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New exports from emerging markets: Do followers benefit from pioneers?☆

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ABSTRACT

We study the micro dynamics of new exports from a country. The modern international trade workhorse models (e.g. Melitz, 2003) assume heterogeneous productivity and, implicitly, predict that the ex-post largest exporters in a new product would be the pioneers, since they can pay back exploration costs. However, using detailed data on the early dynamics of new exports in Chile (1990–2007) we show that, on average, pioneers export *less* than comparable followers in the same new product. Moreover, followers are 40% more likely to enter a product if a pioneer survives more than one year exporting. These facts are consistent with pioneer-to-follower spillovers, or at least with stories in which the cost of entering early is disproportionally higher for larger exporters. Otherwise they would enter first. Firms better at "exploration" could be worse at "exploitation" (scale-up) in a new export product. This phenomenon is scarce, though, since in most new products pioneers are not followed, even if they survive.

1. Introduction

Pioneer firms are the first to export a new product from a country. A fraction of these new exported products also have follower firms, which start exporting after the pioneers in those same products. We try to understand if pioneers are different from followers. Are pioneer firms the first at entering into a new export product because they will export more, so they can more easily pay back any exploration costs? Or is it that pioneers enter earlier because they have lower exploration costs in the product, so it is cheaper for them to try new products? These micro-level questions can have important implications for the way countries diversify their aggregate export baskets and explore their dynamic comparative advantages (e.g. Grossman and Rossi-Hansberg, 2010; Hausmann and Rodrik, 2003).

The dominant paradigm today in international economics is modeling firms with heterogeneous productivity. Applying its standard logic to one particular new product, would predict that firms that end up exporting the most of a particular new product should be the pioneers (e.g. Melitz (2003) and extensions, such as Arkolakis (2010); Eckel and Neary (2010) for multiproduct firms). By having larger expected profits these firms should be willing to pay the sunk cost of exporting before other firms with lower expected revenue in the product. In this empirical paper we find, however, that in the early stages of new exports the largest exporters in a product do not coincide with the pioneers, at least when they have followers.

Using a detailed novel dataset for a developing economy, and a more precise definition of what a new exported product is than the previous literature, we find three stylized facts. First, around 70% of pioneered products do not have followers. Even in the majority of cases when the pioneer survives there are no followers. This could suggest that, in case there is such a thing as pioneer-to-follower informational spillovers, as suggested by Hausmann and Rodrik (2003), this might not be ubiquitous to all products. Some of these cases of "lonely pioneers" could be consistent with the Krugman (1980) model with increasing

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Table 1
Taxonomy of different events of a firm exporting a product.

		Has any firm exported this product from the country before 1995?	
		Yes "*old* product"	No "*new* product"
Is it the first firm exporting the product from the country?	Yes	N/A $N = 0$	$Pioneer_{new\ product}$ $N = 110$
	No	$Follower_{old\ product}$ $N = 8964$	$Follower_{new\ product}$ $N = 288$

Each observation in this table is a unique firm-product combination for all the firms that begin exporting a new product for them; which in most cases is not a new product for the country as a whole. They are organized in a two by two matrix. The columns relate to products (the left column showing old products and the right column showing new products); the rows relate to firms (pioneer or follower). The first row groups pioneers and the second row the followers, depending on whether the firm is among the exporters during the first year of exports for that particular product.

returns to scale, in which there is no room for follower firms in the same product and country. Second, we find that followers are 40% more likely to enter a product if the pioneer survives exporting more than one year. The third stylized fact focuses only on products that do have followers. Despite pioneers and followers coming from a similar distribution of overall export size, we find that pioneers tend to be systematically smaller than followers in the specific new product they pioneered, even if we control for how experienced firms are in the new product as well as for product-year shocks.

This latter finding seems at odds with current standard international trade models of firms with heterogeneous productivity but a homogeneous menu of entry costs. Our facts could be consistent with the possibility that relatively larger exporters in a product may also have higher exploration costs in that new export. This could plausibly be consistent with followers learning about export profitability from a pioneer that enters because of an "exploration advantage".

These pioneer-to-follower informational spillovers in non-excludable innovations have been highlighted at least since Arrow (1962). These theories argue that pioneers of new products are "data producers" (Schumpeter, 1934) generating information about technology and markets from which subsequent followers free-ride. The consequence is that pioneers do not fully internalize the social benefit of the information they create, and as a result there is less than optimal experimentation in new products. This can force countries into an income trap due to their inability to exploit dynamic comparative advantages (e.g. Bardhan, 1971; Hausmann and Rodrik, 2003; Hoff, 1997). For clarity, our results do not prove that there is a market failure in this discovery, since empirically it is almost impossible to discard every other possible alternative story. Having said that, though, there is a relevant related literature claiming that externalities between pioneers and followers would not prevent a country from finding its long run comparative advantage. This could be the case if pioneers can scale-up very large post entry, and therefore they can internalize a large fraction of the "discovery externality", *if* there is one (Grossman and Rossi-Hansberg, 2010). Our evidence, though, shows that pioneers are not the best at scaling up exports of the new product, challenging an important assumption of the Grossman and Rossi-Hansberg (2010) model. Although we cannot rule out that pioneers internalize all the benefit from the export discovery for the products in which there is no room for a second player.

Part of the novelty of our paper relies in the way a new product is defined and the dataset used, which differs from previous empirical literature that analyzed new export products and pioneer-to-follower spillovers (Freund and Pierola, 2009; Iacovone and Javorcik, forthcoming). These papers analyze successful ex-post cases or industries, or use definitions of new products which might be contaminated by "old" products that are intermittently exported. On the contrary, we build a data set of all "new" export products from Chile using transactions data (1990–2006), which allows us to: (i) observe information at firm-product level over time, to distinguish firm behavior from industry behavior; (ii) focus specifically on the subset of new export products, where there is arguably something new to learn[1] and where we can identify the order of entry of firms, so we know who is the pioneer; and (iii) analyze the universe of disaggregated product categories exported in the period, to avoid hindsight biases towards ex post successful cases. With this data, we define a new product as one that has not been exported in the last 5 years, together with several filters which had the goal of being very conservative in the identification of truly new products which reflect the effort of productive firms of selling innovation abroad. These contrasts with the definitions used in the previously mentioned empirical literature, which defines a new product as any code that has not been exported for only 1 year. This short pre-sample period might be problematic, since it can confuse the emergence of truly new products – which have never been exported before – with the re-entry of intermittent exports (products that are exported for a year or more, and then are not exported for 1 or 2 years, returning a few years later). This intermittent entry and exit are not the phenomenon of truly new exports that we would like to pick. Taking a pre-sample of 5 years without exports to classify a product as *new*, reduces the proportion intermittent exporting that may be misclassified as "new". As one can expect, using this criterion alters results significantly when compared to the simpler criteria described in the literature.[2]

Even though new exports are rarely relevant in terms of the overall export value of a country, the study of these early stages is important. All successful products were at some point new, so analyzing their early dynamics and its implications is important for the potential impact they have on future relevant export products or sectors. If one understands new products as options of moving in the ladder of dynamic comparative advantage, then it matters whether the exploration mechanism offered by the market is working reasonably well or whether it suffers from significant market failures. In our sample we do not find a significant number of products that could be classified as "big successes". So we are unable to quantitatively study what differentiates standard pioneers from the pioneers of superstar products. Since big export successes are a very low probability event, studying them would probably require pooling together samples from many countries, which is certainly a challenge for future research.

We focus our analysis in a developing economy for data and conceptual reasons. On the one hand, we had access to detailed and diverse data for Chile. Also, given the way we define newly exported products for a country, it is unlikely that we will identify new products in advanced economies because these countries export many more existing codes in a long time span as the one we use. Second, in a developed economy we would be mixing pioneers exporting with pioneers creating a new product, which is likely to have a more complex R&D process than exporters in our sample, which are inside the global technological frontier. Also, the international Customs classification of products are relevant for our problem only if the entity that updates the global list of goods adds them to the classification before the first export of such a product for a country, which is unlikely to happen in developed economies like

[1] Foster and Rosenzweig (2010), in a review of recent empirical literature on externalities, remark that in order to statistically find learning "*there ought to be something new to learn*". Under this logic, for example Duflo et al. (2009) do not find learning across firms in fertilization of *old* crops in Kenya. In contrast, for the *new* and unknown pineapple crop in Ghana, Conley and Udry (2010) distinguish learning *across* firms. The spirit of our empirical strategy is precisely to focus only on new products, to see whether we can find evidence of learning flowing from the pioneer to the follower.

[2] Iacovone and Javorcik (forthcoming) find many "pioneers" exporting "new" products from Mexico to the US immediately after NAFTA in 1994. Moreover, they find that the largest exporters entered first which is the opposite of our findings. In Section 4 we actually make the presample period shorter to compare results with similar definitions of new products. Shortening the presample period changes our results and end up being similar to that of Iacovone and Javorcik (forthcoming), revealing the importance of a careful definition of new products.

Table 2
Basic descriptive statistics.

Variable	Type	Mean	Median	Min	Max	p5	p25	p75	p95	Total
Number of products	P									273
Number of products with followers	P									69
Number of firms	F									312
# of f-y-p observations	P	2.8	2	1	28	1	1	3	9	777
# of f-y-p-d observations	P	4.8	2	1	167	1	1	3	13.4	1301
Number of years product was exported	P	2.5	1	1	12	1	1	3	7	
Product made it till end of database	P	0.28	0	0	1	0	0	1	1	77
# of firms per product	P	1.5	1	1	7	1	1	2	3	398
# of pioneers per product	P	1.1	1	1	3	1	1	1	1.4	288
# of followers per product	P	0.4	0	0	6	0	0	1	2	110
Value exported at entry (US$ thousand)	P	225.9	27.3	10	15,500	10.8	15.5	87.7	817.5	
Value exported at final year	P	1371.3	29.5	10	207,000	11.3	16.2	101.6	861.7	
% growth in value exported	P	237.5	0.0	−98.8	20,932	−81.2	0.0	13.6	762.2	
Did pioneer survive till end of product?	P	0.8	1	0	1	0	1	1	1	218
Did pioneer (w followers) survive till end of product?	P	0.05	0	0	1	0	0	0	0.4	14
Was product a success 1?	P	0.0	0	0	1	0	0	0	0	8
Did pioneer become market leader in final year of product?	P	0.0	0	0	1	0	0	0	0	7

Note: Type shows the unit in which we are making calculations. F means we are calculating at the firm level, while P is at the product level and Y at the Year level. As an example, f-p-y observations are how many firm-product-year observations we have for each new product considered in the data base. Value exported at entry is how much was exported at the product level, the first year the product was introduced, independent of the number of firms that began exporting the product. We define a successful product as one that grew more than 100% in value between the first and last year explored, if it survived until 2006 and if it ended up being exported in more than US$1 million.

the US.[3] Finally, the emergence of new export products has been associated with episodes of economic accelerations in less-developed economies (Amsden, 1992; Kehoe and Ruhl, 2009; Lucas, 1993).

To interpret our facts, we provide an extremely simplified framework that allows heterogeneous productivity a la Melitz (2003), but also heterogeneity in initial entry costs of exporting a new good. In the latter we try to be more general than Arkolakis (2010) or its implementation in Eaton et al. (2011) (henceforth EKK). We expect firms to differ along productivity and entry costs due to relative comparative advantage. The capabilities required to start exporting a new product might be different from those required to efficiently organize production to take advantage of proved opportunities. Such a perspective is consistent with a descriptive study by Artopoulos et al. (2013), and often found in studies of entrepreneurships and venture capital. A firm that is very good at producing can have a comparative disadvantage in experimenting new things (market, products, etc.), allowing high productivity firms to also have – on *average* – higher entry costs of exporting new products.

Our work is closely related to papers that explore spillovers. Most of this literature uses industry cases, normally biased towards successful ones or industries that grew ex-post (Agosin and Bravo-Ortega, 2009; Artopoulos et al., 2013; Chandra, 2006; Conley and Udry, 2010; Da Rocha et al., 2008; Freund and Pierola, 2009; Mostafa and Klepper, 2010; Porter, 1990, 1998). This view underweighs the overall failure and uncertainty present in the development of new export products, which is ex-ante very important for international entrepreneurs. Another approach has been to use aggregate country-level discovery of new export products (Hidalgo et al., 2007; Klinger and Lederman, 2004). We try to improve on this by including both successful and unsuccessful cases using all transactions and goods for the period we study. Conceptually, the paper also relates to the work of Hausmann and Rodrik (2003) on self-discovery of new exports. They argue that followers destroy profits for pioneers through the bidding up of local factor prices, and that copying is largely technological. Instead, like Artopoulos et al. (2013), we focus more on learning about the requirements and challenges of global markets, rather than about physical productivity improvements.

Our work builds upon "new new" international economics with heterogeneous firms (Melitz, 2003 and uncountable extensions) and the related work on entry into exporting (Das et al., 2007; Roberts and Tybout, 1997). In this literature it is the largest and highest productivity firms the ones which export more products and also the ones most willing to pay a constant sunk cost to export a new product, therefore becoming pioneers. We use this logic as a conceptual benchmark for our findings. The paper also relates to the trade literature on experimentation, in particular to Rauch and Watson (2003), Ruhl and Willis (2009), Albornoz et al. (2010), Segura-Cayuela and Vilarrubia (2008) and Eaton et al. (2010) who look at the relation between uncertainty and experimentation.[4]

Our findings and the conceptual logic that explains them have relevant policy implications. In our work, sunk entry costs into exporting a new product could be heterogeneous across firms, and potentially positively correlated to scale, suggesting that some firms might be better at "exploration" (i.e. start-up of a new product line, lower sunk cost) while other firms could be better at "exploitation" (i.e. scaling up a product line, having higher export revenues in the product). In that context, an exchange rate or tariff movement may not help enough to make high productivity firms to pioneer a new product, since they could be the ones facing high sunk costs of exploration. As a contrast, in the view of Das et al. (2007) sunk costs of entering exporting are both very large and homogeneous across firms. Therefore, they argue, to promote exports it is more important to focus on policies that impact the potential scale-up process after entry, namely exchange rate and tariff reduction that increase profitability once exporting. The alternative focus would be on policies that may reduce the (sunk) entry costs, such as export promotion programs, which however may not be useful for firms that cannot scale-up enough in Das et al. (2007) view. In such a

[3] Also, most of the new products we identify for Chile are in natural resource based sectors which are hard to protect with intellectual property.

[4] Our work relates also to innovation strategy and international marketing. On the strategy side, we explore how the first mover keeps its original advantage, a topic touched before by Gilbert and Newbery (1982); Henderson (1993); and Prusa and Schmitz (1994). We share with this literature the special focus on the *sequencing* of entry. However, we consider products that are well *within* the international frontier of innovation and largely non-patentable. Our paper is also an empirical contribution to the International Marketing literature. Various papers focus on the covariates, like age, of the decision to internationalize the production of a firm (for a review see Andersen (1993)). More recently, this literature has made a distinction between "born globals" that internationalize immediately, from other "gradual globals" that internationalize after some years in the domestic market (Moen and Servais, 2002) or in regional markets (Lopez et al., 2009). Our difference with this literature is the broad coverage of products and the sequence of entry. Other papers in international marketing empirically explore the order of entry (sequencing) as a determinant of profitability in a given market. For example Cui and Lui (2005) look at how early entrant multinationals in China do vis-a-vis late entrants in the same market. Magnusson et al. (2009) look at how sequence of entry affects profitability in many destination markets, but only for multinationals in the advertisement industry. Our analysis is different from this literature because we focus on many industries and mostly on the source country rather than on the destination country.

Table 3
Descriptive statistics of firms in new products.

Variable	Mean	S.E. (mean)	Median	N obs
Exports of new product (US$ thousands)	358	122	45	148
Exports of all other products (US$ thousands)	23,110	16,069	227	148
Number of products exported	3.85	0.26	3.0	148
Export experience in any product (*)	4.1	0.3	4.0	148
Prob of being a large tax payer	0.41	0.04	0	148

Note: Each data point is a firm product-pair. Descriptive statistics were calculated for product-pairs that survived more than 1 year given the volatility and noise of the first year exporting. Comparing the medians, one gets that the share of new products in overall exported value at the median is $64/(64+360) \approx 15\,\%$. (*) The measure of export experience is censored because we observe firm behavior until the beginning of our sample at the firm level, in 1991, so many firms could have more experience.

"*scale-up view*" of exports, what matters more is the future scale of business and that endogenously drives new entry. Our findings, on the contrary, point out that in the very beginning of new export products one should also think of a "*start-up view*", not only a "scale-up" view. Just to clarify, though, the pioneers in our sample are not small firms, but rather large multiproduct exporting firms. We do find that they are smaller than followers after entry in the pioneered product, but not necessarily small. We find that pioneers come from a similar size distribution than other exporter firms, when we look at overall exports; at the same time they are systematically smaller than followers, in those new export products in which there are subsequent entrants. This suggests that pioneers had a lower cost of exploration for given expected export revenues *in this new product*.

The remainder of the paper is organized as follows. Section 2 explains our data of new export products, also analyzing a few canonical examples as a way to establish ideas. Section 3 empirically explores our stylized facts, while Section 4 runs a battery of robustness checks. Section 5 offers a simple theoretical framework to understand how the stylized facts are consistent or inconsistent with some mainstream models of trade, as well as disentangling whether the pioneering decision depends more at the margin of the ability scale up or the ability to explore a new market. Finally, Section 6 concludes with a few remarks. In the web Appendix we also present a variety of additional robustness checks, as well as the methodology used to build a concordance between various vintages of Harmonized System of product classification, which could be of independent interest for future researchers.

2. Our data on new exporters

This section describes our data sources as well as our procedure for constructing a database of new products. It also describes the data leaving some canonical case studies for Appendix E.

2.1. Data construction

We built our data set of pioneers and followers of new products using a detailed Chilean customs exports database, which covers the universe of transactions at firm *i*, product (HS6) *j*, destination *d* and time between 1992 and 2006. We expand the timespan of the database by merging it with COMTRADE product level exports for 1990–1991, thus allowing us to have a database for the period 1990–2006.[5] Each transaction provides us information of exported value in US dollars and unit price, which allows us to build a measure of quantity exported. Relying on Customs data allows us to observe the development of new export industries that go beyond the coverage of manufacturing censuses, which are a more traditional source of data for firm level empirical trade papers. In particular, since diversification in agriculture and mining is important for developing countries, we believe a Customs-based database is better suited for understanding export entrepreneurship in emerging and less developed countries.[6]

A next important step is avoiding misidentifying the re-coding of an existing product as a new product. The HS system used in customs data creates new codes every couple of years, wherein a fraction of the products are re-classified. Not homologating codes through time could spuriously generate "new products" in our panel (and also spurious product "deaths"). To solve this issue, we build a correspondence across three different code classifications present in the data, where re-classifications are recorded as unique codes, following the same principles of Pierce and Schott (2009) (see Appendix A for details). Second, we are aware that some new codes exported by a firm or by a country could be samples (exports with extremely low values), coding mistakes, or reexports. To avoid identifying these as new products, we constructed filters to identify *new* exports as accurately as possible. This process has trade-offs though. On the one hand, if we define a new product too loosely many new products identified would not be so. On the other hand, if we are too tough with the definition of a new product, then the number of cases would dramatically shrink, eliminating real cases of firms that made the effort of penetrating new markets with new products. In this trade-off between "distillation" of new products for the country and the quantity of products identified, we tried to lean towards "distillation" as much as possible, but still keeping enough observations to make the results statistically significant. The filters focus first on ignoring exports of a firm that imported the same product in the recent past. For this we merged our data with an available firm level panel from customs on all imports for the period 1992–2006. Also, since many small retailer transactions across the border, with Argentina or Perú for example, are also considered exports, and these firms tend to export an unrealistically large number of products we defined a cutoff number of products and dropped the firms that export more than 30 products in a given year. Third, we wanted to separate between firms that are actually producers of the exported good (i.e. the actual innovators behind a new product) and firms that were exclusively traders or retailers. For this we merged the data with publicly available firm-level activity codes from the Chilean Tax Revenue Service (SII in Spanish), excluding from the data firms that were exclusively traders. We follow the tradition of most of the trade literature of exploring export costs for firms that do produce goods they export. Intermediaries are a hot area of research, but models recognize that this process is quite distinctive so we kept it out from our current study. More details on these filters can be found in Appendix B.

We want to note that in probably all cases we are not analyzing products that have been invented in Chile, but somewhere else. This will allow us to focus solely on the issue of exporting rather than on more complex R&D processes. This would not be the case for an advanced economy, like the US, where our method might not be advisable to study externalities in exports.

2.2. Defining new and old products, pioneers and followers

After applying the filters, we first divide our data product-wise in two groups: *new* products and existing or *old* products. We define an

[5] Having 2 years of product level data instead of firm level data doesn't pose a problem because, as we will explain in Section 2.2, we use the first 5 years only as a window to identify old products.

[6] There are empirical papers which use similar data sets. Some authors have looked at Chilean trade data to explore patterns of trade. For example, Marshall (1991) explored industry efficiency after trade liberalization in the late 1970s and early 1980s. In many contributions, Roberto Alvarez and various co-authors have been describing the different patterns of Chilean exporters and manufacturers (Alvarez, 2007, 2004; Alvarez and Crespi, 2000; Alvarez and Fuentes, 2009; Alvarez and Görg, 2009; Alvarez and Lopez, 2005; Alvarez et al., 2007). Also, this data has been used by Macchiavello (2009) to explore the duration of relationships between Chilean wineries and foreign buyers. Our main difference with them is that they do not take the perspective of new export products (Besedes and Prusa, 2006a,b; Eaton et al., 2004, 2007, 2008).

Table 4
New export products for Chile, classified according to number of pioneers and followers. Cohorts of products started by some firm in 1995–2005 (A) and 1995–2000 (B).

(A) Only product cohorts before Dec 31, 2005					(B) Only product cohorts before Dec 31, 2000			
	N of pioneers					N of pioneers		
N followers	1	2	3	Total %	N followers	1	2	Total %
0	175	5	1	72.4%	0	102	5	68.2%
1	38	4	0	16.8%	1	24	4	17.8%
2	18	1	0	7.6%	2	15	1	10.2%
3	4	1	0	2.0%	3	3	1	2.5%
4 to 6	2	1	0	0.8%	4 to 6	2	0	1.3%
Total %	94.8%	4.8%	0.4%	100%	Total %	93.0%	7.0%	100.0%
				N = 250				N = 157

Cutoff to define a new product is $10,000 minimum of exports in a given year by a firm. (*) The cohort of products "born" in 2006 is excluded from the calculation in Panel A because there are no followers by definition. That reduces the total sample from 273 products to 250. (**) As a robustness Panel (B) includes only the cohorts of products strictly before 2001, to check that the pattern described before is robust across cohorts.

old product as any HS6 code that was exported during 1990–1994 by a firm for at least $10,000 during a particular year.[7] We call these products old, in the sense that there is some amount of experience in the country about how and where to export it. Our analysis of new product thus begins in 1995, and a product is defined as *new* when it has not been exported in 1990–1994 and it is exported between 1995 and 2006 by at least one firm with a minimum of $10,000.[8] A particular and very relevant feature of our analysis is definition of new products, especially the length of the window we consider to define a product as new. This definition is different from recent studies that have analyzed new exports in the sense that we use a significantly more demanding definition of what is considered new. Iacovone and Javorcik (2010) define new exports as anything that was not exported 1 year before in the sample analyzed. Freund and Pierola (2009) call a new product to any HS code that was not exported at the first year of their sample period (1994) and that was exported for at least 3 consecutive periods after 1994. In contrast, taking 5 years as a window allows us to avoid cases of products being exported in the past but that stopped being exported during a year or two, and which would imply that we are identifying as new products some in which the country has experience. We also believe the 5 year window is appropriate because if we look at the delay between the entrance of the pioneer and the follower, we see that in more than 70% of the cases the first pioneer appears within 5 years of pioneer's entry into exporting, thus if we observe a new export it is likely that it will be a real pioneer. Even if this 5-year filter makes us reduce the number of observations, for our research question we need to take focus on new products. More important, as we show in the robustness checks section, when one reduces this window our main results change significantly. For example, reducing it to 1 year actually changes the sign of our main coefficient and makes our results similar to their paper.

Regarding the cutoff we use, using an arbitrary cutoff in this kind of study is unavoidable. As it is well known in the empirical that uses custom records, if we define too small a cutoff, we can end up considering many products as old when they could be samples that might not reflect the revealing of relevant export information, thus artificially reducing the analysis of new products. In other words, we end up with a disproportionally large share of small transactions in which we consider the country has experience, that were never intended to be a commercial export. In contrast, if we define the cutoff too high, we might not be identifying as "old" many products in which the country has experience, rendering our analysis of new products useless because the potential information spillovers between pioneers and followers might already have taken place. Our benchmark of $10,000 is focal because it coincides naturally with what many governments consider "large" (for example both the US and Chile require to formally declare an international capital flow if it is above 10,000 USD). Also, it is an amount for which access to credit can be important, since only few people can get non-collateralized personal loan for these amounts in Chile. In Section 4, we provide our basic results with alternative cutoffs.

Table 5
New products classified according to length of firm spells and number of firms.

	Duration of the export spell	
	"Successful"	"Failed experiment"
Products w/o followers	7.9% (a) "Successful but lonely pioneer"	61.6% (b) Pioneer "failure"
Products with some follower	5.7% (c) "Pioneer with follower catching up": (a) + (c) Pioneer "successes" 13.6%	24.9% (d) Pioneer "failure" with further entry: (b) + (d) "Failures": 86.4% of products

The categories divide tall new products identified into 4 categories: ((a) Successful but lonely pioneer (where there is only one firm, but it has an export spell of more than 5 years); (b) Failure (only one firm with a spell of 5 years or less); (c) Pioneer with follower catching up: there is more than one firm, at least one lsts more than 5 years, and the follower ends up being larger than the pioneer; (d) there is more than one firm but none last more than 5 years, or if one does, the follower ends up being smaller than the pioneer.

Table 6
Linear probability regressions of followers' entry on pioneer's performance.

	Dependent variable: **1**[# of followers in product > 0]			
	(1)	(2)	(3)	(4)
Duration of pioneer in product >1	0.136* (0.0741)		0.177** (0.0851)	
Duration of pioneer in product >2		0.158* (0.0882)		0.277** (0.119)
Duration of pioneer in product >5			−0.129 (0.130)	−0.242 (0.155)
Constant	0.338*** (0.107)	0.350*** (0.102)	0.339*** (0.107)	0.351*** (0.0996)
Control by cohort	Yes	Yes	Yes	Yes
Observations	177	177	177	177
R-squared	0.070	0.071	0.076	0.087

Robust standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1. We use a pooled cross section of products, where each observation is a new product *i*, and use the following regression:

$$1[\text{Product has followers}] = \beta_0 + \beta_1 1[\text{Pioneer survives}] + \mu_i^{cohort} + \varepsilon_i,$$

μ_i^{cohort} is a set of dummies for the cohort in which each product was exported for the first time. We exclude years 2002–2006 to give a chance of followers to appear after the pioneers, so durations could be analyzed using the linear probability framework to keep the analysis as straightforward as possible. [Duration of pioneer in product > *k*] is a dummy indicating if the pioneer had an exporting spell in the product of *more* than *k* years, and zero otherwise. Note that zero duration in our setting means exporting only the entry season.

[7] For the years 1990–1991, where we don't have firm level data, we counted a product as new if the product was exported in any amount above $1000 to a destination during those years.

[8] We choose this particular pre-sample period because we want to have the longest possible time-frame (and the largest possible sample of new products) to actually perform our analysis of pioneers and followers in new products.

Table 7
Linear regression of firm's export value [log US$] taking product and year fixed effects.

	Dependent variable: firm's export value [log US$]						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1[pioneer]	−1.17**	−2.77***	−3.11***	−2.77***	−2.33***	−2.39**	-2.96***
	(0.501)	(0.481)	(0.564)	(0.475)	(0.611)	(1.025)	(0.475)
Experience in prod. (years)		0.633***	1.939***	0.519**	0.585***		0.870***
		(0.209)	(0.582)	(0.203)	(0.213)		(0.128)
Experience squared			−0.137**				
			(0.063)				
N of prod. exported by firm				0.293***			
				(0.092)			
Share of new prod. in firm's exports					1.737		
					(1.82)		
Constant	12.58***	11.32***	9.483***	10.43***	10.67***	13.62***	10.49***
	(0.281)	(0.596)	(0.770)	(0.442)	(0.948)	(0.563)	(0.347)
Product-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	212	212	212	212	212	108	174
R-squared (within)	0.095	0.335	0.444	0.428	0.357	0.499	0.479

Clustered standard errors at the product-year level in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1. Experience in the product means the number of years the firm has exported the corresponding product in year *t*. The panel regression is the log of exported value, x_{ijt} in product *i* firm *j* and year *t* on the pioneer dummy and a vector of covariates Z_{ijt}. $x_{ijt} = \beta_0 + \beta_1 Pioneer_{ij} + \gamma Z_{ijt} + \mu_{it} + \varepsilon_{ijt}$, where μ_{it} is the fixed effect by product year. One important component of Z_{ijt} is the experience of the firm exporting the product (also called age in the product a_{ijt}), which controls for the Arkolakis (2010) effect, in which not all firms reach all customers immediately; instead, it takes time to build a customer base. Specification (6), instead of controlling for experience, restricts the sample to product-years in which both the pioneer and follower had at least three seasons exporting, which explains the smaller sample size, but also compares firms that have enough comparable experience given the Arkolakis (2010) effect also discussed in Eaton et al. (2011).

Changing the cutoff of our calculation to values between $2000 and $15,000 does not qualitatively alter our main results.

Second, once we have defined products as old or new, we classify *firms*, according to their sequence of entry in a product, as *pioneers* or *followers*. For a new product, we define a *pioneer* as a firm that starts exporting the product in the first year. A *follower* is a firm that began exporting the product at least 1 year after the pioneer did. For the case of old products we do not define a pioneer, because it is (highly) possible that the product was first exported before our pre-sample period of 1991–1994, so we are unable to distinguish which firm was the first to export the product. For example, there are many cases where we have certainty that these products started before 1990, and some of them well before 1900, like nitrates or wines. For old products we also define a follower which is a firm that began exporting an old product after 1994. This means that the product, although being old for the country is still new for the firm. We use this latter definition for benchmarking purposes.

Table 1 shows a summary of the taxonomy we defined. The columns relate to products (the left column showing old products and the right column showing new products); the rows relate to firms (pioneer or follower). The first row shows groups pioneers and the second, followers, depending on whether the firm is the first exporter from the country of that particular product or not. Each data point is a unique firm-product combination for firms that begin exporting a new product for them. Interestingly, most of the firms-product pairs indicate firms that start exporting something new for the firm but old for the country (N = 8964; or 95% of the observations). This makes it clear that, in the study of the early stages of new exports, we are working with a small fraction of the new exports for any firm of a country, since most of it is in old products.

Table 8
Panel regressions for quantities exported controlling by product-year fixed effects.

	Log quantity exported by a firm in a product and year		
	(1)	(2)	(3)
1 if pioneer in product	−1.052*	−2.508***	−2.132***
	(0.551)	(0.578)	(0.621)
Experience exporting the product		0.575**	1.942***
		(0.264)	(0.500)
Experience squared			−0.168***
			(0.061)
N products exported by firm			0.387***
			(0.112)
Share of product in exports of the firm			3.051**
			(1.232)
Constant	10.96***	9.837***	5.254***
	(0.307)	(0.733)	(1.104)
Observations	201	201	201
R-squared (within)	0.069	0.246	0.535

Clustered standard errors at the product-year level, in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. All regressions are estimated using product-year fixed effects. The panel regression is the log of exported quantity, q_{ijt} in product *i* firm *j* and year *t* on the pioneer dummy and a vector of covariates Z_{ijt}. $q_{ijt} = \beta_0 + \beta_1 Pioneer_{ij} + \gamma Z_{ijt} + \mu_{it} + \varepsilon_{ijt}$, where μ_{it} is the fixed effect by product year. One important component of Z_{ijt} is the experience of the firm exporting the product (also called age in the product a_{ijt}). Quantities are measured in the standard units in which the Customs transaction is recorded (e.g. number of computers rather than metric tons of computers). Experience in the product means the number of years the firm has exported the corresponding product in year *t*. Specification (2) is like specification (1), but controlling for experience. Specification (3) includes various additional controls, like product diversification and the share of the value exported in the product as fraction of all exports, to measure the importance of the product for the firm. In specification (2) the F-test indicates that the pioneer coefficient is equivalent to at least 2 years of experience (p-value 0.04).

2.3. Descriptive statistics

Using our definition of new products we find that, out of 4632 possible product-codes in this classification, Chile already exported 2571 products during our pre-sample period 1990–1994. According to our previous definition, we classify these as old products. After applying our preferred filters, we identify 273 new products exported during 1995–2006. Thus, during our sample period of 12 years the country explored 13% of the theoretical potential of products that were not exported before.[9] The total value exported of these new products steadily increased from US$1.5 million in 1995 ($46,000 per product)

[9] The fact that there are many "unexplored" products and that the new products identified represent a small percentage of them, suggests to us that the country is far from hitting the theoretical boundary of the number of products offered by the HS classification, and thus their identification is not affected by the limit in the number total number of exportable products. In large developed economies, like the US, this would not be the case since they export most of the product codes and it is then difficult to observe new products in the database due to how it is constructed, even though they might be occurring. Our method, we believe, is thus more suitable to analyze the innovative export activity in small open developing economies. See Zahler (2007) for a comparison in this dimension across countries.

Table 9
Panel regression of median product prices for each firm, controlling by product-year fixed effects.

	Log median export price of firm in a product in a year		
	(1)	(2)	(3)
1 if pioneer in product	−0.0271	−0.2582	0.0749
	(0.144)	(0.171)	(0.117)
Experience exporting the product		0.091*	−0.239***
		(0.047)	(0.090)
Experience squared			0.0337***
			(0.011)
N products exported by firm			−0.0031
			(0.017)
Share of product in exports of the firm			0.4030
			(0.507)
Constant	1.644***	1.465***	1.783***
	(0.080)	(0.121)	(0.178)
Observations	201	201	201
R-squared (within)	0.001	0.132	0.343

Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. at the product-year level, in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. All regressions are estimated using product-year fixed effects. The panel regression is the log of median export price, $price_{ijt}$ in product i firm j and year t on the pioneer dummy and a vector of covariates Z_{ijt}. Namely $price_{ijt} = \beta_0 + \beta_1 Pioneer_{ij} + \gamma Z_{ijt} + \mu_{it} + \varepsilon_{ijt}$, where μ_{it} is the fixed effect by product year. One important component of Z_{ijt} is the experience of the firm exporting the product (also called age in the product a_{ijt}). The median price is calculated taking all the transactions with the modal unit of measurement and dividing the value exported by the quantity exported.

Table 10
Panel regressions using data at the 4-tuple firm-product-destination-year level.

Variables	Dependent var: log exports (x_{ijdt})		
	(1)	(2)	(3)
Pioneer in product P_{ij}^{Prod}	−1.455**	−0.890*	−0.808**
	(0.609)	(0.447)	(0.276)
Experience in product a_{ijt}^{Prod}	0.286*	0.058	0.004
	(0.150)	(0.0560)	(0.0763)
Pioneer in prod-destination P_{ijd}^{Dest}	0.818***	0.187	−0.212
	(0.141)	(0.243)	(0.585)
Experience in product-destination a_{ijdt}^{Dest}		0.268**	0.379
		(0.113)	(0.255)
Constant	11.33***	11.50***	11.66***
	(0.326)	(0.230)	(0.301)
Observations	122	122	113
R-squared	0.249	0.262	0.303
FE	PDT	PDT	PDT
Clustering SE	prod-dest-year	prod-dest-year	prod-dest-year

Standard errors in parenthesis: 1% ***; 5% ** and 10% *, clustered at the product-destination-year (idt) level. The panel regression is $x_{ijdt} = \beta_0 + \beta_1 P_{ij}^{Prod} + \beta_2 a_{ijt}^{Prod} + \beta_3 P_{ijd}^{Dest} + \beta_4 a_{ijdt}^{Dest} + \mu_{idt} + \varepsilon_{ijdt}$; where the left hand side variable is the log of exported value, x_{ijdt} in product i firm j, destination d and year t, regressed on the two pioneer dummies (one for the pioneer in the product, P_{ij}^{Prod}, and other for the pioneer of the product in a given destination, P_{ijt}^{Dest}, as well as the age of experience exporting to a given product and the product to a given destination, a_{ijdt}^{Dest}. μ_{idt} is the fixed effect by product-year-destination. The sample only includes product-year-destinations pioneers and followers have. While specifications (1) and (2) use all time periods, specification (3) restricts the sample to cases in which firms survive at least one season post entry.

to $353 million in 2006 ($4.3 million per product). This latter value represents a modest 1.1% of non-copper exports from Chile.

Tables 2 and 3 show some basic descriptive statistics of our database of new products. Table 2 shows product-wise statistics. Out of the 273 new product codes there were 312 unique firms participating, either as pioneers or followers. However, only in 69 products there is at least a single follower, revealing that most new products are exported by only one firm. Products have an average of 2.8 firm-year observations and 4.8 firm-destination-year observations, giving a hint of many cases of products with only one firm or with firms that export only a few years (Table 4 shows a better disaggregation of this). At least half of the products are exported only 1 year, and with a mean of 2.5 years of exports. Next we show that only 77 products out of the 273 made it to the last year of the database (28%). Most new products stopped being exported altogether before the end of our sample in 2006. We then show data on the number of firms within each product. Again this number is very low on average, and at least 50% of products have only one firm that exported the product (no followers). In total the database has 398 firm-product observations. Since many products do not have followers the table shows that there are many more pioneers than followers.[10] The table also shows values exported at the product level, the year the product was introduced and the final year it was exported (no matter if the product survived or not). Values show the typical skewed distribution due to a few successful cases. Even though value exported grew on average 237%, the median growth is 0%. Next the table shows information about pioneer–follower dynamics. In most products the pioneer lasts until the last year the product is exported. However, as shown in Table 4 most products do not have followers. That is clearly seen in the next row, where we calculate the proportion of products with followers where the pioneer survives until the last year the product was exported, finding that this only happens in 5% of the products. Finally we look at measures of the pioneer and the product. For the sake of this table, we define a successful product as one that grew more than 100% in value between the first and last year exported, if it survived until 2006 and if it ended up being exported in more than US$1 million. Only 8 products can be considered successes using this definition. The last row indicates how many pioneers became the largest firm at the final year the product was exported, showing that this is the case in the minority of products (considering that there are 69 products with followers).

Table 3 shows a similar picture but where each data point is a firm-product pair at the year of entry of the firm in the product. Firms that enter into exporting a new product for the country, sell overseas a mean of US$ 23 million in *other* products. However, as in most export databases there is massive heterogeneity since the median is US$ 227,000 dollars. The value of the new products exported was on average $1.1 million, with a median of $64,055. Thus, the ratio of the medians suggests new products represented initially around 15% of export sales. Most exporters of new products have already sold something else overseas before. They have an average of *at least* 4 years of experience exporting, and a similar median, indicating that firms that engage in new products have exported other products when becoming pioneers or followers. Also, they have a mean of 4 and a median of 3 export products at the time of entry (in other words, a mean of 3 and a median of 2 *other* products).[11] This implies that we the potential learning we are trying to identify is about exporting a new product, not about exporting per se.[12] Finally, although we do not observe domestic sales, we know that a 41% of these exporters are considered large tax payers according to the local IRS. Overall this is a sample of mostly multiproduct firms of a relevant size.

3. Stylized facts on the dynamics of pioneers and followers

In this section we show three central facts. First is that most products do not have followers. Second is that if the pioneer survives in the product, then the product is more likely to get a follower. Finally and most surprising, we find that pioneers do not end up being the largest

[10] The sum of pioneers plus followers is larger than 312 because some firms are pioneers in a particular product and follower in a different product.

[11] In only 35 observations firms have no experience.

[12] In Section 3.3 we show a specification without firms with no experience to check if our results could be driven by just uncertainty and learning from exporting per se, rather than exporting a new product.

Table 11
Panel regression for the value of all exports of a firm, including also the new product.

	Dependent var: ln [Value *all* exported products]					
	(1)	(2)	(3)	(4)	(5)	(6)
Pioneer	−0.450	−0.897*	−1.073***	−0.0505	−0.253	−0.272
	(0.391)	(0.470)	(0.356)	(0.890)	(0.845)	(0.714)
Importance of product for firm		−2.406	−0.814		−3.357***	−1.998***
		(2.003)	(1.042)		(0.634)	(0.574)
N products per firm			0.485***			0.350***
			(0.0553)			(0.0849)
Constant	14.39***	15.42***	12.89***	14.16***	15.37***	13.42***
	(0.219)	(0.819)	(0.526)	(0.500)	(0.352)	(0.338)
Observations	212	212	212	212	212	212
R-squared	0.023	0.099	0.529	0.000	0.227	0.362
Number of code_year	169	169	169			
Number of HS2 codes				36	36	36

The table displays regressions with the same sample used in our baseline regression in Table 7, but using as left hand side variable the log value of exports in other products, different from the new product. Variables are described in previous tables. Standard errors in parenthesis clustered at the product level, except for (4) to (6) which are at the HS2 group level. Symbols represent statistical significance at * 10%; ** 5% and *** 1%. Alternative clustering schemes (not shown) display qualitatively similar results.

exporters in the product they discovered, suggesting that there might be differential exploration costs across firms.

3.1. Pioneers tend to be unique and most new products do not have followers

Table 4 analyzes the heterogeneity across products, decomposing them according to the number of pioneers and follower firms they have. For the period 1995–2005, it shows that less than 30% of products have one or more followers. Second, only one third of the products with followers have two or more followers. This quantitatively suggests that it is in only a few products that we observe entrants into exporting who can potentially benefit from informational spillovers. This contrasts with the largely publicized cases of new product adoption in agriculture, where by the structure of industry there are many potential entrants (Griliches (1957), and more recently Conley and Udry (2010) and Foster and Rosenzweig (2010)). Second, 95% of the new products have a single pioneer (90% if we consider only products with followers). This prima facie discards the idea that there were many firms waiting for a single bilateral exchange rate change or trade restriction to relax in order to suddenly jump into exporting, which was the setting of Iacovone and Javorcik (forthcoming) with Mexican manufacturing after NAFTA.[13]

Both results shown above – the low fraction of products with followers and the prevalence of products with single pioneers – are robust to modifications to the definitions of new products and to considering only early cohorts of products before 2000, as shown in Panel B of Table 4. This indicates a relationship that is not an artifact of the little remaining sample time that later cohorts have available for the entry of followers. Table 4 indicates that having followers is infrequent and, when it happens, it tends to be in limited numbers. However, it also shows that not all firms enter immediately, making it plausible that in the few cases with followers, these might learn something from the pioneer.

Table 5 classifies products according to the "success" of at least one firm in the product and according to the presence of followers or lack thereof. We define *success* in the introduction of a product or equivalently a *successful firm* in a product if a firm survived five or more consecutive years exporting the product (in this definition we obviously have to exclude products that began being exported after 2001, since the sample ends in 2006). Each quadrant contains the percentage of firms in each group. In Appendix E one can find a canonical example of each case. Theories that focus on externalities from pioneer to follower (like Hoff (1997); or Hausmann and Rodrik (2003)) would focus mostly on quadrant (c), of pioneers with followers. In contrast, the family of models in which "winner takes all" could generate cases like those in quadrant (a). Notably, in only one out of twenty cases we found a case of pioneer with followers with some sustained exporting. On the one hand this is consistent with new products being risky. On the other hand, even among products that had a "successful" pioneer in terms of survival, we observe that followers appear in less than half of the cases (5.7%/13.6%). As mentioned, this behavior on quadrant (a) could be consistent with other models in which there are no reasons to have followers in the same country producing the same product, as in Krugman (1980), due to increasing returns to scale at the firm level. In these cases one can think the firm internalizes the discovery, because increasing returns may act as a "patent" of any product-specific export know how they get, because other firms in the country are unlikely to copy them. Having said that, the rest of our paper would attempt to understand quadrants (b) and (d), where we could learn something about the differential behavior of pioneers and followers.

3.2. Products with surviving pioneers get more followers

A potential follower can update its priors about product profitability after observing whether the pioneer survives or not. In fact, that would predict positive correlation across products between the survival of pioneers and the entry of subsequent followers, since potential followers mimic the pioneer when it succeeds, while avoid the product if the pioneer exits. Table 6 estimates the linear probability that a product receives followers depending on pioneer survival. These regressions

Table 12
Regression of export size of the firm only the year the new product was pioneered in the country.

Dependent variable	Log of overall export size of the firm the year the pioneer started the product	
	(1)	(2)
Pioneer dummy	0.129	0.130
	(0.453)	(0.455)
Constant	13.52***	13.62***
	(0.255)	(0.217)
Observations	135	113
R-squared	0.0001	0.0008

Estimation includes observations of pioneer and follower firms in a product, in the year the product began being exported. It thus compares the exports of the pioneer firm with follower firms that exported other products that same year. Product year fixed effects are included, as well as clustering of standard errors at the product-year level. Specification (2) excludes products where no followers exported other products in the year the pioneer introduced the product.

[13] Although there are exchange rate fluctuations in our period post 1995, they are in the range of +/− 10%. In fact, our results do not correspond to the beginning of a period of export surge cum depreciation as described by Freund and Pierola (2012).

Table 13
Main regressions and statistics with alternative pre-sample windows.

	(1a)	(1b)	(1c)	(2)	(3)	(4)	(5)
	Pre-sample window for old product definition						
	1 year			2 years	3 years	4 years	5 years
Pioneer dummy	0.236	0.850***	−0.277	−0.167	−1.490***	−2.462***	−2.776***
	(0.216)	(0.157)	(0.268)	(0.281)	(0.434)	(0.471)	(0.481)
Experience of firm in product			0.171***	0.105**	0.291***	0.521***	0.632***
			(0.045)	(0.043)	(0.098)	(0.178)	(0.209)
Observations	1060	1863	1060	659	342	280	212
Database info							
# of products	592		592	468	346	317	273
# of firms	754		754	578	402	367	312
# of observations f-p-t	2607		2607	1800	1101	965	777
# of observations f-p-d-t	5479		5479	3461	1885	1626	1301
# of unique pioneers	430		430	362	287	265	234
# of unique followers	454		454	292	153	135	105

Note: Each regression in this table has the same specification as specification 2 in Table 7. We only alter the number of years of pre-sample to analyze new products. 5 year means we are considering a 5 year presample (1990–1994) and we are not considering a new product if the product was exported in during the pre-sample period. 4 year considers a presample of 1990–1993, and so on. Columns (1a) and (1b) are different since we are trying to compare our results with previous papers in the literature who analyze pioneers and followers without controlling for experience. Specification (1b) includes observations of firms that exported the product only 1 year, which we do not consider for the rest of the regressions in the table. The specification we use in this regression is $x_{ijt} = \beta_0 + \beta_1 Pioneer_{ij} + \gamma Z_{ijt} + \mu_{it} + \varepsilon_{ijt}$; where x_{ijt} is the exported value by firm i of new product j in year t; $pioneer_{ij}$ is a dummy which takes the value of 1 if the firm is a pioneer in the product; the vector Z_{ijt} is just composed the experience (number of years exporting) of the firm in the new product in year t; and μ_{it} is a product-year fixed effect. For the regressions in column (1a), (1b) and (1c) we dropped the data from 1990 and considered the first year of exports in the data as 1991. In that way our first year if firm level data (1992) has only 1 year of pre-sample to determine an old product.

allow us to control for cohort effects and changes the structure of standard errors.[14] In particular for each new product i we run

$$1[\text{Product has followers}] = \beta_0 + \beta_1 1[\text{Pioneer survives}] + \mu_i^{cohort} + \varepsilon_i$$

We find that in products where the pioneer survives for more than 1 or 2 years, it is 13 to 15 percentage points more likely that we find followers entering the product during our sample (Specifications 1 and 2). Given the baseline probabilities, the odds of having a follower increase by around 40% when the pioneer survives, which is similar to the result we obtain when we use a two-by-two matrix of entry of followers vs pioneer survival (see Appendix F.1).

In specifications (3) and (4) we replicate specifications (1) and (2) but now simultaneously controlling for the additional effect of surviving more than 5 years. The additional effect of long term survival is not significant, while the coefficients for short term survival remain significant and robust. This is consistent with the idea that information about profitability of exporting the product might be revealed relatively quickly. This relatively quick learning seems more consistent with an interpretation in which potential followers learn about business opportunities (in fact our database was publicly available for firms) rather than learning about new technologies, which may plausibly take longer to spill over[15]. Summing up, pioneer survival in a product is statistically and economically related to the entry of followers in that same product, with early survival being particularly predictive of subsequent entry of at least one firm.

[14] This robustness check is important because there could be something particular about a given entry year. For example, products that are started to be exported later have mechanically less time to have followers. Similarly, a particular year can have systematically more or less products being born, for example because of year-specific exchange rate changes shocks.

[15] Finding that survival of pioneers is positively related to entry is not obvious. In our sample there could be products with extreme first mover advantage. In such cases the survival of pioneers would arguably *discourage* entry of other firms, since the pioneer takes over the domestic market and exports a surplus. In particular, models like Krugman (1980) with increasing returns to scale at a firm level and monopolistic competition demand, would predict a negative correlation between success of the pioneer and entry, since there is room for a single firm in each product.

3.3. Pioneers export less than early followers in the same product

Most modern models of international trade rely on firms with heterogeneous productivity but with homogeneous across firm cost of entry into exporting. As we argue in Section 5, if that were the whole story one would expect pioneers to be larger than followers, since most productive firms would be more willing to pay the fixed cost, and thus enter international markets first. In contrast, in our analysis below we systematically find no support for that view and, moreover, we find the pioneers are smaller, especially when compared with early followers.

Table 7 shows the estimates of panel regressions that analyze whether pioneer end up having higher or lower export volumes than followers in that same product. The regressions perform the analysis on a "leveled playing field", meaning controlling for the same global demand in the product, which in practice is made by adding product-year fixed effects and conditioning on experience, since we know the size at entry might be smaller since firms take time to build a customer base as in Arkolakis (2010) and Eaton et al. (2011). Formally, we estimate a linear regression in product i and firm j in year t:

$$x_{ijt} = \beta_0 + \beta_{Pioneer} 1\left[Pioneer_{ij}\right] + \beta_{Exp} Experience_{ijt} + \mu_{it} + \varepsilon_{ijt}$$

where x_{ijt} is the exported value of firm j in product i at period t, $1[Pioneer_{ij}]$ is a dummy that takes the value one if the firm is the pioneer in the corresponding product, and zero for the follower in the product. $Experience_{ijt}$ is the number of years of experience firm j has in product i at period t. Including this variable in the regression seeks to correct for the fact that at the beginning exporters tend to export low values (Arkolakis, 2010). Importantly, all specifications have product-year fixed effects, $\mu_{i,t}$, to compare only *within* the same product and year, so as to control for general market conditions that may impact pioneers and followers. Additionally, we compare pioneers with followers after 1 year of entry, since in the first year, even when filtering the data, we have much more noise and a higher chance that we are observing early exploration behavior not captured by the coarseness of our framework.

The first column of Table 7 shows that pioneers are *not* larger than followers, which goes against what one would expect from extensions of the Melitz (2003)'s model, in which firms are heterogeneous only in productivity and not exploration costs. Moreover, we observe a

Table 14
Predictions for the number and relative size of pioneers vis-a-vis followers depending on the nature of the shock and whether it was idiosyncratic or common to all firms.

		Scope of the shock	
		Idiosyncratic	Common
Shock type "exploration vs. exploitation"	Product-specific productivity ϕ_{ij}	• Single pioneer • Pioneer are the most productive.	• Multiple pioneering is likely. • Pioneer is the most productive if single pioneer.
	Product-specific export entry costs F_{ij}	• Single pioneer • Pioneer *unlikely* to be most productive.	• Multiple entry is likely. • Pioneer is *likely to be* the most productive if is only one.

point estimate suggesting pioneers are smaller ($\beta_{Pioneer} = -1.17$). However, since we know that pioneers start small and then grow after they survive, we should compare pioneers and followers having the same experience in the product. Once we control for it, in specification (2) we do observe both a much larger coefficient and significance, showing pioneers being smaller.[16]. The coefficients of specification (2) indicate that pioneers export more than an order of magnitude less than the followers ($\exp\{-2.7\} \approx 0.07$) once we control for experience. The point estimate of the pioneer dummy is arithmetically equivalent to 4 years of export experience (i.e. 2.73/0.63). An F-test with this coefficients finds that the pioneer dummy is at least equivalent to 2 years of export experience (p-value = 0.04). In other words, a pioneer requires at least 2 years of experience to export a similar amount that what a follower would in its first year exporting the product, indicating a significant larger export size of followers.

Specification (3) checks whether the previous result was an artifact of the linear specification for experience, but the results remain robust after adding a squared term. Specifications (4) and (5) explore the alternative that maybe our coefficient of interest is driven by a few exporters with lots of product churning and low volumes. So (4) controls for the number of products exported while (5) controls for the share of the product in total firm exports; but both tests indicate that the negative and significant pioneer dummy remain robust, meaning that our findings were not driven by the linear specification on experience or the relevance of the product. In specification (6) we also explore what happens when we do not control for experience in any parametric way, but we instead focus on cases in which *both* pioneer and followers are mature enough in their export experience (in other words, when both the pioneer and follower had at least three seasons exporting). Of course this exercise reduces the number of observations by half, since we are looking to exports *after* the third season, but our stylized fact remains qualitatively intact, with pioneers being smaller than followers by an order of magnitude ($\exp\{\beta_{Pioneer}\} = \exp\{-2.23\} \approx 0.1$). Finally, in specification (7) we exclude product-firm observations where the firm did not have any exporting experience, in order to focus only in the impact of introducing a new product. Results are even stronger than in specification (2), indicating that results are not driven by firms that might be learning from exporting rather than from exporting a new product.

3.3.1. Results are explained by export quantity rather than by prices

Since we are presenting results on export revenues, it could be the case that the differences found between pioneers and followers were driven by differences in export prices rather than quantities. Readers may also be concerned about different qualities within the 6 digit HS classification, which we cannot control by only looking at revenues. Fortunately our database also reports unit values and quantities (and the unit in which the good was priced (tons, cubic meters,...)). This allows us to run additional regressions using quantities exported, although we lose a seven out of the 208 observations because sometimes the units change and we only consider modal units within each product and year for our calculation.

Overall our results with quantities in Table 8 look pretty much alike the ones we previously observed with export values in Table 7, with pioneers being smaller than followers when we take into account the differences in experience. The F-test is also equivalent, indicating again that the pioneer dummy is equivalent to a penalty of at least 2 years of export experience (p-value 0.09).

In contrast to the differences in quantities, we cannot distinguish any "pioneer effect" on prices, as shown in Table 9, using the same specifications of Table 8. This is consistent with our assumption that the action is on quantities rather than on prices. Also, the fact that prices are not significantly different is also reassuring since one could be worried that at the granularity we are working pioneers and followers are producing systematically different kinds of goods (for example pioneers exporting less quantity but of higher quality which would mean a higher price). But we do not find that.

In conclusion, the smaller total trade volume of pioneers vis-a-vis early followers showed in Table 7 seems to be explained by quantities rather than prices, which also help us be less worried that this is driven by quality differences across firms within the same product.

Taking stock, our results indicate that, conditional on multiple entrants, the pioneer might not be the firm that benefits the most (in terms of export volume) from the discovery of a new product. Interestingly, this is not only counterintuitive to current trade models of the steady state (i.e. Melitz, 2003), but it is also contrary to the *assumption* of Grossman and Rossi-Hansberg (2010) that pioneers have a roughly constant returns to scale technology they can quickly upscale. On average, pioneers in our sample do not export the largest amounts in a product. Followers do. The next section proceeds with additional robustness checks of our core facts.

4. Further robustness checks

This section explores arguments that could weaken or contradict our interpretation of the findings, concluding that the main stylized facts found in Section 3 are qualitatively robust to plausible alternative

Table 15
Example of product homologation procedure.

HS92	HS96	Final code
011100	011200	011200
011200	011200	011200
150140	150150	150140
150140	150160	150140
140400	140400	200199
140400	140600	200199
140500	140500	200199
200199	140400	200199
200199	140500	200199

[16] Comparing them on the same year deals with the problem reported by Lieberman and Montgomery (1998), who show that by imputing zero sale for the followers during the years they did not export the product, one can spuriously get a result where the first mover has more rather than less sales. That would give the unconditional difference in export between pioneers and followers across products $\mathbb{E}\left[\Delta x^{Pioneer-Follower}\right]$, rather than the difference conditional on having follower $\mathbb{E}\left[\Delta x^{Pioneer-Follower} | x^{Follower} > 0\right]$. We are not only interested in the latter because it is where spillovers to other firms might be plausible, but also because it allows us to compare pioneers and followers on the same year and product, so controlling for global demand conditions.

Table 16
Robustness: Regression of pioneers and followers at the 4 digit level.

	Log export value at 4-digit HS firm and year							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1[Pioneer]	−1.414***	−3.390***	−1.449***	−3.055***	−1.028 †	−0.484	−3.456***	−3.064***
	(0.481)	(0.499)	(0.476)	(0.500)	(0.666)	(1.172)	(0.498)	(0.422)
Experience		0.781***		0.594***		−0.169	0.617***	0.708***
		(0.235)		(0.201)		(0.389)	(0.196)	(0.180)
1[Product also new for firm at 4 digits]							1.725**	
							(0.681)	
log (all exports)–log (new export)								0.553***
								(0.101)
Constant	13.44***	11.89***	13.46***	12.34***	12.37***	12.60***	12.10***	11.53***
	(0.270)	(0.640)	(0.267)	(0.549)	(0.408)	(0.777)	(0.524)	(0.582)
Observations	212	212	212	212	129	129	212	212
R-squared	0.114	0.414	0.121	0.340	0.206	0.232	0.367	0.477
Number of code_year	169	169						
Number of codehs4_year			164	164	118	118	164	164

For all regressions the dependent variable is the value exported in the group of similar products (at 4-digit, rather than our baseline at HS 6-digit). Columns (1) and (2) are similar to the ones in our baseline in Table 7, but using the 4-digit level exports. Specifications (3) and (4) add to the previous ones fixed effects and clustering at the 4-digit level. Specifications (5) and (6) keep only one product per each group of HS4 codes, which of course reduces by a third our sample size. Despite this massive sample loss, in specification (5) the p-value for the pioneer dummy is only marginally above the standard 10%. When one performs a one tail *t*-test for pioneers being smaller than followers the p-value is 6.5%, signed with a † symbol. Instead of totally excluding those observations where there is more than one HS6 product in an HS4 group, specification (7) uses as a control a dummy that takes the value 1 if the product was new for the firm also at 4 digits (on top of, of course, being new for the firm at 6 digits). Instead of a dummy, specification (8) controls for the relative relevance of other products vis-à-vis the new product. That is performed by using the log difference between other exports of the firm and the exports in the new product.

explanations, additional controls, as well changes in definitions and cutoffs.[17]

4.1. Pioneers in the product versus pioneers in a given destination within the product

We have been framing the analysis as if our results are driven by the firms that discover the profitability of exporting a new good, and which may not benefit the most from the discovery. Empirically, though, this channel may get confused with an alternative story in which pioneers learn from the demand of a product in a particular destination. In that case the relevant information revealed would not be product wise but rather product-destination wise. To tell these two stories apart, we control simultaneously for being pioneer in the product, and pioneer in the product in a specific destination. In particular we estimate a model with observations at a finer granularity: product *i*, firm *j*, destination *d* and year *t*

$$x_{ijdt} = \beta_1 P_{ij}^{Prod} + \beta_2 a_{ijt}^{Prod} + \beta_3 P_{ijd}^{Dest} + \beta_4 a_{ijdt}^{Dest} + \gamma Z_{ijdt} + \mu_{idt} + \varepsilon_{ijt;}$$

where μ_{idt} is a fixed effect for the 3-tuple product-destination-year, P_{ij}^{Prod} and P_{ijd}^{Dest} are dummies for the pioneer in the product and in the product destination, while a_{ijt}^{Prod} is the experience (or age) the firm has in the product and a_{ijdt}^{Dest} is the experience the firm has in the destination for that product. By definition both pairs of variables will be exactly the same for the first destination in which the pioneer firm exported, so our source of identification will come from variation in situation in which there is more than one destination per firm.

Although we do not have an enormous source of variation, the results of this "horse race" in Table 10 suggest that the firm that comparatively lags behind is the pioneer in the product P_{ij}^{Prod}, and not the pioneer of that product in a particular destination. In Column (1) we take our preferred specification from Table 7 and add the pioneer in the product-destination combination, P_{ijd}^{Dest}. Our central variable of interest, P_{ij}^{Prod}, is qualitatively robust, being negative 1.4 log points vis-a-vis a follower with the same experience. In contrast, the pioneer in the destination has a positive effect. When in specifications (2) and (3) we include experience in the particular destination, we observe that the experience in the product a_{ijt}^{Prod} becomes small and insignificant; while the experience in the specific destination with the product takes a positive and statistically significant effect. This is what one should expect in the spirit of Arkolakis (2010) and EKK (2013), in which the customer base is built separately in each country. Having said that, our central variable of interest, P_{ij}^{Prod}, remains robust, suggesting that our result that the pioneer tends to lag behind is a phenomenon at the product level.

4.2. Pioneers are not larger than followers in their overall exports of the firm

Since we are dealing mostly with multi-product firms, it is worth asking whether the pioneers lagging behind vis-a-vis followers are something that is only happening in that particular new product or, instead, that it is a firm-wide phenomenon. Table 11 runs the same baseline panel regressions but using as left hand side variable the total exports of the firm. While in specifications we observe a negative point estimate, in many of them they are not statistically different from zero. Specifications (1) to (3) run the regression at the product-year level; while specifications (4) to (6) do it at the HS2 level. The latter shows of course less precision, but at the same time remarks that our negative point estimates are not an artifact of the level of aggregation or the use of experience in the model, which we do not include in the regression. In general, we cannot discard that pioneers come from the same distribution of exports than followers. Nonetheless, Fig. 2 in the Appendix shows that there could be differences between the distributions at the top. But coincidentally with Table 11, it says that pioneers are not larger than followers, which is what one could have expected using standard models of firms with heterogeneous productivity a la Melitz (2003).

To be fair with theories of heterogeneous productivity, there is also a time issue. Theory would say the pioneer should be the most productive in the year it pioneered the product, so what would be interesting is to compare firms in their main sector vis-à-vis other firms, in the year it was the pioneer. Table 12 does that, meaning that it works only with a cross section of firms in the same product. We have less observations because in many cases, followers did not export anything the year the pioneer began exporting the new product. Specifications (1) and (2) are very similar, but in specification (2) we excluded observations where the pioneer had no follower exporting the year they pioneered

[17] It is worth remarking that besides the robustness checks shown below, we attempted including product and industry characteristics to our main regressions, to see whether our effects were systematically more intense in some industries/products than others. Overall, we did not detect robust correlations. We acknowledge the sample size is unlikely to be large enough as to have enough power for the analysis of heterogeneity across sectors.

Table 17
HS 6 digit products where there is a pioneer and follower(s), indicating whether it is also a pioneer for the country at 4 digits.

HS6	Description
10420	Goats, live
20220	Bovine cuts bone in, frozen
20621	Bovine tongues, frozen
40811	Egg yolks dried
70690	Beetroot, salsify, celeriac, radishes, etc. fresh, chilled
80540	Grapefruit, fresh or dried
110230	Rice flour
110630	Flour, meal, powder of fruit/nut, citrus or melon peel
130232	Mucilages & thickeners, from locust bean, guar seeds
140300	Vegetable mats. of a kind used primarily in brooms/brushes
220710	Undenatured ethyl alcohol >80% by volume
230240	Cereal bran, sharps, residue except maize, wheat, rice
251512	Marble and travertine in blocks, etc.
262011	Ash or residues containing hard zinc spelter
271210	Petroleum jelly
271220	Paraffin wax containing <0.75% oil
281390	Sulfides of non-metals except carbon disulfide
282420	Red lead and orange lead
282520	Lithium oxide and hydroxide
282731	Magnesium chloride
292010	Thiophosphoric esters (phosphorothioates), salts, derivs
293211	Tetrahydrofuran
293500	Sulphonamides in bulk
310420	Potassium chloride, in packs >10 kg
310510	Fertilizer mixes in tablets, etc. or in packs <10 kg
380110	Artificial graphite
380992	Finishing agents & dye carriers – paper industry
390760	Polyethylene terephthalate, in primary forms
391520	Polystyrene waste or scrap
392062	Sheet/film not cellular/reinf polyethylene terephthal
430390	Articles of furskin except clothing and accessories
441090	Particle board of ligneous materials except wood
441840	Shuttering for concrete constructional work, of wood
510620	Yarn of carded, wool, <85% wool, not retail
521021	Plain weave cotton <85% + manmade fiber, <200 g bleached
530921	Woven fabric of flax, <85% flax, unbleached/bleached
550961	Yarn of acrylic staple fiber & wool or hair,not retail
550962	Yarn of acrylic staple fibers & cotton, not retail
600122	Looped pile knit or crochet fabric, of manmade fibers
610311	Mens, boys suits, of wool, fine animal hair, knit
680790	Asphalt or similar material articles not in rolls
700530	Float glass, etc. in sheets, wired
711019	Platinum in semi-manufactured forms
721933	Cold rolled stainless steel, w >600 mm, t 1.0–3.0 mm
731430	Net/fencing, welded iron or non-alloy steel, heavy
740610	Powders, copper, of non-lamellar structure
790112	Zinc, not alloyed, unwrought, <99% pure
820190	Scythes, sickles, etc. used in agriculture, etc.
830910	Corks, crown, of base metal
840211	Water tube boilers, steam production >45 T per hour
840690	Parts of steam and vapor turbines
841810	Combined refrigerator–freezers, two door
841840	Freezers of the upright type, <900 l capacity
842832	Continuous action goods conveyor or elevator (bucket)
842919	Bulldozers and angledozers, wheeled
843351	Combine harvester–threshers
845180	Machinery to impregnate textiles, make linoleum, etc.
845420	Ingot molds and ladles used in metallurgy/foundries
845490	Parts of equipment for metallurgy, foundries
846310	Draw-benches for bars, tubes, profiles wire, etc.
846594	Bending or assembling machines for wood, etc.
850423	Liquid dielectric transformers >10,000 KVA
852390	Unrecorded sound recording media except photo/magnetic
870919	Work trucks except electrically powered
871620	Trailers for agricultural purposes
871631	Tanker trailers and semi-trailers
880520	Flight simulators, parts thereof
961220	Ink-pads
961610	Scent sprays and similar toilet sprays, parts

the product. In both cases the pioneer dummy is nonsignificant, indicating that we cannot reject the hypothesis that they have the same size as followers. This confirms that we do not find evidence that pioneers are larger than followers in their total exports, justifying our focus about the effect of pioneers being smaller in the specific new product pioneered, not overall exports. One cannot say from our data that pioneers were larger than followers.

Table 18
New export products classified by type of product and by existence or absence of followers.

Group of goods	With followers	Without followers	% with followers
Animal & Animal Products	4	6	40.0%
Chemicals & Allied Industries	11	41	21.2%
Foodstuffs	2	8	20.0%
Footwear/Headgear	0	2	0.0%
Machinery/Electrical	14	34	29.2%
Metals	6	34	15.0%
Mineral products	4	10	28.6%
Miscellaneous	2	3	40.0%
Plastics/Rubbers	3	8	27.3%
Raw Hides, Skins, Leather, & Furs	1	1	50.0%
Stone/Glass	3	9	25.0%
Textiles	7	25	21.9%
Transportation	4	2	66.7%
Vegetable Products	6	13	31.6%
Wood & Wood Products	2	8	20.0%
Total	69	204	25.2%

4.3. Importance of long pre-sample to avoid confounding new products with intermittent exports

As highlighted in the introduction, the way we define a new product for a country makes an important difference for our results, particularly when compared with definitions used in other papers. In particular here we analyze the relevance of a long pre-sample period to identify "old" export products, thus affecting the pool of potential new products from which we perform our analysis. Table 13 runs variations on our main regression changing the pre-sample period. Column (5) simply replicates the benchmark result, which uses a 5 year presample period (1990–1994). As we move to the left of Table 13 we start reducing the pre-sample period. Moving to 4 years of pre-sample reduces only slightly the magnitude of our pioneer dummy, followed by an increase in the number of new products and observations. With 3 years of pre-sample in column (3) our result that pioneers are smaller is still statistically significant, albeit with 26% more new products than our benchmark. When we move to even shorter pre-sample periods (2 years or 1 year, as in columns (2) or (1c)) pioneers are no longer smaller in statistical terms. This is probably because we are unlikely to be picking true pioneers and instead getting firms that enter and exit from one product every season due to market conditions. Furthermore, when we attempt to replicate as much as possible the Freund and Pierola (2009) definition of pioneers with our sample, that means leaving only 1 year of pre-sample and not controlling by experience in the product, we find in columns (1a) and (1b) that the pioneers become larger than followers, which is what they get in their sample of Peruvian firms.[18] Overall, this robustness exercise shows that our main result survives reasonable deviations from our definition of new products; but also remarks the relevance we have given to building a long panel and giving room for a longer-than-usual pre-sample, isolating as much as possible the new products from intermittent exporting. Otherwise one may not be able to distil the truly new exports.

[18] The difference between column (1a) and (1b) is that in the former, as in all our specifications, we restrict the sample to firms that survive at least one year in the product. Column (1b) considers all observations.

Table 19
Percentage of products classified according to the survival of pioneers and existence of followers.

Distribution of products according to whether the pioneer survived more than 1 year				
	Product has follower(s)			
	No	Yes	Total	% with followers
Pioneer duration in product ≤ 1 year	45.6	15.4	60.9	25.2
Pioneer duration in product > 1 year	24.2	14.9	39.1	38.0
Total	69.8	30.2	100.0	
			N = 215	
				Pr (Pearson's chi2 > = 4.04) = 0.044

Each observation in this table corresponds to a new product *i*. We only included products whose exports began in 2003 or before, to give at least 3 years before the end of the sample in order to potentially have followers. When export spells are interrupted by a single or 2 years without exporting, we still consider them an export spell.

4.4. Additional tests

In additional robustness checks (shown in Appendix F due to space restrictions) we explore additional concerns, finding that our main facts remain robust. First in Table 20 we explore whether our results were driven by differential growth rates of exports after entry between pioneers and followers, as we allowed for a different slope over time for pioneers. Second, instead of estimating a precise number for how much smaller are pioneers vis-a-vis followers, we explore the probability that pioneers are qualitatively smaller in the new product. Therefore Table 21 replaces our left hand side variable of exports with a dummy for being the largest exporter in the product. We find that pioneers are 40% less likely to be the top exporter in the product. Also, we wanted to make sure the results were robust to reasonable changes in the cutoff of export values that we use to define a new product. Table 22 shows that our results are essentially robust to different cutoffs and thus different samples. Finally we wanted to explore whether it is reasonable to assume that uncertainty is closely related to the product. When we look at differential survival of pioneers and followers in the same product, in Table 23, we cannot discard that the survival rates are the same between pioneers and followers, which is consistent with the idea that a relevant component of profitability could be product specific and could be in principle learned across firms. Regarding the granularity of exports one could be concerned of our results being driven by marginal spinoffs at six digit level. We repeat the exercise looking at exports at 4 digit level on Table 16 (Appendix B), finding also negative estimates.

To conclude this whole section, we can now say that our main stylized facts remain robust to a set of potential alternative explanations and measurement issues. The next section will focus on interpreting our evidence.[19]

5. A simple framework to interpret our evidence

This section discusses the previous findings through the lens of a very simple framework. Rather than introducing new channels, we aim to identify broad families of models that are consistent or inconsistent with our evidence, keeping the setup as broad as possible. In particular, we focus on the role of heterogeneous exploration costs vis-à-vis productivity differences.

Imagine that firms *i* in a country can potentially export a new product *j*, with firms being heterogeneous in two dimensions. On the one hand they have different productivity in the product φ_{ij}, which as usual in the literature is monotonically related to higher exports $x(\varphi_{ij})$ and higher *gross expected* discounted value from exporting the product, henceforth $V(\varphi_{ij})$. We assume they are price takers in a commodity, consistent with evidence that the main channel of action is the quantity and volume exported and not the price or quality. On the other hand, and unlike in most modern applications of international trade, we also assume firms are potentially heterogeneous in their fixed costs of exploring a new product in global markets, which we denote by F_i. The decision to export is given simply by the comparison of the costs F_{ij} and the expected benefits $V(\varphi_{ij})$. Firm *i* will enter into exporting only if $F_{ij} \geq V(\varphi_{ij})$. Since all our products are new exports, we assume that before the year when the pioneer started we had $F_{ij} < V(\varphi_{ij})$ for all firms *i* in product *j*

5.1. Models in the space of productivity and export entry costs

It is now instructive to map prevailing models of international trade in the space of the value of exporting $V(\varphi_{ij})$ versus F_{ij}. Without loss of generality, in a completely unrestricted model the joint density of productivity and export entry costs could take any shape in Fig. 1, with exporters being those to the right of the 45° line that defines $F_{ij} = V(\varphi_{ij})$, with the net expected profit from exporting given by the vertical distance between the entry cost and the 45° line.

The Melitz (2003) model assumes firms with different productivity but with constant fixed cost $F_{ij} = \overline{F}_j$, meaning that the joint density looks like a horizontal straight line in the plot. If we twist this model to predict the pioneering decision, we have that before the pioneer enters all firms are to the left of the 45° line, with no exports. To break that inaction there are two families of things that can happen in this model. One alternative is that the $\overline{F}$ line shifts down until the most productive firm(s) start(s) exporting as pioneers. The other option is that there is a shock that moves to the right the distribution of productivity. In both cases, though, we have the prediction that the pioneer(s) would correspond to the most productive firms, which under the monotonicity assumptions made at the beginning imply that pioneers would export more than followers, which is the opposite of what we see in our data.[20] A second family of models is Arkolakis (2010) and its application in EKK (2011), which extends the Melitz (2003) framework allowing firms to have a menu of fixed costs $F_{ij} \in (F_{min}, F^*)$, rather than a single fixed number. Now any firm can choose to pay a small fixed cost to start exporting small quantities and then subsequently incur in additional fixed costs to reach a larger share of customers abroad. Importantly, although the equilibrium choice of firms for entry costs is potentially different in this model, *the menu is the same* for everybody. Therefore high productivity firms on the very right of the graph can also choose to pay F_{min} and export the first unit abroad, so they are pioneers. In that sense we think the costs in the model are considered "off-the-shelf" as opposed to, for example, organizational costs that

[19] It is worth remarking that we attempted including product and industry characteristics to see whether our effects were systematically more intense in some industries/products than others. But overall, we did not detect robust correlations. We acknowledge the sample size is unlikely to be large enough as to have enough power for the analysis of heterogeneity across sectors.

[20] Note that the relationship between the observed export volume *x* depends not only on productivity φ_i – which maps monotonically into *V* – but it also depends on the experience or age of the firm exporting the product, $a_{i,t}$, as argued by Arkolakis (2010). Therefore when we claim that pioneers are smaller than followers, we are assuming we are comparing exports among firms with similar levels of experience exporting the product and with similar market conditions in year *t*.

Table 20
Panel regression with additional controls and allowing for differential growth rates of exports after entry.

	(1)	(2)	(3)	(4)	(5)
Pioneer	−2.776***	−2.721***	−1.445	−1.898***	0.963
	(0.481)	(0.493)	(1.386)	(0.595)	(1.343)
Experience	0.633***	0.568***	0.705***	0.386*	0.368**
	(0.209)	(0.205)	(0.158)	(0.212)	(0.158)
Pioneer × Experience a_{ijt}			−0.275		−0.389*
			(0.249)		(0.206)
Log of rest of exports of firm in that year		0.240*			0.432***
		(0.139)			(0.127)
Importance of product for firm				3.442***	6.895***
				(1.315)	(1.550)
N products per firm				0.394***	0.166*
				(0.0839)	(0.0870)
Constant	11.32***	8.600***	10.89***	8.828***	2.707
	(0.596)	(1.665)	(0.416)	(0.694)	(1.974)
Observations	212	212	212	212	212
R-squared	0.335	0.427	0.356	0.505	0.675

Standard errors clustered at the product-year level, in parenthesis: 1% ***; 5% ** and 10% *. The specification of the panel regression is the log of exported value, x_{ijt} in new product i firm j and year t on the pioneer dummy and a vector of covariates Z_{ijt}. $x_{ijt} = \beta_0 + \beta_1 Pioneer_{ij} + \gamma Z_{ijt} + \mu_{it} + \varepsilon_{ijt}$, where μ_{it} is a product-year fixed effect. A key component of Z_{ijt} is the experience of the firm exporting the product (also called age in the product a_{ijt}), which controls for the Arkolakis (2010) effect, in which not all firms reach all customers immediately, and instead, they take time to build a customer base.

Table 21
Linear panel regression of being the largest exporter in a product-year.

	Dep. var.: 1 [firm is the *largest* exporter in the product-year]					
	(1)	(2)	(3)	(4)	(5)	(6)
1[pioneer]	−0.41**	−0.83***	−0.95***	−0.83***	−0.70**	−0.83***
	(0.185)	(0.152)	(0.137)	(0.189)	(0.285)	(0.186)
Experience in prod. (years)		0.165***	0.641***	0.145**	0.152**	
		(0.0610)	(0.138)	(0.0673)	(0.0593)	
Experience squared			−0.05***			
			(0.0143)			
N of prod. exported by firm				0.0526		
				(0.0460)		
Share of new prod. in firm's exports					0.495	
					(0.618)	
Constant	0.980***	0.651***	−0.0176	0.492***	0.465	1.292***
	(0.110)	(0.193)	(0.227)	(0.158)	(0.295)	(0.124)
Product-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	212	212	212	212	212	108
R-squared (including FE)	0.121	0.292	0.444	0.324	0.311	0.521

Bootstrapped robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All the specifications contain product-year fixed effects that control for general market conditions. Sample and covariates are the same as in Table 6. Regression is $1[x_{ijt} = max\{x_{ijt}|j \text{ exports good } i\}] = \mu_{it} + \beta Pioneer + \gamma Z$. Since we are dealing with an extreme statistic (the maximum), we used bootstrapped standard errors to mitigate biases due to potential non-normality. Using clustering within product years instead, to account for within product-year negative correlations, shows almost identical standard errors (results not reported but available upon request).

make large organizations less willing to start a new export project and cannot be bought like normal inputs in the market. Overall, the predictions of the Arkolakis (2010) "ladder" of fixed costs are also inconsistent with our stylized fact that pioneers are smaller than followers. In general, frameworks with a non positive correlation of $V(\varphi_{ij})$ and F_{ij} would predict that pioneers would be larger than followers. This in principle would also include models in which there are financial constraints for firms to pay for at least part of the fixed cost F_{ij}, like Manova (2013). One could think that firms with high productivity have in principle no worse access to finance, both because of higher wealth or cash flows from other export products, since most are multi-product firms. But this is a channel that would make large firms more able to be pioneers, which is – again – not what we find in our stylized facts. In short, we see that these standard models that seem to explain well the steady state of exports seem less likely to explain the early dynamics of our new exports.

Table 14 summarizes in a two by two matrix the basic predictions about the number and relative size of pioneers one would get from more general models. The Table has 4 scenarios depending, on the one hand, on whether the pioneering decision is driven by a shock to productivity or to lower exploration costs and, on the other hand, depending on whether the shock was idiosyncratic to the pioneer firm or, instead, it corresponds to a common shock to all firms in the distribution.[21]

The first thing to note is that when shocks are common to all firms, we expect to have multiple firms that become pioneers, unless the joint distribution of firms is very discontinuous around the 45° line for the export cutoff. This seems a plausible explanation for why Iacovone and Javorcik (forthcoming) find multiple pioneers in their sample of Mexican manufacturers, which enter the US market in new products immediately after NAFTA, which was clearly an aggregate shock for the industry. In contrast, in Section 2 we found that in most products of our sample there is a single pioneer and in very exceptional cases one more, suggesting that we have to lean towards the first column of Table 14, where shocks that triggered the pioneering decision could have been idiosyncratic. Now to tell apart whether the shock that made firms pioneer was relatively more important for its productivity or for the entry cost, we have to look at the identity of the pioneer, which in this context corresponds to its post-entry shipments of the product. If the shock that triggers the entry into a new product was disproportionally to productivity of the firm, one would expect that the pioneer ends up being the largest exporter in the product, as in the top left corner of the matrix. But as we mentioned this is not what we see in the data. In fact, our evidence seems consistent with the bottom left corner, where firms face a random shock that lowers the exploration costs F_{ij} (in a similar logic to Eaton et al. (2011)) despite not having the best productivity.[22] This could generate at the margin some steep positive correlation between productivity and entry costs, making large firms less willing to be pioneers. The natural puzzle here becomes what are these costs that make the most productive firms less willing to be pioneers. As mentioned, it cannot be something you could outsource or buy in the market, because these are things large firms are good at. Artopoulos et al. (2013) describe a collection of case studies of new export products, arguing that some large firms may have a disadvantage searching; which is a common theme discussed a lot in the Management literature but that received much less attention in the international trade and development literature. In particular, there is a large literature after March (1991) claiming that firms that are better at "*exploration*" of new opportunities, meaning a low F_{ij}, could be worse at the stage of "*exploitation*", which we measure by φ_{ij}. In previous versions of this paper we have considered at least two

[21] We thank an anonymous referee for suggesting this Table.

[22] In Appendix D, we show that the randomness of the shock to fixed costs, which empirically implies that the pioneers should come from different parts of the distribution of firm size, is actually found in our data.

Table 22
Replications of main estimation and statistics using alternative cutoffs to define an old/new product.

Cutoff for considering a product as new	$2000	$3000	$5000	$8000	$10,000	$12,000	$15,000
Pioneer dummy	−1.93*	−1.94*	−1.89*	−2.76***	−2.77***	−2.75***	−2.51***
	(1.10)	(1.09)	(1.03)	(0.480)	(0.48)	(0.48)	(0.49)
Age of firm in product	0.68**	0.60**	0.60**	0.62***	0.62***	0.63***	0.58***
	(0.32)	(0.30)	(0.30)	(0.20)	(0.20)	(0.20)	(0.20)
Observations	260	261	248	225	212	204	189
Database info							
# of products	377	348	324	293	277	270	252
# of firms	463	416	373	341	315	304	275
# of observations firm-prod-year	1004	953	889	830	798	757	709
# of observations firm-prod-destination-year	1763	1714	1744	1711	1696	1651	1599
# of unique pioneers	323	299	269	252	236	230	208
# of unique followers	177	151	131	117	106	94	89

Note: Each regression in this table has the same specification as specification (2) of Table 7, which is replicated in column (1) for ease of comparison. In subsequent columns we only alter the cutoff for a given value to be considered an export, both for identifying old and new products. The cutoffs are all in US Dollars. The specification we use in this regression is $value_{ijt} = \beta_0 + \beta_1 Pioneer_{ij} + \gamma Z_{ijt} + \mu_{jt} + \varepsilon_{ijt}$, where $value_{ijt}$ is the dependent variable, and is the value exported by firm i of new product j in year t; $pioneer_{ij}$ is a dummy which takes the value of 1 if the firm is a pioneer in the product; Z_{ijt} is the experience (number of years exporting) of the firm in the new product in year t; and μ_{jt} is a product-year fixed effect. The cutoff described in each column is the one used for years 1992 to 1994 in the pre-sample period and the cutoff is at the level we analyze our data: firm-product-year.

channels that could deliver a positive correlation between F_{ij} and φ_{ij}, so large firms are bad at exploring new product.[23] Having said that, we are unable to tell apart the exact channels that make the most productive firms act as if they had a temporarily higher F_{ij}, that decreases after the pioneer enters. An informational externality in which followers learn from pioneers could be one such possible explanation.

6. Concluding remarks

The process of export diversification is at the center of many debates about economic growth and structural transformation in less developed economies. In this paper we investigate the early stages of how countries start exporting new products they did not export before, analyzing the possibility of pioneer-to-follower informational spillovers. Using detailed customs data from Chile we build a panel of pioneers and followers, showing evidence consistent in some dimensions, but not in others, with spillovers in the discovery of new export products. First, we find that most newly exported products do not have followers, even if the pioneer survives, suggesting that these potential spillovers could be in effect in only a small fraction of new products attempted.[24] Second, products with surviving pioneers have a higher chance of having followers, which is congruent with followers either learning from the successes or avoiding the failures of pioneers. Third, for products with both pioneers and followers, we find that pioneers are smaller than followers in their exports, suggesting that the first explorer may not be the firm that benefits the most from its discovery, at least in terms of future revenues.

Our main finding (pioneers being smaller than followers in their exports) seems inconsistent with simple extensions to heterogeneous firm models of export entry in which firms differ only in productivity/size and face a homogeneous menu of entry costs (Melitz, 2003; Arkolakis, 2010), where the largest firm has the greatest incentive to enter into exporting for a given entry cost. Our interpretation is that the early dynamics of a new export product not only depends on the now standard "selection of the fittest" into exporting, which explains well the steady state of exporting across firms. It also supports the idea that shocks and heterogeneity in the costs of exploring a new export may play a crucial role in the early shipments of a new product. Our findings remarks that some high productivity firms may have, at least initially, higher entry costs. This means that firms better at "*exploration*" could be worse at "*exploitation*" (see March (1991)).

Finding that pioneer exporters do not scale a lot their production, which goes against the assumptions of Grossman and Rossi-Hansberg (2010), suggests an important role for policy in case of externalities. If pioneers cannot grow large, then they cannot internalize a large fraction of the value they create, meaning that if there are externalities, then the market on its own may provide too little exploration. At the same time, our finding that the majority of surviving pioneers do not have followers call for some caution about how ubiquitous are pioneer-to-follower spillovers.

Appendix A. New correspondence to merge HS commodity codes across vintages 1992–2006

To measure the decision to export a new product for the country, it was necessary to homologate HS6 product codes through time. The Harmonized System consists of close to 5000 product codes. However, once every 5 years the classification is internationally updated. This implies that several codes are expanded into new codes (i.e. what before could have been portable music players in 1990, could have been expanded into "portable cassette music players" and "portable CD music players", and later on into "MP3 players"). Other codes are collapsed into a single code (i.e. products that are seldom exported) or are taken out of the classification. Some codes are simply relabeled. And there are combinations of the above (i.e. a code that becomes part of two different codes which encompass other codes that are absorbed by each new code). Thus, it is possible that what we observe as new codes are not new products being exported but simply a new codification of a product that could have been exported before under a different code.

Given the above problem, what we need is a common classification across time. This was unavailable in existing correspondences for HS classifications at 6 digits. Correspondences which can be obtained,

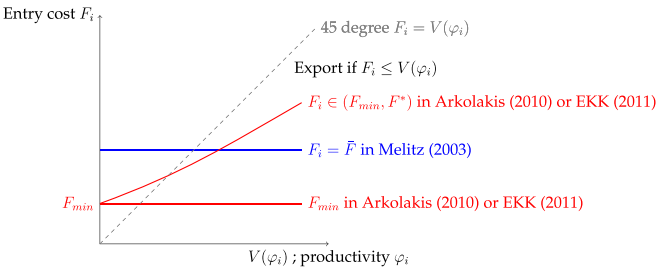
[23] One channel is that large firms have limited managers and they could choose between allocating a manager to a new risky project that is small or instead working on a well known project of the main product line, which could be much bigger in size. The more productive the firm the more it would export of both products, but also the larger the opportunity cost of allocating a manager to a new product line, endogenously rising F_i for the new export product. Moreover, the larger firm has incentives to delay entry until the smaller pioneer reveals the actual profitability and size of the business. A second potential channel we modeled in previous versions was that a random firm in the distribution receives an exogenous shock – for example a phone call from a German supermarket or a brother that went to live in Japan and understands the market opportunities – which effectively reduces F_i below $V(\varphi_i)$, triggering the export decision. And once profitability of the product was revealed to be high, then the most productive firms react by entering the product. Of course a random firm, which is the pioneer, has on average lower size than the top productivity firms, which are those that would enter as followers in case profitability is revealed.

[24] It is worth emphasizing that the very fact that there are no followers is not enough to say that followers get the full reward from the product they pioneer. While for the cases of "successful" pioneers without followers this full internalization seems certainly the case; when a pioneer fails then potential followers may not be showing up precisely because they could have learned from the failure of the pioneer. This free riding in experimentation is remarked by Hausmann and Rodrik (2003).

Table 23
Hazard rate for duration of firm exporting a product depending on whether they were pioneers or followers, as well as the type of pioneer.

Model type	Hazard rate for duration of firm in a product	
	(1) Cox proportional hazard	(2) Hazard with Weibull parametric model
Followers is omitted category		
Pioneer with follower	1.183	0.990
	(0.201)	(0.168)
Pioneer without followers	1.271*	1.297*
	(0.180)	(0.183)
Constant		0.279***
		(0.0362)
ln P		1.239***
		(0.0486)
Year FE		
N	398	398

Standard errors in parenthesis. *** p < 0.01, ** p < 0.05, * p < 0.1; Note: Coefficients are hazard rates so a hazard rate of one means that it has the same hazard as the benchmark group. If the hazard rate is above one then it has a higher hazard of ending the export spell. The coefficient of followers is the omitted category. Regression (1) uses Cox proportional hazards model. Regression (2) uses a Weibull parametric survival model.



Infinite potential joint distribution functions of the gross value of exporting $V(\varphi_{ij})$ and the entry cost F_{ij} can plausibly exist in this space. Exporters are firms located to the right of the 45 degree line. The plot includes the joint distribution of firms in this space for two canonical models of trade. First the Melitz (2003) model with no heterogeneity in entry cost across firms. Second is is Arkolakis (2009) and its application in EKK (2011), in which firms have a menu of fixed costs $F_{ij} \in (F_{min}, F^*)$ available for all firms. Any firm can choose to pay a small fixed cost F_{min} to start exporting small quantities and then incur additional fixed costs to reach a larger share of customers abroad and export more. Importantly, high productivity firms on the very right of the graph can also pay F_{min} and export the first unit abroad. In that sense the costs are considered "off-the-shelf". If pioneers are less productive than followers, which is the view our data supports, one needs that at least in the first year the product is exported by the pioneer, the follower is to the left of the 45 degree line; which requires a strong positive correlation between productivity and fixed costs at the top. This is not achieved in the three models described here.

Fig. 1. Heterogeneous firms plotted in the space of their value of exporting given the firm's productivity $V(\varphi_i)$ and the entry costs into exporting F_i.

with different access levels, from WTO, World Customs Organization, UN-COMTRADE, and the World Bank, only allow us to connect different classifications, but do not provide unique common product codes across time, which is what we need for our paper. In other words, what they provide is a code by code correspondence *between* different classifications. What we need, in contrast, is to generate common codes *across* classifications. To the best of our knowledge, the only work that recently provides this is Pierce and Schott (2009). In their technical paper they provide a homologation procedure across time in order to have consistent codes for US HS 10-digit export and import codes. Although we began working on this homologation before they published their working paper, we have a similar program that shares the same principles of their product code homologation: creating common unique codes for product codes that expand or contract through time. We prefer our algorithm and program to theirs, because of the suitability of the data input (we use 6 digit level full classifications) and the output that we needed (a single homologated HS classification).[25]

A.1. The HS classifications considered: 1992, 1996 2002

Our data consists of a customs database for the period 1994–2006, which we complemented using COMTRADE data since 1990. All the data is classified under the Harmonized System (HS) codification. However the period considers 3 different classifications: HS1992, HS1996 and HS2002. These were major reclassifications which altered the codes in the way explained above. This implies in practice that we need to homologate codes that changed from one classification to the other. There are two major changes: from HS1992 to HS1996 and from HS1996 to HS2002.

A.2. The problem and an example

What we need to do is to avoid counting new codes if they are codes that appeared due to a reclassification. We also need to take into account cases of products that are collapsed into a single code, since we do not know if the new code exists due to which old product. This implies that whenever there is an expansion of codes we need to consider the original code as the correct code, and when there is a collapse of codes we need to consider the new code as the correct and unique code. Since there could be combinations of both and multiple collapses into one product, the most conservative way of avoiding reclassification is an iterative collapsing of codes into a "minimum common code" that subsumes all codes that could reclassified in one or another code category.

For example, Table 15 shows what the procedure would do to the following codes:

In the first set of codes we have two codes that collapse into one. The final code then must be the merged code since we cannot know if it came from the first or second code. The second set shows a split. Since we cannot know if the code in HS92 was 150150 or 150160 we have to consider the most aggregated one. The third case is a little more complicated. 140400 is split, 140500 is not, but 200199 is incorporated into 140400 and 140500. The minimum common code in this case is 200199 For example, let's assume that a firm starts exporting a code 140500 in 1998, under HS96. How can we know if that export corresponds to a real new product or an old 200199 code? Since it is impossible we need to collapse the code to avoid the chance of wrong classification of new codes as new products. The process of generating a minimum common code must be iterative and must be done also across more than one classification (must be done also considering HS vintage 2002 codes).

A.2.1. The procedure

Here we explain the procedure we undertook. Following analogous principles to Pierce and Schott (2009) (but before they published their work) we built a STATA code that first takes two classifications (for example HS92 and HS96) and collapses into a single code any original codes that have expanded or contracted between both classifications. In the example of Table 15, it allocates three unique codes to each of the three examples depicted. The same is then done for the next two classifications (HS96 and HS02). We thus end up with two new *hybrid* product classifications, one that unifies hs92–hs96 and another for hs96–hs02. We use actual HS codes as minimum common code in cases of simple expansion or contraction of codes. For cases of complex

[25] We needed a procedure that considers 3 *complete* classifications and their correspondences (HS-1992 to HS-1996, and HS 1996 to HS 2002) and that could provide us with a unique new classification that could be corresponded to each HS 1992, 1996 and 2002 directly. Although using the same principle to concord classifications through time, Pierce and Schott specific program was not ideally suited for what we needed because the input data they use, which is the US HS 10 digit code changes, is incremental, providing a list of codes that change and (many) different dates in which they change. Our data consists of 2 full correspondences between 3 classifications which were better handled with a different code. In them, we had the data of all codes of an "old" classification and the corresponding codes for the "new" classification. This included codes that did not change through time. Also, the output that we needed was a full correspondence of each original HS classification with a "homologated" HS classification which would allow us to work directly the data with the homologated codes in our paper, and which the procedure of Pierce and Schott did not provide directly.

code grouping the chosen code is the code with the highest exported value in the group, for the whole sample period. We then join both new codifications using the HS96 codes as connectors (which are common in both unified classifications), allowing us to have a correspondence between the two, and we repeat the process one more time. This allows us to have a final unique code throughout the period 1990–2006.

A.2.2. Caveats and limitations

The main limitation of this procedure is that it requires collapsing many different codes into single ones, significantly reducing the number of codes available for analysis, since it collapses any codes that are expanded or contracted across classifications. The consequence is that we lose several and potential relevant disaggregated information.

A.2.3. Downloading the data

The correspondence files are available on the author's website under the name "transcode_XX.dta" where XX is the year of the original HS.

Appendix B. Database construction details and list of products

B.1. Database construction and filters used to define new products

We built our data set of new exporters using Chilean Customs export transactions in all sectors between 1990 and 2006, which we aggregate at the firm-product-year level. For 1990–1991 we did not have firm level information. We thus merged the firm level Customs database with COMTRADE product level export data, which was available from 1990. Thus our full database comprehends the period 1990–2006. Having 2 years of product level data instead of firm level data doesn't pose a problem because, as we explain in Section 3.2 we use the first 5 years only as a window to identify old products.

Empirically identifying a new export from Customs data is not trivial. Many new codes exported by a firm or by a country are samples (exports with extremely low values), coding mistakes, or reexports. For this reason we needed to create filters in the data in order to try to identify correctly new products. This ad-hoc process has problems though. On the one hand if we define a new product too loosely, it would be difficult to identify real spillovers and the possibility of learning a la Foster and Rosenzweig (2010), since many new products identified would not be so. On the other hand, if we are too tough with the definition of a new product, then the number of cases would dramatically shrink, eliminating real cases of firms that made the effort of penetrating new markets with new products. In this trade-off between "distillation" of new products for the country and the quantity of products identified, we tried to lean towards "distillation" as much as possible, but still keeping enough observations to make the results statistically significant.

The filters focus first on ignoring exports of a firm that imported the same product in the recent past. For this we merged our data with an available firm level panel from customs on all imports for the period 1990–2006 . Also, since many small retailer transactions across the border, with Argentina or Perú for example, are also considered exports, and these firms tend to export an unrealistically large number of products we defined a cutoff of number of products and dropped the firms that export more than 30 products in a given year. Third, we wanted to separate between firms that are actually producers of the exported good (the actual innovators behind a new product) and firms that were exclusively traders or retailers. For this we merged the data with publicly available firm level activity codes from the Chilean Tax Revenue Service (SII in Spanish), excluding from the data firms that were exclusively traders. We follow the tradition of most of the trade literature of exploring export costs for firms that do produce goods they export. Intermediaries are a hot area of research, but models recognize that this process is quite distinctive so we kept it out from our current study. SII data was also important to disentangle the end of an exporting spell on the one hand, and the death of the firm, on the other. This, by providing the dates when the firms stop operating. This is relevant because some firms may still be selling in the local market even if they are not exporting.

The following table details the filters, their effect on arguably true new products and in the sample size.

Review of how the filters impact the new firms and the number of products

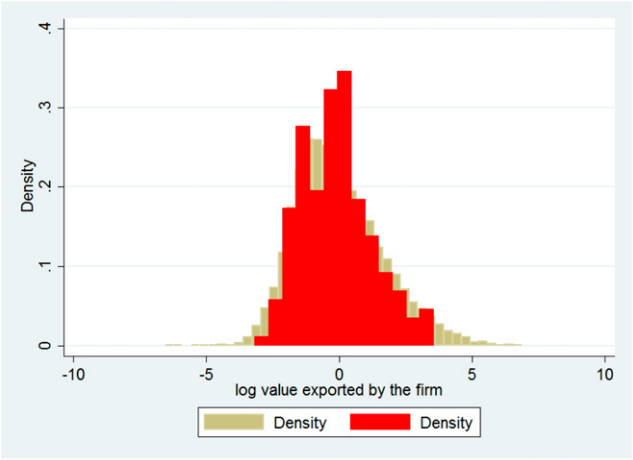
Filters to define product as new for the country		Competing goals: Have a high share of "true new products" in sample	Competing goals: Have a sample of products as large as possible	Comments
For 1990 $\sum_f x_{pf} \leq X$ (for 1990 only aggregate but no firm data)	$X =$ US $1000	+	−	Risk of re-exports
Only considering exports post 1991 by producer firms (traders do not count) {careful with closed firms w/o tax activity code!!}		+	−	Traders are important but out of scope of paper
Re-exports are not counted as export ($x_{pfy} > \theta m_{pfy}$): Higher θ	$\theta = 2$	+ if θ not too large	−	
Drop products with description containing "others" and "NES"		+	−	
Cutoff $x_{pfy} > \geq X$ in pre-sample (1991 to 1994)	$X =$ US $1000	−	+	If $X = 0$ here; then almost no products are left.
Cutoff $x_{pfy} \geq X$ in sample (1995 to 2006)	$X = ?$	+	−	
Implausible jump filter (for machinery)		+	−	Has some ad-hoc component in its definition
Export transactions per year to be considered	$x_{pfy} \geq 2$	+ To avoid returns (especially machines)	− Can lose products with single transaction	Bias towards less failure

B.2. List of products and robustness checks at four digits instead of six

Table 17 displays the code and the description for our sample of products that had at least one follower firm, so they belong to most of the estimations when we compare pioneers and followers in new products. In any case, to mitigate any concerns about our results being driven only by marginal spinoff products, in Table 16 we repeat our baseline specification using the log of exported value in the whole HS 4-digit group rather than only the new HS6-product. In the vast majority of cases results are qualitatively unchanged, with a negative coefficient in all specifications of table suggesting that our central result that pioneers are smaller than followers in the product remains robust to this plausible challenge.

Appendix C. Additional robustness checks and descriptive statistics

Table 18 describes the types of goods we find in our database. The complete list is available from the authors upon request.



This figure shows the histogram of the log total value exported in all goods by firms, demeaning by sector and HS2-digit of the main sector of the firm; for the pioneers and for all exporters (background). In this graph, unlike in most of the paper, not being a pioneer firm means that they could be either followers in new products or followers in old products. The two distributions are different at the 10% level using the Kolmogorov-Smirnov test (p-value = 0.09), but our central point is that pioneers do not necessarily come from the largest exporters. Visually it seems that pioneers come from all portions of the distribution, it is maybe interesting that there are no points at the very top. This could be something probabilistic (since pioneers are fewer observations so the tails are not that well populated), or could also be because large firms in the country are concentrated in old products. In any case, although we are mixing all products together here, the visual impression is not inconsistent with the main view of the paper that pioneers are not necessarily the largest firms in the economy.

Fig. 2. Distribution of all exports for pioneers vis-a-vis the whole distribution of exporters, correcting by sector and year.

Appendix D. Size distribution of pioneers and exports

The hypothesis that the shock of the pioneer goes to the exploration cost in the product is consistent with our main findings. If the shock happens in a random fashion it implies that pioneers should come all over the distribution of firm size in our data. Fig. 2 show the distribution of all exports in the database and those of pioneers, in terms of export size. Although if one performs a Kolmogorov–Smirnov test one rejects the null hypothesis of equal distributions at the ten percent level, the histogram and kernel densities show that pioneers come from all over the support of firm export size, maybe except the very top firms. Fig. 2 corrects for HS 2 digit sector and year fixed effects, so the low exported value is normalized. Performing the same exercise with raw export data obviously changes the shape of the figure but it does not alter our qualitative results. Pioneers come from (almost) all the support of the distribution of exporters.

Appendix E. Canonical case studies to describe patterns of entry

An illustrative preview of our argument can be found in Fig. 3, which shows examples of products according to the "success" of at least one firm in the product and according to the presence of followers or lack thereof. We define *success* in the introduction of a product or equivalently a *successful firm* in a product if a firm survived five or more consecutive years exporting the product (in this definition we obviously have to exclude products that began being exported after 2001, since the sample ends in 2006). Each quadrant contains the percentage of firms in each group as well as a graph with a canonical example of a product in that category. In each graph the horizontal axis shows the year and the vertical the ($\log_{10}$) exports of each firm in the product in a given year, connected by a line for the same firm; so different lines correspond to different firms. Theories that focus on externalities from pioneer to follower (like Hoff (1997); or Hausmann and Rodrik (2003)) would focus mostly on case (C), of pioneers with followers. In contrast, the family of models in which "winner takes all" could generate cases like those in panel (B).

We first focus on what we label "failed experiments" of Panels b and d, where no firm manages to survive successfully. These are by far the most frequent case, representing together between 80 and 90% of the products. The case shown in Panel b is *Sodium Sulphides*, a chemical compound used in the production of pulp.

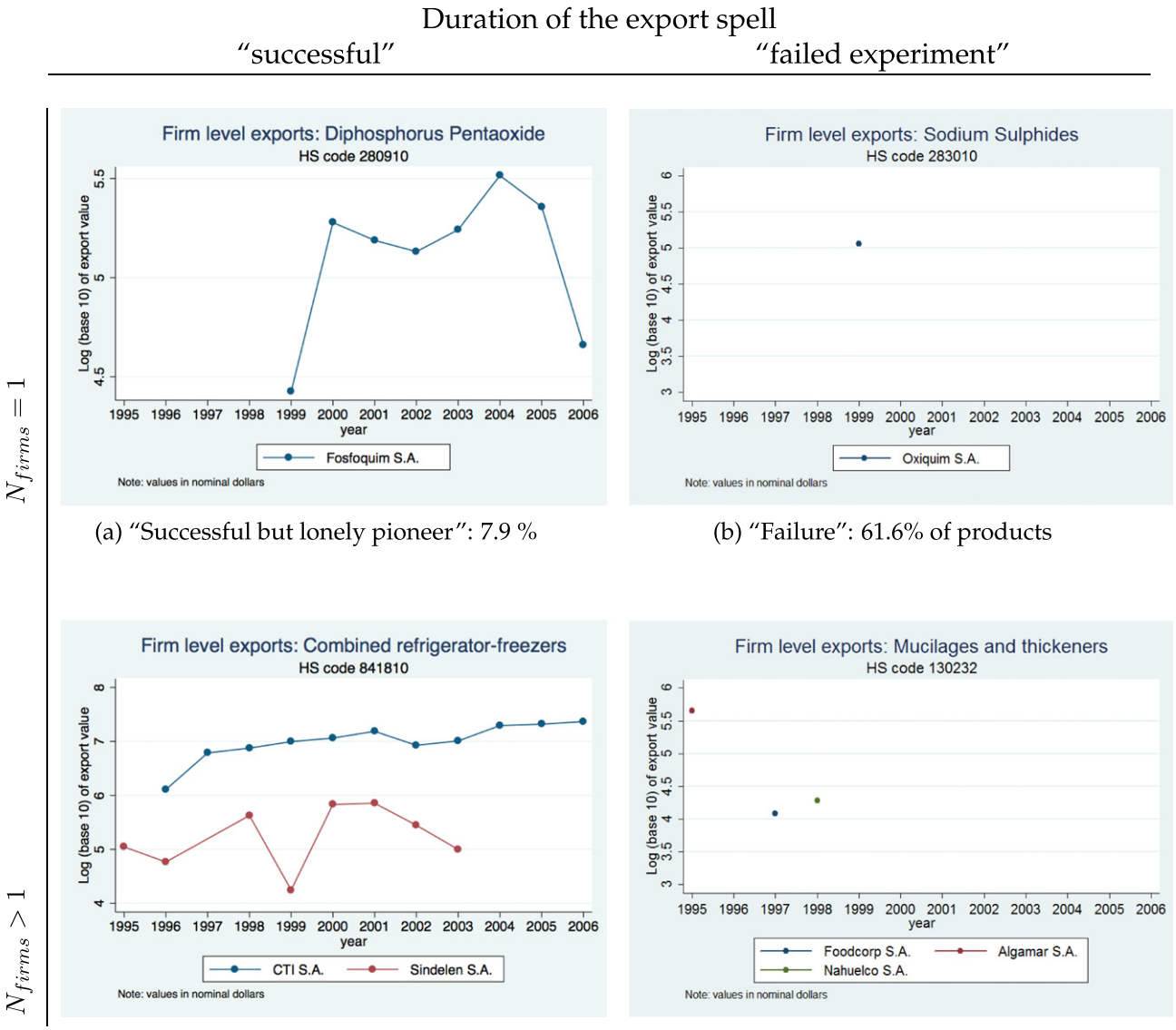
Second, we have products with a single surviving firm exporting, and no followers. This group of products with "successful but lonely pioneer" tend to represent more than half the cases when pioneers survive more than five seasons. The example is *Diphosphorus Pentaoxide*, a chemical (Panel a). A simple study of the industry makes it clear why observing a single exporter is not surprising. "Fosfoquim", founded in 1986, was not only the single producer of this chemical in Chile, but also the only one in South America at the time. In a context of large economies of scale, it would be hard to argue that the pioneer was expecting some followers. In the language of our model, the distribution of potential entrants into exporting, $g(.)$, was arguably populated by a single firm.

Finally, in Panel c we depict a case of a successful pioneer with followers: *Home Refrigerators*. In this product two well experienced firms survived to the trade liberalization period in the 1970s and 1980s, and started to export refrigerators during the mid 1990s. Interestingly, the year that the pioneer started to export refrigerators both firms were exporters of other products. This tells us that firms might be learning about exporting *this product*, rather than a general learning about exporting (which fits the assumption of a product specific cost F in the model). A second remark is that the pioneer firm in refrigerators is systematically smaller than the follower. This is precisely consistent with our model and we will show, in Section 4, that this holds for our sample of new products.

The case of refrigerators, unlike Diphosphorus Pentaoxide, suggests the possibility of a spillover. Nonetheless, refrigerators are still a product with few potential entrants into exporting, because there are few firms in the country, and it is unlikely that the structure of the industry would change so much after starting to export. Successful pioneers receive more followers in, for example, the meat packing industry, where there are more players. For example, Fig. 4 shows five firms following the pioneer exporter of frozen beef tongue, which in 2006 had around 3 million dollars in exports from Chile, mostly to Japan.[26]

Taking stock, the descriptive statistics and narratives we outlined above indicate some characteristics that could fit with pioneer to follower spillovers. First, there is a chance that pioneering results in failure, which gives value to the information released by success and failure. Second is that sectors with followers show a distinctive pattern, in which pioneers tend to export less (ex post) and are less diversified

[26] After a little qualitative research on these exporters we found that exports of this product began in 1999 by "Nippon Meat Packers", which was already an important exporter of frozen pork meat. Until 2002 it was the only exporter of "Bovine tongues, frozen" from Chile. This was a company with little expertise in bovine production, but a lot of expertise on frozen meats and in the Asian market. After four years of "lonely pioneering", in 2003 "Frigorificos Lo Valledor" started to export, with a first year's shipment more than 30% larger than the one used by the Pioneer in its first year . In 2004 many other firms entered (Frigorifico de Osorno; Carnes Nuble; Procesadora Insuban). Interestingly, the followers are overwhelmingly mature firms in the bovine processing industry, which of course did produce beef tongue, but did not freeze or export them to the a market where it was more valuable. Four years after having followers, the pioneer was eventually surpassed in terms of exported value. Not surprisingly, the new leader in sales was the largest meat packer of the country. We do not interpret this surpassing as if it were a closed oligopolistic market (as usual in the Industrial Organization or Business Strategy literature) because many other countries export beef tongue to Japan (Chile represents less than 5% of Japanese imports in this product). Overall, it seems that the pioneer had a comparative advantage in exploring rather than at exporting this particular product.



(a) "Successful but lonely pioneer": 7.9 %

(b) "Failure": 61.6% of products

(c) "Pioneer with follower catching up": 5.7%

(d) Failure with further entry: 24.9%

(b) + (d) Failures: 86.4% of products

The categories divide tall new products identified into 4 categories: ((a) Successful but lonely pioneer (where there is only one firm, but it has an export spell of more than 5 years); (b) Failure (only one firm with a spell of 5 years or less); (c) Pioneer with follower catching up: there is more than one firm, at least one lsts more than 5 years, and the follower ends up being larger than the pioneer; (d) there is more than one firm but none last more than 5 years, or if one does, the follower ends up being smaller than the pioneer. The pioneer can be distinguished because it corresponds to the line that starts closer to the left of each graph. Graphs showing the export sales (in $\log_{10}$ US Dollars) of all firms exporting a given product. Each firm is connected by a line of the same color. The percentage shown below each graph shows the proportion of products that fit in each category.

Fig. 3. Categories of products, according to length of firm spells and number of firms, with a graph example of each.

than followers. Finally, in some products, with successful pioneers it is hard to argue that there is learning from information released within the same product, since there are no followers. Having said that, the evidence could also be consistent with a model in which more productive firms have at least initially a higher entry cost into exporting the product. The open question is why that would be the case.

Appendix F. Additional tests

F.1. Two-way table on pioneer survival and entry of followers

Table 19 complements the regression results on Section 3.2. It shows that when the pioneer quits after the first year only 25% of the products

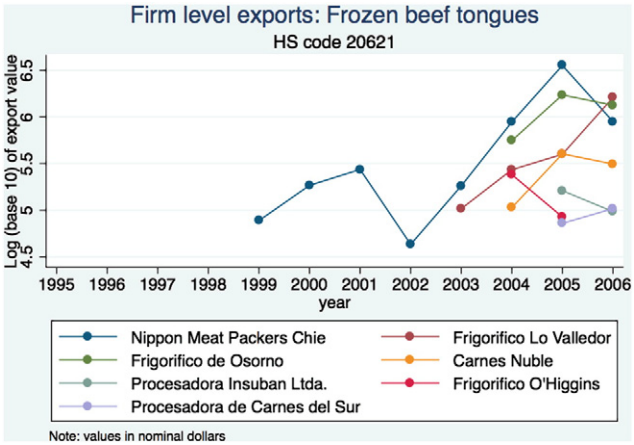


Fig. 4. A case with many potential entrants into exporting.

have a follower. In contrast, when the pioneer survives more than one year exporting the product has more than 38% chance of having followers (p-value of $\chi^2 test$: 0.04).

F.2. Differential growth after entry

So far we have focused on a parameter that we assume stays constant through time and through the evolution of experience in a given product. However, maybe the difference between pioneers and followers could be growing or shrinking. Table 20 displays additional regressions that deal with these issues.

Column (1) shows our base benchmark result from Table 7. In column (2) we control the log export revenues in all other products that the firm exports. The coefficient of this variable is positive, which we expected from theories of multiproduct firms, as larger exporters tend to export more of a new product. It shows an elasticity of 0.2, meaning that a 10% increase in the total exports of the other products is associated with the firm exporting an additional 2% in the new product.[27] To test for the possibility that the pioneer–follower gap is changing over time, in columns (3) and (5) we add an interaction between the experience in the product and the pioneer dummy $1[Pioneer_{ij}] \times a_{ijt}$. Some specifications show a significance for the interaction, indicating that the gap with the pioneer might be widening over time, which reinforces the logic of our results. In other specifications, though, the two variables are too collinear to be independently significant. Having said that, when we run an F-test (not shown in the paper) for the effect at the average level of experience, which is larger than zero, we still find support for the gap. Overall there is some suggestive evidence that the gap between pioneer and early follower might be widening over time, but it is not robust. What matters more for our results is that the gap does not seem to be narrowing over time, so it is unlikely that pioneers are transitorily smaller than early followers. A final control we added in Table 20 is the weight of the product in the firms' exports, which we use just as an additional control in regressions (4) and (5). In column (4) we can observe that although significant, it doesn't alter the significance of the pioneer dummy.

F.3. Lower probability that the pioneer is "the top" exporter

It is worth emphasizing that our main finding is *qualitative* in nature, with pioneers smaller than followers. In some products they might be smaller by just cents; and in some other products they might be smaller by orders of magnitude. Despite that *qualitative* prediction, in Tables 7 and 8 we estimate the *quantitative* magnitude of the smaller revenue, at a risk of imprecisely estimating an average due to the potential heterogeneity of the effects across products. To complement our baseline exercise Table 21 explores the probability of being *the largest* exporter within a product-year combination.

The table shows results that are consistent with what we found in Table 7. Column (1) shows that a pioneer is 40% less likely to be the largest exporter, supporting our qualitative claim. When in specification (2) we control for experience, as in the rest of the paper, the pioneer dummy is even stronger, representing a "handicap" of at least 3 years of export experience (p-value for the F-test lower than 0.05). Mimicking our baseline analysis in Table 7, columns (3) to (5) show that the effect remains consistent across specifications. Also, in column (6) we restrict our sample to comparing product-years in which both pioneer and followers have at least three seasons exporting and, analogous to our findings in Table 6, the results are even stronger with pioneers being 83% less likely to be the largest exporter. We perform this exercise either with bootstrapped or clustered standard errors and the results remain largely unchanged. Overall, the qualitative prediction that pioneers are smaller looks highly significant.

F.4. Results are not an artifact of a specific cutoff to define new products

As discussed, we used a focal cutoff of 10,000 dollars to identify new products. In Table 22 we replicate our main results changing the cutoff from $2000 to $15,000. The table shows that our main result holds under all alternative cutoffs. The bottom line of this exercise is that our results are not produced by the sharp-edged properties of one particular cutoff value.[28]

F.5. We cannot reject equal survival of pioneer and followers in the same set of products

In our framework, since most of the uncertainty is product-specific then there should not be systematic differences in survival rates between pioneers and followers *within the same product*. Table 23 tests this proposition presenting the hazard rates of stopping an export spell. The estimates *cannot* reject the hypothesis that pioneers and followers do not differ systematically in this dimension. Specification (1) uses a Cox proportional hazard model showing that only pioneers *without* followers (so in a different group of products) have a 27% higher hazard rate than our benchmark group (p-value < 0.1); for the case of pioneers *with* followers the hazard rate is not statistically different from one. In other words, we cannot discard pioneers have the same probability that their export spell "dies", when compared to the benchmark group of followers. As additional robustness, specification (2) estimates hazard rates using now a Weibull parametric duration model, finding the same qualitative results.

Appendix G. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jdeveco.2014.12.002.

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[27] In column (5) our main coefficient loses significance, but this is driven by the inclusion of all controls at the same time, and the increasing effect of experience on the gap between pioneers and followers, which is consistent with our main story. Nevertheless, the coefficients associated on the pioneer dummy remains significant and of the same magnitude, suggesting that our main effect is not driven by the scale of overall operations of that firm.

[28] Appendix B has more detail about the cutoffs and filters used.

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