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Agglomeration: A long-run panel data approach

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ABSTRACT

This paper studies the sources of agglomeration economies in cities. We begin by incorporating within and cross-industry spillovers into a dynamic spatial equilibrium model in order to obtain a panel data estimating equation. This gives us a framework for measuring a rich set of agglomeration forces while controlling for a variety of potentially confounding effects. We apply this estimation strategy to detailed new data describing the industry composition of 31 English cities from 1851 to 1911. Our results show that industries grew more rapidly in cities where they had more local suppliers or other occupationally-similar industries. We find no evidence of dynamic within-industry effects, i.e., industries generally did not grow more rapidly in cities in which they were already large. Once we control for these agglomeration forces, we find evidence of strong dynamic congestion forces related to city size. We also show how to construct estimates of the combined strength of the many agglomeration forces in our model. These results suggest a lower bound estimate of the strength of agglomeration forces equivalent to a city-size divergence rate of 1.6–2.3% per decade.

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 firms 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? How do these forces vary across industries? What role does city size play in industry growth? 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 builds on two important 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, labor force similarity, or technology spillovers. These connections are then compared to a cross-section of industry locations (Rosenthal and Strange, 2001; Ellison et al., 2010; Faggio et al., in press).[3] A limitation of this type of static exercise is that it is more difficult to control for locational fundamentals in cross-sectional regressions.

Our approach builds on these previous studies, but also seeks to address some of the remaining issues facing the literature.

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[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. Other alternative approaches use individual-level wage data (Glaeser and Mare, 2001; Combes et al., 2008; 2011) or firm-level data (Dumais et al., 2002; Rosenthal and Strange, 2003; Combes et al., 2012) to investigate the effects of city size. See Rosenthal and Strange (2004) and Combes and Gobillon (2015) for reviews of this literature.

[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 and Cameron (2007) and Lopez and Sudekum (2009).

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Specifically, this study contributes to the existing literature in five ways. First, while this is primarily an empirical paper, we begin by introducing a new dynamic spatial equilibrium model of city-industry growth. This model incorporates a rich set of within- and cross-industry spillover effects, which allows us to ground our study of these agglomeration forces in a theoretically-consistent framework. Recent work has highlighted the need for theoretical foundations in this literature.[4]

Second, motivated by the theory, we introduce a panel-data econometric approach for estimating the magnitude of agglomeration forces.[5] The key feature of our approach is that we are able to estimate the importance of dynamic agglomeration forces related to industry scale, cross-industry connections, and city-size in a unified framework, while dealing with fixed locational fundamentals and time-varying industry-specific shocks. Previous research has examined these elements separately, but we are not aware of existing work that studies all of these effects in a unified way. In addition, the use of panel data offers some well-known advantages relative to the cross-sectional or long-difference methods used in most existing work. However, applying this approach to study agglomeration economies requires overcoming challenges related to identification and correlated errors. Our study makes progress in this direction, allowing us to address some of the identification concerns present in previous work. The approach that we develop can potentially be applied in a wide range of settings in which consistent panels of city-industry employment data can be constructed.

Third, to implement our approach, we construct a rich dataset describing the evolution of city-industry employment over six decades. The availability of detailed long-run city-industry data has been a major impediment to previous work on agglomeration economies. The database constructed in this study helps address this deficiency.[6] 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. This empirical setting offers several important advantages. One advantage is the very limited level of government regulation and interference in the British economy during this period due to the strong free-market ideology that dominated British policymaking and the small size of the central government.[7] A second important advantage is that we are able to study agglomeration using consistent data over many decades. Studying agglomeration over a long time period is desirable because the time needed to build new housing, factories, and infrastructure means that it may take years for cities to respond to changes in local productivity levels. Our data are also quite detailed; they come from a full census and cover nearly the entire private sector economy, including manufacturing, transportation, retail, and services. A third advantage is that we are able to study a long-established urban system. This contrasts with the U.S., where the open western frontier meant that the U.S. city system was in transition until the middle of the 20th century.[8] Our setting was also characterized by a relatively open economy with high levels of migration into and between cities.[9]

Fourth, we provide new results on the strength of different types of agglomeration and congestion forces for one empirical setting. We find that (1) cross-industry effects were important, and occurred largely through the presence of local suppliers and occupationally similar labor pools, (2) the net effect of within-industry agglomeration forces was generally negative, and (3) city size had a clear negative relationship to city growth. The presence of local buyers appears to have had little positive influence on city-industry growth. We provide a variety of tests examining the robustness of these results. For example, we show that our main results are robust to dropping particular cities or particular industries. They are also robust to using an alternative set of matrices measuring cross-industry connections, alternative functional forms for modeling spillovers, or alternative industry definitions. We also show that incorporating cross-city effects, such as market potential or cross-city industry spillovers, has little impact on our results.

Fifth, we introduce a novel approach for measuring the combined strength of the many cross-industry agglomeration forces represented in our model. This is valuable because it provides a convenient way to assess the aggregate strength of these effects and may be useful for studying how these effects vary in different circumstances. Our results suggest that a lower-bound estimate of the agglomeration forces captured by our empirical model are equivalent to a decadal city-size divergence rate of 1.6–2.3%. To our knowledge this is the first paper to show how to measure the combined strength of these many cross-industry connections.

It is important to understand at the outset that the goal of this paper is to assess the role of agglomeration economies in driving city employment growth in different industries, and thereby contributing to overall city growth. Because our interest is in city growth, our analysis focuses specifically on employment as the outcome variable of interest. This is the natural object for our analysis, and one of the few types of data that can be observed at a local level, for many locations, over long time periods.[10] While the contribution of agglomeration economies to employment growth is generated through improved productivity, there is not necessarily a one-to-one mapping between productivity and employment growth. For example, under certain circumstances productivity improvements may reduce employment growth. Thus, our results should not be interpreted as providing a full description of the productivity effects of agglomeration economies.

It is also important to note that this study focuses on dynamic agglomeration economies, i.e., the influence of the current level of economic activity on future growth. This approach is motivated by the endogenous growth literature, and in particular the work of Lucas (1988), who emphasized the important role that localized learning in cities is likely to play in generating sustained economic growth. In some sense our exercise can be thought of as a step towards identifying the patterns that characterize endogenous growth at the urban level. This approach contrasts with work studying static agglomeration effects, where the level of employment or output in one sector influences the level in another sector.

[4] See the handbook chapter by Combes and Gobillon (2015).

[5] Our panel data approach builds on previous work by Henderson (1997) and Dumais et al. (1997). See also Combes (2000) and Dekle (2002). A panel data approach is also used in a recent working paper by Lee (2015) which uses data on U.S. manufacturing industries from 1880 to 1990 to study static agglomeration forces.

[6] Recently, other databases of this type have been developed using data from the U.S. County Business Patterns by Duranton et al. (2014) and from the U.S. Census of Manufacturers by Lee (2015) and others.

[7] This contrasts with modern settings, where the list of confounding factors includes place-based government policies, local land-use regulations such as zoning, environmental policies that vary across locations, local tax incentives, variation in the local burden of national taxation, as well as many other types of regulation. These factors can also affect city growth, making it more difficult to identify and quantify the role of agglomeration forces. To cite some examples, Kline and Moretti (2013) describe the impact of place-based government policies in the U.S. The role of local land use regulations is highlighted by Gyourko et al. (2008). Local environmental policies are studied by Henderson (1996) and Chay and Greenstone (2005), among others. Greenstone and Moretti (2003) describe the impact of local tax incentives, while Albouy (2009) describes how federal tax incentives distort urban growth.

[8] See Desmet and Rappaport (2017). In contrast, Dittmar (2011) finds that Zipf's Law emerged in European cities between 1500 and 1800, well before the beginning of our study period.

[9] See, e.g., Baines (1994) and Long and Ferrie (2004).

[10] Other types of data, such as wages and rents, are more difficult to obtain in a consistent way at the local level over long periods.

While static agglomeration effects are worthy of study, ultimately they cannot provide a theory of sustained urban growth.[11]

This paper analyzes agglomeration patterns across sectors spanning the entire private-sector economy in all of the largest urban centers in England for a period of sixty years. This broad approach allows us to estimate general patterns and to assess their importance for long-run city development. An alternative strand of work on agglomeration economies focuses on overcoming identification issues by comparing outcomes in similar locations, where some locations receive a plausibly exogenous shock to the level of local economic activity (e.g., Greenstone et al., 2010 and Kline and Moretti, 2013). 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 our broader approach, which follows the work of Glaeser et al. (1992), Henderson et al. (1995), and more recently Ellison et al. (2010), as complementary to studies that improve identification by focusing on specific shocks to local economic activity.

The next section presents our theoretical framework while the empirical setting is discussed in Section 3. Section 4 describes the data. In Section 5 we conduct a preliminary analysis that applies existing methodologies to our data. We then introduce our preferred empirical approach in Section 6. Section 7 presents the main results, while Section 8 examines the impact of city size and shows how this can be used to calculate the aggregate strength of the agglomeration forces in our model. Section 9 concludes.

2. Theory

While this paper is primarily empirical, a theoretical model is useful in disciplining the empirical specification. Grounding our analysis in theory can also help us interpret the results while being transparent about potential concerns.

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).[12] 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.

As is standard in urban theories, we assume that goods are freely traded across locations and workers are free to move between cities. To keep things simple, our baseline model omits some additional features, such as savings and capital investment, or intermediate inputs, that one might want to consider. In the Appendix, we explore the impact of adding capital or intermediate goods.[13]

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 $c = \{1, \ldots C\}$ and many industries indexed by $i = \{1, \ldots I\}$. 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,

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

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 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.[14] 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

[11] Some discussion of static vs. dynamic agglomeration forces is provided in Combes and Gobillon (2015). Lee (2015) provides a recent example of a study focusing on static agglomeration forces. He finds that static localized inter-industry spillovers were small and declining in the U.S. across the 20th century. This suggests that static agglomeration forces are unlikely to be behind the growth of cities during this period.

[12] We have also explored models where technological progress is based on R&D effort exerted by firms and the new technologies generated through R&D have spillover benefits for other local industries. Models of this type can generate the same basic estimating equation that we obtain from our learning-by-doing model, but to keep the theory succinct we focus only on the simpler learning-by-doing spillover model here.

[13] The inclusion of these elements does not change the basic estimating equation that we obtain as long as we maintain the assumption of free mobility across locations, though it can change the interpretation of the parameter estimates.

[14] This feature will capture demographic growth and the movement of workers across cities and countries, an important feature of the empirical setting that we consider.

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 and Kovak (2015). 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[15]:

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

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,

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

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.[16] 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 of 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:

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

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

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

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 ($L_{kct} \le 1$), 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 Eq. (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 Eq. (6) into Eq. (5), we obtain our estimation equation:

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

[15] 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.

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

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

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.

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. Note that the inclusion of the ξ_{it} term in Eq. (7) allows for the possibility that some industries were growing much faster nationally than others, an important feature of the empirical setting that we consider.

In the absence of spillovers, and with common technologies across locations, the city size distribution in this model will be determined by the distribution of local resource endowments. Once local technology spillovers are added, city sizes will be determined by a combination of the initial resource endowment and the evolving technology levels. This hybrid of locational fundamentals and increasing returns is consistent with some existing empirical results (e.g., Davis and Weinstein, 2002 and Bleakley and Lin, 2012). Once spillovers are included, the dynamics of the system are complex and depend crucially on the matrix of τ_{ki} parameters.[17] Estimating these parameters is the goal of our empirical exercise.

While our model provides a theoretically-grounded estimation approach, this is not the only potential set of agglomeration forces that can yield an estimation equation that matches the one that we will apply. There are at least two promising alternative theories that may yield similar expressions. One such theory could combine static inter-industry connections, such as pecuniary spillovers through intermediate-goods sales, with changing transport costs. A second alternative combines static agglomeration forces with a friction that results in a slow transition towards a 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. Rather, our empirical results will provide evidence on the pattern of within and cross-industry agglomeration benefits and provide some evidence on the types of inter-industry connections that matter. Further work will be needed to unpack the specific mechanisms through which these inter-industry benefits occur.

3. Empirical setting

The empirical setting used in this paper was chosen because of the rich data available as well as the particularly clean environment it provides for testing models of agglomeration. Relative to modern developed countries, British cities in the early 19th and 20th centuries had few local regulatory constraints on economic growth. For example, the first national zoning laws were not introduced in Britain until 1909, near the very end of our study period.[18] Other regulations, such as environmental controls, were also limited.[19] Of course, the government did have a role to play in the economy during this period. Examples of important national government programs include the Poor Law, which provided support for unemployed workers and the destitute, the Factory Acts, which regulated safety conditions in factories and limited child labor, and tariff policy. Importantly, however, most of these policies applied fairly evenly across the country. At the local level, government regulation was relatively weak and primarily directed towards sanitary improvements (Platt, 1996).

Lee (1984) reports that, in 1881, the middle of our study period, the primary, secondary and tertiary sectors employed 12.5%, 52.6% and 34.7% of British workers, respectively. Thus, in terms of economic structure, among modern economies the setting that we study was most similar to heavily industrialized developing and middle-income countries.[20] As a result, our setting can potentially be used to shed light on such economies, while offering data that are richer and cover a longer period than those available in most modern developing economies. An additional benefit of focusing on a historical setting is that eventually our results can be compared to Britain in the modern period to begin understanding how agglomeration forces evolve as countries develop. However, in this study we end our study period in 1911 for two reasons. First, this is the last census year before the First World War, which brought massive disruption to the British urban system. Second, between 1911 and the first census after the Second World War it is difficult to generate consistent data series.

There are two other features of the empirical setting that should be noted before we move on. First, this setting was characterized by high levels of population mobility and rapid urbanization.[21] Second, this mobility was due in part to the highly developed British transportation system, which connected all of the cities in our database. This system was relatively stable across our study period. Due in part to the stability of this system, as well as the importance of local resources such as coal, existing work suggests that changes in transport costs had little impact on the location of industry in Britain during this period (Crafts and Mulatu, 2006).

4. Data

The main database used in this study was constructed from more than a thousand pages of original British Census of Population summary reports.[22] 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 state their occupation, but the reported occupations correspond more closely to industries than to what we

[17] The dynamics of our model will also depend crucially on city-size congestion forces, which are not fully modeled here. Because the primary goals of this paper are empirical, we leave a full exploration of these dynamics for future work. It is also worth noting that our model has the potential to reproduce some of the patterns of city and city-industry growth documented in Duranton (2007). In particular, under certain configurations of the matrix of spillover parameters our model will feature a churning of industries across cities accompanied by slower changes in relative city size. As in Duranton (2007), any such churning will be driven by cross-industry spillovers.

[18] See Platt (1996, Ch. 6).

[19] See Thorsheim (2006) for details on environmental regulations in Britain during this period.

[20] In China, for example, employment shares of the primary, secondary and tertiary sector in 2012 was 33.6%, 30.3% and 36.1% respectively, according to the CIA's World Fact Book. Other similar examples are Iran, with primary, tertiary and secondary shares of 16.3%, 35.1% and 48.6% respectively, and Malaysia, with shares of 11%, 36% and 53%.

[21] During this period the British population was "highly mobile" in the words of Long and Ferrie (2003), while Baines (1985) shows that population growth in cities was due in large part to the arrival of new migrants, coming both from the English countryside as well as Ireland, Scotland and Wales.

[22] This study uses the most updated version of this database (v2.0). These data and further documentation can be found at http://www.econ.ucla.edu/whanlon/ under Research.

think of as occupations today.[23] A unique feature of this database is that the information is drawn from a full census. Virtually every person in the cities we study provided information on their occupation and all of these answers are reflected in the employment counts in our data.[24]

The database includes 31 cities for which occupation data were reported in each year from 1851 to 1911, containing 28–34% of the English population over the period we study. The geographic extent of these cities changes over time as the cities grow, a feature that we view as desirable for the purposes of our study.[25] The Online Appendix provides a list of the cities included in the database, as well as a map showing the location of these cities in England. In general, our analysis industries cover the majority of the working population of the cities, with most of the remainder employed by the government or in agriculture.

The industries in the database span manufacturing, food processing, services and professionals, retail, transportation, construction, mining, and utilities. Because the occupational categories listed in the census reports varied over time, we combined multiple industries in order to construct consistent industry groupings over the study period. This process generates 26 consistent private sector occupation categories.[26] Of these, 23 can be matched to the connections matrices used in the analysis. Table in Appendix describes the industries included in the database.

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.[27] 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).[28] 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. One drawback of 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 or generate other dynamic benefits.[29] 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.[30] 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.[31] 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.

Both the demographic-based and occupation-based labor force similarity measures are meant to capture the idea that firms can benefit from sharing similar labor pools with other local industries. However, these two measures are meant to reflect two different dimensions along which labor pooling can be constrained. The demographic-based measure reflects the fact that the set of industries available to workers can be constrained by their demographic characteristics, particularly in a historical setting such as the one we consider. The occupation-based measure reflects a different type of constraint, which is more dependent on a worker's education, experience and ability. Note that two industries could use two sets of demographically similar workforces but with completely different occupations, or vice versa, so it is plausible that one channel could matter when the other does not.

5. Preliminary analysis

Before moving on to the main analysis, it is useful to begin by analyzing the data using standard tools from the existing literature. One natural starting point is to apply the agglomeration measure from Ellison and Glaeser (1997) to our data. These results, described in Appendix Tables, show that the agglomeration patterns observed in our data are similar to those documented in modern studies. Specifically, Britain's main manufacturing and export industries, such as Textiles, Metal & Machines, and Shipbuilding, show high levels of geographic agglomeration. Many non-traded services or retail industries, including Merchants, Agents, Etc., Construction, and Shopkeepers, Salesmen, Etc. show low levels of agglomeration. Overall, the median level of industry agglomeration is between 0.02 and 0.026, which is comparable to the levels reported for the modern U.S. economy by Ellison and Glaeser (1997)

[23] 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. In 1921 the Census office renamed what had previously been called "occupation" to be "industry" and then introduced a new set of data reflecting occupation in the modern sense.

[24] This contrasts with data based on census samples, which often covers 5% or 1% of the available data. 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.

[25] 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.

[26] Individual categories in the years were combined into industry groups based on (1) the census' occupation classes, and (2) the name of the occupation. Further details of this procedure are available at http://www.econ.ucla.edu/whanlon/.

[27] 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.

[28] For robustness exercises, we have also collected an input-output table for 1841 constructed by Horrell et al. (1994) with 12 more aggregated industry categories. See Appendix for more details.

[29] Research by Poole (2013) and Balsvik (2011), using data from Brazil and Norway, respectively, has highlighted this channel of knowledge flow.

[30] The importance of the contribution made by industry demographics to agglomeration forces during the period that we study was specifically addressed by Marshall (1890). He gives as an example the benefits that flowed between textiles and the metals and machinery industry due to the fact that the textile industries employed substantial amounts of female and child labor while metal and heavy machinery industry jobs were almost exclusively reserved for adult males.

[31] This is the most detailed breakdown by age and gender available in our data.

and somewhat larger than the levels reported for the modern British economy by Faggio et al. (in press).[32]

Next, we investigate how results obtained using long-difference regressions, in the spirit of Glaeser et al. (1992) and Henderson et al. (1995), compare to existing results. These long-difference regression results, which are presented in the Appendix, are generally similar to the findings reported by Glaeser et al. (1992), which suggest that firms are likely to benefit primarily from spillovers across industries, rather than within industries. Our results contrast with those presented in Henderson et al. (1995), which finds evidence that within-industry effects were more important. As we will see, these basic patterns are largely consistent with the results obtained using our preferred estimation strategy, which we introduce next.

6. Empirical approach

The starting point for our analysis is based on Eq. (7), which represents the growth rate of a city-industry as a function of within and cross-industry agglomeration effects as well as time-varying city-specific and national industry-specific factors. Rewriting this as a regression equation we have,

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

where $\triangle$ is the first difference operator, $\tilde{\tau}_{ii}$ and $\tilde{\tau}_{ki}$ include $1/(1-\alpha)$, θ_{ct} is a full set of city-year effects and χ_{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.[33]

One issue with Eq. (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, we follow recent literature in this area, particularly Ellison et al. (2010), by parameterizing the connections between industries using the available input-output and labor force similarity matrices[34]:

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

Substituting this into Eq. (8) we obtain:

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

Instead of a large number of parameters measuring spillovers across industries, Eq. (9) now contains only four parameters multiplying four (weighted) summations of log employment. Summary statistics for the cross-industry spillover terms are available in Appendix Table while the correlations between the cross-industry terms are available in Appendix Table 7.

There is a clear parallel between the specification in Eq. (9) and the empirical approach used in the convergence literature (Barro and 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 Eq. (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 and Bond (1991), Blundell and Bond (1998), and others, yet these procedures can also generate biased results, as shown by Hauk and Wacziarg (2009). In a recent review, Barro (2015) uses data covering 40-plus years and argues (p. 927) 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 effects.

There are two issues to address at this point. First, there could be 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.[35] Under the assumption that the measurement error in any given city-industry pair is *iid* across cities and time, our instrument is $L^{Inst}_{ict} = L_{ict-1}\times g_{i-ct}$, 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, as in Bartik (1991).

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 omitted 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 of industry i in all cities.[36] 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

[32] Using industry data for 459 manufacturing industries at the four-digit level and 50 states, Ellison and Glaeser (1997) calculate a mean agglomeration index of 0.051 and a median of 0.026. For Britain, Faggio et al. (in press) 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 to his results.

[33] We purposely omitted the last term of Eq. (7), $\Delta\ln(\bar{w}_t)$, 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.

[34] Adding an error term to this equation would imply heteroskedastic standard errors, a possibility that is accommodated by our econometric approach, but would not otherwise alter the basic estimation approach suggested by the theory.

[35] This approach is somewhat similar to the approach introduced by Bartik (1991) and has been suggested by Combes et al. (2011).

[36] 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.

previous work in this area. Now, for the cross-industry case, the summation terms in Eq. (9) such as $\Sigma_{k \neq i} IOin_{ki} \ln(L_{kct})$ are instrumented with $\sum_{k \neq i} IOin_{ki} \ln(L^{Inst}_{kct})$, where L^{Inst}_{kct} is as described above.

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 Appendix 10.5.8 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 for 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.

In order to conduct underidentification and weak-instrument tests while clustering standard errors in multiple dimensions, we have produced new statistical code implementing the approach from Kleibergen and Paap (2006). This was necessary because existing statistical packages are unable to calculate these tests correctly when clustering by more than two dimensions. The procedure used to generate these test statistics is described in Appendix 10.4.2.

Finally, we may be concerned about how well our estimation procedure performs in a data set of the size available in this study. To assess this, we conduct a series of Monte Carlo simulations in which we construct 500 new data sets with a size and error structure based on the true data, but with known spillover parameter values. We then apply our estimation procedure to these simulated data in order to obtain a distribution of placebo coefficient estimates, which can then be compared to the estimates obtained using the true data. These simulations, which are described in more detail in Appendix 10.4.1, suggest that our estimation procedure performs well in datasets with a size and error structure similar to the true data.

To simplify the exposition, we will hereafter collectively refer to the set of regressors $\ln(L_{ict})$ for $i = 1 \ldots I$ as the *within* variables. Similarly, with a small abuse of notation the term $\Sigma_{k \neq i} IOin_{ki} \ln(L_{kct})$ 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.

7. Main results

Our main regression results are based on the specification described in Eq. (9). The 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. Our main results, in Table 1, consider all four channels simultaneously, while Appendix 13 presents regressions including one channel at a time. In Columns 1–3 of Table 1 we estimate a single coefficient reflecting within-industry spillovers, while Columns 4–6 present results in which we estimate industry-specific within-industry effects. These heterogeneous within-industry coefficients, which are not reported in Table 1, will be explored later. Columns 1 and 4 presents OLS results. In Column 2 and 5 we instrument the within-industry terms.[37] In Column 3 and 6 we use instruments for both the within-industry and cross-industry terms.

These results show strong positive effects operating 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. There is little evidence of positive effects operating through local buyers. The results also provide some evidence that the presence of other industries using similar occupations can have dynamic benefits. Also, the results in Columns 1–3 suggest that own-industry employment is negatively related to subsequent growth. In addition, comparing the results in Columns 1–3 with those in Columns 4–6 shows that allowing for heterogeneity in the within-industry effects does appear to be important. Finally, 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. Moreover, the test statistics presented at the bottom of Table 1 suggests that our instruments are sufficiently strong.

Based on the results from Column 6 of Table 1, our preferred specification, a one standard deviation increase in the presence of local suppliers increases city-industry growth by 14.4%. Turning to the occupational similarity channel, a one standard deviation increase in the presence of occupationally-similar local industries leads to a 14.8% increase in city industry growth when using the results from Column 6 of Table 1. Thus, both of these channels appear to exert a substantial positive effect on city-industry growth.

Our analysis can also help us understand the strength of within-industry spillovers, reflected in the $\ln(L_{ict})$ term in Eq. (8).[38] When analyzing these results, it is important to keep in mind that they reflect the *net* effect of within-industry agglomeration 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. 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 relevant for understanding the contribution of within-industry agglomeration forces to city growth. Thus, our results suggest that within-industry agglomeration effects generally do not make a positive contribution to city employment growth.

We have already seen, in Table 1 Columns 1–3, that the average within-industry effect across all industries is negative, but there is also evidence that allowing heterogeneity in these effects is important. We explore these heterogeneous within-industry effects in Fig. 1, which presents coefficients and 95% confidence intervals for industry-specific within-industry spillover coefficients from regressions corresponding to Column 6 of Table 1. In only one industry, shipbuilding, do we observe any evidence of positive within-industry effects. This industry was characterized by increasing returns and strong patterns of geographic concentration. All other industries exhibit slower growth in locations where initial industry

[37] We do not report first-stage 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 and Paap (2006) as well as the test static for weak instruments test based on the Kleibergen–Paap Wald statistic. It is clear from these statistics that weak instruments are not a substantial concern in these specifications.

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

Table 1
Main results for cross-industry connections.

	(1)	(2)	(3)	(4)	(5)	(6)
Log employment in local supplier industries	0.0421	0.0450	0.0388	0.1601***	0.1401***	0.1457***
	(0.0283)	(0.0304)	(0.0283)	(0.0464)	(0.0473)	(0.0472)
Log employment in local buyer industries	0.0334	0.0020	−0.0062	−0.0481	−0.0888	−0.1145
	(0.0301)	(0.0319)	(0.0300)	(0.0693)	(0.0700)	(0.0725)
Log employment in local industries using demographically similar workers	0.0036	0.0036	−0.0099	0.0445	0.1145*	0.0691
	(0.0229)	(0.0241)	(0.0240)	(0.0693)	(0.0616)	(0.0605)
Log employment in local industries using similar occupations	0.0413	0.0309	0.0270	0.1580**	0.1698**	0.1503*
	(0.0363)	(0.0341)	(0.0345)	(0.0777)	(0.0845)	(0.0854)
Log own-industry employment	−0.0871***	−0.0514*	−0.0490*			
	(0.0321)	(0.0279)	(0.0285)			
Observations	4253	3544	3539	4253	3539	3539
Estimation	Ols	2SLS	2SLS	Ols	2sls	2sls
Instrumented	None	Wtn	Wtn-btn	None	Wtn	Wtn-btn
Within terms	Homog	Homog	Homog	Heter	Heter	Heter
KP under		24.86	25.45		22.09	24.52
KP weak		4677.9	858.6		52.36	35.68

Multi-level clustered standard errors by city-industry, city-year, and industry-year in parenthesis. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All cross-industry and within-industry connection variables have been standardized for comparability. Heterogeneous regressors *within* are included in Columns 4–6 but not displayed. City-time and industry-time 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 and Paap (2006). “KP weak id.” denotes the test statistic for a weak instruments test based on the Kleibergen–Paap Wald statistic.

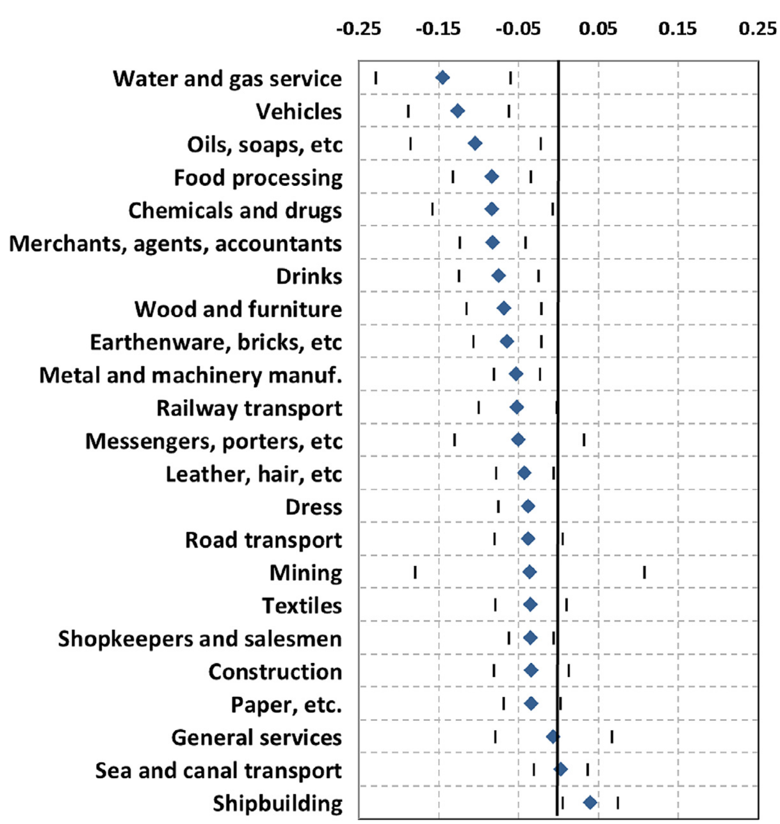

Fig. 1. Strength of within-industry effects by industry. Results correspond to the regression described in Column 6 of Table 1. This figure displays coefficient estimates and 95% confidence intervals based on standard errors clustered by city-industry, city-year, and industry-year. The regression includes a full set of city-year and industry-year effects as well as *between* terms. Both the within and between terms are instrumented using one-decade lags.

employment was large, after controlling for other forces. Within-industry agglomeration benefits, it would appear, are more the exception than the rule.

The results presented so far describe coefficients generated using all industries, where each industry is given equal weight. We have also calculated weighted regressions, where the set of observations for each city-industry is weighted based on employment in that city-industry at the beginning of each period. These results, available in Appendix 10.5.4, show qualitatively similar results to those shown above for the importance of local suppliers, with only slightly smaller estimated coefficients. This provides confidence that our main findings are not being driven by small cities or industries. The weighted results also show stronger evidence of a negative effect through the presence of local buyers, but this finding appears to be quite sensitive to the set of industries included in the analysis. The agglomeration benefits from occupationally similar industries disappear when weighting by city-industry size, suggesting that labor market pooling benefits may be larger for small industries or in small cities.

We have also investigated the robustness of our results to dropping individual industries or individual cities from the analysis database (see Appendix 10.5.2). These exercises show that the significance of the estimates on the importance of local suppliers and occupationally-similar industries are robust to dropping any city or any industry. However, the estimated coefficient and confidence levels for the impact of local buyer industries is sensitive to the exclusion of particular industries. Specifically, when shipbuilding is excluded we observe that the coefficient on local buyer industries becomes positive but not statistically significant.[39] This suggests that in general the presence of local buyers may have a mild positive effect on industry growth. In addition, we have explored the sensitivity of our results to using alternative concave functional relationships such as a square root or fifth root in place of the log specification used in our main results. These results, available upon request, show that our findings are not sensitive to these alternatives. Also, in Appendix 10.5.5 we provide results where, as the outcome variable, we look at city-industry employment growth over two or three-decade differences. These deliver results that are quite similar to those shown in Table 1.

We have also explored the robustness of our results to the use of alternative connections matrices. In particular, in Appendix 10.5.7 we present results obtained while using the less detailed input-output table constructed by Horrell et al. (1994), which covers 12 more aggregated industry categories in 1841. When using this alternative matrix we continue to find evidence of positive effects generated by the presence of local suppliers. These results also suggest that local buyers may generate positive benefits, but as before this result appears to be sensitive to the set of industries included in the analysis.

It is also possible to split our data in order to look at how agglomeration forced differ across time. In Appendix 10.5.6 we present results splitting the data in 1881. In these results we observe similar patterns in both the early and late years, though the strength of the impact of local supplier industries and other occupationally similar local industries increases in the later period. That may indicate that these agglomeration channels strengthened as the country developed, or they may be related to the introduction of many new Second Industrial Revolution technologies, in areas such as chemicals and electronics, during the 1881–1911 period.

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 coefficients 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 10.5.3, 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 23 estimated industry coefficients we cannot draw strong conclusions from these relationships. However, our results do suggest several interesting patterns. The only clear result is that industries that benefit from or produce spillovers for other industries using occupationally-similar labor pools tend to have a higher labor cost to sales ratio, a finding that seems very reasonable. 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 and it fits well with previous work highlighting the importance of inter-industry connections for smaller firms (e.g., Chinitz (1961)).

In Appendix 10.5.3 we look at how the estimated industry-specific within-industry coefficients are related to industry characteristics. 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 spillovers.

While the analysis described above focuses on spillovers occurring within cities, we have also explored the possibility that there may be important cross-city effects. To explore cross-city effects, we have run additional regressions including variables measuring market size as well as cross-industry spillovers occurring across cities. Our results, reported in Appendix 10.5.8, suggest that cross-city effects are much weaker than within-city forces. This makes sense given that we think that the shape of cities reflects the rapidly decaying strength of local agglomeration forces. We also find that accounting for cross-city effects has little impact on our estimates of the strength of within-city agglomeration forces.

8. Strength of the agglomeration forces

In this section we examine the relationship between city size and city-industry growth and show how our city-year effects can be used to construct a summary measure of the aggregate strength of the many cross-industry agglomeration forces present in our model. 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, we have been largely agnostic about the form of the congestion forces, which will be captured primarily by the city-time effects. Thus, examining these estimated city-time coefficients offers an opportunity for assessing the *net* impact of dynamic congestion or agglomeration force related to overall city size.[40] Also, the difference between these estimated city-time effects and city growth rates must be due to the impact of the agglomeration forces in the estimation equation. As a result, comparing the estimated city-time effects to actual city growth rates allows us to quantify the combined strength of the many cross-industry agglomeration forces captured by our measures.

To gain some intuition into this comparative exercise, consider the graphs in Fig. 2. The black diamond symbols in each graph describe, for each decade starting in 1861, the relationship between

[39] Shipbuilding stands out relative to the other industries because it is particularly reliant on local geography.

[40] These results will reflect only the net impact of city size, including both congestion and agglomeration forces.

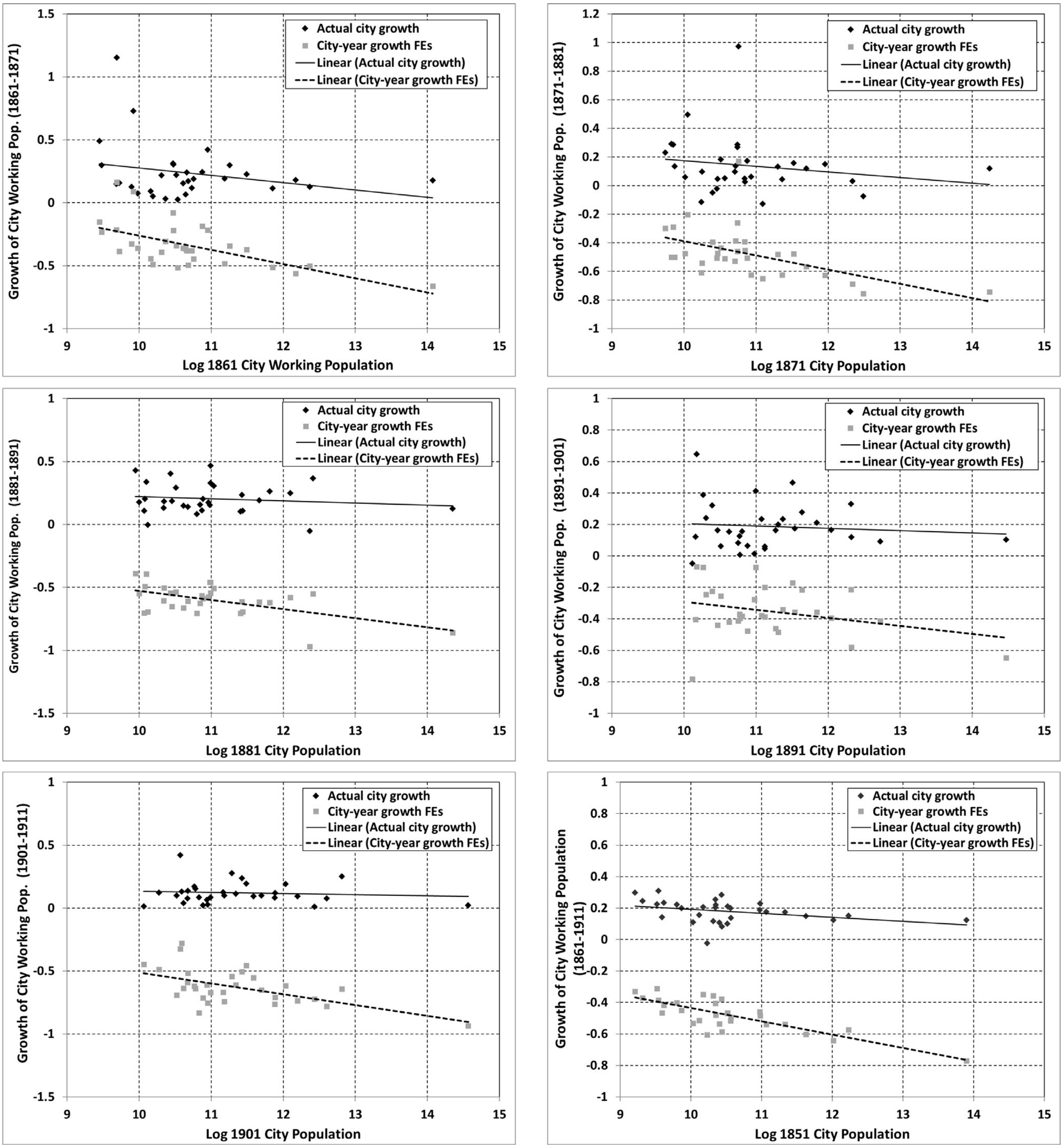

Fig. 2. City size and city growth. Solid lines: Fitted lines comparing actual city growth over a decade to the log of city size at the beginning of the decade. Dotted lines: Fitted lines comparing estimated coefficients from city-time effects for each decade to the log of city size at the beginning of the decade. Black diamonds: Plot the actual city growth over a decade against the log of city population at the beginning of the decade. Gray squares: Plot the estimated city-time coefficients over the same decade (the θ_{ct} terms estimated using Eq. (9)) 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.

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 black diamonds in Fig. 2, to the relationship between these variables obtained while controlling for within and cross-industry agglomeration forces. This can be done using the estimated city-time effects represented by θ_{ct} in Eq. (9). The gray squares in Fig. 2 describe the relationship between the estimated city-year coefficients for each decade, $\hat{\theta}_{ct}$, and the log of city population at the beginning of each decade. In essence, these are showing us the relationship between city size and city growth after controlling for national industry growth trends and the agglomeration forces included in our model.

Table 2
Aggregate strength of the agglomeration forces.

	Results based on $\theta_c t$		Results for actual city growth		Aggregate strength of agglomeration force
	Estimated city-size coefficient	Implied divergence Beta	Estimated city-size coefficient	Implied divergence Beta	(implied divergence rate per decade)
Results based on un-weighted regressions					
1861–1871	−0.076	7.86%	−0.056	5.71%	2.15%
1871–1881	−0.062	6.38%	−0.042	4.26%	2.12%
1881–1891	−0.035	3.60%	−0.015	1.53%	2.07%
1891–1901	−0.014	1.43%	0.006	−0.61%	2.04%
1901–1911	−0.046	4.70%	−0.023	2.37%	2.33%
Results based on regressions weighted by city-industry size in 1851					
	Results based on $\theta_c t$		Results for actual city growth		Aggregate strength of agglomeration force
	Estimated city-size coefficient	Implied divergence Beta	Estimated city-size coefficient	Implied divergence Beta	(implied divergence rate per decade)
1861–1871	−0.066	6.86%	−0.051	5.23%	1.63%
1871–1881	−0.052	5.29%	−0.036	3.61%	1.67%
1881–1891	−0.037	3.79%	−0.021	2.13%	1.66%
1891–1901	−0.026	2.64%	−0.010	1.00%	1.64%
1901–1911	−0.018	1.86%	−0.002	0.20%	1.65%

Column 1 presents the a_1 coefficients from estimating Eq. (10) for each decade (cross-sectional regressions). Column 2 presents the decadal convergence rates implied by these coefficients. Column 3 presents the b_1 coefficients from estimating Eq. (11) and Column 4 presents the decadal divergence rates implied by these coefficients. Column 5 gives the aggregate strength of the divergence force due to the agglomeration economies, which is equal to the difference between the decadal divergence coefficients in Columns 2 and 4. Results in the top panel are unweighted, while results in the bottom panel are from regressions in which each city-industry observation is weighted by the employment in that city-industry at the beginning of the period.

We can draw three lessons from these graphs. First, in all years the fitted lines based on the $\hat{\theta}_{ct}$ terms slope downward more steeply than 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 dynamic 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. Third, the patterns described in Fig. 2 appear to be close to linear in logs, suggesting that these forces do not differ dramatically across different city sizes.

The strength of these effects can be quantified in terms of the implied convergence rate following the approach of Barro and Sala-i Martin (1992). We run,

$$\hat{\theta}_{ct} = a_0 + a_1 \ln(L_{ct}) + \epsilon_{ct} \tag{10}$$

$$\tilde{\theta}_{ct} = b_0 + b_1 \ln(L_{ct}) + \epsilon_{ct} \tag{11}$$

where $\hat{\theta}_{ct}$ is the estimated city-time effect for the decade from t to $t+1$ from a regression based on Eq. (9) (but omitting the within terms, which clearly represent a convergence rather than a divergence force), L_{ct} is the working population of the city in year t, and $\tilde{\theta}_{ct}$ is the industry-demeaned growth rate of city c from t to $t+1$.[41] These regressions are run separately for each decade from 1861 to 1911, either with or without weighting each observation by initial city-industry employment, and using lagged values as instruments as in the main results. Convergence rates are then calculated using the estimated a_1 and b_1 coefficients. A comparison of the a_1 and b_1 coefficients describes, at the city level, the impact of accounting for cross-industry spillovers.

Results based on unweighted regressions are presented in the top panel of Table 2. The two left-hand columns describe the results from Eq. (10) and the annualized city-size divergence rate implied by these estimates. The next two columns describe similar results based on Eq. 11. 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 2.0–2.3% per decade. In the bottom panel of Table 2 we calculate similar results except that the $\hat{\theta}_{ct}$ terms are obtained using regressions in which each observation is weighted based on the employment in the city-industry at the beginning of each period. These results suggest a slightly weaker agglomeration force, equal to an implied divergence rate of 1.6–1.7% per decade.

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

$$\triangle \ln(L_{ict+1}) = \tilde{\tau}_{ii} \ln(L_{ict}) + \theta_{ct}^{WITHIN} + \chi_{it} + e_{ict} \,. \tag{12}$$

which is just Eq. (9) with the cross-industry terms omitted. Next, we use the estimated values of θ_{ct}^{WITHIN} to estimate,

$$\hat{\theta}_{ct}^{WITHIN} = d_0 + d_1 \ln(L_{ct}) + \epsilon_{ct}. \tag{13}$$

We then calculate the convergence force associated with the within-industry terms using the same approach that we used previously, i.e. we compare the d_1 coefficients with the slopes estimated using Eq. (11). Table 3 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 are likely to vary with initial city-industry employment.

One caveat to keep in mind when assessing these results is that there are likely to be agglomeration forces not captured by our estimation, which would lead us to understate the strength of the agglomeration forces. Also, some congestion forces may also be

[41] That is, $\tilde{\theta}_{ct}$ is the estimated value of θ_{ct} obtained from the regression $\triangle \ln(L_{ict+1}) = \theta_{ct} + \chi_{it} + e_{ict}$.

Table 3
Aggregate strength of convergence forces due to the within-industry effects.

Results based on un-weighted regressions

	Results based on θ_{ct}^{WITHIN}		Results for actual city growth		Aggregate strength of agglomeration force
	Estimated city-size coefficient	Implied divergence Beta	Estimated city-size coefficient	Implied divergence Beta	(implied divergence rate per decade)
1861–1871	-0.004	0.43%	−0.056	5.71%	−5.28%
1871–1881	0.009	−0.87%	−0.042	4.26%	−5.13%
1881–1891	0.034	−3.38%	−0.015	1.53%	−4.91%
1891–1901	0.056	−5.41%	0.006	−0.61%	−4.80%
1901–1911	0.025	−2.48%	−0.023	2.37%	−4.85%

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

	Results based on θ_{ct}^{WITHIN}		Results for actual city growth		Aggregate strength of agglomeration force
	Estimated city-size coefficient	Implied divergence Beta	Estimated city-size coefficient	Implied divergence Beta	(implied divergence rate per decade)
1861–1871	−0.048	4.91%	−0.051	5.23%	−0.33%
1871–1881	−0.033	3.38%	−0.036	3.61%	−0.24%
1881–1891	−0.019	1.92%	−0.021	2.13%	−0.21%
1891–1901	−0.008	0.81%	−0.010	1.00%	−0.20%
1901–1911	0.000	-0.01%	−0.002	0.20%	−0.21%

Column 1 presents the d_1 coefficients from estimating Eq. (13) for each decade (cross-sectional regressions). Column 2 presents the decadal divergence rates implied by these coefficients. Column 3 presents the b_1 coefficients from estimating Eq. (11) and Column 4 presents the decadal divergence rates implied by these coefficients. Column 5 gives the aggregate strength of the divergence force due to the agglomeration economies, which is equal to the difference between the decadal convergence coefficients. The negative values in Column 5 indicate that within-industry effects are, on net, a source of convergence across cities. Results in the top panel are unweighted, while results in the bottom panel are from regressions in which each city-industry observation is weighted by the employment in that city-industry at the beginning of the period.

captured by our cross-industry terms. Similarly, there may be some agglomeration forces captured by the within-industry terms, which will also not be reflected in our results. Thus, the strength of the cross-industry agglomeration force measured here is likely to be a lower bound on the true values.

9. 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 particular empirical setting that 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. This suggests that local clusters of firms working in the same industry, which have attracted substantial attention, are unlikely to deliver dynamic benefits. 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. An 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 1.6–2.3% per decade.

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 another promising avenue for future work.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jue.2017.01.001

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