Learning Trade Opportunities through Production Network

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Abstract

Using data on the Spanish firm-level production network we show that firms learn about international trade opportunities and related business know-how from their production network peers. Our identification strategy leverages the panel structure of the data, import origin variation, and network structure. We find evidence of both upstream and downstream network effects, even after accounting for sectoral and geographical spillovers. Larger firms are better at absorbing valuable information but worse at disseminating it. Connections with geographically distant firms provide more useful information to start importing.

Key Words: Production network,Learning, Spillovers, Import.

JEL Codes: D22, D83, F14, L14.

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1 Introduction

A growing body of literature has emphasized the importance of firm heterogeneity in international trade. The existing theoretical and empirical studies primarily highlight that trading firms must incur relevant (fixed and variable) costs and have underlined that heterogeneity in firm productivity is the fundamental driving force for the selection into international trade, both at the export (Roberts and Tybout, 1997; Bernard and Jensen, 1999; Melitz, 2003; Bernard et al., 2003) and the import side (Castellani et al., 2010; Kasahara and Lapham, 2013).

One explanation of the aforementioned heterogeneity in exposure to foreign markets is that firms have heterogeneous and incomplete information about trade opportunities. Forming a new trade relation typically requires substantial effort in gathering information that is not freely available, but it is acquired through search and learning efforts. Indeed, in order to start to trade, firms first need to be aware of the existence of a trading opportunity. Once the potential trading partner has been identified, there are additional obstacles to establishing a successful trade relationship, including learning how to do business in the presence of non-tariff barriers (safety regulations, formal trade procedures, etc.) and issues related to incomplete information (Allen, 2014). For example, a firm's decision to start purchasing an input from a new provider is always, to some extent, characterized by uncertainty about the ability of the potential seller to fulfil its needs in terms of price, quality, and delivery (Rauch and Watson, 2003) and about the cost of integrating the outsourced input into the production process. Also, in the recent literature about production networks (Carvalho and Voigtländer, 2014; Bernard et al., 2019; Bernard and Moxnes, 2018), firm-to-firm connections are characterized by relationship-specific costs possibly related to product customization, contract negotiations, and the degree of trust between parties. In the presence of such trade barriers, the diffusion of information among firms about trade opportunities and business know-how is potentially a strong channel in explaining the cross-firm differences in the propensity to trade. The trade frictions will likely be smaller for firms with better information about establishing trade relations with a potential partner.

In this paper, we focus on the unexplored dimension of firms importing behaviour that can be explained by their position in the domestic production network. We hypothesize that when exchanging goods and services, firms also share valuable information about importing. This includes information on potential foreign trading partners, such as price, quality, trustworthiness, and input compatibility with a firm's production process, as well as specific know-how related to the informational component of (fixed) trade costs, such as institutional conditions, corporate culture, and business practices. A firm's suppliers and customers may have different incentives to share such information with the firm, and they may also transmit distinct types of information. On the one hand, a firm may be incentivized to share information on potential import opportunities with its suppliers that can enhance the quality or decrease the cost of the sourced inputs. On the other hand, suppliers may be reluctant to disclose such information to their customers, as it may put them at risk of being supplanted by the same foreign providers. Furthermore, it is possible that the relevance of information on potential foreign suppliers, whether intentional or not, is more significant when it emanates from suppliers rather than customers, given their upstream position in the production chain. Hence, a priori, it is unclear whether one should expect forward or backward linkages to be a relatively more important source of information spillovers related to importing opportunities and know-how. Therefore, in our analysis, we distinguish between spillovers coming from suppliers and customers.

To test these hypotheses, we empirically investigate the diffusion of information about importing through the domestic production network using a dataset provided by the Spanish Tax Agency (AEAT), which contains data gathered from Value Added Tax (VAT) declarations. This dataset includes anonymized information about the basic characteristics (sales, number of employees, sector, labor costs, location, etc.) of the whole population of Spanish firms, together with the value of their imports for two aggregate geopolitical areas (EU and extra-EU) and all annual domestic transactions between them in the amount larger than 3005 Euros. By leveraging this dataset, we construct the empirical Spanish domestic firm-level production network for each year during the 2010-2014 period. We then empirically examine whether the (geographical area-specific) import experience of a firm's domestic trade partners, differentiating between its providers and customers, is relevant for explaining its decision to start importing (from this area).[1]

We estimate these peer effects in a linear-in-means framework, therefore assuming that the firm's decision to start importing from a given origin/area is affected by the firm's characteristics, a weighted average of its peer characteristics, and the weighted averages of their importing status. The network determines the weights. Unlike the standard linear-in-means setting (i.e. Bramoullé et al. (2009)) we assume that peer effects operate with time lag – it takes time for a firm to utilize the importing relevant knowledge acquired from their peers. The same assumption is made in Bisztray et al. (2018) and Dhyne et al. (2023).

There are several well-known challenges in estimating the linear-in-means model. The most important problem is the correlated effects. Correlation in outcomes among peers may arise due to endogenous choice of peers or to common shocks. This problem is generally present whenever a correlation exists between peers' unobserved characteristics. Moreover, the reflection problem prevents separate identification of the impact of peers' outcomes (endogenous peer effects) and peers' characteristics (contextual peer effects) whenever the peer effects are contemporaneous. The reflection problem, however, can generally be addressed in the case of network interactions. See (Bramoullé et al., 2020) for an excellent review of the identification of peer effects in networks. We tackle these issues by combining different strategies.

As mentioned, we assume the delay in peer effects since we expect information diffusion to take time. This assumption practically makes the reflection problem inconsequential in our setting since it breaks the simultaneity of endogenous peer effects and a firm's decision to import. To deal with the issue of correlated effects, we start from a

[1]We, therefore, focus on firms' importing behavior at the extensive margin, i.e. import starters, and leave the investigation of the intensive margin for future work. In principle, information transmission about importing through the firm-to-firm domestic network could also be relevant for explaining firms' behavior at the intensive margin. For example, this information could be valuable for decreasing the variable costs of importing or simply because a better matching with providers stimulates a higher volume of imports.

commonly made assumption that the network peers are conditionally random (see, for instance, Feld and Zölitz (2017), Hoekstra et al. (2018), and Bramoullé et al. (2020)). By exploiting the panel structure of our data, we control for a substantial set of observable and unobservable characteristics. In our preferred specifications, we control for firm×year and import-origin×firm-sector×firm-location×year fixed effects. Under the assumption of conditionally random peers, the importing status, at $t-2$, of a firm's suppliers of suppliers (customers of customers) that are neither that firm's suppliers nor customers affect the outcome of the firm at time t only through its suppliers (customers), and therefore, can be used as a valid instrument for the suppliers (customers) importing status at $t-1$, thereby addressing the issue of correlated effects on a given network. Finally, we partially address the issue of network endogeneity by considering only supplier-customer connections that appear in the dataset throughout 2010–2014. This choice practically makes the network predetermined, thereby rendering the random network assumption more acceptable.

In our preferred specifications, which combine the most demanding set of fixed effects (i.e., firm×year fixed effects and import-origin×firm-sector×firm-location×year fixed effects) with our IV strategy, we find that a firm's probability of starting importing is positively affected by the share of domestic providers and customers that are importing. In particular, we find that an increase of 10 percentage points in the share of suppliers (customers) that are importing from a given origin increases the probability of starting importing by 10.9% (19.2%). This asymmetry between downstream and upstream effects may arise because of different incentives suppliers and customers have to share import relevant information with a firm. A customer indirectly benefits when its supplier uses more productive or cheaper inputs. In contrast, a supplier of a firm may be replaced with a foreign provider in when the firm starts importing. The spillover is important only for more specialized knowledge (import origin-specific in our case), and we do not find evidence of peer effects for non-origin-specific importing.

There is a substantial heterogeneity in both upstream and downstream effects. We find evidence that larger and more productive firms absorb and utilize import-relevant information better. They are, strategically or not, less effective in disseminating the information. The spillovers are stronger when coming from firms in the same sector due to the similarity in production technology. Interestingly, connections with geographically distant firms provide more useful information for importing. Given the localized nature of production networks, this is consistent with the "strength of weak ties" effect postulated in Granovetter (1973) in the context of social networks.

Information frictions in trade have been studied both theoretically and empirically. On the theoretical side, Allen (2014) shows that, in the context of regional agricultural trade flows in the Philippines, producers/sellers' search costs for acquiring information about market conditions in other locations can explain about half of the observed price dispersion across regions. In related work, Dasgupta and Mondria (2018) build a model in which importers have a limited capability to process information about prices and tend to allocate their scarce resources to countries with lower expected prices.[2] On the empirical side, there are many studies documenting a positive effect of the geographical agglomeration of exporters on the propensity to export (Silvente and Giménez (2007), Koenig (2009), Koenig et al. (2010), Fernandes and Tang (2014); among many others) and interpreting it as evidence for the existence of information spillovers and cost-sharing mechanisms. These papers use as spatial neighborhoods relatively large agglomerations (e.g. cities). Other papers focus on managers' mobility and show that previous managers' export experience increases the probability that a firm starts to export (for instance, Mion and Opromolla (2014), Sala and Yalcin (2015)).[3]

More closely related to our paper, the role of supplier-customer linkages in explaining the extensive margin of international trade as a trade determinant has been studied theoretically and empirically. In Krautheim (2007) firms form information-exchange links with other firms from the same sector, and acquire beneficial information about exporting through these links. In Chaney (2014), exporters search for new customers in a given

[2]Our work is also connected to the strand of literature which has introduced search, matching, and learning in heterogeneous firms trade models (Albornoz et al. (2012); Eslava et al. (2015); among others) to explain exporter dynamics.

[3]Cai and Szeidl (2016) study more in general how information can diffuse through managerial networks.

location by using their existing customers from that location in the spirit of Jackson and Rogers (2007). In the online appendix, Chaney (2018) provides a stylized model in which symmetric firms can buy information about new suppliers from the current suppliers for a fixed and exogenously given price. Following the study of Choquette and Meinen (2015) on exports, Pateli (2016) analyzes the relevance of the backward and forward linkages dimension for the case of import spillovers by using the aggregate input-output tables. Bernard and Moxnes (2018) provides a model of the formation of international supplier-customer connections.

Two papers that are closest to ours are Bisztray et al. (2018) and Dhyne et al. (2023). In Bisztray et al. (2018), the authors also study spillovers in importing across connected firms. Differently from our paper, they focus on spatial spillovers using the fine-grained definition of the neighborhood (i.e., being in the same building). They do not observe the buyer-supplier connections and, therefore, do not study the information propagation associated with these connections, which is the main objective of our paper. Moreover, the spillovers in Bisztray et al. (2018) are group-based. Hence, they cannot exploit the intransitivities in the network structure to identify peer effects, which is our main identification strategy. Therefore, our approach and findings are complementary to those in Bisztray et al. (2018). Using Belgian data on firm-level production networks, contemporary[4] paper Dhyne et al. (2023) studies peer effects in decisions to export in the firm-level production network. While export spillovers have received much attention in economic literature, unlike Dhyne et al. (2023), we focus on import spillovers, which is still a relatively unexplored topic. In Dhyne et al. (2023), the authors use a similar identification strategy as we do – a combination of multidimensional fixed effects and instruments that exploit the network structure. However, they do not control for geographical and sectoral spillovers. In our setting, we demonstrate that this leads to overestimating downstream and upstream effects.

In sum, we contribute to the literature by studying yet unexplored sources of hetero-

[4]We presented our paper at several international conferences, including the 24th Coalition Theory Network Conference, 2019, organized by Aix-Marseille University and the 7th Annual Workshop on Networks in Economics and Finance, 2018, organized by IMT School for Advanced Studies.

geneity in importing arising from production network spillovers. Thanks to the richness of the data at our disposal, we go beyond the spatial/geographical dimension of spillovers and the aggregate input-output dimension. To the best of our knowledge, we provide first empirical evidence that information about importing opportunities propagates through supplier-buyer connections in a domestic production network. We show that both upstream and downstream propagation are significant. We also document important heterogeneities in these propagation effects.

2 Data

Spanish businesses and individuals operating as professionals are required to adhere to the Value Added Tax (VAT) regulations. As part of their yearly tax reporting to the Spanish tax authority (Agencia Estatal de Administración Tributaria, AEAT), they disclose all financial transactions with third parties that exceed a total of 3,005 euros annually, using the M.347 form.[5] We have access to this *confidential* dataset of all firm-to-firm transactions subject to VAT from 2010 to 2014.

While the VAT data we have access to is anonymized, we have information on some important firms' characteristics: type of legal entity, sales, number of employees, sector, labor costs, location at the zip code, and the annual value of trade flows (import and export) with EU countries and with Non-EU Countries. We focus on firms that are classified as corporations (NIF type code A) and LLC's (NIF type code B). We also exclude financial sector firms from the data because of the idiosyncrasies of the financial sector.[6] Using the VAT data we construct the production network of Spanish firms. This network is a directed network and consists of nodes representing firms. We say that there exists a connection $j \rightarrow i$ between supplier firm j and customer firm i in year t if j sells intermediate input to i in that year.

We observe a balanced panel data with 611,996 firms over 5 years (2010–2014), with

[5] More information available at: https://www.agenciatributaria.gob.es.

[6] We exclude financial firms that, according to the IAE classification, are classified as (a)instituciones financieras, (b) seguros, (c) auxiliares financieros y seguros, (d) actividades inmobiliares.

the average of 8,671,919 yearly connections. We focus on stable connections that persist each year throughout the observed period, potentially missing in one year only – in which case we impute this link for the missing year. This restriction further reduces the number of firms in our sample to 575,896 (5.9% reduction). Our restriction on stable links reduces by 41% the sample in terms of the number of links, and the eliminated links account for 15.8% of the overall firm-to-firm trade. This choice is motivated by two key considerations. First, we believe that repeated interactions between trade partners, resulting in stable connections, are more likely to facilitate information transmission and generate positive cost externalities. In contrast, when dealing with suppliers or customers with whom a one-time interaction occurs, there is limited opportunity for learning or synergy. Second, the fact that connections are formed and destroyed in each period may create additional issues related to the network endogeneity in our estimation. To partially address this issue, we opt to maintain a fixed network structure, ensuring that there are no changes in the network topology during the entire period of our analysis. Our final sample is a balanced panel representing a network with 575,896 firms and 5,087,373 annual links for the period 2010–2014.

Main sample and import starters

Since the outcome of interest is *starting to import*, we conduct our analysis on the sample of potential import starters, firms that have not yet imported from the given source region or country. Following Bisztray et al. (2018), our *analysis sample* is, therefore, a three–way panel (firm, the origin of importing, year) including only *potential import starters*: observations in which a firm in the main sample has not yet imported from the given source region up until the previous year (260,668 firms). With respect to firms that are not observed to start sourcing inputs abroad, import starters tend to be bigger, more productive and have more (importing) providers and customers. On average, they have 20.7 suppliers and 20.2 customers, respectively.[7] On average, 41.19% of the suppliers and

[7]These figures refer to the year 2010 for the sample of firms used in our main specification of Table 1. The number of suppliers and customers of firms that do not start are 11.1 and 10.8, respectively.

40.98% of the customers are importing. Descriptive statistics are reported in Table 7.

3 Empirical model

In this section, we describe our empirical strategy. The outcome of interest is a firm's import from a given origin. We are interested in studying the effect of the importing experience of firms' peers in the production network on this outcome. The production network is a network with n nodes (firms) defined with adjacency matrix $\mathbf{G} = (g_{ji})_{j,i=1}^{n}$. Unless stated otherwise, we assume $g_{ji} \in \{0, 1\}$, where $g_{ji} = 1$ means that j supplies input to i. Our central idea is that successful importing relies on import-specific knowledge. The main hypothesis is that firms connected in the production network, besides trading goods, also exchange information relevant for importing. This specialized knowledge spreads through the production network via supplier-customer relationships. As a result, companies are more likely to start importing if their peers have importing experience and, therefore, possess import-relevant knowledge. This knowledge is likely to be even more relevant when it relates to importing from a particular origin region or a country. As in Bisztray et al. (2018) and Dhyne et al. (2023), we assume that the effect of this information diffusion on the outcome comes with a time lag – it takes time for a firm to utilize the source-specific knowledge to start importing.

Because firms typically interact differently with suppliers and customers, we distinguish between the effects attributable to each group. Moreover, customers may have different incentives to share information that is useful for starting to import. While a firm's customer might benefit from the firm discovering a more suitable or productive input supplier, the firm's current supplier may not share this benefit, as their inputs could be substituted by those from the new foreign supplier. However, the relevance of information regarding potential foreign suppliers may be more pronounced when it originates from suppliers rather than customers, given their position upstream in the production chain. It is, therefore, unclear whether one should expect forward or backward linkages to be a more important source of information spillovers related to importing opportunities and know-how.

Our analysis is conceptually similar to studying peer effects in networks using the linear-in-means model of peer effects described in Bramoullé et al. (2009). In the linear-in-means model, agents' outcomes depend on their own characteristics, average peers' characteristics, and average peers' outcomes. The effect of peers' characteristics (observed and unobserved) is known as *contextual peer effect*, while the effect of peers' outcomes is known as *endogenous peer effect*. When the peer effects are contemporaneous, the simultaneity of the outcomes leads to the well-known reflection problem (Manski, 1993), which impedes the identification of endogenous and contextual peer effects.[8] As already mentioned, we assume a delay in peer effects since we expect information diffusion to take time. In particular, we study the effect of the previous year's peers' import experience on firms' decisions to import. This practically makes the reflection problem inconsequential in our setting since it breaks the simultaneity of endogenous peer effects and a firm's decision to import.

We start from the following empirical equation

$$\begin{aligned} y_{i,t} =& \alpha + \sum_{k=1}^{K} \gamma^k x_{i,t}^k + \beta_D \frac{1}{d_i^-} \sum_{j \in N_i^-} g_{ji} y_{j,t-1} + \beta_U \frac{1}{d_i^+} \sum_{j \in N_i^+} g_{ij} y_{j,t-1} + \\ & \sum_{k=1}^{K} \delta_D^k \frac{1}{d_i^-} \sum_{j \in N_i^-} g_{ji} x_{j,t-1}^k + \sum_{k=1}^{K} \delta_U^k \frac{1}{d_i^+} \sum_{j \in N_i^+} g_{ij} x_{j,t-1}^k + \mathrm{FE} + \varepsilon_{i,t}. \end{aligned} \tag{1}$$

In (1) $y_{i,t} \in \{0,1\}$, is an indicator if firm i imports at year t. Recall that, given our sample selection, i belongs to a set of potential import starters in year t as defined in Section 2. The coefficients γ^k, $k = 1, ..., K$ represent the effects of a firm's observable characteristics on starting to import. The sum $\frac{1}{d_i^-} \sum_{j \in N_i^-} g_{ji} y_{j,t-1}$ is a network weighted average import status $y_{j,t-1}$ of firms, indexed by j, that belong to the set of suppliers of firm i (N_i^-) in the previous time period, where d_i^- denotes the cardinality of set N_i^- (i.e. firm i's in-degree).[9] Therefore, the coefficient β_D measures the effect of the weighted

[8] Several studies, including Bramoullé et al. (2009), De Giorgi et al. (2010), and Lin (2010) characterize the identification conditions that address the reflection problem in the context of the linear-in-means model of peer effects when agents interact in a network.

[9] Note that $\frac{1}{d_i^-} \sum_{j \in N_i^-} g_{ji} = 1$. Analogously, N_i^+ is the set of customers of firm i d_i^+ is the out-degree

import experience of suppliers of i on i's probability to import. We refer to β_D as to *supplier effect* or the *downstream effect*, since it measures the effect that comes from suppliers and, therefore, propagates downstream through the network. Analogously, β_U captures the effect of the weighted import experience of customers of i on i's importing. We refer to β_U as to *customer effect* or the *upstream effect*. Therefore, the coefficients β_U and β_D capture the endogenous peer effects and estimating them is the main focus of this paper. The coefficients δ_D^k and δ_U^k capture the contextual peer effects, which are the effects of peers' characteristics $\mathbf{x} = \left(x^k\right)_{k=1}^K$ on the outcome. As discussed later, we estimate different specifications of (1) with different combinations of firm, time, location, sector, and origin of import fixed effects (FE). Importantly, with the inclusion of fixed effects, we can control for other types of externalities and unobservables that may be relevant to the outcome and are correlated to the import experience and the characteristics of peers, such as technological spillovers and common determinants of trade costs at the geographical and sectoral level.

3.1 Identification

To provide causal estimates of peer effects, we need to address the issue of the correlated effects (Manski (1993) Bramoullé et al. (2009)). Intuitively, the issue of correlated effects stems from the fact that unobserved factors shared by firms connected in the production network may bias the empirical estimates of spillovers as long as they are determinants of their importing behavior. This may be the result of, for instance, common shocks experienced by connected firms, or contextual peer effects operating via unobservable characteristics.

We tackle this issue using two different strategies. In both strategies, we assume that the network peers are random conditional on the set of controls. This means that firms' unobserved characteristics are uncorrelated with their peers' observed and unobserved characteristics, conditional on observables and unobservables that we control for. The

of firm i in $\mathbf{G}$, and $\frac{1}{d_i^+}\sum_{j\in N_i^+} g_{ij} = 1$.

assumption that the peers are random conditional on observable characteristics is commonly made in the analysis of peer effects with observational data (see, for instance, Feld and Zölitz (2017), Hoekstra et al. (2018), and Bramoullé et al. (2020)). As discussed in Section 2, in our analysis, we fix the network – we consider only links that appear in all years in the considered period. This decision serves a dual purpose. Firstly, it enables us to focus on the peer effects coming from *stable* peers. Secondly, it essentially makes the network $\mathbf{G}$ predetermined in our analysis, thereby making the conditional randomness assumption more acceptable.

3.1.1 Strategy 1: Fixed-effect regression

In our first strategy we use fixed effects to control for the substantial variation in unobserved characteristics of a firm and its suppliers and customers. In the most strict specifications, we control for *firm*×*year* and *sector*×*zipcode*×*origin*×*year* fixed effects, and estimate the following version of (1):

$$\begin{aligned} y_{ihc,t} =& \alpha + \sum_k \gamma^k x^k_{ihc,t} + \beta_D \frac{1}{d_i^-} \sum_{j \in N_i^-} g_{ji} y_{jhc,t-1} + \beta_U \frac{1}{d_i^+} \sum_{j \in N_i^+} g_{ij} y_{jhc,t-1} + \\ & \sum_k \delta^k_D \frac{1}{d_i^-} \sum_{j \in N_i^-} g_{ji} x^k_{jhc,t-1} + \sum_k \delta^k_U \frac{1}{d_i^+} \sum_{j \in N_i^+} g_{ij} x^k_{jhc,t-1} + \mu_{i,t} + \eta_{hc,t} + \varepsilon_{ihc,t}, \end{aligned} \tag{1.S1.1}$$

where index h stands for *sector*×*zipcode*, and c denotes the import origin (source). The *firm*×*year* fixed effects ($\mu_{i,t}$) control for firm-level time-varying observables and unobservables, whereas $\eta_{hc,t}$ denotes *sector*×*zipcode*×*origin*×*year* fixed effects. Note that this addresses a potential concern that firms that are more prone to import tend to be connected due to their observed or unobserved characteristic. The inclusion of *firm-year* fixed effects implies that in our estimation of endogenous peer effects (parameters β_D and β_U), we rely on import origin variation. Moreover, *firm-year* fixed effects absorb the contextual peer effects of any observable characteristics that are not origin-specific. The *sector*×*zipcode*×*orign*×*year* fixed effects ($\eta_{hc,t}$) control for time-variant import origin-specific variables common to firms located at the same zip code and belonging to the same sector. This very demanding set of fixed effects absorbs common shocks and spillovers at the spatial and sector-specific levels. In particular, it absorbs information regarding the presence of importing neighbors in the geographic/sectoral network.[10] We recall that in (1.S1.1), peer effects operate with a year lag, which rules out correlated effects from non-persistent (temporary) shocks.

In (1.S1.1), the identification of the impact of information spillovers from importing neighbours on a firm's import propensity hinges upon the import-origin variation of the proportion of importing neighbours that is independent of their geographical and sectoral distribution, as well as from the firm's own time-varying characteristics and the time-varying characteristics of its neighbours. Consequently, potential residual threats to identification must manifest at this nuanced level of variation. This may be caused by correlated unobserved firm-origin-time specific characteristics due, for instance, common shocks. In the next subsection, we delineate an instrumental variable strategy devised to address the possible presence of correlated effects at this level of variation.

3.1.2 Strategy 2: Network instruments

Our second identification strategy exploits the structure of the production network. The main idea is that under the assumption of conditionally random peers, the firms' observed and unobserved characteristics are not correlated with their peers' observed and unobserved characteristics conditional on the firms' and their peers' observable and unobserved characteristics we control for. In this case, we argue that the importing status of second-order suppliers (customers) that are neither that firm's suppliers nor customers in $t-2$ can be used as a valid instrument for the supplier's (customers) importing.

To see this formally, let us consider (1.S1.1). For exposition simplicity, assume that there is only one relevant observable characteristic $x_{ihc,t}$. Moreover, let us denote with $\bar{x}^L_{ihc,t}$ and $\bar{y}^L_{ihc,t}$, $L \in \{D, U\}$ the network averages of the respective observed characteristics

[10] We use a more demanding set of fixed-effects compared to both Bisztray et al. (2018) and Dhyne et al. (2023) In Bisztray et al. (2018), authors control for *firm*$\times$*year* and *origin*$\times$*year* fixed effects since, in their work, the spillovers are location-based. Dhyne et al. (2023) in their most demanding specification includes only firm$\times$year and export-destination$\times$year fixed effect

and outcomes of network peers of i. In particular $\bar{x}^D_{ihc,t} \equiv \frac{1}{d^-}\sum_{j\in N_i^-} g_{ji}x_{jhc,t}$; $\bar{x}^U_{ihc,t} \equiv \frac{1}{d^+}\sum_{j\in N_i^+} g_{ij}x_{jhc,t}$; $\bar{y}^D_{ihc,t} \equiv \frac{1}{d^-}\sum_{j\in N_i^-} g_{ji}y_{jhc,t}$; and $\bar{y}^U_{ihc,t} \equiv \frac{1}{d^+}\sum_{j\in N_i^+} g_{ij}y_{jhc,t}$. Finally, let $u_{ihc,t}$ denote the unobserved firm-specific characteristics.[11] We allow for contextual peer effects with respect to $u_{ihc,t}$. We can now rewrite (1.S1.1) as:

$$\begin{aligned} y_{ihc,t} =& \alpha + \gamma x_{ihc,t} + \delta_D \bar{x}^D_{ihc,t-1} + \delta_U \bar{x}^U_{ihc,t-1} + \beta_D \bar{y}^D_{ihc,t-1} + \beta_U \bar{y}^U_{ihc,t-1} + \\ & \zeta_U u_{ihc,t} + \zeta_D \bar{u}^D_{ihc,t-1} + \zeta_U \bar{u}^U_{ihc,t-1} + \mu_{i,t} + \eta_{hc,t} + \nu_{ihc,t}, \end{aligned} \tag{1.S2.1}$$

with $\mathbb{E}(v_{ihc,t}|x_{ihc,t}, u_{ihc,t}, \alpha, \mu_{i,t}, \eta_{hc,t}, \mathbf{G}) = 0$. In (1.S2.1) we decomposed $\varepsilon_{ihc,t}$ from (1.S1.1) as $\varepsilon_{ihc,t} = \zeta u_{ihc,t} + \zeta_D \bar{u}^D_{ihc,t-1} + \zeta_U \bar{u}^U_{ihc,t-1} + \nu_{ihc,t}$, and $\bar{u}^D_{ihc,t-1}$ and $\bar{u}^U_{ihc,t-1}$ are defined analogously to $\bar{x}^D_{ihc,t-1}$ and $\bar{x}^U_{ihc,t-1}$. Hence, we allow for contextual effects operating through unobserved firm characteristics. We also allow for non-zero correlation between observables and unobservables (i.e. $\mathbb{E}(u_{ihc,t}|x_{ihc,t}) \neq 0$).

Let k be a customer of i. By writing a counterpart of (1.S2.1) for firm k at $t-1$ it becomes clear that $\bar{y}^U_{khc,t-1}$ in (1.S2.1) is endogenous as it is correlated with $\bar{u}^U_{ihc,t-1}$ and therefore with $\varepsilon_{ihc,t}$ as well. The analogous argument holds for $\bar{y}^D_{khc,t-1}$. Hence β_U and β_D are not identified in (1.S2.1) due to correlated effects. In our model, this is true whenever an unobserved *firm-origin-sector-zipcode-year* specific variable generates contextual peer effects. Note that our first strategy addresses the issue of correlated effects due to unobserved contextual peer effects generated by unobservables that are not origin-specific since we control for firm×year and sector×zipcode×origin×year fixed effects.

To address this issue, we leverage the network structure. Let $\bar{\bar{y}}^U_{ihc,t-2}$ denote the network average of importing status from a given destination of the second-order customers (customers of customers) of i, that are neither direct suppliers nor customers of i. Analogously, we define $\bar{\bar{y}}^D_{ihc,t-2}$ as the network average of importing status of second-order suppliers of i that are not direct peers of i.[12] It is clear that these averages affect $\bar{y}^U_{ihc,t-1}$

[11]There are likely many different relevant firm-level unobserved characteristics that can be represented with vector $\mathbf{u}$. For expositional simplicity, we assume there is only one. It will be clear that our conclusions are not affected by this simplification.

[12]In the empirical implementation when calculating $\bar{\bar{y}}^U_{ihc,t-2}$ we also exclude suppliers of customers and customers of suppliers of i, and second-order suppliers of i. While this is not necessary for the identification strategy to work, it facilitates the interpretation of IV estimates as the upstream propagation

and $\bar{y}^D_{ihc,t-1}$, respectively.

The assumption of the conditionally random network means that conditional on firm and peers' observables and unobservables we control for, the observables and the unobservables across peers are uncorrelated. Denote the vector of these controls with $\mathbf{z}$. In our case, $\mathbf{z} = (x_{ihc,t}, \bar{x}^U_{ihc,t-1}, \bar{x}^D_{ihc,t-1}, \mu_{i,t}, \eta_{hc,t})$. We argue that $\bar{\bar{y}}^U_{ihc,t-2}$ and $\bar{\bar{y}}^D_{ihc,t-2}$ are valid instruments for $\bar{y}^U_{ihc,t-1}$ and $\bar{y}^D_{ihc,t-1}$ under the additional assumptions: $cov(u_{ihc,t}, u_{ihc,t-q}|\mathbf{z}) = 0$ for all $q \geq 2$. Therefore, we must impose *limited persistence* in unobserved characteristics for this strategy to work.[13] To see this, consider, for instance, a customer of a customer of firm i, that is not a direct peer of i and denote it with ℓ. Firm ℓ enters in $\bar{\bar{y}}^U_{ihc,t-2}$. We write (1.S2.1) for ℓ at $t-2$ as:

$$\begin{aligned} y_{\ell hc,t-2} =& \alpha + \gamma x_{\ell hc,t-2} + \delta_D \bar{x}^D_{\ell hc,t-3} + \delta_U \bar{x}^U_{\ell hc,t-3} + \beta_D \bar{y}^D_{\ell hc,t-3} + \beta_U \bar{y}^U_{\ell hc,t-3} + \\ & \zeta u_{\ell hc,t-2} + \zeta_D \bar{u}^D_{\ell hc,t-3} + \zeta_U \bar{u}^U_{\ell hc,t-3} + \mu_{\ell,t-2} + \eta_{hc,t-2} + \nu_{\ell hc,t-2}. \end{aligned} \tag{1.S2.2}$$

The conditional random network assumption directly implies

$$cov(\gamma x_{\ell hc,t-2} + \delta_D \bar{x}^D_{\ell hc,t-3} + \delta_U \bar{x}^U_{\ell hc,t-3} + \zeta u_{\ell hc,t-2}, \varepsilon_{ihc,t}|\mathbf{z}) = 0.$$

Moreover, since by the construction, the customers of ℓ are neither suppliers nor customers of i, we have that $cov(\bar{u}^U_{\ell hc,t-3}, \varepsilon_{ihc,t}|\mathbf{z}) = 0$. However, because at least one first-order supplier of ℓ is a first-order customer of i, $y_{\ell hc,t-2}$ is correlated with $\varepsilon_{ihc,t} = \zeta u_{ihc,t} + \zeta_D \bar{u}^D_{ihc,t-1} + \zeta_U \bar{u}^U_{ihc,t-1} + \nu_{ihc,t}$ whenever $\bar{u}^D_{\ell hc,t-3}$ is correlated with $\bar{u}^U_{ihc,t-1}$ which will, in turn, be the case if and only if $cov(u_{ihc,t}, u_{ihc,t-2}|\mathbf{z}) \neq 0$[14]. The analogous argument holds for second-order suppliers of i that are not direct peers of i. Finally, the correlation between $y_{\ell hc,t-2}$ and $\varepsilon_{ihc,t}$ may be due to correlation between $\bar{y}_{\ell hc,t-3}$ or $\bar{y}_{\ell hc,t-3}$ with $\varepsilon_{ihc,t}$. However, by writing down (1.S2.1) for first order suppliers/customers of firm ℓ at at $t-3$ it is clear that as long as $cov(u_{ihc,t}, u_{ihc,t-2}|\mathbf{z}) = 0$, this will not be the case.

effect. We use an analogous approach to calculate $\bar{\bar{y}}^D_{ihc,t-2}$.

[13] This condition is crucial and has been overlooked in Dhyne et al. (2023).

[14] The random network assumption rules out the correlation of unobservables across firms. Since the network is connected, the outcome of i's supplier or customer of any order observed at any time period will be correlated with ε_{it} unless we assume some restriction in the form of $cov(u_{it}, u_{i,t-q}|\mathbf{z}) = 0$ for all $q \geq q_0$. If we move "further away" in the network, the required q_0 increases.

4 Results

In this section, we present the results of our estimates using identification strategies discussed in Sections 3.1.1 and 3.1.2.

In Table 1 we present the estimates of the peer effects using strategy outlined in Section 3.1.1 (strategy 1). We estimate different variations of equation (1.S1.1) by OLS, starting from simpler specifications and progressively increasing the complexity. The dependent variable in all specifications is importing status from origin $c \in \{\text{EU}, \text{outside EU}\}$.

In column (1), we initially control for firm fixed effects and origin×year fixed effects (see at the bottom of the tables, *id* and *eu-y*, respectively). The coefficients of interest are reported in the first two rows of Table 1, where $S_{ic,t-1}$ and $C_{ic,t-1}$ denote the suppliers' and customers' network average importing status from origin c (EU or extra-EU) in year $t-1$, respectively. The estimated coefficients in column (1) suggest that a rise of 10 percentage points (from now onward abbreviated to pp) in the proportion of suppliers (customers) that are importing from the same origin at $t-1$[15] is associated with a 0.314 pp (0.317 pp) increase in the probability of starting importing from that origin. Given that the unconditional probability to start importing in our sample is 3.557%, this effect amounts to a probability premium of 8.8% (8.9%).

In column (2), we additionally control for firm-specific observables. In particular, we control for the number of workers, labor costs, number of suppliers, number of customers, intermediate inputs cost, sales to other firms, average sales per customer, labor (revenue) productivity, intermediate input (revenue) productivity, and the average salary paid. The estimated coefficients do not change significantly compared to column (1).

In column (3), we introduce firm×year fixed effects, which capture firm-level time-varying unobservables and observables (see at the bottom of the tables *id-year*). Note that firm×year fixed effects account for the contextual peer effects of observable and unobservable firm-year specific variables. The estimated downstream and upstream effects

[15] A rise of 10 pp in the proportion of suppliers (customers) that are importing is approximately equal to one additional supplier (customer) for an average firm in the sample.

are only slightly smaller compared to column (1).

In column (4) we control for the presence of importers that are neighbors in the geographic/sectoral network (i.e. firms importing belonging to the same zipcode/sector), which are exactly the variables on which the previous studies of trade spillovers have focused. In Table 1 $prop\_imp\_sec_{ic,t-1}$ denotes the proportion of firms that are importing from origin c at $t-1$ and are in the same sector as firm i.; $prop\_imp\_zip_{ic,t-1}$ indicates the proportion of firms that are importing from origin c at $t-1$ and are located in the same zip code as firm i; $prop\_imp\_sec\_zip_{ic,t-1}$ denotes the proportion of firms that are importing from origin c at $t-1$ and are from the same sector and same zip code as firm i. These variables are built using all observed firms, not just the sample of potential import starters that we use in the regressions. We find evidence of positive and significant location, sectoral, and location-sectoral spillovers. Firms in the same zip code likely interact through channels other than the production networks. Firms in the same sector may share more relevant information about potential suppliers as they use similar production technology. Moreover, shocks that affect importing are likely correlated within the location and sector. Incorporating sectoral and geographical spillovers reduces the estimated peer effects by more than half, underscoring the significance of accounting for these spillovers. This is consistent with the existence of location and sector-specific homophily in the production network. The findings in column (4) highlight the necessity of integrating a more nuanced set of fixed effects into the econometric model to capture these localized and industry-specific spillovers and absorb possible common shocks operating at this level. This refinement is implemented in the next specification we estimate, the results of which are presented in column (5).

We present the results of our most demanding specifications in column (5), where we account for time-varying import origin-specific observables and unobservables common to firms belonging to the same zip code and sector. This very demanding set of fixed effects (see at the bottom of the tables, *eu-s-z-y*) also absorbs the information regarding the presence of importing neighbors in the geographic/sectoral network in a nonparametric way. The estimated effects are similar but slightly smaller compared to those reported in column (4). According to these estimates, an increase of 10 pp in the share of suppliers (customers) importing leads to a 0.118 pp (0.102 pp) increase in the probability of starting importing from a given area. This equals a probability premium of 3.32% (3%) calculated at the baseline.

Table 1: OLS results

	(1)	(2)	(3)	(4)	(5)
$S_{ic,t-1}$	0.0314***	0.0313***	0.0302***	0.0142***	0.0118***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0009)
$C_{ic,t-1}$	0.0317***	0.0318***	0.0303***	0.0125***	0.0102***
	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0011)
$prop\_imp\_zip_{ic,t-1}$				0.1886***	
				(0.0037)	
$prop\_imp\_sec_{ic,t-1}$				0.1966***	
				(0.0042)	
$prop\_imp\_sec\_zip_{ic,t-1}$				0.0363***	
				(0.0024)	
Own characteristics	No	Yes	No	No	No
r2	0.2719	0.2726	0.5399	0.5458	0.6574
N	2048865	2048148	1702966	1702966	1238540
fixed effects	*id*	*id*	*id-y*	*id-y*	*id-y*
	eu-y	*eu-y*	*eu-y*	*eu-y*	*eu-s-z-y*
clustering variable	*id*	*id*	*id-y*	*id-y*	*id-y*

Notes: The dependent variable is a dummy equal to one if a firm starts importing from country c at year t. *id* refers to the firm identification code; *eu-y* refers to import origin×year fixed effects; *id-y* refers to firm×year fixed effects; *eu-s-z-y* refers to import origin ×sector×zipcode×year fixed effects. *p<0.1;**p<0.05; ***p<0.01.

Although in Table 1 we can control for firm's and neighbors' observables and unobservables at the origin country-sector-firm location level, it may still be that productivity from importing or the cost of importing from a given origin tends to be correlated across neighbors. We tackle this problem using the instrumental variable approach described in Section 3.1.2. According to Section 3.1.2 we can use second-order neighbors' (that are not first-order neighbors) importing decisions as an instrument for peers' importing. We use this instrumental variable strategy in conjunction with the specification estimated in column (5) of Table 1.

In column (1) we instrument variables $S_{ic,t-1}$ and $C_{ic,t-1}$ with $SS_{ic,t-2}$ and $CC_{ic,t-2}$, network averages of importing of the second order suppliers and customers that are not direct suppliers or customers respectively. The estimated effects, both downstream and upstream, are noticeably larger than those estimated in column (5) of Table 1. According to these estimates, an increase of 10 pp in the share of suppliers (customers) importing leads to an increase in the probability of importing by 0.386 pp (0.684 pp). This translates to 10.85% (19.2%) probability premium at the baseline. A median firm in our sample has 4 suppliers and 2 customers. This means that having one more supplier (customer) importing from a given area implies an increase in the probability of starting importing from that area by 0.97 pp (3.42 pp). For the comparison's sake, moving from the third to fourth quintile in the size distribution implies an increase in the probability of starting importing by 3 pp (see Table 8).

The upstream effect is noticeably stronger than the downstream effect. As we discussed in Section 3, it is not surprising that the upstream and the downstream effects may be of different magnitude. On one side, a firm's customers may gain from the firm discovering a more suitable or productive input supplier, while the firm's current suppliers may not share this benefit, as their inputs could be substituted by those from the new foreign supplier. On the flip side, the significance of information regarding potential foreign suppliers may be more pronounced when it comes from suppliers rather than customers, given their upstream position in the production chain. Our estimates in Table 2 suggest that the former mechanism is dominant. This is consistent with the estimates in the literature suggesting that the intermediate inputs are substitutes (for instance, Carvalho et al. (2021); Huremovic et al. (2023)).

We note that this IV strategy implies a reduction in our sample size, which happens for two reasons. First, since we use variables at $t-2$ as instruments, we reduce the number of years we use in the estimation by 1 (3 instead of 4). Second, we restrict ourselves to firms with both second-order suppliers and second-order customers in the network, reducing the sample size further.

In column (2) we enrich the set of instruments by including in it the network averages of the second-order neighbors importing at $t-3$ ($SS_{ic,t-3}$ and $CC_{ic,t-3}$). It is clear that these instruments satisfy the exclusion restriction whenever $SS_{ic,t-2}$ and $CC_{ic,t-2}$ satisfy the exclusion restriction. The estimated effects are larger but comparable to those from column (1). By including these additional instruments, we can test the over-identifying restriction. The corresponding test's statistics and p-value (Hansen J) are reported in rows labeled with j and jp.

In columns (3) and (4) we repeat the exercises from columns (1) and (2) but without differentiating between origin of import. The outcome of interest there is starting to import (independently of the origin). In this case, we cannot anymore control for the firm$\times$year fixed effects, as they would absorb all the variation in the outcome variable. Therefore, we control for firm fixed effects (together with origin$\times$sector$\times$zipcode$\times$year fixed effects). We also control for firm-specific variables (same as in Table 1 column (2)) and the associated contextual peer effects. In this case, we do not find strong evidence in favor of peer effects in importing. We interpret this negative result to suggest that spillovers are significant only for more specialized knowledge specific to a given geographical area.

Table 2: IV results

	(1)	(2)	(3)	(4)
$S_{ic,t-1}$	0.0386***	0.0561***	0.4314*	0.4334
	(0.0141)	(0.0180)	(0.2133)	(0.2989)
$C_{ic,t-1}$	0.0684***	0.0881***	-0.0899	0.0984
	(0.0205)	(0.0234)	(0.1627)	(0.1334)
r2	0.6568	0.6012	-0.0982	0.3369
N	780210	501566	531893	338016
idstat	932.396	659.486	20.303	10.642
idp	0.0000	0.0000	0.0000	0.0138
widstat	361.510	127.806	27.392	11.04
j		1.338		2.915
jp		0.5121		0.2328
instruments	$SS_{ic,t-2}$	$SS_{ic,t-2}$	$SS_{ic,t-2}$	$SS_{ic,t-2}$
	$CC_{ic,t-2}$	$CC_{ic,t-2}$	$CC_{ic,t-2}$	$CC_{ic,t-2}$
		$SS_{ic,t-3}$		$SS_{ic,t-3}$
		$CC_{ic,t-3}$		$CC_{ic,t-3}$
absvars	id-y	id-y	id	id
	eu-s-z-y	eu-s-z-y	eu-s-z-y	eu-s-z-y
clustvar	id-y	id-y	id	id

Notes: The dependent variable is a dummy equal to one if firm i starts importing from country c at year t. *id-y* refers to firm×year fixed effects; *eu-s-z-y* refers to import origin×sector×zipcode×year fixed effects. idstat refers to the underidentification test (Kleibergen-Paap rk LM statistic; under the null the equation is underidentified); idp is the p-value corresponding to idstat; widstat refers to the weak identification test (Kleibergen-Paap rk Wald F statistic; under the null the IVs are weak, Stock and Yogo (2005)); j refers to the overidentification test of all instruments (Hansen J statistic; under the null the IVs are uncorrelated with the error); jp is the p-value of j. *p<0.1;**p<0.05; ***p<0.01.

5 Heterogeneity

This section investigates the diverse factors contributing to the heterogeneity of the identified spillover effects. We start by investigating node-level heterogeneity – the heterogeneity with respect to firm characteristics and with respect to suppliers' and customers' characteristics. We continue by considering potential heterogeneity stemming from factors specific to firm-supplier and firm-customer relationships – link-level heterogeneity.

We estimate heterogeneous effects by firm characteristics by estimating the modified version of specification (1.S1.1). We consider heterogeneity concerning firm size, labor productivity, intermediate input productivity, and connectivity (number of suppliers and customers). Furthermore, we consider whether the effects differ for wholesalers relative to other firms.[16] We single out wholesalers since Dhyne et al. (2023) finds that spillover effects differ for wholesaler firms when it comes to exporting. To conduct this exercise, we proceed as follows. For the size, productivity, and connectivity, we divide firms into small and big firms using the median of the respective empirical distribution as a cutoff.[17] We estimate the following specification:

$$y_{ihc,t} = \beta_D^{\ell} z_{i,t}^{\ell} \bar{y}_{ihc,t-1}^{D} + \beta_U^{\ell} z_{i,t}^{\ell} \bar{y}_{ihc,t-1}^{U} + \mu_{i,t} + \eta_{hc,t} + \varepsilon_{ihc,t}. \tag{1.H.1}$$

In (1.H.1) $z_{i,t}^{\ell}$ is a binary variable indicating if i at time t belongs to category ℓ (i.e., lower or higher than the respective median). We estimate this equation separately for each variable of interest. In estimating (1.H.1) we include the same set of fixed effects as in column Table 1 column (5). The results are reported in Table 3.

We find that larger (measured by the number of workers but also the number of suppliers/customers) and more productive firms are better able to employ the knowledge about import opportunities. This is consistent with the results found in Bisztray et al. (2018) in the context of location spillovers. We also find wholesalers are more likely to respond to import knowledge from their peers than non-wholesaler firms.

[16]Wholesalers are firms in NACE sectors 45, 46, and 47.

[17]The results are robust if, instead of the median, we use the third quartile as the cutoff.

Table 3: Heterogeneity of peer effect by firm characteristics

		Number of Workers	Number of Suppliers	Number of Customers	Labor Productivity	Intermediate Inputs Productivity	Being a Wholesaler
$S_{ic,t-1}$	Low	0.0045***	0.0018	0.0010	0.0039***	0.0060***	0.0088***
		(0.0013)	(0.0011)	(0.0013)	(0.0014)	(0.0016)	(0.0012)
	High	0.0213***	0.0479***	0.0189***	0.0173***	0.0133***	0.0179***
		(0.0018)	(0.0025)	(0.0016)	(0.0016)	(0.0014)	(0.0034)
$C_{ic,t-1}$	Low	0.0061***	0.0030***	0.0023**	0.0078***	0.0071***	0.0097***
		(0.0012)	(0.0011)	(0.0011)	(0.0013)	(0.0014)	(0.0010)
	High	0.0200***	0.0259***	0.0281***	0.0162***	0.0157***	0.0227***
		(0.0016)	(0.0018)	(0.0017)	(0.0014)	(0.0013)	(0.0030)
N		1,238,540	1,238,540	1,238,540	1,238,540	1,238,540	1,238,540
fixed effects		id-y	id-y	id-y	id-y	id-y	id-y
		eu-s-z-y	eu-s-z-y	eu-s-z-y	eu-s-z-y	eu-s-z-y	eu-s-z-y
clustering variable		id-y	id-y	id-y	id-y	id-y	id-y

Note: The dependent variable is a dummy equal to one if firm i starts importing from country c at year t. Low (high) refers to the interaction of the treatment variables $S_{ic,t-1}$ and $C_{ic,t-1}$ with an indicator variable for having the value of the characteristic at the top of the column below (above) the observed median value of that characteristic. In the last column, high (low) means that the firm is (not) a wholesaler. *id-y* refers to firm×year fixed effects; *eu-s-z-y* refers to import origin×sector×zipcode×year fixed effects. *p<0.1;**p<0.05; ***p<0.01.

To evaluate heterogeneous effects with respect to customer and supplier characteristics, we estimate the following regression

$$y_{ihc,t} = \beta_D^{\ell} \bar{y}^{D,\ell}_{ihc,t-1} + \beta_U^{\ell} \bar{y}^{U,\ell}_{ihc,t-1} + \mu_{i,t} + \eta_{hc,t} + \varepsilon_{ihc,t}, \tag{1.H.2}$$

where $\bar{y}^{D,\ell}_{ihc,t-1}$ and $\bar{y}^{U,\ell}_{ihc,t-1}$ for a given firm i denote the network average of importing status of its suppliers and customers in category ℓ respectively. We find that the spillovers, in general, tend to be stronger when coming from smaller and less productive firms. This contrasts the results found in Bisztray et al. (2018) in the context of location spillovers. Firms seem to learn more from non-wholesaler firms than wholesaler firms, and the difference is more pronounced for the downstream than for the upstream effect.

Table 4: Heterogeneity of peer effect by peers characteristics

	Number of Workers	Number of Suppliers	Number of Customers	Labor Productivity	Intermediate Inputs Productivity	Wholesalers
$S^{Low}_{ic,t-1}$	0.0173***	0.0308***	0.0406***	0.0185***	0.0091***	0.0187***
	(0.0027)	(0.0045)	(0.0120)	(0.0025)	(0.0026)	(0.0016)
$S^{High}_{ic,t-1}$	0.0090***	0.0087***	0.0099***	0.0084***	0.0105***	0.0021
	(0.0012)	(0.0011)	(0.0011)	(0.0012)	(0.0012)	(0.0015)
$C^{Low}_{ic,t-1}$	0.0190***	0.0344***	0.0181***	0.0143***	0.0167***	0.0123***
	(0.0026)	(0.0055)	(0.0025)	(0.0019)	(0.0023)	(0.0012)
$C^{High}_{ic,t-1}$	0.0106***	0.0109***	0.0105***	0.0110***	0.0108***	0.0101***
	(0.0011)	(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0017)
N	1,238,540	1,238,540	1,238,540	1,238,540	1,238,540	1,238,540
fixed effects	id-y	id-y	id-y	id-y	id-y	id-y
	eu-s-z-y	eu-s-z-y	eu-s-z-y	eu-s-z-y	eu-s-z-y	eu-s-z-y
clustering variable	id-y	id-y	id-y	id-y	id-y	id-y

Notes: The dependent variable is a dummy equal to one if firm i starts importing from country c at year t. Low (high) means that the numerator of the treatment variables $S_{ic,t-1}$ and $C_{ic,t-1}$ counts only the neighbours having the value of the characteristic at the top of the column below (above) the observed median value of that characteristic. In the last column, high (low) means that the numerator of the treatment variables counts only the neighbours that are (not) wholesalers. *id-y* refers to firm×year fixed effects; *eu-s-z-y* refers to import origin×sector×zipcode×year fixed effects. *p<0.1;**p<0.05; ***p<0.01.

The spillovers from more productive firms may be more relevant for more productive than less productive firms. In Table 5 we explore if there is such a complementarity in the spillovers with respect to all dimensions considered in Tables 3 and 4. The estimates in Table 5 are consistent with our finding that larger and more productive firms are better at absorbing the information of their peers, while smaller and less productive firms are better at disseminating the relevant information (or worse at protecting such information).

Table 5: Heterogeneity of peer effect by firm characteristics and peers characteristics (1)

		Number of Workers	Number of Suppliers	Number of Customers	Labor Productivity	Intermediate Inputs Productivity	Wholesalers
$S^{Low}_{ic,t-1}$	Low	0.0091***	0.0168***	0.0157	0.0202***	0.0064*	0.0182***
		(0.0030)	(0.0046)	(0.0153)	(0.0037)	(0.0034)	(0.0016)
	High	0.0390***	0.1680***	0.0649***	0.0167***	0.0120***	0.0225***
		(0.0057)	(0.0183)	(0.0181)	(0.0033)	(0.0035)	(0.0052)
$S^{High}_{ic,t-1}$	Low	0.0035**	0.0005	0.0008	0.0006	0.0056***	-0.0009
		(0.0014)	(0.0012)	(0.0013)	(0.0015)	(0.0018)	(0.0015)
	High	0.0188***	0.0434***	0.0183***	0.0172***	0.0135***	0.0148***
		(0.0019)	(0.0025)	(0.0016)	(0.0017)	(0.0015)	(0.0042)
$C^{Low}_{ic,t-1}$	Low	0.0145***	0.0252***	0.0091***	0.0117***	0.0158***	0.0107***
		(0.0029)	(0.0061)	(0.0030)	(0.0025)	(0.0030)	(0.0012)
	High	0.0292***	0.0583***	0.0334***	0.0177***	0.0180***	0.0257***
		(0.0052)	(0.0120)	(0.0043)	(0.0029)	(0.0036)	(0.0042)
$C^{High}_{ic,t-1}$	Low	0.0045***	0.0019*	0.0010	0.0062***	0.0046***	0.0058***
		(0.0013)	(0.0011)	(0.0012)	(0.0015)	(0.0015)	(0.0018)
	High	0.0188***	0.0248***	0.0271***	0.0156***	0.0154***	0.0203***
		(0.0017)	(0.0018)	(0.0019)	(0.0016)	(0.0014)	(0.0040)
N		1,238,540	1,238,540	1,238,540	1,238,540	1,238,540	1,238,540
fixed effects		id-y	id-y	id-y	id-y	id-y	id-y
		eu-s-z-y	eu-s-z-y	eu-s-z-y	eu-s-z-y	eu-s-z-y	eu-s-z-y
clustering variable		id-y	id-y	id-y	id-y	id-y	id-y

Notes: *id-y* refers to firm×year fixed effects; *eu-s-z-y* refers to import origin×sector×zipcode×year fixed effects. *p<0.1;**p<0.05; ***p<0.01.

Finally, we explore if the spillovers are different from firms that belong to the same sector, are located in the same province or zip code area, and come from a firm that is both supplier and customer (reciprocal relationship). Let w^{ℓ}_{it} denote an indicator taking value 1 if the firm and its supplier (customer) belong to the same sector (ℓ) or are located in the same zip code (ℓ), or form a reciprocal relation. We estimate the following regressions (one per dimension of heterogeneity).

$$y_{ihc,t} = \beta^{\ell}_D w^{\ell}_{it} \bar{y}^{D,\ell}_{ihc,t-1} + \beta_D \bar{y}^{D}_{ihc,t-1} + \beta^{\ell}_U w^{\ell}_{it} \bar{y}^{U,\ell}_{ihc,t-1} + \beta_U \bar{y}^{U}_{ihc,t-1} + \mu_{i,t} + \eta_{hc,t} + \varepsilon_{ihc,t}. \quad (1.H.3)$$

We find that spillovers tend to be higher when coming from firms from the same sector, which is intuitive given that those firms are likely to use a similar mix of inputs in production. The spillovers are also stronger when coming from the reciprocal relationship, in which both firms buy and sell to each other. This is intuitive, as these types of relationships indicate more intensive communication between the firms involved. Interestingly, spillovers are stronger from peers located in different locations (identified by the zip code) or provinces (Spain has 50 provinces). Considering that geographic proximity strongly influences the likelihood of connections between firms, this finding evokes the concept of the "strength of weak ties" effect (Granovetter, 1973), emphasizing the importance of non-localized connections in providing access to new information and opportunities.

Table 6: Heterogeneity of peer effect by firm characteristics and peers characteristics (2)

	Same Sector	Same ZIP code	Same Province	Reciprocal Relationship
$S^{No}_{ic,t-1}$	0.0092***	0 .0115***	0.0195***	0.0103***
	(0.0012)	(0.0012)	0.0018)	(0.0011)
$S^{Yes}_{ic,t-1}$	0.0177***	0.0044	0.0048***	0.0217***
	(0.0034)	(0.0026)	(0.0014)	(0.0037)
$C^{No}_{ic,t-1}$	0.0109***	0.0138***	0.0194***	0.0107***
	(0.0011)	(0.0011)	(0.0018)	(0.0010)
$C^{Yes}_{ic,t-1}$	0.0161***	0.0041*	0.0083***	collinear
	(0.0027)	(0.0021)	(0.0012)	with $S^{Yes}_{ic,t-1}$
N	1,238,540	1,238,540	1,238,540	1,238,540
fixed effects	id-y	id-y	id-y	id-y
	eu-s-z-y	eu-s-z-y	eu-s-z-y	eu-s-z-y
clustering variable	id-y	id-y	id-y	id-y

Notes: *id-y* refers to firm×year fixed effects; *eu-s-z-y* refers to import origin×sector×zipcode×year fixed effects. *p<0.1;**p<0.05; ***p<0.01.

6 Concluding remarks

In this paper, we study an unexplored dimension of firms' importing behavior associated with their position in the domestic production network. To do this, we use a rich dataset provided by the Spanish Tax Agency (AEAT), which provides information about firm-to-firm transactions in the period 2010–2014. Using a combination of identification strategies, we find evidence that suppliers' and customers' importing significantly affects a firm's decision to start importing from a given geopolitical area. Larger firms are better at absorbing valuable information but less effective at disseminating it. Linkages with geographically distant firms provide more useful information to start importing.

Our identification relies on standard assumptions shared with other papers aiming to estimate peer effects in the network. We assume the network is fixed and random conditional on observables and unobservable characteristics we control for.

We believe that the mechanism we study transcends the firm's decision to import and is relevant in the formation of domestic firm-to-firm connections. We leave studying the issue of network formation for future research.

References

Albornoz, F., Pardo, H. F. C., Corcos, G., and Ornelas, E. (2012). Sequential exporting. *Journal of International Economics*, 88(1):17–31.

Allen, T. (2014). Information frictions in trade. *Econometrica*, 82(6):2041–2083.

Bernard, A. and Jensen, B. (1999). Exceptional exporter performance: cause, effect, or both? *Journal of International Economics*, 47(1):1–25.

Bernard, A. B., Eaton, J., Jensen, J. B., and Kortum, S. S. (2003). Plants and productivity in international trade. *American Economic Review*, 93(4):1268–1290.

Bernard, A. B. and Moxnes, A. (2018). Networks and trade. *Annual Review of Economics*, 10:65–85.

Bernard, A. B., Moxnes, A., and Saito, Y. U. (2019). Production networks, geography, and firm performance. *Journal of Political Economy*, 127(2):639–688.

Bisztray, M., Koren, M., and Szeidl, A. (2018). Learning to import from your peers. *Journal of International Economics*, 115:242–258.

Bramoullé, Y., Djebbari, H., and Fortin, B. (2009). Identification of peer effects through social networks. *Journal of econometrics*, 150(1):41–55.

Bramoullé, Y., Djebbari, H., and Fortin, B. (2020). Peer effects in networks: A survey. *Annual Review of Economics*, 12:603–629.

Cai, J. and Szeidl, A. (2016). Interfirm relationships and business performance. *The Quarterly Journal of Economics*.

Carvalho, V. M., Nirei, M., Saito, Y. U., and Tahbaz-Salehi, A. (2021). Supply chain disruptions: Evidence from the great east japan earthquake. *The Quarterly Journal of Economics*, 136(2):1255–1321.

Carvalho, V. M. and Voigtländer, N. (2014). Input diffusion and the evolution of production networks. Technical report, National Bureau of Economic Research.

Castellani, D., Serti, F., and Tomasi, C. (2010). Firms in international trade: Importers' and exporters' heterogeneity in italian manufacturing industry. *The World Economy*, 33(3):424–457.

Chaney, T. (2014). The network structure of international trade. *American Economic Review*, 104(11):3600–3634.

Chaney, T. (2018). The gravity equation in international trade: An explanation. *Journal of Political Economy*, 126(1):000–000.

Choquette, E. and Meinen, P. (2015). Export spillovers: Opening the black box. *The World Economy*, 38(12):1912–1946.

Dasgupta, K. and Mondria, J. (2018). Inattentive importers. *Journal of International Economics*, 112:150 – 165.

De Giorgi, G., Pellizzari, M., and Redaelli, S. (2010). Identification of social interactions through partially overlapping peer groups. *American Economic Journal: Applied Economics*, 2(2):241–275.

Dhyne, E., Ludwig, P., and Vandenbussche, H. (2023). Export entry and network interactions: Evidence from the belgian production network. Technical report.

Eslava, M., Tybout, J., Jinkins, D., Krizan, C., and Eaton, J. (2015). A search and learning model of export dynamics. 2015 Meeting Papers 1535, Society for Economic Dynamics.

Feld, J. and Zölitz, U. (2017). Understanding peer effects: On the nature, estimation, and channels of peer effects. *Journal of Labor Economics*, 35(2):387–428.

Fernandes, A. P. and Tang, H. (2014). Learning to export from neighbors. *Journal of International Economics*, 94(1):67–84.

Granovetter, M. S. (1973). The strength of weak ties. *American journal of sociology*, 78(6):1360–1380.

Hoekstra, M., Mouganie, P., and Wang, Y. (2018). Peer quality and the academic benefits to attending better schools. *Journal of Labor Economics*, 36(4):841–884.

Huremovic, K., Jiménez, G., Moral-Benito, E., Peydró, J.-L., and Vega-Redondo, F. (2023). Production and financial networks in interplay: Crisis evidence from supplier-customer and credit registers. *Available at SSRN 4657236*.

Jackson, M. O. and Rogers, B. W. (2007). Meeting strangers and friends of friends: How random are social networks? *American Economic Review*, 97(3):890–915.

Kasahara, H. and Lapham, B. (2013). Productivity and the decision to import and export: Theory and evidence. *Journal of International Economics*, 89(2):297–316.

Koenig, P. (2009). Agglomeration and the export decisions of french firms. *Journal of Urban Economics*, 66:186–195.

Koenig, P., Mayneris, F., and Poncet, S. (2010). Local export spillovers in france. *European Economic Review*, 54:622–641.

Krautheim, S. (2007). Gravity and information: Heterogeneous firms, exporter networks and the 'distance puzzle'. Technical report, European University Institute.

Lin, X. (2010). Identifying peer effects in student academic achievement by spatial autoregressive models with group unobservables. *Journal of Labor Economics*, 28(4):825–860.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The review of economic studies*, 60(3):531–542.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6):1695–1725.

Mion, G. and Opromolla, L. D. (2014). Managers' mobility, trade performance, and wages. *Journal of International Economics*, 94(1):85–101.

Pateli, E. L. (2016). Local and sectoral import spillovers in sweden. Technical report, Centre for Economic Performance, LSE.

Rauch, J. and Watson, J. (2003). Starting small in an unfamiliar environment. *International Journal of Industrial Organization*, 21:1021–1042.

Roberts, M. and Tybout, J. (1997). The decision to export in colombia: an empirical model of entry with sunk costs. *American Economic Review*, 87(4):545–564.

Sala, D. and Yalcin, E. (2015). Export experience of managers and the internationalisation of firms. *The World Economy*, 38(7):1064–1089.

Silvente, F. R. and Giménez, J. C. (2007). Information spillovers and the choice of export destination: A multinomial logit analysis of spanish young smes. *Small Business Economics*, 28(1):69–86.

Appendix

Table 7: Descriptive statistics: characteristics of firms

	(1) EU-Starters	(2) non EU-Starters	(3) non-Starters (constant)
# workers	6.3***	10.8***	9.6***
	(0.5)	(1.1)	(0.1)
# dom. suppliers	8.8***	6.7***	11.2***
	(0.2)	(0.3)	(0.0)
# dom. customers	8.6***	6.7***	10.8***
	(0.3)	(0.4)	(0.1)
int. input cost	554.9***	695.4***	434.6***
	(34.9)	(76.5)	(6.9)
total sales	1271.4***	1442.2***	921.7***
	(87.1)	(141.5)	(10.7)
sales to firms	560.3***	658.8***	411.7***
	(35.0)	(84.7)	(5.4)
domestic sales	1235.2***	1407.1***	918.4***
	(86.8)	(140.7)	(10.7)
sales per customer	38.4***	21.0***	75.8***
	(7.8)	(6.6)	(1.1)
labor productivity	66.8***	31.1***	178.2***
	(10.2)	(9.8)	(1.4)
int. input productivity	23.1**	17.7***	97.7***
	(10.5)	(6.9)	(1.1)
avg. labor cost	1.5***	1.6	28.1***
	(0.5)	(1.0)	(0.1)
Number of firms	30320	13497	142705

Notes: Descriptive statistics for the year 2010 on the sample used for specification (5) of Table 1. Monetary variables are in thousands of euros. We report the estimated coefficients obtained by regressing one by one the relevant characteristics on a constant, a dummy for being an import starter from some EU country and a dummy for being an import starter from some non-EU country. *p<0.1;**p<0.05; ***p<0.01.

Table 8: Observed probability to start importing by number of workers quintile

Probability	Quintile
0.14	1
0.19	2
0.21	3
0.24	4
0.31	5

Notes: Row 1 reports the share of firms that start to import having the number of workers lower than the first quintile of the distribution of number of workers in the sample used to estimate specification (5) of Table 1. Other entries have analogous interpretations. Starters are firms that start to import after 2010.