Exporters and their Networks

The role of domestic network linkages in export entry

*Emmanuel Dhyne[◊], Philipp Ludwig[△] and Hylke Vandenbussche[§]

December 2023

Abstract

In this paper, we move beyond individual firm characteristics to explain export participation and investigate whether firms' domestic network linkages can facilitate export entry. Using rich data on buyer-seller linkages in the Belgian production network, we find that network heterogeneity is a key determinant of the extensive margin of trade. Firms linked to experienced exporters via their business transaction network have a key advantage in accessing foreign markets. Network effects however do not scale with network size. Instead they decrease as the network becomes large. We show that this pattern is closely linked to negative assortative matching in the network formation process. This indicates that small instead of large firms benefit most from network effects on the extensive margin of trade.

Keywords: Export entry, buyer-seller network, information frictions, trade barriers, heterogeneous firms

JEL Classification: F12, F14, D83, D85

[*]We thank Pol Antras, Paola Conconi, Ronald Davies, Xiang Ding, Sharat Ganapati, Kyle Handley, Keith Head, Colin Hottman, Beata Javorcik, Amit Khandelwal, Nuno Limao, Isabelle Méjean, Marc Melitz, Ferdinando Monte, Ralph Ossa, Charly Porcher, Christian Proebsting, Margit Reischer, Massimo Riccaboni, Rowan Shi, Gonzague Vannoorenberghe, Jaume Ventura and participants of the Leuven-Louvain trade workshop, NBB internal seminar, RIEF Doctoral Meeting, EOS conference, SMYE 2022, QMUL PhD Workshop, WIEN Workshop 2022 and lunch seminars at Georgetown and the University of Maryland for valuable comments and discussions. Philipp Ludwig gratefully acknowledges funding from the Research Foundation Flanders (FWO) and thanks the National Bank of Belgium for their hospitality during a research stay where this paper was developed.

[◊]National Bank of Belgium and University of Mons. Emmanuel.dhyne@nbb.be

[△]Department of Economics, KU Leuven. philipp.ludwig@kuleuven.be

[§]Department of Economics, KU Leuven. hylke.vandenbussche@kuleuven.be

1 Introduction

Export participation remains a rare phenomenon with only 4-5% of firms directly engaging in cross-border trade (Bernard et al., 2007; Dhyne et al., 2015). This concentration of economic activity at the extensive margin of trade has far-reaching consequences. Low export participation not only weakens competition in domestic markets by allowing a small number of exporters to consolidate market power (De Loecker and Warzynski, 2012) but also severely restricts aggregate export growth (Eaton et al., 2009a). The key question is therefore to understand why only a handful of firms can overcome entry barriers and access foreign markets.

This paper aims to contribute to this debate by investigating the importance of heterogeneity in firm networks. Traditionally, low export participation has been related to the presence of sunk entry costs allowing only a select number of firms to be profitable in a foreign market. This insight sparked an influential literature of heterogeneous firm trade models which link export entry decisions to individual firm characteristics. Prominent attributes determining export participation are firm productivity (Melitz, 2003), access to finance (Manova, 2013), previous experience in similar markets (Albornoz et al., 2012; Morales et al., 2019) or lower market access costs due to product scope in the destination (Arkolakis et al., 2021). What all these papers share is that they relate export participation to firm-level characteristics. In this paper we ask whether in addition to firm characteristics, the domestic network to which a firm belongs can also affect the decision to export. Firms do not operate in isolation but constantly interact with other firms in their production network. These business transactions connect potential entrants to firms with direct export experience. If any export-related information diffuses along network linkages, export participation decisions may not just be governed by a firm's own characteristics, but also depend on the unique set of interactions occurring in its production network.

Our paper allows for this network-dimension of firm heterogeneity and empirically investigates whether export participation is facilitated by buyer-seller interactions in domestic production networks. Using detailed data from the universe of Belgian firms, we capture each firm's entire domestic production network and export behavior for the years 2002-2014.

A first stylized fact emerging from the network data and presented in section 2, is a strong correlation between network heterogeneity and export participation that goes beyond firm-level productivity. This correlation suggests that network features may play a role in a firm's extensive margin of trade decision. We take the fact as a justification for introducing network interactions into a stylized model of export entry in which firms are heterogeneous along both a firm dimension and a network dimension. The key novelty of the model is to express foreign market access costs as a function of network linkages, using functional form assumptions inspired by the literature of social networks (Bramoullé et al., 2009) and spatial economics (Anselin et al., 2008).

In this network-augmented setting, export entry decisions depend both on the firm's own characteristics as well as the network it interacts with. Any information that diffuses through the network and is relevant for lowering market access costs, can enhance export participation. The framework allows us to separate network effects into different channels (productivity spillovers vs export market information), control for the specificity of the exchanged information (same market or exporting in general) and is not constraint by the spatial proximity of the parties involved[1].

From the model, we derive an estimation equation that takes the form of a time-space recursive model and can readily be taken to the data. The key mechanism we explore empirically is to what extent *current* export information available in the network, facilitates *future* access to foreign markets for connected firms. For this purpose, we exploit changes in the export behavior of network peers[2] and define observed entry decisions to new export destinations as signals which carry valuable entry-related information. We then assess whether connected firms receiving these signals, show a higher probability of

[1]We thereby contribute to an existing spillover literature which has studied correlated import and export behavior of firms located in close geographic proximity (Koenig et al., 2010; Fernandes and Tang, 2014; Bisztray et al., 2018).

[2]The term network peer in this paper describes any (direct) buyer or supplier interacting with the firm in the production network. While our main analysis focuses on interactions with buyers (backward linkages), we also consider linkages to suppliers in section 6.2.4.

entering the same export destination in the next period.

We initially treat network effects as an externality which implies that both network formation and export signals are assumed to be conditionally exogenous. Afterwards, we relax this assumption by introducing a network selection model as in Arduini et al. (2015) and Qu et al. (2017) to control for endogenous network formation and develop a network-based instrument to control for correlated export behavior that is driven by common shocks rather than information diffusion.

Using detailed balance sheet, trade transaction and network data from the universe of Belgian firms, we then empirically estimate the augmented export entry model for the years 2002-2014.

Our findings show that firm networks are an important determinant of export participation. Each incoming export signal on average increases the entry probability for a particular market in the next period by 0.43 percentage points. This effect is equivalent to a 13% increase in productivity of the signal-receiving firm. Signals have no impact on export entry beyond the export destination they originate from. This not only suggests that network effects and entry barriers are highly destination-specific but also underlines the notion that determinants of export participation are both generated within and outside of the firm.

A second stylized fact compares the prevalence of exporting in small and large networks to study how network effects scale with the size of the network. While firms with larger networks mechanically interact with a larger number of exporters, the data show that the share of exporters in the network decreases as the network grows. This increasing exposure to non-exporters generates network noise which acts as an attenuating force for the beneficial impact of export signals.

We show that a falling signal to noise ratio is a direct consequence of negative assortative matching in the underlying network formation process and present empirical evidence that this contributes to a dampened impact of export signals in large networks. This finding highlights an important difference in how firm and network heterogeneity affect the extensive margin of trade. While all firms benefit from higher levels of productivity, network effects appear to be particularly important to connect small firms (with smaller networks) to foreign markets.

By stressing the role of domestic network heterogeneity for the extensive margin of trade, our paper contributes to three broad strands of literature. A first strand studies buyer-seller linkages and sheds light on the role of search costs, matching frictions and two-sided firm heterogeneity in the formation of production networks (Bernard et al., 2022; Dhyne et al., 2021; Panigrahi, 2022; Arkolakis et al., 2023; Huang et al., 2022; Fontaine et al., 2023; Chaney, 2014; Eaton et al., 2022; Bernard et al., 2018). We contribute to this literature by highlighting that diffusion in domestic networks facilitates export entry. This shows that domestic networks play an active role in the formation of international networks. The success of forming international linkages, therefore directly depends on a firm's domestic linkages.

A second strand this paper relates to is a literature on trade intermediation which has emphasized the role of wholesalers in connecting domestic firms to foreign markets (Bernard et al., 2010; Ahn et al., 2011; Fujii et al., 2017; Bernard et al., 2018; Connell et al., 2019; Ganapati, 2021). Our results show that business interactions with any firm, including non-wholesalers, can promote export participation suggesting that information diffusion is a much broader mechanism than previously thought.

Finally, a third strand is the vast literature on peer effects in networks (Advani and Malde, 2018; Bramoullé et al., 2020) which has come up with flexible empirical frameworks to relate individual agent outcomes to network activity. By introducing network linkages to a context of international trade, we not only showcase the usefulness of the framework across different economic domains, but also find a close relationship between the process governing the formation of network linkages and the resulting network effects. The type of network formation is highly context specific. We study a business transaction network which features negative assortative matching among agents and show that this feature contributes to a negative relationship between marginal network effects and network size. Had the network in question been a social one which often feature positive assortative matching, network effects would have instead steadily increased with network size. A priori knowledge about the type of network assortativity can therefore help to form predictions about the expected direction of network effects.

This paper has 8 sections. Section 2 shows a number of stylized facts linking network heterogeneity to export participation. Section 3 presents a stylized model of export entry with network interactions. Section 4 describes data sources and sample selection procedures. Section 5 discusses identification and estimation of our augmented entry model. Results are presented in section 6 and discussed in section 7. The last section concludes.

2 Stylized facts

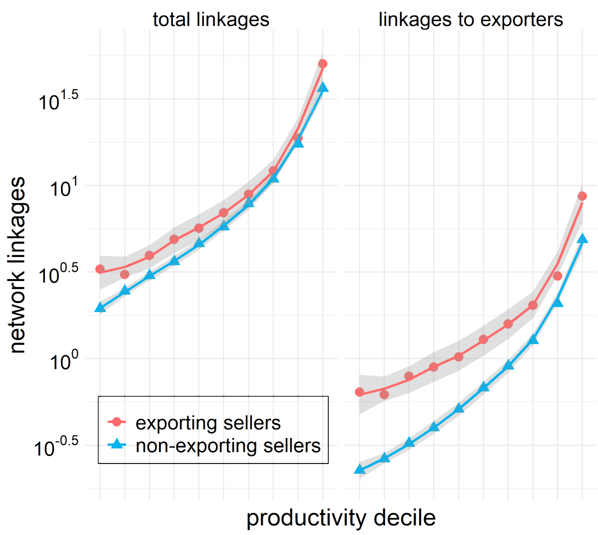
Before formally introducing networks to the entry model in the next section, we first present two stylized facts that suggest that network heterogeneity is not simply a primitive of firm productivity and closely related to export participation.

Figure 1 illustrates our first stylized fact. It uses Belgian firm-level data, explained in detail in section 4.1 and plots the average number of domestic buyer-seller linkages for sellers in a given productivity decile. Both the left and the right side panel plot the number of network linkages of non-exporting (blue triangles) and exporting (red dots) sellers. The vertical distance between both lines represents the difference in network size. The panel on the left plots this difference for the entire buyer network of the seller while the right panel does the same for the subset of linkages which involve exporting buyers.

Focusing on the left panel we observe two patterns. Firstly, across seller types the total number of linkages seems to increase in seller productivity. This pattern is common to production networks (Bernard and Zi, 2022). High productivity sellers are likely to attract more buyers because they can charge lower prices or offer better quality than their competitors. Secondly, we see that non-exporting and exporting sellers interact with a different number of buyers. Across productivity deciles, the average network size premium of exporting sellers (vertical distance between both lines) amounts to 27%. This indicates that exporting sellers overall seem to have more network interactions than domestic sellers, even after controlling for firm productivity.

This difference increases dramatically when we move to the panel on the right, which

Figure 1: Buyer-Seller linkages by TFP decile



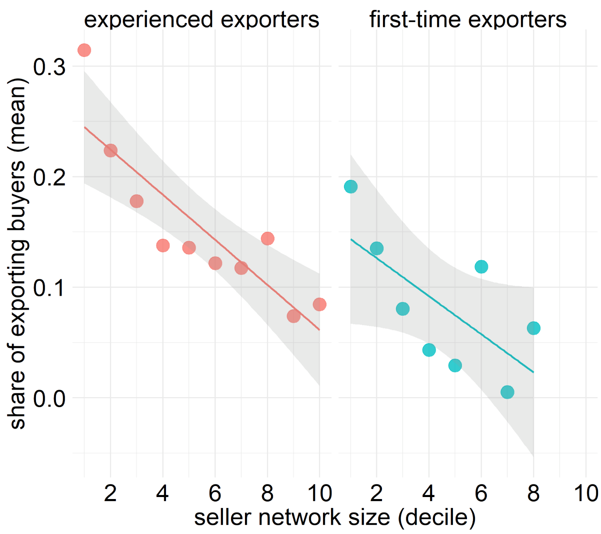
Note: This Figure shows the average number of buyers that a seller in a given productivity decile interacts with. Seller productivity is computed using the approach of Levinsohn and Petrin (2003). Sellers are separated into non-exporters (triangles) and exporters (dots). The left panel shows linkages to any buyer, while the panel on the right, focuses on the subset of linkages involving buyers that export. The Figure uses production network data of Belgian firms explained in detail in section 4.1.

focuses on seller linkages to exporting buyers. Network linkages with exporters appear to be much more common for firms that are exporters themselves. Domestic firms (non-exporting sellers) are much less likely to interact with exporters, which increases the average network size premium of exporting sellers to 103%. This significant wedge in network interactions of non-exporting and exporting sellers cannot be explained by seller productivity (which we condition on) or total network size (as seen on the left side panel) and holds for both incumbent and first-time exporting sellers (as shown in appendix figure 11). We summarize this finding as follows:

Stylized fact 1: *Comparing exporting to non-exporting sellers in the domestic network, we find that the average exporting seller, has twice as many linkages to exporting buyers, even after controlling for seller productivity*

This strong correlation between a seller's export status and linkages to exporters, is a first indication that network heterogeneity might be related to foreign market access. This could be the case if there are information spillovers within the network of exporting firms that facilitate export entry of connected firms. To investigate this channel, we formally introduce network interactions to a standard export entry framework in section 3.2.

Figure 2: Seller network size and mean buyer export probability in 2014



Note: This figure shows the average share of exporting buyers for sellers in a given network size decile. The left panel shows linkages of sellers that have been exporting prior to 2014. The right panel focuses on the subset of sellers that started to export in 2014. The figure uses production network data of Belgian firms explained in detail in section 4.1.

The empirical specification derived from the model will allow us to explore any causal link between a firm's network and its export participation.

A second stylized fact shows how networks change as they become larger. From Figure 1, we can see that more productive sellers have larger networks and are connected to a larger number of exporting buyers as indicated by the upward sloping lines. This positive correlation between seller and network size however does not mean that the average performance of buyers in a large network is superior to buyers in a small network. In fact, seller productivity (and network size) is inversely related to average buyer productivity - a common pattern in production networks also known as negative assortative matching (Bernard and Zi, 2022; Bernard et al., 2022). Applied to our setting where we focus on network linkages to exporters, it manifests as a negative correlation between a seller's network size and the share of exporting buyers in the network.

Figure 2 shows this relationship for both sellers with extensive export experience and those that just started to export for the very first time in 2014. In both cases the share of exporting buyers decreases with network size. This pattern holds across years, seller types and different buyer characteristics such as sales, employment, productivity or the number of export starts as shown in appendix A.4. This leads to our second stylized fact:

Stylized fact 2: *Sellers with larger networks have more linkages to exporters but the overall share of exporting buyers in the network is smaller.*

This distinction between absolute and relative export exposure through network linkages is important because it suggest that network benefits might not scale with network size. We therefore incorporate both approaches in our theoretical framework which is introduced in the following section.

3 Theoretical framework

Our goal is to assess whether foreign market access not only depends on firm characteristics but also benefits from network interactions in the domestic production network. We therefore need a theoretical framework which relates export entry decisions to both dimensions of firm heterogeneity. While the former is a standard component in most trade models since the seminal contribution of Melitz (2003), heterogeneity in firm networks only recently attracted attention in the trade literature[3] and has commonly not been considered as a direct determinant of export participation[4].

For this purpose, we start with a stylized model of export entry where firms initially only differ in productivity. We then introduce network interactions, by allowing entry barriers to vary with the amount of export information received from the network. Firms that receive more information are more likely to enter foreign markets because a larger share of the initial cost burden is offset by incoming export information. The model produces an intuitive estimation equation that can be readily taken to the data. An extended discussion of model identification is deferred to section 5.1.

3.1 Baseline entry framework

We follow Koenig (2009) to study the decision of firm i to enter a specific foreign market d. In this stylized setting, firms have absolute certainty about their expected profits $\Pi_{id,t}$

[3] For an overview of the role of networks in international trade see Chaney (2016).

[4] Notable exceptions are Connell et al. (2019) who relate export entry decisions to interactions with wholesalers.

but face sunk entry costs f_d whenever entering a foreign market. A firm will start to export if the present value of profits (assuming constant discount factor r) exceeds the costs of entry. The probability to enter market d is thus

$$Pr(y_{id,t} = 1) = Pr\left(\frac{\Pi_{id,t}}{r} > f_d\right) \tag{1}$$

Firms face a trade-off between costs and benefits of exporting to the foreign market and their ultimate decision will rest on the relative strength of both elements. Suppressing time subscript t, firm profits in market d can be described as

$$\Pi_{id} = p_{id}q_{id} - a_i w_i q_{id}$$

The first term on the right-hand side represents firm sales as the product of price p_{id} and demand q_{id} in the foreign market whereas the second describes the production costs which per unit of demanded quantity q_{id} amount to $w_i a_i$, the product of nominal wages w_i and inverse productivity a_i[5].

The model relies on a canonical setting where single product firms operate under monopolistic competition and consumers have CES utility which means the demand for firm i's products in market d is given by $q_{id} = p_{id}^{-\sigma} P_d^{\sigma-1} \mu_d E_d$ where $P_d^{\sigma-1} = \left[\int_l p_{ld}^{1-\sigma} dl\right]^{\frac{1}{1-\sigma}}$ represents the price index in market d, σ is the elasticity of substitution, μ_d is the expenditure share devoted to the representative industry and E_d denotes the level of income in d. The optimal mill price charged by firm i in this setting is $p_i = \frac{\sigma}{\sigma-1} a_i w_i$ as a constant markup over marginal costs $a_i w_i$. The final price faced by foreign consumers is $p_{id} = p_i \tau_d$ where τ_d represents ad-valorem iceberg-type trade costs related to shipping goods to market d. The profit of firm i in foreign market d is therefore

$$\Pi_{id} = \left[\frac{a_i w_i \tau_d}{(\sigma - 1) P_d^{1-\sigma}}\right]^{1-\sigma} \mu_d E_d \tag{2}$$

[5]The units of labor needed to produce one unit of q_i.

Plugging Π_{id} into 1 and assuming (for now) that entry barriers f_d are common to all prospective entrants we can express a firm's entry decision as

$$Pr(y_{id,t} = 1) = Pr\left(\left[\frac{a_{i,t}w_{i,t}\tau_{d,t}}{(\sigma-1)P_{d,t}^{1-\sigma}}\right]^{1-\sigma}\frac{\mu_{d,t}E_{d,t}}{r} - f_d > 0\right) \tag{3}$$

Equation 3 illustrates that in the canonical setting all sources of firm heterogeneity are generated from firm-level characteristics, namely wages $w_{i,t}$ and (inverse) productivity $a_{i,t}$. This is emblematic of Melitz (2003) type trade models in which firm productivity is the key determinant in explaining the sorting of firms into exporters and non-exporters. Similarly, the Koenig (2009) model[6] predicts that firms with higher productivity (lower $a_{i,t}$) are more likely to start exporting in the presence of common entry costs f_d.

3.2 Augmented entry framework with network interactions

We treat each firm i's domestic network as a pool of information the firm can draw from. Information about foreign markets is generated by export starters. Each time a firm j in the network of firm i starts to export to a new destination d for the first time, it needs to pay sunk entry cost f_d. This includes expenses to assess local demand preferences, search costs to identify foreign retailers and administrative costs related to obtaining mandatory certification for imported products or other non-tariff barriers. Each of these cost components involve a non-negligible share of information. An export start therefore generates valuable information within firm j for one particular market. We allow this information to diffuse along network linkages s_{ij} to connected firms i which treat incoming information as an *export signal*. Signals reduce market access costs and can thereby alter the export behavior of the signal-receiving firm. Our diffusion process therefore involves an export signal which is initiated by an export start y_{jd}, propagates along network linkages s_{ij} and lowers entry barriers f_d of firms i. Information is assumed

[6]The Koenig (2009) model describes the behavior of export starters which excludes firms that choose to never export ($y_{id} = 0\ \forall\ t$) or export continuously ($y_{id} = 1\ \forall\ t$). By focusing on export profit, it also abstracts from modeling domestic market participation as in Melitz (2003). Despite these simplifications, entry equation 3 captures key characteristics of Melitz-type models by linking entry to firm productivity and sunk entry cost.

to diffuse immediately[7] and is formally treated as an externality[8] which enters firm i's entry equation 1, expressed in logs

$$Pr(y_{id,t} = 1) = Pr(\ln \Pi_{id,t} > \ln r + \ln f_d) \tag{4}$$

via entry cost term $\ln f_d$. This is achieved by making a functional form assumption which is inspired by the literature on social networks (Bramoullé et al., 2009; Calvó-Armengol et al., 2009) and explicitly expresses entry costs as a function of firm i's individual network

$$\ln f_{id,t} = \alpha_d - \delta \sum_j \bar{s}_{ij,t} x_{j,t} - \beta \sum_j s_{ij,t} y_{jd,t} \tag{5}$$

where α_d denotes sunk entry costs incurred in market d, $x_{j,t}$ represents time-varying peer characteristics, $y_{jd,t}$ is an indicator variable[9] for export starts of network peers and $s_{ij,t}$ ($\bar{s}_{ij,t}$) are elements of a (row-normalized) binary interaction matrix S_t[10] which captures all domestic firm-to-firm interactions in the economy in year t.

In this setting, network interactions can affect firm i's entry decision in two distinct ways. First, we allow entry costs f_{id} to directly respond to the average characteristics x_j of firms in the network[11]. This channel controls for network effects unrelated to the diffusion of export signals such as productivity spillovers and creates additional variation in entry barriers at the firm level. Network interactions with productive peers can thereby lead to

[7] Our empirical specification relies on annual firm-to-firm interactions. Immediate diffusion in this context means signals reach a connected firm i within the same calendar year as the export start of firm j.

[8] Treating network effects as an externality to market access costs assumes that the formation of domestic buyer-seller linkages is not driven by a strategic motive to learn about foreign markets. Our framework therefore abstracts from models with network games (König et al., 2019) where optimal firm and network behavior is interdependent due to the presence of strategic complementarities or models with strategic network formation (Badev, 2021; Hsieh et al., 2020) where firms anticipate network effects when choosing which agents to interact with. While we do not allow linkages to form endogenously with the intent to learn, we do account for endogenous network formation that arises from unobserved shocks which simultaneously affect network formation and export entry in section 5.3.

[9] We refrain from weighting export signals due lack of a theory-consistent weighting scheme. Instead, we explore signal heterogeneity empirically in section 6.2 by studying how network effects differ across a range of peer and linkage characteristics.

[10] We will describe interaction matrix S_t in more detail in section 4.1.

[11] We follow the standard convention of the social network literature and assume sunk entry costs respond to average rather than aggregate characteristics in firm i's network. This is achieved by row-normalizing entries in interaction matrix S_t such that $\sum_j \bar{s}_{ij} = 1$. As we are assuming all $s_{ij} \in \{0, 1\}$ in our empirical setting, $\sum_j \bar{s}_{ij} x_j$ simply represents an unweighted average of characteristics of all firms j in the network of firm i.

different entry barriers across individual firms i but not across export destinations. Second, we allow entry costs to depend on export signals y_{jd} received from the network. The term $\sum_j s_{ij,t} y_{jd,t}$ counts the number of incoming export signals by destination. Given that the information contained in export signals will always be destination-specific, we only expect signals to lower entry barriers for the market they originate from. To distinguish between the impact of signals on market access costs of the same and other destinations, we divide them into matching and non-matching export signals and explore the relevance of each signal type empirically in section 6. Together, the combination of a unique set of network linkages (s_{ij}) and destination-specific export signals (y_{jd}) create additional variation in entry barriers at the firm-destination level (f_{id}). Two firms with identical productivity levels (x_i) interacting with equally productive peer groups (x_j) can therefore still take different export decisions because they face different entry barriers across export destinations.

3.3 Signal intensity, clarity and network noise

An important advantage of our augmented framework is the ability to flexibly nest different types of diffusion processes. The only element we need to change is the definition of export signals in equation 5. To illustrate the different approaches we introduce three definitions:

$$\begin{aligned}
\text{signal intensity} &= \sum_j s_{ij,t} y_{jd,t} \\
\text{signal clarity} &= \sum_j \bar{s}_{ij,t} y_{jd,t} = \frac{\text{signal intensity}}{\sum_j s_{ij,t}} \\
\text{network noise} &= 1 - \text{signal clarity}
\end{aligned}$$

If we want to relate export entry to the *absolute* amount of network diffusion, a signal intensity specification which simply counts the number of incoming export signals is most appropriate. If we are instead interested in the *relative* amount of network diffusion, a signal clarity specification is more relevant to use. Here we divide the number export signals by the total number of network linkages. The resulting measure tells us what share of network linkages provide an export signal for market d in any given period.

In a context of export participation, firm-to-firm interactions that do not yield export signals can be considered as network noise because these interactions do not contribute to lower entry barriers but still take up time and resources of firm i. Our definition of signal clarity therefore accounts for network noise as a potentially attenuating force in the network diffusion process. The distinction between signal intensity and signal clarity becomes important to understand diverging network effects for firms with small and large networks which are explained in detail in section 6.3.

3.4 Empirical framework

To arrive at our estimation equation, we adjust equation 5 to the type of diffusion process we want to explore and plug equations 5 and 2 into equation 4. We denote vectors in bold and scalars in plain typeface. This yields our empirical entry equation

$$Pr(y_{id,t}=1) = Pr\left(\boldsymbol{\gamma}'\boldsymbol{x_{id,t}} + \boldsymbol{\delta}'\sum_j \bar{s}_{ij,t}\boldsymbol{x_{j,t}} + \beta\sum_j s_{ij,t}y_{jd,t} - \alpha_d - \varepsilon_{id,t} > 0\right) \quad (7)$$

where vectors $\boldsymbol{x_{id,t}}$[12] and $\boldsymbol{x_{j,t}}$ collect seller and buyer characteristics related to export entry, $\boldsymbol{\gamma}$, $\boldsymbol{\delta}$ and β are parameter (vectors) to be estimated and $\varepsilon_{id,t}$ is an ideosyncratic error term. This equation closely resembles models from the peer effects (Manski, 1993; Bramoullé et al., 2009) and spatial economics (Anselin et al., 2008; Qu and Lee, 2015) literature where it is commonly referred to as a spatial autoregressive (SAR) model with panel data. Both strands guide our identification strategy which is discussed in section 5.1.

4 Data, empirical setting and descriptive statistics

In this section we first describe our main data sources and link them to the augmented framework derived above. We then present descriptive statistics to illustrate how network heterogeneity shapes the diffusion of export information among Belgian firms.

[12] $\boldsymbol{x_{id,t}} = (1-\sigma)(\ln a_{i,t} + \ln w_{i,t} + \ln \tau_{d,t} - (\sigma-1)\ln P_{d,t}^{1-\sigma}) + \ln \mu_{d,t} + \ln E_{d,t}$.

4.1 Data sources and sample selection

At the center of our analysis are three administrative datasets which are linked via unique firm identifiers and capture characteristics, export behavior and network interactions of Belgian firms for the years 2002 – 2014. Firstly, we use the Annual Account Filings database (National Bank of Belgium, 2002–2014a) which collects balance sheet information such as sales, revenues, input costs (labor, capital, material), 4-digit industry codes (NACE), zip code and ownership information from mandatory annual account filings of all firms operating in Belgium. We complement firm characteristics with annual import and export transaction data at HS6 product-level from the International Trade Dataset (National Bank of Belgium, 2002–2014b) which combines information from customs records and intra-EU trade declarations[13]. Together, balance sheet and trade data provide a detailed picture of performance and export activity of Belgian firms but do not grant any insights into firm-to-firm interactions. To fill this gap, we use the Business-to-Business Transactions Dataset (National Bank of Belgium, 2002–2014c) which records any buyer-seller transaction of firms operating in Belgium, provided the annual transaction value amounts to at least 250 €[14]. Belgian firms are required by law to file a breakdown of their annual sales by each individual buyer which allows us to identify individual firms involved in each transaction and thereby capture virtually all firm-to-firm interactions at an annual interval. To handle the vast amount of information contained in the combined dataset we implement important sample restrictions along firm, destination and network dimensions.

At the firm level, we follow the sample selection procedure of Dhyne et al. (2021) which significantly reduces the sample size while remaining very close to aggregate national statistics. In a first step this involves exploiting ownership information to single out observations that have unique identifiers but ultimately relate to the same firm. Identifiers in the data are constructed from value-added tax (VAT) numbers and some firms choose

[13]Intra- and extra-EU transactions have different reporting thresholds which are explained in appendix B.1

[14]For a detailed description of the dataset we refer to Dhyne et al. (2015)

to use multiple VAT numbers for tax or accounting purposes. We aggregate these entries to the level of the firm which reduces the number of observations by around 4%. The second step of the selection procedure was originally introduced by De Loecker et al. (2014) and restricts our sample to firms with at least one full-time employee, more than 100 € of tangible assets, positive total assets in at least one reported year and positive labor costs and output. This step alone excludes more than 80% of the remaining observations as many firms in the original data are one-person companies[15]. The remaining sample is identical to the one used in Dhyne et al. (2021), includes between 90k-100k firms per year and remains very close to aggregate statistics in terms of value added, gross output, exports, and imports[16].

At the destination level, we only consider market access decisions for destinations outside the European Economic Area (EEA) as information frictions are expected to represent a much larger barrier to entry compared to highly integrated EEA countries[17]. Non-EEA destinations on average account for roughly two-thirds of all export starts of Belgian firms which means our sample still captures the majority of activity at the extensive margin of trade. We follow Koenig (2009) and define an export start as a transaction to a destination which has not been served by the firm in the previous two years. Resuming exports to a foreign market after a single year of inactivity therefore are not treated as export starts[18]. This ensures that sufficient time has passed for market conditions to change such that information costs again become a relevant barrier to entry[19]. For our sample this implies that all observations of the first two years are dropped reducing the sample time frame

[15]In 2012 there are 750,100 firms reporting less than 1 full-time employee.

[16]For a detailed comparison with aggregate statistics we refer to Table 1 in Dhyne et al. (2021)

[17]The list of EEA countries includes Greece, Lithuania, Portugal, Bulgaria, Spain, Luxembourg, Romania, Czech Republic, Hungary, Slovenia, Denmark, Croatia, Malta, Slovakia, Germany, Italy, the Netherlands, Finland, Estonia, Cyprus, Austria, Sweden, Ireland, Latvia, Poland, the United Kingdom, Norway, Liechtenstein, Switzerland, Iceland. We disregard all export transactions of Belgian firms to any of these countries for all sample years.

[18]Note that this allows for restarts within firm-destination pairs. In practice only 11% of entries are restarts.

[19]We assume that firms gather entry-related information upon entry. Firms that reenter after a single year of inactivity still possess very recent entry information and could benefit from their previous experience. By enforcing a 2-year period of inactivity we assume that entry requirements, consumer preference and non-tariff barriers in the destination have sufficiently changed such that information again presents a barrier to entry.

to 2004-2014. Further, we only consider firm-destination pairs with at least one export start across years to facilitate comparability across different estimation approaches[20].

At the network level, we start by characterizing the main network components. A network is defined as a collection of nodes and edges which in our case are represented by firms and their business transactions. Transactions (edges) therefore link firms (nodes) to each other and the transaction value (edge weight) gives an indication about the respective strength of each network interaction. In production networks edges are always directed because each firm involved in a transaction either acts as a buyer or a seller. In our setting, we need to distinguish between two distinct types of direction. First, the flow of goods and services from sellers to buyers along the supply chain which we define as a forward linkage. Second, the flow of money for goods and services sent from buyers to sellers which we define as a backward linkage. This distinction is important because network externalities in principle could go in either direction. In this paper we focus on information diffusion along backward linkages meaning sellers learn from their buyers. This direction has been identified as the most relevant one for information diffusion by the preceding export (Choquette and Meinen, 2015) and productivity (Javorcik and Spatareanu, 2011) spillover literature and is favored in our empirical setting. We expect sellers to care less about which buyers they sell to which in turn creates little incentive for them to communicate export-related information along forward linkages. Buyers on the other hand are expected to care about their suppliers as their own performance depends on the quality of sourced inputs. Information in our empirical setting mainly diffuses from buyers to sellers but we offer additional results for alternative diffusion directions in appendix C.4.

While this clearly denotes which firms emit and receive export signals, in practice it is unlikely that all buyer-seller interactions meaningfully contribute to the diffusion of export signals. Suppliers which only account for a small share of total buyer sourcing may

[20] Logistic regressions require variation in the outcome variable. To facilitate a comparison with results from a linear probability model, we require at least one export start within each firm-destination pair which ensures sufficient variation for logistic regressions and allow to use the same sample for both estimation methods.

receive no information because the small transaction size does not necessitate any communication with buyers or indicates a low level of importance attached to the sourced input. We therefore need to distinguish between relevant and non-relevant network linkages and exclude those which are too small to play any meaningful role for the diffusion of export signals. To do so we compute the share of total buyer sourcing accounted for by individual suppliers as

$$\nu_{ij,t} = \frac{\kappa_{ij,t}}{\sum_j \kappa_{ij,t}}$$

where $\kappa_{ij,t}$ represents the value of annual transactions between seller i and buyer j in year t taken from transaction value matrix K_t. An interaction is defined as relevant for diffusion if suppliers account for at least 1% of buyer sourcing. Interactions that account for less than 1% of buyer sourcing[21] are treated as irrelevant for information diffusion and are excluded from the sample[22]. Applying this rule to all entries of transaction value matrix K_t leads to a binary interaction matrix S_t[23] with elements

$$s_{ij,t} = \begin{cases} 1, & \nu_{ij,t} \geq 1\% \\ 0, & \text{otherwise} \end{cases}$$

Each row of matrix S_t contains linkages of seller i and the row sum indicates the number of buyers j a seller interacts with each year. As customary, self-links are not allowed which means all diagonal elements s_{ii} are set to zero.

4.2 Descriptive statistics

After implementing firm, destination and network restrictions our final sample contains characteristics of around 62,000 firms, 25,000 export starts to 188 non-EEA destinations and more than 1,000,000 firm-to-firm interactions per year between 2004 and 2014. The

[21] Our empirical results are robust to alternative thresholds as demonstrated in section 6.2.3.

[22] Our network sample is also subject to the firm-level restrictions described above which exclude 52% of network linkages from the sample. Of the remaining interactions, non-relevant linkages account for 85% in number but only make up 8% of total buyer sourcing. The network restriction therefore retains the majority of sourcing value $\nu_{ij,t}$ which is our key indicator of diffusion probability and greatly facilitates the analysis by reducing the overall sample size.

[23] Our baseline model does not differentiate between transactions beyond the 1% threshold. To learn more about the role of interaction strength for network externalities, please see section 6.2.4.

combined data allows us to trace the diffusion of export signals along network linkages and relate it to the export entry behavior of Belgian firms. To understand how each data source contributes to this analysis we present descriptive evidence about firm behavior at the extensive margin of trade, the prevalence of signal diffusion and the role of network structure for the diffusion process.

4.2.1 Extensive margin of trade

Figure 3 shows the geographic dispersion of non-EEA export starts of Belgian firms between 2004-2014. Export decisions follow the rules of gravity and mainly occur in markets that are attractive due to their large size or limited distance to Belgium. One exception is the concentration of export entry in the Democratic Republic of the Congo. As a former colony the country retains strong ties to Belgium which potentially facilitates market access for Belgian exporters. Another important pattern shown in appendix A.1 is distribution of export entry across geographic regions. While large countries like the US individually still account for the largest number of export starts, the graph shows that more than two-thirds of non-EEA entries occur in Africa and Asia. As these blocks comprise a large number of countries with different import regulations, consumer preferences and local supply networks, we expect entry-related information costs for these destinations to be high. This emphasizes the role of network externalities as many Belgian firms may want to reach the large consumers base in these emerging markets but lack the ability to overcome entry barriers.

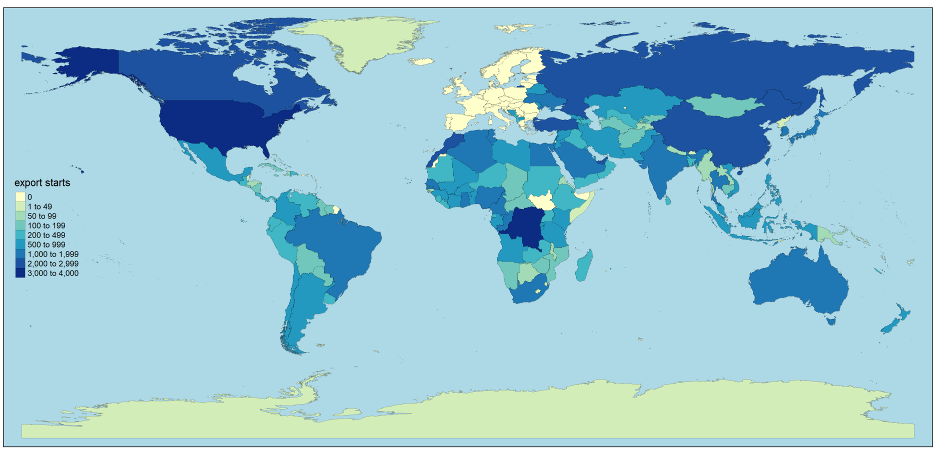


Figure 3: Geographic distribution of export starts (2004-2014)

4.2.2 Prevalence of export signals

Table 1: Share of firms receiving export signals

	per year		2004-2014	
signals	any signal	matching signal	any signal	matching signal
0	0.777	0.945	0.555	0.740
1	0.077	0.041	0.057	0.074
2	0.041	0.008	0.040	0.035
3	0.026	0.003	0.029	0.023
4	0.017	0.001	0.024	0.017
5	0.012	0.001	0.020	0.012
more than 5	0.045	0	0.248	0.081
Number of firms: 61,685				

This table indicates the share of firms that receive export signals in a single year and over the whole sample period. Matching signals represent the subset of total signals that originate in the same market as the subsequent export entry. *Any signal* here refers to the sum of matching and non-matching signals.

The data allows us to identify over 728,000 export signals received by sellers between 2004-2014. We distinguish between matching and non-matching export signals to indicate whether the origin of an incoming signal matches the destination of a seller's subsequent export start. Matching signals therefore represent information of direct relevance to foreign market access whereas non-matching signals capture the general availability of export-related information in the network.

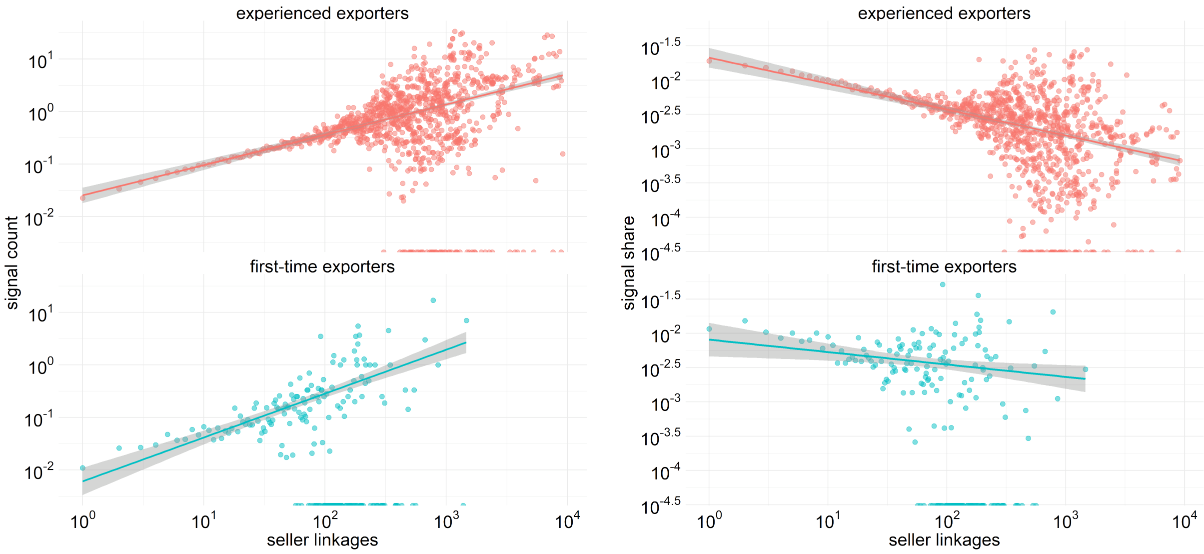
Table 1 illustrates the prevalence of both signal types in each year and over the entire sample period. A first insight is that despite the large number of signals identified, a majority of sellers do not receive any export signals. Each year only 5.5% of sellers (around 3,390 firms) benefit from matching export signals which emphasizes that many entry decisions are still taken in absence of network externalities. This means there remains a large amount of cross-sectional variation we can exploit for our empirical analysis[24]. Second, the distribution of firms receiving export signals appears to be highly skewed. Over the entire sample period roughly one half of all sellers do not receive any signals while a

[24] If most sellers received export signals in every period, identification of network externalities would mostly rely on within-firm variation in incoming export signals over time. Table 1 shows that our analysis can rely on both within- and between-firm variation when estimating network effects.

quarter of them receive more than 5[25].

4.2.3 Network externalities

Figure 4: Network externalities and network size



(a) signal intensity (b) signal clarity

Note: The graphs show our empirical measures of network externalities which are defined in section 3.3.

The concentration of information diffusion among a small number of sellers shown above is directly related to the underlying linkage distribution. While seller networks on average consist of 14 different buyers including 2 exporters and 1 export starter, the overall distribution of seller linkages is highly skewed[26]. Figure 12 in appendix A.3 shows that while 5% of sellers only maintain a single network interaction, sellers in the top decile on average have over 100 linkages to buyers in 2014. These vast differences in network size are closely related to seller characteristics. As shown in stylized fact 1, sellers with higher productivity on average interact with more buyers - a common pattern in production networks (Bernard and Zi, 2022; Bernard et al., 2022). Productive sellers can offer products at better quality or lower prices and thereby attract a larger number of buyers.

In a context of information diffusion, this positive association between seller productivity and network size directly determines which sellers receive the largest number of export

[25] The full distribution of export signals is shown in appendix A.2.

[26] Seller linkages to exporters and export starters are equally skewed as seen in appendix A.3.

signals. Productive sellers with large networks mechanically receive more export signals as each additional linkage is increasing probability of signal diffusion. Signal intensity is therefore increasing in network size as shown in Figure 4a. This absolute advantage of large networks however can be misleading. As shown in the stylized fact section 2, the share of exporters in the network is decreasing with network size. While a larger network provides more information in absolute terms, the relative amount for information per linkage (signal clarity) is decreasing as seen in Figure 4b. This indicates that network effects may not linearly increase in network size which we will account for empirically.

5 Econometric framework

In a previous section, we introduced network interactions to a standard model of export entry. This resulted in an estimable equation 7 which shows how export decisions of sellers are affected by the seller's own characteristics, the characteristics of its buyers and the buyers' export experience. The estimation of the causal impact of networks on seller outcomes poses new identification challenges. However, many of these challenges resemble common and well-known econometric problems which now need to be addressed in a network context.

A first challenge is a simultaneity issue due to contemporaneous buyer-seller behavior which can prevent a separate identification of general and information-specific network effects. We address this *reflection problem*[27] in section 5.1.1 by showing that our network setting meets formal identification conditions and introduce a temporal lag to break the simultaneity of buyer-seller actions. A second challenge are unobserved shocks which create correlation in (lagged) buyer and seller behavior and lead to endogenous export signals. Section 5.1.2 tackles these *correlated effects* by a combination of high-dimensional fixed effects and the introduction of an instrument that exploits indirect linkages to control for endogenous export behavior of direct linkages. This type of instrument is commonly used to identify network effects in social networks but now adjusted to a context of international

[27] Our identification strategy builds on previous work in social networks and spatial economics (Bramoullé et al., 2020; Advani and Malde, 2018) and therefore adopts terminology common to that literature. All *italic terms* are explained in detail in the following sections.

trade. A third and last challenge are *endogenous network linkages*. In section 5.3, we develop a network selection model to account for the presence of unobservables affecting both the formation of domestic (production network) and cross-border (exporting) linkages. The resulting selection correction term takes the familiar form of a Heckman-type mills ratio and can control for selection bias in presence of endogenous network formation. We discuss each of these challenges sequentially to dissect one issue at a time. After each step, we update our estimation equation. The final estimation equation is discussed in section 5.2.

5.1 Identification

We start by rewriting entry equation 7 in matrix notation. All firm characteristics and export starts in a given year are collected in matrices X_t and Y_t, and superscripts indicate the underlying source of variation. Using S_t and $\bar{S}_t$ to indicate standard and row-normalized binary interaction matrices we get

$$Pr\left(Y_t^{(id)} = 1\right) = Pr\left(\boldsymbol{\gamma}' X_t^{(i)} + \delta' \bar{S}_t X_t^{(j)} + \beta S_t Y_t^{(jd)} - \alpha_d + \varepsilon_t > 0\right) \tag{8a}$$

and

$$Pr\left(Y_t^{(id)} = 1\right) = Pr\left(\boldsymbol{\gamma}' X_t^{(i)} + \delta' \bar{S}_t X_t^{(j)} + \beta \bar{S}_t Y_t^{(jd)} - \alpha_d + \varepsilon_t > 0\right) \tag{8b}$$

for signal intensity ($S_t Y_t^{(jd)}$) and clarity ($\bar{S}_t Y_t^{(jd)}$) respectively. Following the terminology of the peer effects literature these are commonly known as local-aggregate and local-average models and here only differ in their treatment of network noise as discussed in section 3.3. Both allow networks to affect seller outcomes in two distinct ways. First, in the form of *contextual* peer effects which relate seller outcomes to buyer characteristics, captured by δ. These capture general externalities unrelated to export information such as productivity spillovers. Second, in the form of *endogenous* peer effects (β) which represent signal intensity (8a) or clarity (8b).

In this section, we start by assuming $E(\varepsilon_t | X_t, S_t) = 0$ which means networks form exogenously after conditioning on observable firm characteristics. This assumption is relaxed in section 5.3 where we control for endogenous network formation more formally.

5.1.1 The reflection problem

A first challenge arises from the joint determination of buyer and seller outcomes Y_t. If both terms enter the equations 8a and 8b contemporaneously, common shocks can lead to a simultaneity of buyer and seller export behavior. This well-known *reflection problem* (Manski, 1993) can prevent the separate identification of contextual and endogenous peer effects δ and β if individual firm networks do not sufficiently overlap[28]. In that case firm-to-firm linkages create separated network clusters in which firms only interact with members of the same cluster but have no linkages with firms in other clusters. If firms then experience a common shock, contextual and endogenous network effects become perfectly collinear as all firms within the same cluster act simultaneously and there is no variation from cross-cluster linkages to separately determine the impact of each network channel.

The separate identification of both network effects is of particular importance in our setting, as we want to ensure that our main coefficient of interest β does not capture general spillover effects unrelated to export information. Bramoullé et al. (2009) and (Liu et al., 2014) show how this can be achieved in network settings for local-average and local-aggregate models respectively. In a local-average model contextual and endogenous network effects are identified if identity matrix I, and interaction matrices S, and S^2 are linearly independent. In a local-aggregate model, separate identification requires the row sums of S to be non-constant and linear independence between I, S, $\bar{S}$ and $S\bar{S}$. Both sets of conditions are met in our setting as linkages in production networks are typically unidirectional which ensures linear independence of network matrices due to the presence of intransitive triads[29] and the fact that each seller interacts with a different number of buyers leading to a non-constant rowsum of S.

Despite meeting the general conditions to identify network effects in a contemporaneous setting, we take a different approach because sellers are expected to respond to incoming export signals with delay. Assuming a temporal lag between signal reception and response

[28] In our setting, firm networks do not overlap if sellers act as exclusive suppliers for all buyers in their network and buyers themselves source but do not sell (= have positive indegree but zero outdegree).

[29] An intransitive triad describes a network structure where firm A interacts with firm B, B interacts with firm C. It is called intransitive if there is no direct interaction between A and C.

is more realistic in our setting as sellers may take time to process information and adjust their production processes before entering a foreign market. Empirically, a delayed response also mitigates concerns related to the timing of buyer and seller export starts within the same year by ensuring that all sellers have sufficient time to react irrespective of the exact time a signal was received[30]. The same is true for contextual peer effects. Lagging both network effects changes our equations for signal intensity and signal clarity to

$$Pr\left(Y_t^{(id)}=1\right)=Pr\left(\boldsymbol{\gamma}'X_t^{(i)}+\delta'\bar{S}_{t-1}X_{t-1}^{(j)}+\beta S_{t-1}Y_{t-1}^{(jd)}-\alpha_d+\varepsilon_t>0\right) \tag{9a}$$

and

$$Pr\left(Y_t^{(id)}=1\right)=Pr\left(\boldsymbol{\gamma}'X_t^{(i)}+\delta'\bar{S}_{t-1}X_{t-1}^{(j)}+\beta\bar{S}_{t-1}Y_{t-1}^{(jd)}-\alpha_d+\varepsilon_t>0\right) \tag{9b}$$

Buyer and seller export starts now no longer occur simultaneously which resolves issues related to Manski's reflection problem. Conceptually, the change also marks a departure from the local-aggregate and local-average models of the peer effects literature. Instead, it brings our approach closer to time-space recursive models[31] studied in spatial economics (Anselin et al., 2008; Halleck Vega and Elhorst, 2017) where current outcomes Y_t are related to past network outcomes $S_{t-1}Y_{t-1}$. An important difference to time-space recursive models is that we do not consider lagged seller outcomes Y_{t-1} as additional controls. This type of autocorrelation cannot occur in our setting due to the definition of export starts[32] which rules out entries to the same destination in two consecutive years.

A delayed response to network externalities facilitates model identification but requires additional assumptions regarding the timing of the underlying diffusion process. First, incoming export signals received in the current period only facilitate foreign market en-

[30] Sellers receive export signals at different points of the year. If responding to signals takes time, then sellers receiving a signal towards the end of the year are disadvantaged which may introduce a downward bias to the estimation of endogenous peer effects.

[31] Time-space here refers to two different types of lag from the perspective of the dependent variable Y_t. A spatial lag S_tY_t indicating the relationship to network outcomes and a temporal lag $t-1$.

[32] An export start requires inactivity in the foreign market in the previous two periods. This implies that the two periods after an export start are excluded from the sample. A firm starting to export in year 3 and stopping in year 5 therefore only faces entry decisions in periods 1,2,3 and 6. Years 4 and 5 are dropped from the sample.

try in the next one. Second, to ensure conditional network exogeneity holds, we need to assume that export signals received in period t do not influence network formation at the beginning of period $t + 1$. This rules out that sellers form linkages strategically with the intent to reduce market access costs in the next period. Choosing to ignore export information received from previous linkages when forming new ones is restrictive but compatible with scenarios where the value of past signals is not yet realized at the beginning of the current period. Relaxing this assumption would require a formal model of strategic network formation as in (Badev, 2021) which is beyond the scope of this paper.

5.1.2 Correlated effects

A second challenge in our setting is to demonstrate that estimated network coefficients δ and β capture a causal relationship between network behavior and seller outcomes instead of a mere correlation driven by unobserved shocks. The latter are typically referred to as *correlated effects* which arise naturally in our study as buyers and sellers face various domestic and foreign shocks that can alter their export participation decision but remain unobserved by the econometrician. Failing to account for correlated effects will introduce a bias to estimated network coefficients and cast doubts on the relevance of network effects for export entry.

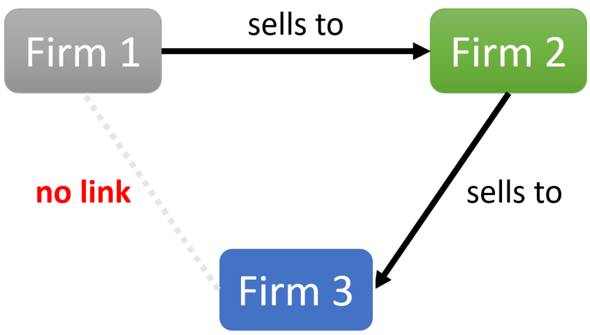
To understand what type of shocks might cause concerns when estimating equations 9a and 9b, it is key to consider the timing assumptions and different levels of observation at which our network effects operate. First, assuming a lagged seller response to network effects rules out most correlated effects from temporary shocks, as buyer and seller actions no longer occur in the same period. Second, while contextual peer effects δ operate at the firm-year level, endogenous peer effects β operate at the firm-destination-year level. This opens up the opportunity to employ high-dimensional fixed effects (FE) to account for a vast array of correlated effects from unobserved supply chain disruptions (firm-year FE), foreign demand shocks (destination-year FE) or export specialization patterns within networks (firm-destination FE)[33].

[33] Firm-year FE are a special case in this context. While including them absorbs contextual network effect δ and many firm-level controls, it allows us to control for *any* unobserved shock at the firm level.

The main concern regarding correlated effects in our setting therefore does not emanate from unobserved time-varying shocks per se, but instead arises from common shocks which buyers and sellers may respond to at different points in time. To illustrate this point, assume Chinese customs officials unexpectedly relax import requirements in period $t-1$ resulting in a decreased sunk entry cost α_d for all Belgian firms. If buyers in the network immediately respond to the shock and start exporting to China but sellers only react to the shock in period t, the delayed shock response of sellers would be observationally equivalent to the network effect we try to capture. To isolate buyer-seller entry variation induced by network effects, we need an instrument that can absorb any correlation in export behavior that is driven by delayed response times to common destination-specific shocks.

In our setting, this means that we need to treat export starts of connected buyers $Y_{t-1}^{(jd)}$ as endogenous and find a suitable instrument that is correlated with buyers' entry behavior in $t-1$ (relevance) but uncorrelated with sellers' entry decision in period t (exclusion restriction). An instrument that meets these requirements are export starts of firms which are directly linked to buyers j in period $t-1$ but have no direct link to the seller i as illustrated in Figure 5.

Figure 5: Instrumentation strategy



Firm 3 is an indirect buyer that operates outside the seller's network. Due to its connection

This includes important examples like supply chain disruptions, efficiency spillovers within networks or changes in local infrastructure and policy. Given they also absorb many variables of interest from the stylized entry model, we do not include them in our benchmark regression and instead only use them in robustness checks shown in section 6.2

to firm 2, unobserved shocks such as a sudden drop in Chinese entry barriers are expected to create contemporaneous[34] correlation in export behavior of firm 2 and 3. If the shock causes both firms to enter the Chinese market in $t-1$, we can use export starts of firm 3 to control for any impact this shock might have on a subsequent export start of firm 1 to the Chinese market in period t. Any remaining correlation between direct buyer 2 and seller 1 must then be driven by network effects. Out-of-network firms therefore allow us to control for endogeneity related to a delayed seller response to unobserved shocks in $t-1$.

The validity of this instrument crucially relies on the assumption that indirect buyers are only linked to sellers via buyers j and do not affect seller outcomes directly. To corroborate the credibility of this exclusion restriction, we exploit the full network structure[35] and exclude all indirect buyers (firm 3) which are connected to sellers (firm 1) directly or via higher-order linkages which do not involve immediate buyers (firm 2). In other words, we exclude all firms from the set of indirect buyers that have a first-, third-, fourth- or fifth-order linkage to sellers i. To curb the influence of unobserved firm linkages created outside production networks, we only consider indirect buyers located outside the province of the seller. The results of this instrumentation strategy are presented in section 6.2.1.

5.2 Estimation

We now present our empirical framework. Under the assumptions discussed in the previous section and assuming networks form exogenously, we only need to make a distributional assumption for error terms ε_t to take models 9a and 9b to the data. As a starting point, our benchmark estimation uses a linear probability model with fixed effects (LPM-FE) which assumes that errors ε_t are $i.i.d$ and follow a normal distribution.

[34]Correlated buyer-seller export behavior due to contemporaneous but unobserved shocks is key motivation to lag network effects in our estimation equation. At the same time, if these shocks occur outside the seller's network and prior to the seller's entry decision, we can exploit their *contemporaneous* nature to build instruments that purge export signals from shock-induced endogeneity such that only remaining variation is related to *intertemporal* network effects.

[35]A natural concern in this setting is that our network sample does not accurately capture all relevant linkages of each seller. While this is likely the case in practice, we expect our approach to perform reasonably well as most social networks are extremely sparse. Missing or misspecified network linkages should therefore only represent a small fraction of total linkages when compared to the correctly identified absence of linkages between most firms.

A key advantage of the LPM-FE is the ability to easily accommodate high-dimensional fixed effects which allows us to capture important unobservable factors in domestic and foreign markets that otherwise may give rise to correlated effects. At the same time, the assumed linearity limits the accuracy of predicted probabilities which can exceed the {0,1} interval.

Non-linear alternatives such as Probit and Logit models restrict predicted probabilities to the unit interval and therefore deliver more precise estimates for extreme values but typically suffer from an incidental parameter problem (IPP) when featuring high-dimensional fixed effects (Neyman and Scott, 1948). If the number of parameters that need to be estimated increases with sample size, maximum likelihood asymptotics no longer converge resulting in inconsistent parameter estimates. Our empirical setting is prone to this issue as the analysis considers export decisions at the firm-destination level which involves a large number of unobserved characteristics that need to be estimated. To evaluate benchmark estimates of LPM-FE model, we therefore contrast them with the fixed-effects logit estimator of Fernández-Val and Weidner (2016) and the fixed effects probit estimator of Hinz et al. (2021) which both feature a bias correction for the IPP while remaining directly comparable[36] to the LPM-FE via average partial effects.

Under normally distributed errors, we estimate the following reduced-form equation based on our time-space recursive lag model:

$$Pr\left(Y_t^{(id)} = 1\right) = Pr\left(\boldsymbol{\gamma}' X_t^{(id)} + \delta' \bar{S}_{t-1} X_{t-1}^{(j)} + \beta S_{t-1} Y_{t-1}^{(jd)} + \psi_i + \psi_{d,t} > \varepsilon_t\right) \tag{10}$$

Seller export starts $Y_t^{(id)}$ are related to their own characteristics $X_t^{(id)}$, network effects in form of buyer characteristics $X_{t-1}^{(j)}$ and export signals $Y_{t-1}^{(jd)}$ and a set of fixed effects ψ. We summarize the variables contained in each component below and present additional details in appendix B.2.

[36]A common approach that avoids the IPP overall is the conditional logit model suggested by Chamberlain (1980). While delivering consistent parameter estimates it is not able to estimate average partial effects and therefore cannot be directly compared to the other methods.

i. Seller characteristics $X_t^{(id)}$ capture determinants that affect seller export decisions in the absence of any network effects. These include firm-level controls such as total factor productivity (TFP), estimated using the procedure of Levinsohn and Petrin (2003), seller wages and employment-based seller size. Higher levels of TFP, wages and size are typically associated with increased export probability Bernard et al. (2003). Complementary to these firm-level controls, we exploit available data about trade transactions to construct additional variables at the firm-destination level. First, we identify the products underlying a seller's export start and use this information to construct a firm-specific measure of import demand in each foreign market. This variable controls for export decisions as a direct response to foreign demand shocks. Second, we control for sellers' experience in a foreign market prior to their export start. Even without network linkages, sellers might accumulate expertise about destinations from other activities. We therefore add dummy variables to control for seller experience from importing, exporting to bordering destinations or destinations with historic ties[37]. Lastly, we control for a seller's overall export expertise via the share of export sales in total sales.

ii. Buyer characteristics $X_{t-1}^{(j)}$ capture general network spillovers that affect seller entry across export destinations. Their presence ensures that the export signal coefficient β is identified from destination-specific variation in the network. We include buyer sales and TFP to control for general spillovers unrelated to entry information.

iii. Lastly, we employ two distinct fixed-effect (FE) specifications to control for correlated effects. In the benchmark case, we include firm and destination-year FE ψ_i and $\psi_{d,t}$. This allows to control for unobserved differences in firm performance and time-varying demand shocks in foreign markets. A second and more stringent specification extends this to firm-year FE. In this case, fixed effects absorb *any* time-varying characteristic at the firm-level which includes most variables of the standard

[37] The sequence of entry decisions is not random. Firms tend to enter markets that are similar to previous destinations (Morales et al., 2019) creating spatially correlated entry patterns (Albornoz et al., 2012)

entry framework as well as network effects from buyer characteristics. To remain as close as possible to the theoretical framework, we therefore rely on the weaker FE specification for the benchmark case and use the more stringent specification as a robustness check.

Table 2: Regression sample (firm-years)

Statistic	N	Min	Pctl(25)	Median	Mean	Pctl(75)	Max
employees	89,120	1.00	4.50	12.60	76.45	36.90	59,691.68
wage (k)	89,120	0.70	39.51	48.59	52.76	60.30	574.71
TFP (log)	89,120	3.39	12.80	13.56	13.69	14.47	21.05
border dummy	89,120	0	0	0	0.15	0.2	1
history dummy	89,120	0	0	0.6	0.52	0.9	1
import dummy	89,120	0	0	0	0.09	0.1	1
export sales share	89,120	0.00	0.00	0.05	0.21	0.38	1.00
export demand (mn)	89,120	0.00	0.01	0.05	6.02	0.30	11,328.10
mean buyer sales (mn)	89,120	0.00	1.14	2.62	30.56	7.85	47,125.25
mean buyer TFP (log)	89,120	2.78	12.00	12.49	12.66	13.15	20.97

Note: This table shows firm characteristics of our final regression sample which includes 22,133 unique firms. All variables have been aggregated to the firm-year level to facilitate interpretation. The reported number of observations therefore differs from the regression tables which capture entry decisions at the firm-destination-year level.

5.3 Endogenous network linkages

The preceding analysis relies on a conditional exogeneity assumption for network formation. As long as $E(\varepsilon_t|X_t^{(id)}, S_{t-1}) = 0$, interaction matrix elements $s_{ij,t-1}$ remain uncorrelated with individual outcome error $\varepsilon_{id,t}$ and network effects δ and β can be accurately estimated. Conditional exogeneity of network linkages, however, is unlikely to hold in practice because firms' ability to sell their products domestically may be systematically correlated with their likelihood of conducting business transactions across borders in the form of exporting. New employees who were originally hired to assess the firm's domestic product appeal might for example develop methodologies that can be employed to foreign markets as well and thereby facilitate the firm's expansion abroad. These firm-level shocks which both affect domestic and foreign link formation (= exporting) are problematic because they render network linkages s_{ij} endogenous and introduce bias to estimated network effects.

To account for endogenous network formation, we introduce the network selection model of Arduini et al. (2015) and Qu et al. (2017) to our estimation procedure. This allows us to express network endogeneity as an unobserved shock to domestic production network S and export behavior $Y^{(id)}$ and correct for the selection bias resulting from correlated linkage formation and entry decisions[38]. Formally, network formation is expressed by equation 11. Firms trade off the value of being linked to other firms and form linkages if

$$V(s_{ij,t} = 1) - V(s_{ij,t} = 0) > 0 = U_{ij,t} + \xi_{ij,t} \tag{11}$$

where $U_{ij,t}$ represents the linkage surplus and ξ is a random error term. The surplus is typically expressed as

$$U_{ij,t}(\theta) = \theta_0 + \boldsymbol{z_{i,t}\theta_1} + \boldsymbol{z_{j,t}\theta_2} + \boldsymbol{z_{ij,t}\theta_3} + \theta_4 A_{ij,t-1} \tag{12}$$

where coefficients $\boldsymbol{\theta_1}$, $\boldsymbol{\theta_2}$, $\boldsymbol{\theta_3}$ and θ_4 capture the impact of individual characteristics of firm i and j, characteristics of the dyad ij and their past relationship status. Dyad characteristics $z_{ij,t}$ are important in this setting because they control for key matching determinants like bilateral distance or common language of buyers and sellers in Belgium. Controlling for past relationship status is important because firm linkages in production networks tend to be very persistent (Martin et al., 2020) due to high search costs involved in the matching process.

If we assume that the random surplus component ξ is i.i.d and follows a logistic distribution, we can write the linkage probability $s_{ij,t}$ as

$$P(s_{ij,t} = 1) = P(U_{ij,t}(\theta) + \xi_{ij,t} > 0) = \frac{e^{U_{ij,t}(\theta)}}{1 + e^{U_{ij,t}(\theta)}} \tag{13}$$

[38]Our approach introduces network endogeneity in form of a correlation between network formation and market access error terms. We believe this modeling choice is appropriate given the similarity of both processes. If exporting is considered as the search for foreign buyers, we can interpret network formation and exporting as domestic and foreign search processes which are likely affected by common unobserved shocks. Arduini et al. (2015) show that this form of endogenous network formation can be controlled for with a standard selection correction term which otherwise leaves the structure of the outcome estimator unchanged. For an empirical application of productivity spillovers see Iyoha (2021). Alternative modeling approaches which link outcome errors to unobserved variables in the formation process (Goldsmith-Pinkham and Imbens, 2013; Hsieh and Lee, 2016) require Bayesian methods to estimate the likelihood functions. To keep the estimation parsimonious, we abstract from these alternatives.

To arrive at this expression, we assume that the conditional probability of i forming a link with j is independent from the decision to interact with another firm k. This implies that there is no strategic behavior in the network formation process which may characterize linkage formation in practice. Given the large network size considered our setting[39] we believe this assumption is appropriate to render the problem computationally tractable. The resulting formation process still includes many important characteristics of production networks. Seller i can interact with multiple buyers j at the same time, demonstrate persistence in their linkage decision and attach value to having business partners in close proximity.

While endogeneity in this context arises from unobserved shocks to network formation and export entry error terms ξ and ε, the timing of events in outcome equation 10 implies that we are mainly concerned about common shocks which have an immediate impact on domestic matching but only alter export decisions in the next period. Continuing the example from above, this would mean that the unexpected change in firm capacity is first employed in the domestic market, before being rolled out to prospective foreign destinations. Shocks affecting network formation and market access contemporaneously do not need to be considered as we only allow (endogenous) network effects to change firms' export decisions with a lag.

Before formalizing the correlation between formation and outcome errors, it is important to underline the dimensions at which both error terms operate. Network formation only considers firm-level characteristics of i and j whereas export decisions occur at the firm-destination level. This implies that our selection correction approach will only be able to capture correlated network and export behavior at the firm-level as formation errors $\xi_{ij,t-1}$ of seller i do not vary across seller export destinations d.

We start by collecting all network formation errors of seller i from dyadic regression 13 in row vector $\xi'_{i,t-1} = \{\xi_{ij,t-1}\}_{j \neq i}$. To relate formation errors to destination-specific outcome errors $\varepsilon_{id,t}$, each block of seller-specific error terms $\xi'_{i,t-1}$ is then repeated for each export

[39]There are around 100k firms in them Belgian production network. Further steps to reduce the dimension of the formation process are discussed in appendix C.3.

destination seller i serves in year t. We denote the extended vector of formation errors as $\xi'_{i\{d\},t-1}$ where subscript d indicates that original formation errors have been repeated d-times for each seller i[40].

The correlation in error terms can then be expressed as $(\varepsilon_{id,t}, \xi'_{i\{d\},t-1}) \sim i.i.d.(0, \Sigma_{\varepsilon\xi})$ where $\Sigma_{\varepsilon\xi} = \begin{pmatrix} \sigma^2_\varepsilon & \sigma'_{\varepsilon\xi} \\ \sigma_{\varepsilon\xi} & \Sigma_\xi \end{pmatrix}$, σ^2_ε is a scalar, $\sigma'_{\varepsilon\xi}$ and $\sigma_{\varepsilon\xi}$ are $(n_{ijd}-1)$-dimensional row and column covariance vectors and Σ_ξ a $(n_{ijd}-1)$ by $(n_{ijd}-1)$ diagonal matrix with scalars σ^2_ξ on the diagonal. If we stack all row vectors of extended formation errors in a matrix:

$$\Xi_{t-1} = \begin{bmatrix} \xi'_{1\{d\},t-1} \\ \xi'_{2\{d\},t-1} \\ \vdots \\ \xi'_{n\{d\},t-1} \end{bmatrix}$$

we can decompose the outcome error as:

$$\varepsilon_t = \eta \Xi_{t-1} + \upsilon_t$$

where $\eta = \Sigma_\xi^{-1}\sigma_{\varepsilon\xi}$, $\sigma^2_\upsilon = \sigma^2_\xi - \sigma'_{\varepsilon\xi}\Sigma_\xi^{-1}\sigma_{\varepsilon\xi}$ and υ_t is independent of formation error ξ_{t-1}. Plugging the decomposed outcome error into equation 10 then yields

$$Pr\left(Y_t^{(id)} = 1\right) = Pr\left(\gamma' X_t^{(i)} + \delta' \bar{S}_{t-1} X_{t-1}^{(j)} + \beta S_{t-1} Y_{t-1}^{(jd)} + \psi_i + \psi_{d,t} + \eta \Xi_{t-1} > \varepsilon_t\right) \quad (14)$$

where $\eta\Xi_{t-1}$ describes the selection bias induced by endogenous network formation. If $\sigma_{\varepsilon\xi} \neq 0$, seller networks S_{t-1} become endogenous and network effects δ and β will be be biased unless we control for Ξ_{t-1}.

To construct the selection correction term, we follow Arduini et al. (2015) and assume that outcome error ε_t is normally distributed. This allows us to use predicted linkage probabilities $p = P(s_{ij,t-1} = 1) = \frac{e^{U_{ij,t-1}(\theta)}}{1+e^{U_{ij,t-1}(\theta)}}$ from equation 13 and construct the selection

[40] Assume there are two sellers A and B. Each form linkages with buyers 1 and 2 but serve a different number of export destinations. Seller A exports to China and India, seller B only exports to India. The destination-extended vector of formation errors for all sellers would thus be $\xi = (\underbrace{\xi_{A1}, \xi_{A2}}_{\text{China}}, \underbrace{\xi_{A1}, \xi_{A2}}_{\text{India}}, \underbrace{\xi_{B1}, \xi_{B2}}_{\text{India}})$.

correction term using a Heckman-type mills ratio:

$$\hat{\Xi}_{i,t-1} = \sum_{j \neq i} s_{ij,t-1} \frac{\phi(\Phi^{-1}(p))}{p} + (1 - s_{ij,t-1}) \frac{\phi(\Phi^{-1}(p))}{1-p} \quad (15)$$

where ϕ and Φ represent probability and cumulative density functions of a standard normal variable. The estimated selection correction term can then be used as an additional regressor in equation 14 to purge the outcome error of unwanted correlation from endogenous network formation. A side effect of implementing this selection correction approach is the ability to directly test whether linkage endogeneity represents a concern when studying export entry decisions. If coefficient η is significantly different from zero, this would suggest that network formation is endogenous and controlling for selection important to recover accurate estimates of network effects.

6 Results

We present three sets of results to explore the role of network heterogeneity for the extensive margin of trade. First, we bring our augmented entry framework to the data and test whether export signals have any impact on entry decisions after controlling for sellers' own productivity and productivity spillovers from network peers. To this end, we present a set of benchmark estimates which rely on a LPM-FE, remain close to the theoretical framework and assume no correlated effects from network signals and linkages. Second, we assess the credibility of our benchmark estimates through a battery of robustness checks. Here we account for endogeneity via network instruments and a dyadic network selection model, test alternative model specifications and sampling approaches, and explore how network effects are shaped by different linkage types, peer characteristics and geography. The third set of results then investigates how network effects contribute to the observed firm-size concentration at the extensive margin of trade. Here we combine empirical and descriptive evidence to showcase how network assortativity determines the efficacy of information diffusion in production networks.

Table 3: Benchmark results - signal type

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Signal type						
matching	0.0043***					
	(0.0011)					
non-matching		3.44×10^{-5}				
		(7.77×10^{-5})				
total			4.14×10^{-5}			
			(7.79×10^{-5})			
EEA				9.03×10^{-6}		
				(0.0001)		
border					0.0003	
					(0.0004)	
history						0.0002***
						(5.93×10^{-5})
Peer characteristics	yes	yes	yes	yes	yes	yes
Destination experience	yes	yes	yes	yes	yes	yes
Firm characteristics	yes	yes	yes	yes	yes	yes
firm FE	yes	yes	yes	yes	yes	yes
destination-year FE	yes	yes	yes	yes	yes	yes
R^2	0.127	0.127	0.127	0.127	0.127	0.127
Observations	474,830	474,830	474,830	474,830	474,830	474,830

This table shows regression results of estimating equation 10 with a LPM-FE. Each column shows the marginal effect of receiving a different type of export signal on a seller's probability to start exporting. Standard errors in parentheses are clustered at the firm level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

6.1 Benchmark results

The main mechanism of our augmented entry framework is the ability of firm networks to provide access to specialized market information in the form of export signals. Receiving an export signal lowers export entry barriers for that particular destination market and induces firms to enter. This represents a key difference to conventional sources of firm heterogeneity like productivity which simultaneously boost entry across export destinations. A natural way to assess the relevance of network effects is therefore to sort incoming export signals by destination and test if signals indeed only facilitate access to the same market they originate from (matching signal) or can also promote entry in other markets (non-matching signal).

Table 3 summarizes the marginal effect of receiving an additional export signal by signal type. The full table is available in appendix C.1. Matching export signals (column 1) appear to be an important determinant for export entry even after controlling for sellers'own productivity, their experience in the foreign markets and other network spillovers related to peer characteristics such as productivity. On average, each incoming matching signal increases the probability to start exporting to the same destination market by 0.43 percentage points which is equivalent to a 13% increase in productivity[41] of the signal-receiving firm. While we have seen in Table 1 that the chance of receiving a matching signal is small, the economic impact of this network effect is remarkable, especially because a firm can receive multiple matching signals in any given period. Moreover, the fact that matching signals are statistically significant even after controlling for seller productivity, underlines that firm and network heterogeneity act as complementary forces which both shape the export participation patters of Belgian firms. In contrast, non-matching (column 2) and total export signals (column 3) seem to have no impact on entry behavior. This finding is important, as it shows that our diffusion mechanism is not picking up more general spillover effects that facilitate market access across destinations. Instead, entry barriers appear to be different in each market and as expected can only be reduced by matching signals.

In the remaining columns we disaggregate non-matching signals into three separate groups to corroborate these findings. Column 4 performs a placebo test by investigating the impact of incoming EEA signals. These destinations have been excluded from the sample in a previous step and signals should therefore under no circumstances have any impact on export decisions which reassuringly is not the case. On the contrary, signals originating in markets with a close relation to the actual export destination could facilitate entry if entry barriers or local demand preferences are correlated in space. Columns 5 and 6 illustrate that there is mild evidence of these indirect channels. This result is interesting, as it shows that previous findings of spatially correlated entry patterns of firms' own export expansion (Albornoz et al., 2012; Morales et al., 2019) carries over to information diffusion. While direct information in the form of matching signals is most valuable, indirect information from related markets, albeit to a much lesser degree, also facilitates entry.

[41] For this comparison we take the estimated coefficient of log TFP from Table C.1. The equivalent productivity effect (in percent) is then 0.0043/(0.01*0.0325).

6.2 Benchmark robustenss

To assess the validity of our benchmark results we perform five sets of robustness checks. Section 6.2.1 starts by addressing endogeneity concerns arising from endogenous export signals and network linkages. Next, we investigate to what extent network effects depend on the chosen model specification and sample selection in sections 6.2.2 and 6.2.3. In section 6.2.4 we then explore how network effects are shaped by heterogeneity in the underlying linkage and peer characteristics. Lastly, we contrast our network-based diffusion mechanism with geography-based spillover proxies in section 6.2.5 to explore how geographic distance shapes the diffusion of export signals.

6.2.1 Model endogeneity

Up to this point, network effects are obtained under the assumption that export decisions of network peers $Y_{t-1}^{(jd)}$ and network linkages S_{t-1} are exogenous. To relax this assumption, we employ the two-stage least squares (2SLS) approach and network selection model outlined in sections 5.1.2 and 5.3 to investigate whether signal and linkage endogeneity change our benchmark estimates.

To rule out that any observed correlation of buyer and seller export decisions is driven

Table 4: Endogenous export signals - 2SLS

Dependent variable: IV stages:	matching signals First	export starts Second	matching signals First	export starts Second
Variables				
second-order signals	0.3848*** (0.0669)		0.4204*** (0.0752)	
matching signals		0.0100** (0.0042)		0.0063** (0.0025)
Peer characteristics	yes	yes		
Destination experience	yes	yes	yes	yes
Firm characteristics	yes	yes		
firm FE	yes	yes		
destination-year FE	yes	yes	yes	yes
firm-year FE			yes	yes
R^2	0.595	0.127	0.678	0.306
Observations	474,676	474,676	904,896	904,896

This table shows results of a 2SLS regression of equation 10. Endogenous export signals are instrumented by second-order signals. Columns 1 and 3 show first-stage results, columns 2 and 4 second-stage results. Standard errors in parentheses are clustered at the firm level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

by a common shock, we instrument export decisions of direct buyers with export decisions of indirect buyers that exclusively interact with sellers through an intermediary[42]. Results of this instrumentation strategy are reported in Table 4. As expected, first-stage estimates in columns 1 and 3 reveal that the direct B2B relationship between first- and second-order buyers indeed results in a strong correlation of export decisions in period $t-1$, underlining the relevance of the proposed instrument. Controlling for this source of correlated effects in our main outcome equation (columns 2 and 4) leads to network effects which remain statistically significant but the marginal effect of export signals exceeds our benchmark estimates by a factor of 1.5-2.5. This not only indicates that accounting for unobserved shocks which create spurious correlation in seller and network export behavior is important but also reveals that true network effects could be much larger than the initial benchmark estimates suggest.

Next, we contrast benchmark estimates to a setting where firms choose linkages according to the dyadic network formation model presented in equation 12. Endogeneity concerns in this setting arise whenever unobserved shocks simultaneously affect domestic (Belgian B2B) and foreign (exporting) business transactions. We follow Arduini et al. (2015) and Qu et al. (2017) and construct a selection correction term which accounts for selection bias from correlated outcome and formation error terms ε and ξ. To render the required estimation of the dyadic formation model feasible for all 100k firms in the network, we take several steps to reduce the dimension of the linkage formation process which are detailed in appendix C.3. One of these steps is to impose restrictions on the number of candidates a firm considers when forming domestic linkages. The true number of candidates a firm considers, but eventually does not decide to interact with, is unobserved. Thus, we compute selection correction terms for different candidate set sizes which are expressed as the number of candidates per actual match.

Results of estimating equation 14 which includes a selection correction term as an additional regressor are presented in Table 5. Despite the fact that selection correction terms

[42] As explained in section 5.1.2, we ensure that second-order buyers are not linked to sellers via higher-order linkages or located in close proximity to each other.

Table 5: Endogenous network linkages - selection correction

Candidates per match:	baseline	n=1	n=5	n=10	n=20
Variables					
matching signals	0.0042***	0.0043***	0.0043***	0.0043***	0.0043***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
selection correction		2×10^{-5}**	1.95×10^{-5}**	1.93×10^{-5}**	1.9×10^{-5}**
		(8.44×10^{-6})	(8.25×10^{-6})	(8.17×10^{-6})	(8.14×10^{-6})
Peer characteristics	yes	yes	yes	yes	yes
Firm destination experience	yes	yes	yes	yes	yes
Firm characteristics	yes	yes	yes	yes	yes
firm FE	yes	yes	yes	yes	yes
destination-year FE	yes	yes	yes	yes	yes
R^2	0.127	0.127	0.127	0.127	0.127
Observations	450,243	450,243	450,243	450,243	450,243

This table shows results of estimating equation 14 which accounts for endogenous network formation via a selection correction term. The selection correction term is based on the dyadic network formation model outlined in equation 12 and calculated for several buyer candidate sets which differ in size. Standard errors in parentheses are clustered at the firm level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

are statistically significant, indicating that the underlying formation process is indeed endogenous, matching signals remain virtually identical to the benchmark estimates. This suggests that while a selection bias from endogenous network formation is present, it does not appear to be a major concern in our setting.

6.2.2 Model specification

Our benchmark estimates are obtained from a LPM-FE whose linearity assumption implies that the marginal impact of matching signals is common to all firms and constant for each additional signal received. Non-linear alternatives such as Logit and Probit models relax this assumption and allow the marginal effects of export signals to vary with characteristics of each seller. At the same time, the inclusion of high dimensional fixed effects presents a real challenge for non-linear models as the asymptotics of the underlying ML estimator break down due to the incidental parameter problem (IPP). As the inclusion of fixed effects is essential to rule out unobserved heterogeneity that would otherwise plague our network estimates, we employ the bias-adjusted non-linear logit and probit models developed by Fernández-Val and Weidner (2016) and Hinz et al. (2021) which mitigate concerns related to the IPP and remain comparable to our linear estimates via average partial effects (APEs). Appendix C.2.1 shows the results from the direct comparison between linear and non-linear models for signal intensity and clarity. While coefficients naturally differ across models, APEs remain remarkably close to each other irrespective of which model is preferred. The comparison also reiterates the importance of network heterogeneity for export entry as matching signals remain statistically significant throughout all specifications.

Next, we compare our benchmark results to estimates obtained from more stringent fixed effect specifications presented in appendix C.2.2. These mark a departure from the baseline model, as the additional firm-year FE and firm-destination FE absorb most controls of the standard entry model. In turn, this allows us to control for *any* unobserved time-varying influence at the firm level and firm's unobserved proclivity towards certain destinations. Results from alternative FE specifications remain very close to our benchmark estimates, indicating that these additional sources of correlated effects are not responsible for the observed network effects.

6.2.3 Sample selection

In appendix C.2.3 we repeat the benchmark estimates using an alternative network cutoff value $\nu_{ij,t} = 5\%$ to define relevant network linkages. Compared to the benchmark case, this significantly reduces the number of network linkages and thus the number of export signals diffusing through the network. While this reduces the chance of receiving export signals, specifying the network in this conservative manner still singles out matching export signals as the dominant source of network effects. The chosen network cutoff therefore does not determine the general mechanism at play but changes the size of the marginal effect of export signals which seems to increase when diffusion is constrained by a more conservative linkage cutoff.

Lastly, we restrict the sample to first-time exporters to ensure that network effects not only act as a catalyst for firms which already have a presence in foreign markets. For this purpose, we define first-time exporters as firms that have not exported anywhere in the first 1, 5 and 10 years of the sample. Estimates obtained from running the benchmark model for these different subsets of firms are shown in appendix C.2.4. Compared to the baseline results, network effects not only remain significant but generally appear to be stronger for first-time exporters. This suggests that having access to the export experience of one's peers via network linkages is particularly important for first-time exporters presumably because these firms have not yet gained any export experience on their own.

6.2.4 Signal heterogeneity

Our benchmark estimates reveal that matching signals facilitate export entry. To ensure that this average effect does not simply reflect an advantage originating from a small subset of linkages or network peers, we disaggregate export signals along several dimensions of linkage and peer characteristics. Here we limit attention to the main findings of this exercise. Further details and a full set of results are available in appendix C.4.

We start by comparing network effects across three linkage dimensions: linkage dependency, proxied by the seller's share in total buyer sourcing, linkage persistence, captured by the continuity of buyer-seller interactions and linkage direction, which contrasts diffusion occurring along backward and forward linkages. Results are displayed in panels (a) to (c) of Figure 15. We find that a strong buyer-seller dependency amplifies the positive impact of export signals but effects remain significant when considering interactions in which sellers are less central to the buyer's overall sourcing strategy. Turning to linkage duration, our results indicate that both new and persistent linkages facilitate export entry. This suggests that sellers not only respond to signals received from trusted sources but also remain open to insights from new business partners. Finally, we find that signals travelling along network linkages can facilitate market access for buyers as well. This diffusion along forward linkages (buyers learn from sellers) however appears less robust than diffusion along backward linkages (sellers learn from buyers) which this study focuses on.

In panels (d) to (f) of figure 15 we turn to peer characteristics and study how network effects differ along peer size, credibility and industry association. Our findings show that signals from both small and large buyers promote export entry but more so if buyer and seller size is positively correlated. This surprising result suggests that information diffusion in production networks is more effective among firms sharing similar characteristics, a pattern commonly known in social networks as homophily. Next, we explore whether sellers differentiate among incoming export signals based on the credibility of individual network peers. We find that export starts that account for a significant share in buyer's total exports create a stronger signal for sellers. While our benchmark analysis treats each incoming signal equally, firms do seem to differentiate between signals they receive which likely leads to an underestimation of the true network effect. Finally, we explore to what extent network effects are driven by peers in wholesale industries. Trade intermediation is often used an intermediate step to reach foreign markets. Our results confirm previous studies which find that interactions with wholesalers can promote foreign market access (Connell et al., 2019) but reveal that the benefits of network diffusion extend far beyond wholesalers. Instead, the majority of network effects seems to be driven by non-wholesalers which underlines the importance of using a general entry framework that considers the entire production network when estimating network effects.

6.2.5 Geographic proximity

To rule out that estimated network effects merely reflect agglomeration economies from buyers in close geographic proximity, we compare the impact of matching signals from distant and nearby buyers. Results of this final robustness check are presented in Figure 16 in appendix C.5.

Reassuringly, we find that signals of buyers located outside the seller's province are equally conducive to export entry as signals originating from buyers located within the same province. This result has two important implications. First, it showcases that our network effects capture a general diffusion mechanism that is not limited to the geographic confines of a province, city or street as in the preceding spillover literature (Koenig et al., 2010; Fernandes and Tang, 2014; Bisztray et al., 2018). Second, it rules out that estimated network effects are merely the result of labor movements[43] between firms. Evidence from Belgian commuter flow surveys shows a strong preference to reside in close proximity to the workplace as 85% of commuters do not cross a provincial border to go to work (Duprez and Nautet, 2019). Network effects extending beyond provincial borders as shown in Figure 16, are therefore unlikely driven by labor movements between buyers and sellers

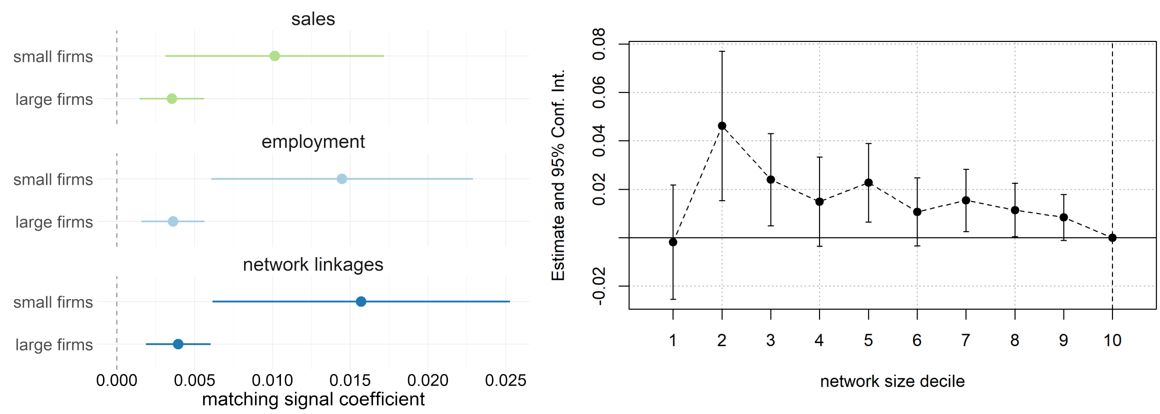
[43] For recent work studying this channel see Choquette and Meinen (2015) and Patault and Lenoir (2021).

as the majority of people do not seek employment outside their province.

6.3 Network heterogeneity and the extensive margin of trade

A large literature in international trade has documented that exporting is dominated by a small number of large and highly productive firms (Bernard et al., 2003; Mayer and Ottaviano, 2008). We show in stylized fact 2 and figure 4a that these firms also happen to have the largest networks and will on average receive the largest number of export signals. This naturally raises the question whether both firm and network heterogeneity are actually complementary sides of the same coin such that export participation equally benefits from firm size and network scale.

Figure 6: Network effects by firm size

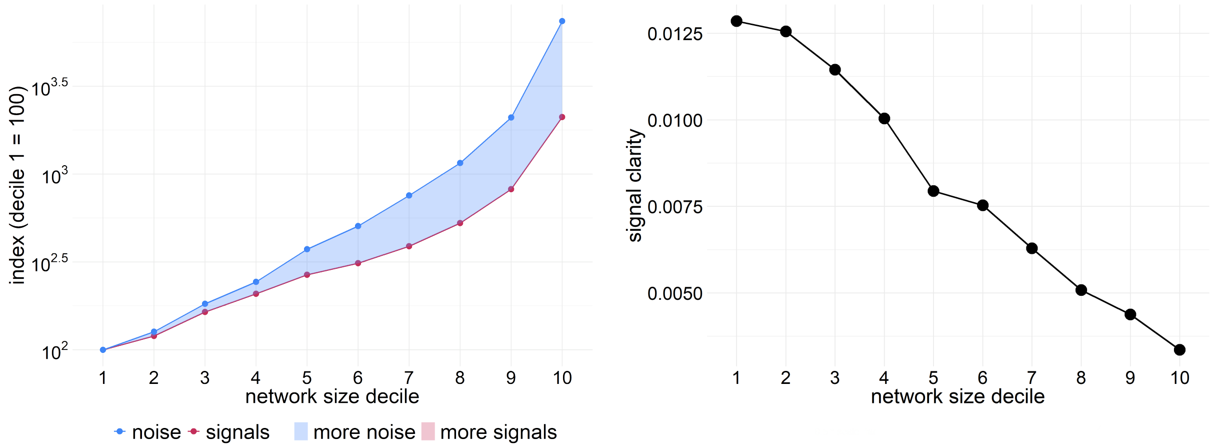


(a) subsample regressions (b) full sample with interaction term

We explore this question in Figure 6 which shows results of two distinct exercises to illustrate how network effects vary across sellers of different size. In Figure 6a we divide sellers into small and large firms based on their median sales, employment and the number of network linkages. We then run separate regressions for each subsample and plot matching signal coefficients. Irrespective of which firm size dimension is considered, we see that the marginal impact of export signals is consistently larger for small firms. For small sellers, a single export signal increases the entry probability by 1.0-1.6 percentage points, outpacing the same effect for large sellers by a factor of 2-4. To corroborate this large difference in network effects by firm size, we separately estimate network effects for each size decile by introducing an interaction term to equation 10. Coefficients are plotted in 6b and expressed relative to firms with the largest networks. Apart from firms with very small networks, marginal effects appear to almost linearly decrease in network size which indicates that network effects exhibit decreasing returns to network scale. In other words, despite having a larger network and receiving more export signals, large firms benefit less from information diffusion.

To rationalize this surprising result two explanations come to mind. First, the value of an export signal decreases the more often it is received. Firms with access to large networks are more likely to receive the same signal multiple times and therefore experience lower marginal network effects. Unfortunately our data does not allow us to compare the information content overlap of individual matching signals. This means we cannot directly test to what extent signal redundancy can explain decreasing returns to network scale. Second, export signals become harder to process if accompanied by large levels of network noise. We define network noise as the share of network interactions that do not yield export signals. If each network linkage takes up time and resources of the firm, network benefits do not scale with the absolute number of signals (signal intensity) but instead depend on the number of signals per linkage (signal clarity). This *relative* measure controls for the level of network noise by penalizing networks in which only a small share of linkages contribute to the diffusion of export information. Processing low clarity signals is more difficult and therefore leads to lower levels of entry, even if the absolute number of signals is high. Systematic differences in signal clarity across small and large networks could therefore also explain why network effects decrease in network size.

Figure 7: Network noise by firm size



(a) signal vs. noise growth rates

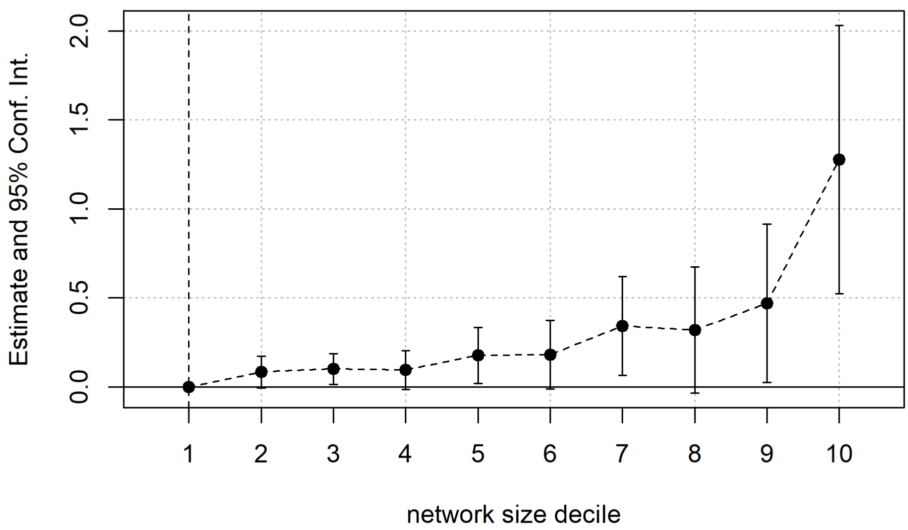
(b) signal clarity

Figure 7a shows a decomposition of signal clarity into export signals (numerator) and network noise (denominator) to investigate how signal clarity differs across network size deciles. We plot the average growth rates of signals (red) and noise (blue) indexed to the first size decile. As expected, both lines are monotonically increasing given that larger networks naturally include a larger number of valuable and non-valuable linkages. The main insight, however, is that both linkage types grow at different rates. While growth rates are comparable across small networks, noise grows faster in medium-sized and large networks as indicated by the shaded blue area between both lines. Firms with large networks therefore receive more export signals in absolute terms, but at the same time are exposed to disproportionate levels of network noise. This results in decreasing levels of signal clarity for firms with larger networks as shown in 7b.

This size penalty is closely related to the underlying network formation process. As discussed by Bernard et al. (2022), the Belgian production network is characterized by negative assortative matching. Highly productive sellers on average interact with less productive buyers. We show that this inverse relationship between buyer and seller performance has direct implications for information diffusion. Decreasing buyer performance in large networks leads to lower levels of signal clarity as an increasing share of buyers does not provide export experience to the seller. Instead, they emit network noise making it harder to process valuable export signals received from other network peers.

To see how these systematic differences in signal clarity affect export entry decisions of

Figure 8: Signal clarity results by network size



small and large firms, we re-estimate equation 10 using signal clarity as our variable of interest and again interact network effects with size deciles. Coefficient β now captures the impact of an increase in signal clarity on the probability of entry. A unit increase in signal clarity can be interpreted as a relative decrease in network noise while holding the absolute number of export signals constant. It therefore shows how sellers would react to a change in their network configuration in which the relative share of exporting to non-exporting buyers increases.

The results are shown in figure 8 and reveal two important findings. First, firms across size deciles benefit from lower levels of network noise in form of an increased propensity to enter foreign markets. This indicates that the effectiveness of information diffusion in production networks depends both on the absolute amount (signal intensity) and signal-to-noise ratio (signal clarity) of transferred information. Second, we see that a relative decrease in network noise is most beneficial for firms with large networks. We interpret this as direct evidence of the predictions made in the descriptive analysis above. Network noise is a bigger impediment to entry for firms with large networks. Seeing that these firms show the largest response to increases in signal clarity also suggests that at they do not yet reap the full benefits of information diffusion. Network noise can therefore at least partially explain the observed decreasing returns to network scale. The alternative explanation of signal redundancy cannot generate this pattern, as it solely focuses on linkages which generate export signals and ignores any impact of network noise. We discuss the consequences of this finding in the next section.

7 Discussion

The results presented above demonstrate that networks act as an important determinant for export participation but do so in a distinctly different way than traditional sources of firm heterogeneity like productivity. This has a number of important implications.

For trade theory, our results suggest that network linkages constitute an important dimension of firm heterogeneity that needs to be considered to understand firm behavior at the extensive margin of trade. Considering a setting with multidimensional firm heterogeneity relaxes the singular focus on firm productivity and offers a new perspective on export participation patterns that was hard to reconcile before. An example is the existence of small exporters which often fail to meet theory-implied productivity thresholds that would justify their participation in foreign markets. Network heterogeneity offers an explanation for this pattern in the sense that suitable network configurations can lower entry barriers to a particular market, allowing firms to enter despite insufficient levels of productivity.

Another important difference to traditional sources of firm heterogeneity is that network effects exhibit decreasing returns to scale. While productivity continues to increase export participation in our theoretical framework even at extreme levels, network effects dissipate as the network grows. This raises interesting questions regarding network efficiency. If network expansion adds noise to export signals but benefits the firm in other dimensions, there could exist an optimal network size which balances both effects. We are not convinced that learning about export markets is a first-order concern in the network formation process, which is why we disregard strategic network formation and treat network effects as a pure externality. Our work nevertheless highlights a potentially important but indirect cost of unrestricted network expansion that goes beyond direct search and matching costs typically associated with the network formation process.

Relatedly, we want to stress the importance of understanding the role of network assortativity in this context. Decreasing returns to network scale in our setting are closely linked to a distinct feature of production networks which are marked by a negative relationship between firm size and average peer performance. The opposite is often observed in social networks where agent and peer characteristics tend to be positively correlated. Realizing that the direction of assortativity varies across settings is important because a production network with positive assortative matching would have resulted in increasing returns to network scale. In this case, sellers would get access to more performant buyers if their network expands. This decreases the average level of network noise and means that export participation monotonically increases in firm and network size. Any study mapping average network characteristics to outcomes should therefore be mindful of the underlying network formation process and consider the possibility of decreasing returns to scale in settings marked by negative assortative matching.

On the policy side, our findings emphasize the role of information frictions in trade. Only matching signals stimulate foreign market access which indicates that informational cost barriers differ substantially across export destinations. Export promotion agencies often address this problem by investing considerable resources to provide a *select group of members* with up-to-date market information and organize costly matching events to connect domestic firms with foreign buyers. Our results suggest that domestic production networks can act as a powerful tool to provide similar benefits to *all domestic firms* in a relatively cost-effective way. Instead of trying to directly link domestic firms to foreign buyers, policy makers could utilize the existing export experience in the network and facilitate the diffusion of specialized export information by creating new linkages among domestic firms. This could be an especially promising strategy to connect small and medium-sized enterprises (SMEs) to global markets as our results indicate that small firms stand to gain most from network externalities.

8 Conclusion

Export participation remains low across countries which causes concerns as it weakens competition in domestic markets (De Loecker and Warzynski, 2012) and restricts aggregate export growth (Eaton et al., 2009b). In this paper, we empirically investigate the determinants of export participation. A large preceding literature of heterogeneous firm trade models has emphasized the role of firm-level characteristics like productivity to rationalize observed entry patterns among firms.

We move beyond firm-level characteristics and investigate whether domestic production networks actively influence export entry decisions. Firms that interact with experienced exporters receive export-related information via network linkages which lowers sunk entry costs and thereby facilitates foreign market access. To formalize this mechanism, we introduce network interactions into a stylized model of export entry. Our augmented framework features firms which differ in both productivity and network linkages which allows us to assess the relevance of each dimension of firm heterogeneity for export participation.

To estimate the model, we rely on detailed data from the universe of Belgian firms which contains firm characteristics, imports, exports and domestic firm-to-firm transactions of every firm operating in Belgium between 2002-2014. Combined, these unique datasets allow us to observe each firm's individual network as well as the export behavior of network peers. Every time a firm starts to export to a new export destination, it emits an export signal to connected firms which contains valuable entry information and lowers market access costs. The number of received export signals varies across firms as each network is unique. Networks thus create a second dimension of firm heterogeneity beyond firm productivity.

Taking this model to the data reveals that network heterogeneity plays a decisive role for export participation even after controlling for productivity for all the firms in the network. Each additional export signal received from the network increases the entry probability to a specific foreign market by 0.43 percentage points which is equivalent to a 13% increase in productivity of the signal-receiving firm. While firms with large networks also receive the highest number of export signals, we find that the marginal effect of signals decreases in network size. We relate this size penalty to negative assortative matching in the underlying network formation process. Network expansions are associated with a disproportionate growth of network interactions that do not yield valuable export signals but still take up time and resources of the firm. We find evidence that this form of network noise mitigates the positive impact of network effects and is partially responsible for the observed decreasing returns to network scale.

Taken together, our findings demonstrate that network heterogeneity acts as an important new determinant of export participation but is unlikely to exacerbate the observed concentration at the extensive margin of trade. At the same time, they raise important questions regarding the strategic link between network formation and export participation and under which conditions networks should be considered efficient. These questions lie outside the scope of the current paper and require a more structural treatment of network linkages and firm outcomes. We believe our results provide important empirical evidence for this future avenue of research and will promote a stronger consideration of networks in international trade.

References

Advani, A. and B. Malde (2018). Methods to identify linear network models: a review. *Swiss Journal of Economics and Statistics 154*(1), 1–16.

Ahn, J., A. K. Khandelwal, and S.-J. Wei (2011). The role of intermediaries in facilitating trade. *Journal of International Economics 84*(1), 73–85.

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

Anselin, L., J. L. Gallo, and H. Jayet (2008). Spatial Panel Econometrics. In L. Mátyás and P. Sevestre (Eds.), *The Econometrics of Panel Data: Fundamentals and Recent Developments in Theory and Practice*, Advanced Studies in Theoretical and Applied Econometrics, pp. 625–660. Berlin, Heidelberg: Springer.

Arduini, T., E. Patacchini, and E. Rainone (2015). Parametric and Semiparametric IV Estimation of Network Models with Selectivity. Technical Report 1509, Einaudi Institute for Economics and Finance (EIEF). EIEF Working Papers Series.

Arkolakis, C., S. Ganapati, and M.-A. Muendler (2021). The Extensive Margin of Exporting Products: A Firm-Level Analysis. *American Economic Journal: Macroeconomics 13*(4), 182–245.

Arkolakis, C., F. Huneeus, and Y. Miyauchi (2023). Spatial production networks. Working Paper 30954, National Bureau of Economic Research.

Badev, A. (2021). Nash Equilibria on (Un)Stable Networks. *Econometrica 89*(3), 1179–1206.

Bernard, A. B., E. J. Blanchard, I. Van Beveren, and H. Vandenbussche (2018). Carry-along trade. *The Review of Economic Studies 86*(2), 526–563.

Bernard, A. B., E. Dhyne, G. Magerman, K. Manova, and A. Moxnes (2022). The origins of firm heterogeneity: A production network approach. *Journal of Political Economy 130*(7), 1765–1804.

Bernard, A. B., J. Eaton, J. B. Jensen, and S. Kortum (2003). Plants and Productivity in International Trade. *The American Economic Review 93*(4), 1268–1290.

Bernard, A. B., J. B. Jensen, S. J. Redding, and P. K. Schott (2007). Firms in International Trade. *Journal of Economic Perspectives 21*(3), 105–130.

Bernard, A. B., J. B. Jensen, S. J. Redding, and P. K. Schott (2010). Wholesalers and Retailers in US Trade. *American Economic Review 100*(2), 408–413.

Bernard, A. B., A. Moxnes, and K. H. Ulltveit-Moe (2018). Two-Sided Heterogeneity and Trade. *The Review of Economics and Statistics 100*(3), 424–439.

Bernard, A. B. and Y. Zi (2022). Sparse production networks. Working Paper 30496, National Bureau of Economic Research.

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

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

Bramoullé, Y., H. Djebbari, and B. Fortin (2020). Peer Effects in Networks: A Survey. *Annual Review of Economics 12*(1), 603–629.

Calvó-Armengol, A., E. Patacchini, and Y. Zenou (2009). Peer Effects and Social Networks in Education. *Review of Economic Studies 76*(4), 1239–1267.

Chamberlain, G. (1980). Analysis of Covariance with Qualitative Data. *The Review of Economic Studies 47*(1), 225–238.

Chaney, T. (2014). The Network Structure of International Trade. *American Economic Review 104*(11), 3600–3634.

Chaney, T. (2016). Networks in International Trade. In Y. Bramoullé, A. Galeotti, and B. Rogers (Eds.), *The Oxford Handbook of the Economics of Networks*, pp. 753–775. Oxford University Press.

Choquette, E. and P. Meinen (2015). Export Spillovers: Opening the Black Box. *The World Economy 38*(12), 1912–1946.

Connell, W., E. Dhyne, and H. Vandenbussche (2019). Learning about demand abroad from wholesalers: a B2B analysis. Working Paper 377, National Bank of Belgium, Brussels.

De Loecker, J., C. Fuss, and J. V. Biesebroeck (2014). International Competition and Firm Performance: Evidence from Belgium. Working Paper 269, National Bank of Belgium, Brussels.

De Loecker, J. and F. Warzynski (2012). Markups and Firm-Level Export Status. *American Economic Review 102*(6), 2437–2471.

Dhyne, E., A. K. Kikkawa, M. Mogstad, and F. Tintelnot (2021). Trade and Domestic Production Networks. *The Review of Economic Studies 88*(2), 643–668.

Dhyne, E., G. Magerman, and S. Rubínova (2015). The Belgian production network 2002-2012. Working Paper 288, National Bank of Belgium, Brussels.

Duprez, C. and M. Nautet (2019). Economic flows between Regions in Belgium. *NBB Economic Review*, 1–19.

Eaton, J., M. Eslava, M. Kugler, and J. R. Tybout (2009a). 8. Export Dynamics in Colombia: Firm-Level Evidence. In E. Helpman, D. Marin, and T. Verdier (Eds.), *The Organization of Firms in a Global Economy*, pp. 231–272. Harvard University Press.

Eaton, J., M. Eslava, M. Kugler, and J. R. Tybout (2009b). Export Dynamics in Colombia: Firm-Level Evidence. In *The Organization of Firms in a Global Economy*, pp. 231–272. Harvard University Press.

Eaton, J., D. Jinkins, J. R. Tybout, and D. Xu (2022). Two-sided search in international markets. Working Paper 29684, National Bureau of Economic Research.

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

Fernández-Val, I. and M. Weidner (2016). Individual and time effects in nonlinear panel models with large N , T. *Journal of Econometrics 192*(1), 291–312.

Fontaine, F., J. Martin, and I. Mejean (2023). Frictions and adjustments in firm-to-firm trade. *mimeo*.

Fujii, D., Y. Ono, and Y. U. Saito (2017). Indirect exports and wholesalers: Evidence from interfirm transaction network data. *Japan and the World Economy 44*, 35–47.

Ganapati, S. (2021). The Modern Wholesaler: Global Sourcing, Domestic Distribution, and Scale Economies. *mimeo*.

Gaulier, G. and S. Zignago (2010). Baci: International trade database at the product-level. the 1994-2007 version. Working Papers 2010-23, CEPII.

Goldsmith-Pinkham, P. and G. W. Imbens (2013). Social Networks and the Identification of Peer Effects. *Journal of Business & Economic Statistics 31*(3), 253–264.

Halleck Vega, S. and J. P. Elhorst (2017). Regional labour force participation across the European Union: a time–space recursive modelling approach with endogenous regressors. *Spatial Economic Analysis 12*(2-3), 138–160.

Hinz, J., A. Stammann, and J. Wanner (2021). State Dependence and Unobserved Heterogeneity in the Extensive Margin of Trade. *mimeo*.

Hsieh, C.-S. and L. F. Lee (2016). A Social Interactions Model with Endogenous Friendship Formation and Selectivity. *Journal of Applied Econometrics 31*(2), 301–319.

Hsieh, C.-S., L.-F. Lee, and V. Boucher (2020). Specification and estimation of network formation and network interaction models with the exponential probability distribution. *Quantitative Economics 11*(4), 1349–1390.

Huang, H., K. Manova, O. Perello, and F. Pisch (2022). Firm Heterogeneity and Imperfect Competition in Global Production Networks. *mimeo*.

Iyoha, E. (2021). Estimating Productivity in the Presence of Spillovers: Firm-level Evidence from the US Production Network. *mimeo*.

Javorcik, B. S. and M. Spatareanu (2011). Does it matter where you come from? Vertical spillovers from foreign direct investment and the origin of investors. *Journal of Development Economics 96*(1), 126–138.

King, G. and L. Zeng (2001). Logistic Regression in Rare Events Data. *Political Analysis 9*(2), 137–163.

Koenig, P. (2009). Agglomeration and the export decisions of French firms. *Journal of Urban Economics 66*(3), 186–195.

Koenig, P., F. Mayneris, and S. Poncet (2010). Local export spillovers in France. *European Economic Review 54*(4), 622–641.

König, M. D., X. Liu, and Y. Zenou (2019). R&D Networks: Theory, Empirics, and Policy Implications. *The Review of Economics and Statistics 101*(3), 476–491.

Levinsohn, J. and A. Petrin (2003). Estimating Production Functions Using Inputs to Control for Unobservables. *The Review of Economic Studies 70*(2), 317–341.

Liu, X., E. Patacchini, and Y. Zenou (2014). Endogenous peer effects: local aggregate or local average? *Journal of Economic Behavior & Organization 103*, 39–59.

Manova, K. (2013). Credit Constraints, Heterogeneous Firms, and International Trade. *The Review of Economic Studies 80*(2), 711–744.

Manski, C. F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies 60*(3), 531–542.

Martin, J., I. Mejean, and M. Parenti (2020). Relationship stickiness and economic uncertainty. *mimeo*.

Mayer, T. and G. I. P. Ottaviano (2008). The Happy Few: The Internationalisation of European Firms: New Facts based on Firm-level Evidence. *Intereconomics 43*(3), 135–148.

Mayer, T. and S. Zignago (2011). Notes on CEPII's Distances Measures: The GeoDist Database. *SSRN Electronic Journal*.

Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica 71*(6), 1695–1725.

Morales, E., G. Sheu, and A. Zahler (2019). Extended gravity. *The Review of economic studies 86*(6), 2668–2712.

National Bank of Belgium (2002-2014a). Annual Account Filings. Confidential Dataset.

National Bank of Belgium (2002-2014b). International Trade Dataset. Confidential Dataset.

National Bank of Belgium (2002-2014c). Business-to-Business Transactions Dataset. Confidential Dataset.

Neyman, J. and E. L. Scott (1948). Consistent Estimates Based on Partially Consistent Observations. *Econometrica 16*(1), 1–32.

Panigrahi, P. (2022). Endogenous Spatial Production Networks Quantitative Implications for Trade and Productivity. *mimeo*.

Patault, B. and C. Lenoir (2021). How valuable are business networks? Evidence from sales managers in international markets. *mimeo*.

Qu, X. and L.-f. Lee (2015). Estimating a spatial autoregressive model with an endogenous spatial weight matrix. *Journal of Econometrics 184*(2), 209–232.

Qu, X., L.-f. Lee, and J. Yu (2017). QML estimation of spatial dynamic panel data models with endogenous time varying spatial weights matrices. *Journal of Econometrics 197*(2), 173–201.

A Additional descriptives

A.1 Export starts

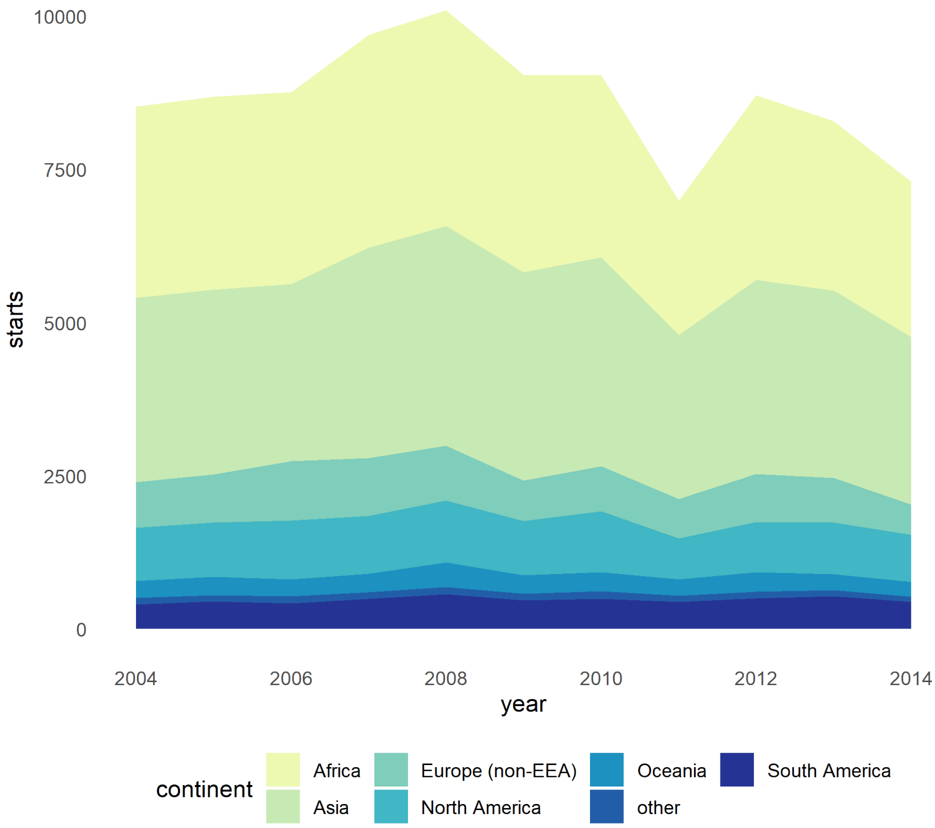
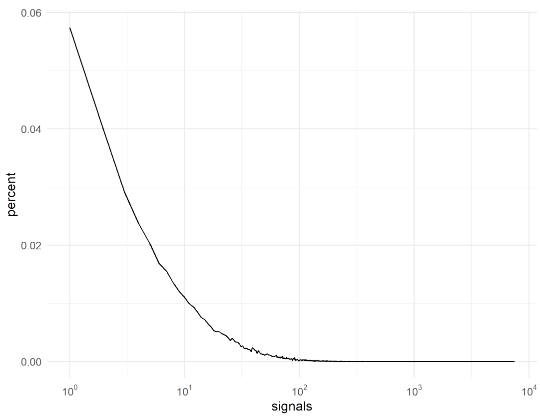
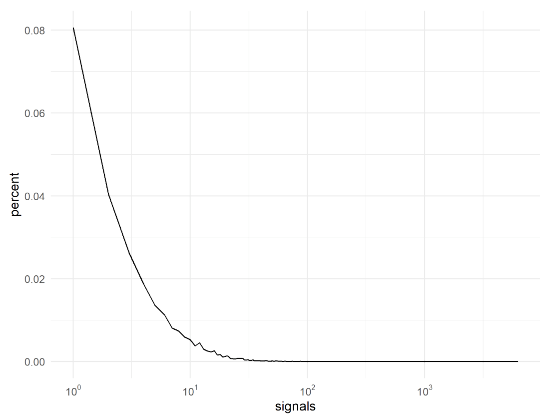


Figure 9: Share of non-EEA starts by region (2004-2014)

A.2 Export signals



(a) any export signal

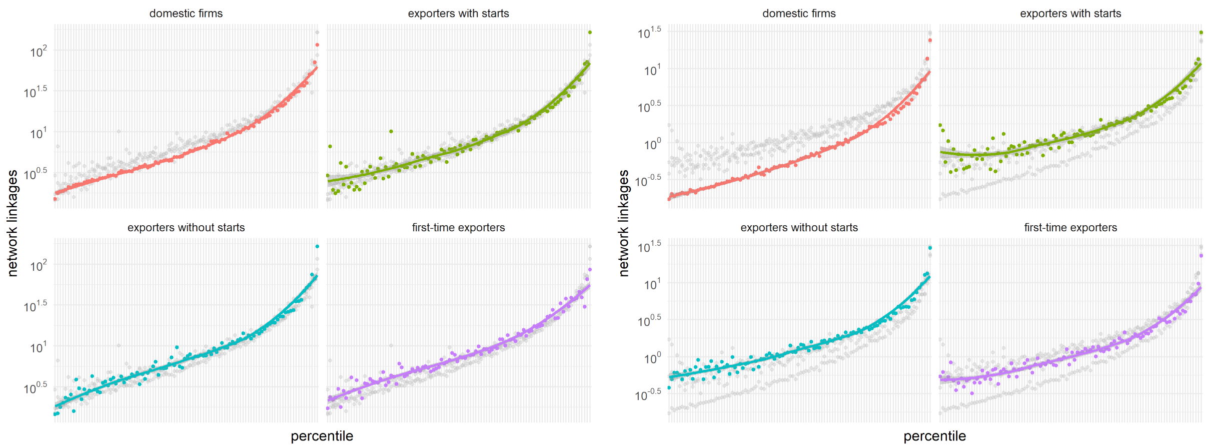


(b) matching export signal

Figure 10: Distribution of firms receiving export signals

A.3 Network linkages

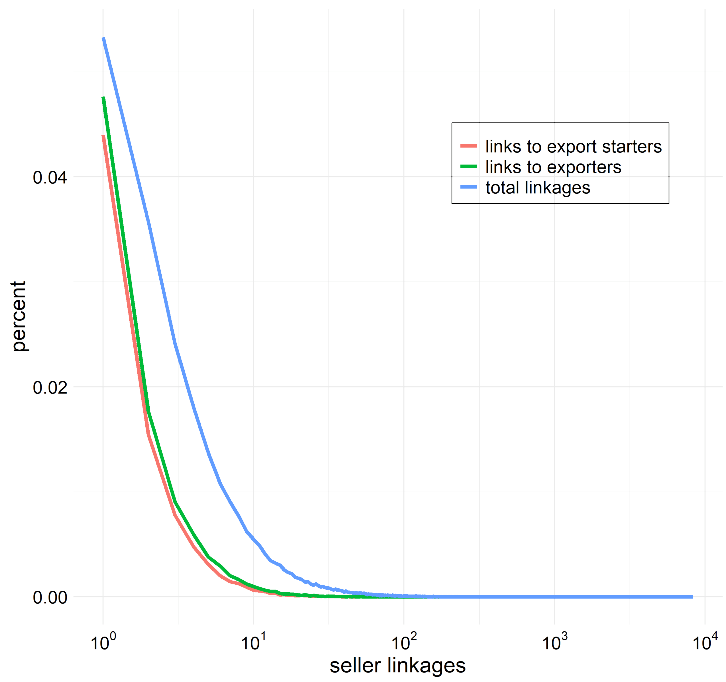
Figure 11: Seller linkages by TFP percentile



(a) all linkages (b) linkages to exporters

Note: This figure shows shows the average number of buyers for a seller in a given productivity percentile. Seller productivity is computed using the approach of Levinsohn and Petrin (2003). Sellers are separated into four types: Non-exporters (red), exporters with export starts (green), exporters without starts (blue) and first-time exporters (purple). Figure 1a plots the average linkages to any buyer, while figure 1b plots the average linkages to buyers that export. The figure uses production network data of Belgian firms explained in detail in section 4.1.

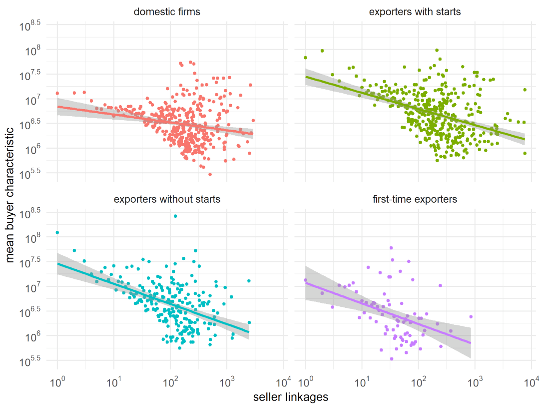
Figure 12: Distribution of seller linkages in 2014



Note: This figure shows the distribution of linkages to different types of buyers in 2014. Each lines indicates what share of sellers interact with a certain number of buyers. The lines are based on a histogram and have been smoothed for visual purposes.

A.4 Network assortativity

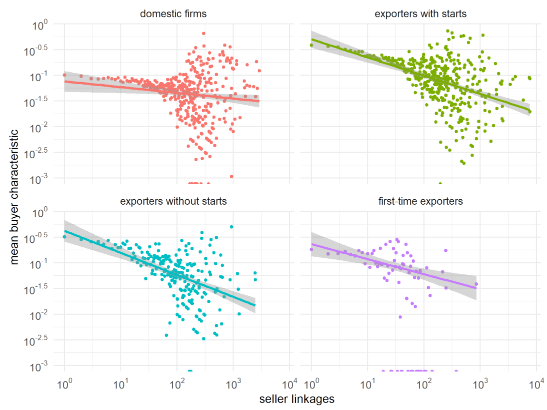
Figure 13: Seller network size and mean buyer characteristics in 2014



(a) average buyer sales

(b) average buyer employment

(c) average buyer productivity



(d) average buyer export start probability

B Additional dataset information

B.1 Reporting thresholds for trade transactions

The reporting thresholds differ across intra-EU and extra-EU trade transactions. Extra-EU export and import transactions follow a common reporting standard across all sample years. They are covered in the dataset if the transaction value exceeds 1,000 € or the volume is bigger than 1,000kg. In rare instances transactions below the minimum volume threshold are observed if the respective firm uses electronic reporting standards.

Intra-EU transaction thresholds are much higher and change over the sample period. Before 2006, they are reported if the combined import and export value of a firm exceeds 250,000 €. Between 2006-2010, the reporting threshold for imports was 400,000 € and 700,000 € for exports before both where harmonized to 700,000 € in 2010.

Our analysis mainly focuses on extra-EU transactions and therefore avoids measurement issues related to changing reporting thresholds or high threshold levels.

B.2 Construction of the regression sample

The variables used in our regression sample draw on the rich information contained in our merged dataset.

i. *Export starts* rely on detailed HS6 product-level export-transaction data which we aggregate to the firm-destination level. A firm with positive export transactions each year is counted as an exporter. An export start is defined as an export transaction to a destination that has not been served in the previous two periods. All observations within the two-year buffer period are dropped as firms by definition do not face an export decision. Likewise, non-starts are also only included in the data, if the firm has not been exporting in the past two years to ensure that a start could have occurred mean the firm faced a actual entry decision.

ii. Data on the number of *employees* and firm *wages* can be directly obtained from the available balance sheet data.

iii. *Total factor productivity* (TFP) is estimated using the approach of Levinsohn and

Petrin (2003). The estimation requires data on firm sales, capital, labor and material inputs which are all available in the balance sheet data. Deflators for each input at 2-digit NACE codes are provided by the NBB based on internal price information. Our estimation is performed sector-by-sector and we only include sectors for which at least 50 non-missing observations are available.

iv. *Export experience dummies* rely on a combination of Belgian trade-transaction data for import and exports and the GeoDist database (Mayer and Zignago, 2011) freely available from CEPII's website. The latter includes information on bilateral relationships between all more than 200 countries including historic links and geographic borders. We merge this country relationship information with trade transaction data to create history and border dummies depending on the recorded relationship between Belgium and the respective trade partner. Import dummies on the other hand are only require the original trade transaction data and mark whether a seller has directly imported products from the future export destination. *Export sales shares* compare aggregate export values to sales information in the balance sheet records.

v. The idea for *export demand* is to capture the demand for the products underlying the export starts of Belgian firms in the foreign market prior to the actual export entry. To do so we proceed in several steps. First, we collect import data at HS6 product level for all destinations and sample years from the BACI database (Gaulier and Zignago, 2010) which we complement with WTO data for missing import information for Taiwan. Next, we identify the products underlying the export starts of each firm using the Belgian trade transaction database. For these products, we compute the export value at HS6 product-level in each destination originating in non-EEA countries. These non-EEA exports should capture changes in product demand in the destination without being correlated with Belgian exports due to common trade policy. For each firm, this gives us a proxy of how strongly their product was demanded in the destination prior to the export start. We then aggregate this export demand information to the firm-destination level and introduce it to the regression sample to control for the firm-specific export demand in each destination in each year t.

vi. Peer characteristics included in our regression sample are buyer *TFP* and buyer *sales* available from the Belgian balance sheet data. To relate buyer characteristics to sellers, we use row-normalized interaction matrices $\bar{S}_t$ and compute the average TFP and sales of buyers in a seller's network.

C Additional results

C.1 Benchmark regressions - full table

Table 6: Benchmark results - signal type

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
matching signals	0.0043***					
	(0.0011)					
non-matching signals		3.44×10^{-5}				
		(7.77×10^{-5})				
total signals			4.14×10^{-5}			
			(7.79×10^{-5})			
EEA signals				9.03×10^{-6}		
				(0.0001)		
border signals					0.0003	
					(0.0004)	
history signals						0.0002***
						(5.93×10^{-5})
log employment	0.0476***	0.0477***	0.0477***	0.0477***	0.0477***	0.0476***
	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)
log wage	0.0127**	0.0127**	0.0127**	0.0127**	0.0127**	0.0127**
	(0.0060)	(0.0060)	(0.0060)	(0.0060)	(0.0060)	(0.0060)
log TFP	0.0325***	0.0325***	0.0325***	0.0325***	0.0325***	0.0326***
	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)
log export demand	0.0179***	0.0179***	0.0179***	0.0179***	0.0179***	0.0179***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
border dummy	0.0693***	0.0694***	0.0694***	0.0694***	0.0694***	0.0694***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
history dummy	-0.0140***	-0.0140***	-0.0140***	-0.0140***	-0.0140***	-0.0140***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
export propensity	0.1702***	0.1701***	0.1701***	0.1701***	0.1701***	0.1701***
	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)
import dummy	0.0980***	0.0982***	0.0982***	0.0982***	0.0982***	0.0982***
	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)
log peer size	-0.0005	-0.0004	-0.0004	-0.0003	-0.0003	-0.0004
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
peer TFP	0.0004	0.0003	0.0004	0.0003	0.0003	0.0004
	(0.0027)	(0.0027)	(0.0027)	(0.0028)	(0.0027)	(0.0027)
firm FE	yes	yes	yes	yes	yes	yes
destination-year FE	yes	yes	yes	yes	yes	yes
R^2	0.127	0.127	0.127	0.127	0.127	0.127
Observations	474,830	474,830	474,830	474,830	474,830	474,830

This table shows regression results of estimating equation 10 with a LPM-FE. Each column shows the marginal effect of receiving a different type of export signal on a seller's probability to start exporting. Standard errors in parentheses are clustered at the firm level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

C.2 Benchmark robustness

C.2.1 Comparison of estimation methods

Table 7: Robustness - Nonlinear models - signal intensity

Model	LPM-FE	Logit-FE	Logit-FE-IPP	Probit-FE	Probit-FE-IPP
Coefficient for *matching signal*	0.0043***	0.0348***	0.0346***	0.0187***	0.0186***
	(0.0011)	(0.0059)	(0.0060)	(0.0034)	(0.0034)
APE for *matching signal*	0.0043***	0.0050***	0.0051***	0.0047***	0.0049***
	(0.0011)	(0.00089)	(0.00090)	(0.00091)	(0.00091)
firm FE	yes	yes	yes	yes	yes
destination-year FE	yes	yes	yes	yes	yes
Observations	474,830	475,928	475,928	477,263	477,263

This table compares regression results of equation 10 for different linear and non-linear models. Standard errors in parentheses are clustered at the firm level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

C.2.2 Different fixed effect specifications

Table 8: Robustness - Fixed effects

Model:	(1)	(2)	(3)	(4)
Variables				
matching signals	0.0043***	0.0052***	0.0043***	0.0041***
	(0.0011)	(0.0008)	(0.0010)	(0.0010)
Peer characteristics	yes			
Firm destination experience	yes			yes
Firm characteristics	yes			
firm FE	yes			
destination-year FE	yes	yes	yes	yes
firm-year FE		yes	yes	yes
firm-destination FE			yes	yes
R^2	0.127	0.293	0.424	0.435
Observations	474,830	929,117	929,117	904,896

This table compares regression results of equation 10 for different fixed effect specifications. Standard errors in parentheses are clustered at the firm level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

C.2.3 Network threshold

Table 9: Robustness - 5% network threshold

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
matching signals	0.0088***					
	(0.0022)					
non-matching signals		0.0001				
		(0.0002)				
total signals			0.0002			
			(0.0002)			
EEA signals				0.0001		
				(0.0005)		
border signals					0.0015*	
					(0.0009)	
history signals						0.0004*
						(0.0002)
Peer characteristics	yes	yes	yes	yes	yes	yes
Firm destination experience	yes	yes	yes	yes	yes	yes
Firm characteristics	yes	yes	yes	yes	yes	yes
firm FE	yes	yes	yes	yes	yes	yes
destination-year FE	yes	yes	yes	yes	yes	yes
R^2	0.124	0.124	0.124	0.124	0.124	0.124
Observations	363,607	363,607	363,607	363,607	363,607	363,607

This table compares regression results of equation 10 using a 5% buyer sourcing threshold to define relevant network linkages. Standard errors in parentheses are clustered at the firm level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

C.2.4 First-time exporters

Table 10: Robustness - First-time exporters

No export activity before:	baseline	2003	2006	2012
Variables				
matching signals	0.0043***	0.0092***	0.0079***	0.0112
	(0.0011)	(0.0028)	(0.0031)	(0.0077)
Peer characteristics	yes	yes	yes	yes
Firm destination experience	yes	yes	yes	yes
Firm characteristics	yes	yes	yes	yes
firm FE	yes	yes	yes	yes
destination-year FE	yes	yes	yes	yes
R^2	0.127	0.233	0.229	0.373
Observations	474,830	140,622	112,884	25,014

This table compares regression results of equation 10 focusing on sellers with no export experience at the firm-level up to the indicated year. Standard errors in parentheses are clustered at the firm level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

C.3 Endogenous network formation

This section provides additional details on how to obtain selection correction terms needed to estimate equation 14.

To begin with, we need to estimate the dyadic formation model outlined in equation 12 which poses two distinct challenges. A first challenge relates to the large sample size n. As the model requires us to estimate the linkage probability between any pair of firms operating in Belgium, each firm in theory considers all $n-1$ other firms as candidates for establishing a linkage. Including all $n * n - 1$ firm pairs in our dyadic formation model is not only computationally infeasible given our sample includes around 100k firms per year, but also highly unrealistic as firms are unlikely to consider the entire population of firms as matching candidates when searching for an individual business partner. A second challenge is that even if the size of candidate sets becomes computationally feasible, the exact candidate set a firm considered in the matching process remains unobserved. Both challenges require additional assumptions which we discuss in turn.

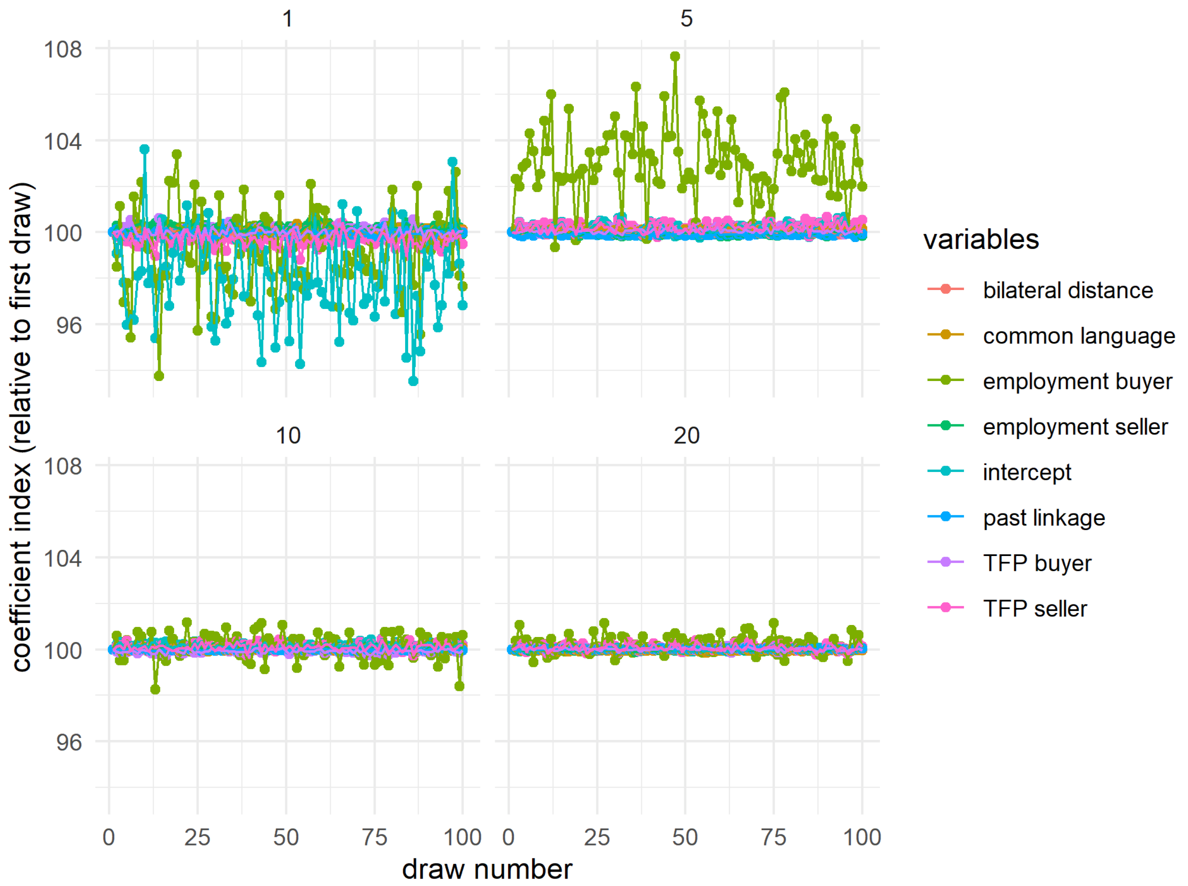
To reduce the dimension of the problem, we impose several restrictions on the n x n firm-to-firm interaction matrix. Instead of treating all $n-1$ firms as potential matching candidates for an observed linkage $s_{ij,t} = 1$, we only consider firms as candidates if they operate in the same 4-digit NACE industry as the actual match and themselves have interacted with firms in the same 4-digit NACE sector of firm i. All candidates which do not meet these criteria are dropped from the candidate set which implies that they were never considered as potential business partners for the observed B2B linkage. This two-sided sector-specific restriction will create a distinct candidate set for each observed linkage and significantly reduces the size of the candidate set such that on average we are left with 50 candidates per observed match.

While this selection potentially introduces some error by potentially excluding individual candidates which firm i did consider as business partners in the matching process, we believe that restricting candidate sets to the sector of the actual match j is intuitive and expected to preserve the majority of true candidates.

As we do not know which of the 50 candidates firm i actually considered in the matching process, we restrict the number of candidates a firm considers per match to $n^{random} = \{1, 5, 10, 20\}$, take a random sample and estimate the dyadic formation model with a logit model for a given draw of n^{random} candidates plus the actual match. As shown in figure 14, the estimated coefficients $\boldsymbol{\theta}$ of the network formation model which controls for individual firm employment and productivity, bilateral distance, common language and past linkage status hardly vary across random samples within a particular candidate set size n^{random}. This indicates that selection correction terms does not depend on the variation created from random sampling *within* given set size, but may still lead to different results due to differences *between* imposed set sizes n^{random}. To mitigate concerns that our results might be driven by the chosen candidate set size, we employ the rare events correction introduced by King and Zeng (2001) which accounts for the different ratios of events ($s_{ij,t} = 1$) to non-events ($s_{ij,t} = 0$) created by the choosing a distinct candidate set size n^{random}.

We then use the estimated formation coefficients $\boldsymbol{\theta}$ to predict linkage probabilities $p = P(S_{ij,t-1} = 1) = \frac{e^{U_{ij,t}(\theta)}}{1+e^{U_{ij,t}(\theta)}}$ and compute selection correction terms $\hat{\Xi}_{i,t-1}$ as shown in equation 15 in the main text.

Figure 14: Variation of network formation coefficients by candidate set size



The figure plots the results of network formation equation 12. For each candidate set size n^{random}, we draw 100 random samples and display the resulting coefficients relative to the coefficient value of the first draw which we index to 100.

C.4 Signal heterogeneity regressions

In this section we provide additional details for the signal heterogeneity results presented in Figure 15. All panels show matching signal coefficients obtained from estimating equation 10 via a LPM-FE. The only difference to our benchmark results is that matching signal counts are disaggregated by linkage or peer type to assess the impact of underlying network heterogeneity. The disaggregation exercise in each panel uses the following definitions:

- Panel (a) uses three approaches to separate linkages into strongly and weakly dependent. First, by ranking ranking all buyers j based to their sourcing share from seller i. Buyers above the median rank are then defined as more dependent and vice versa. As an alternative, we use the observed sourcing shares to define strongly dependent buyers as those that source at least 50% (90%) of domestic inputs from seller i.

- Panel (b) defines linkage persistence as the number of consecutive years a seller-buyer pair ij have interacted with. Incoming export signals are then assigned according to the maturity of linkage ij in year t. To ensure all linkage maturities can be observed in our sample, regressions only consider entry decisions after 2006.

- Panel (c) considers export signals received from backward, forward and mixed linkages. The three linkage types reflect the relationship of buyers and sellers in the production network. Backward linkages capture signals received from buyers, forward linkages capture signals received from suppliers and mixed linkages capture signals received from firms which simultaneously act as buyers and sellers for firm i. The third regression in this panel excludes export starts of wholesalers by droppings operating in NACE sectors 45, 46 and 47 from the sample.

- Panel (d) disaggregates incoming export signal by peer size. We define large an small firms based on sales and use median sales as the cutoff value.

- Panel (e) studies the credibility of export signals in three distinct ways. First, by investigating whether peer entries are persistent or immediately leave the market in $t+1$. Second, by checking whether exports to the new destination account for more than 1% of total peer exports in that year. Third, by examining whether exports to the new market account for more than 1% of total exports in the firm's 4-digit NACE sector.

- Panel (f) finally uses NACE sectors 45, 46 and 47 to identify wholesalers and separetly counts export signals originating from wholesaler and non-wholesaler networks.

The main results of this exercise are briefly summarized in the main text in section 6.2.4. Here we provide additional details about the interpretations of individual signal heterogeneity regressions.

We start by comparing how the strength of B2B linkages shapes the impact of export signals. To this end, panel (a) plots the estimated coefficients of matching signals that have been received via different linkage types. While the seller-specific rank of individual buyers does not seem to matter for the strength of network effects, receiving a signal from buyers which rely on a single seller for a majority of their sourcing (B2B sourcing shares above 50%) appears to have a stronger impact on subsequent entry decisions of sellers. While signals received from buyers with more diversified sourcing strategies still facilitate entry, this suggests that linkage dependency amplifies the impact of export signals.

In panel (b) we study how the duration of the B2B relationship affects network effects. Although network linkages are often sticky given the non-negligible fixed costs involved in identifying suitable business partners (Martin et al., 2020), we find that both new and persistent linkages facilitate export entry. This suggests that sellers not only respond to signals received from trusted sources but also remain open to insights from new business partners.

A last linkage characteristic which we investigate in panel (c) is the direction of the underlying supply chain interaction. While our analysis focuses on backward linkages where sellers receive signals from their buyers, network effects might also arise from forward (the network of suppliers) or mixed linkages where firm i simultaneously acts as a buyer and a supplier for peers j. Coefficients obtained from our benchmark equation 10 with weak and strict FE suggest that all three linkage directions facilitate export entry. A striking results is the large effect of signals received from mixed linkages which are almost three times larger than backward and forward effects. A closer inspection of mixed linkages reveals that most of them involve large wholesalers which naturally hold a dual role as both buyers and sellers in the domestic production network. To ensure that our findings do not simply reflect entry decisions of wholesalers, we re-estimate our strict FE specification excluding export starts of firms i which operate in NACE sectors 45, 46, and 47. Our results show that non-wholesalers only benefit from signals received from backward linkages while forward and mixed linkages no longer promote export entry. Wholesalers which hold special position in domestic production networks therefore seem to benefit from a wider exposure to specialized export information along all three linkage directions, whereas all other firms exclusively benefit from signals received through backward linkages. As our study set out to study network heterogeneity for the entire population of firms, a focus on backward linkages appears to be reasonable. Nevertheless, we take the uncovered sectoral heterogeneity of network effects into account and present additional results for wholesalers in panel (f).

In panels (d), (e) and (f) we study the impact of peer heterogeneity on network effects. Panel (d) starts by investigating the role of peer size. Our findings show that export signals originating from small and large firms both matter for the observed conducive impact on export entry, but also reveal a substantial degree of homophily in the underlying network effects. While foreign market access large firms is disproportionately driven by interactions involving other large firms, the opposite is true for small firms. Our methodology is not equipped to uncover the underlying mechanism at play, but clearly suggests an unequal response of firms to interactions with peers of different size.

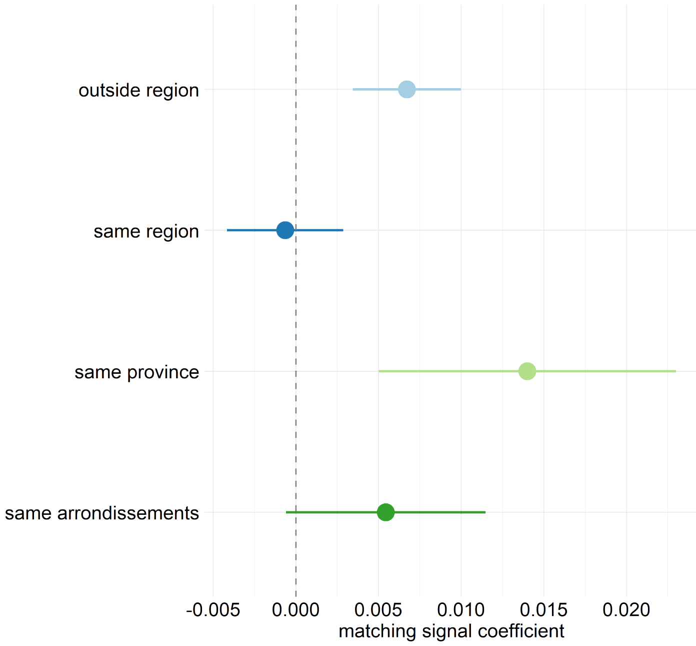
Next, we investigate whether the credibility of export signals shapes the entry behavior of sellers. Results are presented in panel (e). Our first disaggregation accounts for the export behavior of network peers one year after they emitted an export signal. Cases in which peers immediately leave the foreign market after their initial entry could indicate a bad experience which nullifies the positive impact of the emitted signal for the receiver.

Our results do not corroborate this claim suggesting that peers' post-entry behavior has no impact on the strength network effects. Conversely, we do find that signals which are more credible because they account for a significant share in the peer's own or sectoral exports have a larger impact on the receiver. While our benchmark analysis treats each incoming signal equally, firms do seem to differentiate between signals they receive which likely leads to an underestimation of the true network effect.

Lastly, we return the role of wholesalers in panel (f). Trade intermediaries have been shown to play an important role for firms to access foreign markets by initially allowing them to circumvent high entry barriers via indirect exporting before ultimately entering the market directly (Connell et al., 2019). Our mechanism generalizes this idea by considering each firm's entire network as a source of promoting export entry. This allows us to separately account for the role of wholesalers and non-wholesalers in diffusion of export signals. Our results reveal that this distinction is crucial for understanding aggregate network effects. While export signals from wholesalers do contribute to foreign market access of other wholesalers, this is not true to the entire population of firms. Instead, the majority of network effects seems to be driven by non-wholesalers which underlines the importance of considering the entire production network when estimating network effects.

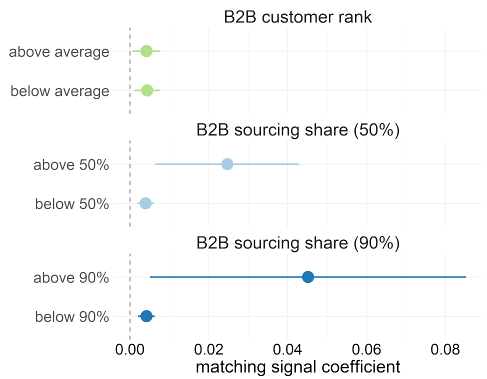
C.5 Signal geography

Figure 16: Geography of matching signals

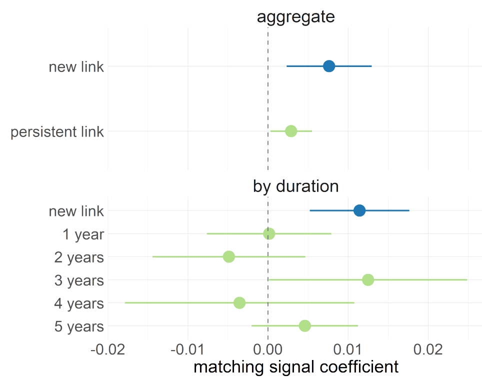


Note: This figure plots results of from a version of equation 10 in which export signals are disaggregated by the geographic location (NUTS codes) of the buyers and sellers. Belgium consists of 4 regions (NUTS 1), 11 provinces (NUTS 2) and 44 arrondissements (NUTS 3). We use these codes to define 4 mutually exclusive categories for buyer-seller location pairs. Signals in the "same region" category for example originate from buyers within the same region but outside the seller's province.

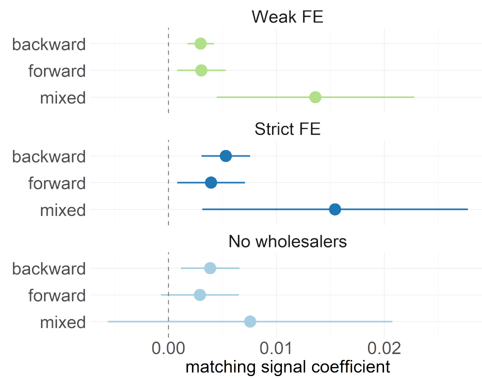
Figure 15: Matching signal heterogeneity



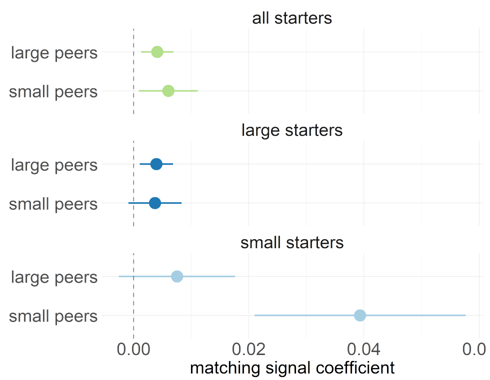
(a) linkage dependency



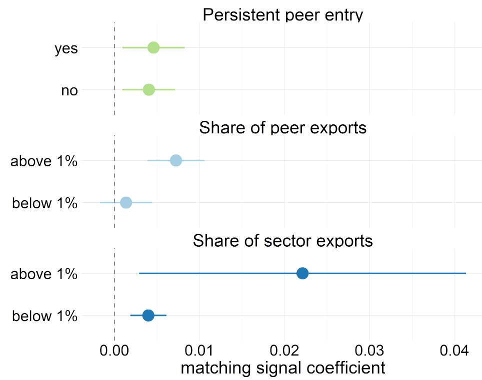
(b) linkage persistence



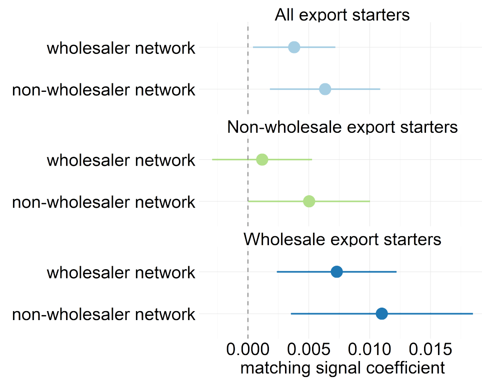
(c) linkage direction



(d) peer size



(e) peer credibility



(f) peer sector