on the knowledge spillover aspect of localization externalities and try to construct an index that captures these effects.[4] In the papers discussed above, this has been implemented by calculating (a) the share of own industry employment in total employment,[5] (b) the level of own industry employment at the beginning of the period, or (c) the number of plants in the own industry. Glaeser et al. (1992), Henderson et al. (1995) and Henderson (1997) all take both, employment shares and levels, as regressors:

$$loc^{a}_{s,r,t} = \frac{L_{s,r,t-1}}{L_{s,t-1}}$$

$$loc^{b}_{r,t} = \ln\left(L_{s,r,t-1}\right)$$

where $L_{s,r,t}$ is the employment of industry *s*, in region *r* at time *t* and $L_{r,t}$ is total employment in region *r* at time *t*.

[4] A notable distinction is Feser (2002), who tries to proxy all different sources of externalities with specific indicators.

[5] Sometimes this is corrected for national shares, leading to location quotients. This, however, should only matter if observations are pooled across industries. Otherwise, the correction term is covered by either a constant term (cross-section) or time dummies (panel data).

These two indicators are clearly functionally related in a structural way. If controls for local market size are added that are highly correlated with total regional employment, $L_{r,t}$, identification critically depends on using a log transformation in the calculation of $loc^{b}_{r,t}$ and no log transformation when calculating $loc^{a}_{s,r,t}$.[6] Combes (2000) and Combes et al. (2004) therefore choose to make use of only one of the above indicators at a time. Furthermore, neither indicator can distinguish between the internal scale, or firm size, and the external scale, or regional size, of an industry. Therefore, if data are available, it is preferable to use the number of own industry plants in a region as a measure of the scale of an industry, as in Henderson (2003). This indicator can only reflect the external scale of the local industry. In plant level studies, however, information on the size of each plant is available and internal scale effects can be controlled for. In this case, none of the above indicators should be problematic.[7]

The externalities derived from local diversity are called Jacobs' externalities. Jacobs' externalities occur because of a love-of-variety effect as present in Dixit-Stiglitz (1977) production functions, lower demand volatility and inter-industry knowledge spillovers. Again, authors often focus on the knowledge externalities. Most authors use a Herfindahl index of local employment diversity.[8] A similar index, used in this article, is the entropy index.

Scale of local activity is measured by variables such as total employment or total population in a region, often expressed as density per square km. Externalities associated with local scale are called urbanization externalities. They derive from the availability of producer services, a good infrastructure, access to all kinds of amenities etc.

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[6] Indeed, as argued in Combes *et al.* (2004), if local size is proxied by $\ln(L_{r,t})$ and the $loc^{a}_{r,t}$ indicator is also log-transformed, identification is not possible due to perfect colinearity.

[7] The same holds for the work of Rosenthal and Strange. As these authors use plant entry and new establishment employment, lagged data measure the scale of the industry before entrance, and capture therefore only external economies of scale.

[8] Only Glaeser *et al.* (1992) use a different measure, based on the share of the five largest industries in the local economy, excluding the own industry.

Apart from these three core regressors, authors often include controls. Most common among these are local competition variables[9] and information on local wages.

Another dimension in which studies differ is the chosen estimation method. Some authors use cross-section methods, whereas other authors use panel data methods. (Fixed effect) panel data models have the distinct advantage that any omitted variables that remain fixed during the period of study, like climate, availability of raw materials, infrastructure and culture, do not bias results. As a result, all inference is based on variation *within* individual cities over time, whereas results in cross-section studies build on the variation *between* cities at one point in time. Other differences in estimation techniques include controls for endogeneity, the estimation of systems of equations, and models that do not focus on the size of an industry in a region, but rather on the question if the industry is present in a region at all. The latter studies typically use logit estimations. Both approaches can be combined using tobit regressions.

Articles also differ in the time period studied, the geographical coverage and the industry under examination. To allow for easy comparison, we only discuss articles that study one of two geographical areas, the United States and France. However, similar studies have been carried out for the Netherlands (Van Oort, 2004), Korea (Lee et al. 2004), Japan (Dekle, 2002) and many other regions in the world. It is not self-evident that agglomeration externalities should play the same role across different regions. As the industry-specific estimates in the studies that cover multiple industries clearly show, agglomeration effects also differ across industries. Tables 1 and 2 summarize the articles in this review, with respect to their sample, the estimation method and the outcomes.

[9] It is interesting to note that Combes (2000) uses the average plant size as an indicator for internal economies to scale, whereas most other authors use the inverse of this variable to measure the degree of local competition.

Our study focuses on the temporal dimension. Previous studies have neglected the possibility that agglomeration effects change over time. However, agglomeration externalities can be expected to vary over time. In the short run, for example, it is not obvious that agglomeration will protect an industry in economic downswings as much as it will spur its growth in upswings. Moreover, taking a long term perspective, the way we travel and do business has changed a lot. Over the course of the twentieth century, innovations in transport and communication technology have made physical distance less of an obstacle. This may have resulted in lower agglomeration externalities. On the other hand, however, the standardized mass production systems of the first half of the century have been replaced by a wide range of different organizational forms, such as lean production (Piore and Sabel, 1984) and the use of out-sourcing to focus on core competences. In these new manufacturing processes, a premium is placed on frequent interaction and knowledge transfer. As knowledge transfers still require significant face-to-face interaction, the importance of the local environment may have increased.

To estimate the impact of each of these developments, we would need information on the timing of all of them. Moreover, the list of changes over the past century and a half is enormous. Therefore, the goal of the second part of this article is not to *explain* changes in externalities over time, but rather to identify general structures in these changes and propose some stylized facts. If it turns out that agglomeration externalities change over time, neglecting this temporal dimension has severe consequences for the validity of parameter estimates.

Table 1 about here

Table 2 about here

3. Estimation Model

The novelty of the estimations in this article compared to the existing literature is the use of time-varying parameters. In order to get some insights into the robustness of the results, the analysis is repeated for seven different industries. As the prime interest lies in parameter changes, hopefully, conclusions will be less sensitive to the exact estimation procedure. Moreover, using the same econometric procedure across all industries ensures the comparability of outcomes.

Let us start from the reduced-form equation in equation (9) that can be justified in any of the ways described in the literature review.

$$\ln\left(L_{s,r,t}\right) = \ln\left(A\left(E_{s,r,t-1}\right)\right)$$

This equation first has to be adapted to a panel data context. In order to capture time-industry effects, such as national business cycles we add time dummies. Region specific effects are controlled for by county dummies:

$$\ln\left(L_{s,r,t}\right) = \ln\left(A\left(\vec{\beta}_t, E_{s,r,t-1}\right)\right) + \eta_{s,r} + \tau_{s,t} + \varepsilon_{s,r,t} \tag{10}$$

$\eta_{s,r}$, the county specific effects, and $\tau_{s,t}$, the time specific effects, are allowed to correlate with the regressors. $\varepsilon_{s,r,t}$ is taken to be white noise.[10] The time varying aspect of coefficients is reflected in the time-subscript of the parameter vector $\vec{\beta}_t$. Now, let us turn to the elements that enter the technology term. Following the literature, three indicators are used, capturing localization, Jacobs' and urbanization externalities.

Localization externalities are measured as the log of lagged own industry employment:

$$\ln\left(L_{s,r,t-1}\right)$$

[10] The fact that $\varepsilon_{s,r,t}$ is not correlated through time can be justified by the sampling rate of 10 years. Any correlation in idiosyncratic shocks should have vanished over such a long time period.

This measure captures the size of the local industry in the past. An estimate higher than 1 indicates that if a region has a higher share of an industry than any other region, this region would move into an explosive growth path, in the long run taking over all of the country's employment in this industry. Estimates between 0 and 1 can be interpreted as reversion to the mean: keeping other variables constant, regions with higher than average employment in an industry will keep a lead over regions with lower than average employment in the industry, but the gap will shrink over time.

Jacobs' externalities are measured by the entropy of all other manufacturing employment in the region. The employment entropy is defined as follows:

$$ent_{s,r,t} = \sum_{v \in S|\{s\}} \left(-\frac{L_{v,r,t}}{\sum_{u \in S|\{s\}} L_{u,r,t}} \log_2 \left(\frac{L_{v,r,t}}{\sum_{u \in S|\{s\}} L_{u,r,t}} \right) \right)$$

where $S|\{s\}$ is the total set of industries, with industry s omitted. [11] The advantage of the entropy-index over the HHI index, where each industry's contribution enters the equation quadratically, is that it is not as dominated by the shares of a few large industries. Moreover, the entropy rises with an increase in diversity,[12] whereas high HHI values correspond to low levels of diversity. The entropy can therefore be interpreted as a diversity measure, without any inverse transformation.

Urbanization externalities are measured by population density:

$$dens_{r,t} = \frac{pop_{r,t}}{area_r}$$

[11] As a reference set, we use all other manufacturing industries, except *Food, Drink and Tobacco*, which, in the nineteenth century, would dominate the index completely due to its size, and *Other Manufacturing Industries*, which is not a proper industry.
[12] With complete specialisation in one industry the entropy is equal to zero (setting 0*log(0) equal to 0). Complete diversity (every share equal to 1/n, with n the total number of industries) leads to a value of n*(1/n)*log(n)= log(n).

The overall estimation equation is now:

$$(11) \quad \ln\left(L_{s,r,t}\right) = \beta_{s,t}^{loc} \ln\left(L_{s,r,t-1}\right) + \beta_{s,t}^{Jac} \ln\left(ent_{s,r,t-1}\right) + \beta_{s,t}^{urb} \ln\left(dens_{s,r,t-1}\right) + \eta_{s,r} + \tau_{s,t} + \varepsilon_{s,r,t}$$

To get rid of fixed effects, we first difference (11):

$$(12) \quad \Delta \ln\left(L_{s,r,t}\right) = \Delta\beta_{s,t}^{MAR} \ln\left(L_{s,r,t-1}\right) + \Delta\beta_{s,t}^{Jac} \ln\left(ent_{s,r,t-1}\right) + \Delta\beta_{s,t}^{urb} \ln\left(dens_{s,r,t-1}\right) + \Delta\tau_{s,t} + \Delta\varepsilon_{s,r,t}$$

As $\Delta\varepsilon_{s,r,t} = \varepsilon_{s,r,t} - \varepsilon_{s,r,t-1}$ and, by construction, $\varepsilon_{s,r,t-1}$ is correlated with $\ln\left(L_{s,r,t-1}\right)$, errors are correlated with the localization term. We therefore have to use instruments. If the errors can be assumed to be white noise, we can use all lags (t – j) with j ≥ 1 of the dependent variable as instruments. This procedure gives the Arellano-Bond estimator (Arrellano and Bond, 1991).

The difficulty in equation (12) is that it requires the estimation of (T-2)*3 parameters. We can economize on the number of parameters, by assuming that parameters vary smoothly over time. By expressing each parameter as a polynomial of time, we can reduce the burden on the econometrics:

$$(13) \quad \beta_{s,t}^{ext} = \beta_{s}^{0,ext} + \beta_{s}^{1,ext} t + \beta_{s}^{2,ext} t^2 + \beta_{s}^{3,ext} t^3 + \ldots$$

where $ext \in \{loc, Jac, urb\}$ and t represents the time period.

Furthermore, as national industries are expected to grow exponentially, we add *t* as a regressor to capture national growth trends. Taking first differences, this amounts to adding an intercept to (12). Adding the intercept and filling in a polynomial of degree two specification for (13) in (12) gives:

$$\begin{aligned}(14)\ \Delta\ln\left(L_{s,r,t}\right)= \ & \alpha_s+\beta_s^{0,loc}\Delta\ln\left(L_{s,r,t-1}\right)+\beta_s^{1,loc}\Delta\left(t\ln\left(L_{s,r,t-1}\right)\right)+\beta_s^{2,loc}\Delta\left(t^2\ln\left(L_{s,r,t-1}\right)\right)+\\ & \beta_s^{0,Jac}\Delta\ln\left(ent_{s,r,t-1}\right)+\beta_s^{1,Jac}\Delta\left(t\ln\left(ent_{s,r,t-1}\right)\right)+\beta_s^{2,Jac}\Delta\left(t^2\ln\left(ent_{s,r,t-1}\right)\right)+\\ & \beta_s^{0,urb}\Delta\ln\left(dens_{r,t-1}\right)+\beta_s^{1,urb}\Delta\left(t\ln\left(dens_{r,t-1}\right)\right)+\beta_s^{2,urb}\Delta\left(t^2\ln\left(dens_{r,t-1}\right)\right)+\Delta\tau_{s,t}+\Delta\varepsilon_{s,r,t}\end{aligned}$$

which corresponds to the following equation in levels:

$$\begin{aligned}(15)\ \ln\left(L_{s,r,t}\right)= \ & \alpha_s t+\left(\beta_s^{0,loc}+\beta_s^{1,loc}t+\beta_s^{2,loc}t^2\right)\ln\left(L_{s,r,t-1}\right)+\\ & \left(\beta_s^{0,Jac}+\beta_s^{1,Jac}t+\beta_s^{2,Jac}t^2\right)\ln\left(ent_{s,r,t-1}\right)+\\ & \left(\beta_s^{0,urb}+\beta_s^{1,urb}t+\beta_s^{2,urb}t^2\right)\ln\left(dens_{r,t-1}\right)+\tau_{s,t}+\varepsilon_{s,r,t}\end{aligned}$$

4. Data and industries

Occupation data

The data have been assembled by Lee (1979) and acquired from Southall et al. (2004).[13] They consist of decennial observations in the period 1841-1971, excluding the war year of 1941.[14] The data cover the combined area of England, Scotland and Wales and are drawn from British occupation censuses. Lee (1979) groups occupation categories into 27 different industries. To achieve a higher level of consistency, we recoded the data into 24 industries.

A possible objection to the use of these data is that they are not exactly industrial employment data. In contrast to what is customary in an industry census, people were

13 The electronic data have been checked against the data in the book by Lee. This has led to some 15 revisions. Data on area have been added from the website *A Vision of Britain through Time* (GBHGIS, 2006).
14 To avoid missing data problems, we leave the year 1951 out of the estimations.

not asked to state the industry they were active in, but only their occupation.[15] However, the use of these data is justifiable, and in some ways, even preferable to industrial census data. Knowledge spills over between employees, who have a specific occupation, not between firms, which belong to an industry. Employees sharing an occupation participate in the same cognitive field, while firms generally employ employees with varying occupations.

Localization externalities are supposed to help firms develop incremental innovations, using highly specialized industry-specific knowledge, whereas Jacobs' externalities are assumed to spur radical innovations that are imported from fields of knowledge outside the own industry (Henderson et al., 1995; Frenken et al., 2007). Therefore, in order to distinguish between localization externalities and Jacobs' externalities, not the industry, but rather the field of knowledge from which spillovers originate, counts. In this respect, occupation data are more appropriate to measure localization and Jacobs' spillovers than industry data, as the former correspond more closely to skills and fields of knowledge than the latter.

Although occupation data have some advantages over industry data when regressors are drawn from them, they are harder to interpret when used in the construction of dependent variables. In general, we are not concerned with how fast the employment in a specific occupation grows, but rather in how fast industries expand. However, the original census data show an extraordinary number of occupation classes allowing a reasonable translation into 24 industry classes.[16] The occupation-grouping, therefore, can be regarded as an approximate industry classification.

Data limitations

Due to some changes in definitions, comparability of the time series over the entire sample is limited. In specific, there is a structural break in the data collection in 1901.

15 This was particularly the case before 1901. In later censuses, also the industry the occupation was held in was registered. For a description of the census procedures, see Lee (1979).

[16] In 1841, for example, 877 different occupation groups were distinguished (Lee, 1979).

However, the two series partially overlap: the first running from 1841 to 1911 and the second from 1901 to 1971. Using the overlapping years to assess the stability of the classification system, 7 industries are chosen that are hardly affected by the structural break.[17] These are the compound industries *metal manufacture & metal goods not elsewhere classified* and *textiles & clothing and footwear* and the industries *mechanical engineering*, *instrument engineering*, *shipbuilding*, *vehicles* and *construction*. A complete list of industries can be found in Appendix A.

A second issue is the distinction between internal and external economies of scale. Localization externalities assume that a firm benefits from an agglomeration of own industry activity in its region. In other words, there should be economies of scale that cross the boundaries of firms. To distinguish this effect from firm internal economies of scale, it is necessary to take into account the size of individual firms. Unfortunately, data on firm size are not available.

Another problem is the lack of control variables. Wages and human capital are no neutral factors in the agglomeration processes, as argued in the literature review. High wages attract people with a high human capital and high average human capital levels may justify higher wages. Moreover, higher wages in large cities represent high factor costs and these may offset some of the productivity advantages deriving from agglomeration externalities. Ideally, we would be able to control for wage levels, but, again, data limitations prohibit this.

Finally, the boundaries of some counties underwent many changes. Therefore, the counties of London, Middlesex, Kent and Surrey have been merged into one county of Greater London. The counties of East Riding and West Riding have been merged as well.

Although these issues are not trivial, the long time-series dimension compensates in part for the shortcomings above. Over longer periods, migration can take place to restore – or at least move towards – equality in real wages across regions. Moreover, taking decennial observations should resolve local business cycle concerns. The fact that data

[17] See Lee (1979) for details.

points are ten years apart makes it unlikely that random shocks to the economy leave temporal correlation traces in the error term.

Counties in the UK

In the estimation we use data from 48 counties. These counties vary to a great extent in surface area. The upper part of Table 3 summarizes this. The least densely populated area in the sample is both in 1971 and in 1841 the Scottish Highlands. The population density in this region even decreased from .043 to .033 people per acre. The most densely populated area is Greater London. This has with 1.552 (1841) and 5.932 (1971) persons per acre between 36 and 180 times the population density of the highlands.

Development of industries in the UK, 1841-1971

Despite difficulties common to most historical data, the data we use are extraordinarily rich. They cover a large part of the history of industrialization in the United Kingdom, which was the first to develop this new mode of production. We now present some facts about this part of British economic history as far as it is covered by the data.

First of all, population in England, Scotland and Wales, all but tripled from a mere 18.5 million inhabitants to 54.0 million. This explosion in population was accompanied by huge employment shifts in the 130 years of economic development. In 1841, agriculture and fishery, for example, made up almost a quarter of British employment, while in 1971 this share had shrunk to 2.7%. Also, the rise and fall of the British textiles industry are clearly visible: in its golden years, from the 1860s until WW I, the industry employed over 1.4 million workers, representing 21% of total British employment. In the 1970s this number had tumbled to a mere 4% of the British workforce, representing at that time one million employees.

Table 3 about here

Another significant event in the time period we study is the rise of the services economy. Until 1931, manufacturing offered higher employment than services, but from that moment on, service industries overtook manufacturing as the largest national employer. In 1971, financial services and professional services alone provided employment for 16% of the workforce. Given that in 1841 this sector started with a combined employment of 2% of the national work force, this increase is remarkable. Table 4 shows how growth rates in manufacturing suffered from this phenomenon.

Table 4 about here

For the seven industries in this study, the bottom part of Table 3 shows several statistics about each industry in 1841 and 1971. A log transformation of the employment data results in relatively symmetric, bell-shaped distributions. Standard deviations are typically between one and two times the mean, reflecting the skewedness of the untransformed data. This is confirmed when looking at the 4th and 5th column. These give the percentage of total employment in the top 20% and bottom 20% of all counties. Generally, the distributions shift in favour of the largest counties, with 5 out of 7 industries showing an increase of the top 20% counties in total national employment. In all industries, the bottom 20% loose employment share. It is therefore interesting to see if and when industries started to agglomerate. In Table 5 Gini coefficients have been calculated for all industries in all years. Overall, concentration of industries increased until the 1930s, but, after that, industries became less concentrated. The bottom part of the table, where changes in the Gini coefficient are displayed, shows this pattern more clearly. Only mechanical engineering and instrument engineering have a declining Gini coefficient early in the sample. However, the decline becomes more pronounced after 1931. The picture that arises suggests that in the beginning of the period there were some advantages of being co-located with other firms in the industry. However, this advantage decreased over time. In the next section, this conjecture will be confirmed in the analysis of the localization parameter.

Table 5 about here

5. Estimation results

To get an impression of how the agglomeration externalities develop over time, we first ran regressions with parameters allowed to vary for each time period. Given the fact that the first two observations have to be used as instruments, estimates are available for 1861 to 1971, excluding 1941. Appendix B shows a graph of the yearly point estimates for each industry. These estimates can only be seen as indicative. Due to the high number of coefficients, precise estimation is impossible. Moreover, time dummies have been omitted, to avoid multicollinearity. The data have been de-trended, however, by incorporating a constant into the equation in differences.[18]

Keeping in mind these reservations, the graphs are suggestive of specific long term patterns: Localization externalities seem to be decreasing linearly over time, whereas urbanization externalities in at least half the industries are clearly increasing although in a more parabolic way than a linear one. Jacobs' externalities do not reveal any stable pattern across industries. To get more precise estimates, we must restrict the number of coefficients. In tables 7 through 12, estimates for four different models are presented. The first column shows the estimates with no time-variation in the coefficients. The second column introduces a linear specification of all parameters, whereas the third takes a quadratic functional form with respect to time for equation (13). For the final column, a mixture of parameterizations is chosen. Here, we have chosen a functional form that is as parsimonious as possible, without loosing important features in the data. For example, if the estimate on the quadratic term of an externality was not significant, it was reduced to a linear shape. For Jacobs' externalities, in most estimations, neither linear nor quadratic representations seemed necessary, so in column (4) Jacobs' externalities are assumed to be constant over time.

[18] These estimates use Roodman's (2005) xtabond2 procedure in STATA for difference equations. All other estimates are calculated using the regular built-in xtabond procedure.

Looking at column (1) – where externalities are assumed to be constant – localization externalities are present in all industries. Six out of seven estimates are larger than 1, indicating explosive growth processes. Regions with a lead have been able to keep their lead and even expand it. Urbanization externalities are significant, but negative, suggesting congestion effects. Evidence on Jacobs' externalities is mixed: *metal manufacturing*, *textiles* and *construction* exhibit positive Jacobs' externalities. *Vehicles*, on the contrary, have negative Jacobs' externalities. The other industries do not show any significant influence of local diversity. However, in most of the estimates in column (1), Sargan statistics are rather high, typically around 35, which is significant at the 5% level. This raises some doubts about the adequacy of the model specification. This problem does not arise in models (2) – (4), indicating that time-varying models do pass miss-specification tests.

Table 6-12 about here

In most industries, Jacobs' externalities can be modelled to be constant over time. The exceptions are *shipbuilding* and *textiles*. In shipbuilding the evidence in column (2) suggests that diversity had a strong and positive influence in the first year, 1861, but then goes down rapidly. For *textiles*, the most adequate estimates may be found in column (3), where all externalities are assumed to change parabolically over time. Jacobs' externalities climb starting from a positive value in 1861 until somewhere between 1881 and 1891 where they reach a maximum before they start declining. Across the board, Jacobs' externalities seem insignificant in most industries. In the vehicles industries, Jacobs' externalities are even negative and significant. The mixed results on the effect of Jacobs' externalities may not be too surprising. Jacobs' externalities are often thought to be beneficial for young or renewing industries (e.g. Henderson et al. 1995). Following industries for over a century, industries will go through several periods of renewal. Without detailed knowledge of the industries' technological trajectories, pinning down the exact periods of renewal is hard. This is even more complicated when the industries are rather broad sectors as in this study.

Considering localization and urbanization externalities, the linear specification proves to be most adequate. In column (3), either the parameter estimates for the quadratic term are insignificant, or the implied minimum or maximum lies outside the sample period. In the latter case, the parabolic specification does not change the qualitative nature of the evolution of externalities: like in the linear specification, the values for in-sample years either rise monotonically or decline monotonically. As the first two years of the sample are lost in the generation of instruments and lags, the in-sample values of t range from 3 to 14. On this interval, in most industries the quadratic function implies about the same yearly estimates as the linear function for the localization and urbanization externalities. The only real differences are generated at the edges, where the quadratic function generates rather extreme values. Only in *instrument engineering*, estimating a parabola for urbanization externalities makes a real difference. There is first a decline until the lowest point in 1901, after which urbanization externalities start going up again.

Concentrating on column (2), the picture for localization externalities is surprisingly similar across all industries. Implied point estimates in 1861 are above or around 1.[19] This means that all industries start out with explosive growth paths: regions with a lead expand their lead, while lagging regions are left further behind. However, localization externalities decline, as indicated by a negative estimate on $\beta_s^{1,loc}$. Given the confidence intervals, it is difficult to plot an exact trajectory, but, by and large, benefits of local specialisation decline. This gives some support for the point of view that advances in transport and communication technology have eroded the advantages of local, county-level, specialization. Inputs can be sourced from farther away with the tremendous decline in costs of transportation taking place over this period. Moreover, the spread of inventions like the telephone, facilitated long distance supplier relationships and the

[19] The only exception is shipbuilding, where the implied point estimate in 1861 is .5.

availability of mass media may also have contributed to the spread of knowledge across long distances, increasing the spatial reach of knowledge spillovers. However, as argued before, our analysis can only be speculative about the exact causes of the decline of localization externalities.

For urbanization externalities, time trajectories are opposite to those of localization externalities. A large population density has a negative effect in the nineteenth century: $\beta_s^{0,urb}$ in column (2) is negative in all industries. Halfway the sample period, in 1911, the average estimate for the linear specification across all industries is -0.46. This indicates that decreasing the log of population density with one standard deviation, yields an increase in employment of 42%. However, due to relatively large standard errors, the estimate is not very precise.

Such diseconomies in the nineteenth century and beginning of the twentieth century may reflect difficulties to manage congestion. Without modern public transportation systems, production in densely populated cities imposes high costs. Not only commuting, but also importing food and goods from the country side is costly. However, the negative effects of urbanization become smaller over time: β_s^{1urb} is positive. The penalty of producing in cities declines. This could again be explained by innovation in transport technologies. Especially for the mostly rather heavy industries in this paper, congestion gives rise to high costs of inner city transportation. With new technologies, like railway infrastructure and lorries to cope with these costs, the benefits of locating in city-area's may start counterbalancing the disadvantages. However, also here, the analysis only allows for speculation as to which are the causes of the observed dynamics.

Robustness

The estimations incorporate both time and county dummies. Any time-invariant county variables that are omitted, like climate, availability of raw materials, infrastructure, culture, etc., should therefore not bias the outcomes. The same holds for all variables that are specific to the industry in a certain year: time dummies should correct for national business cycles and inflation.

In a GMM procedure, parameter estimates are derived from minimizing the sum of moment restrictions. Sets of compatible moments, give rise to small minima. A large Sargan statistic, therefore, indicates that some of the instruments contradict each other. However, the models in columns (2), (3), and (4) have Sargan statistics that are not significantly different from zero, even at the 5% level. Therefore, the Sargan statistic does not raise doubts about the validity of the models in those columns. Furthermore, according to the F-statistics reported, the variables in all models do have a very significant explanatory power; that the outcomes are the result of random variation can be rejected. A third test concerns the autoregressive structure of disturbances. The first differencing involved in the GMM procedure should result in significant first order autocorrelation in disturbances. However, second order autocorrelation should be absent. In 19 out of 28 estimations, first order autocorrelation is significant at the 5% level. Second order autocorrelation is not significant in any of the estimations. This is taken as additional evidence for the adequacy of the econometric models.

A further robustness check is carried out by leaving out the first year of the sample. The measurements in 1841 are reported to be of a lower quality than the rest of the data (Lee, 1979). The general patterns are very similar.[20]

A possible issue concerns the number of lags of the dependent variable used as instruments. Experimenting with this, we found that for lags larger than 3, the Sargan statistic for over-identifying moment restrictions turns significant, indicating that these instruments are invalid. Adding more instruments would also lead to an imbalance in the ratio of the number of moment equations to the number of observations.[21] We therefore only use lags 2 and 3 as instruments. Results are not changed when lag 3 is left out and only lag 2 is used to construct instruments.

Finally, we measured variety levels in terms of HHI of other manufacturing employment. As the HHI is a lack-of-diversity measure, whereas the entropy index is a genuine

[20] Results available on request.
[21] See the discussion in Arrellano (2003, pp. 169,170)

diversity indicator, the sign of the coefficients on Jacobs' externalities changes when switching between specifications. However, all other parameter estimates remain unaffected.

6. Conclusions

The literature on agglomeration externalities has investigated the influence of the local environment on the economic performance of regional industries in a large number of studies. However, externalities are assumed to be stable across the entire sample period. As the time period sometimes covers several decades, this assumption can be questioned. In the case of Britain, this study shows that externalities have changed tremendously between 1861 and 1971. Using a parsimonious time-varying representation of externality parameters, results indicate that localization externalities decline over time, whereas urbanization externalities increase. This finding is remarkably stable across industries.

In six out of seven industries localization externalities at first give rise to explosive regional dynamics. If localization externalities would stay at these levels, industries would concentrate in one county, leaving all other counties empty. However, in all industries localization externalities go down over time, slowing down and even overturning the tendencies towards complete concentration. This picture is confirmed by the evolution of Gini coefficients. In the first part of the sample, Gini coefficients rise, as regional inequalities grow. Later on, however, Gini coefficients go down, which is consistent with a de-concentration of the industry.

Urbanization externalities are first negative in all seven industries. Over time, urbanization externalities become increasingly less negative. This outcome is confirmed for all industries investigated.

The findings on Jacobs' externalities are more erratic, with no stable pattern arising. Jacobs' externalities are often thought to benefit young and renewing industries. Inter-industry spillovers are most important for industries going through radical technological changes. Without any information about the timing of these events, predicting the pattern of Jacobs' externalities may be all but impossible.

In conclusion, externalities do not appear to be stable over time. Localization externalities and urbanization externalities have followed pronounced temporal trajectories in the end of the nineteenth and a large part of the twentieth century. Neglecting this fact will bias estimations. Nevertheless, the results presented in this paper are no more than stylized facts. It may be worthwhile to investigate the variations over time more closely. A promising direction, as suggested above, may be distinguishing between periods of renewal and decline of industries. Another interesting research agenda would include a quantification of changes in infrastructure and communication technology which may have had a profound influence on the evolution of agglomeration externalities. Finally, changes in the organization of firms may well have caused a change in the importance of knowledge spillovers and local learning. Taking all these factors into consideration may go some way in explaining the different findings in the literature and increase our understanding of the way agglomeration externalities take shape.

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Appendix A: Industrial Classification

INDUSTRY NAME
agriculture, forestry and fishing
mining and quarrying
food, drink and tobacco
coal and petroleum products & chemicals and allied industries
metal manufacture & metal goods not elsewhere specified
mechanical engineering
instrument engineering
electrical engineering
shipbuilding and marine engineering
Vehicles
Textiles & clothing and footwear
leather, leather goods and fur
bricks, pottery, glass, cement, etc
timber, furniture, etc
paper, printing and publishing
other manufacturing industries
Construction
gas, electricity and water
transport and communication
distributive trades
insurance, banking, finance and business services
professional and scientific services
miscellaneous services
public administration and defence

Appendix B: yearly point estimates of agglomeration externalities

Note: some years have been dropped due to collinearity.

Figure 1: Urbanization externalities, decadely estimates

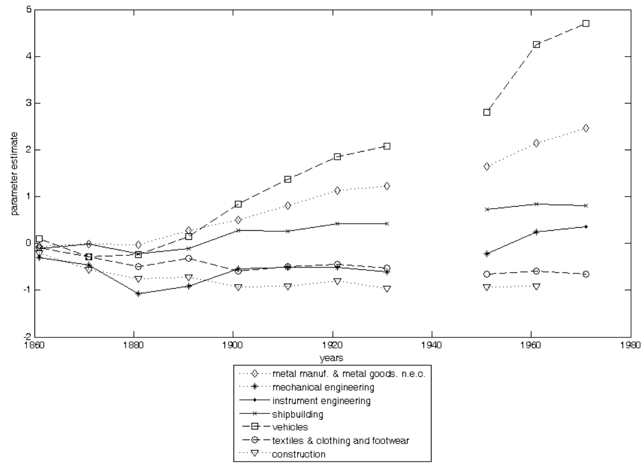

Figure 2: Jacobs' externalities, decadely estimates

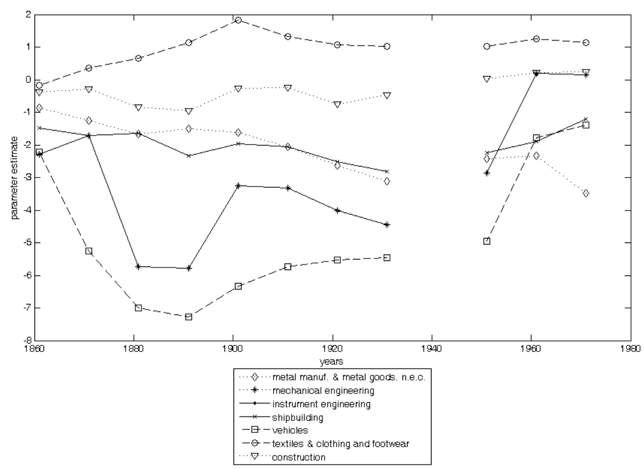

Figure 3: Localization externalities, decadely estimates

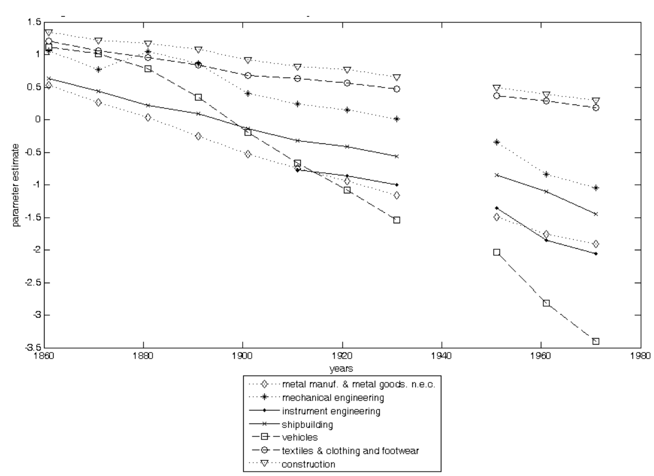

Table 1: Dependent variables and estimation methodology used in the literature

Study	Region	Units	Time period	Dependent variable[22]	Method
Glaeser et al. (1992)	US	City-industries	1956-1987	$\ln\left(\frac{L_{s,c,1987}}{L_{s,c,1956}}\right)$	Cross-section
Henderson et al. (1995)	US	City-industries	1970-1987	$\ln\left(L_{s,c,1987}\right)$	Cross-section and logit (high tech)
Henderson (1997)	US	County-industries	1977-1990	$\ln\left(L_{s,r,t}\right)$	Panel data
Combes (2000)	France	region-industries	1984-1993	$\ln\left(\frac{L_{s,r,1993}}{L_{s,r,1984}} \Big/ \frac{L_{s,1993}}{L_{s,1984}}\right)$	Cross-section (tobit)
Feser (2002)	US	Plants	1992	$\ln\left(output_{s,i,1992}\right)$	Cross-section (price = MFP system)
Henderson (2003)	US	Plants	1977-1992	$\ln\left(output_{s,i,t}\right)$	Panel data
Rosenthal and Strange (2003)	US	Zip-code areas	1996-1997	$L^{entry}_{s,r,'97} / km^2$ $\#entries_{s,r,'97} / km^2$	Cross-section
Combes et al. (2004)	France	region-industries	1984-1993	$\ln\left(L_{s,c,t} / \#\,plants_{s,c,t}\right)$ $\ln\left(\#\,plants_{s,c,t}\right)$	Panel data

[22] The first index (s) indicates the industry, the last index the time period. The middle index represents (c)ity, (r)egion and plant (i). If an index s is omitted, values are summed over it's domain (sometimes excluding the own-cell contributions).

Table2: Overview of regressors and outcomes used in literature

Study	Dependent variable	Localization	outcomes			Jacobs	outcomes			Urbanization	outcomes			Controls
			H	L	S		H	L	S		H	L	S	
Glaeser et al. (1992)	$\ln\left(\frac{L_{s,c,1987}}{L_{s,c,1956}}\right)$	$L_{s,c,'56}$ $\ln\left(L_{s,c,'56}/L_{c,'56}\right)$	- -			Size 5 largest city-ind	+							Region FE Wages, competition
Henderson et al. (1995)	$\ln\left(L_{s,c,1987}\right)$	$\ln\left(L_{s,c,'70}\right)$ $L_{s,c,'70}/L_{c,'70}$	+ +	+ +		HHI	+	ns		Distance national business centre $\ln\left(L_{c,t-1}\right)$	- +	- +		Region dummies Wage education
Henderson (1997)	$\ln\left(L_{s,r,t}\right)$	$\ln\left(L_{s,r,t\ldots t-7}\right)$ $L_{s,r,t-1\ldots t-7}/L_{r,t-1\ldots t-7}$	- +	- +		HHI	+	Ns		$\left(L_{r,t-1}-L_{s,r,t-1}\right)$	+	+		Wages County FE
Combes (2000)	$\ln\left(\frac{L_{s,r,'93}}{L_{s,r,'84}}\Big/\frac{L_{s,'93}}{L_{s,'84}}\right)$	$\ln\left(\frac{L_{s,r,'84}}{L_{r,'84}}\Big/\frac{L_{s,'84}}{L_{'84}}\right)$	-		-	HHI	+		-	$\ln\left(\frac{L_{r,t-1}}{area_r}\right)$	+	+		Competition Plant size
Feser (2002)	$\ln\left(output_{s,i,1992}\right)$	Supplier access Client access Labour pool	+ +	ns - +		Patents	ns	+		University R&D Population density	+ +	ns -		Education Competition
Henderson (2003)	$\ln\left(output_{s,i,t}\right)$	$\ln\left(\# plants_{s,c,t-1}\right)$	+	ns		HHI	ns	ns		$\ln\left(L_{c,t-1}\right)$	ns	ns		MSA FE ind-time FE
Rosenthal and Strange (2003)	$L^{entry}_{s,r,'97}/km^2$	$L_{s,c,'96}$	+			HHI	+			$\left(L_{r,t-1}-L_{s,r,t-1}\right)$	ns			Competition MSA FE
	$\# entries_{s,r,'97}/km^2$	$L_{s,c,'96}$	+			HHI	+			$\left(L_{r,t-1}-L_{s,r,t-1}\right)$	ns			Competition MSA FE
Combes et al. (2004)	$\ln\left(\frac{L_{s,c,t}}{\# plants_{s,c,t}}\right)$	$\ln\left(\frac{L_{s,c,t-1}}{\# plants_{s,c,t-1}}\right)$ $\ln\left(\# plants_{s,c,t}\right)$	+ +		+ +	HHI \# ind.	+ - + -		+ - + -	$\ln\left(L_{r,t-1}\right)$	+		+	Competition Monopoly Ind-reg. FE MA(1)
	$\ln\left(\# plants_{s,c,t+1}\right)$	$\ln\left(\frac{L_{s,c,t}}{\# plants_{s,c,t}}\right)$ $\ln\left(\# plants_{s,c,t}\right)$	- +		- +	HHI \# ind.	+ -		+ -	$\ln\left(L_{s,t-1}\right)$	+		+	Competition Monopoly Ind-reg. FE MA(1)

Remarks:

- '+' signifies significant and positive. '-' significant and negative, 'ns' not significant.
- FE: fixed effects
- MSA: Metropolitan Standard Area
- H: high tech manufacturing; L: low tech manufacturing; S: Services. If cells are merged, regressions have been carried out on all of manufacturing.
- For Jacobs' externalities, many authors use a Hirschman Herfindahl Index (HHI), which measures lack of diversity. Sometimes this measure is transformed into a diversity indicator (e.g. by taking the inverse). In the Jacobs' externality column the entry HHI means a (possibly transformed) HHI based measure. However, in the '+' / '-' coding used in the table, a '+' signifies a positive effect of diversity on the dependent variable.
- For studies that use levels of employment as a dependent variable, it should be noted that estimates between 0 and 1 for lagged employment levels would correspond to estimates between -1 and 0 for growth regressions. In fact, such estimates indicate a reversion to the mean. In this overview, these are interpreted as positive localization externalities, because they indicate that a lead in period t will be associated with a – smaller, but still a – lead in period t +1. As Glaeser et al. (1992) do not take logs of lagged own industry employment, comparisons with the articles that use employment levels instead of employment growth are hard.
- Several authors use separate regressions for individual industries (Henderson et al. (1995), Henderson (1997), Combes (2000), Feser (2002) and Rosenthal and Strange (2003)). Where authors report pooled estimates, I use these outcomes. If there are no estimates for all of high tech and low tech manufacturing, I use the industry names to categorize outcomes.
- Henderson et al. (1995): positive diversity effects are only found in the logit model that estimates the probability of a city to enter a high tech industry between 1970 and 1987.
- Henderson (1997) investigates agglomeration effects using a lag structure of length 7. There are therefore 7 estimates for each indicator. I have tried to let the table reflect the general picture that arises from these 7 estimates.
- Combes (2000) uses besides an HHI-measure a count of active industries in a region to proxy diversity.

Table 3: Description of the data by industry

	Total		Mean		Std.dev.		top 20%		bottom 20%		# > 5% of tot	
	1841	1971	1841	1971	1841	1971	1841	1971	1841	1971	1841	1971
General												
Population (000)	18,489	53,977	385	1,125	449	1,597	52%	60%	6%	3%	3	3
Area (000 acres)[23]	56,374	56,453	1,174	1,176	1,180	1,184	51%	51%	7%	7%	3	3
Population density (levels per acre)			0.375	1.172	0.266	1.119						
Employment in (000)												
Metal manufacture & Metal goods n.e.c.	246	1,137	5.12	23.68	6.88	37.60	66.2%	75.3%	2.9%	0.8%	5	7
Mechanical engineering	32	1,125	0.67	23.43	1.24	31.77	74.9%	62.7%	2.0%	1.7%	6	5
Instrument engineering	16	145	0.33	3.03	0.84	6.81	73.7%	69.6%	3.5%	0.4%	3	4
Shipbuilding	27	180	0.57	3.76	0.99	6.39	73.3%	80.7%	0.3%	0.2%	6	8
Vehicles	39	789	0.81	16.43	1.27	28.11	57.0%	70.3%	2.9%	0.3%	3	4
Textiles & Clothing and Footwear	1,411	1,062	29.40	22.12	52.69	40.34	69.4%	74.3%	3.2%	1.4%	4	5
Construction	370	1,669	7.71	34.77	9.85	49.53	55.4%	58.3%	5.4%	3.8%	4	4

Table 4: National employment growth in broad sectors

	LEVEL		**GROWTH**	
	1841	**1971**		**population indexed**
agriculture and fishery	1,524,249	634,750	-58%	-86%
Manufacturing + mining	2,920,842	10,196,380	249%	20%
Services	1,717,364	10,238,690	496%	104%
Government	87,577	1,571,670	1695%	515%

[23] Source: GBHGIS (2006).

Table 5: Gini coefficients individual industries 1841-1971

Evolution of Gini coefficients													
	1841	**1851**	**1861**	**1871**	**1881**	**1891**	**1901**	**1911**	**1921**	**1931**	**1951**	**1961**	**1971**
metal manufacture & metal goods n.e.c.	0.60	0.64	0.67	0.68	0.69	0.69	0.70	0.70	0.77	0.76	0.75	0.74	0.70
mechanical engineering	0.70	0.73	0.72	0.72	0.71	0.73	0.72	0.71	0.73	0.72	0.68	0.66	0.59
instrument engineering	0.69	0.71	0.73	0.72	0.70	0.70	0.70	0.71	0.88	0.78	0.79	0.81	0.68
Shipbuilding	0.71	0.73	0.74	0.78	0.78	0.80	0.83	0.84	0.82	0.84	0.80	0.79	0.75
Vehicles	0.54	0.52	0.56	0.56	0.58	0.60	0.63	0.67	0.70	0.68	0.70	0.71	0.69
textiles & clothing and footwear	0.64	0.64	0.64	0.66	0.67	0.69	0.70	0.71	0.77	0.77	0.76	0.74	0.69
Construction	0.49	0.50	0.51	0.54	0.56	0.56	0.57	0.57	0.59	0.60	0.57	0.56	0.53

Summary of changes													
	1841	**1851**	**1861**	**1871**	**1881**	**1891**	**1901**	**1911**	**1921**	**1931**	**1951**	**1961**	**1971**
metal manufacture & metal goods n.e.c.		+	+	+	+	+	+	+	+	-	-	-	--
mechanical engineering		+	-	-	-	+	-	-	+	-	--	--	--
instrument engineering		+	+	-	-	-	+	+	+	--	+	+	--
Shipbuilding		+	+	+	+	+	+	+	-	+	--	-	--
Vehicles		--	+	+	+	+	+	+	+	-	+	+	-
textiles & clothing and footwear		+	+	+	+	+	+	+	+	-	-	--	--
Construction		+	+	+	+	+	+	+	+	+	--	-	--

Coding: --: < - .025; -: < 0; +: >0; ++: > .025

Table 6: Metal Manufacturing and Metal Goods n.e.c.

	(1)	(2)	(3)	(4)
$\beta_s^{0,loc}$	2.05 *** (0.26)	1.42 *** (0.14)	1.07 *** (0.16)	1.38 *** (0.14)
$\beta_s^{1,loc}$		-0.14 *** (0.03)	-0.06 (0.08)	-0.13 *** (0.03)
$\beta_s^{2,loc}$			-0.01 (0.00)	
$\beta_s^{0,Jac}$	1.26 *** (0.49)	0.92 (0.61)	-0.17 (0.90)	-0.13 (0.37)
$\beta_s^{1,Jac}$		-0.14 (0.08)	0.20 (0.26)	
$\beta_s^{2,Jac}$			-0.02 (0.02)	
$\beta_s^{0,urb}$	-2.79 *** (0.42)	-1.57 *** (0.29)	-0.32 (0.37)	-1.39 *** (0.27)
$\beta_s^{1,urb}$		0.14 ** (0.07)	-0.22 (0.14)	0.11 * (0.06)
$\beta_s^{2,urb}$			0.03 *** (0.01)	
F-statistic	73.12 (12)	234.94 (15)	242.10 (18)	234.07 (14)
Sargan-statistic	25.37 (26)	13.21 (52)	12.16 (78)	14.02 (52)
p-value AR(1)	0.00	0.08	0.40	0.10
p-value AR(2)	0.72	0.20	0.19	0.18

Dependent variable: log employment. Significance levels: ***: p=0.025; **: p=0.050; *: p=0.100. Instrument lists for terms involving dependent variables: $\Delta \ln(L_{s,r,t-1})$: $\ln(L_{s,r,t-2})$, $\ln(L_{s,r,t-3})$; $\Delta t \ln(L_{s,r,t-1})$: $(t-2)\ln(L_{s,r,t-2})$, $(t-3)\ln(L_{s,r,t-3})$, $(t-4)\ln(L_{s,r,t-4})$; $\Delta t^2 \ln(L_{s,r,t-1})$: $(t-2)^2 \ln(L_{s,r,t-2})$, $(t-3)^2 \ln(L_{s,r,t-3})$, $(t-4)^2 \ln(L_{s,r,t-4})$. Chi-square 5% critical value: 12: 21.03, 14: 23.69, 15: 25.00, 18: 28.78, 26: 38.89, 52: 69.83, 78: 99.62.

Table 7: Mechanical Engineering

	(1)	(2)	(3)	(4)
$\beta_s^{0,loc}$	1.96 *** (0.24)	1.72 *** (0.24)	1.06 *** (0.31)	1.68 *** (0.24)
$\beta_s^{1,loc}$		-0.13 *** (0.05)	0.09 (0.09)	-0.12 *** (0.05)
$\beta_s^{2,loc}$			-0.02 *** (0.01)	
$\beta_s^{0,Jac}$	-0.51 (0.72)	-1.89 (1.17)	-3.59 * (1.89)	-0.83 (0.54)
$\beta_s^{1,Jac}$		0.13 (0.13)	0.76 (0.53)	
$\beta_s^{2,Jac}$			-0.04 (0.03)	
$\beta_s^{0,urb}$	-3.47 *** (0.48)	-2.12 *** (0.52)	-0.25 (0.69)	-2.15 *** (0.52)
$\beta_s^{1,urb}$		0.09 (0.10)	-0.53 *** (0.21)	0.08 (0.10)
$\beta_s^{2,urb}$			0.04 *** (0.01)	
F-statistic	67.72 (12)	156.71 (15)	164.35 (18)	156.02 (14)
Sargan-statistic	18.57 (26)	15.50 (52)	14.55 (78)	14.55 (52)
p-value AR(1)	0.00	0.00	0.00	0.00
p-value AR(2)	0.95	0.89	0.91	0.93

Idem table 6.

Table 8: Instrument Engineering

	(1)	(2)	(3)	(4)
$\beta_s^{0,loc}$	0.92 *** (0.12)	1.78 *** (0.19)	0.79 *** (0.30)	1.38 *** (0.17)
$\beta_s^{1,loc}$		-0.20 *** (0.03)	0.15 (0.12)	-0.13 *** (0.03)
$\beta_s^{2,loc}$			-0.02 *** (0.01)	
$\beta_s^{0,Jac}$	1.14 (0.69)	1.07 (1.20)	-1.23 (1.81)	0.23 (0.59)
$\beta_s^{1,Jac}$		-0.14 (0.14)	0.68 (0.52)	
$\beta_s^{2,Jac}$			-0.06 * (0.03)	
$\beta_s^{0,urb}$	-1.32 *** (0.28)	-1.75 *** (0.42)	0.93 (0.62)	-0.04 (0.47)
$\beta_s^{1,urb}$		0.16 *** (0.06)	-0.77 *** (0.22)	-0.29 *** (0.12)
$\beta_s^{2,urb}$			0.06 *** (0.02)	0.02 *** (0.01)
F-statistic	74.70 (12)	181.29 (15)	174.51 (18)	175.79 (15)
Sargan-statistic	72.42 (26)	36.21 (52)	37.67 (78)	46.86 (52)
p-value AR(1)	0.00	0.00	0.00	0.00
p-value AR(2)	0.13	0.26	0.27	0.16

Idem table 6.

Table 9: Shipbuilding

	(1)	(2)	(3)	(4)
$\beta_s^{0,loc}$	1.39 *** (0.14)	1.01 *** (0.10)	0.75 *** (0.13)	1.05 *** (0.09)
$\beta_s^{1,loc}$		-0.17 *** (0.03)	-0.07 (0.05)	-0.16 *** (0.03)
$\beta_s^{2,loc}$			-0.01 *** (0.00)	
$\beta_s^{0,Jac}$	0.36 (0.79)	1.61 (1.17)	0.65 (1.80)	-0.69 (0.57)
$\beta_s^{1,Jac}$		-0.31 ** (0.15)	0.07 (0.52)	
$\beta_s^{2,Jac}$			-0.03 (0.04)	
$\beta_s^{0,urb}$	-2.24 *** (0.38)	-0.96 *** (0.33)	-0.44 (0.49)	-0.71 *** (0.31)
$\beta_s^{1,urb}$		0.22 *** (0.09)	0.01 (0.16)	0.16 ** (0.08)
$\beta_s^{2,urb}$			0.02 * (0.01)	
F-statistic	109.01 (12)	276.83 (15)	268.72 (18)	278.66 (14)
Sargan-statistic	33.32 (26)	35.23 (52)	26.68 (78)	38.19 (52)
p-value AR(1)	0.00	0.87	0.95	0.61
p-value AR(2)	0.39	0.39	0.33	0.36

Idem table 6.

Table 10: Vehicles

	(1)	(2)	(3)	(4)
$\beta_s^{0,loc}$	1.58 *** (0.21)	1.64 *** (0.26)	0.97 *** (0.39)	1.66 *** (0.25)
$\beta_s^{1,loc}$		-0.18 *** (0.05)	0.05 (0.13)	-0.18 *** (0.05)
$\beta_s^{2,loc}$			-0.02 (0.01)	
$\beta_s^{0,Jac}$	-1.46 *** (0.60)	-0.84 (0.93)	-1.07 (1.47)	-1.05 *** (0.44)
$\beta_s^{1,Jac}$		-0.03 (0.11)	0.07 (0.45)	
$\beta_s^{2,Jac}$			-0.01 (0.03)	
$\beta_s^{0,urb}$	-1.87 *** (0.33)	-1.53 *** (0.50)	-0.11 (0.70)	-1.54 *** (0.50)
$\beta_s^{1,urb}$		0.14 (0.09)	-0.33 (0.24)	0.14 (0.09)
$\beta_s^{2,urb}$			0.03 (0.02)	
F-statistic	67.25 (12)	205.47 (15)	197.56 (18)	204.87 (14)
Sargan-statistic	64.51 (26)	47.38 (52)	47.22 (78)	47.18 (52)
p-value AR(1)	0.00	0.01	0.04	0.00
p-value AR(2)	0.81	0.64	0.65	0.63

Idem table 6.

Table 11: Textiles & Clothing and Footwear

	(1)	(2)	(3)	(4)
$\beta_s^{0,loc}$	2.07 *** (0.25)	1.68 *** (0.16)	0.75 *** (0.21)	1.34 *** (0.18)
$\beta_s^{1,loc}$		-0.17 *** (0.05)	0.13 ** (0.07)	-0.08 *** (0.03)
$\beta_s^{2,loc}$			-0.02 *** (0.00)	
$\beta_s^{0,Jac}$	6.15 *** (0.99)	4.67 *** (0.91)	-1.03 (1.24)	2.07 * (1.09)
$\beta_s^{1,Jac}$		-0.46 *** (0.17)	1.38 *** (0.34)	
$\beta_s^{2,Jac}$			-0.13 *** (0.02)	
$\beta_s^{0,urb}$	-2.43 *** (0.36)	-1.52 *** (0.30)	0.27 (0.37)	-0.83 *** (0.27)
$\beta_s^{1,urb}$		0.13 * (0.07)	-0.46 *** (0.11)	-0.01 (0.04)
$\beta_s^{2,urb}$			0.04 *** (0.01)	
F-statistic	90.85 (12)	259.08 (15)	269.18 (18)	241.93 (14)
Sargan-statistic	28.22 (26)	36.12 (52)	27.10 (78)	39.64 (52)
p-value AR(1)	0.00	0.17	0.34	0.04
p-value AR(2)	0.86	0.90	0.93	0.92

Idem table 6.

Table 12: Construction

	(1)	(2)	(3)	(4)
$\beta_s^{0,loc}$	2.12 *** (0.24)	1.79 *** (0.19)	1.02 *** (0.23)	1.78 *** (0.19)
$\beta_s^{1,loc}$		-0.15 *** (0.06)	0.12 (0.09)	-0.14 *** (0.06)
$\beta_s^{2,loc}$			-0.02 *** (0.01)	
$\beta_s^{0,Jac}$	1.30 *** (0.41)	0.91 * (0.54)	-0.27 (0.85)	0.48 (0.35)
$\beta_s^{1,Jac}$		-0.06 (0.07)	0.34 (0.24)	
$\beta_s^{2,Jac}$			-0.03 * (0.02)	
$\beta_s^{0,urb}$	-2.38 *** (0.31)	-1.45 *** (0.27)	-0.19 (0.33)	-1.38 *** (0.26)
$\beta_s^{1,urb}$		0.08 (0.07)	-0.36 *** (0.11)	0.05 (0.07)
$\beta_s^{2,urb}$			0.04 *** (0.01)	
F-statistic	87.60 (12)	228.40 (15)	229.43 (18)	220.42 (14)
Sargan-statistic	27.41 (26)	34.81 (52)	31.80 (78)	34.55 (52)
p-value AR(1)	0.00	0.03	0.16	0.02
p-value AR(2)	0.56	0.95	0.75	0.97

Idem table 6.