Agglomeration Economies: The Heterogeneous Contribution of Human Capital and Value Chains

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Agglomeration economies: the heterogeneous contribution of human capital and value chains

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Abstract

We document the heterogeneity across sectors in the impact labor and input-output links have on industry agglomeration. Exploiting the available degrees of freedom in coagglomeration patterns, we estimate the industry-specific benefits of sharing labor needs and supply links with local firms. On aggregate, coagglomeration patterns of services are at least as strongly driven by input-output linkages as those of manufacturing, whereas labor linkages are much more potent drivers of coagglomeration in services than in manufacturing. Moreover, the degree to which labor and input-output linkages are reflected in an industry's coagglomeration patterns is relevant for predicting patterns of city-industry employment growth.

JEL classifications: J24, O14, R11

Keywords: Coagglomeration, Marshallian externalities, labor pooling, value chains, manufacturing, services, regional diversification

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1 Introduction

In spite of congestion, elevated factor costs and the risk that trade secrets leak to competitors, firms of the same industry frequently locate close to each other (Ellison and Glaeser, 1999; Rosenthal and Strange, 2001). The resulting agglomerations of firms in the same industry are often attributed to the presence of three different types of externalities, namely the sharing of inputs, labor and knowledge. However, there are good reasons to believe that different industries will benefit to different degrees from agglomeration. Yet, the differential impact of agglomeration externalities for individual sectors of the economy is still poorly understood. In this paper, we aim to assess the relative importance of two major drivers of agglomeration across 120 different industries: the benefits of labor market pooling and close proximity to value chain partners. In doing so, we also shed light on what drives agglomeration in services, which, in spite of being the main employers in modern urban economies, are still relatively understudied.

Marshall (1890) ascribed "the advantages which people following the same skilled trade get from near neighborhood to one another" to three different types of agglomeration externalities: the benefits of a large pool of skilled labor, easy access to local customers or suppliers and local knowledge spillovers.[1] However, in spite of their early recognition and ample subsequent research, the relative importance of each of these Marshallian externalities has fueled debate for over a century. A major obstacle, termed "Marshallian equivalence" by (Duranton and Puga, 2004), is the fact that all three Marshallian agglomeration theories yield the same prediction for the spatial distribution of an industry: economic establishments engaged in similar activities create benefits for one another that provide a rationale for these establishments to agglomerate. This confluence of agglomeration benefits makes it hard to determine which of them carries most weight as an explanation for the observed tendency of industries to concentrate in space.

In a major stride forward Ellison, Glaeser and Kerr (2010), henceforth EGK, studied, not the agglomeration of *individual* industries, but the coagglomeration of *pairs* of industries. The rationale for this is that industries that are similar along some dimensions, may differ along others. For instance, whereas some industries will benefit from being colocated because they employ similar labor, other industries may colocate because they maintain input-output or technological linkages. By analyzing the relationship between locational similarity (coagglomeration) and similarity based on individual Marshallian channels for industry pairs, EGK show that all three Marshallian externalities play a significant role. On average, however, the most important explanation for why industries coagglomerate is input-output linkages, closely followed by the sharing of labor. The weakest determinant of coagglomeration in EGK is the potential for knowledge spillovers between two industries.

[1] Whereas theoretical models tend to divide agglomeration externalities into benefits of sharing, matching and learning in local economies Duranton and Puga (2004), most of the empirical literature on the topic categorizes Marshallian externalities as economies in transportation, coordination or communication when acquiring one of three factors: labor, (intermediate) capital goods and knowledge.

However, such averages conceal marked differences across industries. For instance, whereas making musical instruments requires years of on-the-job training of highly specialized workers, food-processing often employs workers through temporary work agencies on short-term contracts, without much regard for skills. Similarly, whereas car manufacturers often closely collaborate with their local suppliers (Morgan and Cooke, 1998), the principal inputs for steel mills, coal and iron ore, are acquired on anonymous exchanges with little need for interaction with suppliers. And finally, although knowledge spillovers may be important drivers behind the clustering of biotechnology firms (Zucker et al., 1994), they are less important in industries where technology progresses less rapidly. Meta-studies reviewing the empirical literature on agglomeration externalities since the foundational papers by Glaeser et al. (1992) and Henderson et al. (1995) confirm the existence of considerable variation in empirical findings (Beaudry and Schiffauerova, 2009; Groot et al., 2015). We expect these differences to be driven in part by variations across industries in how much they benefit from different types of Marshallian externalities.[2]

In this paper we build on the work of EGK to explore whether the heterogeneity in agglomeration benefits is expressed in the coagglomeration patterns of pairs of industries. While staying close to the EGK framework, we deviate from it in two important respects. First, we do not control for natural advantages, and second, we focus on externalities that arise from labor market pooling and local input-output linkages, but ignore technological linkages. See Section 2.3 for a discussion of these choices.

The paper is set up as follows. We first replicate key parts of the original work by EGK, which was based on US manufacturing industries in the late 1980s and 1990s, using similar data for the 2000s. Mimicking EGK, we do so using both Ordinary Least Squares (OLS) estimation and Instrumental Variables (IV) based strategies that instrument labor and input-output linkages among US industries by analogous measures constructed from data on the Mexican economy. As a second step, we extend the analysis to include other industries, particularly in the services sector, while still excluding primary sector industries and industries that purely cater to the needs of the local population (such as retail activities and hospitals). In a third step, we relax the assumption that agglomeration effects are homogeneous across industries fully and estimate the sensitivity of coagglomeration patterns to a given agglomeration externality type for each industry separately.

In a final section, we explore whether the estimated differences in coagglomeration forces can help predict local industry growth patterns. The empirical exercise in this section is related to work by Dauth (2010), who studies how different agglomeration channels affect the growth of local industries, the literature in economic geography on clusters (Porter, 2003; Delgado et al., 2010) and an emerging literature on related diversification (Neffke et al., 2011; Hausmann et al., 2014). Although all these

[2] The Marshallian externalities reported in the before-mentioned meta-studies vary from significantly negative to significantly positive. The authors of these meta-studies attribute these divergent findings to a variety of factors, such as the geographical area studied and methodological choices. Beaudry and Schiffauerova (2009) find that sectoral differences matter as well, although their study does not identify these as the main reason for the observed differences.

strands of research acknowledge the relevance of different types of inter-industry linkages, little is known about their *relative* importance in the diversification and growth of local economies.

Confirming the results of EGK, we find that labor linkages and input-output linkages are more or less equally important explanations for coagglomeration. This result holds not only when we replicate their analysis for the manufacturing sector, but also when we extend it to include other sectors, notably services. However, there are good reasons to expect coagglomeration tendencies in services to be different from those in manufacturing. First of all, unlike manufactured goods, services are often hard to trade over large distances. Consequently, services industries will need to colocate with their customers. Second, services tend to be labor intensive and, moreover, the quality of services often depends crucially on the quality of face-to-face interactions between a firm's employees and its customers (see for instance Kolko 1999 on the importance of agglomeration in services). Both factors should augment the importance of access to adequate human capital. Taken together, these considerations suggest that value chain and labor market pooling links should be particularly important for coagglomeration patterns in services. This conjecture is confirmed when we consider manufacturing and services separately. OLS effects of input-output linkages on coagglomeration are at least as large in services as in manufacturing and the impact of labor externalities on coagglomeration patterns of services is stronger than on those of manufacturing industries. When we allow full heterogeneity in impacts across industries, we observe an even wider variation in effects. For some manufacturing industries, coagglomeration with other industries can neither be attributed to labor nor to input-output linkages. Typical examples are industries in furniture and food production. In other manufacturing industries, such as machinery industries, coagglomeration patterns seem to be driven entirely by input-output linkages. Coagglomeration rationales in services are even more heterogenous. Some industries, like those in arts and culture cluster along both externality channels. In contrast, for media and knowledge intensive business services, the possibility to pool labor dominates coagglomeration, whereas the main driver of coagglomeration patterns in machinery repair services seems to be a desire to locate close to value-chain partners.

Finally, we propose that the estimated effect-heterogeneity can help gauge an industry's sensitivity to the corresponding type of agglomeration benefits. For example, if a firm is active in an industry that displays a strong dependence on specific labor and skills, then locating close to many other firms sharing its labor needs will be highly beneficial. Conversely, choosing to locate near other firms with similar value chain requirements will have less of an impact. We show this by predicting local industry growth rates from the amount of local employment in industries that are connected by either value chains or labor pooling linkages. Next, we interact these indicators of related local employment with the sensitivity to labor pooling and value chains industries exhibit in their coagglomeration patterns. Our estimates show that the sensitivity to input-output links determines how strongly a local industry's growth rates are affected by a strong local presence of industries to which it is linked in the value chain. Similar, though somewhat less robust, effects are observed for labor market linkages.

Our main contribution is to highlight the variation of agglomeration forces across industries within a unified analysis. Although the heterogeneity in agglomeration effects is widely acknowledged (Rosenthal and Strange, 2004; Beaudry and Schiffauerova, 2009; Groot et al., 2015; Rigby and Brown, 2015) ours is the first paper, to our knowledge, to exploit coagglomeration to measure industry heterogeneity. We find that coagglomeration of services is strongly driven by labor market pooling dynamics and, in some of our specifications, also by value chain linkages. Given services' importance as a driver of urban growth, and against a background of secular decline in manufacturing, these results underscore the importance of cities for the development of a strong service economy. The paper also contributes to the growing literature of regional diversification (Delgado et al., 2010; Neffke et al., 2011; Hausmann et al., 2014) by introducing industrial heterogeneity and asymmetry in the growth and diversification process.

2 Methodology

2.1 Data

Our main datasets describe employment by region-industry pair in the US and Mexico. Geographical employment patterns in the US are derived from the County Business Patterns (CBP) for the years 2003 and 2008.[3] . Employment data for Mexico are taken from the economic censuses in 2003 and 2008. The analysis is carried out at three different levels of geographical aggregation: US counties (of which there are 3,190), cities (939 metropolitan areas) and states (51). In Mexico our geographical units are 2,455 municipalities, 58 cities (metropolitan areas) and 32 states. We will focus the discussion on the results for metropolitan areas (labelled 'cities' hereafter) as the most appropriate spatial unit for defining labor markets and economically integrated regions. For the main results we also report the outcome at county and state level as additional supporting evidence.

Unlike EGK, whose industries follow the Standard Industrial Classification (SIC87), in our paper, industries are classified according to the North American Industry Classification System (NAICS). Unfortunately, although the Mexican classification systems are also based on the NAICS, they are not fully harmonized with those in the US. Starting from 317 4-digit US NAICS codes, we, therefore, aggregate industries where necessary and create a new composite industry classification consisting of 215 distinct industries. After dropping industries for which we lack data to construct all covariates used in this paper, there are 184 industries left. We restrict our sample further by dropping industries for which their spatial distribution is strongly driven by the distribution of population. Examples are retail, auto repair, construction and elementary schools. Note that we do not exclude extractive activities such as mining. Although these activities are obviously restricted in their location choice, it is still informative to see which other industries choose to locate in their vicinity. Following this logic

[3] CBP has different degrees of censoring depending on the geographical level of the data. To attribute a value of employment to a class we follow Holmes and Stevens (2004) For more details, we refer to Appendix D.

we arrive at a list of 120 industries.[4] As a robustness check, we repeat the main analysis using the full sample of 184 industries. The outcomes, which are reported in Appendix A, are in line with those of the restricted sample.

2.2 Dependent variable: coagglomeration

Our main object of interest is the degree to which industries coagglomerate. That is, to what extent do we observe two industries employing workers in the same regions? To quantify the tendency of industry i to coagglomerate with industry j, EGK propose the following measure:[5]

$$EG_{ij} = \frac{\sum_{r=1}^{R} (s_{ir} - x_r)(s_{jr} - x_r)}{1 - \sum_{r=1}^{R} x_r^2}. \tag{1}$$

where s_{ir} is the employment share of industry i in region r, while x_r is the mean of these shares in region r across all industries. Ellison and Glaeser (1999) motivate this index as a measure of the likelihood that establishments in two industries generate spillovers for one another via a model of locational choice. The index has the advantage that it should not be affected by the size distribution of establishments in an industry, nor by the granularity of regional units. Following this logic, we calculate EG indices for all pairs of industries in the US. Table 1 shows the top-10 industry pairs in terms of their coagglomeration.

The EG index is similar in spirit to the measure used by Porter (2003), who quantifies the coagglomeration of two industries as the correlation of the industries' locational employment vectors:

$$LC_{ij} = corr(s_{ir}, s_{jr}), \tag{2}$$

Hausmann et al. (2014) show that LC_{ij} can be derived from a Ricardian trade model as an estimate of the similarity in industries' technology requirements. In the interests of brevity, we focus our discussion on the analysis that uses the EG index. Results using the LC index are reported in Appendix C, unless they lead to qualitatively different conclusions, in which case we discuss them in the main text.

2.3 Independent variables

In our methodology, we stay close to EGK. The main exception, however, is that we neither include natural advantages nor technological linkages in our analysis of coagglomeration. Instead, we limit our analysis to input-output and labor links. The reason for excluding natural advantages is that most of

[4] See Appendix B for a list of included and excluded industries.

[5] This measure is equivalent to the coagglomeration index in Ellison and Glaeser (1999) for the coagglomeration of pairs of industries.

Table 1: Top-10 industry pairs by coagglomeration (Ellison-Glaeser index)

Top-10 co-location (EG index)		
industry i	industry j	value
Cut and Sew Apparel Manufacturing	Agents and Managers	0.0846
Sound Recording Industries	Agents and Managers	0.0796
Independent Artists	Cut and Sew Apparel Manufacturing	0.0754
Independent Artists	Agents and Managers	0.0707
Sound Recording Industries	Cut and Sew Apparel Manufacturing	0.0706
Sound Recording Industries	Independent Artists	0.0569
Cut and Sew Apparel Manufacturing	Accounting Services	0.0463
Agents and Managers	Accounting Services	0.0435
Independent Artists	Accounting Services	0.0414
Support Activities for Mining	Oil and Gas Extraction	0.0376

Here we show the top-10 industry pairs using the coagglomeration metric proposed by Ellison and Glaeser (1999) (see equation (1)) using city-industry employment data for the US (County Business Patterns, 2003). The industry classification is based on NAICS 4-digit industries, and includes 120 distinct industry codes containing both services and manufacturing.

what EGK classify as natural advantages are either better thought of in terms of input-output relations or labor market pooling effects. For instance, EGK include cheap access to inputs like electricity, coal and timber, among natural advantages. However, these inputs are typically acquired from extractive industries. In that sense, they are simply part of a value chain. By analyzing coagglomeration among a wider set of industries that includes a number of extractive industries, any benefits from colocation with such industries are in our paper associated with input-output relations. Similarly, we think it is better to think of the availability of unskilled workers, unionized workers and workers with a bachelor degree or higher, not as natural advantages as in EGK, but rather as counting towards labor market externalities.

Technological linkages are problematic for a different reason: most available proxies are based on patent information.[6] The problem of using patent information is that industries differ widely in how much they rely on patents to protect their intellectual property, see Cockburn and Griliches (1988). Therefore, the accuracy with which the potential for inter-industry knowledge spillovers can be assessed from patent data will differ tremendously by industry. Because this heterogeneity in measurement error will mechanically translate into heterogeneity in observed Marshallian agglomeration benefits, it compromises the main aim of our paper.[7] Below, we describe how we measure the linkages between two industries in terms of labor market pooling and input-output relations.

[6]EGK use patent citations and the technology matrix of Scherer (1984), which itself is based on the assessment of how useful a set of patents filed in one industry is to another industry.

[7]Although heteroscedastic measurement error will to some extent affect all inter-industry proximity measures, the problem is particularly severe in the case of technological similarities. Indeed, for reasons explained above, we believe that the variation in precision with which we can characterize labor and input-output linkages is dwarfed by the variation in measurement error for technological linkages.

Input-output links

Value chains allow individual firms to specialize. However, such specialization also creates costs: intermediates need to be shipped between firms and innovation efforts must be coordinated with suppliers (Richardson, 1972; Abdel-Rahman, 1996; Porter, 1998). Because the costs of transportation and coordination typically rise with distance, the coagglomeration of different parts of a value chain can be an effective cost-reduction strategy.

We measure the strength of input-output relations between a pair of industries using the same indicator as EGK. That is, the input-output proximity of industries i and j is defined as the maximum relative importance of i as a customer or as a supplier of j and vice versa. Let IO_{ij} be an input-output matrix, i.e., IO_{ij} represents the value of goods and services that industry j sources from industry i. We now measure the proximity between i and j in terms of input-output linkages as:

$$P_{ij}^{IO} = max\left(\frac{IO_{ij}}{\sum_k IO_{kj}}, \frac{IO_{ji}}{\sum_k IO_{kj}}, \frac{IO_{ij}}{\sum_k IO_{ik}}, \frac{IO_{ji}}{\sum_k IO_{ik}}\right) \tag{3}$$

For the US, input-output linkages are based on make-and-use tables provided by the Bureau of Economic Analysis (BEA) for the year 2002. To match this data to our coagglomeration data, we create a concordance between the 337 IO codes used by the BEA and our (adjusted) NAICS codes. Whenever an IO code corresponds to several NAICS codes, we split the IO codes by these NAICS codes, using total NAICS employment as reported in the CBP as weights. Next, we use the thus aggregated supply (make) matrix S and demand (use) matrix U to construct an IO-matrix by the standard operation $IO = SD_S^{-1}U$, where D_S is a matrix with all off-diagonal elements equal to zero and diagonal elements equal to the column sums of S. Similar calculations are carried out for Mexico, using input-output data for the year 2008 provided by the Mexican statistical office, Instituto Nacional de Estadistica y Geografia (INEGI). The ten strongest input-output linkages (based on US data) are shown in table 2.

Labor market pooling

A large local pool of specialized labor benefits both firms and workers. For one, larger pools of skilled workers (and firms that want to hire them) may result in better matching of workers to firms (Helsley and Strange, 1990). For another, workers may demand a wage premium as a compensation for moving to regions that offer few alternative employment opportunities in case they lose their jobs. In contrast, having many firms and industries that can absorb each other's redundant workers acts as an implicit insurance scheme and therefore may lower wage costs (Marshall, 1890; Duranton and Puga, 2004).

Following EGK, we measure the potential for two industries to draw from the same pool of workers using industry-occupation employment matrices. In particular, we compute correlation coefficients

Table 2: Top-10 industry pairs by strength of input-output links

Top-10 input-output links		
industry i	industry j	value
Petroleum and Coal Manufacturing	Oil and Gas Extraction	0.6776
Other Apparel Manufacturing	Cut and Sew Apparel Manufacturing	0.6001
Leather and Hide Tanning	Animal slaughtering and processing	0.5811
Motor Vehicle Parts Manufacturing	Motor Vehicle Manufacturing	0.5720
Motor Vehicle Manufacturing	Motor Vehicle Body Manufacturing	0.5351
Pulp, Paper, and Paperboard Mills	Paper Product Manufacturing	0.4617
Support Activities for Mining	Oil and Gas Extraction	0.4575
Motor Vehicle Manufacturing	Audio-Video Equipment Manufacturing	0.4343
Spectator Sports	Radio and Television Broadcasting	0.4269
Motor Vehicle Parts Manufacturing	Leather and Hide Tanning	0.4227

Here we show top-10 industry pairs in terms of input-output linkages, defined as the maximum relative importance of one industry as a customer or as a supplier of the other and vice versa (see equation (3)), based on make-and-use tables provided by the US Bureau of Economic Analysis (BEA) for the year 2002.

across occupations between E_{io} and E_{jo}, where E_{io} represents the number of workers in occupation o that are (nation-wide) employed by industry i:

$$P_{ij}^{L} = corr(E_{io}, E_{jo}). \tag{4}$$

For the US, we use industry-occupation data for the year 2002 as reported in the Occupational Employment Statistics (OES), while for Mexico, we use the Encuesta Nacional de Ocupacion y Empleo (ENOE) for the year 2005.[8] The ten strongest labor linkages (using US data) are reported in table 3.

2.4 Descriptive statistics

Excluding the diagonal, there are 7,140 unique industry pairs in our sample of 120 industries. Table 4 contains descriptive statistics for this sample. All variables have similar means in the US and Mexico. However, it is interesting to note that, for all variables, the dispersion is larger in Mexico, and sometimes substantially so. Although the greater dispersion in the Mexican variables may be structural, it could also mean that the variables constructed from US data are measured more accurately.

Table 5 reports correlation coefficients between the various dependent and independent variables. The Mexican and US versions of input-output and labor proximity measures are relatively highly correlated

[8]The US and Mexico use different classifications of occupations. This is, in principle, unproblematic, because industries are still recorded in both sources according to the NAICS classification. However, because the ENOE uses a mix of 3- and 4-digit classes (consisting of 68 3-digit and 113 4-digit codes), we have to split some 3-digit industries in the ENOE into 4-digit codes. Consequently, some industry pairs in Mexico are mechanically attributed the same P^L values and somewhat under 3% of off-diagonal elements are equal to 1.

Table 3: Top-10 industry pairs by strength of labor links

Top-10 labor links		
industry i	industry j	value
Other Textile Product Mills	Other Apparel Manufacturing	0.9919
Other Apparel Manufacturing	Cut and Sew Apparel Manufacturing	0.9885
Other Textile Product Mills	Cut and Sew Apparel Manufacturing	0.9805
Other Transportation Equipment	Agri/Construction/Mining Machinery	0.9802
Motor Vehicle Parts Manufacturing	Hardware Manufacturing	0.9766
Other Transportation Equipment	Motor Vehicle Body Manufacturing	0.9760
Motor Vehicle Body Manufacturing	Heating/Cooling Equipment	0.9756
Other Machinery Manufacturing	Agri/Construction/Mining Machinery	0.9742
Household Appliance Manufacturing	Hardware Manufacturing	0.9737
Heating/Cooling Equipment	Hardware Manufacturing	0.9715

Here we show top-10 industry pairs in terms of labor linkages, computed as a correlation of industry employment by occupation (see equation (4)), and based industry-occupation data for the year 2002 as reported in the US Occupational Employment Statistics (OES).

Table 4: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
			United States		
EG index	7140	0.0001	0.0047	-0.0232	0.0846
LC index	7140	0.7166	0.1209	0.4854	0.9915
Input-output	7140	0.0124	0.0353	0.0000	0.6776
Labor	7140	0.6013	0.0997	0.4956	0.9919
			Mexico		
EG index	7140	0.0005	0.0477	-0.2579	0.5149
LC index	7140	0.7784	0.1657	0.4399	0.9994
Input-output	7140	0.0143	0.0503	0.0000	1.0000
Labor	7140	0.5565	0.1094	0.4828	1.0000

Here we provide summary data for coagglomeration (EG and LC metrics), input-output and labor linkages for $120 * (120 - 1)/2 = 7140$ unique industry pairs for comparable data in both the US (top) and Mexico (bottom).

Table 5: Correlation coefficients

	EG (US)	LC (US)	IO (US)	Labor (US)	EG (MX)	LC (MX)	IO (MX)	Labor (MX)
EG (US)	1.000							
LC (US)	0.266	1.000						
IO (US)	0.195	0.146	1.000					
Labor (US)	0.228	0.044	0.235	1.000				
EG (MX)	0.193	0.038	0.098	0.158	1.000			
LC (MX)	0.044	0.493	0.058	0.052	0.202	1.000		
IO (MX)	0.129	0.097	0.533	0.215	0.141	0.049	1.000	
Labor (MX)	0.159	-0.018	0.291	0.537	0.191	-0.018	0.282	1.000

Here we show the correlation between each of the metics measuring pairwise industry linkages (coagglomeration using EG and LC definitions, Input-Output and labor) for the US and Mexico (MX). We observe that the Mexican and US versions of Input-Output and labor proximity measures are relatively highly correlated.

(> 0.5). Importantly, the correlations between the different versions of the same variable is higher than between the same versions of different variables. This is reassuring, because it suggests that these measures indeed capture distinct, yet rather general relations among industries.

2.5 Estimation framework

We follow EGK and infer the strength of different agglomeration forces by analyzing the relationship between co-agglomeration patterns and labor and value chain links of industry pairs using the following econometric model:

$$EG_{ij} = \alpha + \beta^{rel} P_{ij}^{rel} + \epsilon_{ij}, \tag{5}$$

where EG_{ij} is the EG-index of coagglomeration for industries i and j, and $rel \in \{IO, L\}$. Matrices P^{IO} and P^{L} contain the inter-industry input-output and labor linkages defined in the previous sections.

While EGK limit their inquiry to manufacturing, we extend the analysis to other sectors of the economy. We do so by expanding both the columns and rows of the EG_{ij} matrix. Next, we split the rows of this sample into a manufacturing and a services part to examine the coagglomeration of manufacturing (or services) industries with all other industries separately. Finally, we allow agglomeration effects to be fully heterogeneous across industries, by estimating the following equation:

$$EG_{ij} = \alpha_i + \beta_i^{IO} P_{ij}^{IO} + \beta_i^{L} P_{ij}^{L} + \epsilon_{ij} \tag{6}$$

That is, parameter estimates β_i^{IO} and β_i^{L} are allowed to vary freely by industry of origin, i. The reason we can estimate a different parameter for each industry and agglomeration channel is that each industry can coagglomerate with all other industries. Consequently, there are 119 observations per industry. Equation (6) can be estimated by running separate regressions for each i. However, it will be more convenient to estimate the coefficients simultaneously using the following two-way fixed effects model:[9]

$$EG_{ij} = \alpha_i + \delta_j + \beta_i^{IO} P_{ij}^{IO} + \beta_i^{L} P_{ij}^{L} + \epsilon_{ij} \tag{7}$$

This procedure yields two vectors with estimates of industry-specific agglomeration effects, $\hat{\beta}^{IO}$ and $\hat{\beta}^{L}$. The elements of these vectors represent the extent to which input-output and labor market linkages are expressed in an industry's coagglomeration patterns.

A possible cause for concern is that P_{ij}^{IO} and P_{ij}^{L} are themselves endogenous. Accordingly, EGK argue that OLS estimates may be upward-biased if the historical coagglomeration of two industries prompted these industries to adjust their production technologies in such a way that they could use each other's outputs or skilled workers. Another concern is that P_{ij}^{IO} and P_{ij}^{L} are only imperfect proxies of the degree to which industries can exchange products and labor. Such measurement error would lead to a downward bias in our estimates. In line with EGK, we therefore also estimate the models in equations (5) and (7) using on IV approach. As instruments, we use analogously constructed variables based on Mexican data. Similar to the UK-based instruments in EGK, our instruments are valid, as long as idiosyncratic patterns in the input-output and labor linkages in Mexico are uncorrelated with coagglomeration patterns in the US.

3 Empirical findings

3.1 Replication of EGK results

We start our analysis of the impact of labor market pooling and input-output relations on coagglomeration assuming that the two factors have homogeneous effects across industries. Later we will relax this assumption more and more. In the analysis below, we rescale all variables such that they are expressed in units of standard deviations.

Table 6 first replicates the results of EGK, including manufacturing industries only.[10] The table shows the results of univariate OLS specifications in which the effect of labor pooling and value chain linkages are estimated separately. The left part of the table (columns 1 to 3) shows our own estimates. For

[9] Moreover, in contrast to estimating separate equations for each industry, equation (7) allows the inclusion of both industry of origin and of destination fixed effects.

[10] For maximal comparability, manufacturing industries are here defined at the 4-digit level of the original US NAICS classification. In all subsequent analysis, we use the NAICS classification that was harmonized with the Mexican implementation of NAICS.

Table 6: OLS univariate regressions (EGK replication)

	EG index (our estimates)			EG index (EGK estimates)		
	(1)	(2)	(3)	(4)	(5)	(6)
	state	city	county	state	city	county
Input-output	0.214	0.177	0.144	0.205	0.167	0.130
	(0.035)	(0.032)	(0.029)	(0.037)	(0.028)	(0.022)
Observations	3655	3655	3655	7381	7381	7381
R^2	0.060	0.060	0.047	0.042	0.028	0.017
Labor	0.181	0.164	0.195	0.180	0.106	0.082
	(0.018)	(0.018)	(0.016)	(0.014)	(0.016)	(0.013)
Observations	3655	3655	3655	7381	7381	7381
R^2	0.029	0.035	0.060	0.032	0.011	0.007

Robust standard errors in parentheses.

Columns 1-3 replicate the univariate regression results of Ellison, Glaeser and Kerr (2010) (shown in columns 4-6) using equivalent data for the US from 2003 for manufacturing industries and three levels of spatial aggregation: states, cities and counties. In all cases the dependent variable is the pairwise EG-based coagglomeration linkages, and the independent variable is either the corresponding metric for value chain linkages or labor pooling (see equation (5)). Most of the new estimates are remarkably close to those of EGK despite the fact that the new sample refers to a different period and more aggregate industry definitions: both externality channels are important and have similar impacts on coagglomeration.

convenience, the findings in the original paper by EGK (Table 3, p. 1204) are shown on the right (columns 4 to 6).

In spite of the fact that our sample refers to a different period and more aggregate industry definitions (manufacturing codes are less detailed at the 4-digit NAICS level than at the 3-digit SIC level), most of our estimates are remarkably close to those of EGK: both externality channels are important and have similar impacts on coagglomeration. The only substantive difference is that we find larger effects of labor pooling at the city and county levels than EGK. As a consequence, our estimates imply that, at the county level, labor pooling is a stronger determinant of coagglomeration than are input-output links instead of vice versa.

3.2 Extended sample

The EGK results are derived only for manufacturing. Do conclusions change when we extend the sample of industries? Using the (adjusted) NAICS classification, there are 83 manufacturing industries, which represent roughly two-thirds of the 120 industries in the overall sample. Consequently, the number of observations rises to 7,140 (= $\frac{120(120-1)}{2}$). Table 7 contains results of the estimations for this extended sample. The first three columns report OLS estimates, columns 4 to 6 show IV estimates, where US input-output proximity (P_{ij}^{IO}) and labor proximity (P_{ij}^{L}) are instrumented by their counterparts constructed from Mexican data.

The OLS regressions show that, in the extended sample, value chain and labor market links are

Table 7: OLS and IV univariate regressions on extended sample

	(1) OLS state	(2) OLS city	(3) OLS county	(4) IV state	(5) IV city	(6) IV county
			EG index			
Input-output	0.295	0.215	0.176	0.372	0.267	0.201
	(0.041)	(0.025)	(0.028)	(0.045)	(0.032)	(0.032)
Observations	7140	7140	7140	7140	7140	7140
R^2	0.069	0.038	0.025	0.064	0.036	0.024
Labor	0.261	0.229	0.178	0.347	0.296	0.194
	(0.012)	(0.011)	(0.011)	(0.031)	(0.020)	(0.018)
Observations	7140	7140	7140	7140	7140	7140
R^2	0.065	0.052	0.030	0.058	0.048	0.030

Robust standard errors in parentheses.

Idem table 6 but in this case we include all industries, not just manufacturing as in the previous table, for a total of 120 industries. We show OLS results for the US (columns 1-3), and using IV estimates where US input-output proximity (P_{ij}^{IO}) and labor proximity (P_{ij}^{L}) are instrumented by their counterparts constructed from Mexican data (columns 4-6). The regressions show that, in this extended sample, value chain and labor market links are even more important drivers of coagglomeration than in the manufacturing only sample.

even more important drivers of coagglomeration than in the manufacturing sample. Focusing on the city-level estimates, a one-standard-deviation increase in human capital similarities increases industries' coagglomeration by 0.23 standard deviations. Similarly, a one-standard-deviation increase in the strength of value-chain linkages between industries increases their coagglomeration index by 0.22 standard deviations. Turning to columns (4) to (6), we find that IV estimates significantly exceed OLS estimates.[11] The effect of a one-standard-deviation increase in the strength of value-chain links increases coagglomeration tendencies by 0.27 standard deviations, whereas a similar increase in human capital similarity increases coagglomeration by 0.30 standard deviations. The fact that IV estimates are higher than OLS estimates is similar to what EGK report, although in EGK this is limited to the effects of input-output linkages.[12] It appears that reverse causality does not lead to a net overall upward bias. Instead, our findings are consistent with the notion that inter-industry proximities are measured with some error.

3.3 Manufacturing versus services

The fact that we find tendencies of industries to coagglomerate along both labor and IO channels to increase as we extend our sample of industries suggests that these factors are stronger drivers of

[11]First-stage results (not reported) are very strong: the estimated effects of the instruments on endogenous variables exhibit t-statistics of 42 for labor similarities and 8.6 for input-output linkages.

[12]For labor linkages, OLS and IV estimates are roughly equal in EGK.

coagglomeration in services than in manufacturing. To analyze this further, we split the sample into manufacturing industries and services. The results are summarized in Figure 1. The panel on the left reports OLS outcomes, whereas the panel on the right shows IV results. Within each panel, the estimated coefficients for β^L, together with their 95% confidence intervals, are plotted in the vertical direction and estimates for β^{IO} are plotted in the horizontal direction. Blue symbols mark the manufacturing sector, red symbols refer to services.

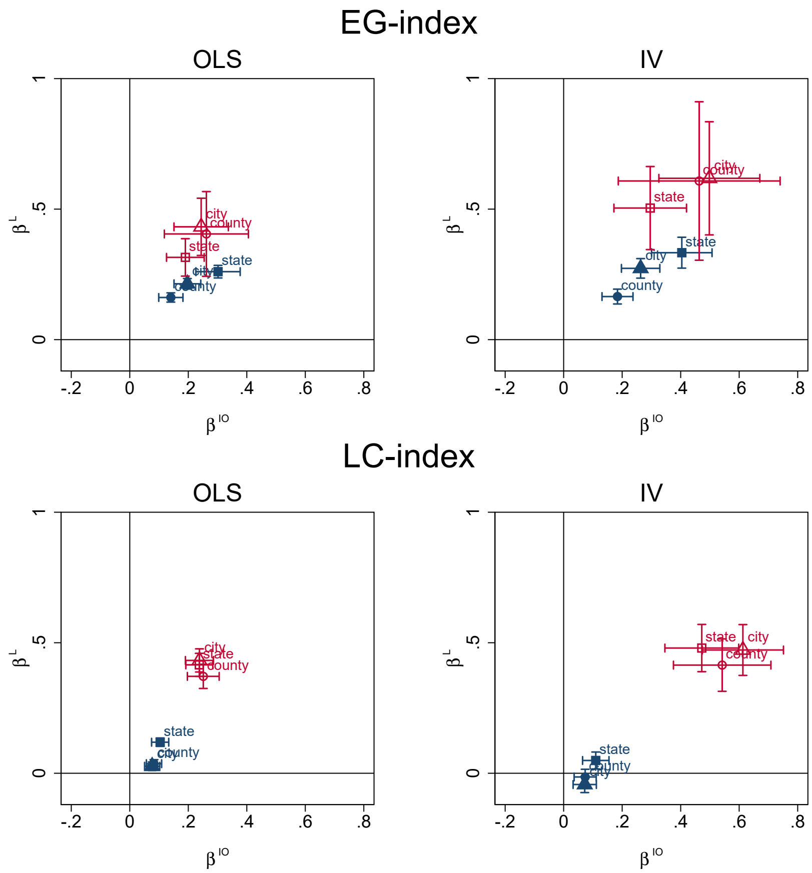
The most striking aspect of Figure 1 is the differences between services and manufacturing. In particular, labor similarity is a stronger predictor of coagglomeration in services than in manufacturing, irrespective of whether we use OLS or IV techniques and input-output similarity is at least as good a predictor of coagglomeration in services as in manufacturing. The IV regressions give rather imprecise results for services, but point-estimates generally exceed the ones in manufacturing. Interestingly, the differences between services and manufacturing are even more pronounced when using the LC index. In particular, the explanatory power of input-output linkages (and not just of labor linkages) is greater in services than in manufacturing in these specifications. These observations are consistent with the view put forward in the introduction that the reliance of services on human capital and the non-tradedness of their output makes services strongly dependent on both types of agglomeration externalities.

3.4 Effect heterogeneity

The observed differences between services and manufacturing industries suggest that there is substantial heterogeneity in why industries coagglomerate. To explore this in greater detail, we allow the effects of labor and value chain linkages to vary freely by industry (see (7)). Whereas we report a full list of industry-specific estimates in appendix B, here, we present results in a more compact way. First, we group the 120 industries into 27 broad categories. Next, we plot the (unweighted) mean of input-output and labor coefficients across the industries in a category in Figure 2. Once again, coefficients for labor linkages are plotted in the vertical direction and input-output linkages are plotted along the horizontal dimension. Results for service industries are colored red, whereas results for manufacturing industries are depicted in blue. To avoid cluttering the graph, we only show city-level estimates.

The effect sizes summarized in Figure 2 are quite heterogeneous, but the general patterns closely track those foreshadowed in Figure 1. Both types of inter-industry similarities exert a greater influence on coagglomeration in services than in manufacturing industries. However, the variation is particularly pronounced when it comes to the effect of labor similarities. For instance, the labor channel's greatest impact on coagglomeration patterns is found in industries in *arts & culture*, *architecture & engineering*, *media* and *knowledge intensive business services* (KIBS). In these categories, industry pairs exhibit an up to 1.5 standard deviations higher EG index for every standard deviation increase in the industries' human capital similarity. In contrast, coagglomeration of *machinery repair services* are not just driven by opportunities for local labor sharing but also by an apparent desire to coagglomerate with value-chain partners. Although the variation is less pronounced than in services, manufacturing industries

Figure 1: Coagglomeration effects, manufacturing versus services



The figures depict estimated labor pooling effects (vertical axis) and value chain effects (horizontal axis) from separate estimations of equation (5) on the sample of services and manufacturing industries. Estimates for the coagglomeration patterns of services are plotted using open, red markers, those for manufacturing industries using solid, blue markers. State-level estimates are marked by squares, city-level estimates by triangles and municipality-level estimates by circles. The crosshairs represent 95% confidence intervals based on robust standard errors. IV estimates use analogous variables for labor pooling and input-output linkages using Mexican data.

display heterogeneous effects as well. For instance, the coagglomeration patterns of industries in *hardware* and in *machinery* manufacturing follow value-chain as well as labor-pooling relations. In contrast, *pharma & medical industries* tend to coagglomerate with customers or suppliers, but not with industries that employ similar labor.

4 Marshallian Externalities and Regional Diversification

So far, we have used the EGK framework to show that the balance between labor market-pooling and value-chain-based agglomeration externalities differs widely across industries. However the co-agglomeration framework is static in nature. Do these differences manifest themselves in the spatial dynamics of agglomeration? To explore this issue, we move to an analysis of industries' growth paths in a particular location, i.e., given an existing portfolio of industries. In doing so, we connect to a large and growing literature that has focused on the role of Marshallian externalities in the evolution of regions' industrial structure. This literature suggests that inter-industry linkages are important for understanding diversification processes, as regions branch into new economic activities that build on existing strengths. Using this approach, industries have been found to grow faster in regions with much employment in related industries (Porter, 2003; Greenstone et al., 2008; Delgado et al., 2010; Neffke et al., 2011; Hausmann et al., 2014).

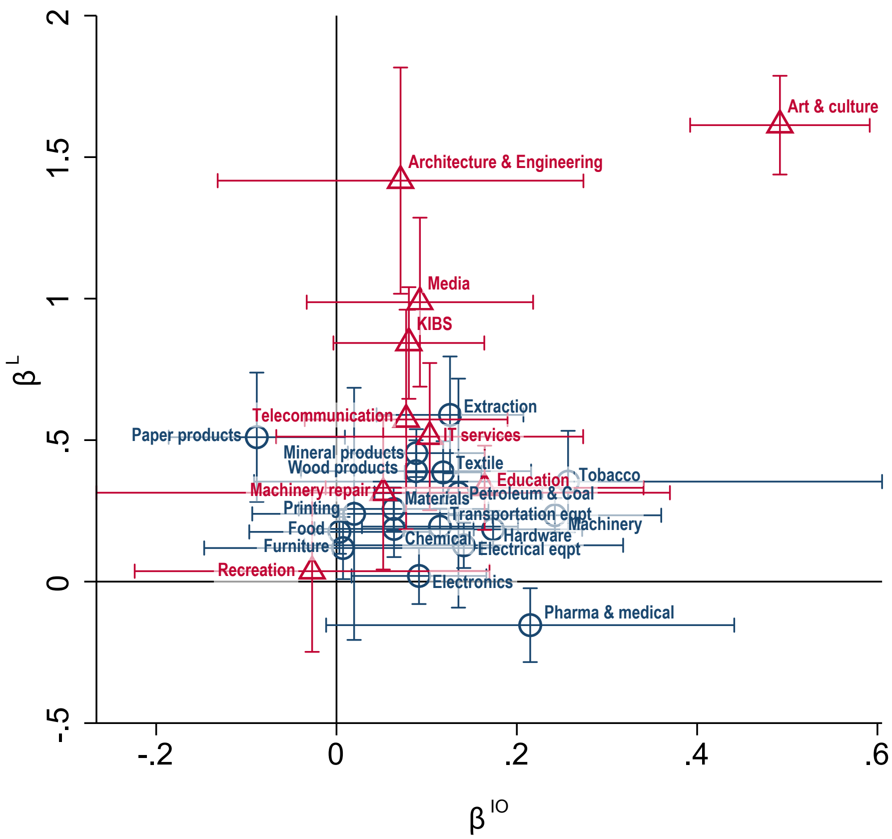
Yet most of this work implicitly assumes that all industries benefit equally from inter-industry spillovers. Moreover, it typically captures relatedness through a single Marshallian channel. In this section, we use the insights on industry-specific (co-)agglomeration externalities gained in the previous section, to enhance the econometric models of local industry growth rates that have been used by authors in this strand of the literature. To do so, let the relatedness between industries i and j be measured by one of our two proximity measures $P_{ij}^{rel} \in \left\{P_{ij}^{L}, P_{ij}^{IO}\right\}$. We can now calculate the proximity-weighted (related) employment for region-industry (i, r) in year t as:

$$E_{irt}^{rel} = \sum_{j} \frac{P_{ij}^{rel}}{\sum_{k \neq i} P_{ik}^{rel}} E_{jrt}.$$

This expression can be interpreted as the amount of related employment already present in the local economy, where what we call "related" depends on rel. For example, in the case of labor E_{irt}^{L} represents an index that reflects the size of the local workforce with skills and know-how that are relevant to industry i.

Letting G_{ir}^{03-08} refer to the logarithm of employment growth of industry i in region r between 2003 and 2008, i.e., $G_{ir} = ln\left(E_{ir08}\right) - ln\left(E_{ir03}\right)$ and restricting the sample to all local industries with non-zero

Figure 2: Coagglomeration effects (EG-index), manufacturing versus services



Labor pooling effects (vertical axis) and value chain effects (horizontal axis) using OLS regression. This figure summarizes the outcomes of estimations of equation (7). Point estimates are averaged across 27 categories (see Appendix B for a full list of results). Estimates for the coagglomeration patterns of services are marked with red squares, those for manufacturing industries with blue triangles. The crosshairs represent 95% confidence intervals for these averages, based on robust standard errors.

employment in 2003,[13] we estimate:

$$G_{ir}^{03-08} = \delta \ln\left(E_{ir03}\right) + \gamma^{rel} \ln\left(E_{ir03}^{rel}\right) + \iota_i + \rho_r + \epsilon_{ir03} \tag{8}$$

where δ captures mean reversion effects, and ι_i and ρ_r are industry and region dummies. The parameter of interest, γ^{rel}, captures to what extent the growth in a local industry can be predicted from the amount of related activity already present in the local economy.

Table 8 contains results when using cities as the spatial unit of analysis. In line with prior literature (e.g., Delgado et al., 2010; Hausmann et al., 2014), we find significant and negative effects for the mean reversion term δ and positive effects of γ^{rel}, regardless of whether we measure proximity in terms of labor or input-output linkages. However, our findings so far suggest that the degree to which each of these proximities matters will vary by industry. We, therefore, augment (8) by interacting the amount of related employment in a city with $\hat{\beta}_i^{rel}$, our estimates for β_i^{IO} and β_i^{L} which contain information on how important a proximity is to an industry. To facilitate interpretation, the $\hat{\beta}_i^{rel}$ are expressed in units of standard deviations from their respective mean. This yields the following equation:[14]

$$G_{ir}^{03-08} = \delta \ln\left(E_{ir03}\right) + \gamma^{rel} \ln\left(E_{ir03}^{rel}\right) + \gamma_{\beta}^{rel} \hat{\beta}_i^{rel} \ln\left(E_{ir03}^{rel}\right) + \iota_i + \rho_r + \epsilon_{ir03} \tag{9}$$

If $\hat{\beta}_i^{rel}$ captures any information on the importance of the corresponding agglomeration externality, we would expect γ_{β}^{rel} to be positive. Table 8 shows that this is indeed the case.

The interaction effect, γ_{β}^{rel}, is always positive, but consistently statistically significant only when using the industry-specific effects derived from regressions using the LC index of coagglomeration (columns (5), (6) and (9)). The marginal effects of related employment are given by:

$$\frac{\partial G_{ir}^{03-08}}{\partial E_{ir}^{rel}} = \gamma^{rel} + \gamma_{\beta}^{rel} \hat{\beta}_i^{rel}.$$

Figure 3 plots these partial derivatives against $\hat{\beta}_i^{rel}$ on a range that reflects the actual coefficient estimates obtained in section 3.4. The strongest interaction effects are visible when using industry-specific effects estimated in regression analysis based on the LC index. In these equations, elasticities for value-chain related employment run from as low as 2% for some industries to as high as 4% for others. The range of elasticities is even greater for employment related in terms of human-capital similarities, starting from a low 4% for industries with coagglomeration patterns that are not very sensitive to human capital similarities and reaching over 10% where such similarities are very strong drivers of coagglomeration. The fact that the industry-specific coagglomeration effects derived in

[13]In the appendix, we also show results for growth at the extensive margin, estimating the entry probability for local industries that were non-existent in 2003. Conclusions derived from this analysis are similar to the ones presented here.

[14]Note that any level-effects of β_i^{rel} will be absorbed in ι_i.

Table 8: Growth in local industries

	City-industry employment growth								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
lnE_{ir03}	-0.1995	-0.2029	-0.1995	-0.2029	-0.1999	-0.2058	-0.2037	-0.2037	-0.2074
	(0.0034)	(0.0035)	(0.0034)	(0.0035)	(0.0034)	(0.0035)	(0.0035)	(0.0035)	(0.0035)
lnE^{IO}_{ir03}	0.0280		0.0280		0.0285		0.0151	0.0152	0.0179
	(0.0045)		(0.0045)		(0.0045)		(0.0046)	(0.0046)	(0.0046)
lnE^{L}_{ir03}		0.0612		0.0612		0.0602	0.0571	0.0571	0.0555
		(0.0050)		(0.0050)		(0.0050)	(0.0051)	(0.0051)	(0.0052)
$lnE^{IO}_{ir03}\hat{\beta}^{IO}_{i,EG}$			0.0030					0.0024	
			(0.0021)					(0.0021)	
$lnE^{L}_{ir03}\hat{\beta}^{L}_{i,EG}$				0.0008				0.0008	
				(0.0020)				(0.0020)	
$lnE^{IO}_{ir03}\hat{\beta}^{IO}_{i,LC}$					0.0070				0.0076
					(0.0020)				(0.0020)
$lnE^{L}_{ir03}\hat{\beta}^{L}_{i,LC}$						0.0234			0.0243
						(0.0020)			(0.0020)
Obs.	37835	37835	37835	37835	37835	37835	37835	37835	37835
$Adj.R^2$	0.1295	0.1325	0.1296	0.1325	0.1298	0.1343	0.1327	0.1327	0.1349

The dependent variable is the logarithm of growth of the employment in local industries between 2003 and 2008. E_{ir03} is the employment in industry i in city r in the year 2003. E^{IO}_{ir03} and E^{L}_{ir03} define the employment related to industry i according to input-output linkages and labor linkages respectively, in region r in the year 2003. The terms $E^{IO}_{ir03}\hat{\beta}^{IO}_{i,EG}$ and $E^{L}_{ir03}\hat{\beta}^{L}_{i,EG}$ refer to the interaction of related employment and the estimated industry-specific effects of input-output linkages or labor linkages in the coagglomeration regressions. Industry-specific coagglomeration effects are centered on their means and scaled by their standard deviations. All regressions include industry and region dummies. Robust standard errors are reported in parentheses.

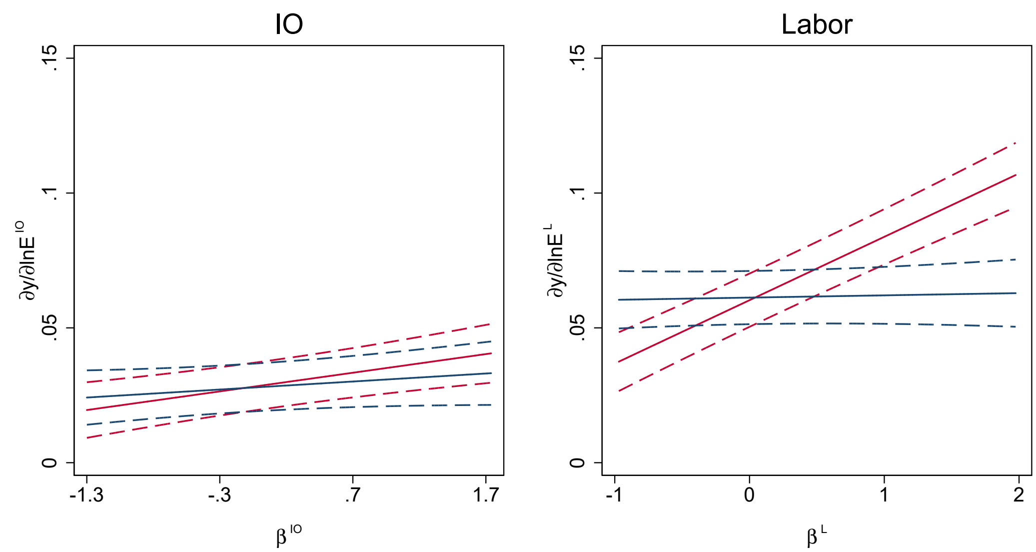
Section 3.4 are also reflected in industries' local growth patterns does not just tell us something about local industries' growth patterns. It also raises our confidence in the estimated effect heterogeneity itself.

5 Conclusion

Extending the work by Ellison, Glaeser and Kerr (2010) on why industries coagglomerate, we find evidence of substantial heterogeneity across industries. Whereas in some industries, firms tend to locate close to their value-chain partners, in others they tend to locate in the vicinity of industries that share their labor requirements. The largest labor-pooling effects are found in the coagglomeration patterns of services. Extreme examples are industries in *architecture & engineering*, *media* and *knowledge intensive business services*. Value-chain effects on coagglomeration are in general weaker, but also quite heterogeneous, with examples of positive outliers in the manufacturing, but also the *repair of machinery*. In general, it is hard to measure the impact of labor-market pooling and input-output effects on the coagglomeration of individual industries. It is therefore noteworthy that our noisily estimated coefficients help improve predictions of local industry growth patterns. Whereas there are ample studies that show that local industries tend to grow faster in regions with much employment in related industries, we are able to show that this relatedness matters more whenever the corresponding inter-industry proximity is more strongly expressed in the industry's coagglomeration patterns.

Our findings have a number of implications for future research. First, the findings in this paper affirm that there is a strong link between the development of a services-oriented economy and cities (e.g., Kolko, 2010). In particular, we show that coagglomeration patterns to a much greater extent are determined by human capital similarities (and, although less so, by input-output linkages) in services than in manufacturing. Given that services increasingly dominate economies in the developed and developing world alike, this may mean that agglomeration externalities will become more important in future, in spite of the tremendous improvements in transportation and communication technology that allow economic activities to become more dispersed. Second, we have shown that the EGK framework can be leveraged to probe deeper into the processes that underlie agglomeration dynamics, and is sufficiently robust to changes in the exact definition of industries, the time period studied, the measure of coagglomeration and the choice of instrumental variable. Third, our paper confirms the finding of a string of other papers, that inter-industry linkages are important to our understanding of the development of local economies. However, we add to this literature that which type of inter-industry linkages matters most varies greatly by industry.

Figure 3: Marginal effects of related employment - Intensive margin



The marginal effects show the differential impact of related employment in different industries. The marginal effects are computed as the partial derivative of growth with respect to related employment. The left panel depicts IO effects, while the right shows labor effects. The horizontal axis is - respectively - β_{IO} and β_L. The range is chosen to reflect the actual coefficient estimates obtained in section 3.4. The blue lines correspond to the estimates using the EG-index and the red to estimates based on the LC-index. Each has three lines showing the mean estimate and the 95% confidence interval of the prediction.

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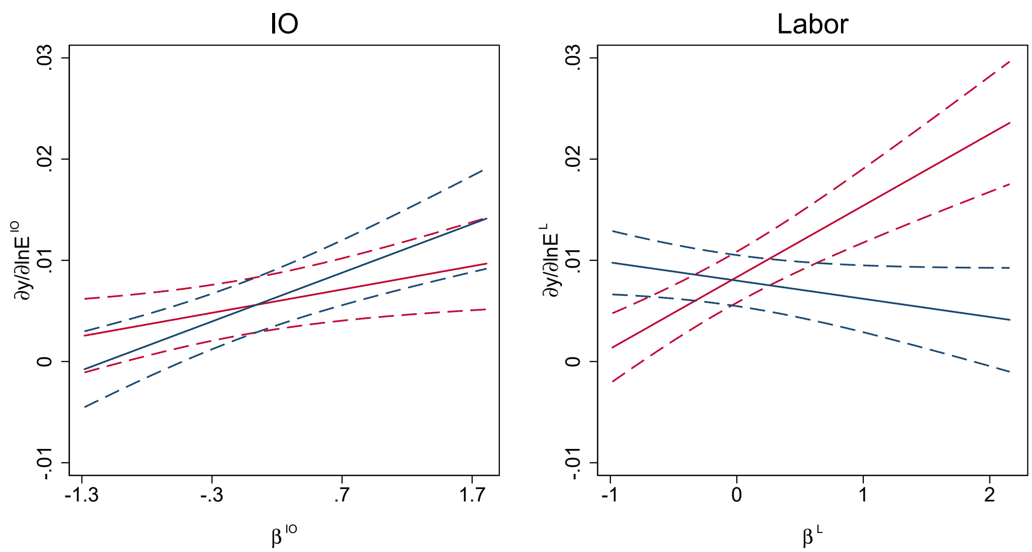
Appendix

A Additional analysis

Figure A.1: Marginal effects of related employment - Extensive margin



The marginal effects show the differential impact of related employment in different industries. The marginal effects are computed as the partial derivative of growth with respect to related employment. The left panel depicts IO effects, while the right shows labor effects. The horizontal axis is - respectively - β_{IO} and β_L. The range is chosen to reflect the actual coefficient estimates obtained in section 3.4. The blue lines correspond to the estimates using the EG-index and the red to estimates based on the LC-index. Each has three lines showing the mean estimate and the 95% confidence interval of the prediction.

Table A.1: OLS and IV univariate regressions separate for industry group (EG-index)

	EG index					
	(1) OLS state	(2) OLS city	(3) OLS county	(4) IV state	(5) IV city	(6) IV county
			All industries			
Input-output	0.174	0.138	0.112	0.237	0.172	0.132
	(0.023)	(0.015)	(0.015)	(0.027)	(0.020)	(0.019)
Observations	16836	16836	16836	16836	16836	16836
R^2	0.033	0.022	0.015	0.028	0.020	0.015
Labor	0.201	0.175	0.129	0.322	0.282	0.191
	(0.009)	(0.007)	(0.007)	(0.023)	(0.016)	(0.015)
Observations	16836	16836	16836	16836	16836	16836
R^2	0.042	0.034	0.019	0.027	0.021	0.015
			Manufacturing			
Input-output	0.239	0.161	0.115	0.293	0.199	0.135
	(0.028)	(0.018)	(0.016)	(0.036)	(0.024)	(0.019)
Observations	11786	11786	11786	11786	11786	11786
R^2	0.048	0.025	0.017	0.045	0.024	0.017
Labor	0.229	0.191	0.121	0.302	0.254	0.137
	(0.010)	(0.007)	(0.006)	(0.025)	(0.015)	(0.011)
Observations	11786	11786	11786	11786	11786	11786
R^2	0.061	0.049	0.027	0.055	0.044	0.026
			Services			
Input-output	0.127	0.171	0.175	0.209	0.290	0.272
	(0.019)	(0.028)	(0.041)	(0.038)	(0.053)	(0.078)
Observations	5360	5360	5360	5360	5360	5360
R^2	0.015	0.016	0.013	0.009	0.008	0.009
Labor	0.213	0.275	0.294	0.421	0.507	0.515
	(0.024)	(0.037)	(0.053)	(0.057)	(0.075)	(0.100)
Observations	5360	5360	5360	5360	5360	5360
R^2	0.019	0.018	0.016	0.001	0.005	0.007

This table repeats the calculations in tables 6 and 7 using all 184 industries as 'destination' industry. Robust standard errors in parentheses.

Table A.2: Growth in local industries, entry regressions

	City-industry appearances								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
lnE^{IO}_{ir03}	0.0054		0.0054		0.0056		0.0039	0.0038	0.0046
	(0.0014)		(0.0014)		(0.0014)		(0.0014)	(0.0014)	(0.0014)
lnE^{L}_{ir03}		0.0082		0.0080		0.0095	0.0074	0.0072	0.0087
		(0.0013)		(0.0013)		(0.0013)	(0.0013)	(0.0013)	(0.0013)
$lnE^{IO}_{ir03}\hat{\beta}^{IO}_{i,EG}$			0.0047					0.0045	
			(0.0011)					(0.0011)	
$lnE^{L}_{ir03}\hat{\beta}^{L}_{i,EG}$				-0.0018				-0.0012	
				(0.0010)				(0.0010)	
$lnE^{IO}_{ir03}\hat{\beta}^{IO}_{i,LC}$					0.0023				0.0023
					(0.0010)				(0.0010)
$lnE^{L}_{ir03}\hat{\beta}^{L}_{i,LC}$						0.0090			0.0092
						(0.0016)			(0.0016)
Obs.	42369	42369	42369	42369	42369	42369	42369	42369	42369
$Adj.R^2$	0.1163	0.1168	0.1168	0.1168	0.1164	0.1175	0.1169	0.1173	0.1178

Idem Table 8, but with as dependent variable an indicator variable that evaluates to one if a local industry came into existence between 2003 and 2008. Coagglomeration is measured as correlation index. Independent variables are log-transformed.

B Industry list with IO and labor coefficients (EG)

	name	group	data avail.	traded	IO coef.	labor coef.
1	Crop production	.	0	0	.	.
2	Animal production	.	0	0	.	.
3	Aviculture	.	0	0	.	.
4	Mixed agriculture	.	0	0	.	.
5	Silviculture	.	0	0	.	.
6	Forestry	.	0	0	.	.
7	Logging	.	0	0	.	.
8	Fishing	.	0	0	.	.
9	Hunting and Trapping	.	0	0	.	.
10	Support Activities for Crop Production	.	0	0	.	.
11	Support Activities for Animal Production	.	0	0	.	.
12	Support Activities for Forestry	.	0	0	.	.
13	Oil and Gas Extraction	1	1	1	0.27	-0.26
14	Coal Mining	1	1	1	0.06	0.97
15	Metal Ore Mining	1	1	1	-0.02	0.82
16	Nonmetallic Mineral Mining and Quarrying	1	1	1	-0.04	0.47
17	Support Activities for Mining	1	1	1	0.36	0.95
18	Utilities	.	1	0	.	.
19	Utility System Construction	.	1	0	.	.
20	Land Subdivision	.	1	0	.	.
21	Highway, Street, and Bridge Construction	.	1	0	.	.
22	Heavy and Civil Engineering Construction	.	1	0	.	.
23	Building Exterior Contractors	.	1	0	.	.
24	Building Equipment Contractors	.	1	0	.	.
25	Building Finishing Contractors	.	1	0	.	.
26	Other Specialty Trade Contractors	.	1	0	.	.
27	Animal Food Manufacturing	2	1	1	0.01	0.24
28	Grain and Oilseed Milling	2	1	1	-0.09	0.35
29	Sugar Product Manufacturing	2	1	1	0.01	0.19
30	Fruit and Vegetable Preserving	2	1	1	-0.00	0.23
31	Dairy Product Manufacturing	2	1	1	-0.16	0.16
32	Animal slaughtering and processing	2	1	1	0.02	0.54
33	Seafood Preparation and Packaging	2	1	1	0.14	-0.06
34	Bakeries and Tortilla Manufacturing	2	1	1	0.08	-0.10
35	Other Food Manufacturing	2	1	1	0.01	0.07
36	Beverage Manufacturing	2	1	1	0.02	0.13
37	Tobacco Manufacturing	3	1	1	0.26	0.35
38	Fiber, Yarn, and Thread Mills	4	1	1	-0.11	2.10
39	Textile and Fabric Mills	4	1	1	0.28	-0.18
40	Textile furnishings mills	4	1	1	0.16	0.21
41	Other Textile Product Mills	4	1	1	-0.01	0.12
42	Apparel Knitting Mills	4	1	1	-0.04	0.69
43	Cut and Sew Apparel Manufacturing	4	1	1	0.31	0.21
44	Other Apparel Manufacturing	4	1	1	0.37	-0.09
45	Leather and Hide Tanning	4	1	1	0.10	0.38
46	Footwear Manufacturing	4	1	1	0.13	0.31
47	Other Leather Manufacturing	4	1	1	0.00	0.11
48	Sawmills and Wood Preservation	5	1	1	0.05	0.64
49	Wood product Manufacturing	5	1	1	0.11	0.31
50	Other Wood Product Manufacturing	5	1	1	0.10	0.22

	name	group	data avail.	traded	IO coef.	labor coef.
51	Pulp, Paper, and Paperboard Mills	6	1	1	-0.13	0.74
52	Paper Product Manufacturing	6	1	1	-0.05	0.28
53	Printing and Related Support Activities	7	1	1	0.02	0.24
54	Petroleum and Coal Manufacturing	8	1	1	0.14	0.31
55	Basic Chemical Manufacturing	9	1	1	0.04	0.36
56	Synthetic Fibers Manufacturing	9	1	1	0.04	0.43
57	Agricultural Chemical Manufacturing	9	1	1	0.01	0.35
58	Pharmaceutical and Medicine Manufacturing	10	1	1	0.30	-0.33
59	Paint, Coating, Adhesive Manufacturing	9	1	1	0.09	0.09
60	Soap, Cleaning Compound Manufacturing	9	1	1	0.17	-0.27
61	Other Chemical Product Manufacturing	9	1	1	0.03	0.16
62	Plastics Product Manufacturing	11	1	1	-0.02	0.20
63	Rubber Product Manufacturing	11	1	1	0.09	0.32
64	Clay Product and Refractory Manufacturing	11	1	1	0.11	0.40
65	Glass and Glass Product Manufacturing	11	1	1	0.06	0.26
66	Lime and Gypsum Product Manufacturing	11	1	1	0.07	0.11
67	Other Mineral Product Manufacturing	12	1	1	-0.02	0.46
68	Iron and Steel Mills	12	1	1	0.13	0.81
69	Steel Product Manufacturing	12	1	1	0.18	0.35
70	Alumina and Aluminum Production	12	1	1	0.04	0.36
71	Nonferrous Metal Production	12	1	1	0.07	0.33
72	Foundries	12	1	1	0.04	0.55
73	Forging and Stamping	12	1	1	0.19	0.32
74	Cutlery and Handtool Manufacturing	13	1	1	0.22	0.17
75	Structural Metals Manufacturing	13	1	1	0.02	0.10
76	Boiler, Tank, Container Manufacturing	13	1	1	0.09	0.28
77	Hardware Manufacturing	13	1	1	0.21	0.19
78	Spring and Wire Product Manufacturing	13	1	1	0.19	0.21
79	Screw, Nut, and Bolt Manufacturing	13	1	1	0.20	0.21
80	Coating, Engraving, Heat Treating	13	1	1	0.28	0.22
81	Other Metal Product Manufacturing	13	1	1	0.17	0.10
82	Agri/Construction/Mining Machinery	14	1	1	0.46	0.18
83	Industrial Machinery Manufacturing	14	1	1	0.09	0.17
84	Service Industry Machinery Manufacturing	14	1	1	0.18	0.08
85	Heating/Cooling Equipment	14	1	1	0.21	0.14
86	Metalworking Machinery Manufacturing	14	1	1	0.31	0.46
87	Engine, Turbine, Transmission Manufacturing	14	1	1	0.16	0.46
88	Other Machinery Manufacturing	14	1	1	0.28	0.15
89	Computer Equipment manufacturing	15	1	1	0.15	0.06
90	Audio-Video Equipment Manufacturing	15	1	1	-0.04	-0.10
91	Semiconductor Manufacturing	15	1	1	0.04	0.13
92	Communications Equipment Manufacturing	15	1	1	0.23	0.01
93	Manufacturing of Magnetic and Optical Media	15	1	1	0.07	0.00
94	Electric Lighting Equipment Manufacturing	16	1	1	0.10	0.01
95	Household Appliance Manufacturing	16	1	1	0.13	0.23
96	Electrical Equipment Manufacturing	16	1	1	0.20	0.15
97	Other Electrical Equipment Manufacturing	17	1	1	0.04	0.12
98	Motor Vehicle Manufacturing	17	1	1	0.11	0.13
99	Motor Vehicle Body Manufacturing	17	1	1	0.00	0.25
100	Motor Vehicle Parts Manufacturing	17	1	1	0.17	0.22
101	Aerospace Product Manufacturing	17	1	1	0.24	-0.08
102	Railroad Rolling Stock Manufacturing	17	1	1	0.24	0.47
103	Ship and Boat Building	17	1	1	0.01	0.27
104	Other Transportation Equipment	17	1	1	0.12	0.17
105	Household Furniture Manufacturing	18	1	1	-0.02	0.29

	name	group	data avail.	traded	IO coef.	labor coef.
106	Office Furniture Manufacturing	18	1	1	0.05	0.10
107	Other Furniture Related Manufacturing	18	1	1	-0.01	-0.04
108	Medical Supplies Manufacturing	10	1	1	0.13	0.02
109	Other Miscellaneous Manufacturing	99	1	1	0.09	-0.04
110	Wholesale Trade	.	1	0	.	.
111	Retail Trade	.	0	0	.	.
112	Scheduled Air Transportation	.	1	0	.	.
113	Nonscheduled Air Transportation	.	1	0	.	.
114	Rail transportation	.	0	0	.	.
115	Water Transportation	.	1	0	.	.
116	Inland Water Transportation	.	1	0	.	.
117	General Freight Trucking	.	1	0	.	.
118	Specialized Freight Trucking	.	0	0	.	.
119	Urban Transit Systems	.	1	0	.	.
120	Interurban Bus Transportation	.	1	0	.	.
121	School and Employee Bus	.	1	0	.	.
122	Charter Bus Industry	.	1	0	.	.
123	Taxi and Limousine Service	.	1	0	.	.
124	Pipeline Transportation of Crude Oil	.	0	0	.	.
125	Pipeline Transportation of Gas	.	1	0	.	.
126	Other Pipeline Transportation	.	1	0	.	.
127	Sightseeing Transportation, Land	.	1	0	.	.
128	Sightseeing Transportation, Water	.	1	0	.	.
129	Sightseeing Transportation, Other	.	1	0	.	.
130	Support for Air Transportation	.	1	0	.	.
131	Support for Rail Transportation	.	1	0	.	.
132	Support for Water Transportation	.	1	0	.	.
133	Support for Road Transportation	.	1	0	.	.
134	Freight Transportation Arrangement	.	1	0	.	.
135	Support Activities for Transportation	.	1	0	.	.
136	Postal Services	.	0	0	.	.
137	Couriers and express delivery services	.	1	0	.	.
138	Local Messengers and Local Delivery	.	0	0	.	.
139	Warehousing and Storage	.	1	0	.	.
140	Publishers	19	1	1	0.18	0.81
141	Software Publishers	21	1	1	0.17	0.61
142	Sound Recording Industries	25	1	1	1.91	1.71
143	Radio and Television Broadcasting	19	1	1	0.01	1.16
144	Satellite Telecommunications	20	1	1	0.11	0.47
145	Data Processing Services	21	1	1	0.04	0.42
146	Other telecommunications	20	1	1	0.05	0.68
147	Real estate and construction	.	1	0	.	.
148	Offices of Real Estate Agents	.	1	0	.	.
149	Activities Related to Real Estate	.	1	0	.	.
150	Automotive Equipment Rental	.	1	0	.	.
151	Consumer Goods Rental	.	1	0	.	.
152	General Rental Centers	.	0	0	.	.
153	Machinery and Equipment Rental	.	0	0	.	.
154	Lessors of Nonfinancial Intangible Assets	23	1	1	-0.20	1.11
155	Legal Services	23	1	1	0.13	2.58
156	Accounting Services	23	1	1	0.44	0.68
157	Architectural and Engineering Services	22	1	1	0.09	0.59
158	Specialized Design Services	22	1	1	0.05	2.25
159	Computer Systems Design	.	0	0	.	.
160	Scientific and R&D Services	.	0	0	.	.

	name	group	data avail.	traded	IO coef.	labor coef.
161	Advertising and Related Services	.	0	0	.	.
162	Professional and Scientific Services	.	0	0	.	.
163	Management of Companies and Enterprises	23	1	1	0.07	0.46
164	Office Administrative Services	23	1	1	-0.04	0.54
165	Facilities Support Services	23	1	1	0.07	0.71
166	Management Consulting Services	23	1	1	0.12	0.13
167	Business Support Services	24	1	1	0.04	0.21
168	Travel Arrangement Services	.	1	0	.	.
169	Investigation and security services	.	1	0	.	.
170	Services to Buildings and Dwellings	.	0	0	.	.
171	Other Support Services	.	0	0	.	.
172	Waste Treatment and Disposal	.	1	0	.	.
173	Elementary and Secondary Schools	.	1	0	.	.
174	Junior Colleges	24	1	1	0.32	0.57
175	Colleges, Universities, Professional Schools	24	1	1	0.07	0.38
176	Business Schools and Computer Training	24	1	1	0.27	0.39
177	Technical and Trade Schools	24	1	1	0.13	0.10
178	Other Schools and Instruction	.	1	0	.	.
179	Educational Support Services	.	1	0	.	.
180	Offices of Physicians	.	1	0	.	.
181	Offices of Dentists	.	1	0	.	.
182	Offices of Other Health Practitioners	.	0	0	.	.
183	Medical and Diagnostic Laboratories	.	0	0	.	.
184	Home Health Care Services	.	0	0	.	.
185	Other Ambulatory Health Care Services	.	1	0	.	.
186	General Medical and Surgical Hospitals	.	1	0	.	.
187	Psychiatric and Substance Abuse Hospitals	.	1	0	.	.
188	Specialty Hospitals	.	1	0	.	.
189	Nursing Care Facilities	.	1	0	.	.
190	Mental Health and Substance Abuse Facilities	.	1	0	.	.
191	Individual and Family Services	.	1	0	.	.
192	Community Food and Housing	.	1	0	.	.
193	Vocational Rehabilitation Services	.	1	0	.	.
194	Child Day Care Services	.	1	0	.	.
195	Performing Arts Companies	25	1	1	-0.01	3.41
196	Spectator Sports	25	1	1	0.03	0.17
197	Promoters of Performing Arts	25	1	1	0.23	0.42
198	Agents and Managers	25	1	1	0.85	2.96
199	Independent Artists	25	1	1	0.26	2.19
200	Museums and Historical Sites	25	1	1	0.18	0.44
201	Amusement Parks and Recreation Industry	26	1	1	0.16	0.15
202	Traveler Accommodation	26	1	1	-0.00	0.13
203	RV Parks and Recreational Camps	26	1	1	-0.24	-0.17
204	Residential Care Facilities	.	1	0	.	.
205	Restaurants	.	1	0	.	.
206	Special Food Services	.	1	0	.	.
207	Drinking Places (Alcoholic Beverages)	.	0	0	.	.
208	Automotive Repair and Maintenance	.	1	0	.	.
209	Machinery Repair and Maintenance	27	1	1	0.05	0.31
210	Household Goods Repair and Maintenance	.	1	0	.	.
211	Other Personal Services	.	1	0	.	.
212	Associations and Organizations	.	1	0	.	.
213	Household services	.	0	0	.	.
214	Other Public Services	.	1	0	.	.
215	Finance and Insurance	23	1	1	0.07	0.53

Table B.1: Average point-estimates by industry group.

group	name	IO coef.	labor coef.
1	Extraction	0.13	0.59
2	Food Manufacturing	0.00	0.18
3	Tobacco Manufacturing	0.26	0.35
4	Textile Manufacturing	0.12	0.39
5	Wood products	0.09	0.39
6	Paper products	-0.09	0.51
7	Printing	0.02	0.24
8	Petroleum and Coal Manufacturing	0.14	0.31
9	Chemical Manufacturing	0.06	0.19
10	Pharmaceutical and medical supply	0.21	-0.15
11	Materials	0.06	0.26
12	Mineral products manufacturing	0.09	0.45
13	Hardware Manufacturing	0.17	0.18
14	Machinery	0.24	0.23
15	Electronics	0.09	0.02
16	Electrical equipment manufacuting	0.14	0.13
17	Transportation Equipment	0.11	0.19
18	Forniture	0.01	0.12
19	Media	0.09	0.99
20	Telecommunication	0.08	0.57
21	IT services	0.10	0.51
22	Architecture and Engineering	0.07	1.42
23	Professional KIBS	0.08	0.84
24	Educational	0.16	0.33
25	Art and culture	0.49	1.61
26	Recreation	-0.03	0.04
27	Machinery repair	0.05	0.31
99	Other	0.09	-0.04

C Analysis using Location Correlation

Table C.1 shows the top 10 industry pairs for the co-agglomeration index based on location correlation, see equation (2).

Table C.2 replicates table 7 of the main text for the LC-based coagglomeration measure. Here value chain links are more important drivers of coagglomeration than labor pooling.

Figure C.1 replicates figure 2 of the main text for the LC-based coagglomeration measure. As in the main text for the EG measure, the effect sizes are quite heterogeneous. Both types of inter-industry similarities exert a greater influence on coagglomeration in services than in manufacturing industries. However, the variation is particularly pronounced when it comes to the effect of labor similarities.

Table C.1: Top-10 industry pairs by coagglomeration (locational correlation index)

Top-10 co-location (LC index)		
industry i	industry j	value
Independent Artists	Cut and Sew Apparel Manufacturing	0.9915
Legal Services	Finance and Insurance	0.9900
Independent Artists	Accounting Services	0.9877
Specialized Design Services	Legal Services	0.9873
Sound Recording Industries	Agents and Managers	0.9861
Publishers	Performing Arts Companies	0.9854
Radio and Television Broadcasting	Legal Services	0.9840
Publishers	Legal Services	0.9837
Cut and Sew Apparel Manufacturing	Agents and Managers	0.9834
Cut and Sew Apparel Manufacturing	Accounting Services	0.9812

Idem table 1 but here we show the top-10 industry pairs using the LC-based coagglomeration metric (see equation (2)) using city-industry employment data for the US (County Business Patterns, 2003).

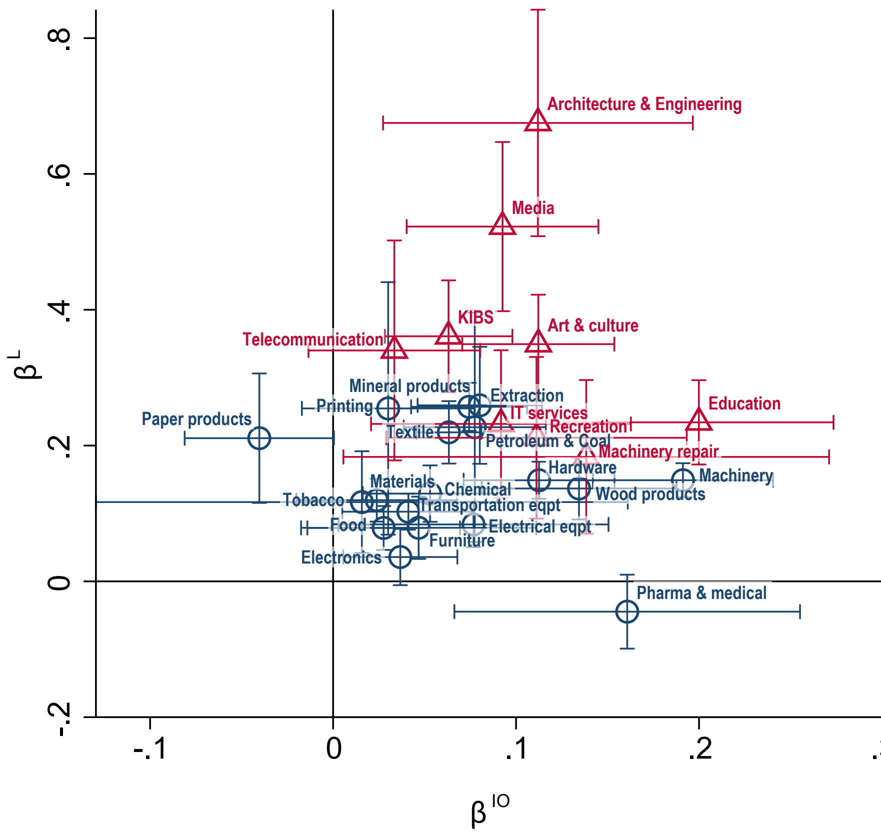
Table C.2: OLS and IV univariate regressions on extended sample

	(1) OLS state	(2) OLS city	(3) OLS county	(4) IV state	(5) IV city	(6) IV county
			LC index			
Input-output	0.132	0.119	0.122	0.162	0.148	0.139
	(0.015)	(0.015)	(0.015)	(0.027)	(0.028)	(0.027)
Observations	7140	7140	7140	7140	7140	7140
R^2	0.024	0.021	0.026	0.023	0.020	0.026
Labor	0.120	0.033	0.044	0.061	-0.025	0.005
	(0.008)	(0.008)	(0.008)	(0.017)	(0.016)	(0.015)
Observations	7140	7140	7140	7140	7140	7140
R^2	0.024	0.002	0.004	0.018	.	0.001

Robust standard errors in parentheses. Robust standard errors in parentheses.

Idem table 6 but in this case we use the LC correlation index in lieu of the EG index. These regressions also show that, in this extended sample, value chain and labor market links are even more important drivers of coagglomeration than in the manufacturing only sample.

Figure C.1: Coagglomeration effects (LC-index), manufacturing versus services



Labor pooling effects (vertical axis) and value chain effects (horizontal axis). The panel on the left reports results of an OLS regression. Estimates for the coagglomeration patterns of services are plotted in red, those for manufacturing industries in blue. The crosshairs represent 95% confidence intervals based on robust standard errors.

D Correction to CBP censoring

In CBP, when the information in a cell (by geography and by industry) reveals information about a firm, the data in the cell is withheld by the Census to avoid disclosure. However in this case CBP offers information about the employment size class. To attribute a single employment value to the employment range of the class, we follow Holmes and Stevens (2004), where the authors provide the following estimate (obtained using national data and a model) of the mean employment for CBP class in the year 2000.

Table D.1: Mean employment by size class in 2000 CBP, as in Holmes and Stevens (2004)

Employment range	Average employment
1-4	1.7
5-9	6.6
10-19	13.5
20-49	30.2
50-99	68.8
100-249	150.1
250-499	340.7
500-999	681.3
1000-1499	1208.8
1500-2499	1892.9
2500-4999	3374.7
5000 or more	9592.0

The CBP classes have changed slightly since Holmes and Stevens (2004). We adapt their estimates to the new classes as follows: categories C, E, F and H use directly their estimate. Categories A, B and G use weighted average from the sub-classes in Holmes and Stevens (2004). Categories I, J, K and L use the average ratio between the estimated employment of classes A to G and the mid-point of the employment classes A to G (0.7974). This ratio is then multiplied by the midpoint of I, J, K and L to obtain an estimate. Categories M lacks an upper bound to compute the mid-point. 125000 is obtained multiplying 100000 by the average of the ratio between minimum and estimated mean of classes I through L. The resulting scheme is used in this paper

Table D.2: Mean employment by size class in 2003 and 2008 CBP, as used in this paper

Class	Employment range	Average employment
A	0-19	5
B	20-99	40
C	100-249	150
E	250-499	341
F	500-999	681
G	1,000-2,499	1488
H	2,500-4,999	3375
I	5,000-9,999	5980
J	10,000-24,999	13955
K	25,000-49,999	29904
L	50,000-99,999	59804
M	100,000 or More	125000