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 technology spillovers within and across industries, as well as city-size effects. The model generates a dynamic panel-data estimation equation that allows us to assess agglomeration economies while controlling for fixed locational fundamentals, time-varying city-specific shocks, and national industry-level shocks. We implement the approach using detailed new data describing the industry composition of English cities from 1851-1911. We find that cross-industry connections can influence industry growth, through either the presence of suppliers or local pools of demographically similar workers. Within-industry effects are not present for most industries, but may be important in a small number of industries. Once we separate these positive agglomeration forces, we find a strong negative relationship between city size and city-industry growth. A lower bound estimate of the overall strength of agglomeration forces suggests that they are equivalent to a city-size divergence rate of 0.5-1% per year.

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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 perhaps even more widespread used in other countries.[1]

Not surprisingly, there is a large body of existing research exploring the nature of agglomeration economies. Leading work in this area can be roughly classed into one of three approaches. 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, 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)). A third approach involves comparing outcomes in similar locations, where some locations receive a plausibly exogenous shock to the level of local economic activity (Greenstone *et al.* (2010) and Hanlon (2013)). This approach has the advantage of more cleanly identifying the causal impact of changes in local economic activity, but is less useful for policy, since it can only be applied under

[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.

special circumstances.

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 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 25 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 are able to construct from the data cover essentially 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).[2] 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 industry connections that we have constructed. Also, to help strengthen identification, we use the instrumental variable approach suggested by Bartik (1991).[3] Specifically, we interact lagged city-industry employment with industry employment growth in all

[2] See also Combes (2000) and Dekle (2002).

[3] The Bartik approach is commonly used in studies in this literature. One recent example is Diamond (2012).

other cities to generate *predicted* employment in industry j in a period. This predicted employment level is then used as an instrument for actual employment in industry j. 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. The Bartik instrumentation allows us to further weaken the assumptions needed to obtain valid estimates.

Our main findings are that (1) cross-industry effects are important, and occur largely through the presence of local suppliers and demographically similar labor pools, (2) within-industry effects are confined to a small number of industries, (3) for both channels, there is substantial heterogeneity across industries, (4) firm size matters, is negatively correlated with cross-industry effects, and is positively correlated with within-industry effects, and (5) city size has a clear negative relationship to city growth. The first four results confirm a number of findings from existing literature, though in a very different setting. The city-size results are novel and provide an opportunity for us to quantify the net strength of city agglomeration forces, which has not been possible in previous work. We find that the overall strength of the agglomeration forces is consistent with a city-size divergence rate of 0.5-1% per year. Moreover, the strength of these agglomeration forces shows a marked decline over the six decades that we study.

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, which focus on agglomeration forces within cities, while Section 6 extends the result to study whether similar effects are operating across cities. Section 7 concludes.

2 Theory

In this section we build a simple model of city growth incorporating localized spillovers within and across industries. 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 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.

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. Goods and services are freely traded across locations.

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

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

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 economics 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. 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 industries in any period.

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[4]:

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

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 can set M_t to zero and then solve for the equilibrium price levels in the economy.[5] 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.

[4] 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.

[5] 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.

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,

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

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

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

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 (e.g., $L_{kct} \leq 1$), 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. These terms appear in the top row in the right-hand side.

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.

3 Data

This study brings together many different data sets and involves the construction of several original databases. This section briefly discusses the sources and construction of the data used in this study. Further details are available in an extensive online appendix.

The data we study cover English cities during the period 1851-1911. It may seem odd that we choose this historical setting in order to study agglomeration economies. However, in addition to offering detailed data (described below), there are several features of this setting that are helpful for our analysis. One central feature of the historical period is the limited amount of government involvement in the economy, and particularly for our purposes, the lack of place-based economic interventions. Also, 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.[6] This period was also characterized by fairly stable internal and external trade costs, particularly after 1880.[7] A final important advantage of studying the British economy is that, even in 1851, the urban system was well-established.

[6]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."

[7]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.

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 each period. 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.

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. [8]

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.[9]

The cities included in the database are those that had a population of 50,000 or more in the 1851 census within the municipal boundaries, plus three slightly smaller towns for which data was previously available from Hanlon (2013).[10] These cities include between 28 and 32% 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[11]. Table 1 provides a list of

[8]In fact, in 1921 the Census office renamed what had previously been called "occupation" to be "industry" and then introduced a new set of data on actual occupations.

[9]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.

[10]An exception to this rule was made for Wolverhampton, Staffordshire, with a population 49,985. Also, Plymouth is excluded from our database because in early years Plymouth data includes nearby Devonport while in later years it does not, resulting in an inconsistent series. The three towns from Hanlon (2013), together with their 1851 populations, are Blackburn (46,536), Halifax (33,582) and Huddersfield (30,880). This means that our database is slightly oversampling industrial cities. London is treated as one metropolitan area in the database.

[11]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

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	28,302	23,731
Birmingham	232,841	112,523	95,796
Blackburn	46,536	26,281	24,248
Bolton	61,171	31,291	28,617
Bradford	103,778	58,565	54,613
Brighton	69,673	33,521	28,048
Bristol	137,328	64,824	54,613
Halifax	33,582	18,159	16,162
Huddersfield	30,880	13,984	12,092
Kingston-upon-Hull	84,690	37,390	31,109
Leeds	172,270	83,980	73,480
Leicester	60,496	31,317	28,409
Liverpool	375,955	166,184	135,068
London	2,362,236	1,096,384	908,818
Manchester	401,321	205,314	180,839
Newcastle-upon-Tyne	87,784	38,804	32,837
Norwich	68,195	34,369	29,666
Nottingham	57,407	34,104	30,995
Oldham	72,357	38,932	35,690
Portsmouth	72,096	31,571	19,047
Preston	69,542	36,998	32,601
Sheffield	135,310	58,775	50,860
Stockport	53,835	30,209	27,632
Sunderland	63,897	24,978	21,562
Wolverhampton	49,985	22,844	19,673

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.[12] 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.

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.

[12] 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.

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 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 27 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	17,814	Professionals*	42,689
Dress	320,613	Clerks*	27,108
Instruments & jewelry*	31,462	General services	464,996
Earthenware & bricks	18,247	Merchant, agent, accountant, etc.	30,492
Leather & hair goods	26,214	Messenger, porter, etc.	71,645
Metal & Machines	161,615	Shopkeeper, salesmen, etc.	26,570
Oil, soap, etc.	12,063		
Paper and publishing	41,805	**Transportation services**	
Shipbuilding	13,962	Railway transport	9,878
Textiles	308,984	Road transport	34,771
Vehicles	8,609	Sea & canal transport	63,569
Wood & furniture	68,587		
Others industries		**Food, etc.**	
Building	134,643	Food processing	111,316
Mining	22,920	Spiritous drinks, etc.	7,892
Water & gas services	3,847	Tobacconists*	3,224

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.

The second necessary piece of data for our analysis is 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.

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.[13] 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. The 1921 Census provides a matrix of employment by occupation and industry. For any two industries, our occupation-based measure of labor force similarity, OCC_{ij}, is the correlation between the two industries in the employment

[13] 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.

share in each occupation.

Finally, we collect 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-output table, we have measures of the share of industry output that is sold directly to households, as well as the share exported abroad. 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 6.

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. We purposely omitted the last term of Equation 7, namely $\triangle \ln(\bar{w}_{t+1})$, 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. We chose to drop in all specifications the industry-year dummies associated with the "General services" sector.

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. We parametrize the connections between industries using the available input-output and labor force similarity matrices:

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

Substituting this into 8 we obtain:

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

Instead of a large number of parameters measuring spillovers across industry, 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 11.

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 what we will call henceforth a Bartik instrument, following an approach similar to Bartik (1991).[14] Under the assumption that the measurement error in any given city-industry pair is *iid* across cities and time, our instrument is $L_{ict}^{Bart} = L_{ict-1} \times g_{i-ct}$, 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

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

$k \neq i$ 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. The Bartik approach can also help us deal with these concerns. 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 $\sum_{k \neq i} IOin_{ki} \ln(L_{kct}^{Bart})$, where L_{kct}^{Bart} is computed as described above.

Finally, note that we would run into the type of endogeneity studied by Arellano & Bond (1991) if we had time-invariant city-industry effects. We do not have such effects because in the model itself these were captured by the term $\bar{R}_{ic}$ and were differenced out when we derived our estimating equation.

The estimation is performed using OLS or, when using the Bartik 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 6 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.

To simplify the exposition, we will hereafter collectively refer to the set of regressors $\ln(L_{ict}), \quad i = 1...I$ 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. Finally, we will 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 labor force similarity. We begin our analysis, in Table 3 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 Bartik instrumentation on the within terms; and Column 3 uses Bartik 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 3 suggest that a one standard deviation increase in local employment in IO-weighted supplier industries would result in an increase in city-industry growth of 18.6-22.5 percent. There is weaker evidence of positive effects operating through the labor force similarity channel based on demographic connections, and negative effects operating through the occupation-based labor force similarity channel. One explanation for this is that industries may benefit from broad labor pools of demographically similar worker, but that competition for workers in more narrowly defined occupations may act as a drag on growth. There is little evidence that the presence of local buyers has a positive effect on industry growth. 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.

Table 3: OLS and IC regressions including only one spillover path at a time

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	lhs	lhs	lhs	lhs	lhs	lhs	lhs	lhs	lhs	lhs	lhs	lhs
IOin	0.0685***	0.0556***	0.0568***									
	(0.0152)	(0.0143)	(0.0150)									
IOout				0.0052	-0.0062	-0.0082						
				(0.0144)	(0.0146)	(0.0145)						
EMP							0.0022	0.0033**	0.0030*			
							(0.0017)	(0.0015)	(0.0016)			
OCC										-0.0053**	-0.0037*	-0.0038*
										(0.0022)	(0.0020)	(0.0020)
Obs	3,300	2,746	2,746	3,300	2,746	2,746	3,300	2,746	2,746	3,300	2,746	2,746
Estimation	ols	2sls	2sls	ols	2sls	2sls	ols	2sls	2sls	ols	2sls	2sls
FE1	Ind*Year	Ind*Year	Ind*Year	Ind*Year	Ind*Year	Ind*Year	Ind*Year	Ind*Year	Ind*Year	Ind*Year	Ind*Year	Ind*Year
FE2	City*Year	City*Year	City*Year	City*Year	City*Year	City*Year	City*Year	City*Year	City*Year	City*Year	City*Year	City*Year
Instruments	none	Bartik	Bartik	none	Bartik	Bartik	none	Bartik	Bartik	none	Bartik	Bartik
Instrumented	none	wtn	wtn-btn	none	wtn	wtn-btn	none	wtn	wtn-btn	none	wtn	wtn-btn

Multi-level clustered standard errors by city-industry, city-year, and industry-year. Regressors *within* and fixed effects included in all regressions but not displayed. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. 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*.

Table 4 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 similar to those from Table 3, though the negative coefficient on the IOout term becomes statistically significant and the positive coefficient on the EMP term strengthened. We interpret the negative coefficients on the IOout term with some caution because the correlation between the IOin and IOout matrices makes this term sensitive to the inclusion of the IOin term.

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 results change very little when individual cities are dropped. However, dropping individual industries can have much larger effects. In particular, while the importance of local suppliers is robust to dropping individual industries, the results on the IOout and EMP terms are highly sensitive to the set of industries included in the analysis. Thus, we find that industries represent the key dimension for heterogeneity in our data.

Table 4: Results with all cross-industry spillover channels

	(1)	(2)	(3)
IOin	0.0653***	0.0563***	0.0623***
	(0.0169)	(0.0166)	(0.0179)
IOout	-0.0156	-0.0273**	-0.0294**
	(0.0116)	(0.0123)	(0.0119)
EMP	0.0025	0.0044***	0.0036***
	(0.0016)	(0.0012)	(0.0013)
OCC	-0.0035	-0.0037*	-0.0029
	(0.0024)	(0.0021)	(0.0021)
Observations	3,300	2,746	2,746
Estimation	ols	2sls	2sls
FE1	Ind*Year	Ind*Year	Ind*Year
FE2	City*Year	City*Year	City*Year
Instruments	none	Bartik	Bartik
Instrumented	none	wtn	wtn-btn

Multi-level clustered standard errors by city-industry, city-year, and industry-year. Regressors *within* and fixed effects included in all regressions but not displayed. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. 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*.

The results above reveal average patterns across all industries. We can further unpack these effects by estimating industry-specific coefficients for each of the spillover channels. Specifically, we replace β_1, β_2, β_3, and β_4 in Equation 9, with industry-specific coefficients β_1^i, β_2^i, β_3^i, and β_4^i. The estimated industry-specific coefficients are presented in the Appendix. We can compare these industry-specific cross-industry spillover coefficients to available information on industry characteristics, in order to identify the features of industries where each type of cross-industry spillover is important.

We focus on several industry characteristics for which data are available: 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.[15] These results can provide suggestive evidence about the characteristics of industries that benefit from different types of cross-industry spillovers.

Table 5 describes the results. In rows 1-2, we see evidence that small firm size in an industry is associated with more cross-industry spillover benefits. Row 3 provides some evidence that industries that export abroad benefit less from localized cross-industry spillovers. Row 4 suggests that there is a weak positive relationship between the cross-industry spillover benefits received by an industry and the share of industry output sold directly to households.

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

Table 5: Features of industries that benefit from each type of cross-industry spillover

Coefficients from univariate regressions				
	DV: Estimated industry-specific cross-industry spillover coefficients			
Industry	Spillovers channel:			
features:	IO-in	IO-out	EMP	OCC
Average firm size	-0.839***	-0.546	-0.0640**	-0.137*
	(0.292)	(1.502)	(0.0291)	(0.0724)
Median worker's firm size	-0.112***	-0.118	-0.00707*	-0.0111
	(0.0322)	(0.175)	(0.00346)	(0.00892)
Share of industry output exported abroad	-0.209**	-0.270	-0.0243**	-0.0296
	(0.0982)	(0.457)	(0.0101)	(0.0264)
Share of industry output sold to households	0.0816*	-0.150	0.00870*	0.0145
	(0.0410)	(0.214)	(0.00430)	(0.0113)

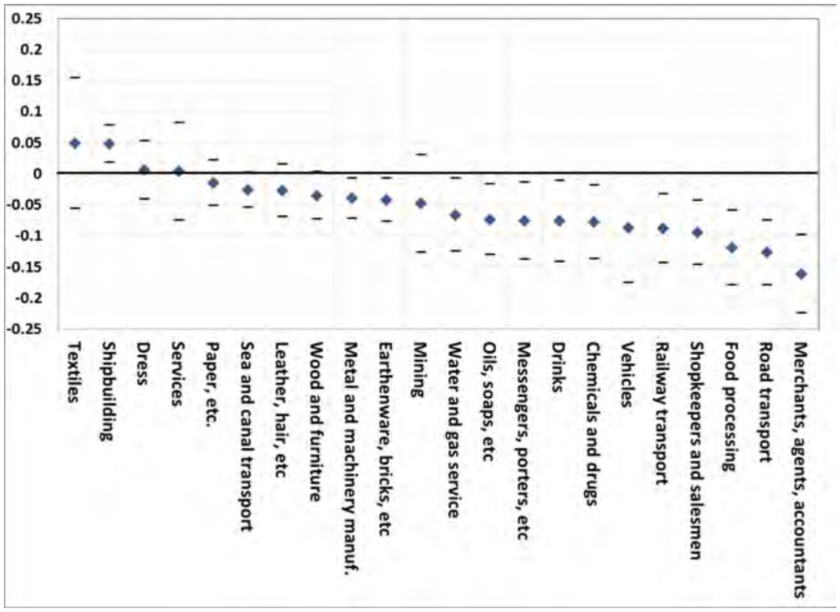
Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The dependent variables are the estimated cross-industry spillover coefficients for each industry and each spillover channel. Additional details are available in the Appendix. Firm size data comes from the 1851 Census of Population. The share of industry output exported or sold to households is from the 1907 Input-Output matrix.

5.2 Within-industry spillovers

Our analysis can also help us understand the strength of within-industry spillovers.[16] These spillovers are reflected in the $\ln(L_{ict})$ term in Equation 8, which is an instrumented variable. Figure 1 presents the within-industry coefficients and 95% confidence intervals for regression specifications corresponding to Columns 3 of Table 4, where the Bartik 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 a small number of industries, such as shipbuilding and textiles, we observe positive within-industry effects. These industries are characterized by increasing returns and strong patterns of geographic concentration. Within-industry agglomeration benefits, it would appear, are more the exception than the rule.

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

Figure 1: Strength of within-industry effects by industry



Results are based on regression in column 3 of Table 4. Multi-level 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 the Bartik approach.

In Table 6 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 strong positive relationship between firm size in an industry and the strength of within-industry spillovers.[17] The third and fourth columns look at the buyers served by each industry. The relationship between within-industry spillovers and the importance of exports is positive but not statistically significant. Within-industry spillovers are associated with a lower share of industry output going directly to households.

[17]More data on firm size by industry are available in the Appendix.

Table 6: Correlates of within-industry spillovers

	DV: Estimated industry-specific within-industry spillover coefficients				
Average firm size	0.592**				
	(0.264)				
Median worker's firm size		0.0713**			
		(0.0307)			
Exports share of industry output			0.140		
			(0.0862)		
Households share of industry output				-0.0902**	
				(0.0388)	
Observations	19	19	22	22	19
R-squared	0.229	0.241	0.117	0.212	0.217

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 4. 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.

5.3 City-wide effects

Next, we want to look for effects operating at the city level. In particular, we are interested in the effect of city size on city-industry growth. City size may reduce city growth through congestion forces, but may also increase city-industry growth if there are substantial agglomeration benefits from being in a large city apart from the other agglomeration forces that we study.[18]

We begin by focusing on the effect of city size on actual city growth. The blue triangle symbols in Figure 2 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.

The red squares in Figure 2 describe the relationship between our estimated city-year fixed effects (θ_{ct}) and the log of initial population in each decade. In essence, these describe the relationship between city size and city growth after controlling for

[18]Such aggregate city-size agglomeration forces play a role 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.

national industry growth trends and the agglomeration forces generated by within and cross-industry spillovers. We can see that in all years, the fitted lines on these series slope downward more steeply than the slopes on the fitted lines for actual city growth. This suggests that, once we control for other factors, city size is negatively related to city growth, consistent with the idea that there are city-size congestion forces. The difference between two slopes of the two sets of 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.

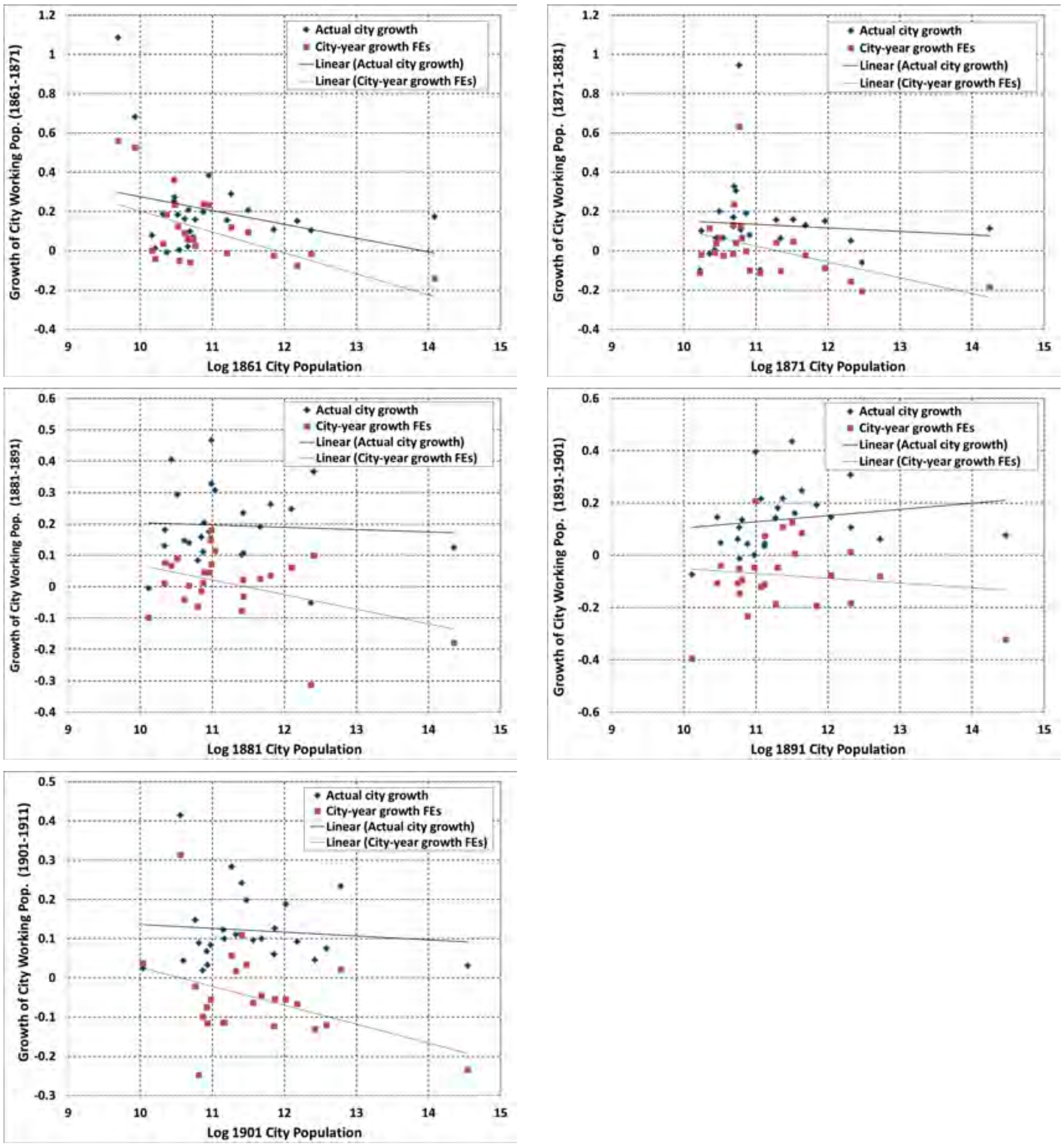
The strength of these effects can be quantified in terms of the implied convergence rate following the approach of Barro & Sala-i Martin (1992). To do so, we run the following regressions:

$$\theta_{ct} = a_0 + a_1 \log(WORKpop_{ct}) + \epsilon_{ct} \tag{10}$$

$$GrowthWORKpop_{ct} = b_0 + b_1 \log(WORKpop_{ct}) + \epsilon_{ct} \tag{11}$$

where θ_{ct} is the estimated city-period fixed effect for the decade from t to $t+1$, $GrowthWORKpop_{ct}$ is the actual growth rate of the city from t to $t+1$, and $WORKpop_{ct}$ is the working population of the city in year t. 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 Table 7. The right-hand column describes the difference between the rate of convergence observed for actual city size and the expected rate of convergence implied by our city-size results. This difference must reflect the average impact of the agglomeration forces captured by our estimation. These results suggest that the strength of city agglomeration forces, in terms of the implied divergence rate, ranged from 0.5-1% per year and showed a downward trend over the period we study.

Figure 2: The effect of city size on city growth



These graphs show scatter plots of actual city growth over a decade compared to the log of city population at the beginning of the decade (blue triangles) and of the city-year fixed effects over the same decade, also compared to the log of city population at the beginning of the decade (red squares). The two fitted lines reflect the linear relationship between each of these and overall city size. The difference between the slope of the fitted lines reflects the strength of the agglomeration forces in the economy.

There are some caveats to keep in mind when assessing these results. These estimates of the strength of agglomeration forces are likely to be lower bounds for

Table 7: Measuring the aggregate strength of the agglomeration forces

	Results for city-year FEs		**Results for actual city growth**		**Difference: aggregate strength of agglomeration forces**
	Estimated city-size coefficient	Implied convergence Beta	Estimated city-size coefficient	Implied convergence Beta	
1861-1871	-0.107 ***	1.13%	-0.028	0.28%	0.85%
1871-1881	-0.081 **	0.84%	0.019	-0.19%	1.03%
1881-1891	-0.047 **	0.48%	0.008	-0.08%	0.56%
1891-1901	-0.018	0.19%	0.037	-0.36%	0.55%
1901-1911	-0.048 *	0.49%	-0.001	0.01%	0.48%

Column 2 presents the a_1 coefficients from estimating Equation 10 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 11 and column 5 presents the convergence rates implied by these coefficients. Column 5 gives the difference between the two convergence rates, which represents the aggregate strength of the divergence force represented by the agglomeration economies.

several reasons. 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 be captured by terms in our estimation other than the city-year fixed effects. Specifically, we have provided evidence that many of the within-industry spillover terms are negative. Since these will not be included in the convergence forces represented in Table 7, they will lead us to understate the strength of the agglomeration forces.

6 Cross-city effects

In this section, we extend our analysis to consider the possibility that city-industry growth may be influenced not just by factors within the city, but also through the influence of other nearby cities. We consider two potential channels for this 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.

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 located a relatively long distance from other cities.

We begin our analysis by collecting data on the distance (as a 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 $d_{ij} = exp(-distance_{ij})$.[19] Our measures of market potential for each city is then,

$$MP_{ct} = \sum_{j \neq c} POP_{jt} * d_{cj}.$$

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,

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

[19]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.

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 8. 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 are always positive and statistically significant at at least the 90% confidence level. This shows that a city's market access contributes positively to city-industry growth. The results provide little evidence that cross-city spillovers matter through any of the channels that we measure.

Table 8: Regression results with cross-city variables

	(1)	(2)	(3)
IOin	0.0577***	0.0674***	0.0636***
	(0.0163)	(0.0168)	(0.0165)
IOout	-0.0315***	-0.0310***	-0.0325***
	(0.0109)	(0.0110)	(0.0108)
EMP	0.0039***	0.0034***	0.0036***
	(0.0012)	(0.0013)	(0.0012)
OCC	-0.0033	-0.0032	-0.0032
	(0.0021)	(0.0023)	(0.0022)
City employment	-0.0134***	-0.0129***	-0.0133***
	(0.0042)	(0.0042)	(0.0043)
MP	0.2559*		0.4204**
	(0.1440)		(0.1974)
IOin*d		0.0028	-0.0012
		(0.0018)	(0.0023)
IOout*d		-0.0007	-0.0001
		(0.0008)	(0.0009)
EMP*d		0.0002	0.0002*
		(0.0001)	(0.0001)
OCC*d		0.0000	-0.0002
		(0.0001)	(0.0002)
Observations	2,746	2,746	2,746
FE1	Ind*Year	Ind*Year	Ind*Year
FE2	City	City	City
instruments	Bartik	Bartik	Bartik
instrumented	wtn-btn	wtn-btn	wtn-btn

Multi-dimensional clustered standard errors by city-industry, city-year, and industry-year. Regressors *within* and fixed effects included in all regressions but not displayed. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Acronyms: wtn = *within*, btn = *between*.

7 Conclusion

In the introduction, we raised 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 tentative answers for the period we study. First, we find evidence that cross-industry agglomeration economies appear more important than within-industry agglomeration forces. Within-industry effects are generally negative, but may be positive in a small number of industries such as textiles and shipbuilding.[20] 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 the co-locate with their suppliers or with other industries that use demographically similar workforces. This result is in line with arguments made by Jacobs (1969), as well as recent empirical findings.[21] Third, we provide evidence that there is substantial heterogeneity in the nature and strength of agglomeration forces across industries.[22] In particular, we find that industries characterized by smaller firm sizes are more likely to benefit from cross-industry agglomeration forces.[23]

Perhaps the most novel finding emerging from this study has to do with the clear negative relationship between city size and city growth that appears once we account for a city's industrial composition. This suggests that Gibrat's law is generated by a careful 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, falls between 0.5-1% and shows a downward trend over the period we study.

[20]Interestingly, textiles also appears as an outlier in modern studies such as Dumais *et al.* (2002).

[21]See Glaeser & Kerr (2009), Glaeser *et al.* (2010), Ellison *et al.* (2010), and Delgado *et al.* (2010).

[22]Henderson *et al.* (1995) and Faggio *et al.* (2013) provide evidence of heterogeneity using modern data.

[23]This finding is consistent with arguments made by Chinitz (1961). We do not identify the direction of causality in this relationship.

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A Appendix

A.1 Data appendix

Table 9: Map showing the location of cities in the analysis database

Table 10: Industry firm size data from 1851 Census of Population

Industry	Median firm size	Median worker's firm size	Average firm size	Median firm size*	Median worker's firm size*	Average firm size*
Chemicals and drugs	1	7	5	2	10	6
Services	1	1	2	1	2	3
Dress	1	5	4	2	6	6
Merchants, agents, accountants	2	9	6	3	10	7
Shopkeepers and salesmen	1	3	3	3	4	5
Road transport	1	3	3	3	5	5
Sea and canal transport	3	20	8	5	20	10
Engineers and surveyors	7	20	11	7	20	11
Vehicles	4	10	7	5	10	9
Shipbuilding	3	40	11	5	40	14
Building	2	7	5	3	8	7
Food processing	1	2	3	2	3	4
Oils, soaps, etc	1	5	4	2	6	5
Leather, hair, etc	2	8	5	3	9	7
Drinks	2	8	6	3	9	7
Tobacco	1	20	7	5	20	11
Wood and furniture	2	6	5	3	7	6
Textiles	3	150	17	5	150	22
Paper, etc.	2	20	8	4	20	11
Mining	3	50	13	4	50	15
Earthenware, bricks, etc	4	100	16	6	100	19
Instruments and jewelry	1	7	5	3	9	7
Metal and machinery manuf.	1	20	6	2	20	8

* Values in columns 3-6 are calculated dropping entries by masters reporting zero employees or not reporting the number of employees.

A.2 Results appendix

A.2.1 Robustness exercises

Figure 3 presents t-statistics for each cross-industry term obtained from running regressions equivalent to column 3 of Table 4, 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.

Table 11: Summary statistics for the cross-industry spillover terms

Spillover measure	Obs.	Mean	SD	Min	Max
$\sum_{k \neq i} IOin_{ki} \ln(L_{kct})$	2875	9.63	3.28	2.24	21.85
$\sum_{k \neq i} IOout_{ki} \ln(L_{kct})$	2875	9.13	6.49	0.00	42.77
$\sum_{k \neq i} EMP_{ki} \ln(L_{kct})$	2875	123.74	52.60	-114.60	228.65
$\sum_{k \neq i} OCC_{ki} \ln(L_{kct})$*	2750	63.04	41.10	-33.63	147.92

*The occupation-based labor force similarity matrix is not available for the Construction industry.

Figure 3: Robustness to dropping one city at a time

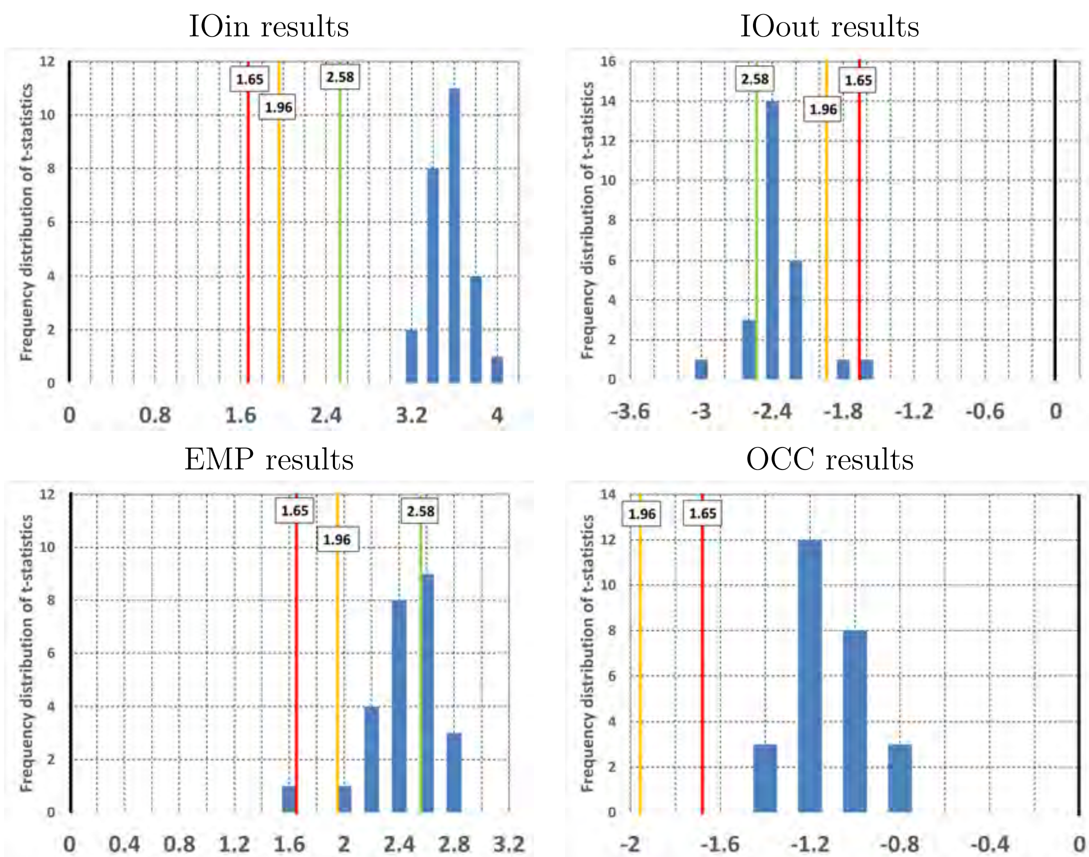

Figure 4: Robustness to dropping one industry at a time

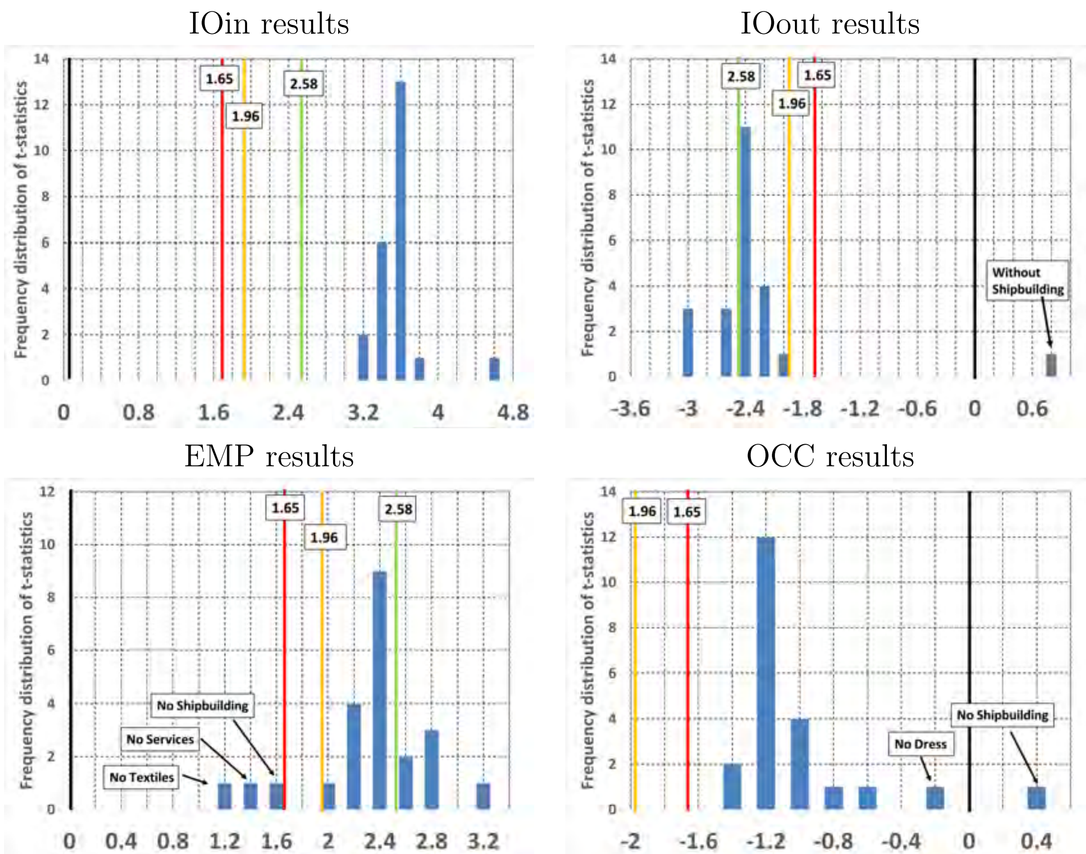

Figure 4 presents t-statistics for each cross-industry term obtained from running regressions equivalent to column 3 of Table 4, where in each regression a different industry is dropped from the dataset. This allows us to assess the extent to which our results are robust to changes in the set of industries included in the analysis. Specifically, while are 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.

A.2.2 Estimated heterogeneous cross-industry effects

Figures 5-8 present the estimated industry-specific cross-industry spillover coefficients for each of the spillover channel measures. Regressions are run with only one channel at a time to keep the number of estimated parameters manageable. Thus, the estimating equation for the first set of results is,

$$\triangle \ln(L_{ict+1}) = \tilde{\tau}_{ii} \ln(L_{ict}) + \beta_1^i \sum_{k \neq i} IOin_{ki} \ln(L_{kct}) + \theta_{ct} + \phi_{it} + \epsilon_{ict}.$$

Results are calculated using instruments for both the within and between terms and multidimensional clustered standard errors by city-industry, industry-year and city-year. The coefficient estimates and 95% confidence intervals for the IOin channel are plotted in Figure 5. These estimates provide the dependent variables for column 1 of Table 5. A similar estimating equation is used for each of the other spillover channels. The result are shown in Figures 6-8. These estimates provide the dependent variables for columns 2-4 of Table 5.

Figure 5: Industry-specific cross-industry spillover coefficients – IO in channel

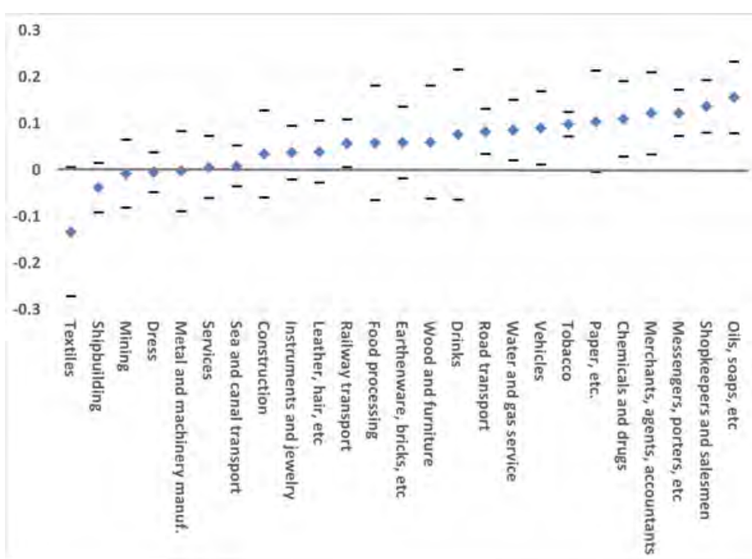

Figure 6: Industry-specific cross-industry spillover coefficients – IO out channel

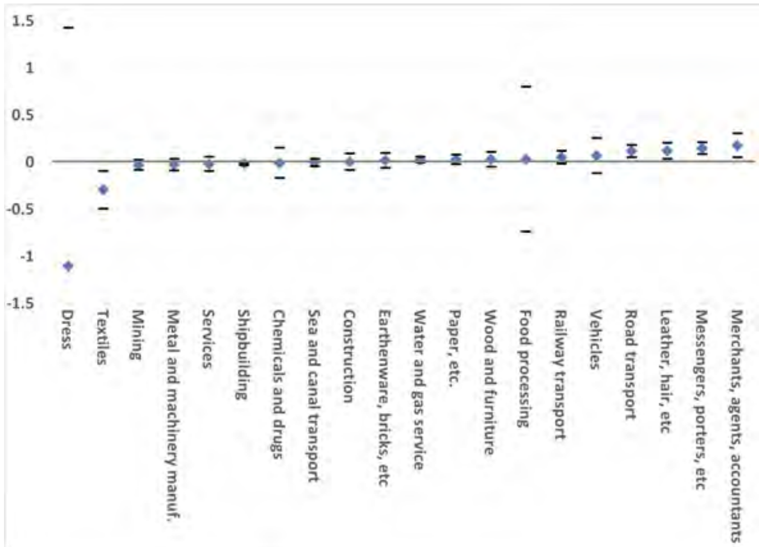

Figure 7: Industry-specific cross-industry spillover coefficients – EMP channel

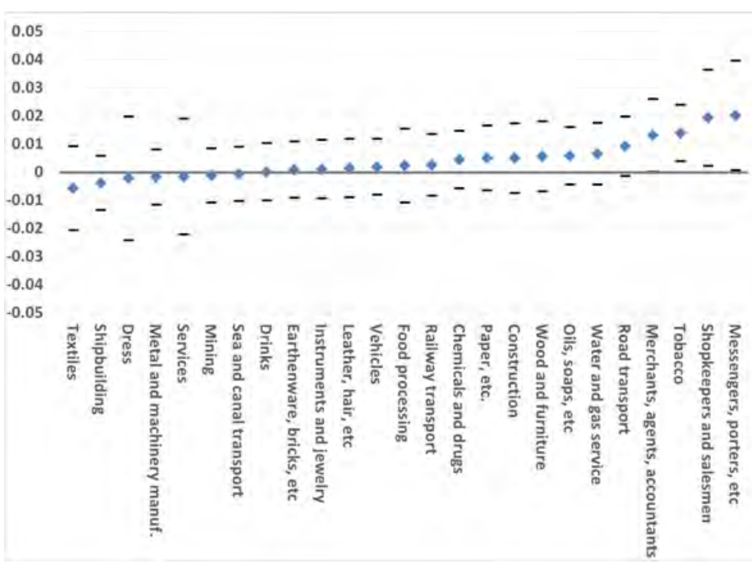

Figure 8: Industry-specific cross-industry spillover coefficients – OCC channel