Journal of Economic Geography, 2026, 1–23
https://doi.org/10.1093/jeg/lbag006
Original Article

OXFORD

Co-location of skill-related suppliers: advancing coagglomeration research using firm-to-firm network data

Sándor Juhász[1,2,3,4,*], Zoltán Elekes[3,5], Virág Ilyés[2,3], Frank Neffke[4,6]

[1]Department of Network Science, Institute of Data Analytics and Information Systems, Corvinus University of Budapest, Fővám tér 8, 1093 Budapest, Hungary
[2]ANETI Lab, Corvinus Institute for Advanced Studies, Corvinus University of Budapest, Fővám tér 8, 1093 Budapest, Hungary
[3]ANETI Lab, Institute of Economics, ELTE Centre for Economic and Regional Studies, Tóth Kálmán utca 4, 1097 Budapest, Hungary
[4]Complexity Science Hub, Metternichgasse 8, 1030 Vienna, Austria
[5]CERUM, Umeå University, Samhällsvetarhuset, 901 87 Umeå, Sweden
[6]Transforming Economies Lab, Interdisciplinary Transformation University (IT: U), Altenberger Straße 66c, 4040 Linz, Austria

*Corresponding author. Department of Network Science, Institute of Data Analytics and Information Systems, Corvinus University of Budapest, Fővám tér 8, 1093 Budapest, Hungary. E-mail: sandor.juhasz@uni-corvinus.hu

Abstract

Firms in industry clusters benefit from locating close to suppliers and customers. However, the pervasiveness of global value chains questions the need for co-location in buyer–supplier relationships. We propose that supply-chain partners are more likely to co-locate if they exchange not only goods but also know-how, implying superadditivity of Marshallian agglomeration channels. We test this in a coagglomeration framework using microdata for Hungary—a small, open economy deeply embedded in global value chains—examining co-location, labor flows, and value chains between firms and industries. We find that supply chains foster co-location primarily among firms in skill-related industries.

Keywords: **co-location; coagglomeration; supply chain; labor flow; skill relatedness.**

JEL classifications: D57, J24, O14, R12.

1. Introduction

Geographic proximity facilitates the exchange of tacit knowledge and know-how, making agglomeration a persistent feature of economic geography (Audretsch and Feldman 1996; Gertler 2003). At the same

Received: 24 May 2024. **Accepted:** 21 December 2025

time, dramatic reductions in transportation and coordination costs have enabled global value chains (GVCs) to span across countries and continents (Baldwin and Freeman 2022; Johnson 2018; Crescenzi and Harman 2023). Yet, buyer–supplier transactions still strikingly often take place over short distances (Bernard et al. 2019). This raises a key question: which types of value-chain relationships continue to rely on co-location despite globalization, and which forms of know-how exchange drive continued agglomeration? We propose that an important reason why some value-chain partners seek each other's geographical proximity is not a reduction in transportation costs but the need to exchange significant amounts of tacit knowledge along with their transactions. We evaluate this conjecture by studying the coagglomeration of industries in Hungary, a country that is deeply embedded in GVCs and thus a critical case to help determine when agglomeration still matters, and for which uniquely rich microdata are available that describe firms' workforces as well as their transactions with other firms.

Following Ellison et al. (2010), a growing literature has analyzed agglomeration externalities by studying coagglomeration patterns (Bertinelli and Decrop 2005; Kolko 2010; Gallagher 2013; Helsley and Strange 2014; Howard et al. 2015; Gabe and Abel 2016; Faggio et al. 2017; Aleksandrova et al. 2020). This stream of research aims to address the problem of "Marshallian equivalence" (Duranton and Puga 2004), where different microfoundations for agglomeration in industrial districts lead to the same observable outcome: firms in the same industry tend to co-locate. Studying coagglomeration tackles this issue by leveraging the fact that firms in different industries maintain different types of inter-industry proximities, whereas firms in the same industry are—at least observationally—equally close to each other in terms of (industry-level) labor demands, input–output linkages, and cognitive proximity. One strand of this literature has used the framework to focus on differences in agglomeration forces across sectors—highlighting, for instance, differences between manufacturing and service industries (Diodato et al. 2018; O'Clery et al. 2021)—or across time (Diodato et al. 2018; Steijn et al. 2022).

Our article builds on this literature, adding a number of important innovations. First, coagglomeration studies have so far focused on the *industries* that coagglomerate. In this article, we instead look into heterogeneity at the level of *links between industries*. Second, the three Marshallian agglomeration forces—labor pooling, value-chain linkages, and knowledge spillovers—have so far been treated as if they acted independently from one another. In contrast, we argue that these forces can reinforce one another. Third, instead of just inferring interactions from aggregate, industry-level data, we validate our results using microdata on transactions and job switches in Hungary, offering uniquely detailed insights into value-chain and labor linkages at the firm-to-firm level. Finally, unlike most existing studies, which focus on coagglomeration in the USA, we instead look at coagglomeration in Hungary. Hungary offers an interesting case study, because its economy is much smaller and therewith more exposed to international trade and GVCs. Moreover, as a post-transition economy, it has rapidly transformed its economic structure, giving ample opportunity for recent agglomeration forces to leave their imprint on its economic geography.

Conceptually, we propose that, while firms coagglomerate to facilitate labor pooling and buyer–supplier relations, these two channels do not operate independently. Instead, we expect that Marshallian channels are "superadditive." In particular, we propose that value-chain partners are more likely to coagglomerate if they operate in skill-related (Neffke and Henning, 2013) industries. This proposition builds on two observations. First, much crucial knowledge underpinning a firm's competitive advantage resides in its human capital (Kogut and Zander 1992; Spender and Grant 1996). The greater the degree to which two firms employ workers with similar skills and know-how, the more likely these firms will be able to share knowledge and learn from one another, that is, the more cognitively proximate they will be (Neffke and Henning 2013; Neffke et al. 2017). Second, value-chain partners differ in the extent to which they need to exchange knowledge to be able to use each other's products: whereas some intermediate products can be used off the shelf, others require a clear understanding of how they are produced to effectively use or process them. In such cases, buyers may need to increase the cognitive proximity to their suppliers. Because geographical proximity facilitates the exchange of tacit knowledge—supporting both interfirm learning and coordination (Jaffe et al. 1993; Audretsch and Feldman 1996; Caragliu 2022;

Lee et al. 2022; Květoň et al. 2022)—value-chain interactions are most likely to benefit from co-location if the industries involved use similar (tacit) knowledge or skills, which we approximate by their skill relatedness.

We provide empirical support for this hypothesis, using uniquely detailed administrative datasets from Hungarian public registers. These data cover all companies operating in Hungary, 50 per cent of their employees, as well as value-added tax records for buyer–supplier transactions among them. Building on the literature on coagglomeration, skill relatedness, and production networks, we use these sources to construct measures of coagglomeration, skill relatedness, and input–output connections between detailed industries.

Equipped with these measures, we first show that Ellison et al. (2010)'s finding that value-chain and labor pooling links drive coagglomeration in the USA also holds for Hungary. To do so, we rely on the same instrumental variables approach as these authors, instrumenting skill-relatedness and input–output linkages in Hungary with analogous quantities calculated in other countries. Next, we document a form of superadditivity: input–output connections lead to stronger coagglomeration, but only if industries are also skill related. In contrast, skill-related industries display strong coagglomeration patterns even when they lack value-chain connections. Finally, we corroborate these aggregate findings at the micro-level, using detailed spatial patterns of interfirm ties.

Our study contributes to several strands of the literature. First, it adds to research on industrial coagglomeration (Ellison et al. 2010; Helsley and Strange 2014; Delgado et al. 2016; Faggio et al. 2017; Diodato et al. 2018; Steijn et al. 2022) by uncovering important interactions between coagglomeration forces. Second, we add evidence from Hungary, a small open economy whose reliance on imported inputs (Halpern et al. 2015), the legacy of the planned economy (Brülhart and Koenig 2006), and recent GVC- and foreign direct investment (FDI)-driven upgrading of the industrial structure (Nölke and Vliegenthart 2009; Baldwin and Lopez-Gonzalez 2015; Damijan et al. 2018; Pinheiro et al. 2022) offer a context where global forces profoundly impact local structures, making the country uniquely suited to study the interplay between geography and value chains. Third, the exceptionally rich data for the Hungarian economy allow us to move beyond studying *potential* interactions between firms to examining *actual* interactions, thereby strengthening the microfoundations in this area of research. In so doing, our study forges connections between economic geography and the growing interdisciplinary literature on firm-to-firm production and supply-chain networks. While high-resolution transaction data have recently enabled major advances (Pichler et al. 2023), the geographical dimension of these networks remains understudied, and understanding co-location through detailed firm-to-firm ties is an important research frontier (Duranton and Puga 2020). Fourth, our conceptual framework connects the literature on coagglomeration to discussions on buyer–supplier linkages in regional innovation systems (Cooke and Morgan 1994; Cooke 1996) and GVCs (Johnson 2018; Baldwin and Freeman 2022; Crescenzi and Harman 2023; Boschma 2024). Finally, our study relates to the field of economic complexity analysis (Hidalgo and Hausmann 2009; Hidalgo 2021; Balland et al. 2022) where many product and industry spaces are derived from coagglomeration patterns. By analyzing the drivers of coagglomeration, we shed light on the forces underlying product and industry spaces in this literature.

The article is structured as follows. Section 2 reviews prior literature and derives hypotheses. Section 3 describes the context, data sources, and construction of coagglomeration, skill relatedness, and input–output metrics. Section 4 reports our empirical findings. Section 5 concludes with a discussion of implications, limitations, and open questions.

2. Co-location of industries and firms

2.1 Coagglomeration

A core insight in economic geography is that firms seek each other's proximity to benefit from agglomeration externalities, resulting in an economic landscape characterized by marked spatial clusters of related industries (Delgado et al. 2014). Marshall's (1920) original account of why such industrial districts form pointed to access to specialized suppliers, skilled labor, and knowledge: firms choose to co-locate with their competitors because accessing these resources becomes harder as distances increase. In spite of substantial decreases in the cost of transporting goods, people, and ideas (Glaeser and Kohlhase 2004; Agrawal and Goldfarb 2008; Catalini et al. 2020), geographical clusters of firms are still thought to be core drivers of firms' competitiveness (Porter 1990, 1998).

A large literature in economic geography and urban economics has studied the role of agglomeration externalities in the success of local industries (Glaeser et al. 1992; Henderson et al. 1995; Rosenthal and Strange 2004; Beaudry and Schiffauerova 2009; Caragliu et al. 2016). However, disentangling the relative importance of different agglomeration forces proved hard because they act concurrently, and all three forces lead to the same observable outcome: firms in the same industry will concentrate geographically. A breakthrough was achieved by Ellison et al. (2010), who focused not on the agglomeration patterns of individual industries, but on the coagglomeration patterns of *pairs* of industries that differ in the extent to which they share supplier, skill, or knowledge relations. Doing so allowed the authors to show that agglomeration is best explained by input–output dependencies, but that the other two forces, labor pooling and technological spillovers, play significant roles as well.

The work of Ellison et al. (2010) has sparked an expanding literature on coagglomeration (Bertinelli and Decrop 2005; Kolko 2010; Gallagher 2013; Helsley and Strange 2014; Howard et al. 2015; Mukim 2015; Gabe and Abel 2016; Faggio et al. 2017; Aleksandrova et al. 2020). One strand highlights heterogeneity in coagglomeration forces. For instance, focusing on heterogeneity across time, Diodato et al. (2018) show that, over the course of the 20th century, the relative importance of labor pooling has increased to the point that it has surpassed input–output linkages as the main driver of coagglomeration patterns. Steijn et al. (2022) found a similar decrease in the relative importance of input–output linkages over time, alongside a growing contribution of knowledge spillovers measured through technological relatedness between industries. They attribute these shifts to increasing import penetration, lower transportation costs, and declining routine tasks.

Heterogeneity also appears across economic activities: Diodato et al. (2018) show that the coagglomeration of service industries tends to be more sensitive to labor-sharing opportunities than that of manufacturing industries. Whereas prior work has examined variation across time and sectors, our analysis instead focuses on heterogeneity within agglomeration forces themselves. As we will argue below, Marshallian channels are unlikely to act in isolation and instead will reinforce each other.

2.2 Relatedness and economic complexity analysis

Another body of related work is the literature on economic complexity analysis (Hidalgo et al. 2007; Hidalgo and Hausmann 2009) and, in particular, its adoption in evolutionary economic geography (EEG) (Boschma et al. 2015; Balland and Rigby 2017; Balland et al. 2022; Mewes and Broekel 2022). This literature argues that places develop by accumulating complementary capabilities that together allow economies to engage in complex economic activities (Hidalgo and Hausmann 2009; Hidalgo 2015; Frenken et al. 2023). Because many capabilities are hard to access from outside the region (Neffke et al. 2018; Frenken et al. 2023), economic development often takes the shape of a branching process in which economies expand by diversifying into activities that are closely related to their current activities (Frenken and Boschma 2007; Neffke et al. 2011; Hidalgo et al. 2018).

Empirical work in economic complexity analysis often constructs abstract spaces that connect industries that are "related." These so-called industry spaces are relevant to our analysis in two ways. First, the most widely used industry (or product) spaces are, in fact, based on coagglomeration patterns (Hidalgo et al. 2007; Hidalgo 2021; Li and Neffke 2023). Consequently, there is a direct link between economic complexity analysis and the coagglomeration literature. In this light, the coagglomeration literature can be seen as an effort to understand the underlying factors that are captured in prominent industry spaces.

Second, economic complexity analysis has constructed industry spaces using information other than coagglomeration patterns. A particularly relevant industry space is based on Neffke and Henning's (2013) "revealed skill relatedness." The authors argue that the degree to which two industries require similar skills can be inferred from cross-industry labor flows. In essence, two industries are deemed *skill related* if labor flows between them are significant compared to a benchmark in which workers move randomly among industries. Using job advertisement data, Henning et al. (2025) recently provided additional empirical validation by showing that labor flows are more intensive between jobs (industry–occupation combinations) that have a strong overlap in demanded skills. In all, the flow-based approach is considered an advancement to the measurement of relatedness by basing it on real interactions (Bathelt and Storper 2023).

In the context of Marshallian agglomeration forces, skill-relatedness offers a natural way to determine which industries draw from the same pool of labor, or from the same "skill basin" (O'Clery and Kinsella 2022). Moreover, worker mobility is an important vehicle for knowledge transfer, as evidenced by productivity growth and spillovers following labor flows and coworker networks (Boschma et al. 2009; Eriksson 2011; Lengyel and Eriksson 2017; Eriksson and Lengyel 2019; Csáfordi et al. 2020). Therefore, apart from identifying skill basins, skill-relatedness is also likely to be a good proxy for cognitive proximity between industries.

This is because a firm's knowledge is embedded individually and collectively in its labor force (Nonaka 1994). Skills have served as the quintessential example of tacit knowledge—not only in Polanyi's original work (Polanyi 1966), but also in Nelson and Winter (1982), which was instrumental in introducing the concept of tacit knowledge first to the field of management, and later—through the field of evolutionary economics—to the field of economic geography. Skill-relatedness, as captured in inter-industry labor flows, not only expresses workers' revealed preferences but also their comparative advantage to offer specific types of work. Because codified knowledge can, in principle, be accessed by anyone, it cannot make individuals stand out on the labor market. Additionally, codified knowledge often has tacit counterparts that enable workers or firms to leverage this knowledge. For instance, engineers understand how to use equations codified in physics textbooks in their work, and this understanding is not easily transferred to others. However, this is conceptually distinct from the pure codified knowledge itself.

2.3 Value chains and knowledge transfer

The importance of local interactions and the cluster literature's emphasis on localized buyer–supplier networks would, *prima facie*, seem at odds with the rapid growth of GVCs over the past decades (Gereffi et al. 2005; Johnson 2018; Baldwin and Freeman 2022). That is, the existence of GVCs suggests that improvements in transportation and communication technologies have allowed coordinating buyer–supplier interactions over long distances. However, this does not hold true for all parts of GVCs: while the production and assembly activities at the middle of the value chain have become geographically mobile, high value-added activities at both ends of the so-called smile curve (Baldwin and Ito 2021), like R&D and design, or marketing and associated services, exhibit substantial spatial (co-)concentration (Mudambi 2008).

One of the characteristics that these spatially sticky elements of GVCs share is their reliance on tacit knowledge. Because tacit knowledge is so hard to transmit over long distances (Jaffe et al. 1993; Audretsch and Feldman 1996), buyer–supplier relations that embed much tacit knowledge will benefit from geographical proximity. This point is well-established in the literature on regional innovation systems (e.g., Cooke and Morgan 1994). Even though the degree of substitutability between geographical and relational proximities remains an open question in general (Boschma 2005; Caragliu 2022; Lee et al. 2022; Květoň et al. 2022), studies highlight situations in which innovation needs to be coordinated along the value chain (Azadegan and Dooley 2010), impelling suppliers to work with their customers to integrate new technologies or to help improve end products. Such interactions require knowledge transfers and learning processes that are facilitated by geographical proximity (Cooke 1996). In other instances, intermediate goods can be used without much knowledge of how they are made, which arguably allows for more spatial separation between value chain partners. While buyer–supplier relationships thus vary widely in the extent to which they need to embed—often highly tacit—knowledge, this heterogeneity has not been explicitly considered in the literature on coagglomeration.

2.4 Main hypothesis

Based on these different bodies of research, we expect the superadditivity of Marshallian agglomeration forces—that is, different channels of agglomeration reinforce each other. In particular, not all buyer–supplier linkages require spatial proximity. Instead, we hypothesize that buyer–supplier linkages will only require that firms co-locate if the transactions also involve transferring (tacit) knowledge. Furthermore, we expect that industries that can exchange workers often rely on similar bodies of codified knowledge, as well as the tacit expertise that allows workers to access and use this codified knowledge. As a consequence, measures that assess the potential for labor pooling, such as labor flow-based skill relatedness, often also shed light on the degree to which industries operate in technologically similar environments.

Taken together, these arguments lead to the main hypothesis in this article: *the effect of input–output connections on industries' coagglomeration is stronger when those industries also exhibit a high level of skill-relatedness*. We test this hypothesis in the context of industrial coagglomeration in Hungary by first adopting the approach proposed by Ellison et al. (2010), and then studying how input–output and skill-relatedness interact at the aggregate level of industry pairs, as well as at the microlevel of firm-to-firm transactions.

3. Empirical setting

3.1 Context and background

Hungary is a small, open economy in central Europe that, like most countries in the wider Central and Eastern European (CEE) region, experienced substantial economic restructuring due to the inflow of FDI after the fall of the Iron Curtain in 1989. At the end of the 1990s, the country's spatial economic structure—similar to that of other CEE economies—still differed from Western market economies. As a remnant from the planned economy, capital cities play an outsize role in the high-wage segment of the labor market and as hosts of service industries. In contrast, manufacturing industries are significantly less concentrated in these capitals (Brülhart and Koenig 2006). From the 2000s on, the Hungarian economy upgraded its productive structure significantly, diversifying into complex manufacturing activities (Pinheiro et al. 2022). This transformation was to a large extent driven by foreign-owned firms, which introduced activities that were relatively unrelated to pre-existing regional specializations, especially outside established manufacturing regions (Elekes et al. 2019).

These developments have also embedded Hungary deeply into GVCs that have brought capital, new technologies, and high-pay jobs (Halpern and Muraközy 2007; Inzelt 2008). This has turned the economy into a dependent market economy in which regional economies function as assembly platforms, especially in the high-tech manufacturing industries favored by FDI (Nölke and Vliegenthart 2009; Damijan et al. 2018). As a result, nowadays, about 40 per cent of inputs in Hungary are imported (Braun et al. 2021), and even exporting firms rely heavily on such imports (Halpern et al. 2015). Like other specialized and open economies that participate in GVCs, Hungary has a few dominant sectors with specialized transaction flows (Kiss et al. 2025). The strongest GVC connections are to the nearby German car manufacturing industry and its supplier networks (Baldwin and Lopez-Gonzalez 2015; Amador and Cabral 2017), betraying the important role that geographical proximity plays in shaping international production linkages in the CEE area (Pavlinek et al. 2009).

Another consequence of these developments is a substantial productivity and performance gap between exporting and nonexporting firms, and between foreign-owned and domestic firms. These gaps offer ample opportunity for spillovers and inter-firm learning—key agglomeration forces—to emerge. Prior research has shown that such spillovers often materialize through labor flows (Csáfordi et al. 2020) and along value chains (Halpern and Muraközy 2007), with the latter's intensity decreasing with geographic distance. Furthermore, firms engaged in trade have been shown to be more productive and agglomerate more strongly within Hungarian regions (Békés and Harasztosi 2013), and firms that operate on international markets or are foreign-owned are generally more productive than domestic or nontrading firms (Békés et al. 2009).

Together, these elements—the heterogeneity in firm productivity, the existence of localized spillovers, Hungary's diverse economic structure consisting of industries with varying knowledge intensity, and the pronounced role of specialized local and international value chains—make Hungary a highly relevant testing ground for our main hypothesis on the interaction between Marshallian agglomeration forces. Moreover, access to highly relevant microlevel data for Hungary allows us to directly observe value-chain connections between firms instead of inferring the existence of such connections from co-location patterns (Javorcik 2004; Halpern and Muraközy 2007; Békés et al. 2009).

3.2 Measuring the coagglomeration of industries

Our empirical work relies first on a firm-level dataset, made available by the Hungarian Central Statistical Office (HCSO) through the Databank of the ELTE Centre for Economic and Regional Studies[1] (ELTE CERS Databank). It contains information from the balance sheets of companies doing business in Hungary. The data include the location of the company seats (headquarters) at the municipal level, the main activity of the firms as four-digit NACE codes (Statistical Classification of Economic Activities in the European Community, NACE Rev. 2 classification), the number of employees, and further balance sheet indicators. We focus on 2017 as this is the year for which all of the datasets used provide information. A detailed description of the firm-level data and the distribution of employment and firms across regions and industries can be found in section 1 of the Supplementary Material.

To measure the degree to which firms from different industries tend to co-locate, we focus on companies with at least two employees and aggregate the firm-level employment data to an industry–region matrix. We use this matrix to quantify the tendency of industry i to coagglomerate with industry j, using the following metric proposed by Ellison et al. (2010):

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

where $s_{ir} = E_{ir}/E_r$ is the employment share of industry i in region r (omitted indices indicate summations such as $E_r = \sum_{i=1}^{I} E_{ir}$), while x_r is the mean of these shares in region r across all industries. Ellison and Glaeser (1997, 1999) show that this index quantifies the likelihood that firms in industries i and j generate spillovers for each other in a simple location choice model. The index is widely adopted and used as a benchmark (see e.g., Diodato et al. 2018; Juhász et al. 2021; Steijn et al. 2022), as it is largely independent of the distribution of firm sizes in industries and the granularity of spatial units. We calculate this index for both NUTS3 and NUTS4 regions in Hungary for all pairs of three-digit industries and hereafter refer to it as *EGK coagglomeration*.

As an alternative, inspired by the measures of Porter (2003), we use the correlation of revealed comparative advantage (*RCA*, identical to the location quotient) vectors to quantify the coagglomeration of

1. Databank of ELTE Centre for Economic and Regional Studies, https://adatbank.krtk.mta.hu/en/

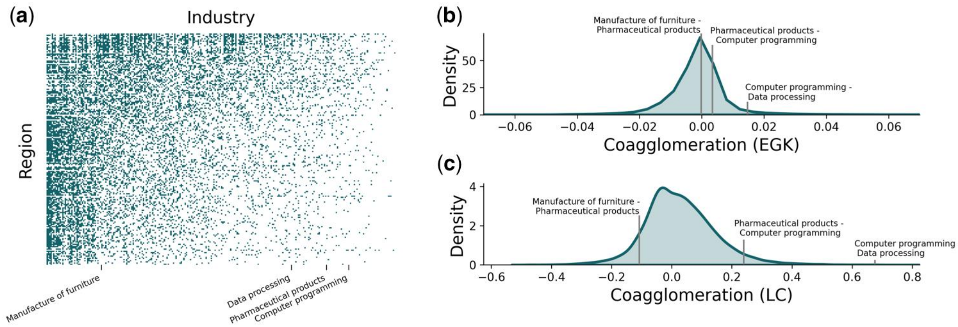

Figure 1. Constructing coagglomeration measures from a region–industry employment matrix. (a) Region–industry matrix based on NUTS3 regions and three-digit NACE codes. (b) The distribution of EGK coagglomeration values. For this illustration, the tail of the distribution with extreme values was cutoff. The unedited figure can be found in section 2 of the Supplementary Material. (c) The distribution of LC coagglomeration values.

industry pairs. This indicator, which we refer to in the following as *LC coagglomeration*, is calculated as follows. First, we calculate the *RCA* of industries in regions:

$$RCA_{ir} = (E_{ir}/E_r)/(E_i/E) \tag{2}$$

A region is specialized in an industry when its *RCA* value is above or equal to 1. Next, we use the *RCA* values to create a binary specialization matrix M_{ir}:

$$M_{ir} = \begin{cases} 1 & \text{if} \quad RCA_{ir} \geq 1 \\ 0 & \text{if} \quad RCA_{ir} < 1 \end{cases} \tag{3}$$

Finally, we calculate the LC coagglomeration of two industries as the correlation between industries' specialization vectors:

$$LC_{ij} = corr(m_i, m_j), \tag{4}$$

where m_i and m_j are column vectors of matrix M that describe the spatial distributions of industries i and j.

We calculate this index on the basis of both NUTS3 and NUTS4 regions in Hungary for all pairs of three-digit industries. The above specifications are two prominent ones among the many ways to calculate coagglomeration indicators (Li and Neffke, 2023). Figure 1 plots distributions of these indicators and visualizes the region–industry matrix from which they are derived. In section 2 of the Supplementary Material we provide detailed descriptive statistics on both variables and compare them to commonly used alternatives.

3.3 Skill relatedness

Previous studies established a number of approaches to capture the extent to which two industries can draw from the same labor pool, including comparing the occupational composition of industries (e.g., Ellison et al. 2010; Diodato et al. 2018), and measuring significant labor flows between them (e.g., Neffke and Henning 2013; Neffke et al. 2017). In this study, we opt for the latter approach, where the central assumption is that workers tend to switch jobs between industries across which they can transfer most of their skills and human capital.

To do so, we rely on a Hungarian matched employer–employee dataset managed by the ELTE CERS Databank. This longitudinal dataset contains the work history of a randomly selected 50 per cent of the total population on a monthly basis between 2003 and 2017. It links data from different registers, including the Pension Directorate, the Tax Office, the Health Insurance Fund, the Office of Education, and the Public Employment Service, thereby providing comprehensive information on workers and their employers. Unique and anonymized identifiers for both individuals and firms allow us to track the transition of individuals between firms. We use all observed employment spells for each individual in the dataset to establish employee transitions from one firm to the next. In cases when an individual had multiple parallel employment spells before switching, we consider labor-flow ties to be created between the new employer and each of the previous employers. This information on monthly labor flows between firms is then pooled across 2015–2017.

To measure the skill relatedness of industry pairs, we aggregate firm-to-firm labor flows to the industry–industry level. Following the approach of Neffke and Henning (2013) and Neffke et al. (2017), the skill relatedness between two three-digit industries (NACE Rev. 2 classification) (i and j) is measured by comparing the observed labor flow between them (F_{ij}) with what would be expected based on their propensity to take part in labor flows ($(F_iF_j)/F$).

$$SR_{ij} = \frac{F_{ij}}{(F_iF_j)/F} \tag{5}$$

Here, F_i is the total outflow of workers from industry i, F_j is the total inflow to j and F is the total flow of workers in the system. Next, we take the average of SR_{ij} and SR_{ji} to obtain a symmetric measure. Finally, due to the asymmetric range of the measure ($[0, \infty)$), we normalize it between -1 and $+1$ ($\tilde{SR}_{ij} = \frac{SR_{ij}-1}{SR_{ij}+1}$) (see Neffke et al. 2017). As a result, positive values of the final skill relatedness measure correspond to larger-than-expected labor flows. Further details can be found in section 2 of the Supplementary Material.

3.4 Input–output relations

To assess the input–output similarity of industries, we rely on two different types of datasets. First, we rely on data from the World Input–Output Database (WIOD). Using the input–output table for Hungary (Timmer et al. 2015) for 2014, we obtain directed buyer–supplier relations between two-digit industries.

Using WIOD tables makes our analysis comparable to previous studies, which have also relied on aggregate input–output tables (Ellison et al. 2010; Diodato et al. 2018). However, these country-level aggregates may hide many important details. Therefore, we use a second, microlevel dataset that records business transactions between companies in Hungary. These data are derived from the value-added tax (VAT) reports collected by the National Tax and Customs Administration of Hungary. Firms are obligated to declare all business transactions in Hungary if the VAT content of their operations exceeds ca. 10,000 EUR in that year. The dataset is anonymized and available for research purposes through the ELTE CERS Databank. It has been used to construct interfirm supplier networks to study production processes, systemic risks, and interdependencies between companies at the national scale (Diem et al. 2022; Pichler et al. 2023; Lőrincz et al. 2024).

We aggregate firm-to-firm supplier transaction values between 2015 and 2017 at the level of pairs of three-digit industries to derive a dataset that is similar in structure to the IO tables in the WIOD data. However, we will also use the microdata themselves to analyze co-location at the firm level.

To construct an indicator that captures the strength of value-chain linkages between two industries, we follow the same approach as for skill relatedness in Equation (5):

$$IO_{ij} = \frac{V_{ij}}{(V_iV_j)/V} \tag{6}$$

Table 1. Descriptive statistics.

Variable	Mean	Std. dev.	Min	Max
Coagglomeration (EGK) NUTS3	−0.001	0.077	−0.319	0.966
Coagglomeration (LC) NUTS3	0.031	0.282	−1.000	1.000
Coagglomeration (EGK) NUTS4	−0.001	0.017	−0.071	0.762
Coagglomeration (LC) NUTS4	0.029	0.119	−0.488	0.807
Labor (SR)	−0.432	0.495	−1.000	0.999
IO (WIOD)	−0.520	0.449	−1.000	0.857
IO (transactions)	−0.691	0.447	−1.000	0.999

Note: Statistics for all variables are calculated from 35,778 observations.

where V_{ij} stands for the total value of goods and services that industry i supplies to industry j and omitted indices indicate summations over the corresponding dimensions. As before, the ratio compares observed flows to expected flows. We once again symmetrize the index, taking the average of IO_{ij} and IO_{ji}, and then use the same rescaling as for skill relatedness to map all values between −1 and +1. We denote the result as $\tilde{IO}_{ij}$.

We calculate this index at the two-digit level using WIOD data (*IO (WIOD)*) and at the three-digit level using the aggregated transaction values from the VAT records (*IO (transactions)*). Basic descriptive statistics for both measures are provided in Table 1. More detailed statistics can be found in section 2 of the Supplementary Material.

4. Results

4.1 Drivers of coagglomeration in Hungary

We start our analysis with a replication of the findings of Ellison et al. (2010) for Hungary. Following Diodato et al. (2018), we focus our main analysis on the labor pooling and input–output channels. Results for knowledge spillovers through patent citation data are presented in section 3 of the Supplementary Material. To assess the relative importance of either channel as a driver of coagglomeration patterns, we estimate the following baseline equation, using Ordinary Least Squares (OLS) regression:

$$Coagglomeration_{ij} = \beta_0 + \beta_1 \tilde{SR}_{ij} + \beta_2 \tilde{IO}_{ij} + \varepsilon_{ij} \tag{7}$$

where $\tilde{SR}_{ij}$ and $\tilde{IO}_{ij}$ refer to the skill relatedness and input–output dependency measures defined in sections 3.3 and 3.4. The dependent variable, $Coagglomeration_{ij}$, is either the EGK or the LC coagglomeration index described in Section 3.2.

Unlike Ellison et al. (2010), who only consider manufacturing industries, and Diodato et al. (2018), who compare manufacturing and service industries, our analysis includes all sectors of the economy. Moreover, we run our analysis twice, where the coagglomeration of industries is either measured within NUTS3 regions or within NUTS4 regions. In Hungary, the NUTS4 level is close to a functional, local labor market, while the NUTS3 level is primarily an administrative category (for details on the difference of these spatial units, see section 1 of the Supplementary Material). Our preferred specifications use NUTS4 regions, where Budapest, the capital of Hungary, is divided into twenty-three microregions.

Table 2 presents the OLS regression results. To facilitate the interpretation of the effect sizes, we rescale all variables such that they are expressed in units of standard deviations. This rescaling is applied to all subsequent analyses. Results are qualitatively in line with those in Ellison et al. (2010) and Diodato et al. (2018): also in Hungary, both Marshallian channels are significant drivers of coagglomeration. Moreover, labor pooling seems to play a more important role than input–output connections. The

Table 2. OLS multivariate regressions.

	Coagglomeration (EGK)				Coagglomeration (LC)			
	NUTS3 (1)	NUTS4 (2)	NUTS3 (3)	NUTS4 (4)	NUTS3 (5)	NUTS4 (6)	NUTS3 (7)	NUTS4 (8)
Labor (SR)	0.096***	0.061***	0.084***	0.057***	0.142***	0.175***	0.106***	0.126***
	(0.019)	(0.012)	(0.020)	(0.012)	(0.018)	(0.024)	(0.016)	(0.020)
IO (WIOD)	0.056***	0.041***			0.064***	0.089***		
	(0.018)	(0.011)			(0.021)	(0.022)		
IO (transactions)			0.050**	0.026*			0.112***	0.153***
			(0.025)	(0.015)			(0.018)	(0.020)
Observations	35,778	35,778	35,778	35,778	35,778	35,778	35,778	35,778
R^2	0.014	0.006	0.013	0.005	0.027	0.043	0.033	0.055
Adjusted R^2	0.014	0.006	0.013	0.005	0.027	0.043	0.033	0.055

Note: Clustered (industry$_i$ and industry$_j$) standard errors in parentheses. Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3. Labor channel through instrumental variable univariate regressions.

	Coagglomeration (EGK)		Coagglomeration (LC)	
	NUTS3 (1)	NUTS4 (2)	NUTS3 (3)	NUTS4 (4)
Labor (SR)	0.403***	0.285***	0.417***	0.575***
	(0.074)	(0.045)	(0.066)	(0.083)
Observations	35,778	35,778	35,778	35,778
R^2	−0.078	−0.043	−0.048	−0.114
Adjusted R^2	−0.078	−0.043	−0.048	−0.114
KP F-statistic	115.955	115.955	115.955	115.955

Note: Clustered (industry$_i$ and industry$_j$) standard errors in parentheses. Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

exception to this is when we measure coagglomeration using locational correlations and input–output linkages based on actual firm-to-firm transactions. In this case, labor pooling and value chain connections contribute about equally to the coaglomeration patterns we observe.

Ellison et al. (2010) raise the concern that coagglomeration patterns may not only be a consequence of labor pooling and value-chain linkages, but also cause these linkages themselves. For instance, industries may use similar labor because they are co-located, not vice versa. Similarly, industries may preferentially use inputs that are available nearby and adjust their production technologies accordingly, instead of value-chain links causing firms to coagglomerate.[2] To address this, the authors instrument the different

2. As an example, Ellison et al. (2010) point to the trade between shoe manufacturers and leather producers. The volume of this trade may reflect more than just the inherent technological features of shoe manufacturing: shoes can be made out of several materials, including leather, but also plastics. The choice of leather as an input to shoe-making may therefore be a consequence of an idiosyncratic historical co-location of leather producers with shoe producers. Similarly, shoe manufacturers may have hired workers, not only considering their suitability for shoe-making, but also according to their availability on the local labor market. In the longer run, shoe makers may have adjusted their production processes to make better use of these locally available workers. This would once again lead to some reverse causation between the linkages between industries and their coagglomeration patterns.

Table 4. Input–output channel through instrumental variable univariate regressions.

	Coagglomeration (EGK)				Coagglomeration (LC)			
	NUTS3 (1)	NUTS4 (2)	NUTS3 (3)	NUTS4 (4)	NUTS3 (5)	NUTS4 (6)	NUTS3 (7)	NUTS4 (8)
IO (WIOD)	0.083***	0.054***			0.083***	0.106***		
	(0.020)	(0.012)			(0.023)	(0.023)		
IO (transactions)			0.475***	0.310***			0.479***	0.609***
			(0.129)	(0.078)			(0.128)	(0.141)
Observations	35,778	35,778	35,778	35,778	35,778	35,778	35,778	35,778
R^2	0.005	0.002	−0.146	−0.066	0.007	0.013	−0.081	−0.122
Adjusted R^2	0.005	0.002	−0.146	−0.066	0.007	0.013	−0.081	−0.122
KP F-statistic	12,000	12,000	38.276	38.276	12,000	12,000	38.276	38.276

Note: Clustered (industry$_i$ and industry$_j$) standard errors in parentheses. Significance codes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

types of linkages between industries with analogous quantities calculated from data for economies of countries other than the USA.

In Tables 3 and 4, we follow the same identification strategy. To instrument our labor market pooling variable, we construct a skill-relatedness measure between three-digit industries using data from the Swedish labor market. To instrument value chain linkages, we average all input–output tables in the WIOD data, excluding the Hungarian tables. Detailed descriptions of the instruments can be found in section 2 of the Supplementary Material. Our instruments are valid, as long as idiosyncratic patterns in the input–output and labor dependencies outside Hungary are exogenous to coagglomeration patterns inside Hungary. As in Ellison et al. (2010), we run univariate analyses, testing for the causal effect of each channel separately. For comparison, (univariate) OLS regressions are provided in section 4 of the Supplementary Material, while we present the first and second stages of instrumental variable estimations separately in Section 5.

Our results corroborate the OLS analysis of Table 2: both channels have a large and causal effect on coagglomeration patterns in Hungary. Moreover, the labor pooling channel has a stronger causal effect than input–output relations, unless we measure the input–output relations using microlevel transaction data. In the latter case, labor pooling and value chains represent about equally strong coagglomeration forces.

These results strengthen the external validity of the literature on coagglomeration, which has mostly focused on the US economy. The generalizability of those results to Hungary is not trivial: the Hungarian economy is much smaller than the US economy. This not only affects the amount of spatial variation that is available for our estimations, but also the degree to which firms can rely on domestic value chains.

In the Supplementary Material, we show multiple robustness checks of these results. In section 6 of the Supplementary Material, we present results derived with alternative instruments for input–output connections, such as US supply tables or the WIOD table for the Czech Republic only. Section 7 of the Supplementary Material presents the above OLS and IV regressions separately for manufacturing and service industries. In section 8, we divide the sample into knowledge-intensive services (KIS) and all other industries, following the OECD definition. In section 9, we apply geographical restrictions and exclude firms located in Budapest from our sample. Furthermore, because some firms may maintain establishments in multiple locations, we re-run our main models using only single-establishment firms. Our main results remained in place for all but a few of the listed combinations of spatial scale and measurement of coagglomeration. Finally, in section 10 of the Supplementary Material, we try estimating multivariate IV regressions, where both agglomeration forces enter the regression simultaneously. However, the Kleibergen–Paap statistic for these analyses indicates that these models typically suffer from weak instruments. That is, there is insufficient variation available in our data to reliably disentangle the causal effects of labor pooling and value-chain linkages within the same model.

4.2 Interaction effects

The main conjecture of this article is that value-chain connections only constrain location decisions if value-chain partners exchange not only goods or services but also (tacit) knowledge. As an illustration, pharmaceutical manufacturing (NACE 211), featured in Fig. 1, is strongly connected to the production of grain mills and starch products (NACE 106) through significant buyer–supplier relationships ($\tilde{IO}_{ij} > 0$). This reflects the use of starches and flours as common inactive ingredients (excipients) in drug manufacturing. However, from a knowledge and technological perspective, pharmaceutical and grain mill production are quite distinct. We would therefore not expect high labor mobility between them or a strong rationale for co-location. Indeed, these two industries tend not to coagglomerate, nor are they skill related ($\tilde{SR}_{ij} < 0$). In contrast, pharmaceutical production tends to coagglomerate with industries such as computer programming (NACE 620), which appears in Fig. 1, and research and experimental development in the natural sciences (NACE 721). These sectors are more similar to pharma in terms of knowledge intensity and required know-how. In addition to coagglomeration, they are also skill-related and exhibit significant input–output linkages (both $\tilde{SR}_{ij} > 0$ and $\tilde{IO}_{ij} > 0$). To examine the degree to which skill relatedness and value-chain linkages reinforce one another as drivers of industrial coagglomeration, we interact the metrics for these two Marshallian channels in the following model:

$$Coagglomeration_{ij} = \beta_0 + \beta_1 \tilde{SR}_{ij} + \beta_2 \tilde{IO}_{ij} + \beta_{12} \tilde{IO}_{ij} \tilde{SR}_{ij} + \eta_i + \delta_j + \varepsilon_{ij} \qquad (8)$$

Because our instruments proved too weak to estimate multivariate models, these models are estimated using OLS regressions. To nevertheless minimize confounding, we add two-way industry fixed effects, denoted by η_i and δ_j.

Table 5 shows results for our preferred specification based on coagglomeration in NUTS4 regions. The interaction effects are positive in all specifications, corroborating our hypothesis that labor pooling and value-chain effects reinforce each other.

Figure 2 visualizes the implied effects of labor pooling for different values of input–output linkages in panels a, c, e, and g. Along the vertical axis, these graphs plot the effect of labor pooling on coagglomeration ($\beta_1 + \beta_{12} \tilde{IO}_{ij}$) for varying levels of value-chain connections between industries i and j ($\tilde{IO}_{ij}$). Note that the range of the horizontal axis is limited to the values that $\tilde{IO}_{ij}$ can theoretically attain. These panels show that labor pooling effects are positive and significant at any level of value-chain linkages.

This contrasts with the effect of value-chain linkages ($\beta_2 + \beta_{12} \tilde{SR}_{ij}$) shown in panels b, d, f, and h. The value chain effect is, in general, positive, but drops to zero when skill relatedness between industries equals −1, which happens in 35 per cent of all industry combinations. In other words, value chain partners only tend to significantly coagglomerate if they are not completely unrelated in terms of the skills of their workforces.

These results hold regardless of whether we use the EGK or LC measures of coagglomeration and whether we measure value-chain linkages using WIOD data or derive them from microlevel transaction data. In section 3 of the Supplementary Material, we also present results that control for knowledge spillovers between industries using patent citation data. These models leave our main findings unchanged. Moreover, in section 11 of the Supplementary Material, we demonstrate the robustness of our findings by estimating interaction effects using various alternative regression specifications.

4.3 Firm-to-firm ties behind coagglomeration

Our data allow us to analyze not only the potential connections between industries that have been the object of study in the coagglomeration literature thus far but also the actual connections between firms,

Table 5. OLS multivariate regressions with interaction effects.

	Coagglomeration (EGK)				Coagglomeration (LC)			
	NUTS4 (1)	NUTS4 (2)	NUTS4 (3)	NUTS4 (4)	NUTS4 (5)	NUTS4 (6)	NUTS4 (7)	NUTS4 (8)
Labor (SR)	0.059*** (0.012)	0.052*** (0.013)	0.057*** (0.011)	0.051*** (0.013)	0.173*** (0.024)	0.164*** (0.016)	0.126*** (0.020)	0.138*** (0.013)
IO (WIOD)	0.037*** (0.011)	0.059*** (0.018)			0.084*** (0.022)	0.057*** (0.020)		
IO (WIOD)*Labor	0.023*** (0.008)	0.016** (0.008)			0.034** (0.015)	0.033*** (0.010)		
IO (trans)			0.012 (0.017)	0.018* (0.011)			0.119*** (0.021)	0.085*** (0.013)
IO (trans)*Labor			0.025*** (0.010)	0.019** (0.009)			0.065*** (0.013)	0.051*** (0.008)
Two-way FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	35,778	35,778	35,778	35,778	35,778	35,778	35,778	35,778
R^2	0.007	0.072	0.006	0.072	0.045	0.317	0.060	0.325
Adjusted R^2	0.007	0.058	0.006	0.058	0.045	0.307	0.060	0.315

Note: Clustered (industry$_i$ and industry$_j$) standard errors in parentheses. Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

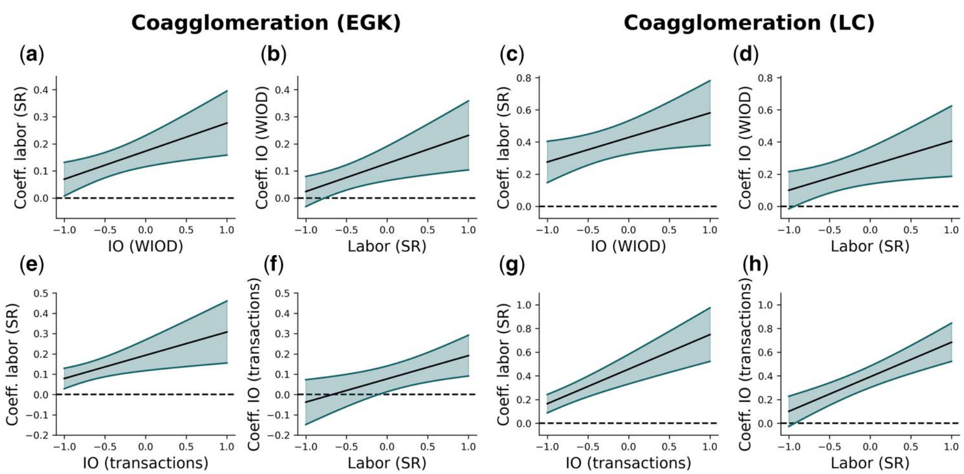

Figure 2. Reinforcing effect of input-output connections and skill relatedness links on coagglomeration. (a) The influence of SR on Coagglomeration (EGK) at different levels of IO (WIOD) connections. (b) The influence of IO (WIOD) connections on Coagglomeration (EGK) at different levels of SR. (c) The influence of SR on Coagglomeration (LC) at different levels of IO (WIOD) connections. (d) The influence of IO (WIOD) connections on Coagglomeration (LC) at different levels of SR. (e)–(h) are based on the same model specifications as in the upper row, but IO connections are measured through the transaction data. Visualizations are based on Table 5, Models (1), (3), (5), and (7). However, the IO and SR variables are presented in their original scales (not standardized) for easier interpretation. Shaded areas depict 95% confidence intervals.

both in terms of transactions and labor flows. This allows us to create networks of firms that are connected either if they supply (or purchase) goods or services, or if workers move from one firm to the other. To simplify the analysis, we consider ties as undirected and unweighted in both networks.

Table 6. Descriptive statistics of the labor flow and supplier networks.

	IO	Labor	IO and labor
Firms connected	72,445	115,519	16,719
Edges	194,231	492,818	14,209
Average degree	5.362	8.534	1.700
Transitivity	0.013	0.027	0.048
Average distance of ties (km)	68	58	40
Share of edges inside NUTS3	41%	48%	63%
Share of edges inside NUTS4	14%	20%	41%
Share of edges inside Budapest	22%	21%	25%

Note: Edges are undirected and unweighted ties that represent any supply or labor exchange between two companies.

Table 6 provides a general description of these networks for the period 2015–2017. Overall, the input–output network has a lower number of connections, which may in part reflect VAT reporting thresholds (Pichler et al. 2023). In addition, it is less transitive than the labor flow network, which is consistent with previous findings that show that production networks have fewer closed triangles than other social networks (Mattsson et al. 2021). When it comes to geography, the descriptive statistics of Table 6 suggest that labor flows are more spatially concentrated than transaction flows. While 48 per cent of the observed labor flows between firms take place within the same NUTS3 region, only 41 per cent of the transaction linkages are intra-regional. Finally, overlapping connections, that is, pairs of firms that exchange both workers and goods or services are rare but highly concentrated geographically.

Figure 3 complements our findings at the level of coagglomerating industries by adding results at the level co-locating firms. Panel a compares the average skill relatedness in pairs of industries that maintain a significant input–output connection between value-chain linked industries that coagglomerate and those that are not. In line with the findings of our interaction models, skill relatedness is significantly higher for value-chain partners that coagglomerate than for those that do not. Figure 3b–d repeats this analysis, but now at the level of pairs of firms that trade with one another. Across all spatial scales we considered, co-located trading partners exhibit significantly higher skill relatedness than distant trading partners ($p < 0.01$ for all comparisons).

Figure 3e further analyzes how the probability of interfirm ties decays with the distance between firms. It plots the likelihood that two firms in Hungary are connected through labor flows, transactions, or both for different distance bins. In line with Bernard et al. (2019), we find that input–output connections are highly concentrated in space. However, labor flow connections are even more sensitive to distance. Within a distance of 10 km, the probability of a labor flow between two firms decreases faster than that of input–output relationships.

The third line shows the likelihood that two firms are connected in both the labor and the IO network. Note that the figure is plotted using logarithmic axes. Consequently, if the probabilities of being connected in either network were independent, the resulting line should equal the sum of the labor and the IO plots.[3] However, the Overlap line—between –8 and –5 log points—lies far above this sum. This means that whenever two firms maintain one type of connection, they are disproportionally likely to also maintain the other connection. Moreover, in line with our finding that labor pooling and value-chain linkages reinforce each other's impact on coagglomeration, the Overlap line exhibits by far the steepest distance-sensitivity, decaying much more rapidly than any of the other lines.

3. In a log-transformation, multiplications become additions: $\log p_{io} p_{sr} = \log p_{io} + \log p_{sr}$, where p_{io} and p_{sr} are the probabilities that two firms are connected through transactions or labor flows, respectively. Note that the exponents on this axis are all negative, such that the sum would be of the order of -10 log points.

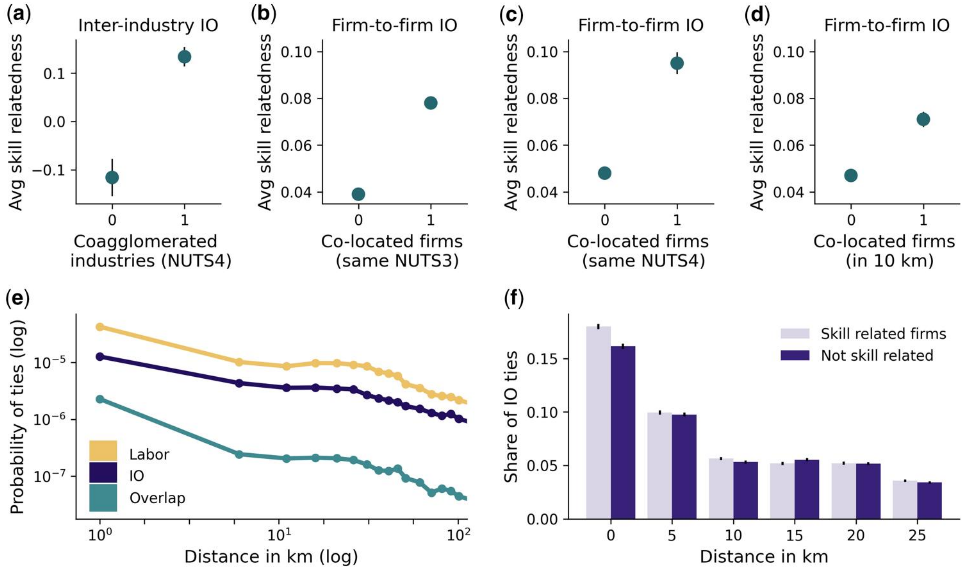

Figure 3. Skill relatedness and co-location of input–output (IO) connections. (a) Average skill-relatedness (SR) of significant industry pairs that maintain substantial input–output connections (i.e., IO_ij > 0) for coagglomerated and not coagglomerated industries (Coagglomeration (LC) values > 0 or not). (b) Average skill-relatedness (SR) in pairs of firms that trade with one another for co-located (same NUTS3 region) and not co-located firms. (c) Same comparison of average skill relatedness for trading ties inside NUTS4 regions and (d) within a distance of 10 km. The differences between all compared averages are statistically significant. (e) Probability of labor flow, input–output connections, and combined (labor and input–output) ties by distance. (f) Share of IO connections between firms in skill-related and not skill-related industries within a distance of 25 km. The figures are based on the sample of firms used in the construction of our inter-industry aggregates. Vertical black lines in all figures indicate 95% confidence intervals.

Finally, Fig. 3f shows how the share of a firm's transaction ties occurs at each given distance band. Focusing on distances up to 25 km, the figure shows that firm-to-firm transaction ties are more likely to be highly localized if firms belong to skill-related industries than if they do not. We interpret this as an indication that suppliers are more likely to co-locate with their buyers (or vice versa) if they operate in industries with high cognitive proximity.

5. Conclusion

This article shows that Marshallian channels of agglomeration reinforce one another. We document a form of superadditivity: consistent with the hypothesis we formulate in this paper, value-chain links lead to stronger coagglomeration only when they coincide with high skill relatedness between industries. In fact, where industries only share a value-chain connection but are not skill related at all, we do not find any evidence that these industries statistically significantly co-locate. Using detailed firm-level microdata, we validate this interaction at both the industry and the firm levels. Our findings indicate that the spatial organization of production is better understood by examining labor flows and buyer–supplier relations jointly instead of as isolated channels.

We revisit the broader question of why buyer–supplier transactions still often take place in close geographic proximity despite the globalization of value chains. Our results suggest that co-location matters when value-chain partners need to exchange not just goods but also know-how. In such cases, spatial closeness facilitates the transfer and coordination of tacit knowledge, strengthening both Marshallian forces. Given that transportation costs are small in many industries today, value-chain links alone rarely justify coagglomeration, unless interactions embed substantial tacit knowledge.

We tested this mechanism by analyzing the drivers of industrial coagglomeration in Hungary. The country offers a particularly interesting setting for studying agglomeration forces. Its economy has undergone a profound structural transformation through integration into GVCs, a process in which global forces have strongly reshaped local economic structures (Pavlinek et al. 2009; Elekes et al. 2019). Moreover, Hungary offers access to detailed datasets from public registers that allow us to complement the traditional coagglomeration framework with a detailed analysis of microlevel firm-to-firm networks.

Our findings contribute to the growing literature on coagglomeration in several ways. First, whereas prior work has explored various sources of heterogeneity at the level of industries themselves, it has so far neglected heterogeneity at the level of the linkages between industries. This has left underexplored the question of whether and when different Marshallian agglomeration channels reinforce one another. Our main finding highlights the importance of such link-level heterogeneity by demonstrating the superadditivity of Marshallian channels of coagglomeration. This finding is highly robust, remaining unaltered when excluding the capital region of Budapest or when considering manufacturing and service sectors separately.

Second, by replicating the empirical findings of Ellison et al. (2010), we show that many of the main findings in the coagglomeration literature extend well beyond the US context and also apply to the rapidly changing economy of countries transitioning from planned to market economies. Specifically, using instrumental variables estimation, we replicate the causal effects of input–output linkages and labor pooling on industrial coagglomeration in Hungary's small and open economy where, unlike in the USA, many inputs need to be imported (Halpern et al. 2015), hindering the formation of long domestic supply chains. Moreover, in line with Diodato et al. (2018) and Steijn et al. (2022), we find that the impact of labor pooling exceeds the impact of value-chain linkages. The Hungarian case thus illustrates how local interactions underpin industrial agglomeration even in economies that underwent substantial structural change and are now deeply embedded in GVCs.

Our analysis furthermore indicates that, although supply-chain connections are a driver of co-location in Hungary, this effect arises less from spatial proximity easing the movement of material inputs than from easing the transfer of tacit knowledge. This has important implications for CEE economies and other countries that depend heavily on GVCs. In such economies, we often observe comparatively large performance gaps and potential for knowledge transfer between foreign and domestic firms, as well as exporting and nonexporting firms (Békés et al., 2009; Békés and Harasztosi 2013). However, our study suggests that value-chain linkages alone may be insufficient for the formation of local clusters and the local spillovers associated with them.

In addition, analyzing actual labor flows and transactions between firms, we show that distance decays are particularly steep in supply-chain connections between firms in cognitively proximate industries. This microlevel evidence lends further plausibility to existing findings about aggregate coagglomeration patterns. Moreover, because coagglomeration patterns are pivotal inputs in the construction of product and industry spaces, our findings also bear relevance to the literature on economic complexity (Hidalgo 2021; Balland et al. 2022). They indicate that localized capabilities stem from value-chain interactions only when these embed tacit knowledge, making such connections important drivers of the place–activity patterns analyzed in economic complexity analysis. Finally, our findings speak to the regional cluster literature, which has traditionally emphasized the importance of value chains as a source of cluster competitiveness. However, our findings suggest that this crucially depends on the extent to which value-chain interactions are enriched with knowledge transfers, possibly facilitated by the exchange of skilled labor.

Our study also has a number of limitations. First, while Hungary represents a novel test case with detailed information on the drivers of industrial coagglomeration, the country is also strongly dependent on exports and imports. Such dependencies are presently not covered in our data and adding export and import data would be a valuable extension of the current work. In addition, FDI and multinational enterprises play an important role in the Hungarian economy. Moreover, this foreign-owned part of the economy may behave very differently from the domestic economy (Békés et al. 2009; Halpern et al. 2015; Elekes et al. 2019), because these firms can access resources in other locations through their internal corporate networks. Distinguishing between coagglomeration patterns of foreign-owned and domestic firms, therefore, represents a promising avenue for future research.

Second, the limited number of years for which all official registers are available prevents us from analyzing how coagglomeration forces evolve over time. We therefore cannot assess whether the stronger co-location of value-chain interactions among cognitively proximate partners is a recent development or a persistent feature. Existing work suggests that labor pooling and knowledge sharing channels have become more important (Diodato et al. 2018; Steijn et al. 2022), consistent with a shift toward service activities that may increase the share of input–output linkages embedding substantial tacit knowledge. Relatedly, although our results are robust to including a patent-based measure of technological relatedness, the very low patenting intensity in Hungary limits what can be concluded about this specific channel of knowledge transfer.

Third, the spatial units used in this article, NUTS3 and NUTS4 regions, do not necessarily represent the most adequate spatial scales for all industries and all interactions. While we demonstrated the robustness of our findings to the changes in spatial scale, we left studying the potential multiscalar nature of coagglomeration for future research. Such research could also exploit the exact geolocations of firms to construct coagglomeration patterns directly from the microgeography of firms.

Fourth, we acknowledge that firms' competitive space and business models are only imperfectly captured by industrial classifications (Ciriaci and Palma 2016; Szalavetz 2022). The porousness of industry boundaries can introduce measurement error when studying agglomeration patterns. However, studies on industry spaces (e.g., Neffke et al. 2011; Eriksson and Lengyel 2019; Csáfordi et al. 2020) address this by identifying clusters of related industries that often cut across sectoral boundaries. Our flow-based measures of input–output and skill relatedness follow this approach: as *ex post* indicators of relatedness, they are less affected by the hierarchical structure of industrial classifications. Thus, while industries may still be imperfectly captured at the most disaggregated level, our metrics mitigate the impact of porous industry boundaries at higher levels of aggregation.

Finally, organizational learning and knowledge management involve mechanisms other than knowledge transfer via labor flows, for instance, in the form of knowledge coordination in firm-internal networks. While revealed skill relatedness is an established approach to deriving an economy-wide measure of cognitive proximity between industries, it cannot account for all aspects of knowledge and learning. This caveat is shared more widely with previous studies on coagglomeration and constitutes an open challenge to be tackled in future research.

Notwithstanding these limitations and open questions, by drawing attention to the importance of knowledge-sharing between value-chain partners, our analysis advances our understanding of why industries coagglomerate. Moreover, it helps understand an important puzzle: why, in a time that value chains have become increasingly globalized, do buyers still sometimes put a high value on proximity to their suppliers?

Acknowledgements

The authors would like to thank the Databank of the ELTE Centre for Economic and Regional Studies for their support. This study was prepared using the data of the Central Statistical Office on firm registrations and value-added tax (VAT) reports. The calculations and conclusions drawn from them contained herein are solely the intellectual property of Sándor Juhász, Zoltán Elekes, Virág Ilyés, and Frank Neffke, as the authors. The authors are grateful for the feedback of Mercedes Delgado, Max Nathan, Neave O'Clery, Cesar Hidalgo, Andrea Caragliu, Rikard Eriksson, Johannes Wachs, and László Czaller.

Conflict of interest. None declared.

Supplementary material

Supplementary material is available at *Journal of Economic Geography* online.

Funding

Sándor Juhász's work was supported by the European Union's Marie Skłodowska-Curie Postdoctoral Fellowship Program (SUPPED, grant number 101062606). Zoltán Elekes and Virág Ilyés were supported by the Hungarian Scientific Research Fund project "Structure and robustness of regional supplier networks" (Grant No. OTKA FK-143064). Frank Neffke acknowledges financial support from the Austrian Research Promotion Agency (FFG) in the framework of the project ESSENCSE (873927), within the funding program Complexity Science.

Data availability

Aggregate data on inter-industry skill relatedness and input–output connections are available at https://doi.org/10.5281/zenodo.13753930. The code to generate the results is available at https://github.com/sandorjuhasz/coagglomeration. The dataset used in this study can be explored through the interactive data visualization platform at https://vis.csh.ac.at/colocation-suppliers/.

References

Agrawal, A. and Goldfarb, A. (2008) 'Restructuring Research: Communication Costs and the Democratization of University Innovation', *American Economic Review*, 98: 1578–90.

Aleksandrova, E., Behrens, K. and Kuznetsova, M. (2020) 'Manufacturing (Co)agglomeration in a Transition Country: Evidence from Russia', *Journal of Regional Science*, 60: 88–128.

Amador, J. and Cabral, S. (2017) 'Networks of Value-Added Trade', *The World Economy*, 40: 1291–1313.

Audretsch, D. B. and Feldman, M. P. (1996) 'R&D Spillovers and the Geography of Innovation and Production', *American Economic Review*, 86: 630–640.

Azadegan, A. and Dooley, K. J. (2010) 'Supplier Innovativeness, Organizational Learning Styles and Manufacturer Performance: An Empirical Assessment', *Journal of Operations Management*, 28: 488–505.

Baldwin, R. and Freeman, R. (2022) 'Risks and Global Supply Chains: What We Know and What We Need to Know', *Annual Review of Economics*, 14: 153–80.

Baldwin, R. and Ito, T. (2021) 'The Smile Curve: Evolving Sources of Value Added in Manufacturing', *Canadian Journal of Economics/Revue canadienne d'économique*, 54: 1842–80.

Baldwin, R. and Lopez-Gonzalez, J. (2015) 'Supply-chain Trade: A Portrait of Global Patterns and Several Testable Hypotheses', *The World Economy*, 38: 1682–1721.

Balland, P.-A. and Rigby, D. (2017) 'The Geography of Complex Knowledge', *Economic Geography*, 93: 1–23.

Balland, P.-A. et al. (2022) 'The New Paradigm of Economic Complexity', *Research Policy*, 51: 104450.

Bathelt, H. and Storper, M. (2023) 'Related Variety and Regional Development: A Critique', *Economic Geography*, 99: 441–470.

Beaudry, C. and Schiffauerova, A. (2009) 'Who's Right, Marshall or Jacobs? The Localization Versus Urbanization Debate', *Research Policy*, 38: 318–37.

Békés, G., Kleinert, J. and Toubal, F. (2009) 'Spillovers from Multinationals to Heterogeneous Domestic Firms: Evidence from Hungary', *World Economy*, 32: 1408–33.

Békés, G. and Harasztosi, P. (2013) 'Agglomeration premium and trading activity of firms', *Regional Science and Urban Economics*, 43: 51–64.

Bernard, A. B., Moxnes, A. and Saito, Y. K. (2019) 'Production Networks, Geography, and Firm Performance', *Journal of Political Economy*, 127: 639–88.

Bertinelli, L. and Decrop, J. (2005) 'Geographical Agglomeration: Ellison and Glaeser's Index Applied to the Case of Belgian Manufacturing Industry', *Regional Studies*, 39: 567–83.

Boschma, R. (2005) 'Proximity and Innovation: A Critical Assessment', *Regional Studies*, 39: 61–74.

Boschma, R. (2024) 'An Evolutionary Approach to Regional Studies on Global Value Chains' *Regional Studies,* 58: 1492–500.

Boschma, R., Balland, P.-A. and Kogler, D. F. (2015) 'Relatedness and Technological Change in Cities: The Rise and Fall of Technological Knowledge in US Metropolitan Areas from 1981 to 2010', *Industrial and Corporate Change*, 24: 223–50.

Boschma, R., Eriksson, R. and Lindgren, U. (2009) 'How Does Labour Mobility Affect the Performance of Plants? The Importance of Relatedness and Geographical Proximity', *Journal of Economic Geography*, 9: 169–90.

Braun, E., Sebestyén, T. and Kiss, T. (2021) 'The Strength of Domestic Production Networks: An Economic Application of the Finn Cycling Index', *Applied Network Science*, 6: 1–26.

Brülhart, M. and Koenig, P. (2006) 'New Economic Geography Meets Comecon: regional Wages and Industry Location in Central Europe', *Economics of Transition*, 14: 245–67.

Caragliu, A. (2022) 'Measuring the Unmeasurable: The Empirics of Non-geographical Proximity', in A. Torre, and D. Gallaud (eds) *Handbook of Proximity Relations*, pp. 138–64. Cheltenham: Edward Elgar Publishing.

Caragliu, A., de Dominicis, L. and de Groot, H. L. F. (2016) 'Both Marshall and Jacobs Were Right!', *Economic Geography*, 92: 87–111.

Catalini, C., Fons-Rosen, C. and Gaulé, P. (2020) 'How Do Travel Costs Shape Collaboration? ',*Management Science*, 66: 3340–3360.

Ciriaci, D. and Palma, D. (2016) 'Structural Change and Blurred Sectoral Boundaries: Assessing the Extent to Which Knowledge-intensive Business Services Satisfy Manufacturing Final Demand in Western Countries', *Economic Systems Research*, 28: 55–77.

Cooke, P. (1996) 'The New Wave of Regional Innovation Networks: Analysis, Characteristics and Strategy', *Small Business Economics*, 8: 159–71.

Cooke, P. and Morgan, K. (1994) 'The Regional Innovation System in Baden–Wurttemberg', *International Journal of Technology Management*, 9: 394–429.

Crescenzi, R. and Harman, O. (2023) *Harnessing Global Value Chains for Regional Development: How to Upgrade through Regional Policy, FDI and Trade*. London: Taylor & Francis.

Csáfordi, Z. et al. (2020) 'Productivity Spillovers Through Labor Flows: Productivity Gap, Multinational Experience and Industry Relatedness', *Journal of Technology Transfer*, 45: 86–121.

Damijan, J., Kostevc, C. and Rojec, M. (2018) 'Global Supply Chains at Work in Central and Eastern European Countries: impact of Foreign Direct Investment on Export Restructuring and Productivity Growth', *Economic and Business Review*, 20: 4.

Delgado, M., Porter, M. E. and Stern, S. (2014) 'Clusters, Convergence, and Economic Performance', *Research Policy*, 43: 1785–99.

Delgado, M., Porter, M. E. and Stern, S. (2016) 'Defining Clusters of Related Industries', *Journal of Economic Geography*, 16: 1–38.

Diem, C. et al. (2022) 'Quantifying Firm-level Economic Systemic Risk from Nation-wide Supply Networks', *Scientific Reports*, 12: 7719.

Diodato, D., Neffke, F., and O'Clery, N. (2018) 'Why Do Industries Coagglomerate? How Marshallian Externalities Differ by Industry and Have Evolved Over Time', *Journal of Urban Economics*, 106: 1–26.

Duranton, G. and Puga, D. (2004) 'Micro-foundations of Urban Agglomeration Economies' in J. Vernon Henderson, and J.-F. Thisse (eds) *Handbook of Regional and Urban Economics*, vol 4, pp. 2063–2117. Amsterdam, The Netherlands: Elsevier.

Duranton, G. and Puga, D. (2020) 'The Economics of Urban Density', *Journal of Economic Perspectives*, 34: 3–26.

Elekes, Z., Boschma, R. and Lengyel, B. (2019) 'Foreign-owned Firms as Agents of Structural Change in Regions', *Regional Studies*, 53: 1603–13.

Ellison, G. and Glaeser, E. L. (1997) 'Geographic Concentration in US Manufacturing Industries: A Dartboard Approach', *Journal of Political Economy*, 105: 889–927.

Ellison, G. and Glaeser, E. L. (1999) 'The Geographic Concentration of Industry: does Natural Advantage Explain Agglomeration?', *American Economic Review*, 89: 311–16.

Ellison, G., Glaeser, E. L. and Kerr, W. R. (2010) 'What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns', *American Economic Review*, 100: 1195–1213.

Eriksson, R. H. (2011) 'Localized Spillovers and Knowledge Flows: How Does Proximity Influence the Performance of Plants?' *Economic Geography*, 87: 127–52.

Eriksson, R. H. and Lengyel, B. (2019) 'Co-worker Networks and Agglomeration Externalities', *Economic Geography*, 95: 65–89.

Faggio, G., Silva, O. and Strange, W. C. (2017) 'Heterogeneous Agglomeration', *Review of Economics and Statistics*, 99: 80–94.

Frenken, K. and Boschma, R. A. (2007) 'A Theoretical Framework for Evolutionary Economic Geography: Industrial Dynamics and Urban Growth as a Branching Process', *Journal of Economic Geography*, 7: 635–49.

Frenken, K., Neffke, F. and Van Dam, A. (2023) 'Capabilities, Institutions and Regional Economic Development: A Proposed Synthesis', *Cambridge Journal of Regions, Economy and Society*, 16: 405–16.

Gabe, T. M. and Abel, J. R. (2016) 'Shared Knowledge and the Coagglomeration of Occupations', *Regional Studies*, 50: 1360–73.

Gallagher, R. M. (2013) 'Shipping Costs, Information Costs, and the Sources of Industrial Coagglomeration' *Journal of Regional Science*, 53: 304–31.

Gereffi, G., Humphrey, J. and Sturgeon, T. (2005) 'The Governance of Global Value Chains', *Review of International Political Economy*, 12: 78–104.

Gertler, M. S. (2003) 'Tacit Knowledge and the Economic Geography of Context, or the Undefinable Tacitness of Being (There)', *Journal of Economic Geography*, 3: 75–99.

Glaeser, E. L. and Kohlhase, J. E. (2004) 'Cities, Regions and the Decline of Transport Costs', *Papers in Regional Science*, 83: 197–228.

Glaeser, E. L. et al. (1992) 'Growth in Cities', *Journal of Political Economy*, 100: 1126–1152.

Halpern, L. and Muraközy, B. (2007) 'Does Distance Matter in Spillover?', *Economics of Transition*, 15: 781–805.

Halpern, L., Koren, M. and Szeidl, A. (2015) 'Imported Inputs and Productivity', *American Economic Review*, 105: 3660–3703.

Helsley, R. W. and Strange, W. C. (2014) 'Coagglomeration, Clusters, and the Scale and Composition of Cities', *Journal of Political Economy*, 122: 1064–93.

Henderson, V., Kuncoro, A. and Turner, M. (1995) 'Industrial Development in Cities', *Journal of Political Economy*, 103: 1067–90.

Henning, M. et al. (2025) 'Job Relatedness, Local Skill Coherence and Economic Performance: A Job Postings Approach', *Regional Studies, Regional Science*, 12: 95–122.

Hidalgo, C. A. (2015) *Why Information Grows: The Evolution of Order, from Atoms to Economies*. New York, NY: Basic Books.

Hidalgo, C. A. (2021) 'Economic Complexity Theory and Applications', *Nature Reviews Physics*, 3: 92–113.

Hidalgo, C. A. and Hausmann, R. (2009) 'The Building Blocks of Economic Complexity', *Proceedings of the National Academy of Sciences*, 106: 10570–575.

Hidalgo, C. A. et al. (2007) 'The Product Space Conditions the Development of Nations', *Science*, 317: 482–87.

Hidalgo, C. A. et al. (2018) *Unifying Themes in Complex Systems IX*, pp. 451–57. Cham: Springer International Publishing.

Howard, E., Newman, C. and Tarp, F. (2015) 'Measuring Industry Coagglomeration and Identifying the Driving Forces', *Journal of Economic Geography*, 16: 1055–1078.

Inzelt, A. (2008) 'The Inflow of Highly Skilled Workers into Hungary: A By-product of FDI', *Journal of Technology Transfer*, 33: 422–38.

Jaffe, A. B., Trajtenberg, M. and Henderson, R. (1993) 'Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations', *Quarterly Journal of Economics*, 108: 577–98.

Javorcik, B. S. (2004) 'Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages', *American Economic Review*, 94: 605–27.

Johnson, R. C. (2018) 'Measuring Global Value Chains', *Annual Review of Economics*, 10: 207–236.

Juhász, S., Broekel, T. and Boschma, R. (2021) 'Explaining the Dynamics of Relatedness: The Role of Co-location and Complexity', *Papers in Regional Science*, 100: 3–21.

Kiss, T., Braun, E. and Sebestyen, T. (2025) 'Production Network Structure, Specialization and Unemployment: Measuring the Structural Resilience of National Economies', *Structural Change and Economic Dynamics*, 72: 11–28.

Kogut, B. and Zander, U. (1992) 'Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology', *Organization Science*, 3: 383–97.

Kolko, J. (2010) *Urbanization, Agglomeration, and Coagglomeration of Service Industries*, pp. 151–80. Chicago, IL: University of Chicago Press.

Květoň, V. et al. (2022) 'The Role of Geographic and Cognitive Proximity in Knowledge Networks: the Case of Joint R&D Projects', *Papers in Regional Science*, 101: 351–73.

Lee, J. A. et al. (2022) 'Proximities in Dimensionality Reduction', in *Handbook of Proximity Relations*, in A. Torre, and D. Gallaud (eds) Handbook of Proximity Relations, pp. 165–203. Cheltenham: Edward Elgar Publishing.

Lengyel, B. and Eriksson, R. H. (2017) 'Co-worker Networks, Labour Mobility and Productivity Growth in Regions', *Journal of Economic Geography*, 17: 635–60.

Li, Y. and Neffke, F. (2023) 'Evaluating the Principle of Relatedness: Estimation, Drivers and Implications for Policy', *Research Policy*, 53: 104952.

Lőrincz, L., Juhász, S. and Szabó, R. O. (2024) 'Business Transactions and Ownership Ties Between Firms', *Network Science*, 12: 1–20.

Marshall, A. (1920) *Principles of Economics*. London: McMillan.

Mattsson, C. E. S., et al. (2021) 'Functional Structure in Production Networks', *Frontiers in Big Data*, 4:666712.

Mewes, L. and Broekel, T. (2022) 'Technological Complexity and Economic Growth of Regions', *Research Policy*, 51: 104156.

Mudambi, R. (2008) 'Location, Control and Innovation in Knowledge-Intensive Industries', *Journal of Economic Geography*, 8: 699–725.

Mukim, M. (2015) 'Coagglomeration of Formal and Informal Industry: Evidence from India', *Journal of Economic Geography*, 15: 329–51.

Neffke, F. and Henning, M. (2013) 'Skill Relatedness and Firm Diversification', *Strategic Management Journal*, 34: 297–316.

Neffke, F. et al. (2018) 'Agents of Structural Change: The Role of Firms and Entrepreneurs in Regional Diversification', *Economic Geography*, 94: 23–48.

Neffke, F., Henning, M. and Boschma, R. (2011) 'How Do Regions Diversify Over Time? Industry Relatedness and the Development of New Growth Paths in Regions', *Economic Geography*, 87: 237–65.

Neffke, F., Otto, A. and Weyh, A. (2017) 'Inter-industry Labor Flows', *Journal of Economic Behavior & Organization*, 142: 275–92.

Nelson, R. R. and Winter, S. G. (1982) *An Evolutionary Theory of Economic Change*. Cambridge, MA: Harvard University Press.

Nölke, A. and Vliegenthart, A. (2009) 'Enlarging the Varieties of Capitalism: The Emergence of Dependent Market Economies in East Central Europe', *World Politics*, 61: 670–702.

Nonaka, I. (1994) 'A Dynamic Theory of Organizational Knowledge Creation', *Organization Science*, 5: 14–37.

O'Clery, N. and Kinsella, S. (2022) 'Modular Structure in Labour Networks Reveals Skill Basins', *Research Policy*, 51: 104486.

O'Clery, N., et al. (2021) 'Unravelling the Forces Underlying Urban Industrial Agglomeration', in Z. P. Neal and C. Rozenblat (eds) *Handbook of Cities and Networks*, pp. 472–92. Cheltenham: Edward Elgar Publishing.

Pavlinek, P., Domański, B. and Guzik, R. (2009) 'Industrial Upgrading Through Foreign Direct Investment in Central European Automotive Manufacturing', *European Urban and Regional Studies*, 16: 43–63.

Pichler, A. et al. (2023) 'Building an Alliance to Map Global Supply Networks', *Science*, 382: 270–72.

Pinheiro, F. L. et al. (2022) 'The Time and Frequency of Unrelated Diversification', *Research Policy*, 51: 104323.

Polanyi, M. (1966) *The Tacit Dimension*. New York, NY: Doubleday.

Porter, M. E. (1990) *The Competitive Advantage of Nations*. New York, NY: Macmillan.

Porter, M. E. (1998) 'Clusters and the New Economics of Competition', *Harvard Business Review*, 76: 77–90.
Porter, M. E. (2003) 'The Economic Performance of Regions', *Regional Studies*, 37: 549–78.
Rosenthal, S. S. and Strange, W. C. (2004) 'Evidence on the Nature and Sources of Agglomeration Economies', in J. V. Henderson and J. F. Thisse (eds) *Handbook of Regional and Urban Economics*, vol. 4, pp. 2119–71. Amsterdam, The Netherlands: Elsevier.
Spender, J. C. and Grant, R. M. (1996) 'Knowledge and the Firm: Overview', *Strategic Management Journal*, 17: 5–9.
Steijn, M. P. A., Koster, H. R. A. and Van Oort, F. G. (2022) 'The Dynamics of Industry Agglomeration: Evidence from 44 Years of Coagglomeration Patterns', *Journal of Urban Economics*, 130: 103456.
Szalavetz, A. (2022) 'The Digitalisation of Manufacturing and Blurring Industry Boundaries', *CIRP Journal of Manufacturing Science and Technology*, 37: 332–43.
Timmer, M. P. et al. (2015) 'An Illustrated User Guide to the World Input–Output Database: The Case of Global Automotive Production', *Review of International Economics*, 23: 575–605.

Journal of Economic Geography, 2026, 00, 1–23
https://doi.org/10.1093/jeg/lbag006
Original Article