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Intermediates trade and knowledge flows the cost-saving mechanism of local buyer networks

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Abstract

This paper shows that firms can substantially reduce their intermediate input expenditures by participating in dense local input-buyer networks. Using detailed administrative data, we construct a measure of buyer-network density based on the number of nearby firms sourcing the same locally produced and imported inputs and document that stronger networks consistently lower input costs, while leaving revenues and productivity unchanged. To explain this pattern, we develop a theoretical framework in which network participation reduces fixed input requirements through knowledge spillovers among buyers. A key prediction is that potential revenue effects depend on the cost of benefiting from the network. Using product-level information on relationship specificity, we confirm that network expansion raises domestic revenues only for relationship-intensive products, where knowledge transmission is more effective.

Keywords Network effects · New economic geography · Vertical linkages

JEL Classification F12 · F15 · R12

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1 Introduction

Production networks play a central role in shaping firm performance, both through the flow of intermediate goods and through the diffusion of information and know-how among firms (Bernard et al., 2019). While a growing literature documents the importance of firm-to-firm links for aggregate outcomes, innovation, and supply-chain resilience, far less is known about how buyer networks influence firm-level outcomes. In particular, the potential for firms to realize cost savings by participating in local buyer networks—distinct from supplier networks—has received little empirical or theoretical attention.

In this paper, we propose and document a novel mechanism: firms can achieve substantial reductions in intermediate input expenditures by operating within dense local input-buyer networks. These savings arise not from technological improvements or scale effects, but from the flow of information within the network. When many nearby firms purchase the same locally produced or imported intermediate inputs, opportunities emerge for shared learning about suppliers, price negotiations, contract terms, and process improvements. The strength of this knowledge flows depends on the local economic environment and the characteristics of the products being transacted. As a result, firms embedded in denser networks benefit from lower effective input costs, potentially enhancing profitability and competitiveness without requiring changes in output or production technology.

To empirically examine this mechanism, we exploit rich register data from Statistics Denmark that allow us to observe firms' expenditures on detailed intermediate inputs. We construct a firm-level measure of local input buyer networks as a weighted average over out-degree centrality measures for intermediate goods a firm is purchasing. Using within-firm variation and controlling for shocks specific to region–industry–year cells, we find a robust and economically significant negative relationship between the size of the input buyer network and firms' intermediate input expenditures. This pattern holds across alternative definitions of local markets, more narrowly defined region–industry cells, different weighting schemes, and different samples. In all cases, firms in denser networks consistently spend less on locally produced and imported inputs. Importantly, these network effects do *not* extend to firm size or efficiency: local buyer networks reduce costs, but do not increase firms' revenues or value added per worker.

These findings suggest that buyer networks primarily generate informational spillovers—such as insights on suppliers, input prices, or contracting norms—rather than driving technology upgrades or expanding output. Thus, we interpret these findings as denser, local networks appear to support knowledge exchange, and better access to information, e.g., on quality and pricing. Indeed, prior work shows that geographic proximity facilitates the spread of economically relevant knowledge (Jaffe et al., 1993), that agglomeration encourages input sharing and information spillovers (Ellison et al., 2010), and that firms' network positions influence input costs and supply access (Bernard et al., 2019). Our results align with these mechanisms: local networks help firms source inputs more efficiently, lowering effective input expenditures without altering production technologies or output levels. Thus, the main effect of

these networks operates through cost efficiency, rather than productivity gains or scale effects.

These facts call for a model capable of generating input-side cost savings without output-side adjustments. To this end, we develop a theoretical framework based on the short-run version of the New Economic Geography (NEG) model of Ottaviano and Robert-Nicoud (2006). We introduce vertical linkages exclusively through fixed costs and incorporate network-driven reductions in the composite fixed input requirement. In the model, firms benefit from knowledge spillovers within their local buyer network, which lower their effective demand for intermediates, both locally produced and imported. However, whether these cost savings translate into higher revenues depends critically on a country- or region-specific network-cost parameter. When this parameter is low – meaning that it is cheap to benefit from network participation – input-side savings increase pure profits and thereby stimulate domestic demand. Contrary, for high values, savings remain confined to the cost side and do not feed through to revenues. The model therefore predicts heterogeneity in the revenue effects of network expansion depending on product characteristics and the strength of knowledge transmission.

Notably, our analysis treats the production network as exogenously given, in line with a substantial literature where the extensive margin of firm-to-firm linkages is taken as predetermined (e.g. König et al. (2019); Huneeus et al. (2021); Dhyne et al. (2022)). As Dhyne et al. (2023) emphasize, exogenous and endogenous network models often yield similar aggregate implications. Given our focus on the role of knowledge flows among buyers rather than on the determinants of network formation, the exogeneity assumption is appropriate and allows us to isolate the cost-saving mechanism generated by buyer-side network interactions.

In a final step, we bring this prediction to the data, by exploiting the product-level relationship stickiness index from Martin et al. (2023), which measures relational specificity based on firm-to-firm relationship durations. Relationship-specific products require repeated interactions, customization, and tacit knowledge exchange. These features make knowledge flows stronger and more valuable, implying lower effective network costs for these products. In contrast, standardized or non-relationship-specific products entail weaker informational spillovers and therefore higher network costs. We use these insights to compute separate network measures for relationship-specific and non-specific products. Consistent with the model, we find that network expansion increases domestic revenues only for relationship-specific products. For non-relationship-specific products, revenue effects are statistically insignificant across all specifications. This asymmetry provides direct empirical support for the theoretical mechanism: network-driven revenue gains arise only when the underlying products exhibit sufficient relational specificity to facilitate knowledge transmission and reduce network frictions.

The paper makes three contributions. First, it provides novel empirical evidence that local input-buyer networks substantially reduce firms' expenditures on intermediate inputs. While prior research has shown that production networks shape firm performance (e.g., through supplier relationships, knowledge spillovers, and access to inputs), the literature has overwhelmingly focused on supplier-side mechanisms rather than buyer-side information flows. Existing work documents how network

positions influence costs and sourcing opportunities (Bernard et al., 2019), how agglomeration facilitates shared learning and input-related spillovers (Ellison et al., 2010), and how proximity supports the diffusion of economically relevant knowledge (Jaffe et al., 1993). However, none of these studies examine whether local buyer networks themselves generate systematic cost savings. By identifying a robust negative relationship between buyer-network density and input expenditures, this paper fills a clear gap in a literature that has largely emphasized upstream linkages and technological spillovers rather than downstream information channels.

Second, the paper develops a theoretical framework that rationalizes these findings through network-driven reductions in fixed input requirements, highlighting conditions under which such cost savings do – or do not – translate into higher revenues. This contributes to the theoretical production-network literature, which typically models firm-to-firm linkages as channels for productivity shocks, factor misallocation, or technology diffusion (e.g., Acemoglu et al. (2012); Baqaee and Farhi (2019)). Unlike models that focus on how networks amplify productivity or demand shocks, our framework is tailored to capture purely informational spillovers among buyers and their implications for fixed-cost structures. In doing so, it complements existing work in New Economic Geography (Ottaviano and Robert-Nicoud, 2006) as well as recent network-based models in which firms' cost structures respond to local informational environments rather than technological complementarities.

Third, the paper empirically validates the model's central prediction by demonstrating that the revenue effects of network expansion depend on product-level relational specificity, following Martin et al. (2023). This connects the analysis to a growing literature showing that relationship-specific products foster tacit knowledge flows, repeated interactions, and learning-by-doing in firm-to-firm relationships (e.g., Antràs (2021)). It also aligns with research emphasizing heterogeneity in knowledge diffusion across sectors and products (Cai et al., 2022; Lind and Ramondo, 2018). By showing that network-driven reductions in input expenditures translate into higher revenues only for relationship-specific products, the paper provides new empirical evidence on how network frictions interact with product characteristics to shape firm performance. This complements recent work documenting the role of information, matchability, and intermediation in production networks (Manova et al., 2025), while offering a novel mechanism – buyer-side informational spillovers – through which these forces operate.

The remainder of the paper is organized as follows. Section 2 describes the data sources. Section 3 develops the buyer network measures and documents their relationship with firms' input expenditures and other firm outcomes. Section 4 presents the theoretical framework. Section 5 distinguishes between relationship-specific and non-relationship-specific networks to test one of the model predictions. Section 6 concludes.

2 Data

We combine several administrative registers from Statistics Denmark for the period 2002–2018. General firm-level information—including industry classification, geographic location, employment, revenues, and value added—is obtained from the FIRM register. Industries follow the 6-digit Danish version of the EU NACE classification, where the first four digits correspond to NACE Rev. 2 and the final two digits reflect Danish subdivisions. We harmonize industry codes over time and exclude firms in the public sector (i.e., utilities, public administration and defense, education, health services, and cultural and entertainment services).

Using firms' municipality codes, we assign each firm to a region within Denmark. Our baseline classification divides the country into five NUTS 2 regions: the Capital Region of Denmark, Region Zealand, Region of Southern Denmark, Central Denmark Region, and North Denmark Region. As an alternative, we consider 11 provinces at the NUTS 3 level: Copenhagen City, Copenhagen Surroundings, North Zealand, East Zealand, West & South Zealand, Bornholm, Funen, South Jutland, East Jutland, West Jutland, and North Jutland.

Information on firms' input purchases is taken from the VARK register, which covers goods and services used in production, regardless of whether they are imported or sourced domestically. Inputs include raw materials, components, parts, and auxiliary goods and services. The classification follows detailed industrial groups (NACE), where each input carries a 6-digit code, with the first four digits aligned with the Combined Nomenclature (CN).[1] For instance, the group "73—Goods of iron and steel" includes twisted wire, cables, ropes, straps, or radiators for central heating, while "84—Boilers; machines, apparatus, and mechanical tools" covers items such as steam turbines or parts for washing machines and textile machinery.

Because Denmark is a small open economy that imports a substantial share of intermediate goods, we supplement VARK with firm-level trade data. Specifically, we merge VARK with the UHDI register, which reports firms' imports (and exports) at the CN 8-digit level. We aggregate imports to the 4-digit level to ensure compatibility with VARK.[2] Using the combined VARK–UHDI information, we compute firm-year totals for input expenditures (domestic and imported) and the number of distinct 4-digit input products. Unfortunately, the VARK register contains only expenditure data and does not distinguish between quantities and prices, unlike, for example, trade-in-goods statistics (UHDI).

Finally, we use the VARS register, the Danish version of the European PRODCOM survey, which provides information on firms' product-level sales. VARS covers manufacturing and raw-material extraction firms with at least 10 employees. Although

[1] For detailed documentation, see https://www.dst.dk/da/Statistik/dokumentation/statistikdokumentation/industriens-koeb-af-varer-og-tjenester.

[2] The VARK survey does not distinguish between domestic and imported inputs. Combining VARK with UHDI allows us to verify whether expenditures on a given 4-digit product exceed reported imports or whether the good is purely imported (in case of 0 or negative values, once subtracting the information from UHDI from VARK) and thus not produced domestically. For the network measures introduced in Sect. 3, we exclude goods and services that are exclusively imported, since our focus is on networks related to both locally sourced and imported intermediates with local buyer network effects.

it represents a subset of firms appearing in FIRM, VARK, and UHDI, VARS allows us to compute domestic sales. Subtracting export sales in UHDI from total sales in VARS yields firm-level domestic sales, which we use in our empirical analysis in Sect. 5.[3]

Summary statistics of the main variables are reported in Table 1. As shown in the table, the average firm in our sample employs approximately 63 workers and purchases around 16 distinct intermediate goods and services.

3 Local input buyer networks and firm outcomes

Our theoretical framework, presented in Sect. 4, highlights the role of vertical linkages on the production side of the economy. In particular, the model features positive network effects that depend, among other factors, on the number of firms within a region that purchase the same locally produced and imported intermediate input. In what follows, we use the detailed Danish register data to motivate this key model ingredient.

3.1 A measure for local input buyer networks

Network measures have been widely applied across disciplines (see Newman (2018) for an introduction). To construct a measure of a firm's local input buyer network, we follow existing approaches, such as in De Benedictis et al. (2014), who develop network measures for bilateral trade data, and adapt it to our setting. Specifically, for each 4-digit intermediate input j, we compute an out-degree centrality measure defined as

$$CND_j^{cell} = \frac{\sum_i^N \mathbb{I}_{ji}^{cell}}{N-1}, \tag{1}$$

Table 1 Summary statistics

Variable	Observations	Mean	Std. Dev.
(log) total revenues	199,344	17.075	1.655
Employment	199,344	62.807	368.282
(log) value added per worker	199,344	13.093	0.682
Number of inputs	199,344	16.074	26.630
(log) expenses on inputs	199,344	14.175	3.305
(log) domestic revenues	15,092	17.386	1.568

The table reports means and standard deviations of firm-year observations for 2002–2018. "Number of inputs" denotes the count of distinct 4-digit intermediate goods and services purchased by the firm; "expenses on inputs" refers to total expenditures across all such products

[3] Previous work combining these registers has documented that, for a small number of product-year observations, exports exceed total sales, resulting in negative domestic sales (see, e.g., Gampfer and Geishecker, 2019; Chan et al., 2025). This discrepancy arises because the two datasets rely on different underlying reporting structures: export values may include re-exports or traded goods, whereas VARS excludes goods purchased for resale. Similar problems arise once combining VARK and UHDI.

where N denotes the number of firms in a given cell, and $\mathbb{I}_{ji}^{cell}$ is an indicator equal to one if firm i reports positive expenditures on input j in that cell. The input j might be sourced locally or imported, while firms sourcing the input are located in the same cell. For the latter, we construct four different definitions of a cell: (i) 5 NUTS 2 regions; (ii) 11 NUTS 3 regions; (iii) 5 NUTS 2 regions within one of 69 industries; and (iv) 11 NUTS 3 regions within one of 69 industries. The latter two definitions therefore restrict the buyer network to firms purchasing the input within the same region *and* the same industry. In all cases, we restrict the construction of these measures to products that are at least partially produced in Denmark, rather than exclusively imported.[4] Put differently, firms in local buyer networks buy not only locally produced but also imported intermediates.

Table 2 lists the twenty CN 2-digit input groups with the highest out-degree centrality in 2018, based on the 5-region cell definition.[5] Since inputs differ in economic relevance, we also compute weighted versions of these measures based on the average expenditure share of each input across firms. The corresponding results are reported in Appendix Table 9.

To obtain a firm-specific measure of input buyer networks, we aggregate the input-level centrality measures across all inputs sourced by the firm. Since the economic

Table 2 Out-degree centrality measures for Top-20 CN2 inputs

Rank	Product	CND
1	39 – Plastics and plastic goods	0.00738
2	48 – Paper and paperboard products	0.00737
3	73 – Articles of iron and steel	0.00473
4	27 – Mineral fuels and related oils	0.00278
5	32 – Dyes, pigments and coloring materials	0.00275
6	35 – Proteins, glues, enzymes and related materials	0.00257
7	76 – Aluminium and aluminium products	0.00238
8	72 – Iron and steel (raw and semi-finished)	0.00217
9	40 – Rubber and rubber articles	0.00185
10	17 – Sugars and sugar products	0.00166
11	25 – Salt, stone, cement and mineral materials	0.00165
12	13 – Natural gums, resins and similar products	0.00143
13	85 – Electrical machinery and equipment	0.00143
14	28 – Inorganic chemical products	0.00130
15	34 – Soaps, waxes and cleaning preparations	0.00130
16	29 – Organic chemical products	0.00116
17	84 – Machinery and mechanical appliances	0.00111
18	83 – Miscellaneous articles of base metal	0.00104
19	4 – Dairy products	0.00103
20	38 – Miscellaneous chemical products	0.00100

Based on Statistics Denmark data for 2018. Product labels combine CN2 codes with shortened official CN descriptions. Values report unweighted out-degree centrality as defined in Eq. (1). Cells correspond to the 5 NUTS 2 regions

[4] Only a very small share of inputs is produced solely in Denmark without being imported. Restricting the sample to such inputs would leave too few observations for meaningful analysis.

[5] Our empirical analysis uses 4-digit input measures, but disclosure rules require aggregation to the 2-digit level for publication.

relevance of each input varies, we weight inputs by their expenditure shares. Formally, we compute the input buyer network IBN_i^{cell} for a firm *i* in a specific cell as

$$IBN_i^{cell} = \sum_j \omega_{ij} \times CND_j^{cell}, \tag{2}$$

where ω_{ij} denotes the expenditure share of firm *i* on input *j*. Summary statistics for these firm-level network measures across the four cell definitions are reported in Table 3.

By construction, a firm's input buyer network measure (IBN_i^{cell}) increases either (i) when more firms within the same cell begin purchasing an input that the firm also sources, thereby raising the centrality measure of inputs, or (ii) when the firm shifts expenditures toward inputs with high centrality. Because narrower cells include fewer firms by definition, the expected level of network centrality is ambiguous a priori. We therefore retain all four cell definitions throughout the main empirical analysis.

3.2 Input buyer networks and firm-level outcomes

We now turn to our input buyer network measures to examine how local buyer networks of locally produced and imported intermediates shape firm performance. In particular, we investigate the effects of network size on firm scale—measured by total revenues—firm efficiency—measured by value added per worker—and firms' expenditures on intermediate inputs. To this end, we estimate the following equation:

$$\text{outcome}_{it} = \beta\, IBN_{it}^{cell} + \mu_i + \mu_{trs} + \epsilon_{it}, \tag{3}$$

where IBN_{it}^{cell} denotes one of the network measures for firm *i* in year *t*, as defined above. The specification includes firm fixed effects μ_i and year-region-industry fixed effects μ_{trs}, while ϵ_{it} is an idiosyncratic error term with zero conditional mean.

The inclusion of year-region-industry fixed effects absorbs all shocks that are common to a given region–industry pair within a year, such as changes in import competition, regional demand shifts, or the introduction of a new intermediate input used by many firms in the same cell. Because the firm-level IBN is a weighted average over input-specific centralities, it varies across firms within the same year×region× industry cell whenever firms differ in their input baskets (weights) or in the centrality of the inputs they purchase. These fixed effects also capture changes in market con-

Table 3 Summary statistics for input buyer network proxies

Variable	Observations	Mean	Std. Dev.
Input Buyer Network: 5-reg.	199,344	0.002	0.003
Input Buyer Network: 11-reg.	199,344	0.002	0.004
Input Buyer Network: 5-reg. & 69 Ind.	199,344	0.009	0.036
Input Buyer Network: 11-reg. & 69 Ind.	199,344	0.011	0.050

Summary statistics for firm-year observations, 2002–2018. Input buyer network measures are computed according to Eq. (2), using four alternative cell definitions: (i) 5 NUTS 2 regions; (ii) 11 NUTS 3 regions; (iii) 5 NUTS 2 regions and 69 2-digit industries; and (iv) 11 NUTS 3 regions and 69 2-digit industries

Table 4 Regional input buyer networks and firm outcomes

Cell	5-regions			11-regions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	0.000923	−0.00282*	−0.137***	−0.00173	−0.00126	−0.132***
	(0.00198)	(0.00160)	(0.00670)	(0.00182)	(0.00159)	(0.00607)
Observations	119,344	119,344	119,344	100,978	100,978	100,978
adj. R^2	0.919	0.562	0.840	0.922	0.565	0.849
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

All dependent variables—revenues, value added per worker, and input expenditures—as well as *IBN* are expressed in logs. IBN^{cell} is computed according to Eq. (2) with cells defined at 5 NUTS-2 regions or 11 NUTS-3 regions. Industry classification follows the 4-digit NACE Rev. 2 system. Standard errors clustered at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively

Table 5 Regional input buyer networks and firm outcomes

Cell	5-regions & 69 industries			11-regions & 69 industries		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	0.00411	−0.00619**	−0.0359***	0.00467	−0.00186	−0.0407***
	(0.00308)	(0.00242)	(0.00821)	(0.00386)	(0.00309)	(0.0108)
Observations	24,252	24,252	24,252	17,341	17,341	17,341
adj. R^2	0.943	0.566	0.867	0.948	0.589	0.866
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

All dependent variables and *IBN* are expressed in logs. Cells are defined at the 5 NUTS-2 regions within one of 69 industries, or the 11 NUTS-3 regions within one of 69 industries. Standard errors clustered at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively

centration arising from firm entry or exit, including potential shifts in the Herfindahl-Hirschman Index. Our parameter of interest is β, which measures the elasticity of the outcome variable with respect to the (log) input buyer network measure. Regression results based on 5- and 11-region cells are reported in columns (1)–(3) and (4)–(6) of Table 4. Table 5 presents estimates using the region–industry cell definitions.

Results in Table 4 indicate that changes in the local input buyer network have no statistically detectable impact on firm size or productivity. These findings hold across all cell definitions, including the more granular region–industry cells reported in Table 5. However, columns (3) and (6) of both tables show a negative and statistically significant relationship between network size and firms' expenditures on intermediate inputs. For instance, the estimate in column (3) of Table 4 implies that a 10% increase in the size of the input buyer network reduces input expenditures by approximately 1.37%.[6] Table 5 shows a similar, albeit slightly smaller, elasticity when using nar-

[6] Note that a 10% increase in IBN corresponds to a 10% increase in the weighted average share of nearby firms buying the same inputs as firm *i*, which can be generated by modest changes in the number of buyers for the specific inputs the firm uses. For example, in a typical 5-region cell with N firms, adding one buyer for an input increases CND_j by $1/(N-1)$, and the implied change in firm-level IBN depends on the firm's expenditure weight on that input.

rower region–industry cells. However, due to our fixed effects (firm FE and year× region×industry FE), identification comes only from within-firm variation in the network measure that is not absorbed by region–industry–year shocks. When the network measure is defined more finely, it becomes closer to the fixed effects and therefore exhibits less residual within-FE variation, leading to more observations/groups contributing no identifying variation (and hence being dropped for collinearity/absorption). Results on a harmonized sample across all specifications, are presented in Appendix Tables 24 and 25 and are in line with those from the main text.

We conduct several robustness checks, reported in the Appendix . First, we re-estimate Eq. (3) separately for each NUTS 2 region, demonstrating that the findings are not driven by specific geographical areas, such as the Capital Region or the Region of Southern Denmark (Appendix Tables 10, 11, 12, 13 and 14). Second, the results are robust to restricting the sample to manufacturing firms (Appendix Table 15) or splitting the sample by firm size using mean employment (Appendix Tables 16 and 17). Third, Appendix Tables 18 and 19 show that the results hold under alternative fixed-effect structures. Fourth, we show robustness to a different clustering strategy, including two-way clustering at the firm and region level (Appendix Table 20). Fifth, we compute buyer network measures for Denmark as a whole (ignoring regional boundaries) and by industry only. Results in Appendix Table 21 confirm the negative relationship between network size and input expenditures, though network size becomes correlated with firm size and efficiency once regional variation is omitted. Sixth, Appendix Table 22 shows that results also hold when using unweighted network measures.[7] Related and finally, we verify that our findings do not simply reflect reallocation toward domestically sourced inputs. Table 6 shows that both domestic and foreign input expenditures decline as the (unweighted) local input buyer network expands.[8] Appendix Table 23 further shows that the results are robust to control for the domestic expenditure share.

The empirical patterns documented in this section suggest that denser local input-buyer networks primarily affect firms' cost structures rather than their scale or performance. Across all specifications, network size has no significant impact on revenues or value added per worker. However, network expansion is consistently associated

[7] Our baseline buyer-network proxy is expenditure-share weighted (Eq. (2)), capturing exposure to buyer density in economically important inputs. By contrast, the unweighted proxy assigns equal weight to all purchased inputs, which might over-weight generic, low-expenditure inputs that tend to have high buyer density. This unweighted measure is therefore more sensitive to changes in the extensive margin of input sourcing (input scope), and it can correlate with revenues even when the weighted measure does not. Consistent with this interpretation, the unweighted revenue effect is attenuated once we account for input scope, while the negative effect on input expenditures remains robust. Specifically, we document in Appendix Table 29, that the unweighted IBN measure is highly correlated with the number of inputs, while this is not the case for the weighted IBN measure.

[8] Regression results on a harmonized sample across all specifications are provided in Appendix Table 26.

Table 6 Regional input buyer networks and domestic or foreign input expenditures

Cell	5-reg.		11-reg.		5-reg. & 69 Ind.		11-reg. & 69 Ind.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Input expenditures	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign
IBN^{cell}	−0.310***	0.0530***	−0.272***	−0.0349***	−0.383***	−0.258***	−0.188***	−0255***
	(0.0942)	(0.00991)	(0.0891)	(0.0105)	(0.0892)	(0.0282)	(0.0651)	(0.0309)
Observations	4,826	119,344	4,826	106,684	3,755	21,740	4,816	19,024
adj. R^2	0.909	0.834	0.909	0.839	0.907	0.860	0.908	0.857
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

All dependent variables and *IBN* are expressed in logs. IBN^{cell} is computed according to Eq. (2). All regressions control for the domestic expenditure share. Standard errors clustered at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively

with statistically significant reductions in input expenditures.[9] These findings point toward a mechanism in which buyer networks generate informational spillovers – for example, regarding supplier alternatives, input prices, and contractual norms – rather than inducing output-expanding changes in technology or production efficiency. Furthermore, it suggests that the network effect is not mechanical, since it does not simply mirror the typical correlation of larger, more productive firms with lower input costs.

Tighter networks may facilitate informal benchmarking, knowledge exchange, and improved access to information about quality and price conditions. Prior work shows that proximity fosters the transmission of economically relevant knowledge (Jaffe et al., 1993), that agglomeration promotes input sharing and information spillovers (Ellison et al., 2010), and that firms' network positions shape input costs and supply access (Bernard et al., 2019). While our data do not allow us to determine whether these effects stem from price reductions or quantity adjustments, our findings align closely with these mechanisms. Local networks enable firms to source inputs more efficiently, thereby lowering effective input prices or improving input quality without changing output levels or production technologies. As a result, networks primarily function through cost-efficiency gains by lowering input expenditures rather than through firm-level productivity improvements or scale effects.

Taking stock, the robust negative relationship between local buyer-network density and input expenditures is consistent with buyer-side knowledge spillovers, but it may also be consistent with other channels. First, denser buyer environments may increase buyer-side bargaining power or facilitate coordination and benchmarking, leading to tougher negotiations and lower effective prices. Second, network density may correlate with supplier-market conditions: if dense buyer environments attract entry of input suppliers or intensify supplier competition, firms may pay lower prices even without buyer learning. Our data primarily identify expenditure effects, and because VARK reports expenditures but not prices and quantities, we cannot fully disentangle price from quantity adjustments.[10] Taken together, Sect. 3 documents an average empirical pattern: denser local input-buyer networks are associated with lower intermediate input expenditures, while effects on total revenues and value added per worker are not statistically detectable. Importantly, a zero average rev-

[9] The zero (or negative) effect on value added per worker may seem surprising given the identity $VA = \text{sales} - \text{inputs}$. However, intermediate input expenditures are measured in VARK (augmented with UHDI), whereas value added is taken from the FIRM register, and these sources differ in coverage and accounting conventions (e.g., inventory adjustments, resale/traded goods, and the scope of intermediate consumption), so FIRM-based value added is not mechanically equal to revenues minus VARK-based inputs. Using an internally consistent proxy $\widetilde{VA} = \text{Revenues} - \text{InputExp}$ yields the expected positive effect, but this proxy omits other components of register-based value added (e.g., wages, inventories, and other operating costs) that can offset intermediate-purchase savings.

[10] To shed light on whether the expenditure effects reflect price or quantity adjustments, we use UHDI import data to decompose imported input expenditures into quantities and unit values. Unit values provide only an imperfect proxy for prices because they conflate quality and composition. Consistent with this, we do not find a stable unit-value response across specifications; instead, networks are associated with re-optimization along both quantity and composition margins. This aligns with our mechanism, which operates through reductions in effective intermediate input requirements rather than systematic changes in per-unit prices. See Appendix Tables 27 and 28.

enue effect does not rule out heterogeneous responses. Our theoretical framework, presented next, predicts that revenue pass-through depends on the effectiveness of knowledge transmission (or, equivalently, on effective network frictions). In Section 5, we therefore focus on a heterogeneity prediction motivated by the knowledge-flow interpretation: revenue effects emerge only for relationship-specific inputs, where tacit knowledge transmission is expected to be stronger, while revenue effects are absent for standardized inputs.

4 Theory

The empirical results in the previous section show that denser local input-buyer networks systematically reduce firms' expenditures on intermediate inputs, while leaving output-side performance measures – such as total revenues and value added per worker – statistically unchanged. This pattern is consistent with mechanisms operating primarily through input-market interactions (e.g., information flows or knowledge spillovers), rather than through changes in production technologies or product-market demand. To interpret these findings within a coherent theoretical structure, we require a model that (i) explicitly incorporates vertical linkages across firms, (ii) embeds network- or locality-driven spillovers, and (iii) allows input-side efficiency gains to occur without inducing direct changes in revenues or firm size.

To model such "network effects" on the production side, we build on the New Economic Geography (NEG) framework of Ottaviano and Robert-Nicoud (2006), which is well suited for our purposes. First, the model emphasizes geographic concentration and local interactions, consistent both with the knowledge-spillover mechanisms discussed in the empirical literature and with the patterns uncovered in Sect. 3. Second, NEG models naturally allow cost-side effects to arise without necessarily affecting firms' revenues or output levels: because output is often constrained by market size and downstream demand – both central elements in NEG models—local improvements in cost conditions (e.g., through network-generated savings) do not automatically translate into expansion. This combination of spatial structure, microfoundations, and vertical linkages makes the framework particularly suitable for interpreting the reduction in input expenditures observed in our data.

In what follows, we modify the Ottaviano and Robert-Nicoud (2006) model with vertical linkages only in fixed costs by introducing positive "network effects" that reduce these fixed costs for firms embedded in local input-buyer networks. More precisely, if we set $\delta_r = \rho_r = 0$ for $r = 1, 2$ in the expressions that follow, we recover the supply side of the NEG model with vertical linkages operating exclusively through fixed costs (i.e. $\alpha = 0$ and $\mu \neq 0$ in their terminology). In this paper, we extend that structure by allowing for network-induced cost savings among firms in the short-run version, that is with a given number of firms in each country, of the so-called "footloose entrepreneur model with vertical linkages" (FEVL).[11]

[11] Introducing vertical linkages also in variable costs would lead to an isomorphic representation. For this reason, Ottaviano and Robert-Nicoud (2006) recommend working with $\alpha = 0$ such that vertical linkages operate only in fixed costs.

4.1 Model setup

We consider a world with two countries/regions, indexed by *r* and *v* (with $r, v = 1, 2$), and two sectors: differentiated-goods (M) and homogeneous-goods sector (A). Both sectors employ labor, while firms in the differentiated-goods sector additionally use the different varieties as intermediate inputs. Workers are immobile across countries, and total world population is L_W. Labor endowments in countries *r* and *v* are given by $L_r = \lambda_r L_W$ and $L_v = (1 - \lambda_r)L_W$, respectively. Goods in both sectors are traded; however, while homogeneous goods are traded frictionlessly, differentiated varieties face iceberg trade costs. A firm producing in country *r* must ship $\tau_{rv} > 1$ units of a variety in order for one unit to arrive in country *v*.

4.2 The production side

Technology in the homogeneous sector is such that one unit of labor produces one unit of the homogeneous good. We assume that the homogeneous good is the numéraire of the model.[12]

The differentiated-goods sector produces a continuum of horizontally differentiated varieties s under increasing returns to scale and Dixit–Stiglitz monopolistic competition. The total number of differentiated-goods producing firms worldwide is $N_W = N_r + N_v$. Firms in this sector use both labor and intermediate inputs produced by domestic and foreign firms.

Producing $x_r(s)$ units of variety s in region *r* requires a fixed amount $\bar{F}$ of a composite input consisting of labor and differentiated intermediates, independent of output, and $a_M x_r(s)$ units of labor as variable input. With wage w_r, total variable cost is therefore $w_r a_M x_r(s)$. The fixed composite input is Cobb–Douglas, combining labor with share $1 - \mu$ and differentiated intermediates with share μ. The differentiated-goods composite is CES across all available varieties, with elasticity of substitution $\sigma > 1$.

Local network effects. We model 'local' (domestic) network effects by assuming that firms in a region have a set of links with other firms producing in the same region. Firms' demand for intermediates decreases in the number of input-buyer links, reflecting benefits from shared knowledge, common procurement practices, and improved access to market information. Networks, however, are costly since a larger set of links requires more coordination or relationship management. Thus, the cost for each firm increases in the mass of links it maintains. As in König et al. (2019), we treat the network structure as exogenously given: conditional on their given set of links, firms choose their optimal use of intermediate inputs. This captures that firms may benefit from 'processes of transmission of knowledge' within local networks, consistent with the empirical mechanisms discussed in Sect. 3.

Let $\Lambda_r(s)$ denote the set of firms in the production network of firm s in region *r*. Firm s's intermediates input demand declines when the average intermediate use of its network neighbors increases. This average is given by

[12] Together with the assumption that the homogeneous good is freely traded, this implies that the wage of workers is equal to one in both countries ($w_r = w_v = 1$).

$$\frac{\int_{\Lambda_r(s)} X_r(i)\, di}{\int_{\Lambda_r(s)} di},$$

and is multiplied by a size effect $S(\Omega(\Lambda_r(s)))$, where $S(\cdot)$ is a non-decreasing function taking values between 0 and $\Omega(\Lambda_r(s))$, the Lebesgue measure of the network.

Formally, the fixed composite input $\bar{F}$ is a Cobb-Douglas combination of labor $L_r(s)$ and of the composite of intermediate goods $\Phi(\cdot)$, with shares $1-\mu$ and μ respectively, given by

$$\bar{F} = F(L_r(s), \Phi(X_r(s), X_{-sr}, \Lambda_r(s))) = \frac{\left[L_r^f(s)\right]^{1-\mu}\left[\Phi(X_r(s), X_{-sr}, \Lambda_r(s))\right]^{\mu}}{(1-\mu)^{1-\mu}\mu^{\mu}}, \quad (4)$$

where

$$\Phi\left(X_r(s), X_{-sr}, \Lambda_r(s)\right) = X_r(s) + \delta_r S(\Omega(\Lambda_r(s)))\frac{X_{-sr}}{\int_{\Lambda_r(s)} di}, \quad (5)$$

and $\delta_r > 0$ measures the magnitude of the externality.[13] The term

$$X_{-sr} \equiv \int_{\Lambda_r(s)} X_r(i)\, di$$

is the total intermediate input used by neighbors of firm s. The network size is $\Omega(\Lambda_r(s)) = \int_{\Lambda_r(s)} di$. The CES differentiated-goods composite in region r is

$$X_r(s) = \left(\int_{j\in N} d_r^s(j)^{\frac{\sigma-1}{\sigma}} dj\right)^{\frac{\sigma}{\sigma-1}}.$$

Using the definition of X_{-sr}, expression (5) can be rewritten as

$$\Phi\left(X_r(s), X_{-sr}, \Lambda_r(s)\right) = X_r(s) + \delta_r S(\Omega(\Lambda_r(s)))\frac{\int_{\Lambda_r(s)} X_r(i)\, di}{\int_{\Lambda_r(s)} di}. \quad (6)$$

Expression (4) implies that firm s uses

$$\left[\frac{\mu^{\mu}(1-\mu)^{1-\mu}\bar{F}}{(\Phi(X_r(s), X_{-sr}, \Lambda_r(s)))^{\mu}}\right]^{\frac{1}{1-\mu}}$$

units of labor in fixed production, and $a_M x_r(s)$ units in variable production. Total labor demand of firm s is therefore

[13] The parameter δ_r may differ across regions, capturing differences in the efficiency of knowledge transmission.

$$L_r(s) = \left[\frac{\mu^{\mu}(1-\mu)^{1-\mu}\bar{F}}{(\Phi(X_r(s), X_{-sr}, \Lambda_r(s)))^{\mu}}\right]^{\frac{1}{1-\mu}} + a_M x_r(s),$$

and the production function becomes

$$x_r(s) = \frac{1}{a_M}\left\{L_r(s) - \left[\frac{\mu^{\mu}(1-\mu)^{1-\mu}\bar{F}}{(\Phi(X_r(s), X_{-sr}, \Lambda_r(s)))^{\mu}}\right]^{\frac{1}{1-\mu}}\right\}. \tag{7}$$

Firms minimize costs subject to (7), leading to optimal choices for $X_r(s)$ (and $L_r(s)$) that are directly (or indirectly) affected by the network.

Before deriving intermediate and labor demand, it is useful to define the *potential value of real network savings*:

$$G_r(s) \equiv S(\Omega(\Lambda_r(s)))\frac{\int_{\Lambda_r(s)} X_r(i)\, di}{\Omega(\Lambda_r(s))}. \tag{8}$$

Under the *additive specification* we adopt below, $S(\Omega(\Lambda_r(s))) = \Omega(\Lambda_r(s)) = \Lambda_r(s)$, and thus $G_r(s) = \int_{\Lambda_r(s)} X_r(i)\, di$.

The total production cost of firm *s* in region *r* is

$$TC_r(s) = w_r a_M x_r(s) + P_r^{\mu} w_r^{1-\mu}\bar{F} - \delta_r P_r G_r(s), \tag{9}$$

where P_r is the CES price index

$$P_r = \left(\int_{j\in N} p_r(j)^{1-\sigma} dj\right)^{\frac{1}{1-\sigma}}.$$

The term $-\delta_r P_r G_r(s)$ in Eq. (9) captures the reduction in fixed cost due to network participation and disappears when $\delta_r = 0$.

Intermediate and labor demand. As shown in the Theoretical Appendix, the firm's demand for variety *h* is

$$d_r^s(h) = \frac{p_r(h)^{-\sigma}}{P_r^{1-\sigma}}\left[\mu P_r^{\mu} w_r^{1-\mu}\bar{F} - \delta_r P_r G_r(s)\right], \tag{10}$$

and its aggregate intermediate demand is

$$X_r(s) = \left(\frac{w_r}{P_r}\right)^{1-\mu}\mu\bar{F} - \delta_r G_r(s), \tag{11}$$

which is smaller when $\delta_r > 0$.[14] Labor demand is

[14] The parameter δ_r must be small enough to ensure $X_r(s) > 0$, as well as $d_r^s(h) > 0$.

$$L_r(s) = a_M x_r(s) + (1-\mu)\bar{F}\left(\frac{P_r}{w_r}\right)^{\mu},$$

which does not depend directly on δ_r.

The cost of maintaining the network is given by $\rho_r \Lambda_r(s)^2$, where $\rho_r > 0$ is the country-specific network-cost parameter.[15] Furthermore, one might interpret ρ as capturing the friction/cost of extracting and implementing knowledge spillovers from the local buyer network, i.e., the cost of benefiting from information about suppliers, prices, and contracting practices, conditional on being embedded in a local buyer environment. Under this interpretation, relationship-specific settings can plausibly lower the effective friction of learning and implementation because repeated interactions and tacit knowledge make information more transferable, credible, and actionable.

Symmetry and additive specification. For analytical transparency, we present in the following the symmetric equilibrium where firms within a region share the same network intensity. In Appendix Section A.4 , we present an asymmetric extension in which network benefits are firm-specific and naturally correspond to the within-firm variation used for identification in the data. Importantly, our empirical identification does not rely on region–industry–year common network shifts: with firm fixed effects and year × region × industry fixed effects, identification comes from within-firm changes in firm-specific exposure to buyer density across the firm's input basket (Eq. (2)). We assume $S(\Omega(\Lambda_r(s))) > 1$ and focus on the additive specification $S(\Omega(\Lambda_r(s))) = \Lambda_r$. Assuming symmetric firms,

$$G_r(s) = \Lambda_r X_r, \tag{12}$$

since $X_r(i) = X_r$ and $\Lambda_r(s) = \Lambda_r$ for all firms.[16]

Multiplying (10) by N_r yields total local demand for variety *h* used as intermediate:

$$d_r^T(h) = d_r^s(h) N_r.$$

Demand from region *v* for variety *h* produced in *r* is

$$d_r^{s*}(h) = \frac{p_r^*(h)^{-\sigma}}{P_v^{1-\sigma}}\left[\mu P_v^{\mu} w_v^{1-\mu}\bar{F} - \delta_v P_v G_v(s)\right], \tag{13}$$

where $p_r^*(h)$ is the price set in the foreign market v for the variety h produced in r, implying foreign intermediate demand of the same variety is

$$d_r^{T*}(h) = d_r^{s*}(h) N_v.$$

[15] Note that given the way the model is written, the direct firm level results would not be affected by considering the cost of maintaining the network as a simple fixed cost, that might be part of some fixed entry costs.

[16] Under symmetry and (11) and (12), $X_r > 0$ requires $\delta_r < \left(\frac{w_r}{P_r}\right)^{1-\mu} \frac{\mu\bar{F}}{\Lambda_r}$.

Using (11) and (12), symmetric-firm intermediate demand becomes

$$X_r = \left(\frac{w_r}{P_r}\right)^{1-\mu} \frac{\mu \bar{F}}{1+\delta_r \Lambda_r}, \tag{14}$$

which is decreasing in network size Λ_r and the knowledge-transmission efficiency δ_r . Thus, intermediate expenditures

$$P_r X_r = P_r^{\mu} w_r^{1-\mu} \frac{\mu \bar{F}}{1+\delta_r \Lambda_r}$$

decrease with network size, in line with our empirical estimates in Sect. 3. In the next section, we close the model and derive testable predictions related to the cost parameter ρ_r of the production network, which we then examine empirically.

4.3 Consumers

The representative consumer in each country/region has a two-tier utility function. The upper tier is Cobb–Douglas across homogeneous and differentiated goods, while the lower tier aggregates differentiated varieties through a CES aggregator:

$$U(C_A, C_M) = \frac{C_A^{1-\gamma} C_M^{\gamma}}{\gamma^{\gamma}(1-\gamma)^{1-\gamma}}, \qquad C_M = \left(\int_{j \in N} c(j)^{\frac{\sigma-1}{\sigma}} dj\right)^{\frac{\sigma}{\sigma-1}}, \qquad 0 < \gamma < 1 < \sigma. \tag{15}$$

As usual, the corresponding indirect utility function is

$$V = \frac{I}{P^{\gamma}}, \tag{16}$$

where P is the CES price index,

$$P \equiv \left(\int_{j \in N} p(j)^{1-\sigma} dj\right)^{\frac{1}{1-\sigma}},$$

and I denotes household income.

Applying Roy's identity to (16), the demand for variety j by the representative consumer is

$$c(j) = \frac{p(j)^{-\sigma}}{P^{1-\sigma}} \gamma I.$$

Thus, total consumer demand for variety j in region r is

$$c_r(j) = \frac{p_r(j)^{-\sigma}}{P_r^{1-\sigma}} \gamma I_r, \tag{17}$$

where I_r is aggregate income in region *r*, given by wages plus pure profits earned by locally owned firms:

$$I_r = w_r L_r + N_r \Pi_r, \tag{18}$$

with Π_r denoting pure average profits of firms operating in region *r*.

Following Ottaviano and Robert-Nicoud (2006); Baldwin et al. (2011), and related contributions such as Nocco (2012) and Navas and Nocco (2021), we impose the standard assumption $\gamma = \mu$. That is, consumers allocate the same expenditure share to differentiated goods as firms devote to intermediate inputs in production. This restriction simplifies the exposition and is consistent with the broad class of NEG models featuring vertical linkages.

4.4 Sales and profits

The total quantity sold by a domestic firm *j* in region *r* to consumers and firms located in the same region is

$$x_{rr}(j) = c_r(j) + d_r^s(j) N_r. \tag{19}$$

Because iceberg trade costs imply that $\tau_{rv} > 1$ units must be shipped from region *r* for one unit to arrive in region *v*, the quantity produced for the foreign market is

$$x_{rv}(j) = \tau_{rv} \left[c_v(j) + d_r^{s*}(j) N_v \right], \tag{20}$$

so that total equilibrium output of firm *j* is

$$x_r(j) = x_{rr}(j) + x_{rv}(j) = c_r(j) + d_r^s(j) N_r + \tau_{rv} \left[c_v(j) + d_r^{s*}(j) N_v \right].$$

Operating profits from domestic and foreign markets are given by

$$\pi_{rr}(j) = \left[p_r(j) - a_M w_r \right] x_{rr}(j), \tag{21}$$

$$\pi_{rv}(j) = \left[\frac{p_r^*(j)}{\tau_{rv}} - a_M w_r \right] x_{rv}(j). \tag{22}$$

Total operating profits are therefore

$$\pi_r(j) = \pi_{rr}(j) + \pi_{rv}(j). \tag{23}$$

Pure profits additionally subtract network costs and fixed production costs (net of network-induced savings). Hence,

$$\Pi_r(j) = \pi_r(j) - \rho_r \left(\Lambda_r(j)\right)^2 - \left[\bar{F} P_r^{\mu} w_r^{1-\mu} - \delta_r P_r G_r(j)\right], \tag{24}$$

where the term $\delta_r P_r G_r(j)$ represents the fixed-cost savings generated by participating in a local network.

Domestic and foreign revenues. Using (19), (10), (17), (18), and (24), it follows that with N_r symmetric firms, domestic revenues of a representative firm in region *r* are

$$p_r\left(c_r + d_r^s N_r\right) = \frac{p_r^{1-\sigma}}{P_r^{1-\sigma}} \left\{\mu \left[w_r L_r + N_r \left(\pi_r - \rho_r \Lambda_r^2 + \delta_r P_r G_r\right)\right] - \delta_r P_r G_r N_r\right\}. \tag{25}$$

Using (13), foreign revenues from exports to *v* are[17]

$$p_r^*\left(c_v + d_r^{s*} N_v\right) = \frac{p_r^{*\,1-\sigma}}{P_v^{1-\sigma}} \left\{\mu \left[w_v L_v + N_v \left(\pi_v - \rho_v \Lambda_v^2 + \delta_v P_v G_v\right)\right] - \delta_v P_v G_v N_v\right\}. \tag{26}$$

These expressions reveal two opposing effects generated by network participation. First, the savings term $-\delta_r P_r G_r N_r$ reduces revenues by lowering intermediate input demand. Second, network participation increases pure profits through the term $+\delta_r P_r G_r$ inside the bracket, raising household income and hence consumer demand. Which effect dominates is a general-equilibrium question, depending on all model parameters, including the network-cost parameters ρ_r and ρ_v. When ρ is small, the profit-increasing effect of network savings is stronger, making higher revenues more likely. This prediction will be examined empirically in the next section.

Prices, pass-through, and freeness of trade. Under Dixit–Stiglitz monopolistic competition, transport costs are fully passed to consumers and mill pricing is optimal:

$$p_r(j) = \frac{\sigma}{\sigma - 1} a_M w_r = p_r, \qquad p_r^*(j) = \frac{\sigma}{\sigma - 1} \tau_{rv} a_M w_r = p_r^* = \tau_{rv} p_r. \tag{27}$$

Thus, prices do not depend on a firm's network position, since networks affect only fixed costs, not marginal costs. This aligns with the empirical analysis in Section 3, showing that local buyer networks leave firm efficiency, measured as value added per worker, unaffected.

Using (22)–(27), operating profits can be expressed as a constant fraction of total revenues:

$$\pi_r(j) = \frac{p_r(j) x_{rr}(j) + p_r^*(j) \frac{1}{\tau_{rv}} x_{rv}(j)}{\sigma}. \tag{28}$$

Choosing units such that $a_M = \frac{\sigma - 1}{\sigma}$ and recalling the numéraire assumption,[18] domestic and export prices simplify to

[17] Firm indices are dropped under symmetry.

[18] Following Ottaviano and Robert-Nicoud (2006).

$$p_r = 1, \qquad p_r^* = \tau_{rv}. \tag{29}$$

The CES price index in region *r* is therefore

$$P_r = (N_r + N_v \phi_{rv})^{\frac{1}{1-\sigma}} = \frac{1}{(N_r + N_v \phi_{rv})^{\frac{1}{\sigma-1}}}, \tag{30}$$

where $\phi_{rv} = \tau_{rv}^{1-\sigma} \in [0, 1]$ measures the *freeness of trade*. An analogous expression holds for P_v:

$$P_v = (N_v + N_r \phi_{vr})^{\frac{1}{1-\sigma}}. \tag{31}$$

While the core model is closed here, further equilibrium derivations are presented in the Theoretical Appendix Section A.3.

5 Relationship-specific networks and domestic sales

A central implication of our model is that the effect of network expansion on domestic revenues depends on the parameter ρ, which governs the cost of operating within a production network. Lower values of ρ strengthen the pass-through of network-generated cost savings into pure profits and, ultimately, into domestic expenditures. Conversely, higher values of ρ constrain firms' ability to convert input-side savings into increased demand and revenues. To empirically operationalize these differences in network costs, we exploit the product-level relationship-stickiness index developed by Martin et al. (2023). Their measure, constructed from the duration of firm-to-firm relationships, captures the extent of relational investment and specificity required to transact a particular product. Crucially, it is strongly correlated with well-established measures of product differentiation and contract intensity – including Rauch (1999) and Nunn (2007) – thus validating it as a proxy for underlying frictions embedded in buyer–supplier exchanges. We match this measure to our Danish data and use it to distinguish between relationship-specific and non-relationship-specific inputs.

Applying the stickiness index enables us to compute separate network measures for relationship-specific and non-relationship-specific products.[19] Specifically, we follow the definition of an input buyer network from Eq. (2) and compute it separately for relationship-specific and non-relationship-specific products, called IBN_{rs}^{cell} and IBN_{nrs}^{cell}, respectively. This decomposition provides a direct empirical counterpart to the model's prediction that domestic revenue responses to network expansion should be stronger for products associated with lower network costs – i.e., with lower ρ. Relationship-specific inputs typically require contract customization, repeated interactions, or tacit knowledge exchange. These features facilitate the transmission of information within the network and make buyer-side spillovers more powerful. In contrast, non-relationship-specific inputs tend to be standardized, more easily trad-

[19] To classify products into relationship-specific or not, we use the median value in the matched (Martin et al., 2023) dataset, which in our data equals 3.0095 (compared to 2.97 in Martin et al. (2023)).

able, and characterized by weaker informational frictions, implying a higher effective ρ. Accordingly, we expect network expansion for relationship-specific products to raise domestic revenues, while no such effect should arise for non-relationship-specific inputs.

Our heterogeneity analysis uses the product-level relationship stickiness index of Martin et al. (2023), which is constructed from the duration of firm-to-firm (buyer-supplier) relationships and captures the extent of relational specificity and switching/search frictions in vertical matches. At first glance, this vertical notion differs from the horizontal interactions emphasized in our buyer-network mechanism (knowledge exchange among co-buyers of the same input). The link is that high-stickiness products typically require greater tacit knowledge and relational investments in procurement (e.g., quality verification, customization, and supplier-specific know-how). In such environments, information shared among co-buyers – about reliable suppliers, contract terms, lead times, handling practices, or input compatibility – has higher marginal value and is more readily actionable. Hence, while stickiness is measured on the vertical margin, it plausibly proxies for lower *effective* frictions of benefiting from co-buyer spillovers (a lower effective network friction parameter, rather than identifying ρ in isolation. Consistent with this interpretation, we find that network expansion increases domestic revenues only for relationship-specific inputs, where tacit knowledge is more important, and not for standardized inputs.

Specifically, we first re-estimate regressions analogous to those in Sect. 3, focusing on input expenditures as dependent variables and constructing network measures separately for relationship-specific and non-relationship-specific products. According to Eq. (14), the parameter ρ does not affect how network size relates to intermediate input demand. Hence, both types of networks should reduce firms' input expenditures. Appendix Table 30 confirms this prediction: irrespective of whether the underlying products are relationship-specific or not, network size negatively affects input demand. Moreover, coefficients are similar in sign and magnitude, consistent with the theoretical prediction that ρ plays no role in the cost-side margin.

Next, we turn to domestic revenues. According to Eq. (25), the impact of network size on domestic sales should differ between relationship-specific and non-relationship-specific inputs. We therefore re-estimate Eq. (3) using domestic revenues as the dependent variable and including separate measures for relationship-specific and non-relationship-specific networks. Put differently, we now examine heterogeneity in revenue responses to network expansion. While Sect. 3 shows that total revenues do not respond on average, the model implies that cost savings can translate into higher domestic sales only when spillovers are sufficiently effective. We therefore focus on domestic revenues (constructed using VARS and UHDI) and distinguish buyer networks based on relationship-specific versus non-relationship-specific inputs. Because VARS covers a subset of firms, the estimates in this section are not directly comparable in sample size to Sect. 3; rather, they are designed to test the model's conditional prediction about when revenue effects arise. Results are reported in Tables 7 and 8. As the substantial lower sample size reduces statistical power, we report estimates under three alternative fixed-effects structures: (i) separate fixed effects for year, industry, and region; (ii) year×industry and region fixed effects; and (iii) full

Table 7 Relationship-specific networks and domestic revenues

Cell	5-regions			11-regions		
	Domestic revenues					
	(1)	(2)	(3)	(4)	(5)	(6)
IBN_{nrs}^{cell}	0.0144*	0.0138*	0.00471	0.00960	0.00873	−0.0128
	(0.00760)	(0.00781)	(0.0119)	(0.00680)	(0.00706)	(0.0139)
IBN_{rs}^{cell}	0.0237**	0.0239**	0.0190	0.0207**	0.0201**	0.00906
	(0.0117)	(0.0118)	(0.0155)	(0.00847)	(0.00850)	(0.0160)
Observations	13282	13282	9518	12510	12509	7497
adj. R^2	0.832	0.832	0.836	0.837	0.837	0.836
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year, Industry, Region FE	Yes	No	No	Yes	No	No
Year×industry, Region FE	No	Yes	No	No	Yes	No
Year×industry×region FE	No	No	Yes	No	No	Yes

The dependent variable, input expenditures, and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2). Inputs are split into relationship and non-relationship-specific products using the measure from Martin et al. (2023). Standard errors clustered at the firm level. ***, **, * denote significance at 1%, 5%, and 10%

Table 8 Relationship-specific networks and domestic revenues

Cell	5-regions & 69 Industries			11-regions & 69 Industries		
	Domestic revenues					
	(1)	(2)	(3)	(4)	(5)	(6)
IBN_{nrs}^{cell}	0.0104	0.0101	−0.00178	0.0131	0.0115	−0.0135
	(0.00806)	(0.00821)	(0.0137)	(0.00800)	(0.00828)	(0.0180)
IBN_{rs}^{cell}	0.0315**	0.0313**	0.0362*	0.0189*	0.0164	0.0111
	(0.0128)	(0.0128)	(0.0185)	(0.0113)	(0.0113)	(0.0180)
Observations	10072	10072	7285	9198	9194	5552
adj. R^2	0.827	0.827	0.831	0.831	0.831	0.836
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year, Industry, Region FE	Yes	No	No	Yes	No	No
Year×industry, Region FE	No	Yes	No	No	Yes	No
Year×industry×region FE	No	No	Yes	No	No	Yes

The dependent variable, input expenditures, and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2). Inputs are split into relationship and non-relationship-specific products using (Martin et al., 2023). Standard errors clustered at the firm level. ***, **, * denote significance at 1%, 5%, and 10%

year×industry×region fixed effects. As expected, the most restrictive specification (columns (3) and (6)) shows the weakest precision.

Overall, the regression results corroborate the theory. Network expansion based on relationship-specific products significantly increases domestic revenues. This aligns with the model's prediction that firms sourcing such inputs face lower effective network costs, enabling stronger translation of input-side savings into pure profits and, ultimately, into domestic demand. These inputs are embedded in repeated, relational exchanges, where informational spillovers are stronger and more valuable. By contrast, networks based on non-relationship-specific inputs show no statisti-

cally detectable effect on domestic revenues. Standardized products, which require little relational investment and exhibit limited tacit knowledge, generate weaker or negligible informational spillovers. Consequently, firms face higher effective ρ, and network-generated input-side savings do not propagate into increased local demand.

Taken together, the results provide strong empirical support for the model: the domestic revenue impact of network expansion is activated only in environments where relational specificity is sufficiently high to facilitate knowledge flows, as captured by Martin et al. (2023).[20]

6 Conclusion

Firms increasingly rely on complex networks of suppliers and buyers to source intermediate inputs. A growing literature highlights that these production networks are not only channels for material flows, but also important conduits for information, knowledge spillovers, and coordination among firms. Yet, while much is known about how production networks shape aggregate fluctuations and productivity, far less is understood about how the structure of local input-buyer networks affects firm-level outcomes in small open economies. In particular, little evidence exists on whether denser local networks generate cost savings, and whether such savings translate into higher firm performance. Using rich register data for Denmark, we document two empirical facts. First, firms embedded in denser local input-buyer networks systematically spend less on intermediate inputs. The effects are robust across definitions of local markets, industry categories, and firm types. Second, despite substantial input-cost savings, network expansion does not affect firms' revenues or value added per worker. Taken together, these results indicate that local input-buyer networks operate primarily through cost-side channels – such as information exchange on suppliers, or contractual norms – rather than through output-expanding mechanisms.

To interpret these findings, we develop a model that adapts the New Economic Geography framework of Ottaviano and Robert-Nicoud (2006) with vertical linkages by incorporating network-generated reductions in fixed production costs. The model highlights that local networks reduce firms' intermediate input demand by facilitating knowledge flows and shared learning among proximate buyers. However, whether these input-side savings translate into higher domestic revenues depends critically on a country-specific network-cost parameter. For low values, cost savings feed into higher pure profits and thereby raise domestic demand. However, for high values, revenue effects vanish.

We test this prediction by exploiting product-level information on relationship specificity from Martin et al. (2023). Matching their measure to Danish data allows us to distinguish between input-buyer networks built on relationship-specific products – where knowledge flows are more valuable and network costs are lower – and

[20] Finally, we also examine how the two network measures affect total revenues and value added per worker. As expected, total revenues also increase for relationship-specific networks, consistent with the positive effects on domestic revenues. By contrast, value added per worker remains unaffected, mirroring the results in Sect. 3.

networks built on standardized, non-relationship-specific products. Consistent with the model, we find that network expansion increases domestic revenues only for relationship-specific products, while networks based on non-specific products exhibit no such effects. Our findings are most directly about intermediate input expenditures. While we interpret the patterns as arising from buyer-side knowledge flows (information about suppliers, contract terms, and procurement practices), alternative channels – such as buyer-power/benchmarking effects or changes in supplier competition – may also contribute. Distinguishing these mechanisms decisively would require observing transaction-level prices and quantities and supplier identities or exploiting exogenous variation in local supplier entry and competition. Within the constraints of the available data, the heterogeneity by relationship specificity provides supportive evidence for knowledge transmission: revenue effects appear only where relational/tacit knowledge is most relevant.

Overall, our results suggest that input-buyer networks matter for firms not because they scale up production, but because they reduce input costs through localized knowledge spillovers. These spillovers translate into higher revenues only in environments where relational investments are sufficiently strong to reduce network-related frictions. Furthermore, our findings suggest that local input-buyer networks can generate sizable cost savings by facilitating the diffusion of procurement-relevant knowledge (e.g., information on supplier options, prices, quality, and contracting practices). This has several implications for place-based and industrial policy. First, the design of industrial zones and parks may benefit from explicitly fostering *buyer co-location*: grouping firms with overlapping intermediate input needs can increase the density of co-buyers for specific inputs and thus enlarge the local "information pool" that underpins the cost-saving mechanism. Second, complementary "soft" infrastructure can amplify these benefits at relatively low fiscal cost: shared procurement and supplier-discovery platforms, regular supplier fairs, training and benchmarking initiatives, and targeted business-to-business matchmaking can reduce the frictions of knowledge transmission and help firms translate network proximity into effective savings. Finally, our heterogeneity results indicate that revenue effects of network expansion arise primarily for relationship-specific inputs, where tacit knowledge is more important and learning is more valuable. This suggests that network-oriented policies may be particularly effective when targeted to sectors and product categories characterized by higher relational intensity.

A Appendix

A.1 Empirical appendix

See Tables 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29 and 30.

Table 9 Out-degree centrality measures for Top-20 CN2 inputs—firm-level weights

Rank	Product	wCND
1	39 – Plastics and plastic goods	0.00038
2	3 – Fish and seafood products	0.00038
3	48 – Paper and paperboard products	0.00031
4	73 – Articles of iron and steel	0.00027
5	72 – Iron and steel (raw and semi-finished)	0.00017
6	27 – Mineral fuels and related oils	0.00016
7	32 – Dyes, pigments and coloring materials	0.00013
8	76 – Aluminum and aluminum products	0.00013
9	13 – Natural gums, resins and similar products	0.00012
10	25 – Salt, stone, cement and mineral materials	0.00012
11	44 – Wood and wood articles	0.00011
12	84 – Machinery and mechanical appliances	0.00009
13	85 – Electrical machinery and equipment	0.00009
14	1 – Live animals	0.00008
15	94 – Furniture, lighting, toys and miscellaneous goods	0.00008
16	4 – Dairy products	0.00008
17	49 – Printed books and other printed matter	0.00008
18	2 – Meat and edible animal products	0.00006
19	23 – Oil seeds, feed residues and similar products	0.00006
20	40 – Rubber and rubber articles	0.00006

Based on data from Statistics Denmark for the year 2018. Product labels combine CN2 codes with shortened official CN product descriptions. Values report firm-level weighted (wCND) out-degree centrality of input links in the production network as defined in Eq. 1, where inputs are weighted according to firms expenditure shares on these inputs. Cells are defined at the level of 5-regions (NUTS 2)

Table 10 Regional input buyer networks and firm outcomes—capital region of Denmark

Cell	5-regions			11-regions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	−0.0000214	−0.00411*	−0.149***	−0.00293	−0.00109	−0.145***
	(0.00284)	(0.00224)	(0.00936)	(0.00242)	(0.00219)	(0.00817)
Observations	59318	59318	59318	47929	47929	47929
adj. R^2	0.922	0.590	0.849	0.927	0.596	0.862
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

The regression sample is restricted to firms in the NUTS 2 area Capital region of Denmark. All dependent variables—revenues, value added per worker, and input expenditures—and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2), with cells defined either at the 5 NUTS-2 regions or the 11 NUTS-3 regions. Industry classification follows the 4-digit NACE rev. 2 version. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance level at 1%, 5% and 10% respectively

A.2 Theoretical appendix

For a given mass of links of the firm $\Lambda_r(s)$ with other firms in their local network, each firm producing variety s solves the following expenditure minimization problem given the technology

$$\min_{L_r(s),\, d_r^s(j)} \quad w_r L_r(s) + \int_{j \in N} p_r(j) d_r^s(j) dj$$

Table 11 Regional input buyer networks and firm outcomes—central Denmark region

Cell	5-regions			11-regions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	0.00730*	0.000545	−0.0864***	0.00446	0.000531	−0.0877***
	(0.00424)	(0.00378)	(0.0147)	(0.00399)	(0.00362)	(0.0129)
Observations	26010	26010	26010	22910	22910	22910
adj. R^2	0.917	0.529	0.831	0.920	0.529	0.840
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

The regression sample is restricted to firms in the NUTS 2 area Central Denmark Region. All dependent variables—revenues, value added per worker, and input expenditures—and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2), with cells defined either at the 5 NUTS-2 regions or the 11 NUTS-3 regions. Industry classification follows the 4-digit NACE rev. 2 version. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance level at 1%, 5% and 10% respectively

Table 12 Regional input buyer networks and firm outcomes—north Denmark region

Cell	5-regions			11-regions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	−0.0135	−0.00586	−0.209***	−0.0135	−0.00586	−0.209***
	(0.00836)	(0.00652)	(0.0282)	(0.00836)	(0.00652)	(0.0282)
Observations	9136	9136	9136	9136	9136	9136
adj. R^2	0.918	0.515	0.840	0.918	0.515	0.840
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

The regression sample is restricted to firms in the NUTS 2 area North Denmark Region. All dependent variables—revenues, value added per worker, and input expenditures—and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2), with cells defined either at the 5 NUTS-2 regions or the 11 NUTS-3 regions. Industry classification follows the 4-digit NACE rev. 2 version. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance level at 1%, 5% and 10% respectively

$$\text{s.t.} \qquad x_r(s) = \frac{1}{a_M}\left\{L_r(s) - \left[\frac{\mu^{\mu}(1-\mu)^{1-\mu}\bar{F}}{(\Phi(X_r(s),X_{-sr},\Lambda_r(s)))^{\mu}}\right]^{\frac{1}{1-\mu}}\right\}$$

$$\text{w} \qquad \text{i} \qquad \text{t} \qquad \text{h}$$

$$\Phi\left(X_r(s), X_{-sr}, \Lambda_r(s)\right) \equiv \left(\int_{j\in N} d_r^s(j)^{\frac{\sigma-1}{\sigma}} dj\right)^{\frac{\sigma}{\sigma-1}} + \delta_r S(\Omega(\Lambda_r(s)))\frac{\int_{\Lambda_r(s)} X_r(i)di}{\Omega(\Lambda_r(s))}$$

The Langrangian is:

$$\ell = w_r L_r(s) + \int_{j\in N} p_r(j) d_r^s(j) dj + \lambda\{x_r(s)$$

$$-\frac{1}{a_M}\left[L_r(s) - \left[\mu^{\mu}(1-\mu)^{1-\mu}\bar{F}\right]^{\frac{1}{1-\mu}}\left[\left(\int_{j\in N} d_r^s(j)^{\frac{\sigma-1}{\sigma}} dj\right)^{\frac{\sigma}{\sigma-1}} + \delta_r S(\Omega(\Lambda_r(s)))\frac{\int_{\Lambda_r(s)} X_r(i)di}{\Omega(\Lambda_r(s))}\right]^{-\frac{\mu}{1-\mu}}\right]\}$$

where λ is the Lagrange multiplier.

The first-order condition (FOC) with respect to $L_r(s)$, $\frac{\partial \ell}{\partial L_r(s)} = 0$, implies that

Table 13 Regional input buyer networks and firm outcomes—region of southern Denmark

Cell	5-regions			11-regions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	0.000824	0.00299	−0.134***	−0.00384	−0.00118	−0.127***
	(0.00432)	(0.00365)	(0.0169)	(0.00455)	(0.00387)	(0.0165)
Observations	18997	18997	18997	16091	16091	16091
adj. R^2	0.920	0.538	0.824	0.919	0.526	0.830
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year× industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The regression sample is restricted to firms in the NUTS 2 area Region of Southern Denmark. All dependent variables—revenues, value added per worker, and input expenditures—and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2), with cells defined either at the 5 NUTS-2 regions or the 11 NUTS-3 regions. Industry classification follows the 4-digit NACE rev. 2 version. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance level at 1%, 5% and 10% respectively

Table 14 Regional input buyer networks and firm outcomes—region Zealand

Cell	5-regions			11-regions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	−0.00932	−0.00832	−0.114***	−0.00779	−0.00437	−0.0800***
	(0.00706)	(0.00560)	(0.0214)	(0.00785)	(0.00546)	(0.0212)
Observations	5590	5590	5590	4649	4649	4649
adj. R^2	0.918	0.525	0.853	0.915	0.553	0.851
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

The regression sample is restricted to firms in the NUTS 2 area Region Zealand. All dependent variables—revenues, value added per worker, and input expenditures—and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2), with cells defined either at the 5 NUTS-2 regions or the 11 NUTS-3 regions. Industry classification follows the 4-digit NACE rev. 2 version. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance level at 1%, 5% and 10% respectively

$$w_r = \lambda \frac{1}{a_M} \tag{32}$$

The FOC with respect to variety j, $\frac{\partial \ell}{\partial d_r^s(j)} = 0$, implies that

$$p_r(j) = \frac{\mu}{1-\mu} \lambda \frac{\left[\mu^{\mu}(1-\mu)^{1-\mu}\bar{F}\right]^{\frac{1}{1-\mu}}}{a_M} \left[\left(\int_{j \in N} d_r^s(j)^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}} + \delta_r S(\Omega(\Lambda_r(s))) \frac{\int_{\Lambda_r(s)} X_r(i) di}{\Omega(\Lambda_r(s))} \right]^{-\frac{\mu}{1-\mu}-1} * \left(\int_{j \in N} d_r^s(j)^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{1}{\sigma-1}} d_r^s(j)^{-\frac{1}{\sigma}} \tag{33}$$

The FOC with respect to variety h, $\frac{\partial \ell}{\partial d_r^s(h)} = 0$, implies that

Table 15 Regional input buyer networks and firm outcomes—manufacturing only

Cell	5-regions			11-regions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	0.00434	−0.00279	−0.0915***	0.00414	0.000534	−0.0810***
	(0.00471)	(0.00375)	(0.0192)	(0.00563)	(0.00396)	(0.0191)
Observations	23178	23178	23178	19206	19206	19206
adj. R^2	0.941	0.508	0.839	0.944	0.524	0.841
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

The regression sample is restricted to firms in the manufacturing sectors. All dependent variables—revenues, value added per worker, and input expenditures—and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2), with cells defined either at the 5 NUTS-2 regions or the 11 NUTS-3 regions. Industry classification follows the 4-digit NACE rev. 2 version. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance level at 1%, 5% and 10% respectively

Table 16 Regional input buyer networks and firm outcomes—small firms

Cell	5-regions			11-regions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	−0.00195	−0.00194	−0.136***	−0.00452**	−0.00131	−0.130***
	(0.00211)	(0.00176)	(0.00686)	(0.00199)	(0.00179)	(0.00647)
Observations	98787	98787	98787	82087	82087	82087
adj. R^2	0.865	0.541	0.822	0.869	0.541	0.833
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

The regression sample is restricted to firms with less than 60 employees. All dependent variables—revenues, value added per worker, and input expenditures—and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2), with cells defined either at the 5 NUTS-2 regions or the 11 NUTS-3 regions. Industry classification follows the 4-digit NACE rev. 2 version. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance level at 1%, 5% and 10% respectively

$$p_r(h) = \frac{\mu}{1-\mu}\lambda \frac{\left[\mu^{\mu}(1-\mu)^{1-\mu}\bar{F}\right]^{\frac{1}{1-\mu}}}{a_M}\left[\left(\int_{j\in N} d_r^s(j)^{\frac{\sigma-1}{\sigma}}dj\right)^{\frac{\sigma}{\sigma-1}} + \delta_r S(\Omega(\Lambda_r(s)))\frac{\int_{\Lambda_r(s)} X_r(i)di}{\Omega(\Lambda_r(s))}\right]^{-\frac{\mu}{1-\mu}-1} * \left(\int_{j\in N} d_r^s(j)^{\frac{\sigma-1}{\sigma}}dj\right)^{\frac{1}{\sigma-1}} d_r^s(h)^{-\frac{1}{\sigma}} \quad (34)$$

The FOC with respect to λ, $\frac{\partial \ell}{\partial \lambda} = 0$, implies that

$$x_r(s) = \frac{1}{a_M}\left\{L_r(s) - \left[\mu^{\mu}(1-\mu)^{1-\mu}\bar{F}\right]^{\frac{1}{1-\mu}}\left(\Phi\left(X_r(s), X_{-sr}, \Lambda_r(s)\right)\right)^{-\frac{\mu}{1-\mu}}\right\} \quad (35)$$

From the ratio of (33) and (34), we get that

Table 17 Regional input buyer networks and firm outcomes—large firms

Cell	5-regions			11-regions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	0.00822	0.00531	−0.178***	0.00838	0.0103**	−0.160***
	(0.00508)	(0.00488)	(0.0292)	(0.00540)	(0.00444)	(0.0251)
Observations	14475	14475	14475	11149	11149	11149
adj. R^2	0.940	0.758	0.896	0.942	0.753	0.895
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

The regression sample is restricted to firms with more or equal than 60 employees. All dependent variables—revenues, value added per worker, and input expenditures—and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2), with cells defined either at the 5 NUTS-2 regions or the 11 NUTS-3 regions. Industry classification follows the 4-digit NACE rev. 2 version. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance level at 1%, 5% and 10% respectively

Table 18 Regional input buyer networks and firm outcomes—alternative FE 1

Cell	5-regions			11-regions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	0.000642	−0.00327**	−0.137***	−0.00139	−0.00268**	−0.133***
	(0.00181)	(0.00147)	(0.00658)	(0.00164)	(0.00131)	(0.00558)
Observations	126551	126551	126551	113977	113977	113977
adj. R^2	0.916	0.557	0.833	0.919	0.558	0.838
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

All dependent variables—revenues, value added per worker, and input expenditures—and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2), with cells defined either at the 5 NUTS-2 regions or the 11 NUTS-3 regions. Industry classification follows the 4-digit NACE rev. 2 version. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance level at 1%, 5% and 10% respectively

$$d_r^s(j) = \left(\frac{p_r(h)}{p_r(j)}\right)^{\sigma} d_r^s(h) \tag{36}$$

Moreover, making use of (32), (33), (36) and of the definition of the price index $P_r \equiv \left(\int\limits_{j\in N} p_r(j)^{1-\sigma} dj\right)^{\frac{1}{1-\sigma}}$, we get the intermediate input demand by firm s

$$X_r(s) = \left(\frac{w_r}{P_r}\right)^{1-\mu} \mu\bar{F} - \delta_r S(\Omega(\Lambda_r(s))) \frac{\int_{\Lambda_r(s)} X_r(i)di}{\Omega(\Lambda_r(s))} \tag{37}$$

The expression above for intermediate input demand by firm s shows that when there is a positive externality ($\delta_r > 0$) due to 'network' effects, intermediate demand by each firm s is reduced.

Table 19 Regional input buyer networks and firm outcomes—alternative FE 2

Cell	5-regions			11-regions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	0.000983	−0.00330**	−0.135***	−0.000956	−0.00258**	−0.131***
	(0.00181)	(0.00146)	(0.00653)	(0.00164)	(0.00130)	(0.00553)
Observations	126551	126551	126551	113977	113977	113977
adj. R^2	0.916	0.557	0.832	0.919	0.558	0.838
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes

All dependent variables—revenues, value added per worker, and input expenditures—and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2), with cells defined either at the 5 NUTS-2 regions or the 11 NUTS-3 regions. Industry classification follows the 4-digit NACE rev. 2 version. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance level at 1%, 5% and 10% respectively

Table 20 Regional input buyer networks and firm outcomes—2-way clustered SE

Cell	5-regions			11-regions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	0.000923	−0.00282	−0.137***	−0.00173	−0.00126	−0.132***
	(0.00205)	(0.00179)	(0.0153)	(0.00175)	(0.00102)	(0.0177)
Observations	119344	119344	119344	100978	100978	100978
adj. R^2	0.919	0.562	0.840	0.922	0.565	0.849
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

All dependent variables—revenues, value added per worker, and input expenditures—and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2), with cells defined either at the 5 NUTS-2 regions or the 11 NUTS-3 regions. Industry classification follows the 4-digit NACE rev. 2 version. Two-way (firm-region) clustered standard errors in parentheses. ***, **, * denote significance level at 1%, 5% and 10% respectively

Substituting $X_r(s)$ into (35), yields labor demand of firm s

$$L_r(s) = a_M x_r(s) + (1-\mu)\,\bar{F}\left(\frac{P_r}{w_r}\right)^{\mu} \tag{38}$$

Thus, labor demand of firm s is indirectly affected by the presence of externalities since these affect the price index (when the number of firms may change) and $x_r(s)$ that has to be equal to the demand for firm s producing in r.

Substituting (36) into intermediate demand (37), yields the demand for each variety h by firm s producing in r

$$d_r^s(h) = \frac{p_r(h)^{-\sigma}}{P_r^{1-\sigma}}\left[\mu P_r^{\mu}\left(w_r\right)^{1-\mu}\bar{F} - P_r\delta_r S(\Omega(\Lambda_r(s)))\frac{\int_{\Lambda_r(s)} X_r(i)di}{\Omega(\Lambda_r(s))}\right] \tag{39}$$

Table 21 Regional input buyer networks and firm outcomes—region Denmark

Cell	Denmark			Denmark & 69 Industries		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	0.00629***	−0.000812	−0.106***	−0.000255	−0.00418**	−0.0478***
	(0.00224)	(0.00185)	(0.00830)	(0.00225)	(0.00199)	(0.00625)
Observations	132638	132638	132638	35606	35606	35606
adj. R^2	0.918	0.564	0.833	0.937	0.541	0.860
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

All dependent variables—revenues, value added per worker, and input expenditures—and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2), with cells defined for Denmark, or industries. Industry classification follows the 4-digit NACE rev. 2 version. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance level at 1%, 5% and 10% respectively

Table 22 Regional input buyer networks and firm outcomes—unweighted network measures

Cell	5-regions			11-regions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	0.0160***	0.00176	−0.0305***	0.0167***	0.000858	−0.0150*
	(0.00298)	(0.00263)	(0.00823)	(0.00342)	(0.00309)	(0.00905)
Observations	119344	119344	119344	100978	100978	100978
adj. R^2	0.923	0.562	0.886	0.926	0.565	0.891
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

All dependent variables—revenues, value added per worker, and input expenditures—and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2), however, by using equal weights ω_j for each input, i.e., the simple mean, with cells defined either at the 5 NUTS-2 regions or the 11 NUTS-3 regions. Industry classification follows the 4-digit NACE rev. 2 version. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance level at 1%, 5% and 10% respectively

Then, making use of (38) and (39), the production cost function $TC_r(s) = w_r L_r(s) + \int_{j \in N} p_r(j) d_r^s(j) dj$ of the firm producing variety s at location r is

$$TC = w_r x_r(s) a_M + \bar{F} P_r^{\mu} w_r^{1-\mu} - P_r \delta_r S(\Omega(\Lambda_r(s))) \frac{\int_{\Lambda_r(s)} X_r(i) di}{\Omega(\Lambda_r(s))}$$

A.3 More results

Let us recall that, given our assumptions, all firms within a country are symmetric. This is due to the fact that all firms in a country have the same cost functions, with the same cost parameters (including δ_r and ρ_r) and factor prices ($w_r = 1$ and P_r), and each of them produces a differentiated variety that enters symmetrically the utility function and the production function. Hence, from now onward, we will drop the

Table 23 Regional input buyer networks and firm outcomes—controlling for the expenditure share of domestic inputs

Cell	5-regions			11-regions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	−0.000580	−0.00261	−0.146***	−0.00292	−0.00115	−0.140***
	(0.00197)	(0.00160)	(0.00665)	(0.00182)	(0.00159)	(0.00604)
Domestic input expenditure share	0.471***	-0.0648**	2.997***	0.423***	-0.0395	2.909***
	(0.0363)	(0.0267)	(0.123)	(0.0382)	(0.0259)	(0.131)
Observations	119344	119344	119344	100978	100978	100978
adj. R^2	0.919	0.562	0.844	0.922	0.565	0.852
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

All dependent variables—revenues, value added per worker, and input expenditures—and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2) with cells defined either at the 5 NUTS-2 regions or the 11 NUTS-3 regions. Domestic input expenditure share is computed as expenditures for domestic purchased inputs over total input expenditures. Industry classification follows the 4-digit NACE rev. 2 version. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance level at 1%, 5% and 10% respectively

Table 24 Regional input buyer networks and firm outcomes—harmonized sample I

Cell	5-regions			11-regions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	0.0133*	−0.00391	−0.123***	0.0104	0.00113	−0.0858***
	(0.00799)	(0.00601)	(0.0266)	(0.00757)	(0.00557)	(0.0226)
Observations	17,341	17,341	17,341	17,341	17,341	17,341
adj. R^2	0.946	0.587	0.865	0.948	0.589	0.867
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

All dependent variables—revenues, value added per worker, and input expenditures—as well as *IBN* are expressed in logs. IBN^{cell} is computed according to Eq. (2) with cells defined at 5 NUTS-2 regions or 11 NUTS-3 regions. Industry classification follows the 4-digit NACE Rev. 2 system. Standard errors clustered at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively

index that denotes the firm and keep only the index that denotes the country in which it is producing. We consider the case in which entry and exit of firms are restricted and, as in a short-run equilibrium, the total number of firms N_W and their number in each country, N_r and N_v, is given.[21] In the short run, consumers maximize utility, firms maximize profits, and all markets clear for given numbers of firms, N_r and N_v . Let us focus on this type of equilibrium and define E_r as follows

$$E_r \equiv I_r + N_r \bar{F} P_r^{\mu} w_r^{1-\mu}$$

[21] Following Fujita et al. (2001) we distinguish between 'short-run' and 'long-run' equilibria, and focus our analysis on the short-run equilibrium.

Table 25 Regional input buyer networks and firm outcomes—harmonized sample II

Cell	5-regions & 69 industries			11-regions & 69 industries		
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues	Va p.w.	Input exp.	Revenues	Va p.w.	Input exp.
IBN^{cell}	0.00722*	−0.00353	−0.0418***	0.00467	−0.00186	−0.0407***
	(0.00425)	(0.00351)	(0.0121)	(0.00386)	(0.00309)	(0.0108)
Observations	17,341	17,341	17,341	17,341	17,341	17,341
adj. R^2	0.946	0.587	0.865	0.948	0.589	0.866
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

All dependent variables and *IBN* are expressed in logs. Cells are defined at the 5 NUTS-2 regions within one of 69 industries, or the 11 NUTS-3 regions within one of 69 industries. Standard errors clustered at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively

and observe that it represents the expenditures in country *r* of consumers (I_r) and of firms before network effects are considered. Indeed, $N_r \bar{F} P_r^{\mu} w_r^{1-\mu}$ represents total fixed cost of firms in *r* that should be paid were network effects absent. Making use of (18) and (24), when network effects are present, with $\delta_r > 0$ and and $\rho_r > 0$, we rewrite E_r as follows

$$E_r = L_r + N_r \left(\pi_r - \rho_r \Lambda_r^2 + \delta_r P_r G_r \right). \tag{40}$$

Specifically, when $\rho_r = \delta_r = 0$ there are no network effects and we fall back in a short-run equilibrium in the framework by Ottaviano and Robert-Nicoud. Clearly, the presence of network effects is captured by $\delta_r \neq 0$ and $\rho_r \neq 0$.

Making use of (10), (13), (17)–(20), (24), (28), (29) and (40), operating profits of a firm producing in *r* can be expressed as follows

$$\pi_r = \frac{1}{\sigma} \left[\frac{1}{P_r^{1-\sigma}} \left(\mu E_r - \delta_r P_r G_r N_r \right) + \phi_{rv} \frac{1}{P_v^{1-\sigma}} \left(\mu E_v - \delta_v P_v G_v N_v \right) \right], \tag{41}$$

with $r \neq v$ and $r, v = 1, 2$.

Recall that labor endowments are, respectively, given by $L_r = \lambda_r L_W$ workers in country *r* and $L_v = (1 - \lambda_r) L_W$ workers in country *v*, with L_W denoting world's population and λ_r the share of workers living in country *r*. Workers are internationally immobile, and the two countries are symmetric not only when $\lambda_r = 1/2$, but all the parameters are symmetric and the two countries host the same number of firms ($N_r = N_v$).

Substituting the value for operating profits given by (41) in (40) for the two countries 1 and 2, we get a system of two equations in two unknowns (E_1 and E_2) that can be solved to find

$$E_1 = \frac{\sigma \left\{ \sigma \lambda_1 - \mu \frac{[\lambda_1 N_2 + N_1 \phi_{12} (1 - \lambda_1)]}{P_2^{1-\sigma}} \right\} L_W + N_1 \left(d_{11} \delta_1 P_1 G_1 - c_{11} \rho_1 \Lambda_1^2 - d_{12} \delta_2 P_2 G_2 - c_{12} \rho_2 \Lambda_2^2 \right)}{\sigma^2 - \sigma \mu \left(\frac{N_1}{P_1^{1-\sigma}} + \frac{N_2}{P_2^{1-\sigma}} \right) + \mu^2 \frac{N_1}{P_1^{1-\sigma}} \frac{N_2}{P_2^{1-\sigma}} \left(1 - \phi_{12} \phi_{21} \right)} \tag{42}$$

with:

Table 26 Regional input buyer networks and domestic or foreign input expenditures—harmonized sample

Cell	5-reg.		11-reg.		5-reg. & 69 Ind.		11-reg. & 69 Ind.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Input expenditures	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign
IBN^{cell}	−0.273**	−0.526***	−0.297***	−0.545***	−0.401***	−0.793***	−0.362***	−0.742***
	(0.107)	(0.135)	(0.110)	(0.134)	(0.0880)	(0.133)	(0.0859)	(0.130)
Observations	3755	3755	3755	3755	3755	3755	3755	3755
adj. R^2	0.907	0.886	0.906	0.888	0.908	0.889	0.907	0.890
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

All dependent variables and *IBN* are expressed in logs. IBN^{cell} is computed according to Eq. (2). All regressions control for the domestic expenditure share. Standard errors clustered at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively

Table 27 Regional input buyer networks and foreign input expenditures—Price vs. Quantities I

Cell	5-reg.				11-reg.			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Input exp.	Price	Quantity	#cn4	Input exp.	Price	Quantity	#cn4
IBN^{cell}	0.0331	0.103	−0.0535	0.0121	0.0231	0.133	−0.0834	−0.00564
	(0.0460)	(0.0803)	(0.0850)	(0.0193)	(0.0437)	(0.0838)	(0.0879)	(0.0186)
Observations	8889	8889	8889	8889	8889	8889	8889	8889
adj. R^2	0.889	0.714	0.799	0.881	0.893	0.710	0.796	0.883
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

All dependent variables and *IBN* are expressed in logs. IBN^{cell} is computed according to Eq. (2). Prices are computed as unit values, i.e., expenditures/quantity. The variable #cn4 denotes the count of distinct 4-digit intermediate goods and services purchased by the firm. Standard errors clustered at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

$$
\begin{aligned}
d_{11} =& \sigma^2 - \sigma\left(\frac{N_1}{P_1^{1-\sigma}} + \mu\frac{N_2}{P_2^{1-\sigma}}\right) + \mu\frac{N_1}{P_1^{1-\sigma}}\frac{N_2}{P_2^{1-\sigma}}\left(1-\phi_{12}\phi_{21}\right) > 0 \\
c_{11} =& \sigma\left(\sigma - \mu\frac{N_2}{P_2^{1-\sigma}}\right) > 0 \\
d_{12} =& \left(1-\mu\right)\sigma\phi_{12}\frac{N_2}{P_2^{1-\sigma}} > 0 \\
c_{12} =& \sigma N_2 \frac{1}{P_2^{1-\sigma}}\phi_{12}\mu > 0
\end{aligned}
$$

where $P_r^{1-\sigma} = N_r + N_v\phi$ and an analogous expression holds for E_2.[22] Clearly, the last expression in the last brackets in the numerator of E_1 disappears when there are no network effects (i.e. $\delta_r = 0$ and $\rho_r = 0$).[23] Notice that these results have been obtained for asymmetric trade costs $\tau_{12} \neq \tau_{21}$ with corresponding asymmetric level of the freeness of trade $\phi_{12} \neq \phi_{21}$.

Let us consider the numerator of E_1 and notice that the term $\delta_1 P_1 G_1$ and $\rho_1 \Lambda_1^2$, respectively, represent the benefit and the cost of the network for each firm producing in country 1 , while $\delta_2 P_2 G_2$ and $\rho_2 \Lambda_2^2$, respectively, represent the benefit and the cost of the network for each firm producing in country 2. Thus, the presence of savings from network effects, and the associated costs, may affect operating profits in (41) in opposite ways, and their overall impact can be eventually empirically assessed. Finally, notice that the values of π_r in the expressions for sales (25) and (26) depends on E_r and E_v that are obtained as described above.

[22] Notice that $0 < \frac{N_r}{P_r^{1-\sigma}} = \frac{N_r}{N_r + N_v\phi} < 1$. Moreover, as the maximum admissible value for μ is 1 (or $\sigma - 1$ for the no black hole condition) we can use this information to study the sign of d_{11}. We know that $\frac{\partial d_{11}}{\partial \mu} < 0$. Thus, given that $d_{11} > 0$ when $\mu = 1$, it will be positive for any other value of $\mu < 1$.

[23] In the specific case of $\delta_r = 0$ and $\rho_r = 0$, we get $E_1 + E_2 = \sigma\frac{L_W}{\sigma - \mu}$, that is the value obtained by Ottaviano and Robert-Nicoud (2006).

Table 28 Regional input buyer networks and foreign input expenditures—Price vs. Quantities II

Cell	5-reg. & 69 Ind.				11-reg. & 69 Ind.			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Input exp.	Price	Quantity	#cn4	Input exp.	Price	Quantity	#cn4
IBN^{cell}	−0.131***	0.362***	−0.331***	−0.165***	−0.162***	0.369***	−0.362***	−0.189***
	(0.0391)	(0.0783)	(0.0839)	(0.0178)	(0.0371)	(0.0803)	(0.0839)	(0.0178)
Observations	8889	8889	8889	8889	8889	8889	8889	8889
adj. R^2	0.890	0.715	0.800	0.885	0.894	0.712	0.797	0.889
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

All dependent variables and *IBN* are expressed in logs. IBN^{cell} is computed according to Eq. (2). Prices are computed as unit values, i.e., expenditures/quantity. Standard errors clustered at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively

Table 29 Regional input buyer networks and number of inputs

Cell	5-regions		11-regions	
	(1) # cn4	(2) # cn4	(3) # cn4	(4) # cn4
$IBN^{cell}_{unweighted}$	0.0554***		0.0100**	
	(0.00496)		(0.00501)	
IBN^{cell}		0.00847***		−0.00145
		(0.00304)		(0.00250)
Observations	100,978	100,978	100,978	100,978
adj. R^2	0.819	0.818	0.820	0.820
Firm FE	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes

The dependent variables—the number of 4-digit input—and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2), with cells defined either at the 5 NUTS-2 regions or the 11 NUTS-3 regions. Industry classification follows the 4-digit NACE rev. 2 version. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance level at 1%, 5% and 10% respectively

Table 30 Regional input buyer networks and input expenditures—relationship-specific networks

Cell	5-regions			11-regions		
	Input expenditures					
	(1)	(2)	(3)	(4)	(5)	(6)
IBN^{cell}_{rs}	-0.145***		−0.0711***	−0.139***		−0.0568***
	(0.00588)		(0.00598)	(0.00182)		(0.00604)
IBN^{cell}_{nrs}		−0.124***	−0.0655***		−0.1144***	−0.0553***
		(0.00550)	(0.00533)		(0.0056)	(0.00517)
Observations	97270	86835	65988	81804	68407	50886
adj. R^2	0.847	0.864	0.870	0.853	0.874	0.874
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×industry×region FE	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable, input expenditures, and IBN are expressed in logs. The term IBN^{cell} is computed according to Eq. (2) with cells defined either at the 5 NUTS-2 regions or the 11 NUTS-3 regions. When computing the measure, inputs are split into relationship and non-relationship specific products according to the measure provided in Martin et al. (2023). Industry classification follows the 4-digit NACE rev. 2 version. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance level at 1%, 5% and 10% respectively

A.4 Firm-specific network benefits

The baseline empirical results show that denser local input-buyer networks reduce firms' intermediate input expenditures, while revenues and value added per worker are largely unaffected. *A priori*, one might worry that the network term in the theory acts as a shifter common to all firms within a region–industry–year cell and would therefore be absorbed by our fixed effects. This concern applies to the symmetric specialization adopted in the main text for tractability. In contrast, prior to imposing symmetry, the model already features firm-specific network objects. In what follows, we provide a minimal asymmetric extension in which network benefits are firm-spe-

cific and naturally correspond to the within-firm variation used for identification in the data.

Recall that before imposing symmetry, each firm s operating in region r has its own set of local network links $\Lambda_r(s)$ and a corresponding network benefit $G_r(s)$, as defined in Eq. (8) in the main text. Under the same technology and cost-minimization problem as in Sect. 4.2, firm s's demand for the manufacturing composite used in fixed production satisfies (Eq. (11) in the main text):

$$X_r(s) \;=\; \left(\frac{w_r}{P_r}\right)^{\frac{1-\mu}{\mu}} \bar{F} \;-\; \delta_r\, G_r(s), \tag{43}$$

which is strictly decreasing in the firm-specific network benefit $G_r(s)$ whenever $\delta_r > 0$. Hence, the model delivers heterogeneous intermediate expenditures across firms as long as $G_r(s)$ differs across firms.

In the main text, we impose symmetry and an additive specification (Sect. 4.2), which sets $\Lambda_r(s) = \Lambda_r$ and $X_r(i) = X_r$ for all firms, implying $G_r(s) = \Lambda_r X_r$ and turning (43) into a region-wide shifter. The purpose of this appendix is to retain the same mechanism while restoring the firm-specific variation that corresponds to our empirical identification.

Let j index intermediate input categories. In the data, our firm-level input-buyer network measure is constructed as a weighted average of input-specific buyer-density measures (Eq. (2) in the main text):

$$IBN_{it}^{cell} \;=\; \sum_j \omega_{ijt}\, CND_{jt}^{cell}, \tag{44}$$

where ω_{ijt} denotes firm i's expenditure share on input j and CND_{jt}^{cell} is the out-degree centrality (buyer density) of input j in the relevant cell and year. Crucially, (44) varies across firms within the same year×region×industry cell because firms differ in their input baskets (the weights ω_{ijt}) and because centrality varies across inputs.

To mirror (44) in the theory, define a firm-specific network exposure index:

$$\mathcal{N}_{st} \;\equiv\; \sum_j \omega_{sjt}\, \mathcal{C}_{jrt}, \tag{45}$$

where $\mathcal{C}_{jrt}$ is the model counterpart to buyer density for input j among nearby buyers in region r at time t. We then posit a reduced-form link between firm-level network benefits and exposure:

$$G_r(s,t) \;=\; \Gamma(\mathcal{N}_{st})\,, \qquad \Gamma'(\cdot) > 0. \tag{46}$$

A convenient special case is linearity, $G_r(s,t) = \mathcal{N}_{st}$, which preserves the interpretation that higher exposure to locally dense buyer groups generates larger knowledge

spillovers (e.g., about suppliers, negotiation, or contracting), while remaining fully nested in our original structure.

Substituting (46) into (43) yields firm-specific intermediate demand:

$$X_{st} = \left(\frac{w_r}{P_{rt}}\right)^{\frac{1-\mu}{\mu}} \bar{F} - \delta_r \, \Gamma(\mathcal{N}_{st}), \tag{47}$$

and hence firm-specific intermediate expenditures $P_{rt}X_{st}$ that decline in $\mathcal{N}_{st}$ (and therefore in the empirical IBN_{it}^{cell}). This delivers the main empirical pattern—lower input expenditures in denser buyer networks—using firm-level variation that is not common within a year×region×industry cell.

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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