Network Effects and Dynamic Pricing in Export Markets

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Abstract

This paper demonstrates that new exporters charge low prices in order to accumulate buyers, then increase prices as their network of buyers expands. I use a novel data set on firm-to-firm exports by Danish firms to document two empirical findings. First, exporters charge different prices from their buyers within narrowly defined markets. Second, exporters with larger buyer networks form more new buyer relationships. Based on these findings, I present a parsimonious dynamic model, where (i) exporters are able to price discriminate between buyers based on when their relationship is formed, and (ii) it is costly to find new buyers, but the cost is decreasing in the size of the network. The model predicts that exporters optimally increase prices as their network grows. Finally, I show that this prediction is in accordance with the data. The presence of network effects improves the benefits of trade policies aimed at matching exporters with foreign buyers and must be accounted for when evaluating such programs.

Keywords: Firm-to-firm trade, network effects, customer accumulation, dynamic pricing

1 Introduction

How do exporters grow? As growth of exporters, especially new exporters, is often an explicit policy objective, this question is important for the design of optimal trade policies. It is well-documented that new exporters, conditional on survival, *do* grow gradually over time (e.g. Ruhl and Willis, 2017). *How* exporters grow, on the other hand, is less clear. Several influential papers have stressed the importance of the extensive buyer margin: New exporters lack immediate access to foreign buyers and must engage in market-specific investments, such as marketing, to reach them (most notably Arkolakis, 2010, 2016; Eaton et al., 2014, 2016). Recently, Rodrigue and Tan (2019) and Piveteau (2019) have suggested that exporters price low early on to accumulate buyers, then increase prices as their market share grows. Fitzgerald et al. (2017) and Berman et al. (2019), however, conclude that this hypothesis is not compatible with the observed patterns of Irish and French exporters, respectively. The extent to which exporters use dynamic pricing as a means of buyer accumulation is, therefore, unresolved. One critical limitation of the existing evidence is, however, the lack of information on individual buyers, such that conclusions are based on more aggregate dynamics of, e.g., sales and prices at the firm $\times$ product $\times$ destination level.

Using a novel data set on firm-to-firm exports by Danish firms, this paper is the first to explicitly document that exporters increase prices as they reach more buyers. Further, I provide an empirically founded, theoretical framework through which this result can be interpreted. To do this, I start by presenting two empirical findings. First, exporters charge different prices from their buyers within narrowly defined markets. This means that exporters price discriminate between their buyers and, thus, are *able* to charge different prices from buyer relationships formed at different points in time. Second, exporters with larger buyer networks form more new buyer relationships. This network effect implies that the value of reaching a new buyer exceeds the profits generated from the particular relationship, and, thus, that exporters have *incentive* to set prices lower than in the static optimum in order to attract more buyers. I then present a parsimonious dynamic model based on these features and show that *if* the size of the network effect is positive, but decreasing in the size of the network, *then* exporters optimally increase prices as their network grows. Based on existing evidence, this condition is likely satisfied. Finally, I show empirically that exporters indeed increase prices as they reach more buyers.

Deviations from the law of one price are classical topics for economic research. In the context of international trade, numerous studies have pointed out the sizable dispersion of prices across *exporters*, within markets, and attributed this to cross-firm heterogeneity in factors such as productivity and product quality (e.g. Kugler and Verhoogen, 2011; Manova and Yu, 2017; Roberts et al., 2017; Piveteau and Smagghue, 2019).[1] The dispersion of prices across *importers*, within exporter × market pairs, on the other hand, has received little attention.[2,3] I show that the price dispersion across importers, within exporter × markets, is substantial: Ranking all exporter × importer relationships in terms of prices, the third quartile is characterized by a price 65 percent larger than the first quartile. I, then, provide evidence suggesting that the dispersion cannot be explained purely by measurement error in unit values, quantity discounts, or quality differentiation. Instead, I interpret the dispersion as a consequence of exporters simply selling seemingly similar products to different importers at different prices, and I will refer to this as *price discrimination*.

The idea that trade propagates through networks is not new. In an early paper, Rauch and Trindade (2002) show that the presence of ethnic Chinese networks facilitates trade between countries. More generally, the importance of intermediaries, agents (such as wholesalers and retailers) that facilitate matching between exporters and foreign buyers, have been documented by several studies.[4] Chaney (2014, 2018) propose models where exporters' geographic expansion abroad depend on the location of existing consumers because existing connections lower the cost of finding new connections nearby. The same logic motivates the recent literature on "extended gravity" as initiated by Morales et al. (forthcoming). Recently, the appearance of transaction-level trade data sets from a number of countries have permitted researchers to study several aspects of how firm-to-firm networks shape international trade (I review this literature below). In this paper, I define an exporter's network as the number of previously served importers and show that the size of the network has a positive and causal impact on the number of new buyer relationships formed by the exporter. I will refer to this as the *network effect*. To do this, I exploit a policy managed by the Trade Council (TC) in Denmark. I combine the transaction-level trade data with data on exporters' purchases of destination-specific "Partner Search and Match Making" (PSMM) services provided by the TC. The explicit purpose of these services is to help Danish exporters find importers abroad. I instrument the purchase decision by exporters using random approaches by the TC, as suggested by Buus et al. (2019), and show that exporters tend to form more new buyer relationships upon purchasing PSMM. Therefore, I can exogenously shift the size of exporters' networks, and, thus, isolate the network effect. I find that adding one importer to an exporter's network increases the number of new buyer relationships formed

[1] Though not based on export prices, Allen (2014) and Steinwender (2018) rationalize spatial price dispersion in homogeneous goods markets with the presence of information frictions. Similar forces are likely to drive some of the price dispersion across exporters in international goods markets.

[2] To the best of my knowledge, this topic has only been touched upon by Monarch (2018) in the context of price dispersion across US importers.

[3] I use the terms *buyer* and *importer* interchangeably throughout the paper.

[4] Among the most notable are Rauch and Watson (2004), Petropoulou (2011), Bernard et al. (2010), Blum et al. (2010), Felbermayr and Jung (2011), Ahn et al. (2011), Antras and Costinot (2011), Bernard et al. (2015), and Akerman (2018).

in the following year by 0.36-0.38. In comparison, the average exporter forms 0.52 new buyer relationships each year.

I make no attempt to explain or rationalize the presence of neither price discrimination nor network effects. Rather, my interest is to examine how these findings affect exporters' expansion strategy, specifically in terms of dynamic pricing. I propose a parsimonious dynamic model where exporters encounter buyers, and trade relationships are established if exporters post a sufficiently low price. The two empirical findings—the presence of price discrimination and network effects—inform the modelling setup. First, exporters are able to charge different prices from their importers. This provides the *possibility* for exporters to price discriminate between importers encountered at different points in time. Second, it is costly to find new importers, but the marginal cost of reaching an importer is decreasing in the size of the buyer network. This provides an *incentive* for exporters to charge prices below the static optimum in order to attract more buyers and extend their network at the expense of lower current profits. I show that *if* the size of the network effect is positive, but decreasing in the size of the network, *then* exporters optimally increase prices as their network grows. Existing evidence suggests that this condition is satisfied. Eaton et al. (2014, 2016) develop and structurally estimate dynamic models of exporters' search for importers, and show that the cost of searching, for a given search intensity, is decreasing in the size of the buyer network. They, too, refer to this as a network effect.

Finally, taking the model to the data, I examine if exporters charge higher prices from new buyer relationships when their network is large than when their network is small. As transactions are recorded at daily frequency, importers can accurately be ranked in the order they match with an exporter. This means that for each exporter $\times$ importer relationship, I observe the exact size of the exporter's network on the *date* of the match. At this highly disaggregated level, variation in prices can more convincingly be attributed to variation in network size. Following a simple, but rigorous, estimation strategy, I exploit variation within narrowly defined export spells and control for (product) market-wide developments. I find that exporters charge higher prices as their network grows. For exporters that managed to form more than five relationships, the price charged from the fifth buyer was about 15 percent higher than the price charged from the first buyer.

This paper touches upon several strands of the economic literature. Most broadly, it relates to the literature on how firms expand in export markets. Though not a novel topic, this question has received a large amount of academic interest in recent years. In a nutshell, it is well-documented that new exporters grow gradually conditional on survival (Ruhl and Willis, 2017, among others). Acknowledging that new exporters do not have immediate access to all customers in a foreign market, accumulation of customers has become a widely accepted source of growth for new exporters. However, there is little consensus on *how* exporters accumulate customers.

In his seminal analysis, Arkolakis (2010) suggests that exporters build a customer base through marketing investments. Arkolakis (2016) shows that this mechanism, in combination with idiosyncratic productivity shocks, is able to predict exporters' growth. Within the macroeconomic literature, Drozd and Nosal (2012) show that a model featuring costly customer accumulation accounts for several puzzles regarding international prices, and Gourio and Rudanko (2014) provides a micro-foundation for such a model using a search theoretical framework. The empirical literature on the effectiveness of export promotion services provides evidence on a wide-spread category of destination-specific investments. Volpe Martincus and Carballo (2008), Van Biesebroeck et al. (2015), Munch and Schaur (2018), and Buus et al. (2019) show that purchasing export promotion services effectively increase firms' sales in existing export markets. In the present paper, I show that a particular type of export promotion services, namely "Partner Search and Match Making", specifically help Danish exporters match with more importers abroad. As such, "Partner Search and Match Making" services can be thought of as akin to marketing investments in the spirit of Arkolakis (2010).

An alternative, though by no means contradicting, mechanism is that exporters' *current* customer base depends positively on *previous* performance. Rodrigue and Tan (2019) develop a model where consumers' utility from a given product depends directly on the product's past market share. Intuitively, this can be interpreted as consumers having taste for "brand recognition": They are more willing to buy the product if many others bought it previously. Piveteau (2019), instead, assume that the customer base itself is increasing in the exporter's previous sales. This mechanism can arise if consumers have imperfect information about product characteristics and, therefore, use previous sales as a signal. Though the underlying modelling assumptions slightly differ, the two models share a central prediction: Exporters face an incentive to set low prices initially, in order to attract customers early on, then increase prices as the customer base grows. Foster et al. (2016) make use of a similar mechanism to explain the gradual growth of newly established firms in the US domestic market for commodity-like products. Similar models have also been applied to explain macroeconomic developments, e.g. by Ravn et al. (2006) and Paciello et al. (2019).

Whereas the importance of marketing investments as a source of growth in foreign markets is well-established, the role of dynamic pricing is unsettled. Naturally, if dynamic pricing plays an important role for the expansion of exporters, one would expect their prices to grow over time. Indeed, the models in Rodrigue and Tan (2019) and Piveteau (2019) are, to some extent, motivated by such findings for Chinese and French exporters, respectively.[5] On the other hand, Fitzgerald et al. (2017) document that Irish firms' export prices are largely *stable* over time and suggest that a model where exporters grow by accumulating customers through marketing investments, in the spirit of Arkolakis (2010), is better in line with their findings. Berman et al. (2019) and Bastos et al. (2018) document that French and Portuguese firms' export prices, respectively, are slightly *decreasing* over time and suggest that these findings are more in line with a model where exporters learn about their idiosyncratic demand, in the spirit of Jovanovic (1982), and surviving exporters grow as they update their demand expectations upwards. Both Fitzgerald et al. (2017) and Berman et al. (2019) explicitly conclude that their findings are at odds with theories on exporter expansion that give rise to dynamic pricing. In light of the inconclusive evidence on this topic, it is important to note that the findings presented in this paper stand irrespective of the "true" relationship between exporters' age and prices: Appropriately choosing the econometric specification allows me to interpret the effect of larger network on prices as *additional* to any effect of age. This is possible only because of the very disaggregated level of my data.

This paper also adds to the relatively new, but rapidly growing, literature on firm-to-firm relationships in international trade, as recently reviewed by Bernard and Moxnes (2018). Benguria (2015), Heise et al. (2016), Bernard et al. (2018), Carballo et al. (2018), Sugita et al. (2019), and Lenoir et al. (2019) propose static matching models to rationalize cross-sectional patterns of exporter-importer relationships. Krolikowski and McCallum (2019) add search frictions to a dynamic Melitz-type framework causing some exporters to be left unmatched, and Monarch (2018) develops a dynamic discrete choice model of importers' sourcing decision where the presence of switching costs affect consumer prices. Closer to my paper are Eaton et al. (2014) and Eaton et al. (2016) both of which develop and structurally estimate complex dynamic models where the presence of search frictions introduce a wedge between exporters and importers that would otherwise have engaged in trade. Both papers allow exporters to have multiple importer relationships and, importantly, feature positive network effects. Specifically, searching for importers is costly, but the cost is allowed to depend on (and found to be decreasing in) the number of previous buyer matches. This is very close in spirit to the class of costumer-base models with costly accumulation. However, neither Eaton et al. (2014) nor Eaton et al. (2016) provide

[5] Zhao (2018) provides similar evidence for Chinese exporters, and Foster et al. (2008) provide similar evidence for the US domestic market for commodity-like products.

exporters with an incentive to use prices as an attraction device. Lastly, two papers examine the trade dynamics *within* existing trade relationships. Monarch and Schmidt-Eisenlohr (2018) rationalizes increasing sales within relationships with a model featuring gradual learning of reliability, and, closer to my paper, Heise (2019) rationalizes decreasing prices within relationships with a model featuring accumulation of relationship capital. None of the cited papers on firm-to-firm trade in export markets examine the role of prices as a device to accumulate importers.

The remainder of the paper is structured as follows. Section 2 outlines the data and present two empirical findings: First, the presence of price discrimination across importers, and, second, the presence of network effects. Section 3 presents a parsimonious model of exporters' use of dynamic pricing, and Section 4 provides empirical evidence in favor of the central model prediction: Exporters increase their prices as their network grows. Section 5 concludes.

2 Empirical Analysis

In this section, I first describe the underlying data sets, outline sample restrictions, and provide brief summary statistics. Then, I present two empirical findings that will guide the model proposed in the following section.

2.1 Data

The backbone of this paper is the Danish transaction-level customs data from 2007 to 2016. It contains all transactions of products from Denmark to countries outside the European Union at the daily level. Classical customs data allows the researcher to identify exports, measured in both values and quantities, by product and destination for all exporting firms. The present data set adds information about the *buyer margin*, that is all transactions contain a unique identifier for the foreign importer.

To be specific, the raw data set's unit of observation is an exporter $\times$ product $\times$ importer $\times$ destination $\times$ date. I refer to such an observation as a *transaction*.[6] An *exporter* is a Danish firm characterized by a unique identifier that allows me to merge the data to other Danish firm-level registers. A *product* is classified according to the 8-digit Combined Nomenclature (CN8). An *importer* is characterized by a unique, but otherwise meaningless, identifier. A *destination* is all countries outside the European Union (EU).[7] The *date* refers to the day on which the transaction was handled by the Danish customs authorities. For each transaction, I observe its f.o.b. value in Danish Kroner (DKK) and its quantity.[8] I construct unit values by dividing values with quantities and refer to these as "prices" in the remainder of the paper.

I restrict and process the data in several ways. First, I exclude exporter $\times$ importer pairs characterized by no more than one transaction throughout the entire sample period. Eventually, I will define an exporter's *network* as the number of importers previously served within a destination. The idea is that exporters are able to reach new importers

[6]Very few importers, served by Danish exporters, operate across destinations, and I do not make any attempt to exploit variation within importers, across destinations. Thus, I consider an exporter $\times$ importer pair (exporter $\times$ importer $\times$ product triplet) to be equivalent to an exporter $\times$ importer $\times$ destination triplet (exporter $\times$ importer $\times$ product $\times$ destination quadruplet).

[7]Danish firms report exports destined for outside the EU to the Danish customs authorities, which then transfer the data to Statistics Denmark. Firm are obliged to inform customs authorities about the buyer's name. For exports destined for inside the EU, Danish firms report directly to Statistics Denmark, and reporting the buyer's name is not mandatory. Therefore, data at this level of aggregation, is not available for Danish firms' exports to destinations within the EU.

[8]The data contains quantities in kilos for all products and, additionally, quantities in a supplementary unit (such as pieces and liters) for a subset of products. If the supplementary unit is present and the same for all trade flows within a product category, I apply quantities in this unit. Otherwise, I apply quantities in kilos.

through their network. Following Eaton et al. (2014), I consider "single-transaction relationships" as "failures" that do not contribute to the network. In order to ensure comparison across all empirical specifications, even those where network does not a play a role, I disregard these single-transaction relationships altogether. Second, I restrict attention to manufacturing (NACE C) firms with employees. The main reason is to avoid whole-sellers that purely distribute products produced by other firms. I obtain information on industry affiliation and number of employees from the Firm Statistics Register, covering the universe of private sector Danish firms. Third, to account for changes in product categories over time, I apply the algorithm proposed by Van Beveren et al. (2012), aggregating categories to the so-called CN8+ level. Fourth, I aggregate the data to the yearly level. In practice, this means that I do not distinguish between exporter-importer relationships characterized by many small transactions and few large transactions, respectively. However, I keep track of the exact date for the *first* transaction for any exporter-importer relationship. Fifth, to address the concern of "partial-year bias", as highlighted by Bernard et al. (2017), I construct so-called pseudo-years and rely on these instead of calendar years. The idea is that the first *calendar* year of an export spell[9] will generally be shorter than 12 months, which biases the first-year level of, say, export value downwards, and biases the first-to-second-year growth rate upwards. In practice, I define spell-specific pseudo-years as 12 months periods starting from the month in which the spell was initiated. As will become apparent later, a major part of my empirical analysis will rely on newly established export spells, and so correcting for partial-year bias is a first-order issue.[10]

I merge the data to two auxiliary data sets. First of all, I obtain information on Danish firms' purchases of export promotion services (EPS) provided by the Trade Council (TC) in Denmark. In Section 2.3, I take advantage of these data to construct an exogenous shock to the number of importer relationships exporters form. This data set is outlined in detail in Buus et al. (2019). In a nutshell, it contains the full list of Danish firms that purchased EPS together with the full list of firms that were approached by the TC and offered EPS, both at the firms × destination × year level. EPS are classified by type. Whereas Buus et al. (2019) utilized all types, I restrict attention to EPS labelled "Partner Search and Match Making" because the explicit purpose of these services is to help Danish exporters find importers abroad. Applying the EPS data restricts the sample in two ways. First, data for 2016 is not available, so the sample is restricted to 2007-2015.[11] Second, as TC does not offer EPS to all destinations, I follow Buus et al. (2019) and restrict attention to destinations for which a Danish firm purchased EPS at some point during the years for which data on EPS is available (2002-2015). In practice, this is of little concern as TC offers EPS to all major Danish export destinations. As a second auxiliary data set, I use the classical, exporter × product × destination × year level, customs data to track the history of each exporter × destination pair back to 2000. This way, I can distinguish new exporters from old exporters in my main sample.

I will refer to the data set outlined above as my *raw sample*. It contains around 3,300 unique Danish exporters, exporting 5,600 unique products to 177,000 unique foreign importers spread across 51 destinations. The largest destinations in terms of export value are the US, Norway, China, Russia, and Japan.

Brief summary statistics are presented in Table 1. The top panel shows the distribution of the number of exporters across four levels of "markets". First, 241.4 Danish exporters served each destination in each year on average. Second, most product × destination × year triplets were served by only one Danish exporter, though the average market was

[9]Throughout this paper, I define *export spells* at several levels of aggregation as sequences of consecutive years during which, e.g., exporter × destination pairs report positive export value.

[10]As described below, I distinguish between spells that are left-censored and *not* left-censored. Whereas the application of pseudo-years is, of course, targeted *not* left-censored spells, I attribute pseudo-years to all spells using the month in which the spell first occurred in my sample.

[11]I will still use 2016 to determine if an export spell ended in 2015.

Table 1: Summary Statistics, Raw Sample

	Mean	Percentiles				
		5	25	50	75	95
Exporters per...						
destination × year	241.4	13.2	59.5	172.7	295.7	845.4
Value (%)	.	100.0	98.3	92.2	75.7	38.0
product × destination × year	2.1	1.0	1.0	1.0	2.0	5.0
Value (%)	.	100.0	100.0	100.0	75.5	50.1
importer × destination × year	1.1	1.0	1.0	1.0	1.0	2.0
Value (%)	.	100.0	100.0	100.0	100.0	18.6
product × importer × destination × year	1.0	1.0	1.0	1.0	1.0	1.0
Value (%)	.	100.0	100.0	100.0	100.0	100.0
Importers per...						
destination × year	987.6	23.4	130.3	441.8	1,053.7	4,475.8
Value (%)	.	100.0	98.3	92.4	76.5	42.2
product × destination × year	4.9	1.0	1.0	2.0	4.0	15.0
Value (%)	.	100.0	100.0	94.1	82.4	55.8
exporter × destination × year	4.6	1.0	1.0	2.0	4.0	15.0
Value (%)	.	100.0	100.0	95.2	83.2	39.8
exporter × product × destination × year	2.4	1.0	1.0	1.0	2.0	7.0
Value (%)	.	100.0	100.0	100.0	85.5	41.8

"Value" is the share of total export sales obtained by exporters (in the top panel) or importers (in the bottom panel) *above and including* the given percentile. Percentiles are calculated as averages of the five adjacent observations around the given percentile in order to comply with Statistic Denmark's rules on data confidentiality.

served by 2.1. However, the markets served by at least two exporters received 75.5 percent of the export value. Third, the majority of foreign importers are served by one Danish exporter only: the 95th percentile is served by two. Fourth, this regularity is even more pronounced at the product level: Basically no foreign importers purchase the same product from two Danish exporters. The bottom panel resembles these statistics, but now from the perspective of the foreign importers. First, the average destination × year pair were inhabited by 987.6 importers, though the distribution is heavily right-skewed.[12] Second, the average product × destination × year triplet was inhabited by 4.9 importers, and markets with at least two importers received 94.1 percent of the Danish export value. Third, Danish exporters served 4.6 importers in each destination × year on average, and 95.2 percent of the export value was sold by exporters serving at least two importers. Fourth, even for the same product, exporters served 2.4 importers per destination × year pair on average, and 85.5 of the export volume was sold by exporters serving at least two importers per product.

There are three main takeaways from these summary statistics. Firstly, several foreign importers serve Danish exporters in each product × destination × year market. Thus, it is *not* the case that foreign markets are dominated by a single importer. Secondly, most Danish exporters serve multiple importers in each destination, and exporters with multiple importers are responsible for the lion's share of the total export value. This means that Danish exporters do *not* generally trade with a single local partner. Thirdly, even though most Danish exporters serve only one foreign importer for each of their products, around 35 percent of exporter × product pairs make use of at least two importers in the same destination, and these constitute 85.5 percent of the export value. These regularities motivate an analysis of how exporters expand in foreign markets characterized by many potential buyers, where exporters have incentives to serve multiple, and not just one, importer.

For my empirical analysis, I need to adjust the raw sample to two different levels of aggregation.

For my analysis of export prices in Section 2.2 and 4, I make use of the raw sample at its existing level of aggregation, that is the exporter × product × importer × destination × year level. However, I clean the data set in the following way. It is well-established in the empirical literature on export prices, obtained as unit values, that these are exposed to measurement error (ME), e.g. due to misreporting. As I will examine the distribution of export prices in my empirical analysis, mitigating the impact of measurement error is a first-order concern, which I address in two ways. Firstly, the extensive use of fixed effects throughout the paper will absorb any ME that systematically varies across the level of fixed effects. For example, in Section 2.2, I examine the price distribution within exporter × product × destination × year quadruplets, across importers. This eliminates concerns associated with, e.g., that some products are more difficult to measure, that some exporters tend to misreport more, that some destinations are more closely monitored by the Danish customs authorities, that rules on reporting changes over time, or *any* combination of these separate concerns. Secondly, following common practice in the literature, e.g. Manova and Zhang (2012), I suspect outliers to be the result of severe ME. Specifically, I consider an observation to be an outlier if it meets either of the following two criteria: (i) the value, quantity, and/or price is below the 1st percentile or above the 99th percentile of the respective distribution, and/or (ii) the year-to-year price growth is below the 1st percentile or above the 99th percentile of the price-growth distribution.[13] This way, I exploit both the cross-sectional and across-year variation to detect outliers. If an observation is considered an outlier, I disregard the entire exporter × product × importer × destination *spell*. I consider this to be a conservative approach to the concern of ME.

[12] For comparison, Bernard et al. (2018) report that Norwegian exporters served 5,992 importers in the US and 1,489 importers in China in 2006. In the present sample, Danish exporters served 4,818 importers in the US and 2,081 importers in China in 2007 (2006 is not available).

[13] Addressing that different products are measured in different units and that the level of prices varies systematically across destination and over time, I purge values, quantities and prices for product × destination × year fixed effects before imposing criterion (i).

For my analysis of network effects in Section 2.3 I simply aggregate the raw sample to the exporter × destination × year level.[14] The main variable of interest is the number of importer relationships formed by exporters by destination and year.

Finally, for each of the two estimation samples, I distinguish between exporter × destination spells that are left-censored and *not* left-censored. The reason for doing so is, as we will see, that an exporter's network is not properly defined if it belongs to a left-censored spell. I define a spell as *not* left-censored if it meets either of the following conditions: (i) the spell was initiated later than 2007, or (ii) the spell was initiated in 2007 *and* the exporter did not export to the particular destination at any point in time from 2000-2006 according to the general customs data.

Having outlined the data, I now present two empirical findings. First, in Section 2.2, I document that exporters price discriminate between their buyers. Then, in Section 2.3, I document that exporters face network effects. I use both findings to guide the model presented in Section 3.

2.2 Price Discrimination

In this subsection, I document that exporters generally obtain quite different prices from their buyers within narrow markets, defined as product × destination × year triplets. That is, the price dispersion across buyers, within exporter × market pairs, is substantial. I further provide evidence suggesting that this dispersion is not entirely explained by three simple factors: measurement error in prices, quantity discounts, and quality differentiation.

For this part of the analysis, I apply the exporter × product × importer × destination × year data set, cleaned for price outliers as described in Section 2.1. As I do not require information on the lengths of any export spells and in order to make the analysis as general as possible, I apply both left-censored and *not* left-censored spells in this part of the analysis. Focusing solely on *not* left-censored spells, however, produce qualitatively similar results.

Table 2 shows that the cleaned sample consists of 211,757 markets of which 66,345 are served by more than one Danish exporter. It is a well-known fact that exporters, serving the same market, obtain very different prices. Define exporter × market prices, p_{im}, as

$$p_{im} = \log\left(\frac{\sum_{j\in\Omega_{im}} S_{ijm}}{\sum_{j\in\Omega_{im}} Q_{ijm}}\right),$$

where S_{ijm} is the value sold by exporter i to importer j in market m, Q_{ijm} is the quantity, and Ω_{im} is the set of importers served by i in m. Prices are then de-meaned by market fixed effects in order to facilitate comparison across exporters, within markets, and dubbed $\tilde{p}_{im}$. This leaves 274,806 observations of $\tilde{p}_{im}$.

Figure 1 shows the distribution of $\tilde{p}_{im}$ (dashed line), and Table 2 (top panel, third row) provides the corresponding statistics. The third (first) quartile is 0.66 (-0.68), meaning that the exporter on the third quartile obtains a price almost twice as high as the mean exporter.[15] I will refer to the width of this distribution as the degree of price *dispersion*.

Dis-aggregating further, the cleaned sample consists of 420,218 exporter × market pairs of which 139,930 served more than one importer. Define exporter × importer × market prices simply as

$$p_{ijm} = \log\left(\frac{S_{ijm}}{Q_{ijm}}\right). \tag{1}$$

Prices are then de-meaned by exporter × market fixed effects in order to facilitate comparison across buyers, within exporter × market pairs, and dubbed $\tilde{p}_{ijm}$. This leaves 670,535 observations of $\tilde{p}_{ijm}$.

[14] I re-formulate the pseudo-years to this level of aggregation such that pseudo-years are exporter × destination spell-specific.

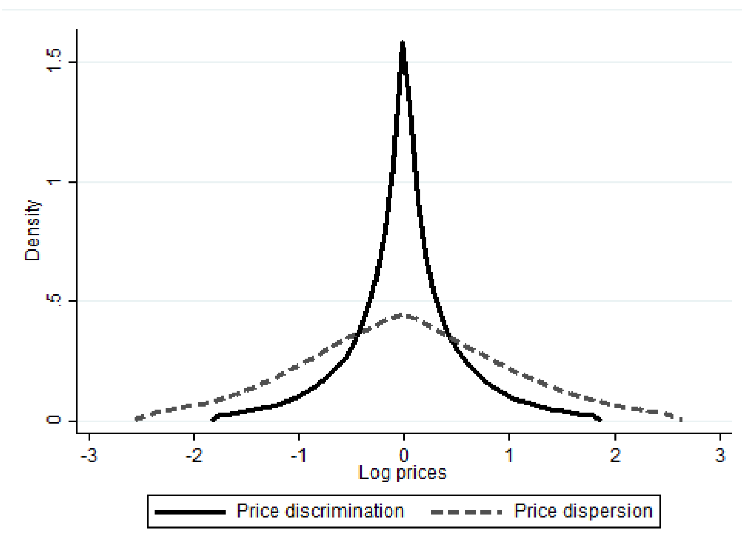
[15] $(\exp(0.66) - 1) \times 100\% = 94\%$.

Table 2: Summary Statistics, Cleaned Sample

	N	Mean	SD	Percentiles				
				5	25	50	75	95
#Exporters per market	211,757	1.98	4.66	1.00	1.00	1.00	2.00	5.00
... given #Exporters> 1	66,345	4.14	7.90	2.00	2.00	2.00	4.00	10.00
Prices ($\tilde{p}_{im}$)	274,806	0.00	1.05	-1.75	-0.68	-0.01	0.66	1.80
Quantities ($\tilde{q}_{im}$)	274,806	0.00	2.00	-3.32	-1.36	0.00	1.35	3.34
#Importers per exporter × market	420,218	2.26	5.93	1.00	1.00	1.00	2.00	6.00
... given #Importers> 1	139,930	4.79	9.79	2.00	2.00	3.00	4.00	13.00
Prices ($\tilde{p}_{ijm}$)	670,535	0.00	0.62	-1.01	-0.25	0.00	0.25	1.03
Quantities ($\tilde{q}_{ijm}$)	670,535	0.00	1.40	-2.33	-0.84	0.00	0.85	2.32
Quality ladders ($\tilde{\lambda}_{p}^{\text{quality}}$)	1,306	0.00	0.52	-0.90	-0.28	0.08	0.36	0.70
Price ladders ($\tilde{\lambda}_{m}^{\text{price}}$)	16,487	0.00	2.11	-3.40	-1.34	-0.07	1.36	3.46
Price ladders ($\tilde{\lambda}_{im}^{\text{price}}$)	38,714	0.00	2.54	-4.33	-1.59	0.10	1.76	3.85

Exporter × market level prices and quantities ($\tilde{p}_{im}$ and $\tilde{q}_{im}$) are log-transformed and de-meaned by market fixed effects (FEs) (excl. singletons). Exporter × importer × market level prices and quantities ($\tilde{p}_{ijm}$ and $\tilde{q}_{ijm}$) are log-transformed and de-meaned by exporter × market FEs (excl. singletons). Price and quality ladders ($\tilde{\lambda}_{p}^{\text{quality}}$, $\tilde{\lambda}_{m}^{\text{price}}$, and $\tilde{\lambda}_{im}^{\text{price}}$) are constructed as explained in section 2.2.3 and de-meaned by destination × year FEs. Percentiles are calculated as averages of the five adjacent observations around the given percentile in order to comply with Statistic Denmark's rules on data confidentiality.

Figure 1: Price Discrimination and Price Dispersion



Notes: "Price discrimination" is the distribution of ijm level prices, de-meaned by im fixed effects (excl. singletons), where i refers to an exporter, j to an importer, and m to a (product × destination × year) market. "Price dispersion" is the distribution of im level prices, de-meaned by m fixed effects (excl. singletons). The bottom and top 1 percent of each distribution are excluded as outliers.

Figure 1 (solid line) shows the distribution of $\tilde{p}_{ijm}$ and Table 2 (middle panel, third row) provides the corresponding statistics. The third (first) quartile is 0.25 (-0.25), meaning that importer on the third quartile pays a price almost one third higher than the mean importer.[16] I will refer to the width of this distribution as the degree of price *discrimination*.

Whereas, as expected, the degree of price *dispersion* is much larger, the degree of price *discrimination* is substantial. The term "price discrimination" indicates my interpretation of this finding: Exporters are able to charge different prices from their buyers without otherwise treating them differently. I incorporate this feature in my theoretical model, presented in Section 3, by allowing exporters to charge different prices from concurrent relationships. However, the observed degree of price discrimination could be explained in other ways. In the remainder of this subsection, I will propose three simple factors that would rationalize this finding and provide evidence suggesting that this is *not* the case in the data.

2.2.1 Measurement Error

It is well-known that export prices, obtained as unit values, suffer from measurement error. Presence of (a large degree of) measurement error would in principle be able to explain the observed price discrimination.

Assume that the observed price discrimination is entirely explained by measurement error. Then, exporters actually obtain the same price, $\bar{p}_{im}$, from all its buyers in market m, and the observed prices are merely

$$p_{ijm} = \bar{p}_{im} + \epsilon_{ijm}, \tag{2}$$

where ϵ_{ijm} is an i.i.d. (measurement) error. If this was the case, the observed degree of price discrimination (*across* importer, *within* markets) would be no larger than the dispersion in prices *within* exporter × importer pairs, *across* years. In other words, the *intra*-temporal dispersion should be no larger than the *inter*-temporal dispersion.[17] Figure 2 clearly shows that this is not the case: The *intra*-temporal distribution (solid line), that is the degree of price discrimination, is wider than the *inter*-temporal distribution (dashed line).

Further, if the observed price discrimination was entirely due to an i.i.d. measurement error, an exporter's ranking of buyers, rank_{ijm}, in terms of price would evolve randomly over time.[18] To test this, I estimate the simple equation

$$\text{rank}'_{ijm} = \alpha_0 + \alpha_1 \text{rank}_{ijm} + error_{ijm} \tag{3}$$

with OLS where rank'_{ijm} is the ranking in year $y+1$ *among* the relationships present in year y (so that newly established relationships do not influence the ranking of existing relationships).

Table 3 shows that the inter-temporal rank correlation is large and highly statistically significant (0.812), even for exporters that serve many buyers in the same market (0.675 for exporters serving more than 20 importers).

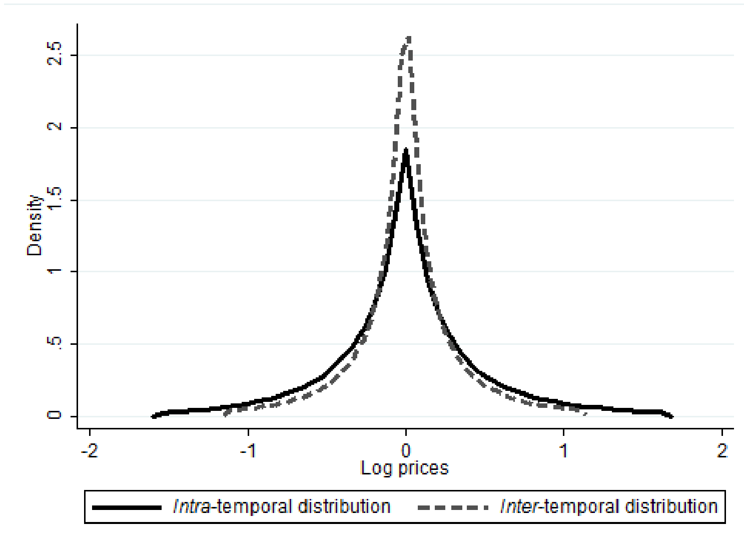
In total, the facts that (i) the intra-temporal dispersion of prices (what I have dubbed price discrimination) is larger than the inter-temporal dispersion, and (ii) the inter-temporal rank correlation of prices is large suggest that the observed degree of price discrimination is not entirely due to measurement errors (that is, equation (2) does not hold).

[16] $(\exp(0.25) - 1) \times 100\% = 28\%$.

[17] To be specific, I define the inter-temporal dispersion as the distribution of p_{ijm} de-meaned by exporter × product × importer × destination and destination × year fixed effects. The destination × year fixed effect ensures that the inter-temporal dispersion is not magnified by macroeconomic fluctuations in prices and exchange rates.

[18] Applying rank correlations are popular in settings where mis-measured variables are prevalent, such as in the inter-generational mobility literature, see e.g. Chetty et al. (2014a,b).

Figure 2: Price Discrimination - Measurement Error



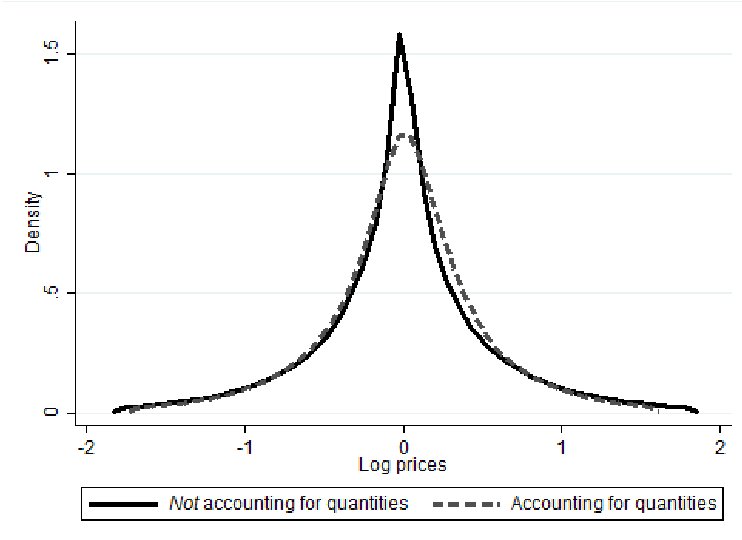
Notes: "*Intra*-temporal distribution" is the distribution of ijm level prices, de-meaned by im fixed effects (excl. singletons), where i refers to an exporter, j to an importer, and m to a (product × destination × year) market. "*Inter*-temporal distribution" is the distribution of ijm level prices, de-meaned by $ijpd$ spell and dy fixed effects (excl. singletons). "*Intra*-temporal distribution" differs from "price discrimination" in Figure 1 because "*intra*-temporal distribution" only includes those observations, where "*inter*-temporal distribution" also exists. The bottom and top 1 percent of each distribution are excluded.

Table 3: Rank Correlation of Prices

	(1)	(2)	(3)	(4)	(5)
#Importers	>1	>5	>10	>15	>20
rank'_{ijm}	0.812***	0.765***	0.729***	0.700***	0.675***
	(0.009)	(0.013)	(0.015)	(0.017)	(0.019)
R-squared	0.660	0.585	0.531	0.490	0.456
Observations	187,760	95,685	70,509	57,570	48,989

The unit of observation is exporter × importer × market (ijm), where a market is a product × destination × year (pdy) triplet. Each column represents separate OLS estimates of the rank correlation α_1 in equation (2). "#Importers" refers to the number of importers served by the exporter. Standard errors clustered at exporter × product are reported in parentheses. Asterisks indicate statistical significance: * p<0.1; ** p<0.05; *** p<0.01.

Figure 3: Price Discrimination - Quantity Discounts



Notes: "*Not* accounting for prices" is the distribution of ijm level prices, de-meaned by im fixed effects (excl. singletons), where i refers to an exporter, j to an importer, and m to a (product $\times$ destination $\times$ year) market. The distribution is identical to "price discrimination" in Figure 1. "Accounting for quantities" is the distribution of the residuals, $\hat{\varepsilon}_{ijm}$, from equation (4). The bottom and top 1 percent of each distribution are excluded.

2.2.2 Quantity Discounts

The observed price discrimination could be entirely due to quantity discounts. In this case, the variation in quantities should explain the corresponding variation in prices.

To test this, I simply estimate the correlation between prices and quantities q_{ijm} from the regression equation

$$p_{ijm} = \beta q_{ijm} + \mathbf{FE}_{im} + \varepsilon_{ijm}, \tag{4}$$

where the exporter $\times$ market fixed effect, $\mathbf{FE}_{im}$, ensures that only within-exporter variation identifies β. I obtain the OLS estimate $\hat{\beta} = -0.163$, which is highly statistically significant. As expected, larger quantities sold is associated with lower prices, suggesting that quantity discounts are indeed present. Furthermore, the variation in quantities does explain a non-negligible share of the price variation (the within-R^2 of regression (4) is 0.137). Needless to say, this is purely a correlation, and the attribution to quantity discounts is only suggestive.

Figure 3 plots $\tilde{p}_{ijm}$, that is the degree of price discrimination, together with the residuals from equation (4), $\hat{\varepsilon}_{ijm}$. Per construction, the standard deviation of $\tilde{p}_{ijm}$ exceeds that of $\hat{\varepsilon}_{ijm}$. Figure 3 shows that quantities do explain the tails of the price distribution, such that very small and very large prices are indeed explained by differences in quantities sold. It seems reasonable that very small and very large orders are affiliated with very large and very small prices, respectively. Also, as it is commonly accepted that measurement errors in prices primarily stem from measurement errors in quantities, controlling for quantities remedy the observations where quantities are unreasonably small or large compared to values.

However, whereas Figure 3 shows that the tails of the price distribution are to a large degree explained by variation in quantities, the price variation around the mean is not. In fact, whereas the third (first) quartile of $\tilde{p}_{ijm}$ is 0.25 (-0.25), the third (first) quartile of $\hat{\varepsilon}_{ijm}$ is 0.26 (-0.27). This means that conditioning on quantities *widens* the interquartile range of the price distribution. Therefore, quantity discounts seem unable to explain the overall presence of price discrimination.

2.2.3 Quality Differentiation

In the empirical international trade literature, price dispersion across exporters, within markets, is often rationalized with quality differentiation. That is, conditional on quantities sold, variation in prices across exporters must be due to differences in product quality. In this case, the degree of dispersion in prices and quality should be positively, and closely, correlated across markets.

Khandelwal (2010) estimates product-specific degrees of quality dispersion, referred to as quality ladders, based on US import data. That is, if a large, or long, quality ladder is assigned to a product, it means that the US imported a broad spectre of quality levels for this product. Table 2 (bottom panel, first row) shows that quality ladders are available for 1,306 unique products.[19]

There is no a priori guarantee that these ladders coincide with those faced by Danish exporters, especially outside the US. If, however, these serve as a reasonable proxy, we should expect the quality ladders to be positively and strongly correlated with observed price dispersion. This is because we expect markets with large room for quality differentiation to also be the markets where exporters are able to charge very different prices.

To test this, I construct market specific measures of price dispersion, in the spirit of Khandelwal (2010), as the log-difference between the market's maximum and minimum price: $\lambda_m^{\text{price}} = \log\left(P_m^{\max} - P_m^{\min}\right)$. I then estimate the equation

$$\lambda_m^{\text{price}} = \gamma\lambda_p^{\text{quality}} + \mathbf{FE}_{dy} + error_m, \tag{5}$$

where $\lambda_p^{\text{quality}}$ is Khandelwal (2010)'s quality ladders. I include a destination $\times$ year fixed effect to account for the fact that the level of price dispersion is likely to vary systematically across countries and time. The conjecture is that the OLS estimate of γ is positive.

Table 4 presents the results. Column 1 shows that price dispersion is indeed positively and strongly correlated with quality dispersion. As quality and price "ladders" are more meaningful in markets served by many exporters, column 2-4 re-estimate equation (5) for markets served by more than 5, 10, and 15 exporters, respectively. Whereas the smaller sample sizes mitigate statistical significance, the estimated correlations magnify.

Now, if the observed price discrimination is due to quality differentiation by exporters across their buyers, we would expect exporters that serve markets with long quality ladders to have large room for quality-based price discrimination, and vice versa.

To test this, I, equivalent to above, construct exporter $\times$ market specific measures of price discrimination as the log-difference between the exporter $\times$ market pair's maximum and minimum price, $\lambda_{im}^{\text{price}} = \log\left(P_{im}^{\max} - P_{im}^{\min}\right)$, and estimate the equation

$$\lambda_{im}^{\text{price}} = \delta\lambda_p^{\text{quality}} + \mathbf{FE}_{dy} + error_{im}. \tag{6}$$

A positive OLS estimate of δ would imply that exporters operating in markets with long quality ladders tend to price discriminate a lot between their buyers. Column 5 in Table 4 shows that δ is small—and even negative when

[19]Quality ladders are obtained from Amit Khandelwal's personal website. I aggregate them from the HS10 level to the CN8+ level using simple averages. As Khandelwal (2010) does not consider the universe of products, quality ladders are available only for a subset of my sample. Specifically, of the 670,535 observations of $\tilde{p}_{ijm}$, 26.0 percent are matched to a quality ladder. These constitute a somewhat larger share in terms of export sales, namely 33.9 percent.

Table 4: Quality Differentiation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.:	λ_m^{price}				$\lambda_{im}^{\text{price}}$			
#exporters$_m$ / #importers$_{im}$	>1	>5	>10	>15	>1	>5	>10	>15
$\lambda_p^{\text{quality}}$	0.567***	0.743**	0.639	1.124*	0.00625	-0.395	-0.497	-0.262
	(0.190)	(0.364)	(0.517)	(0.663)	(0.364)	(0.485)	(0.469)	(0.398)
dy FE	YES	YES	YES	YES	YES	YES	YES	YES
R-squared (within)	0.017	0.038	0.030	0.084	0.000	0.006	0.001	0.003
Observations	16,487	2,417	786	324	38,714	6,103	2,116	1,173

Column 1-4 contains estimates of γ from equation (5), and the unit of observation is market (m), where a market is a product × destination × year (pdy) triplet. Column 5-8 contains estimates of δ from equation (6), and the unit of observation is exporter × market (ijm). "#exporters$_m$" refers to the number of exporters present in a market. "#importers$_{im}$" refers to the number of importers served by an exporter. Standard errors clustered at product (the level of $\lambda_p^{\text{quality}}$) are reported in parentheses. Asterisks indicate statistical significance: * p<0.1; ** p<0.05; *** p<0.01.

Table 5: Average Number of New Importer Relationships and Network Size by Exporter Age

	Total	Exporter age								
		1	2	3	4	5	6	7	8	9
#importers$_{idy}$	0.52	0.54	0.48	0.50	0.52	0.51	0.50	0.49	0.52	0.54
network$_{idy}$	1.57	0.54	1.40	2.20	2.98	3.73	4.51	5.26	6.13	7.51
N	60,851	29,789	11,831	7,064	4,725	3,230	2,128	1,231	657	196

Unit of observation is exporter × destination × year. #importers$_{idy}$ is the number of *new* importers served by exporter i in destination d in year y. network$_{idy}$ is the sum of all new importers encountered by i in d *prior* to year d (see equation (8). Exporter age is the tenure within an export × destination spell.

restricting attention to exporters serving many importers in column 6-8—and highly statistically insignificant. This means that exporters that are able to price discriminate a lot across their buyers are *not* over-represented in markets with long quality ladders.

In conclusion, these results are hard to reconcile with the hypothesis that the observed price discrimination is entirely due to quality differentiation across buyers.

2.3 Network Effects

In this subsection, I document that Danish exporters face considerable network effects in foreign markets. Specifically, I find that exporters that served more importers in the past, and, thus, have a larger network, are able to form more new importer relationships subsequently, and I claim that this effect is causal.

For this part of the analysis, I apply the exporter × importer × destination × year data set as outlined in Section 2.1. As will become apparent shortly, the network variable is not properly defined for left-censored export spells, and these are therefore excluded. This leaves 60,851 exporter × importer × destination × year quadruplets.

The first row of Table 5 shows that the average exporter forms 0.52 new importer relationships each year.[20] Further,

[20]Prior to constructing Table 5 and estimating any regressions, I exclude exporters that form extremely many new relationships in the same year. Specifically, I consider an exporter × destination × year triplet "unusual" if the number of new relationships exceeds the 99th percentile. If an

this number is strikingly stable over the export spell: Old exporters do not generally match with more new importers than new exporters and vice versa.[21] However, I will examine if exporters are able to form more buyer relationships when their network is large than when their network is small.

To fix ideas, consider the regression equation

$$\#\text{importers}_{idy} = \alpha \text{network}_{idy} + \mathbf{FE}_{id} + \mathbf{FE}_{dy} + error_{idy}, \tag{7}$$

where $\#\text{importers}_{idy}$ is the number of *new* importer relationships formed by exporter i in destination d in year y. I define network_{idy} as the sum of all importers served by exporter i in destination d *prior* to year y. To be exact, network_{idy} is defined as

$$\text{network}_{idy} = \begin{cases} 0 & \text{if } T_{idy} = 1 \\ \sum_{s=1}^{T_{idy}-1} \#\text{importers}_{idy-s} & \text{if } T_{idy} > 1 \end{cases}, \tag{8}$$

where T_{idy} is the *tenure* of exporter i in destination d in year y.[22] The second row of Table 5 shows that the network indeed grows gradually as exporters mature. The remaining elements of equation (7) are as follows. α represents the size of the network effect. $\mathbf{FE}_{id}$ is an exporter × destination spell fixed effect (FE) that controls for any time-invariant heterogeneity in exporters' ability to form new importer relationships, including productivity and destination-specific ties. $\mathbf{FE}_{dy}$ is a destination × year FE that controls for any market-wide factors, including exchange rate fluctuations and business cycles.

Whereas the framing provided here indicates that α in equation (7) is expected to be positive, this is not a priori obvious. In his analysis of the effect of marketing costs in international trade, Arkolakis (2010) assumes that the cost of reaching new consumers *increases* with the number of consumers reached, because, in the words of Eaton et al. (2014), the pool of easy-to-reach buyers becomes "fished out". This argument implies a negative value of α. Nevertheless, Eaton et al. (2014) structurally estimate a model of exporters' search for importers and find that search costs are *decreasing* in the size of the network, thus implying positive network effects.

Column 1 in Table 6 presents the OLS estimate of equation (7). An increase in the network by one importer is associated with 0.299 more new importer matches. However, there is no reason to believe that this reflects the causal effect. As is well-known in the econometric literature on dynamic panel models, the FE specification of equation (7) produces an estimate of α that is biased and inconsistent.[23] In the context of dynamic panel models, the canonical solution is an instrumental variable technique where the lagged dependent variable is instrumented by its higher-order lags. This approach is not applicable here, as the network is a function (the sum) of the entire history of lagged dependent variables, see equation (8), and, thus, we need a different identification strategy. I show below that the network effect is identified, if equation (7) can be augmented by a strictly exogenous variable, that is a regressor that can provide exogenous variation in $\#\text{importers}_{idy}$.

exporter × destination spell contains an "unusual" triplet, I exclude the entire spell. After doing so, the maximum number of relationships formed in a year is four.

[21] It can seem self-contradicting that the average exporter at age one, the first export year, can form less than one new importer relationship. However, recall from Section 2.1 that we only consider exporter-importer relationships that exchanged at least two transactions throughout the sample years.

[22] In the empirical specifications below, I define T_{idy} as the tenure within a exporter × destination *spell*, where a spell is defined as a sequence of consecutive years during which i exported to d. This means that former exporters that re-enter a destination are not able to take advantage of its previous network.

[23] The reason is that the within-transformed error terms in equation (7) exhibit auto-correlation, which introduces a non-zero correlation between the within-transformed lagged dependent variable and the within-transformed error term.

Table 6: Network Effects (I)

Dep. var.: $\#\text{importers}_{idy}$	(1)	(2)	(3)	(4)	(5)
Estimator	OLS	OLS	IV	OLS	IV
network_{idy}	0.299***				
	(0.009)				
PSMM_{idy}		-0.0334	0.830**		
		(0.0782)	(0.415)		
$\text{PSMM}_{idy,y-1}$				0.0799	0.259
				(0.0865)	(0.302)
id spell FE	YES	YES	YES	YES	YES
dy FE	YES	YES	YES	YES	YES
First-stage F-statistic			39.8		52.7
R-squared (within)	0.126	0.000	-0.004	0.000	0.000
Observations	42,886	42,886	42,886	42,886	42,886

The unit of observation is exporter × destination × year (idy). The dependent variable is $\#\text{importers}_{idy}$, the number of *new* importer relationships formed by i in d in y. network_{idy} is the sum of importers served by i in d previous to y. PSMM_{idy} ($\text{PSMM}_{idy,y-1}$) is an indicator variable equal to 1 if i purchased "Partner Search and Match Making" services for d in y (or $y-1$). "IV" indicates that PSMM_{idy} ($\text{PSMM}_{idy,y-1}$) is instrumented by approach_{idy} ($\text{approach}_{idy,y-1}$), an indicator variable equal to one if i was approached by the Trade Council in Denmark and offered export promotion services for d in y (or $y-1$). Standard errors clustered at the exporter are reported in parentheses. Asterisks indicate statistical significance: * p<0.1; ** p<0.05; *** p<0.01.

As proposed by Buus et al. (2019), I take advantage of a policy managed by the Trade Council (TC) in Denmark. The TC organizes all governmental export promotion activities in Denmark, and offers tailored and destination-specific export promotion services (EPS) to Danish firms. Crucially, the TC actively approaches Danish firms and offer them EPS. Buus et al. (2019) show that exporters are much more likely to purchase EPS if they were approached by the TC and, therefore, propose to use an indicator for whether an exporter was approached by the TC as an instrument for whether the exporter purchased EPS. This addresses the concern of endogeneity induced by self-selection. Call the instrument approach_{idy}. See Buus et al. (2019) for more details and evidence on the instrument's exogeneity.

One group of EPS is labelled "Partner Search and Match Making" (PSMM), and the explicit purpose of these services is to help Danish exporters find importers abroad. As this is exactly what we are looking for, I restrict attention to EPS of the type PSMM. To test if purchases of PSMM, instrumented by approach_{idy}, actually does provide variation in $\#\text{importers}_{idy}$, I estimate the simple auxiliary regression equation

$$\#\text{importers}_{idy} = \beta \text{PSMM}_{idy} + \mathbf{FE}_{id} + \mathbf{FE}_{dy} + error_{idy}, \tag{9}$$

where PSMM_{idy} is a binary indicator for whether exporter i purchased PSMM in destination d in year y.[24] The FE specification of equation (9) resembles that of equation (7). $\mathbf{FE}_{id}$ is a firm × destination *spell* FE, accounting for any time-invariant ability to form new importer relationships and, in the context of PSMM, any time-invariant characteristics that would make an approach by TC more or less likely, such as industry affiliation. $\mathbf{FE}_{dy}$ is a destination × year FE controlling for any market specific developments, including the intensity with which the TC approaches exporters.

[24] To be specific, I assume that PSMM is effective in 12 months upon purchase. I set PSMM_{idy} equal to one if the exporter × destination specific pseudo year, y, contains any of these months. In practice, this closely assembles the assumption of Broocks and Van Biesebroeck (2017) and Buus et al. (2019) who define define a treatment indicator to take value one if EPS were purchased in *calendar* year y and/or $y-1$.

Column 2-3 in Table 6 presents the OLS and IV estimates, respectively, of equation (9). The OLS estimate is close to zero (-0.0334) and highly statistically insignificant, whereas the IV estimate is close to one (0.830) and statistically significant at the 5 percent level. The relationship between the IV and OLS estimates broadly resembles the findings of Buus et al. (2019) who show that exporters increase their export sales upon purchasing EPS, and that the OLS estimate is biased towards zero. This is possibly because exporters that self-select into EPS have recently been hit by a negative shock and seek assistance to recover or even survive in the foreign market. The result that exporters on average find almost one new exporter upon purchasing PMSS seems reasonable as PMSS have that particular purpose.[25]

The conclusion from this exercise is that PSMM_{idy} instrumented by approach_{idy} serves as a proper shifter for the amount of new importer relationships an exporter forms. I will now show how this can be exploited to identify the network effect.

Augmenting regression equation (7) by adding PSMM_{idy} as predictor (where FEs are ignored for the sake of notational simplicity) yields

$$\#\text{importers}_{idt} = \alpha \text{network}_{idt} + \beta \text{PSMM}_{idt} + error_{idt}, \tag{10}$$

where t refers to the tenure of exporter i in destination d. Now, consider an exporter with a tenure of T years, and write the panel equation (10) as a system of equations:

$$\begin{aligned}
\#\text{importers}_{id1} &= \alpha \text{network}_{id1} + \beta \text{PSMM}_{id1} + error_{id1} \\
\#\text{importers}_{id2} &= \alpha \text{network}_{id2} + \beta \text{PSMM}_{id2} + error_{id3} \\
\#\text{importers}_{id3} &= \alpha \text{network}_{id3} + \beta \text{PSMM}_{id3} + error_{id3} \\
&\vdots \\
\#\text{importers}_{idT} &= \alpha \text{network}_{idT} + \beta \text{PSMM}_{idT} + error_{idT},
\end{aligned}$$

Simply applying the definition of network_{idt} in equation (8) and substituting in its components using the system's remaining equations then yields

$$\begin{aligned}
\#\text{importers}_{id1} &= \beta \text{PSMM}_{id1} + error_{id1} \\
\#\text{importers}_{id2} &= \beta \text{PSMM}_{id2} + \alpha\beta \text{PSMM}_{id1} + \widetilde{error}_{id2} \\
\#\text{importers}_{id3} &= \beta \text{PSMM}_{id3} + \alpha\beta \left[(\alpha+1)\text{PSMM}_{id1} + \text{PSMM}_{id2}\right] + \widetilde{error}_{id3} \\
&\vdots \\
\#\text{importers}_{idT} &= \beta \text{PSMM}_{idT} + \alpha\beta \left[\sum_{s=1}^{T-1} (\alpha+1)^{T-1-s} \text{PSMM}_{ids}\right] + \widetilde{error}_{idT},
\end{aligned} \tag{11}$$

where "tildes" indicate that the error terms are composites of present and prior errors. α is identified from the *dynamic* effect of purchasing PSMM. To be specific, the implicit identifying assumption is that purchases of PSMM instantly affects the exporter's ability to match with new importers (the first term in each equation in system (11)), whereas *previous* purchases of PSMM affects the *current* ability to match with new importers only through the accumulation of

[25]In its own right, this finding is a small contribution to the literature on the effects of firm-specific trade policies and adds to the explanations of how these work. For example, Buus et al. (2019) find that exporters manage to increase their sales of existing products on existing markets upon purchasing EPS. A part of the explanation is likely to be that the TC helps exporters find new importers.

Table 7: Network Effects (II)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
#Equations	2	3	4	5	6	7	8
network$_{idy}$	1.012	0.503*	0.380**	0.241	0.364**	0.006	0.080
	(1.480)	(0.277)	(0.188)	(0.198)	(0.144)	(0.173)	(0.072)
PSMM$_{idy}$	0.402	0.741*	0.661	0.515	0.723	0.668**	0.756
	(0.414)	(0.403)	(0.413)	(0.462)	(0.466)	(0.333)	(0.477)
id spell FE	YES	YES	YES	YES	YES	YES	YES
dy FE	YES	YES	YES	YES	YES	YES	YES
Hansen p-value	0.892	0.341	0.579	0.366	0.768	0.296	0.667
Observations	11,828	7,063	4,724	3,229	2,128	1,231	657

The unit of observation is exporter × destination × year (idy). The dependent variable is #importers$_{idy}$, the number of *new* importers served by i in d in y. network$_{idy}$ is the sum of importers served by i in d previous to y. PSMM$_{idy}$ is an indicator variable equal to 1 if i purchased "Partner Search and Match Making" (PSMM) services for d in y. Estimates are obtained from numerical, iterative GMM estimation of equation system (11). The weight matrix is robust to arbitrary correlation among observations within exporters. PSMM$_{idy}$ is instrumented by approach$_{idy}$, an indicator variable equal to one if i was approached by the Trade Council in Denmark and offered PSMM for d in y. FEs are accounted for by within-transformation of all variables prior to estimation. Standard errors clustered at the exporter are reported in parentheses. Asterisks indicate statistical significance: * p<0.1; ** p<0.05; *** p<0.01.

importers in the year PSMM was purchased, that is, through the network effect (the remaining terms in each equation in system (11)).

Hence, a potential threat to this identification strategy is that previous purchases of PSMM directly affects the exporter's current ability to form new importer relationships. This would be the case if the implementation process is slow and extents beyond the one year period assumed above. Such direct lagged effects of PSMM would, in system (11), be attributed to the network effect, which would then be biased upwards. To get a rough idea of whether the applied time horizon of PSMM's effectiveness is appropriate, I re-estimate the auxiliary model (9), but extent the assumed effectiveness of PSMM from one to two years upon purchase. Call the re-formulated indicator PSMM$_{idy,y-1}$. If two years is a more appropriate time horizon for the effectiveness of PSMM than one year, we should expect PSMM$_{idy,y-1}$ to be a better predictor of new importer matches than PSMM$_{idy}$. The results are presented in column 4 and 5 in Table 6. Compared to the original results (column 2 and 3), the OLS estimate (0.0799) is still close to zero, but the IV estimate (0.259) is more than three times smaller and statistically insignificant. This result suggests that the effectiveness of PSMM does not generally extent beyond one year, that PSMM$_{idy}$ is a reasonable representation of the effect of PSMM, and that it is reasonable to attribute the effects of previous purchases of EPS to the network effect.

I estimate α and β from the equation system (11) using a system-of-equations general method of moments (GMM) procedure, where all occurrences of PSMM$_{idt}$ are instrumented by approach$_{idt}$. The identifying assumption resembles that of two-stage least squares (2SLS) fixed effects estimation: all instruments must be uncorrelated with all error terms, within and across equations.

The results are presented in Table 7. Each column represents separate estimations of system (11), where I vary the amount of equations to include in the estimation procedure. Specifically, column 1 presents results based on only the top two equations in (11), restricting the sample to exporter × destination spells that reach a tenure of *at least* two years. This is the minimal requirement in order to identify α. On the other hand, column 7 presents results based on eight equations, restricting the sample to exporter × destination spells that reach a tenure of *at least* eight years.[26] This represents the extremes in a trade-off between, on the one hand, exploiting the structure of system (11) as much as possible by including many equations, and, on the other hand, maximizing the sample size by using few equations.

Including between three and six equations (column 2-5 in Table 7) produce estimates of the network effect, α in equation (10), between 0.241 and 0.503, with varying levels of significance. Focusing on the two estimates that are statistically significant at the 5 percent level (column 3 and 5), these are almost identical: 0.380 and 0.364, respectively. I consider these the best estimates of the network effect. This means that increasing an exporter's network by one exporter will, all else equal, induce the exporter to form almost 0.4 more new importer relationships in the subsequent year.

Table 7 also presents estimates of the effect purchasing PSMM, β in equation (10). Though of secondary interest, the relatively stable coefficients across columns (between 0.515 and 0.741 in columns 2-5), and the fact that these, though slightly smaller, are easily within reach of the causal estimate of 0.83 in column 3 of Table 6 are reassuring and add credibility to the estimation procedure.

The takeaway from this subsection is that exporters face considerable network effects: Exporters are able to form more new importer relationships when their network is large than when their network was small. This feature is a crucial component in the theoretical model, presented in Section 3, as it provides exporters with an incentive to price low upon entry in order to attract more new importers and expand their network.

2.4 Within-Relationship Dynamics

Recall that the objective of this paper is to examine exporters' pricing behavior *across* importers. However, in order to formulate the theoretical model, presented in Section 3, we must take a stand on potential dynamics *within* existing exporter × importer relationships.[27] In this section, I show that neither prices nor quantities sold develop systematically within relationships beyond market-wide growth. Through the lens of a model of firm dynamics, this motivates a simple setting where exporters expect to sell a constant quantity of goods at constant price throughout a relationship (conditional on market-level aggregates).

To fix ideas, consider the regression equation

$$y_{ijm} = \alpha \text{age}_{ijm} + \mathbf{FE}_{ijpd} + error_{ijm}, \tag{12}$$

where y_{ijm} is the outcome variable of interest, e.g. the price charged by exporter i from importer j in market m,[28] age_{ijm} is the age of the relationship spell, and $\mathbf{FE}_{ijpd}$ is a relationship spell fixed effect. The OLS estimate of α reveals if y_{ijm} develops linearly with relationship age within that particular relationship. I estimate equation (12) applying the exporter × product × importer × destination × year data set, cleaned for price outliers as described in Section 2.1. This is the same data set I used to document the presence of price discrimination across importers in Section 2.2. However, for this section, I exclude left-censored spells, as relationship age is otherwise not properly defined.

[26]In principle, the sample length of nine years allows a maximum of nine equations. However, as only 196 exporter × destination observations reached a tenure of nine years, the GMM procedure is unable to converge.

[27]To be precise, I define a relationship in this section as an exporter × product × importer × destination spell. Making relationships product specific, in contrast to Section 2.3, is necessary in order to properly define prices. I follow the same approach when examining price dynamics *across* importers in Section 4.

[28]Recall from Section 2.2 that a market is defined as a product × destination × year (pdy) triplet.

Table 8: Within-Relationship Dynamics in Prices and Quantities

Sample:	Full				$ijpd$ relationships that lasted at least six years			
Dep. var.:	p_{ijm}	$\tilde{p}_{ijm}$	q_{ijm}	$\tilde{q}_{ijm}$	p_{ijm}	$\tilde{p}_{ijm}$	q_{ijm}	$\tilde{q}_{ijm}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
age$_{ijm}$	0.0233***	-0.00684	0.00510	-0.0111				
	(0.00418)	(0.00422)	(0.0110)	(0.0117)				
age$_{ijm}$=2					0.0817***	0.0482*	0.0672	-0.0562
					(0.0205)	(0.0282)	(0.0463)	(0.0550)
age$_{ijm}$=3					0.0890***	0.0177	0.195***	0.0856
					(0.0223)	(0.0360)	(0.0549)	(0.0686)
age$_{ijm}$=4					0.0952***	-0.0202	0.218***	0.121*
					(0.0216)	(0.0289)	(0.0612)	(0.0665)
age$_{ijm}$=5					0.112***	0.00529	0.203***	-0.00588
					(0.0241)	(0.0308)	(0.0755)	(0.0930)
$ipjd$ FE	YES	YES	YES	YES	YES	YES	YES	YES
R-squared (within)	0.004	0.000	0.000	0.000	0.013	0.003	0.010	0.006
Observations	25,155	19,923	25,155	19,923	4,405	3,621	4,405	3,621

The unit of observation is exporter × importer × market (ijm), where market is a product × destination × year (pdy) triplet. p_{ijm} and q_{ijm} are log of prices and log of quantities, respectively. Tildes indicate that the variable is demeaned by market-level means (market-level singletons are excluded). age$_{ijm}$ is the age of the ijm relationship within a spell. When these are included as dummies (column 5-8), age$_{ijm}$=1 is the omitted reference category. The last year of each spell is excluded as to avoid the influence of partial-year bias. Standard errors clustered at the exporter-product are reported in parentheses. Asterisks indicate statistical significance: * p<0.1; ** p<0.05; *** p<0.01.

Column 1 in Table 8 shows the result from regression (12), where the outcome variable is log-price ($y_{ijm} = p_{ijm}$). For each year the relationship matures, the price increases by 2.33 percent. Instead of solely relying on the linear effect, I augment equation (12) with a full set of age dummies and re-estimate. Column 5 reports the price trajectory for the first five years of relationships lasting at least six years.[29] These results confirm that prices are indeed increasing within relationships.

Heise (2019) shows that exporters systematically obtain lower prices from their US importers as the relationship matures relative to market-wide price trends. Specifically, he shows that prices decline by about 0.03 percent per *month* with additional declines in relationships that trade often (exchange many transactions).

In order to disentangle relationship specific price dynamics from market-wide developments (such as inflation), I follow Heise (2019) and de-mean log-prices by the market-level averages and re-estimate equation (12).[30] Column 2 in Table 8 shows that relative prices fall slightly by 0.684 percent when relationships mature by one year, but this effect is statistically insignificant at any appropriate level. In principle, this effect is larger in magnitude than the one documented by Heise (2019) (converting his result to the yearly level yields $((1 - 0.0003)^{12} - 1) \times 100\% = -0.36\%$). However, as I fail to obtain a statistical significant effect (potentially due to my much smaller sample compared to Heise (2019)), and as the dummy specification reveals a highly non-monotonic trajectory of relative prices (column 6), I conclude that systematic dynamics in relative prices within relationships are either absent or negligible in my sample.

Column 3 in Table 8 shows the result from regression (12), where the outcome variable is log-quantity ($y_{ijm} = q_{ijm}$). For each year the relationship matures, the quantity increase by 0.510 percent, but this is highly insignificant. However, the dummy specification (column 7) reveals that quantities increase significantly the first couple of years, then stagnate at a level significantly higher than the initial amount. This is in line with Monarch and Schmidt-Eisenlohr (2018) who show that trade between exporters and US importers are increasing as relationships mature, then falls off towards their end.[31]

Following the approach outlined above, I now test if quantities evolve within relationships *beyond* market-wide developments, by re-estimating equation (12) with relative quantities (quantities de-meaned by market-level averages) as outcome. Column 4 in in Table 8 shows that the linear effect of age on relative quantities is slightly negative and insignificant, and the dummy specification (column 8) shows that the trajectory is non-monotonic and that relative quantities five years into the relationship are no larger than in the initial year. I conclude that quantities do increase within relationships, but that I am unable to reject that this is entirely due to market-wide trends.

Overall, the takeaway from these exercises is that neither prices nor quantities evolve systematically within relationships *beyond* market-wide developments. This motivates the conveniently simple model setting I propose in the next section.

[29] I require relationships to last six years instead of five, because I exclude the last year of each relationship to avoid influence of partial-year bias. The use of pseudo-years (see Section 2.1) removes any partial-year bias in a spell's first year, but *not* in a spell's last year. As this is of little concern when examining price developments, it is a first-order concern when examining quantities, as I do below.

[30] The reason for de-meaning the dependent variable prior to estimation instead of simply including a market fixed effect on the right-hand side of equation (12) is that α in this case would not be identified, as within-relationship changes in age and years are indistinguishable.

[31] Monarch and Schmidt-Eisenlohr (2018)'s approach differs slightly from mine as they (i) consider sales, not quantities, and (ii) aggregate sales across products within relationships.

3 Model

In this section, I present a parsimonious model of dynamic price setting based on the empirical findings presented in the previous section. Most importantly, (i) sellers are able to charge different prices from their buyers, and (ii) sellers enjoy network effects. Furthermore, I abstract from within-relationship dynamics of prices and quantities sold. I assume that sellers need to reach buyers, thus building a customer base, in order to sell their products. Sellers actively make use of price posting as an attraction device, and the model predicts that sellers will increase their prices as their customer base—or, in other words, network—grows.

The model is close in spirit to the customer accumulation models presented by Rodrigue and Tan (2019) and Piveteau (2019). In contrast to these papers, but in line with the search models of Eaton et al. (2014, 2016), I assume that the network effect works through the cost of reaching new buyers. Though Heise (2019) models sellers' optimal price setting *within* existing buyer relationships, the dynamic trade-off between current and future profits that sellers face in my model closely resembles his framework.

In the model presented below, sellers can only affect the network accumulation process through their price setting behavior. In Appendix A, I extend the model such that sellers endogenously choose the intensity with which they search for more buyers.[32] The extended model more closely resembles the empirical findings in Section 2.3, but as predictions regarding sellers' optimal price setting are unaffected, the details are relegated to the appendix.

3.1 Setup

The market is inhabited by a mass of buyers, each characterized by unit-demand and an unobservable reservation price r, distributed according to the commonly known cumulative distribution function G. Exporters are single-product producers and produce at constant marginal costs mc.

In order for trade to occur, the exporter must reach the individual buyer. In every period, exporters reach an exogenous mass (normalized to one) of hitherto unreached buyers and post a non-negotiable price p. If a buyer is reached and p does not exceed the buyer's reservation price, they form a relationship. This means that a seller posting the price p forms $\Pr(p \leq r) = 1 - G(p)$ new relationships.

A seller-buyer match exchange one unit of quantity at price p in all subsequent periods.[33] Constant quantities and prices throughout relationships are motivated by the findings presented in Section 2.4. The price is never re-negotiated, even if the seller chooses to post a different price for new buyers. The fact that sellers are able to charge one price from new relationships, while maintaining another for existing relationships, is motivated by the findings presented in Section 2.2. This setup allows sellers to disregard existing relationships when choosing the optimal price to charge from new buyers, which greatly simplifies the model.

Reaching out to buyers is costly, and sellers incur a mandatory per-period search cost $c(m)$, where m is the mass of a seller's relationships, which I refer to as its *network*. Importantly, I assume that $c'(m) < 0$, that is, as the seller's network expands, reaching new buyers becomes less expensive. This assumption is motivated by the empirical findings presented in Section 2.3, and I refer to this as the *network effect*. The network effect is essential to the model, because it provides the seller with an incentive to reach buyers in the present period—besides extracting profits from the particular

[32] Though I use the word "search", neither the benchmark model nor the extended model are search models in line with, e.g., Eaton et al. (2014, 2016). Rather, "search" in my model is closer in the spirit to the marketing investments in Arkolakis (2010).

[33] Allowing relationships to dissolve for exogenous reasons is simple, and this possibility is ignored only for the sake of notational simplicity.

buyer—in order to reach buyers less costly in subsequent periods. Further, I assume that $c''(m) > 0$, that is, c is convex such that the *marginal* gain from a larger network is decreasing (or, in other words, the effect of larger network on search costs becomes less negative as the network grows). This assumption is motivated by structural estimates provided by Eaton et al. (2014, 2016). They present a theoretical framework where exporters search for foreign importers, and where exporters incur search costs that depend on the size of their network. The estimated search cost function is decreasing and convex in the size of the exporter's network.

A sellers network m evolves as

$$m' = m + \big(1 - G(p)\big) + \varepsilon, \tag{13}$$

where primes indicate the next period, $1 - G(p)$ is the mass of relationships established in the present period, and ε is a mean-zero i.i.d. disturbance term that captures e.g. fluctuations in the quality of new relationships.[34,35]

3.2 Seller's Optimization Problem

I now turn to the seller's inter-temporal optimization problem. Recall that when seller-buyer relationships are formed, they never dissolve, the price p is never re-negotiated, and one unit of quantity is traded in each period. This means that profits stemming from existing relationships can be ignored when the seller chooses which price to optimally post for potential new buyers.

Setting price p implies an immediate profit flow of $(p - mc)(1 - G(p))$ from new buyers, where $p - mc$ is the immediate per-buyer profit flow, and $1 - G(p)$ is the mass of new buyers. Given that sellers discount future profits by $0 < \beta < 1$, the continuation value of this profit flow, $\pi(p)$, is

$$\pi(p) = \frac{(p - mc)(1 - G(p))}{1 - \beta}. \tag{14}$$

Therefore, the seller's value function is

$$V(m) = \max_{p} \left[\pi(p) - c(m) + \beta E V(m')\right], \tag{15}$$

where the expectation operator is with respect to ε.

Differentiating the value function (15) with respect to p and applying (13) and (14), I obtain the first-order condition

$$p - \frac{1 - G(p)}{g(p)} = mc - \beta(1 - \beta) E V(m'), \tag{16}$$

where $g(p) = G'(p)$.

In order to obtain a closed-form solution for the optimal price p, I impose a parametric assumption on the distribution of buyers' reservation prices $G(r)$. Specifically, I assume that r is Pareto distributed with shape parameter $\eta > 1$, that is,

$$G(r) = 1 - r^{-\eta}. \tag{17}$$

The shape parameter η is an inverse measure of the dispersion of reservation prices. That is, if η is large, most buyers have relatively small reservation prices and only few buyers have relatively high reservation prices. It is often

[34]Allowing the network to depreciate over time is simple, and, again, is ignored only for simplicity.

[35]In the context of "Partner Search and Match Making" services as applied in Section 2.3 to provide exogenous variation in exporters' networks, the model counterpart to an approach by the Trade Council is a positive realization of ε.

argued, e.g. by Chaney (2008), that the distribution of productivity across firms is Pareto. If more productive importers tend to have higher reservation prices, assumption (17) seems reasonable.

Substituting (17) into (16) and re-arranging yields

$$p = \frac{\eta}{\eta - 1}\left[mc - \beta(1-\beta)EV'(m')\right]. \tag{18}$$

Disregarding the dynamic network accumulation for a moment, the Pareto distribution delivers a well-known solution, where sellers set prices as a constant markup, $\eta/(\eta-1)$, over marginal costs, mc. If η is large, so that most buyers have relatively low reservation prices, sellers optimally charge relatively low markups.

Two features of expression (18) merit note. Firstly, it defines the optimal price posted by the seller only through an implicit function, as next period's network, m', depends on the price. Secondly, in the presence of dynamic network accumulation, sellers generally post lower prices than the standard static framework entails. That is, firms could increase their instant profits by increasing their prices. However, firms optimally post lower prices to attract more buyers, which extents their network, and, thus, lower their search costs in subsequent periods.

To see this more explicitly, differentiate the value function (15) with respect to m, apply the envelope condition, and substitute into (18) recursively to obtain

$$p = \frac{\eta}{\eta - 1}\left[mc - (1-\beta)E\sum_{j=1}^{\infty}\beta^j \underbrace{\left(-c'(m_j)\right)}_{>0}\right], \tag{19}$$

where m_j is the size of the network j periods ahead.

Expression (19) shows that the negative impact by network on search costs (the fact that $c'(m) < 0$) is driving the price below the static optimum. Furthermore, as c is convex (the fact that $c''(m) > 0$), the *marginal* effect of larger network on search costs goes to zero as m becomes large. This means that, as m becomes large, the entire infinite sum in equation (19) will go to zero, and, consequently, the optimal price will approach the optimal static price equal to $\left[\eta/(\eta-1)\right] mc$.

To sum up, sellers with small networks face large search costs. However, they also face large *reductions* in search costs if they manage to expand their network, and, hence, they charge low prices—and forgo present profits—in order to attract new buyers. As the network expands, search costs fall, but so do potential reductions in search costs from further enlarging the network. Therefore, the incentive to accumulate buyers is smaller, and sellers will charge higher prices. In the end, as reductions in search costs diminish, sellers will charge a price close to the static optimum.

One might be interested in the *speed* with which prices approach the static optimum as a function of network size. Unfortunately, this is, in principle, not determined from the current assumptions. Simple, and quite general, assumptions about the shape of the cost function, c, however, imply that the speed with which sellers increase prices is decreasing in network size. For instance, this is the case for the function $c(m) = m^{-\delta}$ for $\delta > 0$. This implies that prices increase quickly for small network sizes, then level off as they approach the static optimum.

Note that the simple implementation of network effects through the cost of acquiring a fixed number of new customers have implications that are at odds with the empirical findings presented in Section 2.3. There, I showed that exporters with larger network are able to form more new relationships. However, in the model sellers are introduced to a fixed number of buyers in each period, but sellers with larger network sell to a *smaller* fraction simply because they require higher prices. In Appendix A, I extent the model with an endogenous search effort and show that sellers still increase their prices as their network grows *and*, under some regularity conditions, form more new relationships.

Table 9: Average Prices by Exporter × Product Age

	Total	Exporter × product age								
		1	2	3	4	5	6	7	8	9
All exporter × product pairs										
Mean	0.00	0.00936	-0.0134	-0.00380	-0.00829	-0.0228	-0.0180	-0.0196	-0.0640	-0.0558
N	75,232	44,309	11,662	7,054	5,081	3,218	1,826	1,061	714	307
Exporter × product pairs that formed at least 6 importer relationships										
Mean	0.00	-0.00529	0.00464	0.00282	0.00262	-0.00551	0.0219	0.0124	-0.0427	-0.0360
N	26,323	7,112	5,939	4,175	3,505	2,413	1,371	865	646	298
Exporter × product pairs that formed at least 11 importer relationships										
Mean	0.00	-0.00509	-0.0104	0.00950	0.0171	-0.0103	0.0190	0.0193	-0.0279	-0.0295
N	14,694	3,294	2,947	2,294	2,179	1,641	882	625	557	275

The unit of observation is exporter × importer × market (ijm), where market is a product × destination × year (pdy) triplet. Only the first year of each $ipjd$ relationship within a id spell is kept. Prices are de-meaned by market fixed effects. Exporter × product age is the tenure within an export × destination spell. fpd triplets that obtain a network larger than the 99th percentile are excluded.

4 Dynamic Pricing

The model presented in Section 3 predicts a simple pattern for exporters' dynamic price setting. Upon entry into a new market in which the exporter does not have a network, the exporter should post relatively low prices. As the exporter accumulates importers, it should post higher prices to potential new buyers. This prediction is easily testable.

In the theoretical model, exporters were presented as single-product producers. In practice, many exporters produce and export several products to the same destination. In line with the evidence of exporters' price discrimination across their importers presented in Section 2.2, I will here treat an exporter × product pair as the data counterpart to an exporter in the model. This means that exporters build a network for each of their products separately. In line with Section 2.3, I assume that networks are built within exporter × destination spells, and, consequently, that networks are lost upon exit, even in the case of later re-entry.

For this part of the analysis, I apply the exporter × product × importer × destination × year data set, cleaned for price outliers as described in Section 2.1. As in Section 2.3, the network variable is not properly defined for left-censored spells, and these are excluded. Further, for each relationship within an exporter × destination spell, I keep only the *first year* of data.[36,37] This way, potential *within*-relationship price developments, of which the theoretical model is silent, do not interfere with the *across*-relationship price developments, which are the main interest of this paper. This leaves 75,232 observations. Table 9 presents average prices across exporter × product pair age. There is a small tendency for first-year exporters to obtain relatively high prices, but this could be purely a selection effect.

To test the central model prediction—that exporters increase their prices as their network grows—I simply regress the (log) price obtained from an exporter × product × importer relationship on the size of the exporter × product pair's network. The conjecture is that the OLS estimate is positive.

[36]Recall that as all years are converted to pseudo-years, the first year of a relationship is indeed the relationship's first 12 months.

[37]To be precise, I keep only the first year of data for each exporter × product × importer × destination quadruplet within an exporter × destination spell. This means that if an exporter × product pair forms several relationship spells with the same importer within the same exporter × destination spell, only the first year of the first relationship spell will be kept for this analysis.

Consider the regression equation

$$p_{ijm\tau} = \gamma \text{network}_{im\tau} + \mathbf{FE}_{ipd} + \mathbf{FE}_{m} + \mathbf{FE}_{month} + error_{ijm\tau} \tag{20}$$

where τ is the exact *date* of which the relationship was established. $p_{ijm\tau}$ is the log price obtained by the exporter during the relationships *first year* only. The network, network$_{im\tau}$, is the number of importers served prior to date τ. The FE specification largely resembles that of equation (7). In particular, $\mathbf{FE}_{ipd}$ ensures that γ is identified from variation *within* an exporter × product × destination triplet, *across* importers encountered at different points in time.[38] $\mathbf{FE}_{m}$ controls for market-level price-developments, such that the potential network effect on prices is identified as relative to product-specific inflation (recall that a market is defined as a product × destination × year triplet). Importantly, the combinations of $\mathbf{FE}_{ipd}$ and $\mathbf{FE}_{m}$ controls for linear effects of export × product pairs' age on prices. This is because within-exporter changes in age and years are indistinguishable. In turn, this means that if exporters change their prices systematically with their age, the estimated effect should be interpreted as additive to this age effect.[39] To address the concern of within-year inflation, I add $\mathbf{FE}_{month}$ in order to control for the month in which the relationship was initiated. This allows for proper comparison between relationships initiated in, say, January and December.

I do not make an attempt to exploit the instrumental variable approach proposed in Section 2.3. Recall that the key identifying assumption necessary to identify model (10) from the system of equations (11) was that the dynamic effect of purchasing PSMM works *only* through the network effect. Model (10) is formulated at the yearly level, which makes this assumption plausible. However, model (20) is formulated at the daily level, which make the assumption impractical (for example, it seems far-fetched to assume that PSMM purchased in February was the direct cause of the meeting of an importer in March, but not in April). A compromise would be to perform the present exercise on more aggregated, e.g. yearly, data. However, this would eliminate within-year variation in price setting caused by within-year variation in network size, which is a considerable part of the present identifying variation. Instead, I will rely on, potentially, non-causal evidence, but interpret the results through the lens of the theoretical model formulated in Section 3.

As presented in column 1 of Table 10, exporters increase prices by 0.792 percent each time it forms a new relationship, but the estimate is highly statistically insignificant. If dynamic pricing is indeed present in the data, two factors (or a combination of the two) could explain the insignificant estimate. First, statistical significance might be mitigated by the presence of a large amount of relatively small (in terms of export sales) exporter × pairs that are either very short-lived or only manage to accumulate a very few importers. Second, recall from the model that we should expect prices to develop non-linearly: Prices should increase relatively fast for small network sizes, then level off as they approach the static optimum. In this case, the presence of exporter × product pairs with relatively large networks would drive the estimate towards zero.

In order to eliminate the first concern—the presence of small, "short" spells—I restrict the estimation sample to exporter × product pairs that managed to form more than five importer relationships. Table 9 shows that this leaves 26,323 observations.[40] Column 2 in Table 10 shows that the estimated effect of network size on price (γ from equation (20)) is only slightly larger than before and still statistically insignificant.

[38]To be accurate, $\mathbf{FE}_{ipd}$ is a product × (exporter × destination spell) FE.

[39]The fixed effects specification in equation (20) controls for linear age trends, but not for potential nonlinearities, that is deviations from the linear trend. Explicitly adding a full set of age dummies to (20) solves this issue. I do so as a robustness check by the end of this section, and show that the results are unchanged.

[40]Exporter × product pairs that manage to form more than five importer relationships within an exporter × destination spell constitute 42.5 percent of the total export value among the sample of all *not* left-censored spells. However, shorter spells are, of course, over-represented in this sample.

Table 10: Network Effect on Prices

Dep. var.:	$p_{fpid\tau}$					$q_{fpid\tau}$	
Sample:	Full	Exporter × product pairs that formed more than 5 importer relationships		Exporter × product pairs that formed more than 10 importer relationships			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
network$_{im\tau}$	0.00792	0.00877		0.0109*		0.0112	
	(0.00501)	(0.00554)		(0.00623)		(0.00807)	
$\mathbb{1}$ (network$_{im\tau}$ = 1)			0.0471		0.0520		0.0822
			(0.0311)		(0.0478)		(0.101)
$\mathbb{1}$ (network$_{im\tau}$ = 2)			0.102***		0.0825*		-0.0482
			(0.0341)		(0.0479)		(0.105)
$\mathbb{1}$ (network$_{im\tau}$ = 3)			0.115***		0.0581		-0.00561
			(0.0368)		(0.0544)		(0.109)
$\mathbb{1}$ (network$_{im\tau}$ = 4)			0.145***		0.0739		0.0150
			(0.0426)		(0.0546)		(0.114)
$\mathbb{1}$ (network$_{im\tau}$ = 5)			0.155***		0.131**		-0.0270
			(0.0488)		(0.0608)		(0.123)
$\mathbb{1}$ (network$_{im\tau}$ = 6)					0.0779		0.0600
					(0.0511)		(0.120)
$\mathbb{1}$ (network$_{im\tau}$ = 7)					0.106*		-0.0172
					(0.0597)		(0.124)
$\mathbb{1}$ (network$_{im\tau}$ = 8)					0.0546		0.136
					(0.0624)		(0.131)
$\mathbb{1}$ (network$_{im\tau}$ = 9)					0.144**		0.0885
					(0.0654)		(0.146)
$\mathbb{1}$ (network$_{im\tau}$ = 10)					0.150**		0.157
					(0.0640)		(0.156)
fpd FE	YES	YES	YES	YES	YES	YES	YES
pdy FE	YES	YES	YES	YES	YES	YES	YES
month FE	YES	YES	YES	YES	YES	YES	YES
R-squared (within)	0.001	0.001	0.003	0.004	0.003	0.001	0.002
Observations	49,802	22,961	13,023	11,332	6,957	11,332	6,957

The unit of observation is exporter × product × importer × destination × date ($fpid\tau$). The dependent variables, $p_{fpid\tau}$ and $q_{fpid\tau}$, are the log-price obtained from and log-quantity sold to, respectively, importer i, encountered at τ, in the *first* year of the $fpid$ relationship, *within* the current fd spell. $\mathbb{1}$ (network$_{im\tau}$ $= k) = n$ is a dummy equal to one if f had a network of n importers in d in y. The omitted reference category is $\mathbb{1}$ (network$_{im\tau}$ $= k) = 0$. Column 1 presents results based on all observations. Column 2-3 (4-5) present results based on fpd triplets that formed more than 5 (10) importer relationships. fpd triplets that obtain a network larger than the 99th percentile are excluded. Standard errors clustered at the exporter-product are reported in parentheses. Asterisks indicate statistical significance: * p<0.1; ** p<0.05; *** p<0.01.

In order to address the second concern—that the price effect is non-linear and that exporter × product pairs with large networks keep prices relatively stable—I reformulate regression equation (20) to include a full set of network-size dummies:

$$p_{ijm\tau} = \sum_{k=1}^{K} \gamma_k \mathbb{1}\left(\text{network}_{im\tau} = k\right) + \mathbf{FE}_{ipd} + \mathbf{FE}_{m} + \mathbf{FE}_{month} + error_{ijm\tau}, \tag{21}$$

where $\mathbb{1}(\cdot)$ is the indicator function, K is the size of the sample's largest network, and network$_{im\tau} = 0$ is the omitted reference category.

I estimate equation (21) on the same sample of "long" spells as above, and restrict interest to the first six relationships formed by each exporter × product pair, that is setting $K = 5$.[41] Column 3 in Table 10 shows the results. Upon entry, exporter × product pairs rapidly increase prices as they form more relationships: The price charged from the third relationship (formed when the network consisted of two importers) is 10.2 percent larger than the price charged from the first relationship (formed without a network). Then, prices keep increasing, but at a more modest rate, such that exporter × product pairs earn a price premium of 15.5 percent from their sixth relationship relative to their first relationship. Recall that these price premiums should be interpreted *beyond* any market-wide developments *and*

To examine the price trajectory for even "longer" spells, I further restrict the sample to consist only of exporter × product pairs that formed more than ten importer relationship within an exporter × destination spell. First, I re-estimate the linear effect from equation (20). Column 4 in Table 10 shows that exporter × product pairs increase prices by 1.09 percent each time they form a new importer relationship (statistically significant at the 10 percent level). Second, I allow for a non-linear effect by re-estimating equation (21) and restricting interest to the first eleven relationships, that is setting $K = 10$. Column 5 shows the results. Relative to the price charged from their first relationship, exporter × product pairs charge 8.25 percent higher prices from their third relationship, 13.1 percent higher from their sixth relationship, and 15.0 percent higher from their eleventh relationship. Though the trajectory is less monotone than before, the qualitative picture is the same: Exporter × product pairs first rapidly increase prices, then dampen the the growth rate as their network expands.

Before concluding this section, I perform three simple robustness checks to support my findings. In the first check, I examine the corresponding development in quantities across importers. In the latter two, I augment the fixed effects specifications in equation (20) and (21).

The theoretical model formulated in Section 3 attributes the price premium documented above entirely to the network effect, but completely disregard any developments in the amount of *quantity* sold to different importers encountered at different points in time. If, on the other hand, exporters generally meet larger importers first—simply because they are more visible—they will tend to sell smaller quantities along the way. In the presence of quantity discounts, which I document in the cross-section in Section 2.2, this could explain the increasing prices. To test this hypothesis, I re-estimate equation (20) and (21) with log quantities sold as dependent variable. A large negative estimate would support this hypothesis. Column 6 and 7 in Table 10 present the results for exporter × product pairs that form more than 10 importer relationships. The linear effect on larger network on quantities is positive, but insignificant, and the quantity trajectory for the first eleven relationships is highly non-monotonic with no point estimate significantly

In the full sample including both left-censored and *not* left-censored spells, that is the sample applied in Section 2.2, exporter × product pairs for which we *observe* more than five importer matches constitute 75.6 percent of the total export value. As we do not observe the full network for left-censored spells, the true export value share constituted by exporter × product pairs that form more than five importer relationship is generally larger. In conclusion, this sub-sample of exporter × product pairs is responsible of the lion's share of Danish export value.

[41]Recall that an exporter × product pair has a network of five importers when the sixth importer relationship is formed.

different from zero. Therefor, I find no evidence suggesting that the positive network effect on prices is explained by a corresponding fall in quantities sold.

I now turn to the fixed effects (FE) specification in equation (20) and (21). A threat to my identification strategy is that underlying factors—that are not accounted for by included FEs—are driving both the increase in network size and the price growth. First, recall that the current FE specification includes both an exporter × product × destination FE ($\mathbf{FE}_{ipd}$) and a market FE ($\mathbf{FE}_m$). As mentioned above, this controls for linear effects of exporter × product × destination specific age on prices, but not deviations around such a trend. Rodrigue and Tan (2019) and Piveteau (2019) document that that prices for Chinese and French exporters, respectively, do increase over time. In the present context, network size is, per construction, weakly increasing in age. To rule out that age is driving the results, I augment equation (20) and (21) with age dummies. Table 11 presents the results, resembling the structure of Table 10. Point estimates change only slightly, and all qualitative conclusions prevail. Second, underlying supply-side dynamics could drive both the increase in network and the growth in prices. In Rodrigue and Tan (2019), exporters respond to growing foreign demand by improving product quality, which further increase both market share and prices. A similar mechanism, where exporters expand their customer base by offering products of higher quality, could explain the simultaneous increase in network and prices. As is common in the literature (e.g. Manova and Zhang, 2012; Fitzgerald et al., 2017), I address this concern by augmenting the FE specification with an exporter × product × year FE. The underlying assumption is that marginal production costs are identical across destinations, and that quality upgrading requires more expensive production inputs which will increase marginal production costs. Table 12 presents the results. Point estimates change only slightly, and all qualitative conclusions prevail.

In conclusion, I have found that exporters charge higher prices from new buyers as their network grows, which is in accordance with the predictions produced by the model outlined in Section 3. Further, these price increases are *beyond* those potentially caused by (i) market-wide developments, (i) systematic dynamics related to age, and (iii) costly quality upgrading.

5 Conclusion

The goal of this paper has been two-fold. First, to empirically document that exporters charge higher prices as they form more importer relationships. Second, to provide empirical regularities as well as a simple theoretical framework that, combined, demonstrate that firms use dynamic pricing as a strategy to expand in export markets.

Using a novel data set on firm-to-firm exports by Danish firms, I presented two empirical findings. First, Danish exporters *price discriminate* between their foreign buyers: Ranking all importer relationships in terms of prices, the third quartile is characterized by a price 65 percent larger than the first quartile. Second, Danish exporters enjoy large *network effects* in foreign markets: Adding one importer to an exporters network increases the number of new buyer relationships formed in the following year by 0.36-0.38. I implement these findings in a simple dynamic model, where exporters must match with foreign importers in order to trade. The model predicts that exporters price low upon entry, then increase prices as their network expands.

These findings speak directly to a series of concurrent academic papers, examining expansion strategies of firms in general and exporters in particular. Whereas the bulk of these papers rely on more aggregated data, this paper illustrates that firm-to-firm trade data provides valuable information to the literature. As most existing papers using similar transaction level trade data are exploring cross-sectional regularities, only few examine how firm-to-firm relationships shape exporters' gradual expansion in foreign markets. Therefore, there is both need and room for more research on these topics.

This paper is relevant for how policy-makers should optimally design firm specific trade policies, and how the value of such policies should be properly evaluated. The presence of sizable network effects in foreign markets implies that exporters value their importer relationships *beyond* the profits generated from the particular match as the network itself is a source to further expansion. Further, exporters' first relationships are particularly valuable. Therefore, matching exporters, especially new exporters, to foreign importers should be a primary objective to policy-makers that wish to promote export participation and sales. In turn, this means that proper evaluation of firm specific trade policies, aiming at matching exporters with importers abroad, should take the network effects into account. Failing to account for the indirect value of matching with an importer—the value of more easily forming relationships subsequently—would undervalue the policy, especially as such programs are often targeted new exporters.

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A Model Extension

In this section, I extent the model presented in Section 3 with an endogenous search effort. In the model outlined in Section 3, exporters reach a fixed mass (normalized to one) of new importers in each period and form $(1 - G(p))$ new relationships, where p is the posted price, and G is the commonly known distribution of importers' reservation prices. As in the main text, I impose the assumption $G(p) = 1 - p^{-\eta}$, where $\eta > 1$ is the Pareto distribution's shape parameter.

Now, I allow exporters to reach s new importers. This means that exporters sell to $sp^{-\eta}$ new importers in each period and obtain an immediate profit flow of $(p - mc)sp^{-\eta}$, where mc is the constant marginal production cost. As in the main text, relationships never dissolve and prices are never re-negotiated, which means that the continuation value of this profit flow is

$$\pi(p, s) = \frac{(p - mc)sp^{-\eta}}{1 - \beta}, \tag{22}$$

where β is the discount factor.

The network, m, evolves as

$$m' = m + sp^{-\eta} + \varepsilon, \tag{23}$$

where ε is a mean-zero i.i.d. disturbance term.

Reaching s new importers is associated with a cost of $c(s, m)$. To fix ideas, I specifically assume that

$$c(m, s) = s^{\gamma} m^{-\delta}, \tag{24}$$

where $\gamma > 1$ and $\delta > 0$. This implies that $c(s, m)$ is increasing and strictly convex in s ($c_s(s, m) > 0$) and $c_{ss}(s, m) > 0$) and, as in the main text, decreasing and strictly convex in m ($c_m(s, m) < 0$) and $c_{mm}(s, m) > 0$). To ensure that $c(m, s)$ is convex, I further assume $\gamma - 1 > \delta$.

The exporter's value function is

$$V(m) = \max_{p,s} \left[\pi(p, s) - c(m, s) + \beta E V(m')\right]. \tag{25}$$

The first order condition with respect to p is identical to the one obtained in (18) the main text:

$$p = \frac{\eta}{\eta - 1} \left[mc - \beta(1 - \beta) E V'(m')\right]. \tag{26}$$

The first order condition with respect to s is

$$s = \left(\frac{m^{\delta}}{\gamma} p^{-\eta} \left[\frac{p - mc}{1 - \beta} + \beta E V'(m')\right]\right)^{\frac{1}{\gamma - 1}}. \tag{27}$$

Substituting (26) into (27) and re-arranging yields an expression of s as a function of m and p:

$$s = \left(\frac{1}{\gamma\eta(1 - \beta)} p^{1-\eta} m^{\delta}\right)^{\frac{1}{\gamma - 1}}. \tag{28}$$

To obtain an easily interpretable expression for how search effort varies with the size of the network, simply take the elasticity w.r.t. m on both sides of (28):

$$\frac{\mathrm{d}s}{\mathrm{d}m} \frac{m}{s} = \frac{1}{\gamma - 1} \left(\delta - (\eta - 1) \frac{m}{p} \frac{\mathrm{d}p}{\mathrm{d}m}\right). \tag{29}$$

As the size of the network increases, this affects optimal search effort through two channels. First, a larger network diminishes the cost of searching, which increases the optimal search effort. This effect is increasing in δ, the rate at which search costs falls with the size of the network.[42] I refer to this as the "cost channel". Second, a larger network leads to increasing prices as shown in (26) and discussed in the main text. This leads to two opposing effects on search effort. Firstly, higher prices increase the per-buyer profits, which increases the marginal return to search effort. Secondly, higher prices decrease the share of buyers among the reached importers, which decreases the marginal return to search effort. The net effect on search through higher prices, however, is surely negative as $\eta > 1$. I refer to this as the "indirect price channel". Whether the "cost channel" dominates the "indirect price channel", such that search effort is increasing in the size of the network, depends on model parameters.

However, for the amount of new importers ($sp^{-\eta}$) to be increasing in the size of the network, the requirement is even stronger. This is due to the "direct cost effect", where the positive impact of network on prices directly decreases the amount of new importers. From (29) we easily obtain

$$\frac{\mathrm{d}(sp^{-\eta})}{\mathrm{d}m}\frac{m}{sp^{-\eta}} = \frac{1}{\gamma-1}\left(\delta - (\eta\gamma-1)\frac{m}{p}\frac{\mathrm{d}p}{\mathrm{d}m}\right). \tag{30}$$

For expression (30) to be positive, we require

$$\begin{aligned}\delta &> (\eta\gamma-1)\frac{m}{p}\frac{\mathrm{d}p}{\mathrm{d}m}\\ &= (\eta\gamma-1)\frac{\eta-1}{\eta}\frac{-\beta(1-\beta)EV''(m')}{mc-\beta(1-\beta)EV'(m')}m,\end{aligned} \tag{31}$$

where the equality comes from (26) and that $\mathrm{d}p/\mathrm{d}m = -\beta(1-\beta)EV''(m')$, where $EV''(m') < 0$ is from the concavity of the value function.[43]

Whether this inequality holds, such that the number of new importer relationships is increasing in the size of the network, depends on the underlying parameters and the shape of the value function (for which there is no intuitive expression). It is easy to show, however, that a sufficient condition for (31) to hold for large m is that the elasticity of the marginal value function, that is $\mathrm{El}_m V'(m)$ is asymptotically constant as m grows. Under this relatively mild regularity condition, the "cost channel" will dominate both the "indirect price channel" and the "direct price channel", such that sellers will sell to a growing number of new buyers as m grows, at least for large m.

[42]Note from (24) that $\delta = -\frac{m}{c(s,m)}\frac{\mathrm{d}c(s,m)}{\mathrm{d}m}$.

[43]The value function is concave as long as $\pi(p,s) - c(m,s)$ is concave. $\pi(p,s)$ is concave for all prices, p, below (and including) the static optimum. As claimed above, $c(m,s)$ is convex for $\gamma - 1 > \delta$. Thus, under this assumption, $\pi(p,s) - c(m,s)$ is concave.

B Additional Tables

Table 11: Network Effect on Prices, Including Age FE

Dep. var.:	$p_{fpid\tau}$					$q_{fpid\tau}$	
Sample:	Full	Exporter × product pairs that formed more than 5 importer relationships		Exporter × product pairs that formed more than 10 importer relationships			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{network}_{im\tau}$	0.00797	0.00890		0.0109*		0.0122	
	(0.00502)	(0.00556)		(0.00627)		(0.00802)	
$\mathbb{1}(\text{network}_{im\tau}=1)$			0.0572*		0.0549		0.0777
			(0.0313)		(0.0481)		(0.101)
$\mathbb{1}(\text{network}_{im\tau}=2)$			0.119***		0.0884*		-0.0575
			(0.0343)		(0.0481)		(0.106)
$\mathbb{1}(\text{network}_{im\tau}=3)$			0.134***		0.0655		-0.0187
			(0.0371)		(0.0547)		(0.111)
$\mathbb{1}(\text{network}_{im\tau}=4)$			0.165***		0.0815		0.00135
			(0.0427)		(0.0549)		(0.115)
$\mathbb{1}(\text{network}_{im\tau}=5)$			0.170***		0.139**		-0.0417
			(0.0487)		(0.0614)		(0.124)
$\mathbb{1}(\text{network}_{im\tau}=6)$					0.0861*		0.0436
					(0.0514)		(0.121)
$\mathbb{1}(\text{network}_{im\tau}=7)$					0.114*		-0.0328
					(0.0601)		(0.125)
$\mathbb{1}(\text{network}_{im\tau}=8)$					0.0627		0.119
					(0.0626)		(0.131)
$\mathbb{1}(\text{network}_{im\tau}=9)$					0.151**		0.0720
					(0.0657)		(0.146)
$\mathbb{1}(\text{network}_{im\tau}=10)$					0.156**		0.143
					(0.0643)		(0.156)
age FE	YES	YES	YES	YES	YES	YES	YES
fpd FE	YES	YES	YES	YES	YES	YES	YES
pdy FE	YES	YES	YES	YES	YES	YES	YES
month FE	YES	YES	YES	YES	YES	YES	YES
R-squared (within)	0.001	0.001	0.003	0.004	0.003	0.001	0.002
Observations	49,802	22,961	13,023	11,332	6,957	11,332	6,957

The unit of observation is exporter × product × importer × destination × date ($fpid\tau$). The dependent variables, $p_{fpid\tau}$ and $q_{fpid\tau}$, are the log-price obtained from and log-quantity sold to, respectively, importer i, encountered at τ, in the *first* year of the $fpid$ relationship, *within* the current fd spell. $\mathbb{1}(\text{network}_{im\tau}=k)=n$ is a dummy equal to one if f had a network of n importers in d in y. The omitted reference category is $\mathbb{1}(\text{network}_{im\tau}=k)=0$. Column 1 presents results based on all observations. Column 2-3 (4-5) present results based on fpd triplets that formed more than 5 (10) importer relationships. fpd triplets that obtain a network larger than the 99th percentile are excluded. Standard errors clustered at the exporter-product are reported in parentheses. Asterisks indicate statistical significance: * p<0.1; ** p<0.05; *** p<0.01.

Table 12: Network Effect on Prices, Including fpy FE

Dep. var.:	$p_{fpid\tau}$					$q_{fpid\tau}$	
Sample:	Full	Exporter × product pairs that formed more than 5 importer relationships		Exporter × product pairs that formed more than 10 importer relationships			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{network}_{im\tau}$	0.0102	0.0111*		0.0108		0.0160*	
	(0.00647)	(0.00655)		(0.00697)		(0.00862)	
$\mathbb{1}(\text{network}_{im\tau} = 1)$			0.0586*		0.0505		0.0857
			(0.0318)		(0.0485)		(0.102)
$\mathbb{1}(\text{network}_{im\tau} = 2)$			0.124***		0.0964**		-0.0692
			(0.0348)		(0.0486)		(0.107)
$\mathbb{1}(\text{network}_{im\tau} = 3)$			0.134***		0.0715		-0.0237
			(0.0375)		(0.0553)		(0.112)
$\mathbb{1}(\text{network}_{im\tau} = 4)$			0.164***		0.0877		-0.00471
			(0.0434)		(0.0549)		(0.115)
$\mathbb{1}(\text{network}_{im\tau} = 5)$			0.163***		0.139**		-0.0504
			(0.0496)		(0.0618)		(0.125)
$\mathbb{1}(\text{network}_{im\tau} = 6)$					0.0914*		0.0391
					(0.0513)		(0.121)
$\mathbb{1}(\text{network}_{im\tau} = 7)$					0.119*		-0.0370
					(0.0606)		(0.127)
$\mathbb{1}(\text{network}_{im\tau} = 8)$					0.0665		0.112
					(0.0628)		(0.132)
$\mathbb{1}(\text{network}_{im\tau} = 9)$					0.145**		0.0824
					(0.0662)		(0.147)
$\mathbb{1}(\text{network}_{im\tau} = 10)$					0.133**		0.187
					(0.0649)		(0.159)
fpy FE	YES	YES	YES	YES	YES	YES	YES
fpd FE	YES	YES	YES	YES	YES	YES	YES
pdy FE	YES	YES	YES	YES	YES	YES	YES
month FE	YES	YES	YES	YES	YES	YES	YES
R-squared (within)	0.001	0.001	0.003	0.004	0.003	0.001	0.002
Observations	44,894	22,354	12,566	11,215	6,883	11,215	6,883

The unit of observation is exporter × product × importer × destination × date ($fpid\tau$). The dependent variables, $p_{fpid\tau}$ and $q_{fpid\tau}$, are the log-price obtained from and log-quantity sold to, respectively, importer i, encountered at τ, in the *first* year of the $fpid$ relationship, *within* the current fd spell. $\mathbb{1}(\text{network}_{im\tau} = k) = n$ is a dummy equal to one if f had a network of n importers in d in y. The omitted reference category is $\mathbb{1}(\text{network}_{im\tau} = k) = 0$. Column 1 presents results based on all observations. Column 2-3 (4-5) present results based on fpd triplets that formed more than 5 (10) importer relationships. fpd triplets that obtain a network larger than the 99th percentile are excluded. Standard errors clustered at the exporter-product are reported in parentheses. Asterisks indicate statistical significance: * p<0.1; ** p<0.05; *** p<0.01.