Agglomeration: A Dynamic Approach*

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Abstract

This paper studies the sources of agglomeration economies in cities. We begin by introducing a simple dynamic spatial equilibrium model that incorporates spillovers within and across industries, as well as city-size effects. The model generates a dynamic panel-data estimation equation. We implement the approach using detailed new data describing the industry composition of 31 English cities from 1851-1911. We find that industries grow faster in cities where they have more local suppliers or other occupationally-similar industries. Industries do not grow more rapidly in locations in which they are already large, though there can be exceptions. Thus, dynamic agglomeration appears to be driven by cross-industry effects. Once we control for these cross-industry agglomeration effects, we find a strong negative relationship between city size and city-industry growth. This allows us to construct the first estimate of the aggregate strength of the cross-industry agglomeration forces. Our results suggest a lower bound estimate of the overall strength of agglomeration forces equivalent to a city-size divergence rate of 2.1-3.3% per decade.

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1 Introduction

What are the key factors driving city growth over the long term? One of the leading answers to this question, dating back to Marshall (1890), is that firms may benefit from proximity to one another through agglomeration economies. While compelling, this explanation raises further questions about the nature of these agglomeration economies. Do firm primarily benefit from proximity to other firms in the same industry, or, as suggested by Jacobs (1969), is proximity to other related industries more important? Or is overall city size the key factor in determining agglomeration economies? How do these forces vary across industries? How do these benefits compare to the cost of proximity arising through congestion forces? How can we separate all of these features from the fixed locational advantages of cities? These are important questions for our understanding of cities. Their answers also have implications for the design of place-based policies, which can top $80 billion per year in the U.S. and are also widely used in other countries.[1]

Not surprisingly, there is a large body of existing research exploring the nature of agglomeration economies. This study draws on two important existing strands of this literature.[2] One approach uses long-differences in the growth of city-industries over time and relates them to rough measures of initial conditions in a city, such as an industry's share of city employment or the Herfindahl index over major city-industries (Glaeser *et al.* (1992), Henderson *et al.* (1995)). The main concern with this line of research is that it ignores much of the richness and heterogeneity that are likely to characterize agglomeration economies. A more recent approach allows for a richer set of inter-industry relationships using connection matrices based on input-output flows,

[1] *The New York Times* has constructed a database of incentives awarded by cities, counties and states to attract companies to locate in their area. The database is available at http://www.nytimes.com/interactive/2012/12/01/us/government-incentives.html.

[2] There are several other strands of the agglomeration literature which are less directly related to this paper. One strand focuses on addressing identification issues by comparing outcomes in similar locations, where some locations receive a plausibly exogenous shock to the level of local economic activity (Greenstone *et al.* (2010), Kline & Moretti (2013), Hanlon (2014)). This approach has the advantage of more cleanly identifying the causal impact of changes in local economic activity, but it may also be less generalizable and more difficult to apply to policy analysis. Thus, we view this line of work as complementary to the our approach. Other alternative approaches use individual-level wage data (Glaeser & Mar (2001), Combes *et al.* (2008), Combes *et al.* (2011)) or firm-level data (Dumais *et al.* (2002), Rosenthal & Strange (2003), Combes *et al.* (2012)) to investigate the effects of city size. See Rosenthal & Strange (2004) and Combes & Gobillon (Forthcoming) for reviews of this literature.

labor force similarity, or technology spillovers. These connections are then compared to a cross-section of industry locations (Rosenthal & Strange (2001), Ellison *et al.* (2010), Faggio *et al.* (2013)).[3] A limitation of this type of static exercise is that it is more difficult to control for locational fundamentals in cross-sectional regressions.

This study offers an alternative approach that builds on previous work, but also seeks to address some of the remaining issues facing the literature. To begin, we ground our estimation strategy in a dynamic spatial equilibrium model of city-industry growth. While simple, our model serves both to discipline our empirical exercise and to highlight potential concerns in the estimation of agglomeration economies. The theory delivers a relationship between local employment growth in industry i during a period and the local level of employment in all industries at the beginning of the period, weighted by a vector of parameters representing the strength of spillovers between industry pairs, the strength of spillovers across firms within industry i, time-varying city effects, and shocks to industry growth at the national level.

To implement this approach, we build a uniquely rich long-run dataset describing the industrial composition of English cities over six decades. These new data, which we digitized from original sources, cover 31 of the largest English cities (based on 1851 population) for the period 1851-1911. The data come from the Census of Population, which was taken every decade. These data have two unique features. First, they come from a full census, not a sample of the census, which is important in reducing error when cutting the data by city and industry. Second, the 23 industry groups that we use in the analysis cover nearly the entire private sector economy of each city. We add to this four measures of inter-industry connections reflecting input and output linkages and the demographic and occupational similarity of industry workforces.

Motivated by the theory, we offer a panel-data econometric approach to estimating agglomeration economies that builds on previous work by Henderson (1997).[4] The use of panel data offers well-known advantages over the cross-sectional or long-difference approaches used in most of the existing literature. Following Ellison *et al.* (2010), we parameterize the pattern of connections between industries using the matrices of in-

[3]These studies are part of a broader literature looking at the impact of inter-industry connections, particularly through input-output linkages, that includes work by Amiti & Cameron (2007) and Lopez & Sudekum (2009).

[4]A similar approach is explored in Dumais *et al.* (1997). See also Combes (2000) and Dekle (2002).

dustry connections that we have constructed. Also, to help strengthen identification, we use an instrumental variable approach in which we interact lagged city-industry employment with industry employment growth in all other cities to generate *predicted* employment in industry j in a period.[5] This predicted employment level is then used as an instrument for actual employment in industry j which will be independent of contemporaneous local shocks. Put another way, we take advantage of the national industry growth rate to generate predicted industry employment levels within a city that are plausibly exogenous to local spillovers in the current period.

One contribution of this paper is to estimate the importance of dynamic agglomoeration forces related to industry scale, cross-industry connections, and city-size in a unified framework, while controlling for fixed city-industry factors and time-varying industry-specific shocks. We find that (1) cross-industry effects are important, and occur largely through the presence of local suppliers and occupationally similar labor pools, (2) the net effect of within-industry agglomeration forces are generally negative, with a small number of exceptions, and (3) city size has a clear negative relationship to city growth. The presence of local buyers appears to have little positive influence on city-industry growth. Our methodology also allows us to examine heterogeneity in the extent to which industries produce and benefit from agglomeration forces.

We provide a variety of tests examining the robustness of these results. For example, we show that our results are not substantially changed if we drop particular cities or particular industries. They are also robust to using an alternative set of matrices measuring cross-industry connections as well as a more aggregated set of industry definitions. In addition, we have constructed a new matrix of industry technology similarity using patent data that can be used to investigate agglomeration forces operating through this channel. Including this technological similarity matrix does not substantially impact our main results. We also show that incorporating cross-city effects, such as market potential or cross-city industry spillovers has little impact on our results. These cross-city factors appear to be relatively weak compared to the within-city effects that we observe.

A second contribution of this paper is to produce an estimate of the aggregate strength of the agglomeration forces captured by our measures. This is done by comparing actual city growth in a decade to the estimated city-time fixed effect for

[5]This approach is somewhat similar to the technique used in Bartik (1991).

that decade from a model that includes the cross-industry connection variables. The wedge between actual city growth and the estimated fixed effect must be equal to the total impact of the agglomeration force. These results suggest that the agglomeration forces captured by our empirical model are equivalent to a decadal city-size divergence rate of 2.1-3.3%. This is likely to be a lower bound estimate as it will not reflect any agglomeration forces not captured by our measures of cross-industry connections. To our knowledge this is the first paper to show how the aggregate strength of these many cross-industry connections can be measured.

The next section presents our theoretical framework, while Section 3 describes the data. The empirical approach is presented in Section 4. Section 5 presents the main results, while Sections 6 and 7 investigate the robustness of our results to using alternative connection matrices or to including of cross-city effects. Section 8 concludes.

2 Theory

In this section, we build a simple model of city growth incorporating localized spillovers within and across industries and use it to derive our empirical specification. Authors such as Combes & Gobillon (Forthcoming) have highlighted the need to ground empirical studies of agglomeration economies in theory.[6] Grounding our analysis in theory can help us interpret the results while also being transparent about potential concerns. However, it is important to keep in mind that theories other than the one offered here may also generate a similar empirical specification. Thus, our analysis should not be interpreted as a test of the particular mechanisms described by the theory.

The model is dynamic in discrete time. The dynamics of the model are driven by spillovers within and across industries which depend on industry employment and a matrix of parameters reflecting the extent to which any industry benefits from learning

[6] In a recent handbook chapter on agglomeration economies, Combes & Gobillon (Forthcoming) write (p. 87), "this strand of the literature is an interesting effort to identify the mechanisms underlying agglomeration economies...Ultimately though, it is very difficult to give a clear interpretation of the results, and conclusions are mostly descriptive. This is due to the weak links between estimated specifications and theoretical models...the presence and channels of endogeneity are difficult to assess, and it is hard to conclude that some instruments are valid, as estimated specifications have usually not been derived from any precise theoretical framework."

generated by employment in other industries (i.e., learning-by-doing spillovers). These dynamic effects are external to firms, so they will not influence the static allocation of economic activity across space that is obtained given a distribution of technology levels. Thus, we can begin by solving the allocation of employment across space in any particular period. We then consider how the allocation in one period affects the evolution of technology and thus, the allocation of employment in the next period. The benefit of such a simple dynamic system is that it allows the model to incorporate a rich pattern of inter-industry connections.

The theory focuses on localized spillovers that affect industry technology and thereby influence industry growth rates. In this respect it is related to the endogenous growth literature, particularly Romer (1986) and Lucas (1988). This is obviously not the only potential agglomeration force that may lie behind our results; alternative models may yield an estimation equation that matches the one we apply. However, because we are interested in dynamic agglomeration, focusing on technology growth is the natural starting point.

To keep things simple, our baseline model omits some additional features, such as capital and intermediate inputs, that one might want to consider. In Appendix A.1, we describe a more complex model that incorporates these features and show that it delivers essentially the same estimating equation. There are two important simplifying assumptions in our theory. First, as in most urban models, goods and services are freely traded across locations. Second, the production function parameters do not vary across industries. In Appendix A.1 we discuss the implications of altering these assumptions.

2.1 Allocation within a static period

We begin by describing how the model allocates population and economic activity across geographic space within a static period, taking technology levels as given. The economy is composed of many cities indexed by $c = \{1, ...C\}$ and many industries indexed by $i = \{1, ...I\}$. Each industry produces one type of final good so final goods are also indexed by i.

Individuals are identical and consume an index of final goods given by D_t. The corresponding price index is P_t. These indices take a CES form,

$$D_t = \left(\sum_i \gamma_{it} x_{it}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \qquad , \qquad P_t = \left(\sum_i \gamma_{it}^{\sigma} p_{it}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$$

where x_i is the quantity of good i consumed, γ_{it} is a time-varying preference parameter that determines the importance of the different final goods to consumers, p_{it} is the price of final good i, and σ is the (constant) elasticity of substitution between final goods. It follows that the overall demand for any final good is,

$$x_{it} = D_t P_t^{\sigma} p_{it}^{-\sigma} \gamma_{it}^{\sigma}. \tag{1}$$

Production is undertaken by many perfectly competitive firms in each industry, indexed by f. Output by firm f in industry i is given by,

$$x_{icft} = A_{ict} L_{icft}^{\alpha} R_{icft}^{1-\alpha}, \tag{2}$$

where A_{ict} is technology, L_{icft} is labor input, and R_{icft} is another input which we call resources. These resources play the role of locational fundamentals in our model. Note that technology is not specific to any particular firm but that it is specific to each industry-location. This represents the idea that within industry-locations, firms are able to monitor and copy their competitors relatively easily, while information flows more slowly across locations.

Labor can move costlessly across locations to achieve spatial equilibrium. This is a standard assumption in urban economic models and one that seems reasonable over the longer time horizons that we consider. The overall supply of labor to the economy depends on an exogenous outside option wage $\bar{w}_t$ that can be thought of as the wage that must be offered to attract immigrants or workers from rural areas to move to the cities. Thus, more successful cities, where technology grows more rapidly, will experience greater population growth.

We also incorporate city-specific factors into our framework. Here we have in mind city-wide congestion forces (e.g., housing prices), city-wide amenities, and the quality of city institutions. We incorporate these features in a reduced-form way by including a term $\lambda_{ct} > 0$ that represents a location-specific factor that affects the firm's cost of employing labor. The effective wage rate paid by firms in location c is then $\bar{w}_t \lambda_{ct}$. In practice, this term will capture any fixed or time-varying city amenities or disamenities that affect all industries in the city.

In contrast to labor, resources are fixed geographically. They are also industry-specific, so that in equilibrium $\sum_f R_{icft} = \bar{R}_{ic}$, where $\bar{R}_{ic}$ is fixed for each industry-location and does not vary across time, though the level of $\bar{R}_{ic}$ does vary across locations. This approach follows Jones (1975) and has recently been used to study the regional effects of international trade by Kovak (2013) and Dix-Carneiro & Kovak (2014). These fixed resources will be important for generating an initial distribution of industries across cities in our model, and allowing multiple cities to compete in the same industry in any period despite variation in technology levels across cities.

Firms solve:

$$\max_{L_{icft}, R_{icft}} p_{it} A_{ict} L_{icft}^{\alpha} R_{icft}^{1-\alpha} - \bar{w}_t \lambda_{ct} L_{icft} - r_{ict} R_{icft}.$$

Using the first order conditions, and summing over all firms in a city-industry, we obtain the following expression for employment in industry i and location c[7]:

$$L_{ict} = A_{ict}^{\frac{1}{1-\alpha}} p_{it}^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{\bar{w}_t \lambda_{ct}} \right)^{\frac{1}{1-\alpha}} \bar{R}_{ic}. \tag{3}$$

This expression tells us that employment in any industry i and location c will depend on technology in that industry-location, the fixed resource endowment for that industry-location, factors that affect the industry in all locations (p_{it}), city-specific factors (λ_{ct}), and factors that affect the economy as a whole ($\bar{w}_t$).

To close the static model, we need only ensure that income in the economy is equal to expenditures. This occurs when,

$$D_t P_t + M_t = \bar{w}_t \sum_c \lambda_{ct} \sum_i L_{ict} + \sum_i \sum_c r_{ict} \bar{R}_{ic}.$$

where M_t represents net expenditures on imports. For a closed economy model we

[7]With constant returns to scale production technology and external spillovers, we are agnostic about the size of individual firms in the model. We require only that there are sufficiently many firms, and no firms are too large, so that the assumption of perfect competition between firms holds.

can set M_t to zero and then solve for the equilibrium price levels in the economy.[8] Alternatively, we can consider a (small) open economy case where prices are given and solve for M_t. We are agnostic between these two approaches.

2.2 Dynamics: Technology growth over time

Technological progress in the model occurs through localized learning-by-doing spillovers that are external to firms. One implication is that firms are not forward looking when making their employment decisions within any particular period. Following the approach of Glaeser *et al.* (1992), we write the growth rate in technology as,

$$\ln\left(\frac{A_{ict+1}}{A_{ict}}\right) = S_{ict} + \epsilon_{ict}, \tag{4}$$

where S_{ict} represent the amount of spillovers available to a city-industry in a period. Some of the factors that we might consider including in this term are:

$$S_{ict} = f\Big(\text{within-industry spillovers, cross-industry spillovers,} \\ \text{national industry technology growth, city-level aggregate spillovers}\Big).$$

We can use Equation 4 to translate the growth in (unobservable) city-industry technology into the growth of (observable) city-industry employment. We start with Equation 3 for period $t+1$, take logs, plug in Equation 4, and then plug in Equation 3 again (also in logs), to obtain,

[8] To solve for the price levels in the closed economy case, we use the first order conditions from the firm's maximization problem and Equation 3 to obtain,

$$p_{it} = \left(\frac{\alpha}{\bar{w}_t}\right)^{\frac{\alpha}{\alpha\sigma-\alpha-\sigma}} \left(\sum_c A_{ict}^{\frac{1}{1-\alpha}} \bar{R}_{ic} \lambda_{ct}^{\frac{\alpha}{\alpha-1}}\right)^{\frac{1-\alpha}{\alpha\sigma-\alpha-\sigma}} (D_t P_t^{\sigma})^{\frac{\alpha-1}{\alpha\sigma-\alpha-\sigma}} \gamma_{it}^{\frac{\sigma(\alpha-1)}{\alpha\sigma-\alpha-\sigma}}.$$

This equation tells us that in the closed-economy case, changes in the price level for goods produced by industry i will depend on both shifts in the level of demand for goods produced by industry i represented by γ_{it}, as well as changes in the overall level of technology in that industry (adjusted for resource abundance), represented by the summation over A_{ict} terms.

$$\ln(L_{ict+1}) - \ln(L_{ict}) = \left(\frac{1}{1-\alpha}\right)\Bigg[S_{ict} + \Big[\ln(P_{it+1}) - \ln(p_{it})\Big] + \Big[\ln(\lambda_{ct+1}) - \ln(\lambda_{ct})\Big] + \Big[\ln(\bar{w}_{t+1}) - \ln(\bar{w}_t)\Big] + e_{ict}\Bigg]. \quad (5)$$

where $e_{ict} = \epsilon_{ict+1} - \epsilon_{ict}$ is the error term. Note that by taking a first difference here, the locational fundamentals term $\bar{R}_{ic}$ has dropped out. We are left with an expression relating growth in a city-industry to spillovers, city-wide growth trends, national industry growth, and an aggregate national wage term.

The last step we need is to place more structure on the spillovers term. Existing empirical evidence provides little guidance on what form this function should take. In the absence of empirical guidance, we choose a fairly simple approach in which technology growth is a linear function of log employment, so that

$$S_{ict} = \sum_k \tau_{ki} \max(\ln(L_{kct}), 0) + \xi_{it} + \psi_{ct} \quad (6)$$

where each $\tau_{ki} \in (0, 1)$ is a parameter that determines the level of spillovers from industry k to industry i. While admittedly arbitrary, this functional form incorporates a number of desirable features. If there is very little employment in industry k in location c ($L_{kct} \leq 1$), then industry k makes no contribution to technology growth in industry i. Similarly, if $\tau_{ki} = 0$ then industry k makes no contribution to technology growth in industry i. The marginal benefit generated by an additional unit of employment is also diminishing as employment rises. This functional form does rule out complementarity between technological spillovers from different industries. While such complementarities may exist, an exploration of these more complex interactions is beyond the scope of the current paper.

One feature of Equation 4 is that it will exhibit scale effects. While this may be a concern in other types of models, it is a desirable feature in a model of agglomeration economies, where these positive scale effects will be balanced by offsetting congestion forces, represented by the λ_{ct} terms.

Plugging Equation 6 into Equation 5, we obtain our estimation equation:

$$
\begin{aligned}
\ln(L_{ict+1}) - \ln(L_{ict}) &= \left(\frac{1}{1-\alpha}\right)\Bigg[\tau_{ii}\ln(L_{ict}) + \sum_{k\neq i}\tau_{ki}\ln(L_{kct}) \\
&+ \Big[\ln(P_{it+1}) - \ln(P_{it})\Big] + \xi_{it} \\
&+ \Big[\ln(\lambda_{ct+1}) - \ln(\lambda_{ct})\Big] + \psi_{ct} \\
&+ \Big[\ln(\bar{w}_{t+1}) - \ln(\bar{w}_t)\Big]\Bigg] + e_{ict}.
\end{aligned} \tag{7}
$$

This equation expresses the change in log employment in industry i and location c in terms of (1) within-industry spillovers generated by employment in industry i, (2) cross-industry spillovers from other industries, (3) national industry-specific factors that affect industry i in all locations, (4) city-specific factors that affect all industries in a location, and (5) aggregate changes in the wage (and thus national labor supply) that affect all industries and locations. To highlight that this expression incorporates both within and cross-industry spillovers we have pulled the within-industry spillover term out of the summation.

This expression for city-industry growth will motivate our empirical specification. One feature that is worth noting here is that we have two factors, city-level aggregate spillovers (ψ_{ct}) and other time-varying city factors (λ_{ct}), both of which vary at the city-year level. Empirically we will not be able to separate these positive and negative effects and so we will only be able to identify their net impact. Similarly, we cannot separate positive and negative effects that vary at the industry-year level.

There are at least two promising alternative theories that may yield an empirical specification similar to the expression generated by our model. One such theory could combine static inter-industry connections, such as pecuniary spillovers through intermediate-goods sales, with changing transport costs.[9] A second alternative combines static agglomeration forces with a friction that results in a slow transition towards the static equilibrium. Our empirical exercises cannot make a sharp distinction between the mechanisms described in our framework and these alternatives, so they should not be interpreted as a direct test of the particular agglomeration mechanism described by the theory.

[9]Further discussion of a theory of this type is available in Appendix A.1.

3 Empirical setting and data

This study looks at English cities over the period 1851-1911. This historical setting offers several advantages when studying agglomeration economies. First, there was a very limited amount of government involvement in the economy, and particularly for our purposes, the lack of place-based economic interventions. In modern economies these interventions can be large (Greenstone & Moretti (2004), Kline & Moretti (2013)), perhaps large enough to impact estimates of agglomeration economies. Second, this period was characterized by fairly high levels of labor mobility; some authors, such as Baines (1994) argue that internal migration was easier during this period than it is in Britain today.[10] Third, local governments placed very few limits on development. The first town planning act in Britain was passed in 1909, at the very end of our period, was limited in its extent, and was implemented too slowly to have substantially impacted the period we study.[11] This contrasts sharply with many modern economies, where limits on local development have a substantial impact on city growth (Glaeser *et al.* (2005)). Fourth, even in 1851 the urban system in Britain was well-established. For instance, Dittmar (2011) argues that Gibrat's law emerged in Europe by 1800, suggesting that the urban system was close to spatial equilibrium during this period. This is a good fit for our model, where the economy is in spatial equilibrium period-by-period.[12]

The main database used in this study was constructed from thousands of pages of original British Census of Population summary reports. The decennial Census data were collected by trained registrars during a relatively short time period, usually a few days in April of each census year. As part of the census, individuals were asked to provide one or more occupations, but the reported occupations correspond more closely to industries than to what we think of as occupations today.[13]

[10] Baines writes, "Although it is notoriously difficult to measure, we can be fairly sure that internal migration rates were high in the nineteenth century...We could also say that both the housing and labor markets were more open than today and that migrants were less likely to be deterred by the problems of educating children or looking after relatives."

[11] The 1909 town planning act allowed British cities to implement town planning in a limited way, but did not make such planning mandatory. Sutcliffe (1988) reports that by 1913 only 66 towns were preparing town planning schemes and in only three towns had such schemes been approved by the Local Government Board, the main oversight body.

[12] In contrast, Desmet & Rappaport (2014) find that Gibrat's law didn't emerge in the U.S. until the middle of the 20th century due to the entry of new locations, which suggests that the U.S. was on a long transition path over that period and could have been far from spatial equilibrium.

[13] In fact, in 1921 the Census office renamed what had previously been called "occupation" to be

A unique feature of this database is that the information is drawn from a full census. Virtually every person in the towns we study provided information on their occupation and all of these answers are reflected in the employment counts in our data. This contrasts with data based on census samples, which often use just 5% and sometimes just 1% of the available data.[14]

The database includes the 31 cities for which occupation data were reported in each year from 1851-1911. These cities include 28-34% of the English population over the period we study. The geographic extent of these cities does change over time as the cities grow, a feature that we view as desirable for the purposes of our study.[15] Table 1 provides a list of the cities included in the database, as well as the 1851 population of each city, the number of workers in the city in 1851, and the number of workers in 1851 that are working in one of the industry groups that are used in the analysis.[16] A map showing the location of these cities in England is available in the Appendix. In general, our analysis industries cover most of the working population of the cities.

The occupations listed in the census reports closely correspond to industries, an important feature for our purposes. Examples from 1851 include "Banker", "Glass Manufacture" or "Cotton manufacture". The database does include a few occupations that do not directly correspond to industries, such as "Labourer", "Mechanic", or "Gentleman", but these are a relatively small share of the population. These categories are not included in the analysis.

A major challenge faced in using these data is that the occupational categories listed in the census reports varied over time. To deal with this issue we combined multiple industries in order to construct consistent industry groupings over the study

"industry" and then introduced a new set of data on actual occupations.

[14]We have experimented with data based on a census sample (from the U.S.) and found that, when cutting the data to the city-industry level, sampling error has a substantial effect on the consistency and robustness of the results obtained even when the analysis is confined only to large cities.

[15]Other studies in the same vein, such as Michaels *et al.* (2013), also use metropolitan boundaries that expand over time. The alternative is working with fixed geographic units. While that may be preferred for some types of work, given the growth that characterizes most of the cities in our sample, using fixed geographic units would mean either that the early observations would include a substantial portion of rural land surrounding the city, or that a substantial portion of city growth would not be part of our sample in the later years. Either of these options is undesirable.

[16]Much of the remaining working population is employed by the government or in agricultural work. For example, in Portsmouth, the large gap between working population and workers in the analysis industries is due to the fact that this was a major base for the Royal Navy.

Table 1: Cities in the primary analysis database

City	Population in 1851	Working population in 1851	Workers in analysis industries in 1851
Bath	54,240	27,623	23,609
Birmingham	232,841	111,992	101,546
Blackburn	46,536	26,211	24,458
Bolton	61,171	31,211	28,885
Bradford	103,778	58,408	55,223
Brighton	69,673	32,949	27,954
Bristol	137,328	64,025	54,962
Derby	40,609	19,299	16,787
Gateshead	25,568	18,058	8,562
Halifax	33,582	18,058	16,488
Huddersfield	30,880	13,922	12,465
Kingston-upon-Hull	84,690	36,983	31,513
Ipswich	32,914	14,660	11,996
Leeds	172,270	83,570	7 4,959
Leicester	60,496	31,140	28,481
Liverpool	375,955	165,300	142,197
London	2,362,236	1,088,285	930,797
Manchester	401,321	204,688	187,000
Newcastle-upon-Tyne	87,784	38,564	33,271
Northampton	26,657	13,626	12,062
Norwich	68,195	34,114	29,710
Nottingham	57,407	33,967	31,106
Oldham	72,357	38,853	35,958
Portsmouth	72,096	31,345	19,039
Preston	69,542	36,864	33,085
Sheffield	135,310	58,551	53,472
South Shields	28,974	11,114	10,028
Southampton	35,305	14,999	12,215
Stockport	53,835	30,128	27,836
Sunderland	63,897	24,779	21,639
Wolverhampton	49,985	22,727	19,851

period. Individual categories in the years were combined into industry groups based on (1) the census' occupation classes, and (2) the name of the occupation. This process generates 26 consistent private sector occupation categories. Of these, 23 can be matched to the connections matrices used in the analysis. Table 2 describes the industries included in the database.

Table 2: Industries in the primary analysis database with 1851 employment

Manufacturing		**Services and Professional**	
Chemicals & drugs	18,514	Professionals*	40,733
Clothing, shoes, etc.	328,669	General services	460,885
Instruments & jewelry*	31,048	Merchant, agent, accountant, etc.	58,172
Earthenware & bricks	19,580	Messenger, porter, etc.	72,155
Leather & hair goods	26,737	Shopkeeper, salesmen, etc.	27,232
Metal & Machines	167,052		
Oil, soap, etc.	12,188		
Paper and publishing	42,578	**Transportation services**	
Shipbuilding	14,498	Railway transport	10,699
Textiles	315,646	Road transport	35,207
Vehicles	9,021	Sea & canal transport	66,360
Wood & furniture	69,648		
Food, etc.		**Others industries**	
Food processing	113,610	Construction	137,056
Spiritous drinks, etc.	8,179	Mining	24,505
Tobacconists*	3,224	Water & gas services	3,914

Industries marked with a * are available in the database but are not used in the baseline analysis because they cannot be linked to categories in the 1907 British input-output table.

To gain some understanding of these data, Table 3 describes the pattern of industry agglomeration across the analysis cities using the index from Ellison & Glaeser (1997). We can see that Britain's main manufacturing and export industries, such as "Textiles", "Metal & Machines", and "Shipbuilding" show high levels of geographic agglomeration.[17] Many non-traded services or retail industries, including "Merchants, agents, etc.", "Construction", and "Shopkeepers, salesmen, etc." show low levels of agglomeration. It is somewhat surprising that a few of the service industries, such as "Professionals" and "General services" show evidence of agglomeration. Table 12

[17]Shipbuilding shows an upward trend reflecting the shift to capital-intensive iron ships.

in the Appendix shows that this pattern is driven by London. Overall, the median level of industry agglomeration is between 0.020 and 0.027. This is comparable to the levels reported for the modern U.S. economy by Ellison & Glaeser (1997) and somewhat larger than the levels reported for the modern British economy by Faggio *et al.* (2013).[18]

This study also requires a set of matrices measuring the pattern of connections between industries. These measures should reflect the channels through which ideas may flow between industries. Existing literature provides some guidance here. Marshall (1890) suggested that firms may benefit from connections operating through input-output flows, the sharing of labor pools, or other types of technology spillovers. The use of input-output connections is supported by recent literature showing that firms share information with their customers or suppliers. For example, Javorcik (2004) and Kugler (2006) provide evidence that the presence of foreign firms (FDI) affects the productivity of upstream and downstream domestic firms. To reflect this channel, we use an input-output table constructed by Thomas (1987) based on the 1907 British Census of Production (Britain's first industrial census). This matrix is divided into 41 industry groups. We construct two variables: $IOin_{ij}$, which gives the share of industry i's intermediate inputs that are sourced from industry j, and $IOout_{ij}$ which gives the share of industry i's sales of intermediate goods that are purchased by industry j. The main drawback in using these matrices is that they are for intermediate goods; they will not capture the pattern of capital goods flows.

[18]Using industry data for 459 manufacturing industries at the four-digit level and 50 states, Ellison & Glaeser (1997) calculate a mean agglomeration index of 0.051 and a median of 0.026. For Britain, Faggio *et al.* (2013) calculate industry agglomeration using 94 3-digit manufacturing industries and 84 urban travel-to-work areas. They obtain a mean agglomeration index of 0.027 and a median of 0.009. Kim (1995) calculates an alternative measure of agglomeration for the U.S. during the late 19th and early 20th centuries, but given that he studies only manufacturing industries, and given the substantial differences between his industry definitions and our own, it is difficult to directly compare these patterns with his results.

Table 3: Industry agglomeration patterns based on the Ellison & Glaeser index

Industry	1851	1861	1871	1881	1891	1901	1911
Textiles	0.166	0.178	0.182	0.195	0.182	0.159	0.150
Metal & machines	0.094	0.089	0.086	0.093	0.087	0.079	0.088
Shipbuilding	0.081	0.079	0.121	0.142	0.197	0.252	0.254
Paper & publishing	0.076	0.067	0.067	0.049	0.045	0.035	0.025
Mining related	0.075	0.108	0.106	0.151	0.166	0.166	0.165
Professionals	0.070	0.047	0.056	0.050	0.043	0.030	0.036
Sea & canal transport	0.056	0.057	0.058	0.087	0.067	0.080	0.077
Instruments & jewelry	0.053	0.054	0.051	0.050	0.037	0.024	0.023
Oil, soap, etc.	0.028	0.017	0.008	0.007	0.008	0.024	0.042
Road transport	0.027	0.024	0.028	0.012	0.021	0.010	0.010
Leather, hair, etc.	0.025	0.020	0.025	0.026	0.023	0.023	0.039
General services	0.021	0.021	0.017	0.024	0.020	0.025	0.026
Vehicles	0.021	0.012	0.006	0.005	0.033	0.049	0.053
Tobacco	0.020	0.022	0.010	-0.008	-0.008	0.011	0.016
Earthenware & bricks	0.018	0.026	0.032	0.024	0.015	0.009	0.007
Wood & furniture	0.016	0.016	0.022	0.019	0.015	0.009	0.010
Chemicals & Drugs	0.013	0.000	0.007	0.008	-0.004	0.001	0.004
Drinks	0.012	0.011	0.010	0.017	0.008	0.001	-0.002
Food processing	0.009	0.004	0.003	0.001	0.001	0.001	0.001
Clothing, shoes, etc.	0.006	0.007	0.006	0.005	0.008	0.007	0.008
Shopkeepers, salesmen, etc.	0.006	0.001	-0.003	-0.003	-0.004	-0.004	-0.004
Construction	0.004	0.004	0.002	0.003	0.002	0.001	0.002
Merchants, agents, etc.	-0.040	-0.048	-0.041	-0.050	-0.049	-0.054	-0.060
Median	0.021	0.021	0.022	0.019	0.020	0.023	0.023
Mean	0.037	0.035	0.037	0.039	0.040	0.041	0.042

This table reports industry agglomeration in each year based on the index from Ellison & Glaeser (1997). This approach adjusts for the size of plants in an industry using an industry Herfindahl index. We construct these Herfindahl indices using the firm size data reported in the 1851 Census and apply the same Herfindahl for all years, since firm-size data are not reported in later Censuses. This may introduce bias for some industries, such as shipbuilding, where evidence suggests that the average size of firms increased substantially over the study period. Some analysis industries are not included in this table due to lack of firm size data.

Another channel for knowledge flow is the movement of workers, who may carry ideas between industries. Research by Poole (2013) and Balsvik (2011), using data from Brazil and Norway, respectively, has highlighted this channel of knowledge flow. To reflect this channel, we construct two different measures of the similarity of the workforces used by different industries. The first measure is based on the demographic characteristics of workers (their age and gender) from the 1851 Census. These features had an important influence on the types of jobs a worker could hold during the period we study.[19] For any two industries, our demographic-based measure of labor force similarity, EMP_{ij}, is constructed by dividing workers in each industry into these four available bins (male/female and over20/under20) and calculating the correlation in shares across the industries. A second measure of labor-force similarity, based on the occupations found in each industry, is more similar to the measures used in previous studies. This measure is built using U.S. census data from 1880, which reports the occupational breakdown of employment by industry. We map the U.S. industry categories to the categories available in our analysis data. Then, for any two industries our occupation-based measure of labor force similarity, OCC_{ij} is the correlation in the vector of employment shares for each occupation.

In addition to the primary inter-industry connection matrices described above, we will also conduct robustness exercises in Section 6 using two additional matrices. One of these is an input-output table for 1841 constructed by Horrell *et al.* (1994). This table is used to construct a matrix of supplier industries, $IOin1841$ and customer industries, $IOout1841$, mirroring those available from the 1907 table. These matrices, which can be used with 12 more aggregated industry categories, have the advantage that they come from a decade prior to the first observation in the city-industry database. This can help us deal with potential concerns related to the endogeneity of the pattern of input-output connections, as well as concerns that these patterns may have changed substantially over the study period. We have also constructed a matrix reflecting the technological similarity of industries. This matrix, which we call $TECH$, is based on patent data from 1800-1841 which have been hand-matched to industry categories by Nuvolari & Tartari (2011). Technological similarity between industries i and j is measured based on the share of inventors patenting in industry i that also patent in industry j, under the assumption that it is easier for inventors to move back and forth between more technologically similar industries. This matrix is available for nine aggregated industry categories related to manufacturing, mining, construction, or utilities.

Finally, we have collected data on a variety of other industry and city characteristics. The 1851 Census of Population was particularly detailed, and provides information on firm sizes in each industry at the national level. From the 1907 input-

[19]For example, textile industries employed substantial amounts of female and child labor, while metal and heavy machinery industry jobs were almost exclusively reserved for adult males.

output table, we have measures of the share of industry output that is sold directly to households, as well as the share exported abroad. The 1907 Census of Production provides us with information on the total wage bill of each industry and the value of output for each industry. These are used to construct, for each industry, estimates of the ratio of labor cost to total sales and, together with the input-output table, the ratio of intermediate cost to total sales. Finally, we collect data on the distance between cities (as the crow flies) from Google Maps, which we will use when considering cross-city effects in Section 7.

4 Empirical approach

The starting point for our analysis is based on Equation 7, which represents the growth rate of a city-industry as a function of the learning spillovers as well as time-varying city-specific and national industry-specific factors. Rewriting this as a regression equation we have,

$$\triangle \ln(L_{ict+1}) = \tilde{\tau}_{ii} \ln(L_{ict}) + \sum_{k \neq i} \tilde{\tau}_{ki} \ln(L_{kct}) + \theta_{ct} + \phi_{it} + e_{ict} \tag{8}$$

where $\triangle$ is the first difference operator, $\tilde{\tau}_{ii}$ and $\tilde{\tau}_{ki}$ include the coefficient $\left(\frac{1}{1-\alpha}\right)$, θ_{ct} is a full set of city-year effects and ϕ_{it} is a full set of industry-year effects. The first term on the right hand side represents within-industry spillovers, while the second term represents cross-industry spillovers.[20]

One issue with Equation 8 is that there are too many parameters for us to credibly estimate given the available data. In order to reduce the number of parameters, we need to put additional structure on the spillover terms. As discussed in the previous section, the recent literature on knowledge spillovers motivates us to parametrize the connections between industries using the available input-output and labor force similarity matrices:

[20]We purposely omitted the last term of Equation 7, $\triangle \ln(\bar{w}_{t+1})$, because although it could be estimated as a year-specific constant, it would be collinear with both the (summation of) industry-year and city-year effects. Moreover, in any given year we also need to drop one of the city or industry dummies in order to avoid collinearity. In all specifications we chose to drop the industry-year dummies associated with the "General services" sector.

$$\tilde{\tau}_{ki} = \beta_1 IOin_{ki} + \beta_2 IOout_{ki} + \beta_3 EMP_{ki} + \beta_4 OCC_{ki} \quad \forall\, i,\, k$$

Substituting this into 8 we obtain:

$$\begin{aligned} \triangle \ln(L_{ict+1}) &= \tilde{\tau}_{ii} \ln(L_{ict}) + \beta_1 \sum_{k \neq i} IOin_{ki} \ln(L_{kct}) + \beta_2 \sum_{k \neq i} IOout_{ki} \ln(L_{kct}) \\ &+ \beta_3 \sum_{k \neq i} EMP_{ki} \ln(L_{kct}) + \beta_4 \sum_{k \neq i} OCC_{ki} \ln(L_{kct}) + \theta_{ct} + \phi_{it} + e_{ict} \end{aligned} \tag{9}$$

Instead of a large number of parameters measuring spillovers across industries, Equation 9 now contains only four parameters multiplying four (weighted) summations of log employment. Summary statistics for the summed cross-industry spillover terms are available in Appendix Table 13.

There is a clear parallel between the specification in Equation 9 and the empirical approach used in the convergence literature (Barro & Sala-i Martin (1992)). A central debate in this literature has revolved around the inclusion of fixed effects for the cross-sectional units (see, e.g., Caselli *et al.* (1996)). In our context, the inclusion of such characteristics could help control for location and industry-specific factors that affect the growth rate of industry and are correlated with initial employment levels. However, the inclusion of city-industry fixed effects in Equation 9 will introduce a mechanical bias in our estimated coefficients (Hurwicz (1950), Nickell (1981)). This bias is a particular concern in a setting where the time-series is limited. Solutions to these issues have been offered by Arellano & Bond (1991), Blundell & Bond (1998), and others, yet these procedures can also generate biased results, as shown by Hauk Jr. & Wacziarg (2009). In a recent review, Barro (2012) uses data covering 40-plus years and argues (p. 20) that in this setting, "the most reliable estimates of convergence rates come from systems that exclude country fixed effects but include an array of X variables to mitigate the consequence of omitted variables." Our approach essentially follows this advice, but with the additional advantage that we have two cross-sectional dimensions, which allows for the inclusion of flexible controls in the form of time-varying city and industry fixed effects.

There are two issues to address at this point. First, there could be a measurement error in L_{ict}. Since this variable appears both on the left and right hand side, this would mechanically generate an attenuation bias in our within-industry spillover estimates. Moreover, since L_{ict} is correlated with the other explanatory variables, such measurement error would also bias the remaining estimates. We deal with measurement error in L_{ict} on the right hand side by instrumenting it with lagged city-industry employment.[21] This approach is somewhat similar to the approach introduced by Bartik (1991). Under the assumption that the measurement error in any given city-industry pair is *iid* across cities and time, our instrument is $L_{ict}^{Inst} = L_{ict-1} \times g_{i-ct}$, where L_{ict-1} is the lag of L_{ict} and g_{i-ct} is the decennial growth rate in industry i computed using employment levels in all cities *except* city c.

Second, we are also concerned that there may be omitted variables that affect both the level of employment in industry j and the growth in employment in industry i. Such variables could potentially bias our estimated coefficients on both the cross-industry and (when $j = i$) the within-industry spillovers. For instance, if there is some factor not included in our model which causes growth in two industries i and $k \neq i$ in the same city, a naive estimation would impute such growth to the spillover effect from k to i, thus biasing the estimated spillover upward. Our lagged instrumentation approach can also help us deal with these concerns. Specifically, when using instruments with a one-decade lag to address endogeneity concerns the exclusion restriction is that there is not some omitted variable that is correlated with employment in some industry k in period t and affects employment growth in industry i from period $t+1$ to $t+2$. Moreover, the omited variable cannot affect growth in all industries in a location, else it would be captured by the city-year fixed effect, nor can it affect the growth rate in industry i in all cities.[22] Thus, while our approach does not allow us to rule out all possible confounding factors, it allows us to narrow the set of potential confounding forces relative to most previous work in this area. Now, for the cross-industry case, the summation terms in Equation 9 such as $\sum_{k \neq i} IOin_{ki} \ln(L_{kct})$ are instrumented with $\sum_{k \neq i} IOin_{ki} \ln(L_{kct}^{Inst})$, where L_{kct}^{Inst} is computed as described above.

[21]This approach is inspired in part by Combes *et al.* (2011), who discuss the possibility of using lagged instrumentation to study agglomeration economies.

[22]The results are not sensitive to the length of the lag used in the instrumentation. We have experimented with two- and three-decade lags and obtained essentially the same results.

The estimation is performed using OLS or, when using instruments, two-stage least squares. Correlated errors are a concern in these regressions. Specifically, we are concerned about serial correlation, which Bertrand *et al.* (2004) argue can be a serious concern in panel data regressions, though this is perhaps less of a concern for us given the relatively small time dimension in our data. A second concern is that industries within the same city are likely to have correlated errors. A third concern, highlighted by Conley (1999) and more recently by Barrios *et al.* (2012), is spatial correlation occurring across cities. Here the greatest concern is that error terms may be correlated within the same industry across cities (though the results presented in section 7 suggest that cross-city effects are modest).

To deal with all of these concerns we use multi-dimensional clustered standard errors following work by Cameron *et al.* (2011) and Thompson (2011). We cluster by (1) city-industry, which allows for serial correlation; (2) city-year, which allows correlated errors across industries in the same city and year; and (3) industry-year, which allows for spatial correlation across cities within the same industry and year. This method relies on asymptotic results based on the dimension with the fewest number of clusters. In our case this is 23 industries $\times$ 6 years = 138, which should be large enough to avoid serious small-sample concerns. Because using multi-dimensional standard errors is not yet standard in the literature, we also report more conventional robust standard errors in all results tables.

To simplify the exposition, we will hereafter collectively refer to the set of regressors $\ln(L_{ict}), for \quad i = 1...I$ as the *within* variables. Similarly, with a small abuse of notation the term $\sum_{k \neq i} IOin_{ki} \ln(L_{kct})$ is referred to as $IOin$, and so on for $IOout$, EMP, and OCC. We collectively refer to the latter terms as the *between* regressors since they are the parametrized counterpart of the spillovers across industries.

5 Main results

Our main regression results are based on the specification described in Equation 9. Regressions based on this specification generate results that can tell us about cross-industry spillovers, within-industry spillovers, and city-wide factors. In the following subsections, we will discuss results related to each of these in turn, but it is important to keep in mind that these results are coming out of regressions in which all of these factors are present. We begin by considering the pattern of spillovers across industries.

5.1 Cross-industry spillovers

Our estimation strategy involves using four measures for the pattern of cross-industry spillovers: forward input-output linkages, backward input-output linkages, and two measures of labor force similarity. We begin our analysis, in Table 4 by looking at results that include only one of these proxies at a time. Columns 1-3 include only the forward input-output linkages; Columns 1 presents OLS results; Column 2 presents results with lagged instrumentation on the within terms; and Column 3 uses lagged instrumentation for both the within and between terms. A similar pattern is used for backward input-output linkages in Columns 4-6, the demographic-based labor force similarity measure in Columns 7-9, and the occupation-based labor force similarity measure in Columns 10-12.

These results show strong positive spillovers through forward input-output connections, suggesting that local suppliers play an important role in industry growth. The importance of local suppliers to industry growth is perhaps the clearest and most robust result emerging from our analysis. In terms of magnitude, the coefficients in Table 4 suggest that a one standard deviation increase in the local presence of supplier industries ($IOin$) would result in an increase in city-industry growth of 13.9-19.3 percent. There is little evidence of positive effects operating through local buyers. The results do provide some evidince that the presence of other industries using similar labor pools may increase growth, particularly when using the more detailed OCC measure. A comparison across columns for each spillover measure shows that the IV results do not differ from the OLS results in a statistically significant way, suggesting that any measurement error or omitted variables concerns addressed by instruments are not generating substantial bias in the OLS results.

We do not report first-stage regression results for our instrumental variables regressions because these involve a very large number of first-stage regressions. Instead, for each specification we report the test statistics for the Lagrange Multiplier underidentification test based on Kleibergen & Paap (2006) as well as the test static for weak instruments test based on the Kleibergen-Paap Wald statistic.[23] It is clear from

[23]These test statistics are calculated under robust standard errors because the methodology for calculating these test statistics under multidimensional standard errors is still being refined.

these statistics that weak instruments are not a substantial concern in any of the specifications used in this study.

Table 4: OLS and IV regressions including only one spillover path at a time

	(1)	(2)	(3)	(4)	(5)	(6)
IOin	0.0588***	0.0446***	0.0423***			
	(0.0127)	(0.0112)	(0.0113)			
	[0.0076]	[0.0080]	[0.0082]			
IOout				-0.0025	-0.0101	-0.0138
				(0.0108)	(0.0112)	(0.0114)
				[0.0063]	[0.0069]	[0.0067]
Observations	4,263	3,549	3,549	4,263	3,549	3,549
Estimation	ols	2sls	2sls	ols	2sls	2sls
Instrumented	none	wtn	wtn-btn	none	wtn	wtn-btn
KP under id.		568.74	631.43		425.22	433.12
KP weak id.		262.97	268.98		195.55	193.68
	(7)	(8)	(9)	(10)	(11)	(12)
EMP	0.0009	0.0022*	0.0017			
	(0.0016)	(0.0013)	(0.0014)			
	[0.0009]	[0.0010]	[0.0010]			
OCC				0.0057*	0.0057*	0.0059*
				(0.0030)	(0.0032)	(0.0032)
				[0.0017]	[0.0019]	[0.0019]
Observations	4,263	3,549	3,549	4,263	3,549	3,549
Estimation	ols	2sls	2sls	ols	2sls	2sls
Instrumented	none	wtn	wtn-btn	none	wtn	wtn-btn
KP under id.		481.15	465.41		350.76	328.59
KP weak id.		235.06	195.09		162.3	133.28

Multi-level clustered standard errors by city-industry, city-year, and industry-year in parenthesis. Significance levels based on clustered standard errors: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets. Regressors *within*, city-by-year and industry-by-year fixed effects are included in all regressions but not displayed. 2SLS regressions use lagged instruments. Note that the number of observations falls for the instrumented regressions because the instruments require a lagged employment term. Thus, data from 1851 are not available for these regressions. Acronyms: wtn = *within*, btn = *between*. "KP under id." denotes the test statistic for the Lagrange Multiplier underidentification test based on Kleibergen & Paap (2006). "KP weak id." denotes the test statistic for a weak instruments test based on the Kleibergen-Paap Wald statistic.

Table 5 considers all four channels simultaneously. Columns 1 presents OLS results. In Column 2 we instrument the within terms. In Column 3 we use instruments for both the within and between terms. The results are generally similar to those from Table 4; the presence of local suppliers or industries employing a similar labor force both appear to enhance city-industry growth. The presence of local buyers has no positive effect. In the Appendix, we investigate the robustness of these results to dropping individual industries or individual cities from the analysis database. These exercises show that the significance of the estimates on the *IOin* and *OCC* channels are robust to dropping any city or any industry. However, the estimated coefficient and confidence levels for the *IOout* coefficient is sensitive to the exclusion of particular industries.

Table 5: Results with all cross-industry spillover channels

	(1)	(2)	(3)
IOin	0.0763***	0.0628***	0.0626***
	(0.0169)	(0.0157)	(0.0159)
	[0.0085]	[0.0089]	[0.0091]
IOout	-0.0050	-0.0143	-0.0176
	(0.0095)	(0.0105)	(0.0110)
	[0.0072]	[0.0081]	[0.0079]
EMP	0.0001	0.0020*	0.0016
	(0.0016)	(0.0012)	(0.0013)
	[0.0009]	[0.0010]	[0.0010]
OCC	0.0086***	0.0069**	0.0068**
	(0.0029)	(0.0032)	(0.0032)
	[0.0019]	[0.0022]	[0.0022]
Observations	4,263	3,549	3,549
Estimation	ols	2sls	2sls
Instrumented	none	wtn	wtn-btn
KP under id.		433.62	449.52
KP weak id.		163.5	113.73

Multi-level clustered standard errors by city-industry, city-year, and industry-year in parenthesis. Significance levels based on clustered standard errors: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets. Regressors *within*, city-by-year and industry-by-year fixed effects are included in all regressions but not displayed. 2SLS regressions use lagged instruments. Note that the number of observations falls for the instrumented regressions in columns 3-6 because the instruments require a lagged employment term. Thus, data from 1851 are not available for these regressions. Acronyms: wtn = *within*, btn = *between*. "KP under id." denotes the test statistic for the Lagrange Multiplier underidentification test based on Kleibergen & Paap (2006). "KP weak id." denotes the test statistic for a weak instruments test based on the Kleibergen-Paap Wald statistic.

Based on the results from Column 3 of Table 5, a one standard deviation increase

(3.24) in the presence of local suppliers (the $IOin$ channel) increases city-industry growth by 20%. Turning the the occupational similarity channel, OCC, a one standard deviation leads to a 17% increase in city industry growth when using the results from Column 3 of Table 5. Thus, both of these channels appear to exert a substantial positive effect on city-industry growth.

The results presented so far describe coefficients generated using all industries, where each industry is given equal weight. We may be concerned that these results are being driven primarily by smaller industries or smaller cities. To check this, we have also calculate weighted regressions, where the set of observations for each city-industry is weighted based on employment in that city-industry in 1851.[24] The results are presented in Table 6. These weighted regressions continue to highlight the important role played by local suppliers. Thus, this result is not driven by smaller industries or cities. However, we no longer observe positive results associated with the occupational similarity measure. This suggests that the positive impact of local industries employing similar workers observed in Table 5 is being driven by smaller industries, an interesting result in itself.

The results discussed so far reveal average patterns across all industries. An additional advantage of our empirical approach is that it is also possible to estimate industry-specific coeffients in order to look for (1) heterogeneity in the industries that benefit from each type of inter-industry connection or (2) heterogeneity in the industries that produce each type of inter-industry connections. In Appendix A.3.2, we estimate industry-specific coefficients for both spillover-benefiting and spillover-producing industries and then compare them to a set of available industry characteristics such as firm size, export and final goods sales shares, and labor or intermediate cost shares. With only 20 estimated industry coefficients we cannot draw strong conclusions from these relationships. However, our results do suggest several interesting patterns. The strongest result is that industries that benefit from or produce spillovers through the OCC channel tend to have a higher labor cost to sales ratio, a finding that is reasonable if not surprising. We also observe a consistent negative relationship between firm size and all types of inter-industry connections. While this relationship is not statistically significant, it is consistent across all spillover types

[24]Specifically, this is done by weighting the importance of each city-industry observation based on the number of workers it represented in 1851. We base the weights for all years on initial city-industry employment to avoid the potential for endogeneity in the city-industry weights.

and it fits well with existing work highlighting the importance of inter-industry connections for smaller firms Chinitz (1961). Next, we consider within-industry effects.

Table 6: Weighted regression results with all cross-industry spillover channels

	(1)	(2)	(3)
IOin	0.0303**	0.0317***	0.0363***
	(0.0136)	(0.0120)	(0.0126)
	[0.0083]	[0.0089]	[0.0092]
IOout	-0.0037	-0.0109	-0.0106
	(0.0130)	(0.0139)	(0.0143)
	[0.0081]	[0.0088]	[0.0088]
EMP	0.0002	0.0008	0.0007
	(0.0009)	(0.0008)	(0.0009)
	[0.0006]	[0.0006]	[0.0006]
OCC	-0.0023	-0.0022	-0.0014
	(0.0028)	(0.0029)	(0.0029)
	[0.0017]	[0.0020]	[0.0019]
Observations	4,253	3,541	3,541
Estimation	ols	2sls	2sls
Instrumented	none	wtn	wtn-btn
KP under id.		87.14	89.11
KP weak id.		37.13	34.55

Multi-level clustered standard errors by city-industry, city-year, and industry-year in parenthesis. Significance levels based on clustered standard errors: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets. Regressors *within*, city-by-year and industry-by-year fixed effects are included in all regressions but not displayed. 2SLS regressions use lagged instruments. Note that the number of observations falls for the instrumented regressions in columns 3-6 because the instruments require a lagged employment term. Thus, data from 1851 are not available for these regressions. Acronyms: wtn = *within*, btn = *between*. "KP under id." denotes the test statistic for the Lagrange Multiplier underidentification test based on Kleibergen & Paap (2006). "KP weak id." denotes the test statistic for a weak instruments test based on the Kleibergen-Paap Wald statistic.

5.2 Within-industry spillovers

Our analysis can also help us understand the strength of within-industry spillovers, reflected in the $\ln(L_{ict})$ term in Equation 8.[25] When analyzing these results, it is important to keep in mind that they reflect the *net* effect of within-industry agglom-

[25]In a static context these are often referred to as localization economies.

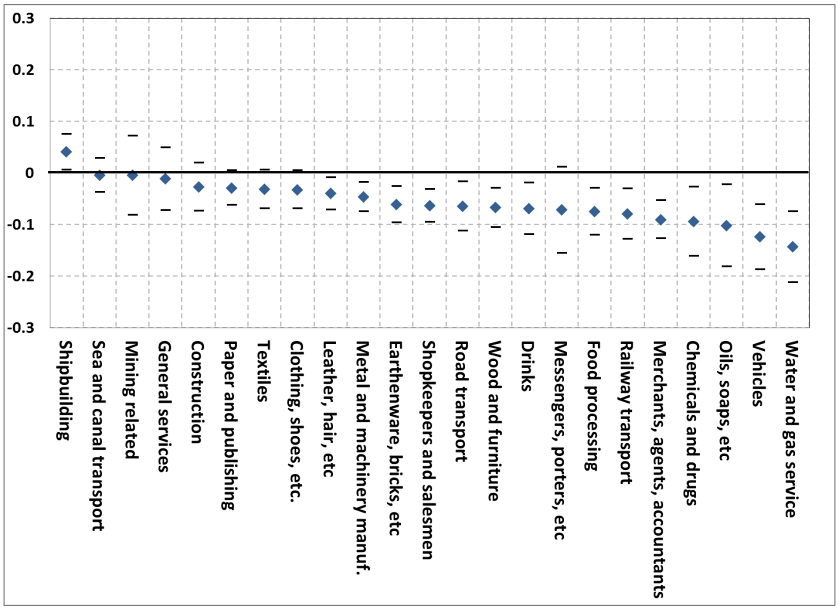
eration forces, which may be generated through a balance between agglomeration forces and negative forces such as competition or mean-reversion due to the diffusion of technologies across cities.[26] We cannot identify the strength of local within-industry agglomeration forces independent of counteracting forces. However, it is the net strength of these forces, which we are able to estimate, that is most relevant for understanding the contribution of within-industry agglomeration forces to city growth.

Figure 1 presents the within-industry coefficients and 95% confidence intervals for regression specifications corresponding to Columns 3 of Table 5, where lagged instruments are used for both the within and between terms. These results suggest that within-industry effects are often negative, consistent with competition for scarce local inputs or other within-industry congestion forces. In only one industry, shipbuilding, do we observe positive within-industry effects. This industry was characterized by increasing returns and strong patterns of geographic concentration. Within-industry agglomeration benefits, it would appear, are more the exception than the rule.

We can also compare these estimated industry-specific coefficients to industry characteristics such as average firm size, the share of exports or final goods in total sales, or the ratio of labor or input costs to total sales. This is done in Appendix A.3.2. With such a small number of industry coefficients we cannot draw strong conclusions from these results. However, we do observe some evidence that within-industry connections are more important in industries with larger firm sizes, which contrasts with the consistent negative relationship that we observe between firm size and cross-industry benefits.

[26]This issue is discussed in Dumais *et al.* (2002).

Figure 1: Strength of within-industry effects by industry



Results are based on regression in column 3 of Table 5. Multi-dimensional clustered standard errors by city-industry, city-year, and industry-year. These regressions include a full set of city-year and industry-year terms, and both the within and between terms are instrumented using one-year lags.

5.3 City-size effects and the aggregate strength of agglomeration forces

Next, we look at the effect of city size on city-industry growth. In standard urban models, the impact of agglomeration forces is balanced by congestion forces related to city size, operating through channels such as higher housing prices or greater commute times. In our model, this congestion force is reflected in the λ_{ct} term. There may also be agglomeration forces related to city size, apart from the other agglomeration forces we study.[27] This agglomeration force is represented by the ϕ_{ct} term in the model.

Empirically, both the congestion and agglomeration forces related to overall city size will be captured by the estimated city-time effects. Thus, examining these es-

[27]There is a substantial empirical literature, reviewed by Combes & Gobillon (Forthcoming), that focuses on estimating agglomeration economies related to overall city size. City-size agglomeration forces also appear in existing theories, such as Davis & Dingel (2012), though Davis & Dingel specify a model in which the aggregate city-size agglomeration force will have heterogeneous effects across industries.

timated city-time coefficients offers an opportunity for assessing the net impact of congestion and agglomeration force related to overall city size. Also, the difference between these estimated city-time effects and actual city growth rates must be due to the impact of the other agglomeration forces in the estimation equation. Thus, comparing the estimated city-time effects to actual city growth rates allows us to quantify the overall strength of the cross-industry agglomeration forces captured by our measures.

To make this comparison more concrete, consider the graphs in Figure 2. The dark blue diamond symbols in each graph describe, for each decade starting in 1861, the relationship between the actual growth rate of city working population and the log of city population at the beginning of the decade. The slopes of the fitted lines for these series fluctuate close to zero, suggesting that on average Gibrat's Law holds for the cities in our data.

We want to compare the relationship between city size and city growth in the actual data, as shown by the dark blue diamonds in Figure 2, to the relationship between these variables obtained while controlling for cross-industry agglomeration forces. To do this, we estimate the following regression specification:

$$\begin{aligned} \triangle \ln(L_{ict+1}) &= \beta_1 \sum_{k \neq i} IOin_{ki} \ln(L_{kct}) + \beta_2 \sum_{k \neq i} IOout_{ki} \ln(L_{kct}) \\ &+ \beta_3 \sum_{k \neq i} EMP_{ki} \ln(L_{kct}) + \beta_4 \sum_{k \neq i} OCC_{ki} \ln(L_{kct}) + \theta_{ct}^{CROSS} + \phi_{it} + e_{ict} \,. \end{aligned} \tag{10}$$

This specification is exactly the same as our baseline specification except that the within-industry terms have been omitted because the negative coefficients estimated on those terms in the baseline specification suggests that within-industry employment is generally not an agglomeration force.

The red squares in Figure 2 describe the relationship between the estimated city-year coefficients for each decade, θ_{ct}^{CROSS}, and the log of city population at the beginning of each decade. In essence, these describe the relationship between city size and city growth after controlling for national industry growth trends and the agglomeration forces generated by cross-industry spillovers. We can draw two lessons from these graphs. First, in all years the fitted lines based on the θ_{ct}^{CROSS} terms slope downward more steeply than the slopes on the fitted lines for actual city growth. This suggests that, once we control for cross-industry agglomeration forces, city size is negatively related to city growth, consistent with the idea that there are city-size congestion forces. Second, the difference between the slopes of the two fitted lines can be interpreted as the aggregate effect of the various agglomeration forces in our model averaged across cities. Put simply, if we can add up the strength of the convergence force in any period and compare it to the actual pattern of city growth, then the difference must be equal to the strength of the agglomeration forces.

The strength of these effects can be quantified in terms of the implied convergence rate following the approach of Barro & Sala-i Martin (1992). To do so, we run the following regressions:

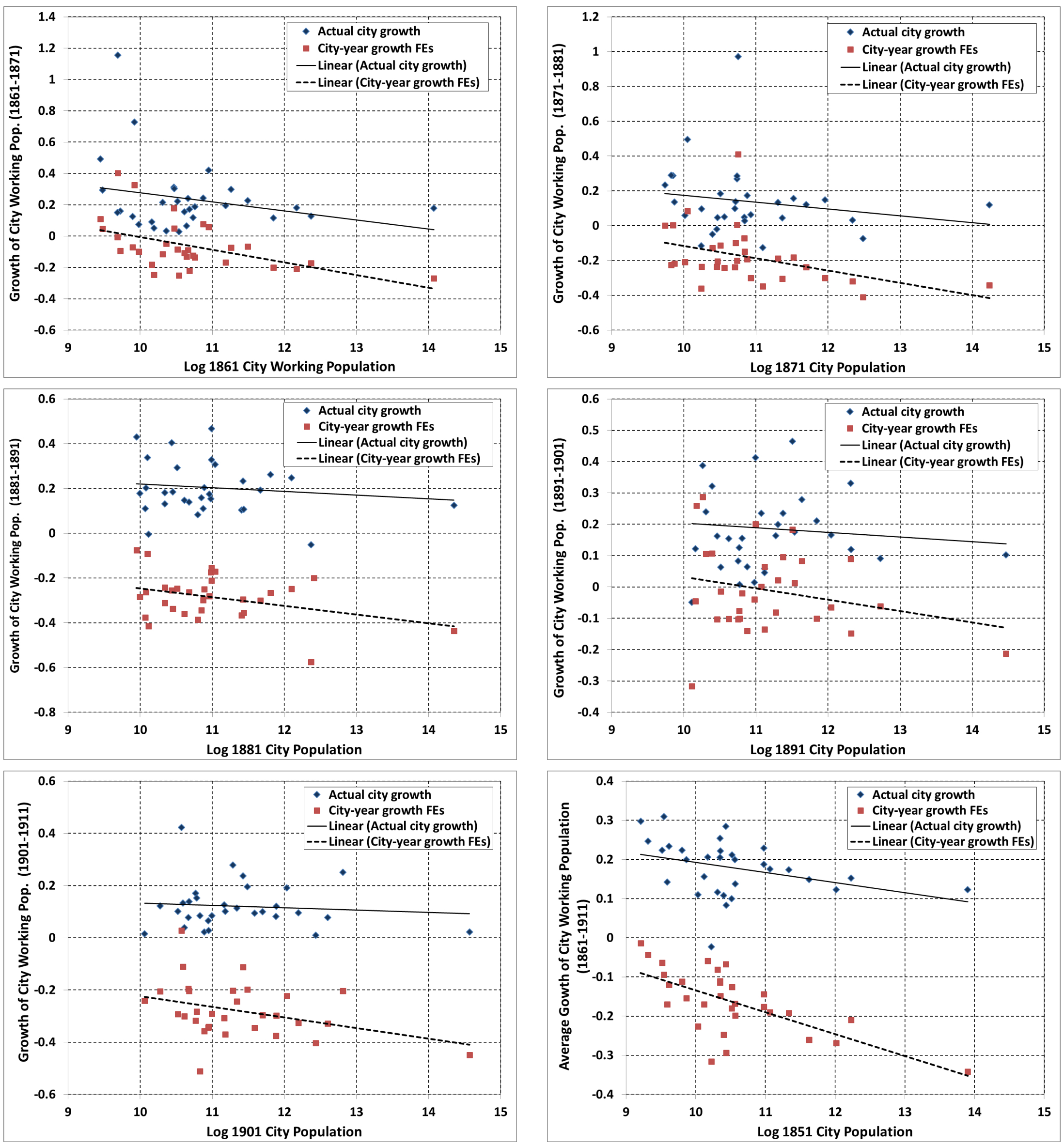
$$\theta_{ct}^{CROSS} = a_0 + a_1 \ln(WORKpop_{ct}) + \epsilon_{ct} \tag{11}$$

$$GrowthWORKpop_{ct} = b_0 + b_1 \ln(WORKpop_{ct}) + \epsilon_{ct} \tag{12}$$

where θ_{ct} is the estimated city-time effect for the decade from t to $t+1$, $WORKpop_{ct}$ is the working population of the city in year t, and $GrowthWORKpop_{ct}$ is the actual growth rate of the city from t to $t+1$. These regressions are run separately for each decade from 1861 to 1911. Convergence rates can be calculated using the estimated a_1 and b_1 coefficients.

The results are presented in the top panel of Table 7. The two left-hand columns describe the results from Equation 11 and the annualized city-size divergence rate implied by these estimates. The next two columns describe similar results based on Equation 12. The difference between these two city-size divergence rates, given in the right-hand column, describes the aggregate strength of the agglomeration force reflected in the cross-industry terms. These results suggest that the strength of city agglomeration forces, in terms of the implied divergence rate, was generally around 2.2-3.3% per decade. In the bottom panel of Table 7 we calculate similar results except that the θ_{ct}^{CROSS} terms are obtained using regressions in which each observation is weighted based on the employment in each city-industry in 1851. These results suggest agglomeration forces equal to an implied divergence rate of 2.1-3.3% per decade.

Figure 2: City size and city growth



Solid lines: Fitted lines comparing actual city growth over a decade to the log of city size at the beginning of the decade. **Dotted lines:** Fitted lines comparing estimated city-time coefficient for each decade to the log of city size at the beginning of the decade. Blue diamonds plot the actual city growth over a decade against the log of city population at the beginning of the decade. The red squares plot the estimated city-time coefficients over the same decade (the θ_{ct}^{CROSS} terms estimated using Equation 10) against the log of city population at the beginning of the decade. The bottom right-hand panel compares the log of city population in 1851 to the average of city growth rates over the entire 1861-1911 period and the average of city-time fixed effects across the entire 1861-1911 period.

Table 7: Measuring the aggregate strength of the agglomeration forces

Results based on unweighted regressions

	Results based on θ^{CROSS}		Results for actual city growth		Aggregate strength of agglomeration force (implied divergence rate per decade)
	Estimated city-size coefficient	Implied divergence Beta	Estimated city-size coefficient	Implied divergence Beta	
1861-1871	-0.081	0.84%	-0.058	0.60%	2.41%
1871-1881	-0.071	0.73%	-0.039	0.40%	3.29%
1881-1891	-0.039	0.40%	-0.017	0.17%	2.30%
1891-1901	-0.036	0.37%	-0.015	0.15%	2.20%
1901-1911	-0.041	0.42%	-0.009	0.09%	3.26%

Results based on regressions weighted by city-industry size in 1851

	Results based on θ^{CROSS}		Results for actual city growth		Aggregate strength of agglomeration force (implied divergence rate per decade)
	Estimated city-size coefficient	Implied divergence Beta	Estimated city-size coefficient	Implied divergence Beta	
1861-1871	-0.077	0.81%	-0.058	0.60%	2.06%
1871-1881	-0.067	0.69%	-0.039	0.40%	2.92%
1881-1891	-0.049	0.50%	-0.017	0.17%	3.31%
1891-1901	-0.042	0.43%	-0.015	0.15%	2.83%
1901-1911	-0.032	0.33%	-0.009	0.09%	2.38%

Column 2 presents the a_1 coefficients from estimating Equation 11 for each decade (cross-sectional regressions). Column 3 presents the annual convergence rates implied by these coefficients. Column 4 presents the b_1 coefficients from estimating Equation 12 and column 5 presents the annual convergence rates implied by these coefficients. Column 6 gives aggregate strength of the divergence force represented by the agglomeration economies, which is equal to the difference between the decadal convergence coefficients. The results in the top panel are based on city-time effects estimated from unweighted regressions while the results in the botton panel are based on city-time effects estimated using weighted regressions based on city-industry employment in 1851.

We may be concerned that the results described in Table 7 are driven in part by the inclusion of industry-time effects in the regressions used to obtain the θ_{ct}^{CROSS} terms. One way to assess this is to estimate alternative city-time effects from,

$$\triangle \ln(L_{ict+1}) = \theta_{ct}^{FE} + \phi_{it} + e_{ict}\,, \tag{13}$$

and then estimate,

$$\theta_{ct}^{FE} = c_0 + c_1 \ln(WORKpop_{ct}) + \epsilon_{ct}. \tag{14}$$

Because the only difference between the specification in Equation 10 and that in Equation 13 is the inclusion of the cross-industry agglomeration terms, we can be sure that any differences between the estimated θ_{ct}^{CROSS} terms and the θ_{ct}^{FE} terms are due to cross-industry agglomeration effects. The results, in Table 8, show similar pattners to those described previously. It is clear that the measured strength of the agglomeration force is not simply a byproduct of controling for industry-time effects.

Table 8: Measuring the aggregate strength of the agglomeration forces against an estimated baseline

Results based on unweighted regressions

	Results based on θ^{CROSS}		Results based on θ^{FE}		Aggregate strength of agglomeration force (implied divergence rate per decade)
	Estimated city-size coefficient	Implied divergence Beta	Estimated city-size coefficient	Implied divergence Beta	
1861-1871	-0.081	0.84%	-0.054	0.55%	2.86%
1871-1881	-0.071	0.73%	-0.044	0.45%	2.81%
1881-1891	-0.039	0.40%	-0.013	0.13%	2.70%
1891-1901	-0.036	0.37%	-0.010	0.10%	2.71%
1901-1911	-0.041	0.42%	-0.013	0.13%	2.85%

Results based on regressions weighted by city-industry size in 1851

	Results based on θ^{CROSS}		Results based on θ^{FE}		Aggregate strength of agglomeration force (implied divergence rate per decade)
	Estimated city-size coefficient	Implied divergence Beta	Estimated city-size coefficient	Implied divergence Beta	
1861-1871	-0.077	0.81%	-0.049	0.50%	3.08%
1871-1881	-0.067	0.69%	-0.038	0.39%	3.08%
1881-1891	-0.049	0.50%	-0.020	0.20%	2.99%
1891-1901	-0.042	0.43%	-0.014	0.14%	2.94%
1901-1911	-0.032	0.33%	-0.004	0.04%	2.93%

Column 2 presents the a_1 coefficients from estimating Equation 11 for each decade (cross-sectional regressions). Column 3 presents the convergence rates implied by these coefficients. Column 4 presents the c_1 coefficients from estimating Equation 14 and column 5 presents the convergence rates implied by these coefficients. Column 6 gives aggregate strength of the divergence force represented by the agglomeration economies, which is equal to the difference between the decadal convergence coefficients. The results in the top panel are based on city-time effects estimated from unweighted regressions while the results in the botton panel are based on city-time effects estimated using weighted regressions based on city-industry employment in 1851.

Finally, we can use a similar exercise to estimate the aggregate strength of the convergence force due to within-industry effects. We begin by estimating,

$$\triangle \ln(L_{ict+1}) = \tilde{\tau}_{ii} \ln(L_{ict}) + \theta_{ct}^{WITHIN} + \phi_{it} + e_{ict} \,, \tag{15}$$

and then estimating,

$$\theta_{ct}^{WITHIN} = d_0 + d_1 \ln(WORKpop_{ct}) + \epsilon_{ct}. \tag{16}$$

We then calculate the convergence force associated with the within-industry terms using the same approach that we used previously. Table 9 describes the results. The negative measured divergence force in this table highlights that within-industry effects, on net, act as a convergence force. The strength of this force is sensitive to whether the regressions are weighted, which suggests that the negative within-industry employment effects tend to be stronger for smaller industries.

There are some caveats to keep in mind when assessing these results. First, there are likely to be agglomeration forces not captured by our estimation. These omitted agglomeration forces may be partially reflected in the city-year fixed effects, which would lead us to understate the strength of the agglomeration forces. Second, some congestion forces may also be captured by our cross-industry terms. Thus, the strength of the cross-industry agglomeration force measured here is likely to be a lower bound.

Table 9: Measuring the aggregate strength of the divergence force associated with the within-industry effects

Results based on unweighted regressions

	Results based on θ^{WITHIN}		Results for actual city growth		Aggregate strength of agglomeration force (implied divergence rate per decade)
	Estimated city-size coefficient	Implied divergence Beta	Estimated city-size coefficient	Implied divergence Beta	
1861-1871	-0.003	0.03%	-0.058	0.60%	-5.74%
1871-1881	0.007	-0.07%	-0.039	0.40%	-4.68%
1881-1891	0.037	-0.36%	-0.017	0.17%	-5.30%
1891-1901	0.040	-0.39%	-0.015	0.15%	-5.43%
1901-1911	0.035	-0.35%	-0.009	0.09%	-4.37%

Results based on regressions weighted by city-industry size in 1851

	Results based on θ^{WITHIN}		Results for actual city growth		Aggregate strength of agglomeration force (implied divergence rate per decade)
	Estimated city-size coefficient	Implied divergence Beta	Estimated city-size coefficient	Implied divergence Beta	
1861-1871	-0.042	0.43%	-0.058	0.60%	-1.74%
1871-1881	-0.031	0.32%	-0.039	0.40%	-0.86%
1881-1891	-0.013	0.13%	-0.017	0.17%	-0.33%
1891-1901	-0.007	0.07%	-0.015	0.15%	-0.77%
1901-1911	0.003	-0.03%	-0.009	0.09%	-1.17%

Column 2 presents the d_1 coefficients from estimating Equation 16 for each decade (cross-sectional regressions). Column 3 presents the convergence rates implied by these coefficients. Column 4 presents the b_1 coefficients from estimating Equation 12 and column 5 presents the convergence rates implied by these coefficients. Column 6 gives aggregate strength of the divergence force represented by the agglomeration economies, which is equal to the difference between the decadal convergence coefficients. The results in the top panel are based on city-time effects estimated from unweighted regressions while the results in the botton panel are based on city-time effects estimated using weighted regressions based on city-industry employment in 1851.

6 Robustness: Alternative connection matrices

This section revisits the analysis presented above using some alternative measures of inter-industry connections. In particular, we use an alternative matrix of input-output connections constructed by Horrell *et al.* (1994) for Britain in 1841. Generating results with this alternative matrix, which comes from before the study period, can help address concerns that the results we find are dependent on the specific set of matrices we consider or are due to a process of endogenous inter-industry connection formation. The cost of using this matrix is that we are forced to work with a smaller set of 12 more aggregated industry categories.[28]

We also introduce a matrix of industry technological similarity. This matrix reflects the possiblity that technology may flow more rapidly between more technologically similar industries. While we have not been able to construct a technological similarity matrix for the more detailed industry categories used in the previous section, it is possible to construct measures of technological similarity for the more aggregated categories corresponding to the 1841 input-output matrix. As discussed in Section 3, this is done using patent data from 1800-1841.[29] This matrix is available for nine aggregate industry categories. Note that the sample size drops somewhat when analyzing the technological similarity matrix, since the transportation, distribution and service industries are not included in that matrix.

Because we are now working with a smaller number of industry categories, we focus our analysis on regressions that incorporate one spillover channel at a time. Table 10 describes the results.[30] These results also suggest that the presence of local suppliers positively influenced city-industry growth. In terms of magnitude, these results imply that a one standard deviation increase in presence of local suppliers will increase city-industry growth by 9.9-13.8%. There is also some evidence that local buyers may have positively influenced growth, but further exploration reveals that this finding is sensitive to the exclusion of particular industries. There is also evidence that industries may have benefitted from the presence of other occupationally-similar industries in the same locality, but these results are not as strong as the benefits of local suppliers. A one standard deviation increase in the demographically-similar local industries (EMP) is consistent with an increase in city-industry growth of 7-13%, while a one standard deviation increase in occupationally-similar industries (OCC) is consistent with an increase in city-industry growth of 7.6-9.5%. Finally, while we do observe positive coefficients on the $TECH$ term, we do not observe strong evidence that industries benefitted from the local presence of other technologically

[28]The industry categories are: "Mining & quarrying," "Food, drink & tobacco", "Metals & Machinery," "Oils, chemicals & drugs," "Textiles, clothing & leather goods," "Earthenware & bricks," "Other manufactured goods," "Construction," "Gas & water," "Transportation," "Distribution," and "All other services."

[29]The online Data Appendix provides further details about the construction of the technological similarity matrix.

[30]Results that incorporate all of the spillover channels together are available in the Appendix.

similar industries. However, this result should be interpreted with caution given the rough nature of the available technology similarity matrix.

Table 10: Alternative matrix regressions with one channel at a time

	(1)	(2)	(3)	(4)	(5)	(6)
IOin1841	0.0484***	0.0346*	0.0415*			
	(0.0186)	(0.0202)	(0.0229)			
	[0.0134]	[0.0152]	[0.0164]			
IOout1841				0.0384*	0.0561***	0.0585***
				(0.0222)	(0.0209)	(0.0219)
				[0.0141]	[0.0150]	[0.0152]
Observations	2,232	1,860	1,860	2,232	1,860	1,860
Estimation	ols	2sls	2sls	ols	2sls	2sls
Instrumented	none	wtn	wtn-btn	none	wtn	wtn-btn
KP under id.		327.49	262.45		352.23	297.98
KP weak id.		295.71	181.65		369.5	243.27
	(7)	(8)	(9)	(10)	(11)	(12)
EMP	0.0028	0.0049*	0.0052*			
	(0.0030)	(0.0028)	(0.0030)			
	[0.0019]	[0.0019]	[0.0020]			
OCC				0.0057	0.0048	0.0046
				(0.0066)	(0.0072)	(0.0074)
				[0.0035]	[0.0041]	[0.0041]
Observations	2,232	1,860	1,860	2,232	1,860	1,860
Estimation	ols	2sls	2sls	ols	2sls	2sls
Instrumented	none	wtn	wtn-btn	none	wtn	wtn-btn
KP under id.		493.35	445.57		302	308.52
KP weak id.		496.32	392.88		349.01	262.08
	(13)	(14)	(15)			
TECH	0.0062	0.0173	0.0319			
	(0.1887)	(0.2124)	(0.2074)			
[0.1057]	[0.1294]	[0.1235]				
Observations	1,674	1,395	1,395			
Estimation	ols	2sls	2sls			
Instrumented	none	wtn	wtn-btn			
KP under id.		204.19	258.25			
KP weak id.		271.33	370.75			

Multi-level clustered standard errors by city-industry, city-year, and industry-year in parenthesis. Significance levels based on clustered standard errors: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets. Regressors *within*, city-by-year and industry-by-year fixed effects are included in all regressions but not displayed. 2SLS regressions use lagged instruments. Note that the number of observations falls for the instrumented regressions because the instruments require a lagged employment term. Thus, data from 1851 are not available for these regressions. Acronyms: wtn = *within*, btn = *between*. "KP under id." denotes the test statistic for the Lagrange Multiplier underidentification test based on Kleibergen & Paap (2006). "KP weak id." denotes the test statistic for a weak instruments test based on the Kleibergen-Paap Wald statistic.

To summarize, we find that all three types of inter-industry connections – through input-output linkages, occupational similarity, and technological similarity – exhibit a positive relationship to city-industry growth. Of these, we find the strongest effects reflected by the input-output channels, followed by occupational similarity. This ordering bears a striking resemblence to the results obtained by Ellison *et al.* (2010) using modern U.S. data and a very different set of industry categories, suggesting that there may be substantial persistence in the importance of particular connection channels.

7 Robustness: Cross-city effects

In this section, we extend our analysis to consider the possibility that city-industry growth may also be affected by forces due to other nearby cities. We consider two potential channels for these cross-city effects. First, industries may benefit from proximity to consumers in nearby cities. This *market potential* effect has been suggested by Hanson (2005), who finds that regional demand linkages play an important role in generating spatial agglomeration using modern U.S. data. Second, industries may benefit from spillovers from other industries in nearby towns, through any of the channels that we have identified. We analyze these effects using the more detailed industry categories from Section 5.

There is substantial variation in the proximity of cities in our database to other nearby cities (see the Appendix for a map). Some cities, particularly those in Lancashire, West Yorkshire, and the North Midlands, are located in close proximity to a number of other nearby cities. Others, such as Norwich, Hull, and Portsmouth are relatively more isolated.

We begin our analysis by collecting data on the distance (as the crow flies) between each of the cities in our database, which we call $distance_{ij}$. Using these, we construct a measure for the remoteness of one city from another $d_{ij} = exp(-distance_{ij})$.[31] Our measures of market potential for each city is then,

$$MP_{ct} = \ln\left(\sum_{j\neq c} POP_{jt} * d_{cj}\right).$$

[31]This distance weighting measure is motivated by Hanson (2005). We have also explored using $d_{ij} = 1/distance_{ij}$ as the distance weighting measure and this delivers similar results.

where POP_{jt} is the population of city j. This differs slightly from Hanson's approach, which uses income in a city instead of population, due to the fact that income at the city level is not available for the period we study.

We also want to measure the potential for cross-industry spillovers occurring across cities. We measure proximity to an industry i in other cities as the distance-weighted sum of log employment in that industry across all other cities. Our full regression specification, including both cross-city market potential and spillover effects, is then,

$$\begin{aligned}
\triangle \ln(L_{ict+1}) &= \tilde{\tau}_{ii} \ln(L_{ict}) \\
&+ \beta_1 \sum_{k \neq i} IOin_{ki} \ln(L_{kct}) + \beta_2 \sum_{k \neq i} IOout_{ki} \ln(L_{kct}) \\
&+ \beta_3 \sum_{k \neq i} EMP_{ki} \ln(L_{kct}) + \beta_4 \sum_{k \neq i} OCC_{ki} \ln(L_{kct}) \\
&+ \beta_5 \left[\sum_{k \neq i} IOin_{ki} \sum_{j \neq c} d_{jc} * \ln(L_{kjt}) \right] + \beta_6 \left[\sum_{k \neq i} IOout_{ki} \sum_{j \neq c} d_{jc} * \ln(L_{kjt}) \right] \\
&+ \beta_7 \left[\sum_{k \neq i} EMP_{ki} \sum_{j \neq c} d_{jc} * \ln(L_{kjt}) \right] + \beta_8 \left[\sum_{k \neq i} OCC_{ki} \sum_{j \neq c} d_{jc} * \ln(L_{kjt}) \right] \\
&+ \beta_9 MP_{ct} + log(WORKpop_{ct}) + \theta_c + \phi_{it} + \epsilon_{ict}.
\end{aligned}$$

One difference between this and our baseline specification is that we now include city fixed effects (θ_c) in place of city-year effects because city-year effects would be perfectly correlated with the market potential measure. To help deal with city-size effects, we also include the log of $WORKpop_{ct}$, the working population of city c in period t. To simplify the exposition and in analogy with the previous section, we will refer to the cross-city term $\sum_{k \neq i} IOin_{ki} \sum_{j \neq c} d_{jc} * \ln(L_{kjt})$ as $IOin * d$, and similarly for the other cross-city terms $IOout * d$, $EMP * d$, and $OCC * d$.

The results generated using this specification are shown in Table 11. The first thing to take away from this table is that our baseline results are essentially unchanged when we include the additional cross-city terms. The city employment term in the fifth column reflects the negative growth impact of city size. The coefficients on the market potential measure is always positive but not statistically significant.

Table 11: Regression results with cross-city variables

	(1)	(2)	(3)
IOin	0.0580***	0.0611***	0.0594***
	(0.0144)	(0.0155)	(0.0166)
	[0.0095]	[0.0104]	[0.0111]
IOout	-0.0247**	-0.0250**	-0.0255**
	(0.0110)	(0.0110)	(0.0112)
	[0.0084]	[0.0084]	[0.0085]
EMP	-0.0026	-0.0029	-0.0029
	(0.0018)	(0.0018)	(0.0018)
	[0.0011]	[0.0011]	[0.0011]
OCC	0.0063*	0.0061*	0.0060*
	(0.0033)	(0.0034)	(0.0034)
	[0.0023]	[0.0025]	[0.0025]
City employment	-0.3390***	-0.3308***	-0.3332***
	(0.0760)	(0.0750)	(0.0765)
	[0.0424]	[0.0421]	[0.0428]
Market Potential	0.1579		0.1099
	(0.1614)		(0.2636)
	[0.1139]		[0.1834]
IOin*dist		0.0012	0.0004
		(0.0018)	(0.0024)
		[0.0015]	[0.0020]
IOout*dist		-0.0008	-0.0007
		(0.0010)	(0.0010)
		[0.0009]	[0.0009]
EMP*dist		0.0002	0.0001
		(0.0001)	(0.0001)
		[0.0001]	[0.0001]
OCC*dist		-0.0001	-0.0001
		(0.0002)	(0.0002)
		[0.0002]	[0.0002]
Observations	3,549	3,549	3,549
KP under id.	548.86	552.92	546.27
KP weak id.	48.5	51.45	48.27

Multi-level clustered standard errors by city-industry, city-year, and industry-year in parenthesis. Significance levels based on clustered standard errors: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets. Regressors *within*, industry-by-year and city fixed effects are included in all regressions but not displayed. All regressions instrument the *within* and *between* regressors with lagged instruments. Acronyms: wtn = *within*, btn = *between*. "KP under id." denotes the test statistic for the Lagrange Multiplier underidentification test based on Kleibergen & Paap (2006). "KP weak id." denotes the test statistic for a weak instruments test based on the Kleibergen-Paap Wald statistic.

The results do not provide statistically significant evidence that cross-city spillovers matter through any of the channels that we measure. However, these results are imprecisely measured. The coefficients estimated on the $IOin * dist$ term suggest that a one standard deviation increase in the presence of suppliers in other nearby cities could increase city-industry growth by 6.1-18.3%. The coefficients on the EMP term are consistent with effects of a similar magnitude. Thus, we should not rule out important cross-city effects based on these results. However, it is clear that omitted cross-city effects are not driving our findings regarding the importance of within-city cross-industry agglomeration forces.

8 Conclusion

In the introduction, we posed a number of questions about the nature of localized agglomeration forces. The main contribution of this study is to provide a theoretically grounded empirical approach that can be used to address these questions and the detailed city-industry panel data needed to implement it.

We can now provide some answers for the period we study. First, we find evidence that cross-industry agglomeration economies were more important than within-industry agglomeration forces for generating city employment growth. Within-industry effects are, on net, generally negative, but may be positive in a small number of industries such as shipbuilding. This suggests that industries clusters, which have attracted substantial attention, are more the exception than the rule. Second, our results suggest that industries grow more rapidly when they co-locate with their suppliers or with other industries that use occupationally-similar workforces. This result is in line with arguments made by Jacobs (1969), as well as recent empirical findings. We document a clear negative relationship between city size and city growth that appears once we account for agglomeration forces related to a city's industrial composition. This suggests that Gibrat's law is generated by a balance between agglomeration and dispersion forces. A lower bound estimate of the overall strength of the agglomeration forces captured by our approach, in terms of the implied annual divergence rate in city size, is around 2.1-3.3% per decade.

One of the most striking features of our results is how similar they look to some of the existing findings in the literature, most of which are based on modern U.S. or

European data. In particular, the ordering of importance for the different spillover channels – with input-output paths showing the strongest effects, followed by occupational similarity, and with only weak effects associated with technological similarity – looks very similar to the ordering obtained by Ellison *et al.* (2010). This provides suggestive evidence that there may be substantial persistence in the importance of these agglomeration economies over time and across space.

The techniques introduced in this paper can be applied in any setting where sufficiently rich long-run city-industry panel data can be constructed. Recent work has made progress in constructing data of this type for the U.S. in both the modern and historical period. Applying our approach to these emerging data sets is one promising avenue for future work.

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A Appendix

A.1 Theory appendix

The main text presents a simple theoretical framework used to motivate our analysis. In this appendix, we show that we can add additional complexity to the model without substantially changing the final estimating equation. In particular, we introduce capital and intermediate inputs into the production function. The new production function is,

$$x_{icft} = A_{ict} L_{icft}^{\alpha} K_{icft}^{\beta} I_{icft}^{\gamma} R_{icft}^{1-\alpha-\beta-\gamma},$$

where we have introduced capital inputs, K_{icft}, and intermediate inputs I_{icft}, into the production function, while retaining the same basic Cobb-Douglas structure. The parameters α, β, and γ determine the relative importance of these inputs in the production process of each industry. For now, we make the simplifying assumption that these parameters are constant across all industries, but at the end of this section we discuss the possibility that they may differ across industries. In this extended model, we make the same assumptions about technology, labor and resources as in the baseline model.

Capital is mobile across locations with a national price given by r_t. The overall supply of capital in the economy is $\bar{K}_t$. While we could model the evolution of this object, doing so would merely distract from the key focus of our theory.[32] Thus, to keep things simple we take the overall supply of capital in any given period as exogenously given. The income from capital is assumed to be spread evenly across individuals.

The set of intermediate inputs used in production differs across industries, but within each industry, all firms use inputs in the same fixed proportions. Because we assume free trade, this feature is a result, rather than an assumption. Let Z be an input-output matrix, with element z_{ij} such that I_{it} units of intermediate input to industry i requires $I_{it} z_{ij}$ units of output from industry j, i.e., the production function

[32] Moreover, the substantial level of international capital flows that took place during the period that we study suggest that a closed economy model of the evolution of this quantity may be inappropriate for the empirical setting.

for intermediate inputs is Leontief. Then total intermediate demand for the output from industry j is equal to $x_{jt}^{IO} = \sum_i I_{it} z_{ij}$. With costless trade, each industry will face a national-level industry-specific intermediate input price in each period, denoted q_{it}.

The resulting firm optimization problem is,

$$\max_{L_{icft}, K_{icft}, I_{icft}, R_{icft}} p_{it} A_{ict} L_{icft}^{\alpha} K_{icft}^{\beta} I_{icft}^{\gamma} R_{icft}^{1-\alpha-\beta-\gamma} - \bar{w}_t \lambda_{ct} L_{icft} - r_t K_{icft} - q_{it} I_{icft} - d_{ict} R_{icft}.$$

Using the first order conditions, and summing over all firms in a city-industry, we obtain the following expression for employment in industry i and location c,

$$L_{ict} = A_{ict}^{\rho} p_{it}^{\rho} \left(\frac{\alpha}{\bar{w}_t \lambda_{ct}} \right)^{\rho(1-\beta-\gamma)} \left(\frac{\beta}{r_t} \right)^{\rho\beta} \left(\frac{\gamma}{q_{it}} \right)^{\rho\gamma} \bar{R}_{ic} \, , \tag{17}$$

where $\rho = 1/(1 - \gamma - \beta - \alpha) > 0$. This expression tells us that, as in the baseline model, employment in any industry i and location c will depend on technology in that industry-location, the fixed resource endowment for that industry-location, factors that affect the industry in all locations (p_{it}, q_{it}), city-specific factors (λ_{ct}), and factors that affect the economy as a whole ($\bar{w}_t$, r_t). Note that ρ represents the inverse of the exponent on fixed city-industry resources. Thus, we can see that the impact of a city-specific shock that increases costs (higher λ_{ct}) on city-industry employment will be greater the less important are fixed city-industry resources in production, i.e., when industries are able to more easily move production to other cities.

Equilibrium within a period is defined as the set of prices $\{P_t, p_{it}, r_t, q_{it}, d_{ict}\}$ and quantities $\{D_t^F, x_{ict}, L_{icft}, K_{icft}, I_{icft}, R_{icft}\}$ such that given the set of technologies $\{A_{ict}\}$,

1) The first order conditions of the firm optimization problem are satisfied

2) Labor markets clear in each city, i.e., $\sum_i \sum_f L_{icft} = L_c t$ for all c

3) The capital market clears, i.e., $\sum_c \sum_i \sum_f K_{icft} = \bar{K}_t$

4) Local resource markets clear, i.e., $\sum_f R_{icft} = \bar{R}_{ic}$ for all i and c

5) Output markets clear, i.e., $\sum_c \sum_f x_{icft} = x_{it} = x_t^F + x_{it}^{IO}$

6) Total income (after any savings) is equal to total final goods expenditures

Equilibrium condition (6) requires that,

$$D_t P_t + M_t + B_t = \sum_c \sum_i \bar{w}_t \lambda_{ct} L_{ict} + \sum_c \sum_i r_t \bar{K}_{ict} + \sum_c \sum_i d_{ict} \bar{R}_{ic}.$$

where M_t represents net expenditures on imports and B_t represents the (exogenously given) amount of savings in the period. For a closed economy model we can set M_t to zero and then solve for the equilibrium price levels in the economy. Alternatively, we can consider a (small) open economy case where prices are given and solve for M_t. We are agnostic between these two approaches.

We continue to use the same expression describing the evolution of technology as in the baseline model (Equation 4). Starting with Equation 17 for period $t+1$, taking logs, plugging in Equation 4, and then plugging in Equation 17 again (also in logs), we obtain,

$$\begin{aligned} \ln(L_{ict+1}) - \ln(L_{ict}) &= \rho S_{ict} + \rho\Big[\ln(p_{it+1}) - \ln(p_{it})\Big] \\ &- \rho(1-\beta-\gamma)\Big[\ln(\lambda_{ct+1}) - \ln(\lambda_{ct})\Big] \\ &+ \rho(1-\beta-\gamma)\Big[\ln(\bar{w}_{t+1}) - \ln(\bar{w}_t)\Big] \\ &- \rho\beta\Big[\ln(r_{t+1}) - \ln(r_t)\Big] + \rho\gamma\Big[\ln(q_{it+1}) - \ln(q_{it})\Big] + e_{ict}. \end{aligned} \tag{18}$$

where $e_{ict} = \epsilon_{ict+1} - \epsilon_{ict}$ is the error term.

Finally, plugging Equation 6 into Equation 18, we obtain,

$$\begin{aligned} \ln(L_{ict+1}) - \ln(L_{ict}) &= \rho\tau_{ii}\ln(L_{ict}) + \rho\sum_{k\neq i}\tau_{ki}\ln(L_{kct}) \\ &+ \rho\Big[\ln(p_{it+1}) - \ln(p_{it})\Big] \\ &+ \rho\gamma\Big[\ln(q_{it+1}) - \ln(q_{it})\Big] + \rho\xi_{it} \\ &+ \rho(1-\beta-\gamma)\Big[\ln(\lambda_{ct+1}) - \ln(\lambda_{ct})\Big] + \rho\psi_{ct} \\ &+ \rho(1-\beta-\gamma)\Big[\ln(\bar{w}_{t+1}) - \ln(\bar{w}_t)\Big] \\ &+ \rho\beta\Big[\ln(r_{t+1}) - \ln(r_t)\Big] + e_{ict}. \end{aligned} \tag{19}$$

This expression mirrors the estimating equation given in Equation 7 up to the parameters ρ, β and γ. As in our baseline estimating equation, the change in employment growth is expressed as a function of the initial level of employment, a set of national industry-specific factors, a set of city-specific factors that affect all industries, and national wage and capital rental rates that affect all industries and all cities.

We can use this expression to consider some of the assumptions made in the main text in more detail. First, consider the possibility that trade costs, rather than technology spillovers, might be driving the effects we observe. To represent this, suppose that we modified the model to incorporate trade costs while at the same time eliminating technology spillovers. Ignoring for now general equilibrium effects, Equation 19 tells us that trade costs will affect city-industries through either the price of inputs (e.g., through local suppliers) or the price of outputs (e.g., through market access). With trade costs, both the input and the output prices faced by firms in industry i can vary across cities.

Now, focusing on the input prices side, suppose that there are two cities, A and B, and that City A has many more of industry i suppliers than city B so that the cost of intermediate inputs to industry i is lower in City A than in City B. From Equation 17 we can see that, all else equal, this implies that employment in industry i will be larger in City A than in City B in some initial period: this is static agglomeration. However, as we roll the model forward, Equation 18 shows that, absent other changes, industry i will *not* grow faster in City A than in City B. In the absence of other effects, input-output connections alone cannot act as a dynamic agglomeration force. Where input-output connections can generate dynamic agglomeration is by transmitting the effects of other changes, such as falling transport costs. However, falling trade costs cannot be a sustained force of dynamic agglomeration, since trade costs are bounded below by zero and were fairly stable over at least part of the period we study.[33] This suggests that input-output connections and trade costs can be an important static force, but these forces are unlikely to generate the dynamic agglomeration patters studied here.

A second interesting extension to consider is the possibility that the share of each input in the production function varies across industries. In particular, suppose that

[33]Crafts & Mulatu (2006) conclude that, "falling transport costs had only weak effects on the location of industry in the period 1870 to 1911." Jacks *et al.* (2008) find a rapid fall in external trade costs prior to 1880, with a much slower decline thereafter.

we allow the production function parameters to vary across industries. Indexing these parameters by i, we now have the following expression for city-industry employment growth,

$$\begin{aligned}
\ln(L_{ict+1}) - \ln(L_{ict}) &= \rho_i \tau_{ii} \ln(L_{ict}) + \rho_i \sum_{k \neq i} \tau_{ki} \ln(L_{kct}) \\
&+ \rho_i \Big[\ln(p_{it+1}) - \ln(p_{it}) \Big] + \rho_i \gamma_i \Big[\ln(q_{it+1}) - \ln(q_{it}) \Big] + \rho_i \xi_{it} \\
&+ \rho_i (1 - \beta_i - \gamma_i) \Big[\ln(\lambda_{ct+1}) - \ln(\lambda_{ct}) \Big] + \rho_i \psi_{ct} \\
&+ \rho_i (1 - \beta_i - \gamma_i) \Big[\ln(\bar{w}_{t+1}) - \ln(\bar{w}_t) \Big] \\
&+ \rho_i \beta_i \Big[\ln(r_{t+1}) - \ln(r_t) \Big] + e_{ict} \, .
\end{aligned}$$

We can see that the impact of spillovers on city-industry growth in this setting will depend on the industry-specific parameter ρ_i, where $\rho_i = 1/(1-\gamma_i-\beta_i-\alpha_i) > 0$. This parameter is the inverse of the exponent on local resources. Thus, the more important are fixed local resources in the production process, the weaker will be the impact of spillover on city-industry employment growth. This makes sense because when fixed local resources are important it is more difficult to shift industry employment across locations.

The estimates obtained in the empirical portion of this paper will reflect the impact of spillover reflected in city-industry employment, which will incorporate both the spillover term and the importance of fixed local resources. In further work, it would be interesting to separate these two factors, which is possible when sufficient data are available to estimate industry-specific input parameters. However, for city growth the relevant value is the coefficient that we estimate, which reflects the combination of the strength of spillovers and the extent to which industry employment can respond to those spillovers.

A.2 Data appendix

Figure 3: Map showing the location of cities in the analysis database

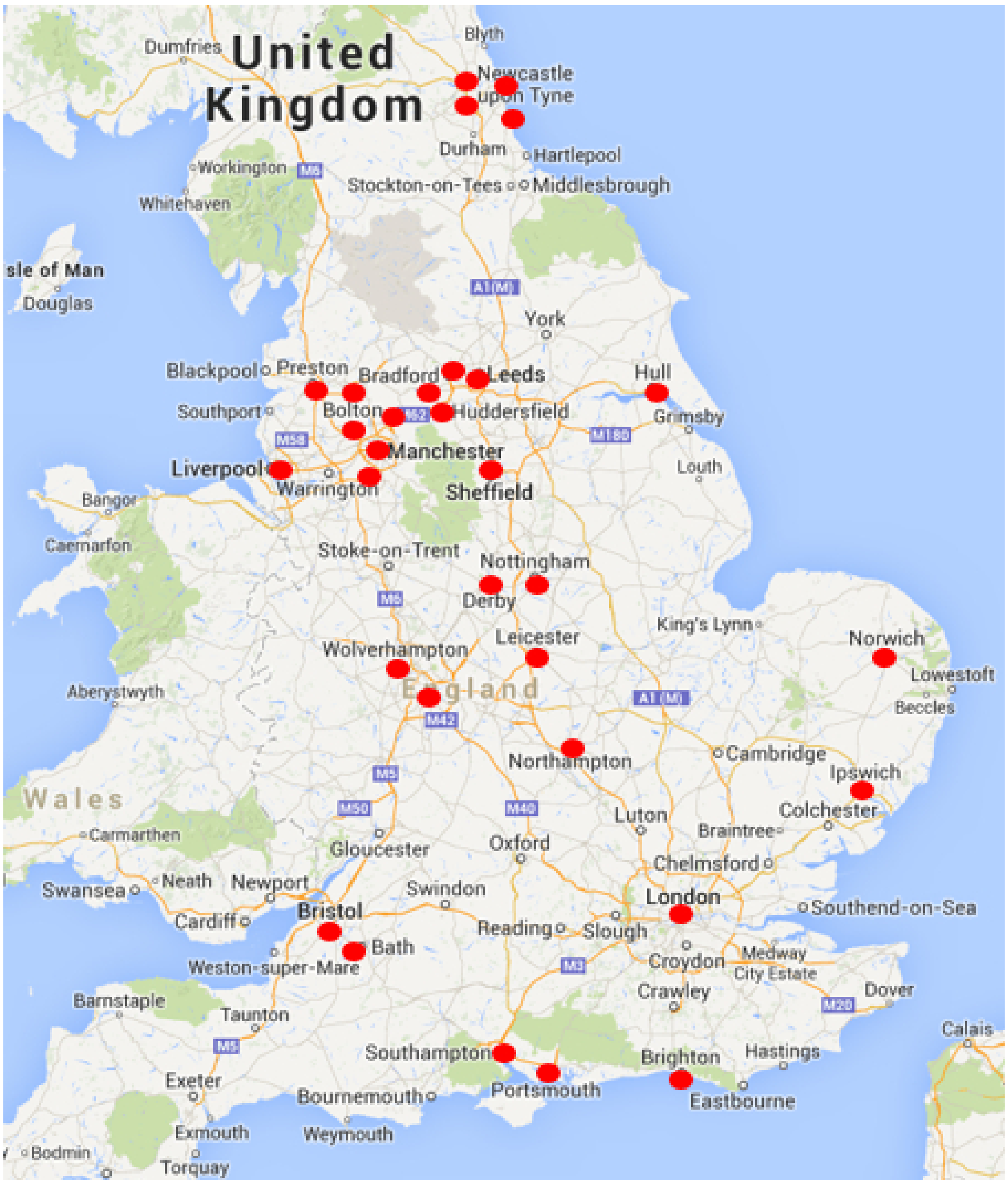


Table 12: Industry agglomeration patterns excluding London

Industry	**1851**	**1861**	**1871**	**1881**	**1891**	**1901**	**1911**
Shipbuilding	0.204	0.216	0.204	0.197	0.208	0.249	0.219
Sea & canal transport	0.196	0.235	0.229	0.268	0.252	0.245	0.211
Instruments & jewelry	0.162	0.181	0.153	0.173	0.101	0.063	0.052
Oil, soap, etc.	0.081	0.053	0.036	0.031	0.033	0.070	0.068
Metal & machines	0.063	0.046	0.040	0.041	0.037	0.033	0.031
Textiles	0.049	0.050	0.048	0.053	0.051	0.053	0.052
Chemicals & Drugs	0.032	0.013	0.018	0.012	0.001	0.014	0.023
Mining related	0.028	0.035	0.019	0.025	0.030	0.031	0.033
Leather, hair, etc.	0.021	0.023	0.034	0.030	0.030	0.027	0.024
Earthenware & bricks	0.020	0.013	0.011	0.011	0.014	0.015	0.014
Vehicles	0.018	0.029	0.018	0.018	0.056	0.061	0.094
Road transport	0.014	0.017	0.010	0.011	0.006	0.003	0.002
Drinks	0.011	0.011	0.012	0.009	0.006	0.004	0.001
Tobacco	0.011	0.005	-0.001	0.021	0.021	0.045	0.078
Clothing, shoes, etc.	0.010	0.008	0.010	0.016	0.026	0.019	0.018
Shopkeepers, salesmen, etc.	0.008	0.003	0.002	0.006	0.002	0.000	-0.003
Food processing	0.007	0.004	0.003	0.002	0.002	0.003	0.003
Wood & furniture	0.007	0.006	0.006	0.004	0.004	0.004	0.004
Paper & publishing	0.006	0.005	0.004	0.005	0.005	0.004	0.006
General services	0.004	0.001	0.000	-0.001	-0.001	-0.001	-0.002
Construction	0.004	0.002	0.002	0.002	0.001	0.001	0.001
Professionals	-0.005	-0.006	-0.006	-0.007	-0.007	-0.008	-0.007
Merchants, agents, etc.	-0.041	-0.044	-0.046	-0.060	-0.065	-0.066	-0.066
Median	0.014	0.013	0.011	0.012	0.014	0.015	0.018
Mean	0.040	0.039	0.035	0.038	0.035	0.038	0.037

This table reports industry agglomeration in each year based on the index from Ellison & Glaeser (1997). This approach adjusts for the size of plants in an industry using an industry Herfindahl index. We construct these Herfindahl indices using the firm size data reported in the 1851 Census and apply the same Herfindahl for all years, since firm-size data are not reported in later Censuses. Some analysis industries are not included in this table due to lack of firm size data.

Table 13: Summary statistics for the cross-industry spillover terms

Main analysis matrices and industry categories (1851-1911)					
	Obs.	Mean	SD	Min	Max
$\sum_{k \neq i} IOin_{ki} \ln(L_{kct})$	4,263	9.30	3.21	2.09	21.86
$\sum_{k \neq i} IOout_{ki} \ln(L_{kct})$	4,263	8.79	6.26	0.00	42.77
$\sum_{k \neq i} EMP_{ki} \ln(L_{kct})$	4,263	100.7	42.50	-92.52	191.50
$\sum_{k \neq i} OCC_{ki} \ln(L_{kct})$	4,263	36.25	25.70	-1.10	111.10
Alternative matrices and aggregated industry categories (1851-1911)					
	Obs.	Mean	SD	Min	Max
$\sum_{k \neq i} IOin1841_{ki} \ln(L_{kct})$	2,232	2.87	2.85	0.00	12.10
$\sum_{k \neq i} IOout1841_{ki} \ln(L_{kct})$	2,232	3.98	3.88	0.00	11.77
$\sum_{k \neq i} EMP_{ki} \ln(L_{kct})$	2,232	50.19	24.97	-29.45	95.33
$\sum_{k \neq i} OCC_{ki} \ln(L_{kct})$	2,232	24.89	16.60	-0.66	67.22
$\sum_{k \neq i} TECH_{ki} \ln(L_{kct})$	1,674	1.25	0.53	0.37	3.14
Cross-city connection measures (1861-1911)					
	Obs.	Mean	SD	Min	Max
$\sum_{k \neq i} IOin_{ki} \sum_{j \neq c} d_{jc} * \ln(L_{kjt})$	3,549	237.3	72.0	65.8	389.9
$\sum_{k \neq i} IOout_{ki} \sum_{j \neq c} d_{jc} * \ln(L_{kjt})$	3,549	223.4	152.2	0.00	741.7
$\sum_{k \neq i} EMP_{ki} \sum_{j \neq c} d_{jc} * \ln(L_{kjt})$	3,549	2,570	986.7	-1,607	3,418
$\sum_{k \neq i} OCC_{ki} \sum_{j \neq c} d_{jc} * \ln(L_{kjt})$	3,549	926.2	631.6	-19.6	1,996
MP_{ct}	3,549	15.7	0.242	14.76	16.07

Note: We report cross-city summary statistics for 1861-1911 because we only report instrumented cross-city regression results in the main text, which means that 1851 is used only to construct lagged values. For the others, we report summary statistics using the full 1851-1911 period since we report both OLS and instrumented results.

A.3 Results appendix

A.3.1 Main analysis robustness exercises

Figure 4 presents t-statistics for each cross-industry term obtained from running regressions equivalent to column 3 of Table 5, where in each regression a different city is dropped from the dataset. This allows us to assess the extent to which our results are robust to changes in the set of cities included in the analysis. These results indicate that our estimates are not sensitive to dropping individual cities from the analysis database.

Figure 4: Robustness to dropping one city at a time

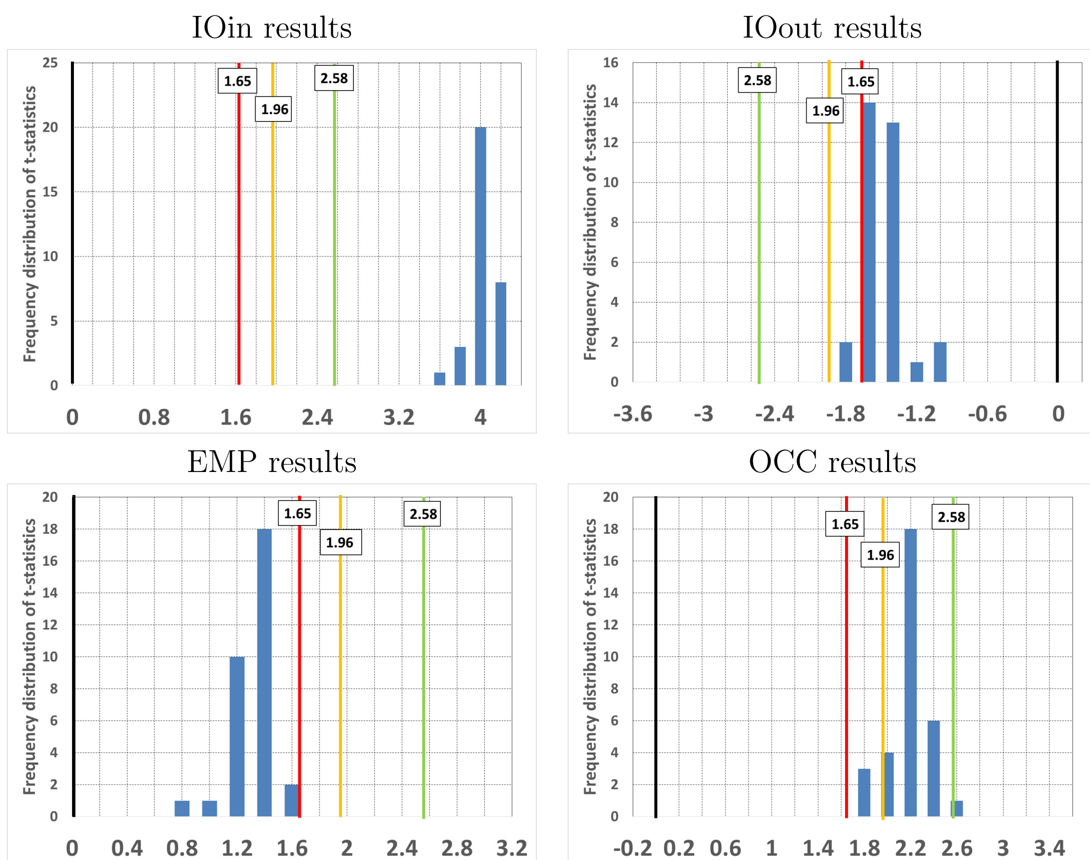
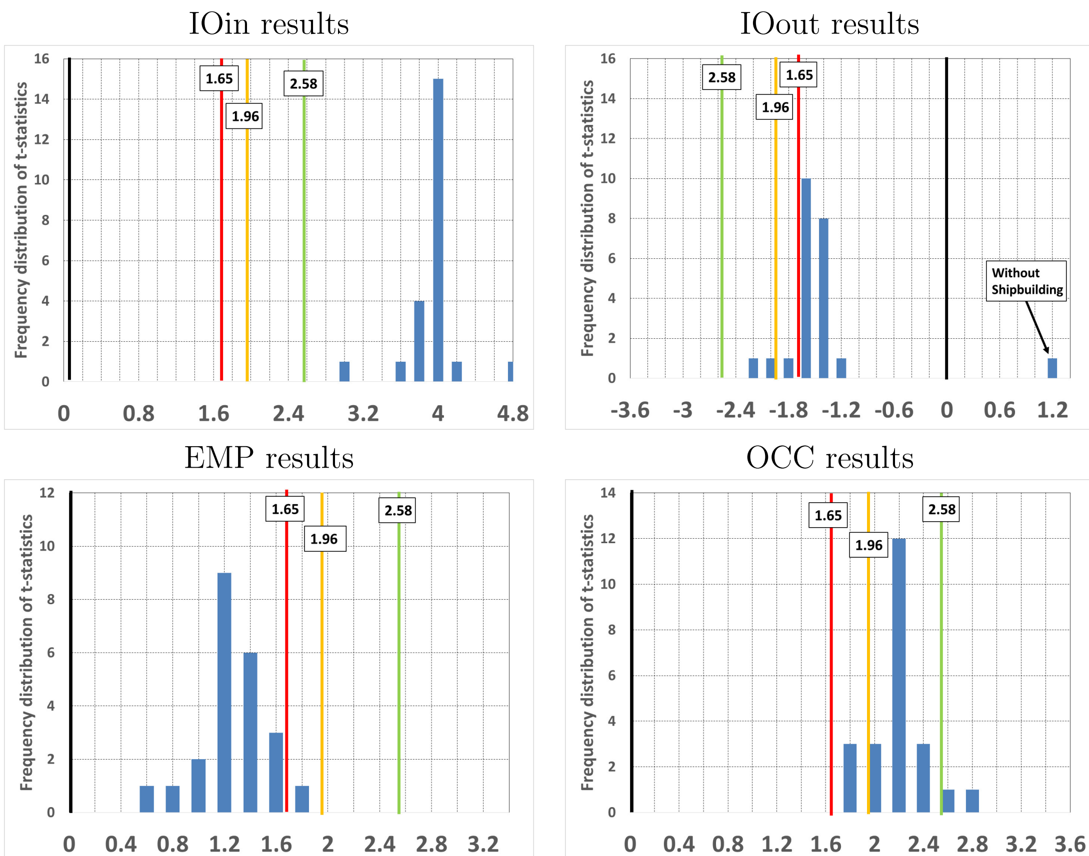


Figure 5 presents t-statistics for each cross-industry term obtained from running regressions equivalent to column 3 of Table 5, where in each regression a different industry is dropped from the dataset. This allows us to assess the extent to which our results are robust to changes in the set of industries included in the analysis. Specifically, while our IOin results are robust to dropping individual industries, we see that the estimates on the IOout and EMP terms are highly sensitive to the inclusion of particular industries. These results indicate that our estimates are much more sensitive to dropping industries than they are to dropping cities. This suggests that heterogeneity across industries is more important than heterogeneity across cities.

Figure 5: Robustness to dropping one industry at a time



A.3.2 Heterogeneous effects

In this section we look at heterogeneity in the pattern of cross-industry and within-industry effects across different industries. We begin by considering heterogeneous cross-industry effects. Specifically, we can run two alternative versions of Equation 9,

$$\triangle \ln(L_{ict+1}) = \tilde{\tau}_{ii} \ln(L_{ict}) + \beta^i \sum_{k \neq i} CONNECT_{ki} \ln(L_{kct}) + \theta_{ct} + \phi_{it} + e_{ict} \tag{20}$$

$$\triangle \ln(L_{i \neq k\, ct+1}) = \tilde{\tau}_{ii} \ln(L_{ict}) + \beta^k CONNECT_{ki} \ln(L_{kct}) + \theta_{ct} + \phi_{it} + e_{ict} \tag{21}$$

where $CONNECT_{ki}$ is one of our four measures of cross-industry connections. Equation 20 allows us to estimate industry-specific coefficients β^i describing how much each industry i benefits from cross-industry connections. This specificatoin can be estimated using the same approach as was used for our baseline regressions. Using Equation 21, we estimate industry-specific coefficients β^k that reflect the extent to which industry k generates spillovers that benefit other industries. Estimating this value requires a different approach to avoid conflating the within and between impact of industry k when estimating β^k. Specifically, we run separate regressions corresponding to Equation 21 for each industry k. In each of these regressions, only employment in industry k (interacted with a cross-industry connection measure) is included as an explanatory variable and observations from industry k are not included in the dependent variable.

Once the industry-specific β^i and β^k terms are estimated, we compare them to available measures of industry characteristics: firm size in each industry, the share of output exported, and the share of output sold to households. In each case we run a simple univariate regression where the dependent variable is the estimated industry-specific cross-industry spillover coefficient and the independent variable is one of the industry characteristics.[34] These results can provide suggestive evidence about the characteristics of industries that produce or benefit from different types of cross-industry spillovers, but because of the small sample size we will not be able to draw any strong conclusions.

Table 14 describes the characteristics of industries that *benefit from* cross-industry connections. In rows 1-2, we see evidence that small firm size in an industry is associated with more cross-industry spillover benefits, but this pattern is not statistically significant at standard confidence levels. The only strong result coming out of this

[34]Univariate regressions are used because we are working with a relatively small number of observations.

table is that industries that benefit from connections to other local industries with similar labor pools tend to have a larger labor cost share relative to overall industry sales, as well as a smaller intermediate cost share.

Table 15 describes the characteristics of industries that *produce* cross-industry connections. These results also suggest that industries with smaller firm sizes produce more beneficial cross-industry spillovers, but again, these results are not statistically significant. There is also evidence that industries with a greater labor cost share (and smaller intermediate cost share) relative to overall sales produce more cross-industry benefits to other occupationally similar industries.

Table 14: Features of industries that benefit from each type of cross-industry spillover

Coefficients from univariate regressions				
	DV: Estimated industry-specific β^i coefficient			
Spillovers channel:	IO-in	IO-out	EMP	OCC
Average firm size	-0.231	-0.910	-0.0363	-0.140
	(0.316)	(0.562)	(0.0353)	(1.169)
Median worker's firm size	-0.0200	-0.109	-0.00296	-0.0418
	(0.0374)	(0.0654)	(0.00420)	(0.137)
Share of industry output exported abroad	0.0119	-0.123	-0.0167	-0.319
	(0.0977)	(0.179)	(0.0115)	(0.347)
Share of industry output sold to households	0.0316	0.122	0.00761	0.174
	(0.0439)	(0.0867)	(0.00521)	(0.157)
Labor cost/output ratio	-0.135	-0.179	-0.00776	0.464**
	(0.146)	(0.282)	(0.0100)	(0.207)
Intermediate cost/output ratio	0.0200	0.0785	-0.000369	-0.404**
	(0.108)	(0.195)	(0.00738)	(0.136)

Estiamted coefficients from univariate regressions. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable in each regression is the estimated β^i coefficient from the regression in Equation 20. The dependent variables are the estimated cross-industry spillover coefficients for each industry and each spillover channel. Firm size data comes from the 1851 Census of Population. The share of industry output exported or sold to households is from the 1907 input-output table. The labor cost share is constructed from industry wage bills from the 1907 Census of Manufactures. The intermediate cost share is based on the 1907 input-output table. We do not report robust standard errors because these generate smaller confidence intervals, probably due to small-sample bias. We have also explored regressions in which we weight results by the inverse of the standard error of each estimated within-industry coefficient in order to account for the precision of those estimates and these deliver similar results.

Table 15: Features of industries that produce each type of cross-industry spillover

Coefficients from univariate regressions				
	DV: Estimated industry-specific β^k coefficient			
Spillovers channel:	IO-in	IO-out	EMP	OCC
Average firm size	-1.467	-4.002	0.0416	-0.995
	(1.241)	(6.524)	(0.177)	(2.174)
Median worker's firm size	-0.163	-0.640	0.000403	-0.147
	(0.147)	(0.760)	(0.0208)	(0.255)
Share of industry output exported abroad	0.0627	-0.820	0.00181	-0.339
	(0.408)	(2.017)	(0.0545)	(0.660)
Share of industry output sold to households	0.153	0.0588	-0.0163	0.416
	(0.202)	(0.916)	(0.0244)	(0.286)
Labor cost/output ratio	-0.318	0.598	-0.0264	1.014*
	(0.630)	(3.249)	(0.0452)	(0.534)
Intermediate cost/output ratio	-0.222	-0.0339	0.0151	-0.892**
	(0.421)	(2.287)	(0.0319)	(0.345)

The dependent variable in each regression is the estimated β^k coefficient from the regression in Equation 21. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variables are the estimated cross-industry spillover coefficients for each industry and each spillover channel. Firm size data comes from the 1851 Census of Population. The share of industry output exported or sold to households is from the 1907 input-output table. The labor cost share is constructed from industry wage bills from the 1907 Census of Manufactures. The intermediate cost share is based on the 1907 input-output table. We do not report robust standard errors because these generate smaller confidence intervals, probably due to small-sample bias. We have also explored regressions in which we weight results by the inverse of the standard error of each estimated within-industry coefficient in order to account for the precision of those estimates and these deliver similar results.

Next, we undertake a similar exercise with our estimated within-industry coefficients. In Table 16 we consider some of the industry characteristics that may be related to the range of different within-industry spillover estimates we observe. Columns 1-2 focus on the role of firm size using two different measures. We observe a positive relationship between firm size in an industry and the strength of within-industry spillovers, but this results is not statistically significant

Table 16: Features of industries that benefit from within-industry spillovers

DV: Estimated industry-specific within-industry spillover coefficients						
Average firm size	0.300					
	(0.196)					
Median worker's firm size		0.0263				
		(0.0236)				
Share of industry output exported abroad			0.0465			
			(0.0708)			
Share of industry output sold to households				-0.0397		
				(0.0314)		
Labor cost/output ratio					0.136	
					(0.0984)	
Intermediate cost/output ratio						-0.0110
						(0.0754)
Observations	20	20	23	23	16	16
R-squared	0.115	0.065	0.020	0.071	0.119	0.002

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The number of observations varies because the explanatory variables are drawn from different sources and are not available for all industries. The within coefficients come from the specification used in column 3 of Table 5. Firm size data comes from the 1851 Census of Population. The export's and household's share of industry output come from the input-output table. Total labor cost and total output values come from the 1907 Census of Production. Intermediate cost is constructed based on data from the 1907 Input-Ooutput matrix. We do not report robust standard errors because these generate smaller confidence intervals, probably due to small-sample bias. We have also explored regressions in which we weight results by the inverse of the standard error of each estimated within-industry coefficient in order to account for the precision of those estimates and these deliver similar results.

A.3.3 Further results using alternative connections matrices

This section presents additional results obtained using the alternative connections matrices introduced in Section 6. Table 17 presents results for regressions including multiple spillover channels. Columns 1-3 use the twelve aggregated industry categories available when using the 1841 input-output table. Columns 4-6 use the more limited set of nine industry categories that are available in our technology similarity matrix.

As in the main results, we observe positive effects occuring through the IOin channel and these results are generally statistically significant. Results obtained for the IOout and the two labor force similarity channels is clearly sensitive to the underlying set of industries used, while we observe no positive effect associated with the technology similarity matrix. However, we should use caution when interpreting any of these results because we are working with a small number of industry categories and correlated measures of cross-industry connections. Comparing these results to those described in the main text makes it clear that the correlations between the various spillover channels are having an important influence on the results. This may result in us observing insignificant or even negative results for channels that are important but poorly measured, which is a particular concern for the technological similarity channel.

Table 17: Alternative matrix regressions with all spillover channels

	With twelve aggregated industry categories			With the nine categories in the technology similarity matrix		
	(1)	(2)	(3)	(4)	(5)	(6)
IOin	0.0478**	0.0300	0.0359	0.0452**	0.0388*	0.0456**
	(0.0188)	(0.0204)	(0.0232)	(0.0198)	(0.0220)	(0.0226)
	[0.0137]	[0.0158]	[0.0169]	[0.0148]	[0.0160]	[0.0164]
IOout	0.0350	0.0532**	0.0551**	-0.0226	0.0122	0.0150
	(0.0228)	(0.0212)	(0.0220)	(0.0328)	(0.0238)	(0.0252)
	[0.0150]	[0.0158]	[0.0161]	[0.0240]	[0.0233]	[0.0240]
EMP	-0.0017	0.0004	0.0004	0.0262***	0.0191***	0.0188***
	(0.0037)	(0.0029)	(0.0031)	(0.0081)	(0.0064)	(0.0064)
	[0.0022]	[0.0022]	[0.0022]	[0.0060]	[0.0061]	[0.0064]
OCC	0.0086	0.0072	0.0077	0.0284***	0.0238**	0.0234**
	(0.0067)	(0.0076)	(0.0078)	(0.0080)	(0.0100)	(0.0100)
	[0.0037]	[0.0043]	[0.0044]	[0.0054]	[0.0070]	[0.0070]
TECH				-0.4476**	-0.2911*	-0.2498
				(0.1871)	(0.1678)	(0.1802)
				[0.1520]	[0.1729]	[0.1761]
Observations	2,232	1,860	1,860	1,674	1,395	1,395
Estimation	ols	2sls	2sls	ols	2sls	2sls
Instrumented	none	wtn	wtn-btn	none	wtn	wtn-btn
KP under id.		252.32	237.47		129.85	127.33
KP weak id.		195.54	125.39		108.32	58.28

Multi-level clustered standard errors by city-industry, city-year, and industry-year in parenthesis. Significance levels based on clustered standard errors: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in brackets. Regressors *within*, city-by-year and industry-by-year fixed effects are included in all regressions but not displayed. 2SLS regressions use lagged instruments. Note that the number of observations falls for the instrumented regressions in columns 3-6 because the instruments require a lagged employment term. Thus, data from 1851 are not available for these regressions. Acronyms: wtn = *within*, btn = *between*. "KP under id." denotes the test statistic for the Lagrange Multiplier underidentification test based on Kleibergen & Paap (2006). "KP weak id." denotes the test statistic for a weak instruments test based on the Kleibergen-Paap Wald statistic.