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Internalization of externalities in international trade

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Abstract
Using disaggregated customs data about exporters from nine countries, I demonstrate that informational externalities are determinants of entry, survival, and growth of exporters at the product–destination market level. I show that exporters who optimize entry decisions and internalize informational externalities survive longer and grow faster. Then, I conceptualize why exporters enter certain international markets and why not all exporters from the same origin survive and grow in these markets. I incorporate the interaction between the performance and number of peers in a given market to identify a potential learning externality that exporters may be exposed to. Also, I highlight that, even without the formation of formal networks, the observation of the actions of peers in export markets can deliver implications for export flows: exporters may not need to start small in new markets if the actions of peers in those markets reveal enough information. By helping to explain how export relationships survive and grow, I complement the literature on the determinants of export diversification and signal to export promotion agencies the importance of internalization of informational externalities by exporters.

Keywords Exporters dynamics · Peer effects · Informational externalities · Market entry · Diversification · Trade · Development

JEL Codes: D81 · F14 · F23 · F63 · L11 · L25

1 Introduction

First movers generate information that can be used by late movers to a market. This information is typically concerned with market supply and demand. Whether information can be transferred among firms has been the subject of various studies since

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Arrow (1962). Exporters, as firms, can influence the survival and growth of each other in different ways. From one end, exporting peers[1] can learn from each other about the product demand and consumer preferences at destination. From another end, exporting peers can inform each other about quality standards, regulations, and distribution networks at destination. Thus, to gain market information, exporters usually engage in several activities. For instance, Rauch and Watson (2003) showed that when a commercial relationship begins, the buyer might experience uncertainty about the supplier's ability to successfully fulfill large orders. Lederman et al. (2010) documented how informal networks help exporters make more informed decisions and, thus, have a higher likelihood of surviving and growing. Among the remaining questions to investigate, as well as the scope of this paper, is whether or not peer effects (i.e., informational externalities) exist in the firm internationalization process, and if they do in fact factor into the equation, what role do they play.

It is important to understand the dynamics of peer effects[2] in export markets for an array of reasons. First, a clear idea about how exporters learn from each other would allow us to know more about market exploration mechanisms and whether or not market failures exist. Second, given exporters and exported products are new at some point, knowing which exporters survive longer and grow faster is key for trade growth and economic development; as documented by Amsden (1992), Kehoe and Ruhl (2013), and Lucas (1993), new exported products and economic growth are correlated within the industrialization process of countries.

In this paper, I conceptualize why exporters enter certain markets and why not all exporters from the same origin survive and grow in these markets. I show that the exporters who optimize entry decisions and internalize externalities are those who survive longer and grow faster. Accordingly, I investigate whether information flows from more-informed exporters to less-informed exporters. The conceptual framework follows Melitz (2003) while adopting the decision-making process demonstrated in Rob (1991), which is generally pursued by exporters that are monopolistically competitive and heterogeneously productive. The profits of each exporter depend on their productivity, the demand on their products, and aggregate market demand. While the more-informed exporters are the ones already present in a given market, the less-informed exporters are the ones who have still not entered the same given market. To exist in a given product–destination market, exporters need to pay a sunk entry cost plus the fixed cost of exporting to that market. Although exporters learn about their productivity level and the sunk entry cost in advance, they can only know the demand on their products, the aggregate market demand, and the fixed cost of exporting to a given product–destination market after entering that market. The exporter thus can only know the per-period fixed costs that would allow them to survive in the marker after having joined the product–destination market. The exporter would survive in that market if their per-period export revenues cover the per-period fixed costs of existence. Thus, advanced knowledge of the per-period fixed costs would help exporters survive in a given market and not pay the sunk cost only to exit. By

[1] Throughout this paper, an exporting peer is defined as an exporter shipping the same product from the same origin to the same destination.

[2] Throughout this paper, I use the terms "informational externalities" and "peer effects" interchangeably.

observing the actions of other exporters from her origin to a given product–destination market, an exporter can gain advanced knowledge. This observation creates a learning framework with endogenous timing in a way that the most productive exporters enter a given product–destination market first while the less productive exporters wait to gain advanced knowledge about the per-period fixed costs.

This conceptual framework helps in identifying the equilibrium path of survival and growth by employing Melitz (2003) properties without parameterization. It considers the effect of entrants not only on informational externalities, but also on individual revenues through the general equilibrium effect on prices. In other words, it is not necessary to solve for the price indices; it is sufficient to identify the path navigated by surviving and growing exporters in terms of properties of the price indices. Thus, this conceptual framework deviates from standard strategic interactions (i.e., through pay-offs). For example, an exporter deciding to enter a given product–destination market does not consider the effect that their entry may have on the entrance and pay-offs of other exporters. Instead, they assess the number and performance of peers existing in that market with their knowledge of it, with entrance being incentivized by many peers entering, and doing well in, that market. Thus, the conceptual framework incorporates the interaction between the performance and number of peers in a given market to identify a potential externality that an exporter may be exposed to.

This conceptual framework advances a clear mechanism. The lack of product–destination market information blocks exports to that market, even those by more productive exporters. Correspondingly, the more productive exporters always enter markets that they have knowledge about. As soon as an exporter enters a certain product–destination market, they reveal—via their survival in that market—knowledge to other exporters. Given this new knowledge, exporters then decide whether or not to join the first exporter. However, entry into the new market may cease before full market information becomes known. The marginal entrant, for example, may not find it profitable to enter when the informational externalities stop being enough to compensate the risk of entering a product–destination market. In other words, both the average and volatility of the performance of peers factor into an exporter's decision to enter a given market. When a given market peers' performance improves and becomes less volatile, less-productive exporters become incentivized to enter. This conceptual framework identifies the sufficient and necessary conditions for informational externalities, before initial entry, that allow for the survival and growth of exporters after entry. In summary, the number, state, and volatility of the performance of peers, in addition to the information available on the market, are determinants of exporters' decision to enter said market and of their probability to survive and grow in it.

To test the predictions of the conceptual framework, I utilize a unique exporter-level customs dataset from nine countries.[3] This dataset allows for distinguishing old products from new ones at the origin–firm–product–destination level over time. It would thus provide an opportunity to chronologically order precisely the entry of firms and products from country of origin to that of destination as well as to analyze all (successful and failed) cases of exporters and exported products. In comparison

[3] These countries are Burkina Faso, Bulgaria, Egypt, Guatemala, Jordan, Mexico, Malawi, Peru, and Senegal.

with previous literature (i.e., Cebeci et al. (2012)), I define a new product as one that has not been exported over the last two years. This way, I can ensure that re-entry of intermittent products (i.e., those that were exported for a year, then not exported for a year, before being exported again) are not counted as new products when ordering the movers to a given product–destination market.

I document that survival and growth of exporters are increasing functions of the number and performance of their peers. In addition, I show that exporters learn more from their peers than from exporters from other origins to same product–destination markets. The results are robust to a number of robustness checks, and they confirm the conceptual framework about whether or not informational externalities can help us understand why (only some, not all) exporters survive and grow. These results also hold in the presence of fixed effects that control for supply and demand shocks.

In accordance with these results, I make 4 contributions in this paper. First, I conceptualize why exporters enter certain international markets and why not all exporters from the same origin survive and grow in these markets. I incorporate the interaction between the performance and number of peers in a given market to identify a potential externality that an exporter may be exposed to. Second, I analyze a uniquely detailed dataset comprising firm-level exports disaggregated at product–destination levels, for nine origin countries. With respect to the existing literature, this level of data disaggregation provides valuable information to assess informational externalities. Third, I show that exporters who optimize entry decisions and internalize externalities are those who survive longer and grow faster. Fourth, I highlight that, even without the formation of formal networks, the observation of the actions of peers in export markets can deliver implications for export flows: exporters may not need to start small in new markets if the actions of peers in those markets reveal enough information.

On the policy front, by helping to explain how export relationships survive and grow, I complement the works of Easterly et al. (2014), Grossman and Rossi-Hansberg (2010), and Hausmann and Rodrik (2003) on the determinants of national exports diversification and success. I document that if more exporters from the same origin target the same product–destination market, their survival and growth chances increase. I signal to export promotion agencies the importance of internalization of informational externalities by exporters. Given that exporters may not have incentives to assist their peers, the design of export promotion programs is key. Also, an increase in national exports can come from new or existing exporters to new or existing export markets. Before entering a new market, which is rarely without hesitance, exporters need knowledge about said market. Thus, understanding the relationship between peer effects and the mechanisms of exporters survival and growth can enhance assessments of the potential contributions of extensive and intensive margins of exports. If the goal is to increase exports, it is important to identify export policies that can encourage exploration and harnessing of export markets by exporters.

The remainder of the paper is structured as follows. The second section reviews the related literature. The third section presents a conceptual framework. The fourth section explains the dataset. The fifth section describes the identification strategy and estimation issues. The sixth section presents the empirical analysis. The seventh section concludes.

2 Related literature

Many authors have taken interest in informational externalities. However, their works differed in several important aspects, among which are the definition of informational externalities (i.e., restricted to multinational firms or including all exporters) or the level of data disaggregation. For example, Aitken et al. (1997) studied the relationship between the presence of multinational firms and the export behavior of Mexican plants in the period spanning 1986 to 1989. Also, Kinuthia (2017) used firm-level data from Kenya and Malaysia for 2000-05 to investigate the existence of export spillovers from foreign-owned firms to domestic firms and their transmission mechanisms. Greenaway et al. (2004) showed that multinational firms located in the UK positively influenced the export decision of domestic firms over the years 1993–1996. Further export spillovers from foreign direct investment were investigated by Kneller and Pisu (2007) employing UK data from 1992 to 1999. The authors found that the presence of foreign multinationals in the same industry or region positively affects the intensive and extensive margins of trade. Also, using UK data, Greenaway and Kneller (2008) showed that regional and sectoral agglomerations are beneficial for the entry of new firms on export markets. In addition, Kang (2016) showed that agglomeration of exporters affects export decisions.[4] They measured agglomeration by the number of skilled workers. On the other hand, two papers underlined the absence of evidence of export spillovers. Barrios et al. (2003) studied the export decision and the export intensity of Spanish firms between 1990 and 1998 and did not find evidence that Spanish firms benefit from spillovers through the presence of other exporters or multinational firms. Furthermore, Bernard and Jensen (2004) found no effect of export spillovers on export decision in a panel of U.S. manufacturing firms, regardless of whether or not the spillovers are region specific but outside the industry, industry specific but outside the region, or region and industry specific.

Others have examined how a firm's decision to start exporting is affected by the availability of information on export markets. For example, Ramos and Moral-Benito (2017) used a dataset of Spanish exporters with rich spatial information to document the existence of agglomeration economies by export destination. They found that firms selling to countries with worse institutions, a dissimilar language, and a different currency are significantly more agglomerated. In addition, Inui et al. (2015) examined whether main banks act as a conduit of information on export markets. They found that information spillovers through main banks positively influence client firms' decision to start exporting (extensive margin), implying that information on foreign markets provided by banks substantially reduces the fixed entry cost of exporting. The fact that banks have different branches at the country level may mean that information spillovers need not be physically local. However, the authors did not find any evidence that information provided by banks had an effect on the export volume or growth. Clercq et al. (2008) drew on the knowledge spillover literature to suggest that a country's proportion of new export-oriented ventures represents an outcome of knowledge spillovers that stem from export spillovers. Using macro-level data from 34 countries during the period 2002–2005, they found that a country's proportion of export-oriented

[4] See related work by Broocks and Van Biesebroeck (2017).

ventures affects the subsequent emergence of new businesses. Moreover, Harasztosi (2016) examined whether or not there are spillover effects in exporting activity, using Hungarian product–country-level manufacturing trade data. He illustrated that exporting activity exhibits spillovers and benefits that are country and product specific. In addition, he highlighted that export spillovers demonstrated considerable heterogeneity: while foreign-owned firms benefit from peers generally, domestic firms only avail themselves to the agglomeration of domestic exporters.[5] Also, Kasahara and Tang (2019), using transaction-level data for all Chinese firms exporting between 2000 and 2006, found evidence to support the hypothesis that firms' high entries and exits are outcomes of their rational self-discovery of demand in an unfamiliar market. And, using a firm–product-level dataset on China's exports during the period 2000–11, Zhou et al. (2019) compared the impacts of intra- and inter-firm knowledge spillovers on the emergence of new products at the firm level. Their empirical results indicated that firm diversification is dependent on both intra- and inter-firm knowledge spillovers, though the effect of the former is much greater. Moreover, Sui et al. (2019) investigated how home-peer entry density (the number of same-industry firms that originate from the same country and export to the same foreign market) affects the export market exit of small firms. Drawing on panel data from 41,445 Canadian small business exporters, the authors found a U-shaped relationship between home-peer entry density and small firms' hazard of exit from an export market; that is, firms' hazard of exit decreases as the home-peer density increases to a certain point and increases after that point.

In addition, Koenig et al. (2010) highlighted the localized feature of the positive effects on firms' export performance captured in the spillovers, i.e., market externalities of exporters agglomeration (cost sharing) and information flows between exporters. The authors showed that spillovers seem to be highly localized and have a decreasing trend with distance from the initial firm. The probability of starting to export increases by 0.9 percentage point when an additional firm exporting the same product to the same country locates in the same area. The effect, however, is almost three times smaller for a firm locating in the region but in a different area (0.3 percentage point) and almost six times smaller when locating in a different region (0.17 percentage point). These results attest that spillovers on the export decision exist with product- and destination-specific neighbors, and decrease with the geographic extent in which the authors count the number of exporting firms. One can reasonably think that the larger the distance, the more difficult and costly the cooperation between firms, and consequently the less powerful the information spillovers. Moreover, flows of information have been shown to be geographically restricted by Jaffe et al. (1993).

Also, using Russian customs data, Cassey and Schmeiser (2013) documented that regional destination-specific export spillovers exist for developing countries. Along the same lines, Farole and Winkler (2014) assessed how firm location determines the likelihood of exporting. They showed that, in addition to firm-specific characteristics, agglomeration factors have a significant impact on export participation. And, Arguello et al. (2020) explored whether agglomeration of exporters enhances duration of export flows at the firm–product–destination level using transaction-level data for the universe of exports in Colombia between 2005 and 2011. They found that both the presence

[5] Bisztray et al. (2018) used firm-level data from Hungary to estimate knowledge spillovers in importing.

and size of agglomerations increase the survival rate of trade flows, defined by the triple firm–product–destination.

Moreover, there is a growing literature providing insights on the mechanism of industrial agglomeration and policy. Fontagné et al. (2013), for example, shed light on the selection of beneficiaries from the French competitiveness cluster policy. They analyzed the selection and self-selection effects, as emphasized in the theoretical literature on regional and industrial policy. Their main conclusion was that winners were (self-)selected at both steps of the procedure and that this holds for the three cluster types: "worldwide," "potentially worldwide," and "national clusters." Furthermore, based on the Annual Survey of Industrial Firms in 2002 and 2007 in China, He et al. (2016) investigated the driving forces of the spatial agglomeration of exporters as well as the co-agglomeration of exporters and non-exporters using three-digit-level industries as observations. Their results indicated that agglomeration benefits underpin the agglomeration of exporters and their co-agglomeration with non-exporters.

My work also supplements innovation strategy and international marketing literature. It shares with this literature the focus on order of market entry (Gilbert and Newbery (1982), Henderson (1993), and Prusa and Schmitz (1994)) as well as on stages of internalization at the firm level (Moen and Servais (2002)). However, it contrasts this literature in its observation of all exporting firms, exported products, and industries in a country. In addition, it is related to recent papers on export growth in various developing countries. These papers highlight case studies of successful export experiences at the sector and product levels (i.e., Artopoulos et al. (2013), Conley and Udry (2010), Hidalgo et al. (2007), and Porter (1990, 1998)) but give relatively less attention to failing export experiences. By employing data about all the export transactions from nine countries, I am able to compare both successful and less successful export experiences.

In this paper, I complement the above literature by showing that, even without the formation of formal networks, the observation of the actions of peers in export markets can deliver implications for export flows. Also, exporters may not need to start small in new markets if the actions of peers in those markets reveal enough information. While other studies[6] underscore the importance of uncertainty in explaining survival in export markets, I explore the contribution of informational externalities to the determination of exporters entry to as well as survival and growth at export markets. I document that exporters who optimize entry decisions and internalize externalities are those who survive longer and grow faster. I accordingly also contribute to the burgeoning microeconometric literature on exporters dynamics (Eaton et al. (2004, 2011), Iacovone and Javorcik (2010), Khandelwal and Topalova (2011), Berman et al. (2012), Cadot et al. (2013), and Berthou and Fontagné (2013), Broocks and Van Biesebroeck (2017), Kinuthia (2017), Ramos and Moral-Benito (2017), Bisztray et al. (2018), Sui et al. (2019), and Zhou et al. (2019), Kasahara and Tang (2019), Arguello et al. (2020), and (Haidar 2020, 2017, and 2012).[7]

[6] See, for example, the works of Das et al. (2007), Caplin and Leahy (1993, 1998), and Rob (1991).

[7] Thanks to the recent World Bank Exporters Dynamics Database (Cebeci et al. (2012)), more studies on exporters dynamics are now feasible given data availability.

3 Conceptual framework

I designed a conceptual framework to guide my analysis on how informational externalities may influence exporters entry, exports, survival, and growth during the internationalization process. This conceptual framework displays the effects of informational externalities caused by peers by building on the seminal work of Jovanovic (1982). While Foster and Rosenzweig (1995) and Conley and Udry (2010) studied the effects of informational externalities on production technology, I study the effects of informational externalities by peers on demand. I deviate from learning about production and instead focus on the reasons why exporters refrain from exporting to more markets. It has been established that the majority of exporters do not export to many markets because they are either uncertain about the demand at foreign markets or are not productive enough to make profits by exporting to more markets (see Bernard et al. 2012).

An exporter holds an expectation about the demand at a given product–destination market before entering it. The exporter updates both their past knowledge about the market demand and the precision of their expectation after observing how their peers perform in that market. Following Melitz (2003), I assume that exporters are heterogeneous in terms of productivity and product markets are monopolistically competitive. Also, I assume constant-elasticity-of-substitution preferences and that each exporter faces her own downward-sloping demand. Before entering a new product–destination pd market, an exporter e draws productivity from a cumulative distribution function.

Each exporter knows their own productivity before entering a given product–destination market. However, they do not know their export profit due to random exporter product–destination demand. I assume that the market-specific demand component, which is common for all exporters, and the exporter's product-specific appeal at destination are time invariant. While the exporter can infer the market-specific demand from peers, they can realize their own product-specific appeal at destination only after exporting for the first time to that destination.

I am interested in studying whether or not an exporter learns from their peers, not from their self. Others have also looked at learning-by-exporting mechanisms (Clerides et al. 1998). If the market-specific demand from peers and the exporter's product-specific appeal at destination are time variant, as long as each of them is autocorrelated across time with a permanent component, then exporters will still learn from their peers. That is why I control for time-varying components, in the identification strategy and empirical analysis below, by including exporter–year, destination–year, and origin–year fixed effects.

The results below would still hold if I assume market-specific demand is time-varying and positively correlated across time. Additionally, the assumption that product-specific appeal at destination is time invariant is consistent with recent findings. For instance, Eaton et al. (2007) showed that the 2-year survival rate of Colombian exporters is 90% and does not change in subsequent years. Two exporters can have different profits in the same product–destination market even if they maintain the same productivity level due to differences in exporter-level product-specific appeal at destination. I assume that exporter-level product-specific appeal at destination is unknown ex ante to the exporter. The expected revenue of the exporter depends on

both the average value of exports at the product–destination market and its variance. Thus, a higher level of market uncertainty should thus reduce entry, especially given that exporters would have to pay a sunk cost to enter a given market. Accordingly, the exporter would not attempt to enter a given market if they expect a stream of per-period revenues that are lower than the sunk entry cost.

Each exporter has a number of peers. I assume that the exporter observes the average peers' export revenue to a product–destination (pd) market. Nonetheless, I understand that the exporter may not be able to observe all the exporters given networks matter. Though, for now, I keep the conceptual framework simple and explore differential peer effects in the empirical analysis. Also, I assume that the exporter knows the time-varying conditional mean of peers' productivity. Following Dinlersoz and Yorukoglu (2012), I further assume that exporters have limited memory and do not remember the productivity thresholds.

The exporter's decision to enter the pd market also depends on the number of peers in the pd market and on the expected revenues. I neither look at why some exporters decide to enter given markets before others nor at the strategic interactions among exporters. In other words, I do not study whether the entry of a given exporter affects the entry decision of other exporters. I assume that exporters have strong incentives to hide information from potential competitors. Therefore, the exporter may prefer to delay entry in order to avoid informational spillovers to potential competitors and to obtain more information from existing exporters. The exporter will enter a pd market after revealing expectation that lowers the entry threshold.

A stronger revealed expectation in the presence of peers serving market pd will decrease the entry threshold and, subsequently, increase entry as well as the number of peers. The threshold decreases because the precision of the revealed expectation will improve when there are more peers. When the precision of the revealed expectation improves, potential entrants would put more weight on it than on their own prior knowledge about the given market. However, the direction of the relationship between the number of peers and the entry threshold is not clear because peers can reveal different kinds of signals (i.e., good and bad news about the market). Depending on the signal, a higher number of peers may lead to opposite impacts on exporters' entry. Conditional on the average level of revealed expectation, a less precise revealed expectation is correlated with a smaller entry response. Similarly, less precise past knowledge is correlated with a larger response to a given average revealed expectation, suggesting that the exporter will put a larger weight on the revealed expectation and a smaller weight on their own past knowledge about a given market.

Exporters typically enter given markets with low export values (Iacovone and Javorcik (2010)). It is important to study whether or not first-time export values of a given entrant to a given pd market are associated with revealed expectations from peers. The first-time export values of a given entrant, with a given productivity, to a given pd market depends on the exporter's productivity, posterior expected demand, and the variance of the revealed expectation. Thus, an increase in revealed expectations leads to a higher first-time export value by a given exporter to a pd market. By looking at the interaction between the revealed expectations and the number of peers, I can identify the peer effect on exporter's first-time exports to a given pd market. An exporter's first-time exports to a given market increase in the strength of the revealed expectation

received from peers about *pd* market's demand as well as if the expectation is revealed by more peers.

Each exporter is expected to survive in a given *pd* market if their profit exceeds their per-period fixed cost of exporting. The number of peers affects the number of entrants by changing the entry threshold, but should have no effect on an exporter's survival. Precisely, given sunk entry costs, positive signals from peers may lead to more entry of less productive exporters to *pd* market. However, given per-period fixed exporting costs, the less productive exporters have a higher probability to exit after entering a given market. The conceptual framework assumes that (i) productivity is exporter specific and (ii) product appeal is not known before entering market. In the empirical analysis, we control for exporter–year fixed effects to focus on within-exporter variation in survival. The probability of exporter's survival in a new market is independent of the number of peers but increases with the information revealed by peers about market's demand. Moreover, the growth rate of exports of exporters to a new market increases in the level of the ex ante expectation about *pd* market's demand and if the expectation is revealed by more peers.

4 Data

I employ a rich customs dataset that is disaggregated at the exporter–product–destination–value–year level. It has been collected from raw data files of customs authorities in nine countries: Burkina Faso, Bulgaria, Egypt, Guatemala, Jordan, Mexico, Malawi, Peru, and Senegal. All non-oil exporting firms and export transactions from these countries are included in the dataset. The periodicity of the observations is annual. The data include the following variables for each export transaction: exporter ID, product ID, destination of shipment, value of exports[8], and year of transaction. The HS-6-digit-level product classification illustrates the narrowness of product definitions and the richness of micro-level information available in the dataset.[9] To test the quality of the data, I compared it with (i) UN-Comtrade data and (ii) mirror data (what every other destination reports as imports from each of the nine countries of origin that are covered in this study). The customs dataset is highly correlated with both UN-Comtrade data and mirror data.

This customs dataset has specific advantages. First, given that it includes export records at the exporter–product–destination–year level, it allows monitoring micro-level dynamics, such as entry and exit rates, export volumes and distributions, and prices and growth at the exporter–product–destination level. Second, it assists in distinguishing between the number of products that are exported by each exporter to each destination—the extensive margin—and the export value per product per exporter to each destination—the intensive margin. Within country pairs, for example, I define the extensive margin with an exporter–product dimension rather than with a simple product dimension, since each exporter is likely to export more than one product. Third,

[8] I deflated export values to their first year equivalents using the monthly US consumer price index (from Global Financial Data).

[9] The raw customs data from Egypt in the dataset include only the HS-4-digit-level product classification.

it allows for identifying first movers and late movers to given product–destination markets at the origin–firm level. I define a first mover as a firm that started exporting a given product to a given destination first and a late mover as a firm that began exporting the same product to the same destination at least one year after the first mover stepped in. Fourth, it allows for distinguishing new products from old products. I define a new product as an HS-6-digit code that was not exported by any existing exporter during the first two years of available data for any country in the dataset. This way I do not count new exporters of new products as first movers to a given destination. Instead, I focus only on surviving exporters, i.e., existing exporters who introduced new products to a given destination to avoid mixing between new exporters (i.e., ones without prior experience) and existing exporters who step into a new market.

This dataset has three disadvantages as well. First, its observations are likely to be subject to two types of censoring: left censoring, or right censoring. In the case of left censoring, I cannot determine whether an exporter with a positive export value in the first year of the dataset started exporting in that year or before (i.e., if it is a new exporter or not). Thus, for accuracy purposes, I only consider exporters that started exporting strictly during the second year of the country's sample when I estimate the effect of informational externalities on entry rates. Similarly, for right-censored observations, I cannot determine whether exporters reporting a positive export value in the last year of the country's sample exited the next year. Accordingly, I only consider the exits that took place before the last year in the sample when I estimate the effect of informational externalities on exit rates.

Second, I cannot know the probability of a firm becoming an exporter. This statistic, however, is beyond the scope of this paper as I am mainly interested in studying whether or not existing exporters enter, survive, and grow in given markets as a function of peer effects, and if they do, how exactly these elements interrelate. I only have data on firms that export, and accordingly, that serve the purpose of this study.

Third, the dataset excludes any other characteristic of exporters. I neither, for example, know the ownership, employment, capital, and location of the exporter nor have access to information on their finances. However, given the scope of and the question asked in this paper, this caveat is not a hurdle.

Table 1 presents basic descriptive statistics about exporter-level customs data. For each source country, it shows the annual average number of exporters, products per exporter, destinations per exporter, exporters per product, exporters per destination, export value per exporter, among other information. Peru has the longest time-series (13 years) followed by Senegal (11 years). On annual average basis, Mexico has the highest average number of exporters (33,725) followed by Bulgaria (16,252). In terms of average number of HS-6-digit products per exporter, Jordan is the least diversified (2.65), and Guatemala is the most diversified (7.89). In terms of average number of destinations per exporter, Mexico is the least diversified (1.9), and Senegal is the most diversified (3.21). In all countries in the sample, the high exit rates after the first year suggest that a binary coding of survival based on second-year outcomes is a good summary measure of survival. Overall, the descriptive statistics in Table 1 indicate that exporters from developing countries do not shy away from trying and experimenting with products and destinations. The Hausman and Rodrik (2003) "self-discovery" process thus seems to hold not only at the national level, but also at the

Table 1 Descriptive statistics of exporter-level customs data

Country	BFA	BGR	EGY	GTM	JOR	MEX	MWI	PER	SEN
Sample period	05-10	01-06	06-12	03-10	03-12	00-06	04-09	97-09	00-10
# of exporters	408	16252	8244	4386	1785	33725	631	5225	643
# of entrants	185	7103	2029	1390	683	12408	279	2145	265
# of exiters	178	8210	2132	1328	541	12537	429	1837	229
Herfindahl–Hirschman Index	0.219	0.009	0.005	0.009	0.038	0.007	0.128	0.033	0.078
# of HS6 products per exporter	3.76	5.44	4.2	7.89	2.65	4.79	4.25	6.61	6.11
# of Destinations per exporter	2.35	2.12	2.59	2.44	2.97	1.90	1.93	2.63	3.21
# of Exporters per HS6 product	2.42	22.97	8.3	11.21	4.07	39.20	3.21	12.21	2.90
# of exporters per destination	11.51	184.94	123.05	80.59	37.03	339.43	11.25	85.54	22.11
Export value per exporter (in millions)	1.50	0.54	1.89	1.33	1.60	4.83	1.07	2.34	1.13
Export value per entrant (in millions)	0.21	0.06	0.26	0.15	0.24	0.44	0.31	0.15	0.11
Export value per exiter (in millions)	0.23	0.04	0.44	0.12	0.09	0.33	0.04	0.13	0.11
Export value per survivor (in millions)	0.43	0.13	0.43	0.34	0.46	0.98	2.24	0.27	0.17
Firm entry rate	0.43	0.45	0.25	0.31	0.37	0.37	0.52	0.40	0.40
Firm exit rate	0.42	0.48	0.26	0.31	0.32	0.37	0.61	0.37	0.36
Firm survival rate	0.43	0.30	0.53	0.40	0.47	0.40	0.25	0.44	0.39
Growth rate of export value of survivor	0.43	0.47	0.64	0.49	0.56	0.35	0.09	0.42	0.42
Share of entrants in total export value	0.08	0.04	0.03	0.04	0.05	0.03	0.12	0.03	0.04
Destination entry rate of incumbents	0.40	0.29	0.25	0.23	0.34	0.15	0.32	0.28	0.36
Destination exit rate of incumbents	0.41	0.28	0.27	0.22	0.32	0.14	0.30	0.26	0.35
Destination entry rate of survivors	0.45	0.33	0.26	0.31	0.40	0.17	0.35	0.31	0.45

Table 1 continued

Country	BFA	BGR	EGY	GTM	JOR	MEX	MWI	PER	SEN
Destination survival rate of 2-year incumbents	0.35	0.44	0.37	0.46	0.47	0.44	0.40	0.43	0.39
Share of new destinations in TEV of survivors	0.42	0.29	0.22	0.26	0.33	0.14	0.28	0.25	0.42
HS6 product entry rate of survivors	0.55	0.47	0.41	0.42	0.48	0.42	0.58	0.45	0.55
Share of new products in TEV of survivors	0.47	0.38	0.34	0.32	0.40	0.32	0.49	0.33	0.48
Product survival rate of 2-year incumbents	0.27	0.34	0.28	0.35	0.35	0.34	0.20	0.35	0.27

The first row lists the 3-letter codes of the relevant countries: Burkina Faso, Bulgaria, Egypt, Guatemala, Jordan, Mexico, Malawi, Peru, and Senegal. The second raw lists the sample period of the customs data available and used for each country. Each statistic represent annual average over the sample duration for each country. Exporter is any firm that exports in year t. Entrant is a firm that does not export in year t-1 but exports in year t. Exiter is a firm that exports in year t but not in t+1. Incumbent is a firm that exports both in t-1 and t. Survivor is a firm that does not export in t-1 but exports in both t and t+1. In other words, incumbents in one year are total firms in last (entrants+incumbents) minus exits from last year. Growth of export value per survivor = (ln(exports value of a specific survivor in t+1) - ln(exports value of the same survivor in t)). Firm entry rate = number of entrants / number of exporters. Firm exit rate = number of exiters / number of exporters. Firm survival rate = number of survivors / number of entrants. Share of entrants in TEV = total export value of entrants / total export value in that year. % Share of new products = export value of new HS6 products exported by a specific incumbent / total export value of the same incumbent. Destination entry rate of incumbent = number of destinations not exported in t-1 but exported in t by a specific incumbent / number of all destinations exported by the same incumbent in t. Destination entry rate of survivors = number of destinations not exported in t but exported in t+1 by a specific survivor / number of all destinations exported by the same survivor in t+1. % Share of new destinations in TEV of survivors = value of new destinations exported by a specific survivor / total export value of the same survivor

exporter level. This pattern is also consistent with the notion that exporters face, ex-ante, uncertainty about export costs, demand parameters, and their own capacity to "match" these parameters. This notion is central to the literature on the heterogeneous-firm model.

5 Identification strategy

Given that the primary interest is in the survival and growth of entering exporters, I defined a (e, p, d, t) spell in the first year of its existence in dataset. I consider that this spell (i) survives if it lasts more than one year and (ii) grows if the growth rate of the associated export value is above zero. Then, for each following year, I associated the spell with a survival dummy equal to one and with a growth dummy equal to one. If otherwise the spell lasts only one year, the survival dummy is zero. Likewise, if the growth rate of the export value associated with the spell is equal to or less than zero, the growth dummy is zero. Multiple spells account for only a small number of observations given that the sample periods are relatively short in terms of the number of years. I dropped the spell if it exited in the first year. Doing so permits bypassing the issue of how long a spell break should be to be considered the death of an exporter in a given export market, especially as there is no consensus on this issue in the survival literature. Two more reasons justify using this binary definition of survival. First, the duration of the data is relatively short. Second, as Table 1 shows, once an exporter has survived the first year, their survival probability increases.

Following the literature on the intensive and extensive margins (i.e., Eaton et al. 2007)), I grouped the primary units of observations into (i) new exporters, NE, (ii) new products, NP, (iii) new destinations, ND, and (iv) continuing exporter–product–destinations, $CEPD$. Formally, let $v_{ei,t-1}$ designate exporter e's total exports in year $t-1$, $v_{eip,t-1}$ designate exporter e's exports of product p in year $t-1$, $v_{eid,t-1}$ designate exporter e's exports to destination d in year $t-1$, and $v_{eipd,t-1}$ designate exporter e's exports of product p from origin i to destination d in year $t-1$. These four categories are:

$$\begin{aligned} NE &= \left\{(e,i,p,d,t) \quad \text{s.t.} \quad v_{eipdt} > 0 \quad \text{and} \quad v_{ei,t-1} = 0\right\} \\ NP &= \left\{(e,i,p,d,t) \quad \text{s.t.} \quad v_{eipdt} > 0, \quad v_{ei,t-1} > 0, \quad \text{and} \quad v_{eip,t-1} = 0\right\} \\ ND &= \left\{(e,i,p,d,t) \quad \text{s.t.} \quad v_{eipdt} > 0, \quad v_{ei,t-1} > 0, \quad \text{and} \quad v_{eid,t-1} = 0\right\} \\ CEPD &= \left\{(e,i,p,d,t) \quad \text{s.t.} \quad v_{eipdt} > 0 \quad \text{and} \quad v_{eipd,t-1} > 0\right\} \end{aligned} \tag{1}$$

The dollar value of exports in the first three categories can only go from zero in year $t-1$ to some positive value in year t; these variations add up to the extensive margin. Similarly, changes in the dollar value of exports in the last category form the intensive margin. The above transformation steps lead to new exporter–product–destination spells. Each of these spells is one of four types: those that survive, and those that do not survive; those who survive and grow, and those who survive but do not grow.

The main dependent variables are:

$$Enter_{eipdt} = \begin{cases} 1 & if \quad v_{eipd,t-l} = 0 \quad \text{and} \quad v_{eipd,t} > 0 \\ 0 & if \quad v_{eipd,t-l} = 0 \quad \text{and} \quad v_{eipd,t} = 0 \end{cases} \tag{2}$$

$$Survive_{eipdt} = \begin{cases} 1 & if \quad v_{eipdt} > 0, \quad v_{eipd,t-l} = 0 \quad \forall l > 0, \quad \text{and} \quad v_{eipd,t+1} > 0 \\ 0 & if \quad v_{eipdt} > 0, \quad v_{eipd,t-l} = 0 \quad \forall l > 0, \quad \text{and} \quad v_{eipd,t+1} = 0 \end{cases} \tag{3}$$

$$Grow_{eipdt} = \begin{cases} 1 & if \quad v_{eipdt} > 0, \quad v_{eipd,t-l} = 0 \quad \forall l > 0, \quad \text{and} \quad v_{eipd,t+1} > v_{eipd,t-1} \\ 0 & if \quad v_{eipdt} > 0, \quad v_{eipd,t-l} = 0 \quad \forall l > 0, \quad \text{and} \quad v_{eipd,t+1} \leq v_{eipd,t-1} \end{cases} \tag{4}$$

and the estimations take the form of:

$$\begin{aligned} Pr\,(DV = 1) = {} & \alpha_0 + \alpha_1 \left[ln\left(n_{ipd,t-1}\right) \times \triangle ln\left(v_{ipdt}\right) \right] + \gamma \triangle ln\left(v_{ipdt}\right) \\ & + \beta_2 ln\left(n_{ipd,t-1}\right) + \beta \mathrm{X}_{eipdt} + \beta_3 \left[ln\left(n_{(-i)pd,t-1}\right) \times \triangle ln\left(v_{(-i)pdt}\right) \right] + \{FE\} + u_{pd} \end{aligned} \tag{5}$$

where the DV is either $Enter_{eipdt}$, $Survive_{eipdt}$ or $Grow_{eipdt}$. Also, $\triangle ln\left(v_{ipdt}\right)$ is the average growth rate of exports of peers, and $n_{ipd,t-1}$ is the number of peers in the set of peers that export from i to pd market in both $t-1$ and t, $N_{ipd,t-1}$. New entrants at t and one-time exporters at $t-1$ are not included in $N_{ipd,t-1}$. I define $\triangle ln\left(v_{ipdt}\right)$ as

$$\triangle ln\left(v_{ipdt}\right) = \frac{1}{n_{ipd,t-1}} \sum_{i \in N_{ipd,t-1}} \left[ln\left(v_{eipdt}\right) - ln\left(v_{eipdt}\right) \right]. \tag{6}$$

The vector of regressors X_{eipdt} comprises measures of the exporter's scope. They are (i) n_{ept}, the number of destinations to which exporter e exports product p; (ii) n_{edt}, the number of products that exporter e exports to destination d; (iii) n^i_{dt}, the number of (product×exporter) combinations active in the bilateral trade between origin i and destination d; and (iv) z_{ep}, the share of product p in exporter e's overall export values. These counts encompass the observation they are attached to and are, hence, never zero, so no observations are lost by taking logs. I also include various fixed effects, FE, to control for supply and demand shocks and capture the effects of peers and their performance on entering exporters.

If there are peer effects, then the number of peers may positively affect the decision of a given firm i to export to a given product–destination market at date t and/or on its volume of exports. However, one can reasonably expect few estimation concerns.

First, there is an endogeneity problem. If exporter i's activity is affected by the activities of their nearby exporters, then one can be concerned about dual causality too. Simultaneity is another concern given that unobserved demand or supply side frictions can affect the export activity of the exporter and their peers. To rest this concern, I used lagged independent variables.

Second, larger and more integrated markets exhibit in equilibrium more productive firms and lower markups, due to endogenous differences in the fierceness of competition. Since only productive firms are able to face the higher competition, there is a selection of the most productive firms in denser areas. Besides, the existence of

Marshallian externalities can also explain how the agglomeration of firms in the same industry generates export gains (Melitz and Ottaviano (2008)). Thus, from one end, firms in agglomerated areas are more productive because of a selection effect or due to Marshallian externalities. Also, from another end, more productive firms export more. Accordingly, I included the number of destinations to which the exporter exports a given product p and the number of products that the exporter exports to a given destination to proxy for exporter productivity and provide a conservative estimate of informational externalities.

Third, there is a potential for reverse causality between the existence of peers and their export performance. Do exporters export more because more of them exist together or are they existing together because they export more? To perform better in export markets, exporters need proper infrastructure, for example, among other factors. I therefore also control for time-invariant geographic characteristics by origin fixed effects.

Fourth, omitted components of trade costs may create the observed relationship between peer effects and performance of exporters. For instance, the existence of a common border between origin and destination countries or the presence of migrant networks can explain why there are a lot of exporters from a given origin trading intensively in a certain market. I hence include origin–destination fixed effects to capture this potential specificity, following Cadot et al. (2013).

Fifth, while I control for a proxy for exporter productivity, I do not have information about firm's product competence. As documented by Bernard et al. (2012), the performance of exporters is influenced by its productivity and product-level competence. If exporters with certain product competence are located close to each other (i.e., for the purposes of accessing certain natural resources), then my coefficient of peer effects would be biased upward. Accordingly, I control for exporter–product fixed effects to distinguish peer effects from product-specific patterns.

Sixth, one can be concerned about the number of exporters in certain countries. While many countries have thousands of exporters, some countries have relatively small number of exporters. For instance, Senegal and Malawi had only 643 and 631 exporters, respectively. Relevant literature (i.e., Cadot et al. (2013)) showed that Mali had 280 firms and 7 firms per destination. It is not uncommon to see relatively small number of exporters in different countries. The empirical strategy followed Cadot et al. (2013) to rest concerns about the relatively small number of exporters in some countries. In addition, following Moulton (1990), I clustered robust standard errors at the product–destination level because all variables of interest are at the origin–product–destination–year level, but the dependent variables are at the exporter–origin–product–destination–year. Clustering at the product–destination level accounts for correlated demand shocks affecting all exporters in a product–destination cell. Likewise, clustering at the product–origin level (accounts for supply shocks) gives similar results. And, following Koenig et al. (2010), I use a linear probability model. This way I can control for exporter–year fixed effects. This way I can control for exporter–year fixed effects.[10]

[10] Although the effect of peers on exporter's entry to a given product–destination market can be nonlinear, the coefficients of the average marginal effects in the probit model are typically similar to the estimates of the linear probability model (i.e., see Wooldridge (2003) and Bernard et al. (2012)).

Peer effects can be also perceived as counter-intuitive. One can reasonably argue that exporters of same products to same destination from the same origin may optimize by crowding out each other. They can do so either through price competition or simply by exercising more marketing to push buyers at destination to shift from one seller to another. Such behavior can decrease the survival and growth of exporters from the same origin to same destination. The results could also be driven by omitted-variable bias such as a certain comparative advantage at the origin level. To rest these concerns, I controlled separately for the origin's comparative advantage index.[11]

6 Empirical results

I employ exporter-level customs data from nine economies to test the predictions of the conceptual framework. By exporters dynamics, I refer to an exporter's entry and first-time exports to a given a market, as well as their survival and growth in given product–destination markets. First, I look at the impact of peers on an exporter's probability of entering a given market. I use the average growth rate of the exports of peers at each product–destination market, $\triangle ln\left(v_{ipdt}\right)$, as a proxy for the performance inferred from the peers which is also the demand factor in the conceptual framework.

The conceptual framework predicts that the performance level and the number of peers selling to a given market increase the probability of an exporter entering a given market. Correspondingly, I estimate a linear probability model of entry, with independent variables capturing (i) the performance and number of peers separately and (ii) the interaction of the performance with the number of peers. Precisely, I estimate:

$$\begin{aligned} Pr\left(Enter_{eipdt}\right) = {} & \alpha_0 + \alpha_1\left[ln\left(n_{ipd,t-1}\right) \times \triangle ln\left(v_{ipdt}\right)\right] + \gamma \triangle ln\left(v_{ipdt}\right) \\ & + \beta_2 ln\left(n_{ipd,t-1}\right) + X'\beta + \beta_3\left[ln\left(n_{(-i)pd,t-1}\right) \times \triangle ln\left(v_{(-i)pdt}\right)\right] + \{FE\} + u_{eipdt}. \end{aligned} \tag{7}$$

The above estimation allows for identifying the impact of the number of peers, the proxy for their performance, and the interaction between these two variables. I include controls for exporter–year, origin–year, destination–year, and origin–destination fixed effects. These fixed effects control for shocks that may affect demand at the destination level as well as supply at the origin and exporter level[12]. This way, I can also address the selection bias, which may result from endogenous entry decisions that vary across exporters, by investigating the within-exporter cross-country correlation between performance of entrants to and existence of peers at a given market. Moreover, I incorporate the interaction between the (i) number of exporters of the same products to the same destinations but from different origins, $ln\left(n_{(-i)pd,t-1}\right)$, and (ii) the performance of these exporters, $\triangle ln\left(v_{(-i)pdt}\right)$. I use the latter control as a placebo to see if exporters from a given origin learn from ones from other origins.

[11] I used Balassa's revealed comparative advantage index (Balassa (1965)) to proxy for comparative advantage at country of origin.

[12] These shocks can be ones that affect the competitiveness of a market, time-varying exchange rates, demand, and import policies at destination as well as export policies that may affect exporters at origin.

Table 2 The effect of externalities on entry and initial exports of exporters

	$Pr\left(Enter_{eipdt}\right)$			$ln\left(v_{eipdt}\right)$		
	(1)	(2)	(3)	(4)	(5)	(6)
$ln\left(n_{ipd,t-1}\right) \times \triangle ln\left(v_{ipdt}\right)$	0.028^{a}	0.024^{a}	0.041^{a}	0.034^{a}	0.035^{a}	0.052^{a}
	[0.007]	[0.000]	[0.000]	[0.000]	[0.000]	[0.003]
$\triangle ln\left(v_{ipdt}\right)$	0.423^{a}	0.716^{a}	0.601^{a}	0.221^{a}	0.262^{a}	0.281^{a}
	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.002]
$ln\left(n_{ipd,t-1}\right)$	0.047^{a}	0.039^{a}	0.030^{a}	0.012^{b}	0.014^{a}	0.017^{a}
	[0.009]	[0.000]	[0.000]	[0.040]	[0.000]	[0.005]
$ln\left(n_{ept}\right)$	0.051^{b}	0.113^{c}	0.279^{c}	0.152^{b}	0.144^{c}	0.148^{a}
	[0.034]	[0.065]	[0.051]	[0.042]	[0.053]	[0.000]
$ln\left(n_{edt}\right)$	0.093^{a}	0.142^{b}	0.142^{b}	0.061^{a}	0.064^{a}	0.053^{a}
	[0.009]	[0.023]	[0.015]	[0.001]	[0.000]	[0.000]
$ln\left(n^{i}_{dt}\right)$	0.011^{c}	0.026^{c}	0.018^{b}	0.014^{a}	0.020^{b}	0.024^{b}
	[0.092]	[0.071]	[0.047]	[0.000]	[0.049]	[0.031]

Table 2 continued

	$Pr\left(Enter_{eipdt}\right)$			$ln\left(v_{eipdt}\right)$		
	(1)	(2)	(3)	(4)	(5)	(6)
$ln\left(z_{ep}\right)$	0.115^{b}	0.235^{b}	0.136^{a}	0.125^{a}	0.131^{a}	0.135^{a}
	[0.021]	[0.036]	[0.000]	[0.001]	[0.000]	[0.005]
$ln\left(n_{(-i)pd,t-1}\right) \times \triangle ln\left(v_{(-i)pdt}\right)$	0.041	0.025	−0.073	0.056	0.051	0.065
	[0.142]	[0.631]	[0.102]	[0.218]	[0.348]	[0.114]
origin–destination FE	Yes	Yes	Yes	Yes	Yes	Yes
destination–year FE	Yes			Yes		
origin–year FE		Yes			Yes	
exporter–year FE			Yes			Yes
Number of Observations	4481195	4481195	4481195	1445864	1445864	1445864

Note: t-statistics are in brackets. ^{a}, ^{b}, and ^{c} represent statistical significance levels at the 1, 5, and 10% levels, respectively. All coefficients are multiplied by 100. The mean of $\triangle ln\left(v_{ipdt}\right)$ is 0.377. The median of $\left(Enter_{eipdt}\right)$ is 0.51%. The standard deviation of is $ln\left(n_{ipd,t-1}\right)$ 1.1. n_{ept} is the number of destinations to which exporter e exports product p. n_{edt} is the number of products that exporter e exports to destination d. n^{i}_{dt}, is the number of (product×exporter) combinations active in the bilateral trade between origin i and destination d. z_{ep} is the share of product p in exporter e's overall export values

Columns 1–3 of Table 2 report the results of the estimation equation (7). The results show that an exporter's probability to enter a given product–destination market rises with the average performance of their peers in that market and increases more with the number of peers in that market. The effects of the number, performance, and interaction between the number and performance of peers on exporter's entry probability are positive and statistically significant at the 1% level. The coefficients of the interaction term between the number and performance of exporters of the same products to the same destinations who are from different origins are not statistically insignificant (and even negative in column 3) confirming the main results. The probability of an exporter entering a new product–destination market increases with the performance and number of their peers in that market. Precisely, an increase that is equivalent to the average growth rate (37.7%) of the exports of peers to a given product–destination market is correlated with a 0.226, $\left(\frac{0.601}{100} \times \frac{37.7}{100}\right)$, percentage point rise in the probability of exporter's entry into that market. Given that the median of the exporter's entry rate to a given product–destination market is 0.51%, then the above 0.226 percentage point increase corresponds to a 44.42% $\left(\frac{0.226}{0.51}\right)$ increase in the exporter's entry rate to a given product–destination market. In other words, a 37.7% average growth rate in exports of the peers is associated with a 44.42% increase in the exporter's entry rate, a 1% increase in the growth rate of exports of the peers in a given product–destination market is associated with a 1.178% increase in the exporter's entry rate to that market, evaluated at the median. Moreover, the coefficient of 0.041 means that an increase that is equivalent to the average growth rate (37.7%) of the exports of the peers to a given product–destination market is correlated with a 0.015, $\left(0.041 \times \frac{37.7}{100} \times 1.1\right)$, percentage point increase in the probability of exporter's entry into that market when $ln\left(n_{ipd,t-1}\right)$ increases by one standard deviation (1.1). This rise is 7.1% in the entry rate, evaluated at the median of entry rate.

Second, I investigate the impact of peers on exporters' initial exports. The conceptual framework predicts that the initial exports of exporters to a given product–destination market rise with the performance of their peers. So, I estimate

$$\begin{aligned} ln\left(v_{eipdt}\right) = {} & \alpha_0 + \alpha_1\left[ln\left(n_{ipd,t-1}\right) \times \triangle ln\left(v_{ipdt}\right)\right] + \gamma \triangle ln\left(v_{ipdt}\right) \\ & + \beta_2 ln\left(n_{ipd,t-1}\right) + X'\beta + \beta_3\left[ln\left(n_{(-i)pd,t-1}\right) \times \triangle ln\left(v_{(-i)pdt}\right)\right] + \{FE\} + u_{eipdt} \end{aligned} \tag{8}$$

where $ln\left(v_{eipdt}\right)$ represents the entering exporter's first-time exports to a given pd market.

Columns 4–6 of Table 2 report the results. I use similar fixed effects as in Columns 1–3 of Table 2 for the same reasons. The separate and joint effects of the performance of peers, $\triangle ln\left(v_{ipdt}\right)$, and the number of peers, $ln\left(n_{ipd,t-1}\right)$, on initial export levels of entrants are positive, as predicted in the model, as well as statistically significant. Column 6 shows that if peers' exports to a given product–destination market grow at the sample mean rate (37.7%), then a new exporter's first-time exports of a given product to a given destination will be 10.59%, $\left(0.281 \times \frac{37.7}{100} \times 100\right)$, on average, relative to product–destination markets with zero average peers' export growth. Furthermore, the estimated coefficient on the interaction term between the performance and number of peers is 0.052, suggesting that based on the sample average export

growth of peers, one standard-deviation increase in the (log) number of peers exporting to a given product–destination market is associated with an additional 2.15%, $\left(0.052 \times \frac{37.7}{100} \times 1.1\right)$, initial exports in the same market.

Third, I study the impact of peers on the survival of entering exporters at a given product–destination market. The conceptual model shows that the survival rate of new exporters rises with the performance revealed by their peers regardless of latter's number. The reason is that while the number of peers affects the number of entrants by changing the entry threshold, conditional on entry, any ex ante information was already taken into account by the entrant at the time of entry and will no longer affect its exit decision. To empirically examine this proposition, I use the $Survive_{eipdt}$ dummy that is defined in equation (3) to estimate:

$$\begin{aligned} Pr\left(Survive_{eipdt}\right) = \alpha_0 + \alpha_1 \left[ln\left(n_{ipd,t-1}\right) \times \triangle ln\left(v_{ipdt}\right)\right] + \gamma \triangle ln\left(v_{ipdt}\right) \\ + \beta_2 ln\left(n_{ipd,t-1}\right) + X'\beta + \beta_3 \left[ln\left(n_{(-i)pd,t-1}\right) \times \triangle ln\left(v_{(-i)pdt}\right)\right] \\ + \{FE\} + u_{eipdt} \end{aligned} \tag{9}$$

Columns 1–3 of Table 3 report the results. The coefficients on the number of peers, $ln\left(n_{ipd,t-1}\right)$, and its interaction with the performance of peers, $ln\left(n_{ipd,t-1}\right) \times \triangle ln\left(v_{ipdt}\right)$, are positive but statistically insignificant. However, column 3 shows a positive and statistically significant coefficient on the term related to the performance of peers, $\triangle ln\left(v_{ipdt}\right)$. These results remain the same regardless of whether controls to capture potential learning effects from exporters to other countries are incorporated or not as well as regardless of which fixed effects controls are included.

Fourth, I look at peer effects on exporter's growth. The conceptual framework predicts that the growth of surviving exporters is increasing in the performance of peers, and increasingly more if there are more peers in a given market. To test this prediction, I use the $Grow_{eipdt}$ dummy that is defined in equation (4) and estimate:

$$\begin{aligned} Pr\left(Grow_{eipdt}\right) = \alpha_0 + \alpha_1 \left[ln\left(n_{ipd,t-1}\right) \times \triangle ln\left(v_{ipdt}\right)\right] + \gamma \triangle ln\left(v_{ipdt}\right) \\ + \beta_2 ln\left(n_{ipd,t-1}\right) + X'\beta + \beta_3 \left[ln\left(n_{(-i)pd,t-1}\right) \times \triangle ln\left(v_{(-i)pdt}\right)\right] \\ + \{FE\} + u_{eipdt}. \end{aligned} \tag{10}$$

Columns 4–6 of Table 3 report the results with different sets of fixed effects included. The results lend support to the conceptual framework. They show positive and statistically significant coefficients on the three regressors of interest: the number of peers, $ln\left(n_{ipd,t-1}\right)$, the performance of peers, $\triangle ln\left(v_{ipdt}\right)$, and the interaction between those two variables. They suggest that the probability for an exporter's exports to grow after entry in a market rises with the performance of existing exporters serving that market from the same origin and more so with a higher number of peers. In particular, in the sixth column, where I control for exporter–year and origin–destination fixed effects, I obtain an estimated coefficient on the interaction term of 0.412. This coefficient means that an increase that is equivalent to the average growth rate (37.7%) of the exports of peers to a given product–destination market is correlated with a 0.171, $\left(0.412 \times \frac{37.7}{100} \times 1.1\right)$, percentage point increase in the probability of exporter's growth at that market when $ln\left(n_{ipd,t-1}\right)$ increases by one standard deviation (1.1). These results show that peers reveal information about product–destination markets

Table 3 The effect of externalities on survival and growth of exporters

	$Pr\left(Survive_{eipdt}\right)$			$Pr\left(Grow_{eipdt}\right)$		
	(1)	(2)	(3)	(4)	(5)	(6)
$ln\left(n_{ipd,t-1}\right) \times \triangle ln\left(v_{ipdt}\right)$	0.033	0.024	0.067	0.213^{a}	0.218^{b}	0.412^{a}
	[0.332]	[0.440]	[0.112]	[0.000]	[0.039]	[0.000]
$\triangle ln\left(v_{ipdt}\right)$	0.427^{c}	0.531^{b}	0.342^{a}	0.324^{a}	0.023^{c}	0.112^{a}
	[0.056]	[0.035]	[0.000]	[0.005]	[0.051]	[0.000]
$ln\left(n_{ipd,t-1}\right)$	0.025	0.031	0.024	0.032^{a}	0.041^{c}	0.031^{a}
	[0.102]	[0.120]	[0.132]	[0.001]	[0.063]	[0.000]
$ln\left(n_{ept}\right)$	0.091^{b}	0.084^{c}	0.063^{b}	0.013^{c}	0.047^{a}	0.012^{b}
	[0.041]	[0.066]	[0.042]	[0.063]	[0.000]	[0.036]
$ln\left(n_{edt}\right)$	0.061^{c}	0.069^{c}	0.051^{c}	0.144^{b}	0.213^{c}	0.048^{b}
	[0.063]	[0.058]	[0.072]	[0.041]	[0.051]	[0.021]
$ln\left(n^{i}_{dt}\right)$	0.051^{a}	0.043^{a}	0.021^{a}	0.128^{c}	0.014^{a}	0.035^{a}

Table 3 continued

	$Pr\left(Survive_{eipdt}\right)$			$Pr\left(Grow_{eipdt}\right)$		
	(1)	(2)	(3)	(4)	(5)	(6)
	[0.003]	[0.000]	[0.000]	[0.052]	[0.000]	[0.000]
$ln\left(z_{ep}\right)$	0.092^{b}	0.071^{c}	0.036^{c}	0.237^{c}	0.317^{b}	0.047^{a}
	[0.045]	[0.051]	[0.072]	[0.049]	[0.045]	[0.000]
$ln\left(n_{(-i)pd,t-1}\right) \times \triangle ln\left(v_{(-i)pdt}\right)$	0.081	0.190	0.212	0.182	0.153	0.231
	[0.532]	[0.131]	[0.224]	[0.281]	[0.203]	[0.229]
origin–destination FE	Yes	Yes	Yes	Yes	Yes	Yes
destination–year FE	Yes			Yes		
origin–year FE		Yes			Yes	
exporter–year FE			Yes			Yes
Number of Observations	1445864	1445864	1445864	623892	623892	623892

Note: t-statistics are in brackets. ^{a}, ^{b}, and ^{c} represent statistical significance levels at the 1, 5, and 10% levels, respectively. All coefficients are multiplied by 100. The mean of $\triangle ln\left(v_{ipdt}\right)$ is 0.377. The median of $\left(Survive_{eipdt}\right)$ is 0.39%. The median of $\left(Grow_{eipdt}\right)$ is 0.37%. The standard deviation of is $ln\left(n_{ipd,t-1}\right)$ 1.1. n_{ept} is the number of destinations to which exporter e exports product p. n_{edt} is the number of products that exporter e exports to destination d. n^{i}_{dt}, is the number of (product×exporter) combinations active in the bilateral trade between origin i and destination d. z_{ep} is the share of product p in exporter e's overall export values

and, thus, trigger new entrants to encourage exporters to enter a new market with a larger order, survive longer, and grow faster.

As robustness checks, to address the concern related to the selection of exporters into certain product–destination markets and to give a potential explanation for how peer effects may actually operate, following Koenig et al. (2010), I undertake two further steps in the empirical analysis. First, I control for a potential omitted variable that could bias the results if the country of origin had a comparative advantage in a given product. Such comparative advantage can actually explain both how the country had more exporters of that product to any destination and why the exporters of that product may survive longer and grow faster. To rest this concern, I control for the average value (over the sample period for each country) of Balassa's revealed comparative advantage index for product p, $BRCA^i_p$, where $BRCA^i_p = \frac{v_{ip}}{v_{iP}} / \frac{v_{wp}}{v_{wP}}$. The $BRCA^i_p$ is equal to the proportion of the country's exports that are of the product under consideration, $\frac{v_{ip}}{v_{iP}}$, divided by the proportion of world exports that are of that product, $\frac{v_{wpt}}{v_{wPt}}$.[13] A comparative advantage is revealed if $BRCA > 1$. If $BRCA < 1$, then the country is said to have a comparative disadvantage in that product. The results hold after including this control as shown in Table 4.

7 Conclusion

Recent evidence on exporters dynamics showed that exporters from developing countries face low survival and growth rates. The relevant studies linked exporters survival and growth to exporters characteristics such as productivity, employment, size, and management. In this paper, I study the impact of informational externalities caused by peers on the survival and growth of exporters. I demonstrate how peer effects are determinants of the survival and growth of exporters; this is especially seen in how an exporter's uncertainty about a given export market decreases after they observe the behavior of their exporting peers. Hence, I document that peer effects not only exist, but can also explain why some exporters survive longer and grow faster when they internalize externalities.

Using disaggregated customs data from nine countries, I found peer effects that could be identified only by using exporter-level data. My empirical results support the main predictions of the conceptual framework. These results show that exporters to the same product–destination market enhance the survival and growth probability of new entrants from the same origin to that market. In other words, an increase in the number of exporting peers can lower the cost of exporting to and uncertainty at a given market as well as reduce the probability of exiting. The fact that peer effects do not appear to happen between exporters from different origins strengthens this result. In addition, when I examined the impact of exporters of the same products to the same destination who are from different origins on the survival and growth of exporters, I found that peer effects disappear.

Further research can proceed in at least three different directions. First, it can study the dynamics of an exporter's survival and growth once informational externalities

[13] I used UN-Comtrade, not the customs, data to calculate $BRCA$.

Table 4 Robustness checks

	$Pr\left(Enter_{eipdt}\right)$ (1)	$ln\left(v_{eipdt}\right)$ (2)	$Pr\left(Survive_{eipdt}\right)$ (3)	$Pr\left(Grow_{eipdt}\right)$ (4)
$ln\left(n_{ipd,t-1}\right) \times \triangle ln\left(v_{ipdt}\right)$	0.040^{a}	0.048^{a}	0.042	0.325^{a}
	[0.000]	[0.001]	[0.235]	[0.000]
$\triangle ln\left(v_{ipdt}\right)$	0.598^{a}	0.264^{a}	0.291^{a}	0.101^{a}
	[0.000]	[0.000]	[0.000]	[0.000]
$ln\left(n_{ipd,t-1}\right)$	0.027^{a}	0.014^{a}	0.015	0.029^{a}
	[0.000]	[0.000]	[0.214]	[0.000]
$ln\left(n_{ept}\right)$	0.284^{c}	0.151^{a}	0.052^{b}	0.010^{b}
	[0.053]	[0.002]	[0.033]	[0.029]
$ln\left(n_{edt}\right)$	0.135^{b}	0.049^{a}	0.063^{c}	0.031^{b}
	[0.012]	[0.001]	[0.055]	[0.017]
$ln\left(n^{i}_{dt}\right)$	0.015^{b}	0.031^{b}	0.034^{a}	0.033^{a}
	[0.035]	[0.029]	[0.000]	[0.000]
$ln\left(z_{ep}\right)$	0.114^{a}	0.127^{a}	0.024^{b}	0.041^{a}
	[0.000]	[0.000]	[0.042]	[0.000]
$ln\left(n_{(-i)pd,t-1}\right) \times \triangle ln\left(v_{(-i)pdt}\right)$	0.071	0.036	0.204	0.222
	[0.111]	[0.156]	[0.315]	[0.198]

Table 4 continued

	$Pr\left(Enter_{eipdt}\right)$ (1)	$ln\left(v_{eipdt}\right)$ (2)	$Pr\left(Survive_{eipdt}\right)$ (3)	$Pr\left(Grow_{eipdt}\right)$ (4)
$BRCA_p^i$	0.00003	0.000028	0.000034	0.000029
	[0.415]	[0.109]	[0.127]	[0.218]
origin–destination FE	Yes	Yes	Yes	Yes
exporter–year FE	Yes	Yes	Yes	Yes
Number of Observations	4481195	1445864	1445864	623892

Note: t-statistics are in brackets. ^{a}, ^{b}, and ^{c} represent statistical significance levels at the 1, 5, and 10% levels, respectively. All coefficients are multiplied by 100. The mean of $\triangle ln\left(v_{ipdt}\right)$ is 0.377. The median of $\left(Survive_{eipdt}\right)$ is 0.39%. The median of $\left(Grow_{eipdt}\right)$ is 0.37%. The standard deviation of is $ln\left(n_{ipd,t-1}\right)$ 1.1. n_{ept} is the number of destinations to which exporter e exports product p. n_{edt} is the number of products that exporter e exports to destination d. n_{dt}^i, is the number of (product× exporter) combinations active in the bilateral trade between origin i and destination d. z_{ep} is the share of product p in exporter e's overall export values. $BRCA_p^i$ is Balassa's revealed comparative advantage index for product p from origin i

cross the sector or country of origin dimension. For example, information about a given sector in a given country may help in learning about the same sector in neighboring countries or other sectors in the same country. Second, it can look at the importance of private information in multi-product exporters and whether or not it can be a determinant for the fact that these exporters enter many markets per product. It may be the case that informational externalities shape the boundaries of an exporter. Third, it can investigate the role of peer effects in investment flows, survival, and growth while this paper looked solely at the survival and growth of export relationships at the exporter level.

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Declarations

Conflict of interest Jamal Ibrahim Haidar declares that he has no conflict of interest.

Human and animals rights This article does not contain any studies with human participants or animals performed by the author.

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