The Pennsylvania State University
The Graduate School
College of the Liberal Arts

ESSAYS ON INTERNATIONAL TRADE AND INDUSTRY DYNAMICS

A Dissertation in
Economics
by
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Submitted in Partial Fulfillment
of the Requirements
for the Degree of

Doctor of Philosophy

December 2017

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Abstract

This dissertation consists on three essays on international trade and industry dynamics. All three essays study empirical applications of open economy environments with heterogeneous firms who make decisions over time.

The first essay studies trade policy and the dynamics of the solar photovoltaic manufacturing industry in the U.S. In it I develop a computable, continuous-time dynamic model of the industry where domestic firms engage in price competition against each other and an importing sector to sell solar panels to domestic consumers. Firms can attain cost reductions through learning by doing and R&D investments. I use the model to estimate its main parameters using firm-level survey data from the Department of Energy and then simulate the application of countervailing duties to imports of solar panels, analyzing the implications for the evolution of the industry and welfare. In a scenario where a 30% duty is applied to imports, domestic firms respond by increasing R&D expenditures, therefore increasing productivity and setting lower prices, even when concentration increases as high productivity domestic firms gain market share.

The second essay is on the dynamics of the textiles and garments industry in Bangladesh. First, it shows that, in contrast to the standard description of entry into foreign markets, Bangladeshi exporters are fully committed to foreign markets, exporting most of their output abroad; they start big, not small, and show high survival rates once they start exporting. They are born to export firms who operate in orphan industries, with essentially missing domestic demand for their products. In addition to the usual fixed and sunk costs of exporting, they must face presumably higher costs of starting up new businesses. Then it compares these patterns with those of China, Colombia and Taiwan, and find similar but less-striking patterns for China. These features seem to be missing in Taiwan and Colombia, which accord with other typical cases described in the literature. Finally, it adapts a search and learning model of export dynamics to show how the presence of high sunk costs of establishing a new business and the absence of a domestic market can generate export trajectories similar to the ones we observe in Bangladesh.

The third essay focuses on the links between productivity and exporting. The trade literature has identified three relationships. First, that productivity causes exporting, so that there is selection into exporting by more productive firms. Second, that exporting generates productivity growth through, for example, learning-by-exporting. Third, that firms make choices that make them more productive in preparation to export. The essay shows that patterns of Chinese exporters are consistent with all three hypotheses. Exporters are more productive than non-exporters, which is consistent with selection. For successful exporters, most of the productivity growth during the period occurred after entering export markets, rather than before. For unsuccessful exporters, on the other hand, this pattern is reversed. Average annual productivity growth, however, is higher prior to entry for both groups. Finally, new exporters increase sales expenditures and earn higher revenue from new products than other firms before they start exporting. This is true when compared to both non-exporters and continuous exporters.

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Acknowledgements

I am in debt with Kala Krishna, Paul Grieco, and especially Jim Tybout for their time, guidance, and support.

For helpful discussions and suggestions in Chapter 1 I would like to thank Ufuk Akcigit, Lorenzo Caliendo, Jonathan Eaton, Ed Green, Alex Fakos, Martin Hackman, David Jinkins, Ken Judd, Ahmad Lashkaripour, Alejandro Molnar, Eduardo Morales, Esteban Rossi-Hansberg, Andrés Rodríguez-Clare, Spiro Stefanou, Steve Yeaple. Uri Doralszelski kindly shared with me C code for computing a Markov Perfect Equilibrium. Jeffrey Brownson provided insightful comments about the solar industry. I am also grateful to Jacob Bournazian, Joe Conklin, Lawrence Stroud, Andrew Thomson, and Peter Wong at the Energy Information Administration for their assistance in accessing and understanding their data.

Results and data included in Chapter 1 have been reviewed by the Energy Information Administration of the U.S. Department of Energy to ensure no confidential information has been disclosed. The project included in that chapter was partially supported by a RGSO Dissertation Grant from the College of the Liberal Arts of the Pennsylvania State University.

Chapter 2 was written in colaboration with Jonathan Eaton, Kala Krishna, Bee Aw Roberts, Andrés Rodríguez-Clare, and James Tybout. The project included in this chapter was partially supported by the International Growth Centre. Jonathan Eaton and James Tybout acknowledge support from the National Science Foundation (Grant SES-0922358). Wahid Mahmud, Mustazur Rahman, Fahmida Khatun, Hiau Looi Kee, and participants at the BRAC-iiG-IGC Conference on Entrepreneurship and Development (March 2011), the IGC Trade Program Meeting at Penn State (April 2011) and the Universidad de San Andrés Economics Alumni Annual Meeting (2013) gave helpful comments and suggestions. Anik Ashraf, Ravid Chowdhury and Ummul Ruthbah provided invaluable help and guidance in accessing and collecting data in Bangladesh. Bibhuti Sarker provided excellent research assistance.

Chapter 3 was written in colaboration with Xue Bai and Kala Krishna. Amit Khandelwal, Ann Harrison, Hong Ma and participants at the PSU-Tsinghua Conference on the Chinese Economy (2012) contributed with comments and suggestions.

Parts of this dissertation were written while I was appointed at the Ministry of Production of Argentina. The views and opinions contained here are those of the authors and do not necessarily reflect reflect the views and opinions of the Ministry of Production of Argentina or any of its officials.

Dedication

A los amigos, a mi familia, a Lulú.

Chapter 1
Trade Policy and Industry Dynamics in U.S. Solar Photovoltaic Manufacturing

1.1 Introduction

Despite its relatively small size, the solar industry has emerged as a strategic industry in the U.S. and the U.S. government has continued to announce commitments and executive actions to advance solar deployments.[1] In particular, the industry has recently been the focus of major trade policies aimed at protecting it. To give a sense of how relevant these policies have been, after the U.S. government decision to impose countervailing duties on solar panels imported from China in 2014, the New York Times labeled the policy as "among the biggest in American history".[2]

Trade and industrial policies directed towards the solar photovoltaics industry have received scant attention in the economics literature, however.[3] In particular, few studies have considered the manufacturing sector, its market structure, and the effects of foreign competition on industry dynamics. The contribution of this paper is to study the effects of trade policy on the dynamics of U.S. solar photovoltaics manufacturing, taking into

[1]Notwithstanding that Democrat administrations have tended to give more importance to it than Republican administrations, some long term programs have received continued funding. For example, despite Trump's position on climate change and even if solar energy is not mentioned in Trump's America First Energy Plan, 29 states have renewable portfolio standards policies and, in September 2017, the Department of Energy announced the achievement of the SunShot Initiative goals, maintaining funding and supporting the goals set in 2016 for 2030. See `https://energy.gov/articles/energy-department-announces-achievement-sunshot-goal-new-focus-solar-energy-office` and `https://energy.gov/eere/solar/sunshot-2030`.

[2]See Bradsher and Cardwell (2012).

[3]The literature on renewable electricity generation and markets, on the other hand, is much more developed. See Borenstein (2012) for a review.

account key characteristics of the industry.

To assess the effects of trade policy on the solar panel manufacturing sector, I first develop a computable dynamic model of the industry that features imperfect competition, investment in research and development, learning by doing, and import competition in continuous time. Domestic firms engage in price competition against each other and foreign rivals to sell solar panels to domestic consumers. Firms can attain cost reductions through two mechanisms. First, as firms produce they generate ideas which can eventually translate into an increase in productivity and lower marginal cost, i.e. there is learning by doing. This gives rise to dynamic pricing decisions: firms' equilibrium behavior takes into account the fact that production today can affect future costs. Moreover, since there is imperfect competition, a firm also understands that its pricing decisions will affect other firms' current production levels and hence their future costs. Second, firms can invest in research and development to increase efficiency and reduce costs. Import competition has two effects. On the one hand, cheaper panels from abroad increase competition, put downward pressure on prices and decrease domestic firms' market shares, potentially inducing exit of incumbents and reducing the profitability of R&D investment. On the other, since domestic firms have lower market shares, the likelihood that they will experience a successful idea through learning is lower.

I estimate the main parameters of the model using firm-level data and then simulate the application of countervailing duties to imports of solar panels, analyzing the implications for the evolution of the industry and welfare. The estimation quantifies the mechanisms that shape the dynamics of productivity, prices, shipments, and firm turnover. The estimates suggest that R&D is far more important than learning by doing in driving productivity improvements in the industry, and that import competition (in the form of lower prices of the imported variety) decreases the incentives of domestic firms to invest in R&D.

In a scenario where a 30% duty is applied to imports, domestic firms respond by increasing R&D expenditures, therefore increasing productivity and setting lower prices, even when concentration increases as high productivity domestic firms gain market share. Compared to the baseline case, the domestic (as opposed to the imported variety's) average selling price of panels is \$/Watt 0.20 lower. Domestic firms are also more likely to stay in the market. As a result of higher import prices, consumer surplus decreases but the increase in aggregate profits more than compensates for this loss. If we take into account the fact that unproductive firms would have otherwise exited the market and received some scrap value for their assets, total welfare becomes *lower* in the counterfactual with duties.

The paper connects with a wide literature on trade policy and firm dynamics in international trade. Early work by Dixit (1988), Baldwin and Krugman (1988), Venables (1994), and Klepper (1994), among others,[4] applied simulation-based methods to quantify the welfare effects of trade and industrial policies. The general conclusion of these first generation of studies is that, if there were positive effects at all, they were rather small. Melitz and Burstein (2013) and Costantini and Melitz (2008) explore firm-level innovation responses to trade liberalization over time. Unlike here, their focus is on the interaction of innovation with the decision to export. The paper is more closely related to Erdem and Tybout (2004), who adapt the Pakes and McGuire (1994) model to quantify the long run effects of import competition on productivity and the incentives to innovate. After calibrating the model to stylized facts from trade liberalization studies, they find that import competition decreases the relative quality of domestic varieties, but there are net welfare gains from consumers' access to cheaper goods.

In this paper I implement a dynamic structural model to study policy experiments. The use of these types of models to evaluate policy in specific industries has now an established tradition in the industrial organization literature, which includes applications to the hospital industry (Gowrisankaran and Town 1997), the aircraft industry (Benkard 2004), ready-mix concrete (Collard-Wexler 2013), and the cement industry (Ryan 2012), among others. The advantage of adopting a structural approach is that I can quantify the effects of an actual policy change. Focusing on a single industry, moreover, allows me to consider relevant industry-specific knowledge that can help to identify the mechanisms driving the results. More generally, the paper tries to bring this methodology closer to the international trade literature in order to quantify the effects of trade policy on industry performance.

The model applies Doraszelski and Judd (2012)'s extension to continuos time of the class of dynamic oligopoly models first developed by Ericson and Pakes (1995) and Pakes and McGuire (1994). Adapting these types of frameworks to continuous time settings is becoming increasingly popular due to their ability to circumvent dimensionality problems in complex models. Doraszelski and Judd (2012) show that adapting Pakes and McGuire (1994)'s algorithm to continuous time results in a significant reduction in the computational burden, thus allowing to compute equilibria with a larger number of firms. Arcidiacono et al. (2015) develop a framework to estimate dynamic discrete choice games and apply it to study the effect of Walmart's entry into the retail grocery industry; continuous time allows them to analyze the effect on both chain and single stores, which had previously been prohibitive due to a large state space. Other recent applications include Jeziorski (2014), who estimates the welfare effects of alternative merger policies in the U.S. radio

[4]See Grossman (1990) for an early review of the literature on industrial policy and international trade. Krugman and Smith, eds (1994) edit a collection of related studies.

industry, and Eaton et al. (2014), who estimate search costs and learning effects in a model of export dynamics.

Finally, the paper is related the economics literature on the solar industry. Pillai and McLaughlin (2013) develop a model of international competition in the solar industry and use it to evaluate the effects of a reduction in the price of polysilicon on the price of solar panels. The model is static, however, and hence market structure is fixed and plays no role in the *evolution* of prices. Gillingham et al. (2014) examine the determinants of solar photovoltaics pricing, including market structure and government policies, but focus on solar installations, abstracting from manufacturing. Moreover, their reduced form approach does not allow them to consider counterfactual exercises to assess the effects of policies. Bollinger and Gillingham (2012) study peer learning effects in the diffusion of solar panels in California, and Bollinger and Gillingham (2014) look at the existence of appropriable and non-appropriable learning by doing among installers and contractors, but take solar panels' cost and the whole manufacturing segment as given.

The rest of the paper is organized as follows. In the next section I present an overview of the industry, describing the technology, main trends and policies. Section 3 develops the theoretical model and discusses its main assumptions. Section 4 describes the data used. Sections 5 to 7 present the estimation procedure, main results and counterfactual. The last section concludes.

1.2 Industry background

In this section I present a summary of recent trends of the industry and key technological and market aspects that inform the development of the model in the next section. The description of technology and product characteristics draws mainly from U.S. Department of Energy (2011, 2012), and U.S. International Trade Commission (2012), which contain more detailed descriptions and analyses. Statistics describing recent trends are from the Energy Information Administration (EIA), unless otherwise noted.[5] For a thorough history of solar photovoltaics see Perlin (1999) and Roessner (1982). The reader familiar with the industry can skip this section and go straight to the next, where I develop the theoretical model.

[5] Aggregate industry statistics are publicly available at `http://www.eia.gov/renewable/annual/solar_photo/`.

1.2.1 Industry trends and market structure

The U.S. solar industry has undergone significant changes in the last 25 years. Panel (a) of Figure 1.1 illustrates the main trends in shipments and prices. The module average selling price decreased significantly between 1989 and 2015 from US$/watt 5.14 to US$/watt 0.71. Most of this decline occurred after 2008, after a short lived increase in prices due to silicon shortage in 2006-2007. Total module shipments (domestic shipments plus exports) have increased consistently since the 1980s but growth accelerated in recent years, with a more than 70-fold increase between 2002 and 2013. The source of shipments has also changed dramatically. Imports grew 43% per year on average between 1999 and 2015, and represented 98% of total shipments in 2015, compared to only 11% in 1999.

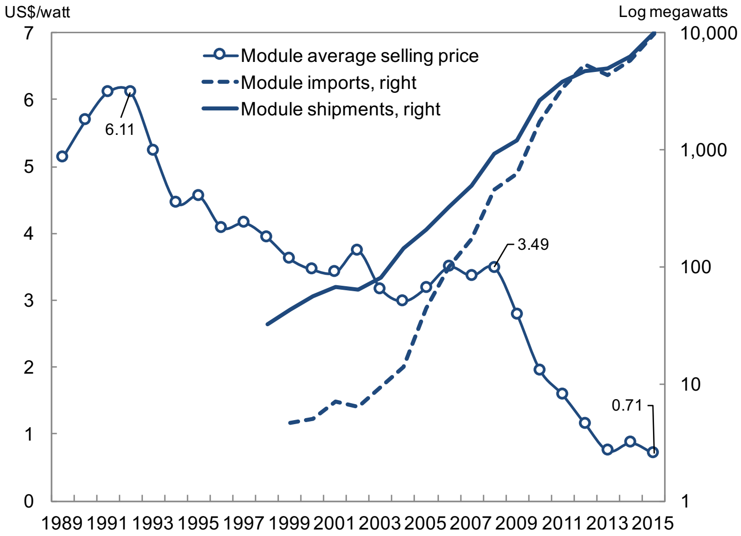
Most of the increase in imports is explained by the emergence of a fully export-oriented solar industry in China, which replaced Japan as the major exporter to the U.S. market. While Japan accounted for 90% of U.S. imported shipments in 2005, in 2013 its share was 2.7%. China's share increased from 3% to 35% in the same period. Shipments from Malaysia (33% of the total in 2013), Philippines (8%) and Mexico (11%) have also contributed to higher imports, resulting from the activities of U.S. firms that established manufacturing facilities in these locations and exported finished or semi-finished products back to the U.S. The increase of import penetration in the U.S. market reflects the transition of an industry which was once dominated by the U.S. but became globally integrated, with new countries becoming important players. While in 1982 the U.S. accounted for almost 60% world production, in 2012 its share was around 3%.[6] China, which started production of photovoltaics in the late 1990s, now accounts for more than 50% of world production.[7]

Panel (b) in Figure 1.1 and Table 1.1 summarize the evolution of the industry structure in the last years. The number of operating firms, including manufacturers, installers and distributors, was relatively stable at around 20 during the 1990s, increased from 19 in 1999 to more than 120 in 2012, and, after a shake out period, decreased to 54 in 2015. The number of manufacturers with plants located in the U.S. more than tripled over the 1999-2009 period. Although most of the new entrants were (and remained) small, many of them shipping prototypes for demonstration purposes only, concentration decreased significantly (see columns 3 and 4 in Table 1.1). The domestic market share of the six largest firms decreased from 74% in 1999 to 58% in 2009 and that of the three largest

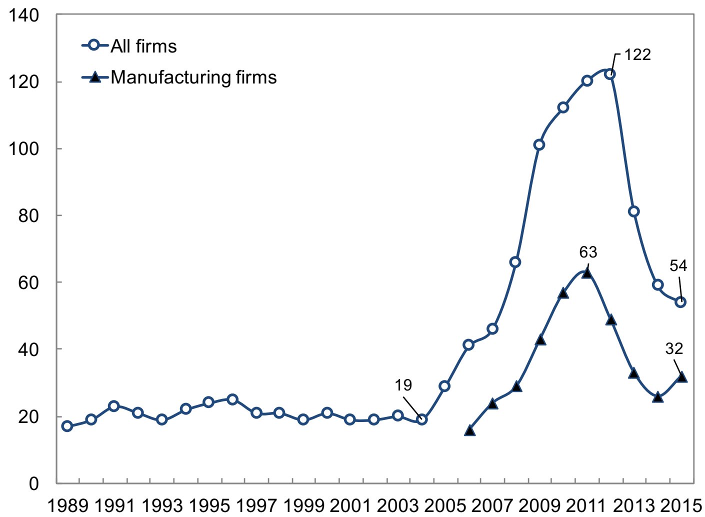
[6] Between 1999 and 2009 exports accounted for around 50% of U.S. total module shipments. This share decreased steadily and reached only 2% in 2015.

[7] World production figures are from the Earth Policy Institute (EPI). See `http://www.earth-policy.org/data_center/C23`.

firms decreased 24 percentage points from 1999 to 2009.[8] Following this period of fast growth, a combination of oversupply, entry of relatively unproductive firms during the preceding years, steadily falling prices, and financial bottlenecks for solar firms led to the shake out phase during 2012-2014 (Mehta 2012).



(a) Module shipments and prices



(b) Solar firms

Figure 1.1. U.S. solar panel industry main trends, 1989-2015.

[8]The exact figures corresponding to the domestic market share of the three largest firms is not included in Table 1.1 to avoid disclosure concerns.

Table 1.1: Structure of the U.S. solar panel industry.

Year	U.S.-based manufacturers			
	Number of firms	Share of domestic production	C6 index	Cum. change of C3 index
1999	10	74.2	73.9	-
2000	14	85.8	84.2	-1.0
2001	13	84.5	81.1	-4.3
2002	13	80.2	76.8	-5.6
2003	13	80.6	77.4	-9.0
2004	16	87.4	79.6	-6.2
2005	18	72.8	64.4	-16.2
2006	19	67.5	57.6	-26.9
2007	21	62.8	56.6	-26.0
2008	25	63.7	56.9	-27.6
2009	36	65.9	57.9	-23.8

Notes: U.S.-based manufacturers were those firms with a manufacturing facility in the U.S. The share of domestic production in column 2 is computed as the share of manufacturing firms on total shipments to the domestic (U.S.) market. C6(3) is the combined domestic market share of the top-6(3) manufacturing firms. The last column reports the cumulative change of the C3 index between 1999 and each year, in percentage points. Based on microdata from the U.S. Energy Information Administration (EIA) "Annual Photovoltaic Cell/Module Manufacturers Survey" (Form EIA-63B).

1.2.2 Technology and product characteristics

The building block of solar photovoltaic systems is the solar module or panel. A module is an array of photovoltaic cells manufactured from semiconductor materials that convert sunlight into electricity. There are two main semiconductor technologies: crystalline silicon-based (c-Si) and thin-film. c-Si technologies are based on high grade silicon and have been the dominant, first-generation technology in the industry, comprising approximately 90% of installed world capacity, and have a longer history of experimentation and improvements. Thin-film technologies are more recent, second-generation technologies and were developed to provide lower cost alternatives to silicon, as they employ other semiconductor and photovoltaic substrates which can significantly reduce material costs.

Typical manufacturing processes under c-Si technologies consist of three stages: (i) silicon ingot and wafer manufacturing, (ii) cell manufacturing and (iii) module assembly. In the first stage, ingots are produced from melted crystalline silicon and then sliced into thin wafers. Ingot formation and wafer slicing are typically carried out in the same plant, although each step is done in different buildings. In the second step wafers are turned into solar cells. This part of the process is the most capital intensive and includes doping the wafer to alter its electrical properties and treating it with chemical products to enhance its light-absorbing capabilities. Finally, cells are soldered, laminated and framed to produce solar modules. Assembly into modules is a relatively more labor intensive activity, accounting for the majority of labor costs, and automation can vary across countries (e.g. U.S. plants are perceived to have more automated processes than plants in China.)

Thin film manufacturing processes are fundamentally different from those used for crystalline silicon modules. Most importantly, the silicon ingot and wafer manufacturing stage is absent in thin film modules manufacturing. Instead, the fist stage consists in direct deposition of photovoltaic material on a glass, plastic or metal substrate. Photovoltaic materials are different from those used in c-Si modules. Most commonly used materials are amorphous silicon (a-Si), cadmium telluride (CdTe) or copper indium gallium selenide (CIGS). The second stage involves defining cells, the specific process depending on the substrate employed (i.e. laser definition, cutting cells on a flexible plastic substrate, etc.) Modules are laminated in the last stage, the particular process depending on the type of technology and materials employed.

The differences between c-Si and thin film manufacturing processes imply that they do not share manufacturing facilities or employees. Moreover, firms producing thin film modules tend to be more capital and skill intensive and are less able to split the process in multiple plants, producing cells in one plant and assembling modules in another.

The most common characteristic that is used to measure the performance of a solar panel is conversion efficiency. Conversion efficiency indicates the amount of electricity that can be converted from solar energy absorbed by the solar panel. It depends on the amount of power the module can generate (its nameplate power rating) and its area: if two modules have identical nameplate power ratings, the one with a smaller area has a higher conversion efficiency. Commercially available panel efficiencies range from 2% to 30% and are usually guaranteed by the manufacturer.[9] Nameplate power rating is measured in watts (W) and is the metric under which modules are sold ($/W).[10] An additional dimension of module quality is reliability, defined as the usable lifetime of the product. Solar modules lifetimes range from 10 to 30 years, with some degradation in per-year performance in most PV systems.

The nature of technological change in solar photovoltaics is a combination of R&D directed to improve materials, manufacturing processes and increase module efficiency, and learning by doing within existing processes to increase yield (the share of output that can be commercialized). Regarding the latter, experimentation to determine the trade-off between manufacturing speed and and product quality is critical. This includes detecting defects early in the manufacturing process and minimizing the variation in cell efficiencies.

[9] Solar PV efficiency is one of the lowest among methods of converting energy sources into useful electricity. To put it in perspective, the hydroelectric, fossil fuels and wind turbines (theoretical) efficiencies are around 90%, 45% and 35%, respectively.

[10] This is not to be confused with watt hours (Wh) which is a measure of energy generated and depends on geography and other characteristics of the PV electricity generation and distribution sectors.

The importance of dynamic economies of scale has been a topic of interest and an oft-cited argument supporting the implementation of stimulus policies. The OECD's International Energy Agency has stated that "experience curves demonstrate that investment in the deployment of emerging technologies could drive prices down so as to provide new competitive energy system for CO_2 stabilisation" and that deployment support "is considered legitimate because prices are expected to fall as producers and users gain experience."[11] Using average selling prices and accumulated production from 1978 to 1998, Green (2000) argued that an "80% learning curve" described the data well and that, given this, "the key to reducing photovoltaic costs lies in increasing quantity sold."[12]

These claims notwithstanding, there is not wide consensus as to the prevalent role of learning in solar manufacturing. Nemet (2006) estimated a model of solar PV costs using data from 1979 to 2001 and found that experience played a small role in explaining the evolution of overall costs. Papineau (2006) estimated experience curves for solar and wind energy technologies and found that the significance of experience indices was not robust to including a time trend.

Finally, the extent to which techniques are appropriable is not easy to determine. While there are many instances of public-private partnerships involving teams of firms and national laboratories where major improvements are developed, manufacturing processes vary across firms, some of them applying specific and sophisticated proprietary equipment and processes, especially vis-à-vis cell design, which is one of the main determinants of the ultimate quality and performance of a solar module. Therefore, while basic research and innovations are hardly privately appropriated, details of manufacturing and specific techniques are highly appropriable.[13]

1.2.3 Policies

The U.S. federal government has recently implemented several policies to support the solar manufacturing sector, including tax credits, loan guarantees, and targeted research and development programs. Moreover, many state governments mandate that utilities obtain specified percentages of their electricity from renewable sources. These policies have played

[11] See International Energy Agency (2000), p. 3 and p. 10.

[12] See p. 997. The "80% learning curve" can be misleading given how the literature usually refers to learning curves. In any case, Green meant to indicate that costs fall by 20% with a doubling of accumulated production. In the following paragraph he added: "Fortunately, a market-pull mechanism seems to have been recently put into place that seems likely to provide healthy growth and cost reductions over the coming decade. This is by the subsidisation of rooftop mounted systems in urban areas of the developed world."

[13] There is also a difference between c-Si and thin-film. c-Si technologies are more standardized when compared to thin-film, where technologies are more heterogeneous across firms share and depend relatively more on intellectual property and ongoing research and development.

an important role in expanding demand. An existing 10% investment tax credit (ITC) for property owners installing solar energy systems was increased to 30% in 2005, when congress passed the Energy Policy Act. This ITC was extended for one additional year in the Tax Relief Act of 2006 and subsequently for eight more years by the Emergency Economic Stabilization Act of 2008. The American Recovery and Reinvestment Act of 2009 further introduced policies that augmented the support to the industry, including a 30% advanced Manufacturing Tax Credit (MTC) to support manufacturers who invested in manufacturing facilities built in the U.S.,[14] a loan guarantee program administered by the DoE,[15] and a cash grant program for owners of renewable energy systems.[16]

The U.S. Department of Energy (DoE) runs a number of initiatives aiming at making solar energy cost competitive with other sources of energy and accelerate deployment of new technologies. These include the National Renewable Energy Laboratory (NREL), which started operating in 1977 as the Solar Energy Research Institute, and the SunShot initiative, launched in 2011. The NREL conducts research in collaboration with universities and the solar industry through research partnerships to improve solar cell conversion efficiencies, lower the cost of solar cells, modules, and systems, and improve the reliability of PV components and systems. As an example of the span of the NREL's projects, consider the PV Manufacturing R&D project initiated in 1991. The project was a share-cost partnership between the NREL and private-sector companies, and since its creation it has issued more than 70 subcontracts to more than 40 solar companies. In 2005 only, the project funding amounted to $288 million, split almost equally between the DoE and the industry.[17]

The SunShot initiative's goal is to decrease the cost of solar energy systems so that the price of solar electricity is driven down to $0.06 per kilowatt-hour by 2020 without subsidies. Some examples of specific programs directed towards solar PV under SunShot are the Scaling Up Nascent PV At Home (SUNPATH) Initiative, a $50 million fund to support domestic start-up manufacturers so that they can increase productive capacity, the Photovoltaic Manufacturing Initiative (PVMI), a $112.5 million investment to develop advanced manufacturing techniques of producing PV panels, and the Photovoltaic Supply

[14] Solar panel manufacturing reached its cap of $2.3 billion in 2010.

[15] The program provided loan guarantees for renewable energy projects, including solar manufacturing. 82% of the loan guarantees ($13.3 billion) have been for solar projects, including four manufacturing programs (Platzer 2012). Solyndra, which participated in the program, declared bankruptcy in 2011 and defaulted on its $535 million loan.

[16] The 1603 Treasury Cash Grant program allowed owners of renewable energy systems to cover 30% of the costs of the systems. By the first quarter of 2012, the program had awarded $2.1 billion to solar projects.

[17] A summary of the project's accomplishments, which include development of new modules and manufacturing processes, can be found at `http://www.nrel.gov/pv/pv_manufacturing_accomplishments.html`.

Chain and Cross-Cutting Technologies program, which works to accelerate the development of products and processes. Under the latter, in 2011 four companies were awarded grants between \$3 and \$4.5 million each targeting manufacturing and product cost reductions with an impact horizon of within two to six years.

Finally, the industry has been the focus of recent trade disputes. In October 2011, Solar World, an Ohio-based manufacturer, filed a petition to the U.S. International Trade Commission alleging solar modules imported from China were being sold at less than fair value. The petition led to antidumping and countervailing duty investigations, which ultimately resulted in the application of countervailing duties of between 18.32% and 249.96% to Chinese firms.[18] A new petition by Solar World was filed later in December 2013, destined to close some loopholes the first determination had left open. In particular, it included an antidumping investigation of imports from China and Taiwan and a countervailing duty investigation of imports from China. The Department of Commerce reached an affirmative final determination in December 2014, establishing dumping margins of between 26.71% and 165.04%.[19] After developing and estimating the model in the next two sections, I focus on this policy event and estimate its effects on the evolution of prices, the composition of the industry, and its welfare implications.

1.3 A model of solar industry evolution

In this section I develop a model of the U.S. solar photovoltaic manufacturing industry. The model is set in continuous time and the horizon is infinite. Exogenous processes and firms' decisions determine the arrival rates of jumps, so that industry variables evolve over time as Poisson jump processes.

1.3.1 Consumer demand

At any moment in time there at most N active firms in the market, indexed by j, that produce a single differentiated variety of solar panels. Solar modules consumption is modeled as a static discrete choice problem. Domestic consumers continuously arrive at the market and choose a variety $j = 0, 1, \ldots, J$ of solar modules, where 0 indexes an imported solar module variety (the outside alternative) and J is the number of domestic

[18] See U.S. International Trade Commission (2012) for an account of the investigation.

[19] The factsheet describing the determination can be accessed at `http://enforcement.trade.gov/download/factsheets/factsheet-multiple-certain-crystalline-silicon-photovoltaic-products-ad-cvd-f pdf`.

firms active in the market. Consumer i's utility from solar module j at time t is given by

$$u_{ijt} = -\alpha p_{jt} + \epsilon_{ijt}, \tag{1.1}$$

where p_j is the price of variety j and ϵ_{ijt} is an i.i.d. Type-1 extreme value consumer-variety-specific random taste shock. This implies that firm j's market share is defined by

$$s_{jt} = \frac{\exp(-\alpha p_{jt})}{\sum_{k=0}^{J} \exp(-\alpha p_{kt})}. \tag{1.2}$$

Domestic firms take the price of the imported variety (inclusive of transport costs), p_0^*, as given. Imports could be subject to a tariff $\tau >= 0$, so that their final price in the domestic market is $p_0 = p_0^*(1+\tau)$.

This demand specification is typical of many studies that deal with differentiated products. However, some industry analysts consider solar modules to have become a commodity, given the widespread diffusion and standardization of some technologies. Certainly, the degree to which solar modules differentiate from one another is not as high as one would expect in other industries such as cars or textiles, as final consumers typically care about the product generating the promised amount of electricity under guaranteed conditions. Nevertheless, differentiation is key for gaining market share.[20] Module quality (the rate at which they degrade or how prone they are to failures such as delaminations, corrosion or cell joints degradation) is the primary dimensions along which panels differentiate. Module technology also matters, since it affects physical characteristics of modules, usually determining what application the panel is more appropriate for.[21] Finally, modules from different manufacturers can also differ in design.

Available data suggests that, indeed, there is scope for differentiation among solar modules producers. From a directory including more than 18,000 models from more than

[20] In an article discussing survival of small solar companies in the U.S., the MIT Technology Review asked "... can U.S.-based manufacturers (...) compete with alternative technology in what has rapidly become a commodity business?" (LaMonica 2012). At GTM's Solar Summit 2013, Martin Hermann, CEO of one of the largest PV developers in the U.S. and former CSO of Advent Solar, stated that "modules are more like the memory component of a computer than the processor component (...) Quality matters, but modules from Vendor A and Vendor B, if they are bankable modules, are interchangeable from project to project." Conrad Burke, Global Marketing Director of PV Solutions at DuPont, argued that "it is ludicrous to view solar panels as something like coffee or copper" and that "maintaining quality through the drive for cost-cutting is critical". Almost all of the audience (around a hundred people), voted that solar modules are not a commodity (yet).

[21] Crystalline silicon panels target high performance, lowering cost per watt by increasing efficiency and power and are best suited for rooftops, where space is scarce and high efficiency is needed. Thin film panels trade off efficiency for lower costs and lighter materials, which make them more appropriate for ground-mounted installations (where space is not a limitation) and rooftops that cannot support heavy materials.

600 manufacturers worldwide,[22] I found significant differences in weight and a measure of potential mismatch between different modules assembled in the same system.[23] The average number of models produced by a single company was 70, with a maximum of 273. Given the lack of time series data on the product basket of the firms in the sample, and to keep the model simple, I abstract from the multi-product dimension of solar panel manufacturers.

Pricing methods in the solar PV industry vary across firms and market segments. Contracting depends on the activity the company is engaged in. Companies that are more actively engaged in selling modules for large-scale solar developments (power plants or solar farms) tend to use short- and long-term contracts specifying fixed quantities and price, while those most active in retail and wholesale distribution sell through spot sales. U.S. International Trade Commission (2012) reported that "the most commonly reported pricing method for both U.S. producers and importers is transaction-by-transaction negotiations" (p. V-4), but acknowledged differences across distribution channels. Producers in the investigation also declared making discounts for higher volume clients, quarterly volume sales and prices set by distribution. Since most of the manufacturers' sales in the sample were destined to residential and commercial users, not considering negotiated prices or other contracting issues seems reasonable. Moreover, in this dynamic setting, it would imply that firms play a repeated game with consumers when setting prices, which would greatly complicate the model.[24]

The model assumes away dynamic considerations that could be present in consumers' decisions to install solar panels. While the model features productivity improvements that can lead to lower prices in the future (explained below), consumers are myopic and cannot alter their decisions based on their expectations about the evolution of productivity. Hence, consumers' incentives to wait are not considered by producers when designing their pricing strategies.

Models of dynamic demand that incorporate these forces are receiving increased attention in the literature.[25] Melnikov (2013) estimates the demand for computer printers in the U.S. allowing for intertemporal demand substitution and shows that forward-looking

[22] Data are from Posharp.com's solar panel database, available at http://www.posharp.com/photovoltaic/database.aspx (accessed September 2013). Summary statistics on panel characteristics are available upon request.

[23] Manufacturers usually indicate a tolerance range between the maximum and minimum power that could be generated by the module. A module with a wider tolerance range could generate power that is very different from the one indicated on the nameplate. Interconnected modules that do not share identical properties and generate different power can give rise to mismatch losses in energy. It is common practice when designing solar systems to take into account the potential for mismatches.

[24] See Grennan (2013) and Gowrisankaran et al. (forthcoming) for empirical applications where firms engage in negotiated contracts with buyers.

[25] Aguirregabiria and Nevo (2013) provide a complete survey of dynamic demand estimation.

behavior is an important factor explaining the dynamics of the industry. Gowrisankaran and Rysman (2012) allow consumers to evaluate when to make a purchase, taking into account that prices, quality and the set of available models may change over time. Applying their model to the camcorder industry, they find that consumers delayed their purchases in order to take advantage of the availability of cheaper and better models in the future, thus reducing the initial market share for digital camcorders. Schiraldi (2011) studies the effects of replacement subsidies on substitution patterns in the Italian car market and finds that, due to dynamic factors affecting consumers' behavior, incentives to replace used cars have different short- and long-run effects on demand, as the distribution of car ages changes over time. Goettler and Gordon (2011) allow for dynamic behavior in both demand and supply: while consumers take into account that prices and quality can change in the future, firms understand that their pricing and R&D policies affect consumers' decisions of when to purchase. Their market structure is a stable duopoly, however, so that the computational burden is constrained.

There is some evidence that improvements in productivity (that are reflected in future lower prices) and uncertainty regarding subsidies, the environment, and energy prices may create an option value of waiting to install solar panels. Ansar and Sparks (2009) calibrate and simulate a stochastic model of investment in solar installations and find that experience curve effects can explain implicit discount rates that rationalize actual energy-saving investments. Bauner and Crago (undated) extend Ansar and Sparks (2009) to include uncertainty in installation costs and find an option value multiplier of 1.8. Consumers could also have an incentive to wait if there is peer-learning about new solar panel installations, which Bollinger and Gillingham (2012) find to be of importance, at least in California.

Allowing consumers to solve a dynamic problem to determine solar panel installations would greatly complicate the computational strategy of the model in the current setup. Moreover, lack of time-varying data on firm-level product quality and/or solar panel models release would leave price as the only dynamic variable in consumers' decisions, hence complicating the identification of static and dynamic demand substitution patterns.

1.3.2 Technology

Firms produce a single variety of solar panels. Since what finally matters to consumers is the amount of power a solar panel can generate, I measure production in terms of the services (watts) a solar panel provides and define the production function of watts as:[26]:

$$q_{jt} = \xi_{jt} A_{jt},$$

where ξ is conversion efficiency (adjusted for light incidence on the panel) and A is the area of solar panels that is produced. Although typically firms produce several models of solar modules with different levels of conversion efficiency, I abstract from multi-product production to keep the model simple and interpret ξ as average firm conversion efficiency. I assume that $A \equiv \varphi_{jt} f(\mathbf{K}_{jt})$, where φ is a measure of factor efficiency and $\mathbf{K}$ is a vector of factors used in the production of solar panels. I further assume that f is constant returns to scale so that marginal cost can be written as

$$c_{jt} = (\xi_{jt}\varphi_{jt})^{-\beta} c_0(\mathbf{r}_t), \tag{1.3}$$

where $\mathbf{r}$ are factor prices and c_0 is a function that depends on the parameters of f. The interpretation of (1.3) is straightforward: everything else equal, higher conversion efficiency or higher efficiency in combining inputs allow a firm to deliver more watts using the same amount of inputs, decreasing marginal cost with elasticity β. Note, also, that conversion efficiency does not depend on the firm's choice of inputs. Strictly speaking, conversion efficiency does vary depending on which factors the firm uses to produce panels (e.g. silicon or cadmium telluride), but the differences do not depend on the quantity of material, rather on the inherent technology used. However interesting the solar technology choice problem may be, I abstract from it to keep the model simple and assume technology is given and embedded in time-invariant differences in ξ across firms. I further make two simplifying assumptions. First, to keep the computational burden of the model low, I collapse the two dimensions of cost heterogeneity and define "productivity" as $\omega_{jt} \equiv \xi_{jt}\varphi_{jt}$, $\omega_{jt} \in \Omega \equiv \{\omega_1, \omega_2, ..., \omega_M\}$. Second, I assume away factor price differences over time, so that $\mathbf{r}_t = \mathbf{r}$. I return to discussing this assumption in the empirical implementation section below. The cost function is therefore

$$c_{jt} = c_0 \omega_{jt}^{-\beta}. \tag{1.4}$$

Firms' operating profit flows from the sale of solar panels are given by:

$$\pi_{jt}(\mathbf{p}_t, \omega_{jt}) = D_t s_{jt}(\mathbf{p}_t)[p_{jt} - c_{jt}(\omega_{jt})], \tag{1.5}$$

where s_j is firm j's market share, D is aggregate demand for solar panel installations, and

[26]See Pillai (2014).

$\mathbf{p} \equiv (p_j)_{j=0}^J$ is the vector of prices.

Productivity evolves as a controlled Poisson process. Firms can affect its evolution in two ways. First, firms can make R&D investments to improve conversion efficiency. Second, there is learning by doing: as firms produce, they generate ideas which can eventually translate into successful process innovations and increase productivity. With this specification I let the model accommodate two oft-cited mechanisms through which firms can increase productivity and later let the data determine which is more important quantitatively. I abstract, however, from knowledge spillovers that could affect the evolution of productivity, mostly through R&D performed in public research institutions. Shutting down this channel could bias upwards the estimated effectiveness of private R&D in driving successful innovations. Apart from the fact that incorporating spillover effects would significantly complicate the model, data limitations prevent me from properly identifying them in the current setting.

Given a level of investment $x \in \mathbb{R}_+$ and quantity produced $q(\mathbf{p}) = Ds(\mathbf{p}) \in \mathbb{R}_+$, the arrival rates of R&D- and learning by doing-related productivity improvements are given by[27]

$$\phi_x(x) = \eta_1 x^{\eta_2}, \tag{1.6}$$

$$\phi_q(\mathbf{p}) = \eta_3 q(\mathbf{p})^{\eta_4}. \tag{1.7}$$

Moreover, firms are subject to idiosyncratic negative productivity shocks which arrive with hazard rate δ. While δ could be interpreted as organizational forgetting (Benkard 2000, Besanko et al. 2010), this is not obvious in the context of the solar industry, which in the U.S. is characterized by low labor intensity and low turnover, which suggests forgetting shouldn't play a major role in productivity dynamics. One could also argue that most of the learning that takes place in solar firms is quickly embodied in the organization, and is not so important at the worker level. [28] A more plausible interpretation for the negative productivity shock is as a decrease in firm average conversion efficiency. Although solar panel conversion efficiencies rarely decrease, recall that ξ represents firm-level conversion efficiency, which depends on the set of module varieties offered by the firm. If a model with above-average efficiency is discontinued, or a new model with below-average efficiency is introduced, conversion efficiency at the firm level can decrease.

[27]Note that, under this specification, the learning and R&D elasticities are the same for large and small firms. This could be different under alternative specifications. For instance, if $\phi_q = \eta q/(1+\eta q)$ and $\eta > 0$, small firms would benefit more on the margin from an increase in market share than large firms.

[28]Levitt et al. (2013) find that the knowledge that is generated by learning in a highly automated auto plant is not retained by workers, but quickly conveyed into the plant's organizational capital. See also Thompson (2012) for a discussion on learning at the organization level.

The hazard rate of a change in productivity is then given by the superposition of three independent Poisson processes:

$$\phi_\omega(x, \mathbf{p}) = \phi_x(x) + \phi_q(\mathbf{p}) + \delta. \tag{1.8}$$

Conditional on a productivity jump at time t, the transition probabilities of productivity are described by:

$$\mathbb{P}(\omega'|\omega_k, x, \mathbf{p}) = \begin{cases} (\phi_x + \phi_q)/\phi_\omega & \text{if } \omega' = \omega_{k+1}, k < M, \\ \delta/\phi_\omega & \text{if } \omega' = \omega_{k-1}, k > 1, \\ 1 & \text{if } \omega' = \omega_2, k = 1, \text{ or } \omega' = \omega_{M-1}, k = M, \end{cases}$$

where ω_k is the productivity right before the jump.

Note that the chosen specification of organizational learning by doing is silent about the microeconomic mechanisms that may lead to it. Several channels have been emphasized in the literature, such as process R&D investments which are complementary with production (Cabral and Riordan 1994) and/or improved practices by workers on the production line (Thompson 2012, Levitt et al. 2013). Moreover, in the model the learning rate and firms' new R&D investments are unrelated. A more general model, that is beyond the scope of this paper, would feature investment decisions that give rise to technological innovations (e.g. a new technical process or development of a new product), after which a period of learning about it sets in.[29]

1.3.3 Entry and exit

Incumbents face opportunities to liquidate and exit the industry. Opportunities to exit arrive with hazard rate λ. If an exit opportunity arrives at t, the firm draws a privately observed scrap value κ_j from a distribution G, which it takes and exits with probability χ_{jt}. I assume that, once a firm exits, it dies and does not consider potential re-entry into the industry. To keep notation consistent, exiting firms' productivity transits to a terminal state ω_{M+1}.

If the number of active firms J is lower than N, one potential entrant may decide to enter the industry. Opportunities to enter arrive with hazard rate λ_e. If an entry opportunity arrives at t, the firm draws a privately observed entry cost κ_e from a distribution G_e. The potential entrant chooses to pay the entry cost and enter with probability χ_e. Upon entry,

[29] Levitt et al. (2013) document that the introduction of a new car model triggered a new learning process among workers. See also Thompson (2012), Thompson (2010), and the references cited therein for alternative learning specifications.

the initial productivity of a potential entrant is ω_e.

As will become clear below, although the arrival rate of the *opportunity* to enter is exogenous, actual entry depends on firms' forward-looking decisions. Hence, the entry probability χ_e is endogenous and state-dependent. In particular, it will depend on the price of imports and the productivities of the potential entrant's competitors if it were to enter the market.

1.3.4 Transitions of exogenous variables

The foreign variety's price, $p_0 \in \{\underline{p_0}, ..., \overline{p_0}\}$, and the size of the domestic market, $D \in \{\underline{D}, ..., \overline{D}\}$ evolve as independent exogenous Poisson processes. With hazard rate γ_{p_0} p_0 will jump to a new level p_0' and, similarly, with hazard rate γ_D d will jump to a new level D'. To make notation more compact, let $\varsigma \equiv (D, p_0)$ define the aggregate (common) state faced by all firms and let γ_ς define the hazard rate of a change from ς to some other ς', derived from γ_{p_0} and γ_D.

1.3.5 Firms' decisions

Incumbent firms choose prices, R&D investment and whether to continue in or exit the industry so as to maximize their expected present discounted value. The following Bellman equation characterizes the problem of an incumbent firm j:

$$\begin{aligned} \rho V_j(\omega, \varsigma) = \max_{p_j, x_j, \chi_j} \; & \pi_j(\mathbf{p}) - x_j + (\phi_{xj} + \phi_{qj}) \cdot \mathbb{1}\{\omega_j \neq \omega_M\} \left[V_j(\omega_j^+, \omega_{-\mathbf{j}}, \varsigma) - V_j(\omega, \varsigma) \right] \\ & + \sum_{i \neq j : \omega_i \neq \omega_{M+1}} (\phi_{xj} + \phi_{qj}) \cdot \mathbb{1}\{\omega_i \neq \omega_M\} \left[V_j(\omega_i^+, \omega_{-\mathbf{i}}, \varsigma) - V_j(\omega, \varsigma) \right] \\ & + \sum_i \delta \cdot \mathbb{1}\{\omega_i \neq \omega_1\} \left[V_j(\omega_i^-, \omega_{-\mathbf{i}}, \varsigma) - V_j(\omega, \varsigma) \right] \\ & + \lambda \chi_j \left[(1/\chi_j) \int_{\kappa_j \geq G^{-1}(1-\chi_j)} \kappa_j dG(\kappa_j) - V_j(\omega, \varsigma) \right] \\ & + \sum_{i \neq j : \omega_i \neq \omega_{M+1}} \lambda \chi_i \left[V_j(\omega_{M+1}, \omega_{-\mathbf{i}}, \varsigma) - V_j(\omega, \varsigma) \right] \\ & + \lambda_e \chi_e \left[V_j(\omega_e, \omega, \varsigma) - V_j(\omega, \varsigma) \right], \\ & + \sum_{\varsigma'} \gamma_{\varsigma'} \left[V_j(\omega, \varsigma') - V_j(\omega, \varsigma) \right] \end{aligned} \tag{1.9}$$

where ρ is the discount factor and, $\mathbb{1}\{\cdot\}$ is the indicator function, ω_e is the productivity of entrants upon entry, and, with some abuse of notation, ω_j^+ (ω_j^-) indicates a one step increase (decrease) in the index of the productivity level of firm j, and $\omega_{-\mathbf{i}}$ is the vector of productivity levels of all firms other than i.

The interpretation of problem (1.9) is as follows. The first line corresponds to flow profits (net of investment costs) plus the effect of the arrival of successful ideas (either from R&D or learning) for firm j. The second line incorporates the effect of the arrival of successful ideas for firm j's competitors. It is implicit here that ϕ_{qj} depends on the vector of prices $\mathbf{p}$ through quantities produced. The third line captures negative shocks to productivity. The fourth and fifth lines capture firm j's and its competitors' exit decisions. The first term is the hazard of an exit decision: the hazard of an exit opportunity arriving, λ, times the probability that the firm takes it, χ_j. The second term follows from noting that what matters to firm j is the scrap value conditional on accepting it (Doraszelski and Judd 2012):

$$E(\kappa_j|\kappa_j > \bar{\kappa}_j) = \frac{1}{1 - G(\bar{\kappa}_j)} \int_{\kappa_j > \bar{\kappa}_j} \kappa_j dG(\kappa_j). \tag{1.10}$$

The sixth line includes the expected value of a potential entrant entering the industry. Finally, the seventh line corresponds to the evolution of the common state (a foreign price-domestic demand combination).

In turn, the problem of a potential entrant can be characterized by the following Bellman equation:

$$\rho V_e(\omega, \varsigma) = \max_{\chi_e} \left\{ 0, \lambda_e \chi_e \left[-(1/\chi_e) \int_{\kappa_e \leq G_e^{-1}(\chi_e)} \kappa_e dG_e(\kappa_e) + V_i(\omega_e, \omega_{-i}, \varsigma) \right] \right\}, \tag{1.11}$$

where the second term bears a logic analogous to that behind the derivation of (1.10). Note that this formulation implies entrepreneurs commit to an entry *probability* before observing their entry cost. If they observed the entry cost before moving their decision would be a discrete action, which would complicate the computation of an equilibrium (see Doraszelski and Judd (2012)).

Finally, note that I assume that domestic firms take the foreign variety's price as given and that foreign rivals do not choose this price (nor R&D) strategically taking into account domestic firms' behavior. Apart from making the model simpler, this assumption is justified based on the observation that almost all of the increase in foreign competition during the period I study was due to Chinese firms increasing their presence not only in the U.S. market, but the global market for solar photovoltaics more generally. I hence interpret the behavior of Chinese exporters as deriving from the Chinese government's plan of becoming an important global player, independently from the behavior of individual U.S. manufacturers. Moreover, most of the penetration of imported panels in the U.S. during the period I study was through entry of small local distributors and installers, each with little market power (see Figure 1.1).

1.3.6 Policy functions

While in most existing dynamic oligopoly models with learning by doing firms use one instrument (prices) to affect both current profits and the evolution of marginal cost,[30] in this model firms have two instruments: R&D investments and prices. Assuming that the hazard rates of R&D and learning by doing affect productivity in a separable fashion (see equation (1.8)), however, simplifies the firm's problem by allowing to solve the firm's first order conditions separately.[31] In what follows I characterize these first order conditions, which describe firms' pricing and R&D choices.

Firm j's pricing decision is characterized by the following first order condition:[32]

$$0 = z_j \equiv \frac{1}{\alpha(1-s_j)} - p_j + c_j - \phi'_{qj}\Delta V_{jj} + \sum_{i \neq j} \phi'_{qi} \frac{s_i}{(1-s_j)} \Delta V_{ji}, \tag{1.12}$$

where $\Delta V_{ji} \equiv [V_j(\omega_i^+, \omega_{-i}, \varsigma) - V_j(\omega, \varsigma)]$ and $\phi'_{qi} \equiv (\partial \phi_q / \partial q)(q_i)$. Manipulating (1.12):

$$p_j = c_j + \frac{1}{\alpha(1-s_j)} - \phi'_{qj}\Delta V_{jj} + \sum_{i \neq j} \phi'_{qi} \frac{s_i}{(1-s_j)} \Delta V_{ji}. \tag{1.13}$$

The first two terms in the pricing equation (1.13) comprise the well known optimal pricing rule of static multinomial logit models, i.e. marginal cost plus a mark-up $1/\alpha(1-s_j)$. The third and fourth terms capture dynamic incentives to deviate from the static pricing policy. The first of the latter reflects the fact that, by reducing its price today, firm j can increase it's market share, which would make it more likely to experience a productivity jump in the future and hence increase firm j's value. The second reflects the fact that by pricing lower today, the firm can induce consumers to substitute away from competitors, therefore decreasing their market share and reducing the likelihood that they will experience a productivity jump in the future, affecting firm j's value. In fact, note that $s_i/(1-s_j) = (\partial s_i/\partial p_j)/(\partial s_j/\partial p_j)$, so that firm j considers the sum of each of its competitors' effects weighted by the change in each competitor's share relative to the change in firm j's share when j varies its price.

These "advantage-building" and "advantage-denying" motives (Besanko et al. 2014)

[30] This has non-trivial implications for pricing policies. See Cabral and Riordan (1994), Benkard (2004), Besanko et al. (2010) and Besanko et al. (2014).

[31] This would not be the case if the functional form of equation (1.8) were Cobb-Douglas, say, so that $\partial \phi_\omega / \partial q$ would depend on x.

[32] To make the exposition clearer, I omit the adjustment for those cases in which $\omega_j = \omega_M$ and/or $\omega_i = \omega_M$ for some i.

incorporate the dynamic externality implied when there is learning by doing (i.e. $\phi'_{qj} \neq 0$). The underlying assumption is that $V_j(\omega, \varsigma)$ is non-decreasing in own productivity and non-increasing in competitors' productivities. While, intuitively, this assumption should be expected to hold, it does not necessarily arise in general.[33] For example, consider a low productivity firm A competing against a high productivity firm B. An increase in firm B's productivity can increase the value of firm A if it decreases the probability of entry, so that the benefits from lower expected competition more than compensate the losses from a lower market share for firm A. This case can be actually verified under some parameterizations of the model. When I estimate the model below, I check whether these conditions hold.

The R&D investment policy is characterized by

$$\phi'_{qj} \mathbb{1}\{\omega_j \neq \omega_M\} \Delta V_{jj} = 1, \tag{1.14}$$

for an interior solution, and $x_j = 0$ when $\omega_j = \omega_M$. Equation (1.14) simply states that the firm sets investment so that the marginal benefit from it equals its marginal cost. Note that, although the R&D and pricing decisions are not directly related, the expected return to R&D investments is higher than in an environment where there is no learning. The reason is that, everything else equal, a successful R&D endeavor increases productivity, lowers prices, increases a firm's market share and quantities shipped, and therefore its hazard rate of learning.

Finally, the first order conditions for exit and entry policies are, respectively

$$\chi_j = 1 - G[V_j(\omega, \varsigma)], \tag{1.15}$$

$$\chi_e = G_e[V_i(\omega_e, \omega_{-e}, \varsigma)]. \tag{1.16}$$

The interpretation is straightforward. Conditional on the arrival of an exit opportunity, an incumbent sets the probability of exiting equal to the probability of receiving a scrap value greater than or equal to the discounted present value of remaining in the industry. Analogously, given an opportunity to enter, a potential entrant optimally enters with the probability of drawing an entry cost less than or equal to the discounted present value of being an incumbent.

1.3.7 Equilibrium

I focus on symmetric, anonymous Markov perfect equilibria in pure strategies. Symmetry and anonymity are standard assumptions that reduce the computational burden of the

[33] Besanko et al. (2014) confirm these properties in their results, but cannot provide a proof.

algorithm. We can apply them in this framework since the primitives of the problem are symmetric (i.e. profits). Under these assumptions the number of states can be reduced by focusing on a subset $\tilde{\Omega}_\varsigma \equiv \{(\varsigma, \omega^1, \omega^2, ..., \omega^N) : \omega^1 < \omega^2 < ... < \omega^N\}$ (Pakes et al. 1993). Relaxing these restrictions would imply introducing additional state variables to identify firms and allow them to follow different strategies when faced with the same state and number of competitors.

Sufficient conditions for existence of an equilibrium in pure strategies with continuous actions are provided by Doraszelski and Judd (2012).[34] A key assumption of their theorem is that the maximizing choice of the firm is single-valued for all players' actions and all value functions. A sufficient condition for this is that the maximand in the Bellman equation is strictly quasi-concave, so that the correspondence that maps values and policies to the set of possible policies of the firm's problem is continuous.

Uniqueness of the equilibrium is more difficult to establish.[35] Differentiating the first-order condition (1.12) one more time with respect to p_j gives, after some manipulation:

$$\frac{\partial z_j}{\partial p_j} = -1 + s_j z_j + \alpha q_j \left[\phi''_{qj}(1 - s_j)^2 \Delta V_{jj} + \sum_{i \neq j} \phi''_{qi} s_i^2 \Delta V_{ji} \right].$$

Then, if the first-order condition is satisfied ($z_j = 0$) the equilibrium is unique provided there is no entry nor exit and the following second-order condition is satisfied:

$$\frac{1}{\alpha q_j} > \phi''_{qj}(1 - s_j)^2 \Delta V_{jj} + \sum_{i \neq j} \phi''_{qi} s_i^2 \Delta V_{ji}, \tag{1.17}$$

where $\phi''_{qi} \equiv (\partial^2 \phi_q / \partial q^2)(q_i)$. This is readily satisfied if ϕ_{qj} is linear in q_j (the right-hand side becomes 0), but linearity of the learning by doing hazard imposes too much structure and implies a unit elasticity. Moreover, it is known that entry and exit can generate multiple equilibria in discrete-time environments, since a firm can alter its pricing decisions to induce exit of competitors (Cabral and Riordan 1994). Moreover, as Besanko et al. (2010) have shown, the presence of a negative productivity shock when there is learning by doing induces bidirectional movements in the state space and can give raise to multiple equilibria. In the present model with R&D-driven productivity dynamics firms do not rely solely on prices to attain future cost reductions, so the effect of negative productivity shocks in generating multiple equilibria may be alleviated. While I cannot prove uniqueness of the equilibrium in this setting, when solving the model below I always check that the solution

[34] The proof is different from the discrete-time case (Doraszelski and Satterthwaite 2010) and involves an application of Brouwer's fixed point theorem (see their Proposition 1 in their appendix).

[35] Doraszelski and Judd (2012) provide no discussion on uniqueness of the equilibrium in a continuous-time framework.

satisfies condition (1.17). Investment, exit and entry policies are unique from (1.14), (1.15) and (1.16).

1.4 Estimating sample data

The main database used for estimation is derived from confidential data produced by the U.S. Energy Information Administration (EIA) "Annual Photovoltaic Cell/Module Manufacturers Survey" (Form EIA-63B) from 1999 to 2009. The survey is mandatory under the Federal Energy Information Administration Act of 1974 for all companies (U.S.- or foreign-based) that engage in photovoltaic-related activities within the U.S.[36]

From 1999 to 2009 I have information on companies' main activities (manufacturing, installing, retail distribution, prototype development, etc.), total shipments, exports and imports (in watts), value of total shipments of photovoltaic cells and modules (in U.S. dollars), production technology (crystalline silicon, thin film, etc.), number of workers, an indicator of whether the company is planning to introduce a new product, and shipments to the domestic market by end use (residential, commercial, etc.). I use module shipments and revenue to construct firm level average selling prices. Additionally, for 2007-2009 the survey reports companies' production by U.S. state and for 2004-2009 it reports imports by country of origin.

I complement this data set with three additional sources of data. First, I collect information on company birth date and whether it has a manufacturing facility in the U.S. and/or abroad from various sources (mainly company information publicly available on the internet). Second, I use Photon's Solar Module Database[37] to construct a measure of firm-level average conversion efficiency. Third, for a subsample of firms included in the survey I collect research and development expenditures as reported in their publicly available financial statements (10-K forms).

After cleaning the data for duplicate IDs, changes in companies' names and/or ownership and removing companies that are inactive for the whole period, I assess the coverage of the survey by comparing U.S. solar photovoltaic production computed using the survey for 2007-2009 with production data from the Earth Policy Institute (EPI).[38] Solar photovoltaic

[36]Failure to respond to the survey may result in monetary penalties and misreporting is considered a criminal offense. The EIA identifies companies to include in the survey by periodically monitoring the industry through its main organizations and publications, such as the Solar Energy Industries Association (SEIA).

[37]Photon is a leading research and consulting firm in solar photovoltaics. See `http://photon.info/en/photon-databases`.

[38]The EPI compiles its data from sources other then the EIA (i.e. consulting firms, specialized magazines and other research institutes). Data are publicly available at `http://www.earth-policy.org/data_center/C23`.

production figures in the survey are 108%, 103% and 95% of EPI figures for 2007, 2008 and 2009, respectively. For years before 2007, for which production figures are not available in the survey, shipments excluding imports as reported by firms are, on average, 95% of production as reported by the EPI, and between 113% (1999) and 86% (2002).[39]

I then restrict the sample as follows. I only consider module shipments, ignoring cell shipments, since cell shipments are not purchased by end-consumers but are used as inputs for solar panels. On average, the share of firm revenue which corresponds to modules was never lower than 75% and in general higher than 85%. I ignore concentrated solar production, which has a very different production technology and demand, and accounted for a negligible share of total solar module shipments during the period. While in the model firms produce a single variety, in reality solar module manufacturers produce several models and, although most firms are highly specialized in and derive most of their revenue from a single technology, some large firms produce with more than one technology. Unfortunately I do not observe data on different models. Firms do report shipments by technology, however. When a firm reports shipments of both silicon and thin film panels, I classify the firm in the technology with a revenue share higher than 75%. Finally, I only consider firms producing with silicon (as opposed to thin film) technologies. Although the demand side would be better specified if I were to allow substitution between silicon and thin film alternatives, focusing on this set of firms is reasonable for two reasons. First, production processes and materials differ considerably across both technologies, with silicon being more labor intensive, and I do not observe capital but only labor. By restricting the sample to silicon producers I limit the effect of technology-specific shocks, not included in the model, that could affect some firms but not others (for example, a shock to polysilicon prices, which would not affect costs for thin-film producers). Second, imports from foreign producers (especially China) were concentrated on silicon rather than thin film, and trade policies were aimed at that particular type of module.

To separate shipments by U.S.-based manufacturers from imported shipments I divide the sample in two groups. The first group consists of firms with manufacturing facilities in the U.S. The second group consists of manufacturers that do not have a production facility in the U.S. (but export directly to the U.S. market) and mostly small local distributors and installers that sell imported modules. I interpret the latter as a competitive importing fringe that competes against U.S.-based manufacturers. I use firms' market shares within this group to construct an average weighted price of imports.

[39]Since solar cells and modules are durable products that can be held as inventories, which I don't observe, I also compare cumulative production form the EPI to cumulative shipments excluding imports form 1982 to 2009 (aggregate data on shipments are available from the EIA prior to 1999). During the whole period cumulative shipments are more than 80% of cumulative production, and for the period covered by the survey the ratio is more than 90% for any year.

The number of U.S.-based silicon manufacturing firms after cleaning the data ranges from 10 in 1999 to more than 30 in 2009. Most of these firms had a very small share of the U.S. market, including some that shipped small volumes as experimental production. Since it is computationally infeasible to handle such a large number of firms in the present framework, I focus on firms that had, on average, market shares equal to 4% or more throughout the period.

The resulting sample is summarized in Table 1.2. It includes between 4 and 7 relatively large U.S.-based silicon module manufacturers (the average firm has more than 250 workers) and covers more than 90% of total silicon module shipments in any given year.[40]

Table 1.2: Estimating sample summary statistics.

Year	U.S.-based manufacturers				Import competing fringe		Estimating sample share
	Number of firms	Shipments (MW)	Avg. price ($/W)	Avg. number of workers	Shipments (MW)	Avg. price ($/W)	
1999	4	12	3.618	400	3.6	9.856	0.98
2000	6	14	3.203	250	2.2	10.231	1.00
2001	5	20	3.203	400	4.7	6.258	0.98
2002	6	21	3.357	350	6.0	7.396	1.00
2003	6	34	2.916	350	9.4	6.935	1.00
2004	7	55	2.691	250	9.6	8.902	0.95
2005	7	78	2.911	250	24.8	6.039	0.92
2006	7	111	3.034	250	49.6	3.716	0.96
2007	6	139	2.965	400	80.4	3.425	0.97
2008	6	259	2.846	450	155.5	3.055	0.98
2009	6	296	2.232	550	175.5	2.081	0.97

Notes: U.S.-based silicon module manufacturers selected based on whether they had a market share of 4% or more, on average, during the period. "Shipments" are quantities shipped to the domestic (U.S.) market, in megawatts (MW). Prices are expressed in U.S. dollars per watt ($/W), deflated using the 1999 CPI. The average number of workers is rounded to the nearest 50th worker to avoid disclosure concerns. The last column reports the estimating sample share of total silicon module shipments for each year (both domestic and imported).

1.5 Taking the model to the data

The features of the model and the nature of the data make the estimation procedure a non-trivial matter. Typically, lack of firm-level cost data leads researchers to use the structure of the model, such as the optimality condition (1.12), as a basis for a generalized method of moments (GMM) strategy to recover parameters of the policy functions. Applying this reasoning here is complicated by the fact that the dynamic nature of firms' pricing decisions implies firm j's value function appears in equation (1.12). Without enough

[40]Ruegg and Thomas (2011), in a DoE study of R&D linkages in solar PV, consider only the top eight producers since "the reported production output of producers below the top eight was negligible" (p. 3-9).

data to approximate the value function at least at some points of the state space, it is infeasible to treat (1.12) as an Euler equation and apply GMM.[41] A second complication is that, whereas in the model firms make continuous pricing decisions, I only observe annual averages.

I attempt to circumvent this issues by employing the Simulated Minimum Distance (SMD) estimator suggested by Hall and Rust (2003), similar in nature to the Indirect Inference method of Gouriéroux et al. (1993) and Gouriéroux and Monfort (1996). I complement it by estimating the exogenous foreign price process and the demand system separately. In what follows I describe each step in detail.

1.5.1 Foreign price process

Given the assumptions of the model, the imported variety's price p_0 follows an exogenous stochastic process that could be estimated from the data. In continuous time environments, Shimer (2005) and Eaton et al. (2014) interpret the observed annual trajectory of exogenous variables as discrete realizations of Ornstein-Uhlenbeck (OU) processes and approximate them by fitting the data to an Ehrenfest diffusion process. If y follows an Ehrenfest diffusion process, it can be discretized into a grid with $2n+1$ values, $n \in \mathbb{Z}^+$, i.e. such that $y \in \{\bar{y}-n\Delta, \bar{y}-(n-1)\Delta, ..., \bar{y}, ..., \bar{y}+(n-1)\Delta, \bar{y}+n\Delta\}$, for a cell size Δ and some $\bar{y}$. With hazard γ_y, y will jump to a new value y' with

$$\Pr(y'|y) = \begin{cases} 0.5[1-(y-\bar{y})/n\Delta] & \text{if } y' = y+\Delta, \\ 0.5[1+(y-\bar{y})/n\Delta] & \text{if } y' = y-\Delta, \\ 0 & \text{otherwise.} \end{cases}$$

As the grid becomes finer, such a process asymptotes an OU process. Essentially, then, this method fixes a grid length n and a transition matrix $\Pr(y'|y)$ and calibrates γ_y and Δ based on parameter estimates of an AR(1) process using the data.

Applying this procedure in this context is not straightforward. Assuming a transition matrix like $\Pr(y'|y)$, which implies reversion to $\bar{y}$ with $(n-1)/2$ adjacent cells equally spaced at Δ intervals, will make it very hard for this method to fit the apparent downward trend of the foreign price process illustrated in Table 1.2. This is even more complicated by the very low number of observations I have. With this considerations in mind, I therefore calibrate the foreign price process as follows. First I specify a grid that does not necessarily have equally spaced intervals, but covers the range of observed prices. Second, I specify

[41] Berry and Pakes (2000) suggest a technique to estimate parameters of dynamic models with interactions among agents based on optimality conditions.

a transition matrix up to a parameter to be calibrated. Finally, I choose γ_{p_0} and the transition matrix parameter so as to minimize the distance between the long-run mean and standard deviation implied by an AR(1) fitted to the data and those implied by an AR(1) fitted to simulated data from the calibrated process.

Specifically, p_0 is discretized into a grid with 5 values $\{p_0^1, p_0^2..., p_0^5\}$ such that: (1) p_0^1 is the average over 1999-2000, (2) p_0^2 is the average over 2001-2005, (3) p_0^3 is the average over 2006-2009, (4) p_0^4 is the average over 2010-2013, (5) p_0^5 is a projected value of modules imported from China for 2014-2015. I calibrate the transition matrix so that

$$\Pr(p_0'|p_0) = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0.25 & 0 & 0.75 & 0 & 0 \\ 0 & 0.05 & 0 & 0.95 & 0 \\ 0 & 0 & \Pr_{43} & 0 & 1-\Pr_{43} \\ 0 & 0 & 0 & 1 & 0 \end{pmatrix}.$$

The second and third rows are fixed to allow the price process to reach low prices rapidly and remain in that region, as in the data. $\Pr_{43}$ is calibrated as follows:

1. For some guess of $(\gamma_{p_0}, \Pr_{43})$ I simulate 500 trajectories $\{p_{0t}^s\}_{t=1}^{25}$.
2. For each s, I estimate the parameters of an AR(1) process $p_{0t+1}^s = a^s + b^s p_{0t}^s + \epsilon_t^s$ to obtain the implied long run mean $me_s \equiv a^s/(1-b^s)$ and the the standard deviation of the disturbance $sd_s(\epsilon^s)$.
3. The guess is updated until (me, sd) is as close as possible to the data, where $me = (1/S)\sum_s me_s$ and $sd = (1/S)\sum_s sd_s(\epsilon^s)$.

I use imported modules' average selling prices reported in the survey for 1999-2009 and, for 2010-2015, I compute imported modules' unit value using the value of module imports (in US$) as reported by the USITC and total imported shipments (in watts) as reported by the EIA.[42] The results are summarized in Table 1.3. Although the simulated process has lower volatility than the data (as expected), the implied long run mean is very close to the data. The calibrated hazard rate implies that the foreign price changes approximately $\exp(0.4198) = 1.5$ times per year. Figure 1.2 plots the average over $S = 500$ simulations of the calibrated process (starting at p_0^5) against the data.

[42]Module imports from the USITC correspond to HTS number 8541406020, "Solar cells assembled into modules or panels". Figure **??** in the appendix shows the time series of import prices derived from the EIA survey and unit values derived using USITC data.

Table 1.3: Imported variety price process.

Parameter	Description	Value
$\{p_0^1, ..., p_0^5\}$	Foreign price grid	$\{10.044,\ 7.106,\ 2.500,\ 0.8864,\ 0.6703\}$
γ_{p_0}	Hazard of a jump	0.4198
$\Pr_{43}$	$\Pr(p_0^3 \vert p_0^4)$	0.4199
$(me^{\text{data}}, sd^{\text{data}})$	AR(1) targets (data)	(0.57213, 1.4130)
(me, sd)	AR(1) targets (simulated)	(0.5729, 1.0569)
Norm	Distance between data and simulation	0.2336
$\Pr^*(p_0)$	Implied ergodic distribution	$\{0.0036,\ 0.0143,\ 0.2147,\ 0.4857,\ 0.2817\}$

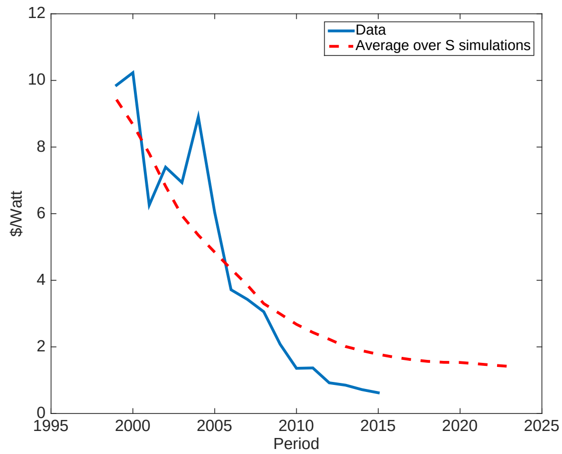


Figure 1.2. Foreign price: data and simulated process.

1.5.2 Consumer demand

I estimate the demand parameter α in a first stage using instrumental variables and the whole, unrestricted sample. I use a slightly modified version of the demand model in order to include observable characteristics of solar modules $\mathbf{o}_{jt}$ and an unobserved (to the econometrician) variety-specific attribute ι_{jt} (such as bankability of the firm or durability of the panel), and follow Berry (1994) to invert aggregate market shares for variety j, s_{jt} and obtain the following estimating relationship

$$\ln s_{jt} - \ln s_{0t} = -\alpha(p_{jt} - p_{0t}) + \mathbf{o}_{jt}\beta + \iota_{jt}, \tag{1.18}$$

where the normalization $\iota_{0t} = 0$ is implicit. I obtain consistent estimates of (α, β) through GMM using a set of moment restrictions

$$E(\iota_{jt} | Z_{jt}, \alpha, \beta) = 0, \tag{1.19}$$

where Z_{jt} is a vector of instruments and, from (1.18), $\iota_{jt} = \ln s_{jt} - \ln s_{0t} + \alpha(p_{jt} - p_{0t}) - \mathbf{o}_{jt}\beta$.

Survey data provide limited information on product characteristics. Solar module efficiencies started being reported for most firms only in 2007. I construct a time-invariant measure of firm module efficiency by combining survey information with data from Photon's solar module database. The vector of observables $\mathbf{o}_{jt}$ includes this measure of (average) module efficiency and year dummies (in the baseline specification) to control for factors affecting differences between U.S.-based firms and importers.

Since price may be correlated with unobservables, leading to an upward bias in the price coefficient α, I employ instrumental variables for prices. Variables that shift costs and affect competition are potential instruments. As cost shifters I consider an indicator variable for whether a firm has a manufacturing facility abroad, an indicator variable for whether a firm's major technology is silicon-based (rather than thin film), firm age (to proxy learning), the price of silicon and the share of imports in a firm's total shipments (with a logic similar to the one used to employ the foreign plant indicator). Since I don't allow firms to switch technologies, the technology indicator variable induces variation across firms but not over time. Plant location (U.S. and abroad) varies over time and firms as U.S. firms opened facilities in South East Asia and Germany (especially after 2005) and by foreign firms entering the U.S. market by opening a plant there.

Table 1.4 presents parameters estimates from OLS and GMM regressions. The OLS regressions in columns (1)-(4) retrieve a negative price coefficient but small in absolute value. Module efficiency yields positive and significant marginal utility, as expected: conditional on price, firms selling more efficient modules should be more attractive to consumers. Adding time dummies increases the absolute value of the price coefficient and significantly reduces the percentage of the variance accounted for by unobservable characteristics. Adding firm fixed effects yields a price coefficient that is even lower in absolute vale than in column (1). Having only a single market, once firm dummies are included identification relies exclusively on variation of market shares and prices over time. Note that, as reported in the last row of Table 1.4, all OLS estimates imply a large number of inelastic demands.[43]

Columns (5) to (9) use different sets of instruments to account for the possible correlation between price and unobservable characteristics. Column (5) uses two cost cost-side measures: technology and plant location. The price coefficient increases more than sixfold from column (3) and the coefficient on efficiency does not change significantly. Although the p-value of the Hansen J-test indicates that overidentifying restrictions are not rejected, the Kleibergen-Paap rk F-statistic suggests instruments may be weak. Adding age to the

[43]Demand is inelastic for firm j if its own price elasticity, given by $\alpha p_j s_j(1 - s_j)$ under this logit specification, is greater than -1.

Table 1.4: Demand estimation results.

	OLS				IV				
	1	2	3	4	5	6	7	8	9
Price	-0.296	-0.381	-0.395	-0.258	-2.779	-0.599	-0.503	-0.581	-0.519
	(0.158)	(0.151)	(0.066)	(0.061)	(0.997)	(0.225)	(0.210)	(0.201)	(0.211)
Efficiency			0.268		0.219	0.314	0.248	0.268	0.247
			(0.074)		(0.150)	(0.061)	(0.061)	(0.060)	(0.061)
Constant	-3.237	-1.356	-4.813	-2.768	-5.954	-8.637	-7.575	-8.024	-7.558
	(0.488)	(0.555)	(1.025)	(0.021)	(2.515)	(0.950)	(0.939)	(0.931)	(0.936)
Obs.	150	150	150	150	150	142	142	142	142
R^2	0.062	0.236	0.392	0.858					
Year FE		×	×	×	×	×	×	×	×
Firm FE				×					
Overid.					0.385	0.000	0.000	0.977	0.000
Weak id.					2.191	36.86	24.07	35.61	38.85
Inelastic	113	69	61	123	0	10	26	11	22

Notes: Newey-West robust (HAC) standard errors in parenthesis. "Overid." indicates the p-value for the Hansen J-test of overidentifying restrictions. "Weak id." indicates F-statistics for the Kleibergen-Paap rk weak identification test.

set of instruments used in column (5) does not change the price coefficient significantly and overidentifying restrictions are strongly rejected. Columns (7) to (9) include the average lagged price of competitors together with age, technology, plant location, respectively. These specifications yield similar price coefficients but, although higher than those using OLS, imply unreasonable own price elasticities. Moreover, with the exception of column (8), overidentifying restrictions are strongly rejected.

1.5.3 Parameters not estimated

I fix some remaining parameters which are hard to identify with the model given available data. Since the data is uninformative about the discount factor ρ, I adopt a conventional view and set $\rho = 0.078$, which implies a discount factor of $e^{-\rho} = 0.925$ in a discrete time analogue of the model where the time unit is one year.

I assume that scrap values and entry costs are distributed as uniform random variables with supports $[\underline{\kappa}, \overline{\kappa}]$ and $[\underline{\kappa}_e, \overline{\kappa}_e]$, respectively. The range of entry costs and scrap values are difficult to measure given available data. The U.S. Department of Energy (2011) reports a generic factory capital investment cost of around \$120 million for a 100MW c-Si vertically integrated plant with wafering (\$60 million), cell manufacturing (\$40 million) and module assembly (\$20 million). In 2000 Cypress Semiconductor invested \$150 million in Solar Power, up to that time a mostly research-oriented firm, to scale up to commercial manufacturing (which started fully in 2004) (Colatat et al. 2009). Evergreen Solar, Inc.

estimated total cost of \$55 to \$60 million for a 100MW wafering facility in China in 2009. In 2009 Schott Solar's 200,000 square-foot facility in Albuquerque represented an initial investment of over \$100 million. The entry cost distribution is then set to be close to \$120 million. The scrap value distribution is set to be close to \$80 million.

A complication of the period under study is that demand for solar installations has an upward trend. In the model, however, the exogenous processes need to be stationary. Including growth would greatly complicate the computation of the model. Therefore, I initially set the level of aggregate demand for solar panels at D =160MW, the average annual installations in the sample. An alternative is to allow for, say, three levels of aggregate demand ("high","medium" and "low") and set the intensity matrix so that the process shows a persistence that matches the data. This specification is left for future versions of the paper.

The productivity grid is set to approximate the distribution of labor productivity in the sample. Specifically $\{\omega_1, ..., \omega_6\} = \{1\ 1.9\ 3.7\ 7.6\ 14.5\ 19.7\}$, which replicate, respectively, the 5th, 25th, 50th, 75th, 90th, and 95th percentiles of the labor productivity distribution relative to the 5th percentile. That is, if ω_c^L is the cth percentile of labor productivity in the sample data, $\omega_1 = \omega_{5\text{th}}^L/\omega_{5\text{th}}^L$, $\omega_2 = \omega_{25\text{th}}^L/\omega_{5\text{th}}^L$, and so on. The choice of entrants' productivity ω_e is driven by inspection of the labor productivity of entrants in the sample and set to $\omega_e = \omega_{\hat{j}-2}$, where $\hat{j}$ is the index of the highest productivity firm active in the market at the time of entry. Labor productivity is computed as total shipments (measured in watts) divided by the number of workers.

Finally, for the baseline estimation I set tariffs τ equal to zero.

1.5.4 Minimum distance estimation

1.5.4.0.1 The SMD estimator The remaining 9 parameters to be estimated are those affecting firms' marginal cost, productivity dynamics and exit and entry opportunities. These parameters are collected in the vector $\theta \equiv (c_0, \beta, \eta_1, \eta_2, \eta_3, \eta_4, \delta, \lambda, \lambda_e)$. I apply the Simulated Minimum Distance (SMD) estimator suggested by Hall and Rust (2003).[44] The SMD estimator relies on moments or targets generated from simulated realizations of the model for a guess of θ. The estimation procedure chooses the guess that minimizes an appropriately defined distance between the moments estimated using the observed data and those estimated using the simulated data. The estimator for θ is defined by

$$\hat{\theta} = \arg\min_{\theta \in \Theta} \left[\mathbf{m}_{ST}(\theta) - \mathbf{m}_T\right]' W_T \left[\mathbf{m}_{ST}(\theta) - \mathbf{m}_T\right], \tag{1.20}$$

[44] Goettler and Gordon (2011) apply the SMD estimator to estimate a dynamic duopoly model of R&D investment.

where $\mathbf{m}_T$ is the $L \times 1$ vector of moments estimated using the observed data, $\mathbf{m}_{ST}(\theta)$ is its counterpart based on S simulations of T periods at parameter θ, and W_T is a $L \times L$ weighting matrix.

The estimation procedure requires a nested-fixed point algorithm: each time the parameter θ is updated, optimal policies are re-computed and the model is re-simulated for T periods using a set of realizations from uniform random variables which are fixed at the beginning of the algorithm. While the observed data records annual values, the continuous time simulations produce observations at a higher than annual frequency, so values used to compute simulated moments are integrated over the course of a year and discounted whenever appropriate. Prices are computed as they are in the data, i.e. as the ratio of simulated annual revenues to simulated annual shipments. Formal details about the estimator and computation of standard errors are discussed in the appendix.

1.5.4.0.2 Choice of targets Identification of the model's parameters rests on an appropriate selection of the targets included in $\mathbf{m}_T$, which should capture in the data the main statistical relationships that the model should be able to replicate. I use data on prices, revenues, shipments, firm entry and exit and R&D expenditures described in section 1.4 to construct $\mathbf{m}_T$. Specifically I choose the following groups of sample statistics to match:

1. *Price statistics.* Without information on firms' costs, I use moments of the module price distribution of the pooled sample. I target the 90th percentile of the price distribution, and the 90th to 5th percentile price ratio. I also include the autocorrelation between current and one-period lagged domestic prices. Prices are measured in U.S. dollars per watt and deflated using the 1999 CPI.

2. *Entry and exit.* I target the firm entry and exit rates using the pooled sample of firms. The entry (exit) rate is computed as the fraction of firms that enter (exit) the market in year t averaged over the sample period.

3. *Shipments, revenue and R&D.* I include the coefficients of two AR(1) regression models of firms' (log) revenues and (log) R&D investments, which include a time trend to account for the fact that the industry was growing over the sample period. For the two firms with greatest increases in market share during the sample period, I compute average R&D investment per unit revenue.[45] In the model the levels of R&D expenditures and shipments affect the arrival rate of productivity jumps. Although

[45] The restriction to two firms is due to data limitations, as I do not have R&D expenditures data for all firms in the estimating sample. While R&D expenditures come from firms' financial statements, revenues come from the survey data and correspond to silicon module sales only, as in the model.

the relationship between labor productivity and lagged research expenditures and lagged shipments is positive, significant, and high in my sample, the discretization of the productivity space in the model prevents me from matching these patterns accurately to the data. Therefore, I try to capture these relationships indirectly through their effects on the evolution of prices by targeting the coefficients from a regression of (log) prices on accumulated research expenditures and accumulated domestic shipments:

$$\ln p_{jt} = \mathrm{b}_0 + \mathrm{b}_1 \ln \sum_{l=1}^{t} q_{jl} + \mathrm{b}_2 \ln \sum_{l=1}^{t} x_{jl} + \epsilon_{jt}.$$

Both revenues and research expenditures are measured in 1999 dollars.

I choose the weighting matrix to be the inverse of the bootstrapped covariance matrix of the moments estimated with the data with off-diagonal elements set to zero.

1.5.4.0.3 Identification Even though the characteristics of the model make all parameters influence all targets, some parameters are more directly identified by variation in particular targets. Conditional on the elasticity parameter β and productivity, the scale constant in the marginal cost equation, c_0, affects all firms' price levels equally and can therefore be identified by the percentiles of the price distribution. I choose the 90th percentile of the price distribution and not lower percentiles since the former should capture the prices of the most unproductive firms, which presumably have not experienced gains in productivity through R&D and/or learning yet (note that the parameters of the productivity improvement hazard are not firm-specific). The elasticity parameter β, on the other hand, affects *relative* prices of firms at different points of the productivity space. The 90th to 5th percentile price ratio should therefore help to pin down this elasticity.

The negative productivity shock δ primarily drives firm revenues and should be disciplined by the AR(1) coefficient on firm (log) revenues. Conditional on scrap values and entry costs, the mean exit and entry rates drive the arrival rates of exit and entry opportunities λ and λ_e.

The parameters that govern the arrival rate of positive productivity shocks are harder to identify without information on costs and given that productivity as defined in the model is not observed in the data. The returns to doing R&D are affected by η_1 and η_2 through their effect on the arrival rate of productivity improvements, so average R&D investment per unit revenue and the AR(1) coefficient on R&D investment should help to pin them down. A higher η_1, for example, makes R&D more effective driving down R&D investment per unit revenue. More effective R&D will also translate into lower prices, since productivity jumps arrive more frequently, so the 90th percentile of the price distribution will also discipline these parameters. The learning by doing hazard parameters, η_3 and η_4, affect how aggressively a firm wants to price over time as she moves through the productivity space. The AR(1) coefficient on price should help to identify these parameters. Finally, the parameters of the regression of prices on accumulated shipments and research expenditures should also help to identify parameters of the productivity hazard ϕ_ω by providing information on the importance of R&D relative to learning in driving productivity and in turn cost and prices.

Estimating the model in a way that relies on simulated equilibria merits some remarks. As mentioned in section 1.3.7, models of this type are known to exhibit multiple equilibria, which would render the estimation meaningless without an appropriate selection mechanism. Computing an equilibrium in each iteration of an estimation routine can result in prohibitive computational burden too, specially within the class of dynamic oligopoly models applied here. Another popular approach to estimating dynamic models with continuous actions that does not rely on equilibrium computation has been proposed by Bajari et al. (2007). They apply a two-stage method in which the policy functions are recovered from observed actions in the first stage (therefore not relying on equilibria being computed). Remaining parameters are estimated applying a minimum distance estimator based on optimality conditions in the second stage.[46] The limited data in this study, however, do not meet the demands needed to accurately recover the parameters of the policy functions in a first stage, and that is why I rely on model-simulated data to recover the parameters.

1.6 Analysis and properties of results

The initial conditions for the simulations assume a state with 4 active firms with productivity levels $(\omega^1, \omega^2, \omega^3, \omega^4) = (\omega_1, \omega_1, \omega_1, \omega_3)$, which approximately resembles the state of the industry in the first year of data (proxied by labor productivity as measured by shipments per worker), and the foreign variety's price at its highest level, $p_0 = \bar{p}_0$. The optimization problem in (1.20) is solved by a genetic algorithm. Additional computational details are included in the appendix. Table 1.6 reports the comparison between the data- and simulation-based estimates of the targets.

The model does a reasonable job matching the price and R&D patterns discussed above, with the 90th percentile of the price distribution and the R&D rates of the two firms with largest market shares increase close to the data. While the model qualitatively matches entry and exit patterns (the entry rate is higher than the exit rate), it generates less turnover than we observe. In particular, the model generates very little exit, which results in revenues being more persistent than in the data. Finally, the model predicts a

[46] Ryan (2012) and Benkard (2004) apply versions of this method to estimate dynamic models.

Table 1.5: Parameter values.

Parameter	Description	Value	Std. error
Demand (first stage)			
α	Price coefficient	2.779	0.997
γ_{p_0}	Foreign price hazard	0.4198	-
SMD estimation			
η_1	R&D hazard scale	0.8703	0.134
η_2	R&D hazard elasticity	0.5014	0.033
η_3	LBD hazard scale	0.6439	0.209
η_4	LBD hazard elasticity	0.0062	0.012
λ	Arrival rate of exit opportunities	2.2742	4.708
λ_e	Arrival rate of entry opportunities	4.7454	7.127
δ	Hazard rate of negative productivity shock	1.0526	0.279
c_0	Cost function scale constant	15.4769	3.788
β	Cost function elasticity parameter	0.7849	0.066
Fixed parameters			
D	Aggregate demand (MW)	160	-
ρ	Discount factor	0.078	-
$[\underline{\kappa}, \overline{\kappa}]$	Range of scrap values (US$ million)	$[50, 100]$	-
$[\underline{\kappa}_e, \overline{\kappa}_e]$	Upper bound of entry costs (US$ million)	$[115, 150]$	-

Notes: see the appendix for the derivation of the analytical standard errors reported for the SMD estimated parameters.

Table 1.6: Empirical and simulated moments.

Target	Data		Model
90th percentile of price distribution	3.4647	(0.0490)	3.4583
90th/5th price percentile ratio	1.5271	(0.1094)	1.7976
Mean entry rate	0.0714	(0.0141)	0.0131
Mean exit rate	0.0411	(0.0294)	0.0194
Autocorrelation of current and past price	0.3812	(0.0848)	0.4341
Log R&D investment AR(1)	0.7712	(0.0879)	0.5319
Log revenues AR(1)	0.7240	(0.0852)	0.9042
Price on accumulated shipments ($\hat{b_1}$)	0.0098	(0.1336)	-0.1315
Price on accumulated R&D ($\hat{b_2}$)	-0.0670	(0.3167)	0.0965
R&D investment per unit revenue, firm #1	14.3241	(3.1234)	15.6866
R&D investment per unit revenue, firm #2	15.0901	(6.2900)	9.8625
Metric (weighted)			370.946
Metric (unweighted)			0.256

Notes: Bootstrapped standard errors for data-estimated moments in parenthesis. Simulated values from the model are averages over 500 11-period simulations.

negative effect of accumulated shipments on prices (learning) and a positive effect of R&D. The estimates using the data have opposite signs, but are not statistically different from zero.

1.6.1 Interpretation of the estimates

Estimated parameters imply that R&D-related productivity improvements are more likely than learning-related ones. At parameters $(\eta_1, \eta_2) = (0.8703, 0.5014)$, \$15 million worth of R&D investment (the average annual R&D expenditure in the sample) generate a productivity improvement every $12/(0.8703 \times 15^{0.5014}) \approx 3.6$ months. The elasticity of success with respect to investment expenditures implies that a one percent increase in R&D expenditures decreases the expected time to an investment success by 0.5%. The arrival rate of successful learning events, on the other hand, is essentially driven by the scale parameter $\eta_3 = 0.6439$ and not very sensitive to the level of flow shipments, as the elasticity η_4 is very close to zero. Therefore, learning-related improvements arrive approximately every $12/0.6439 \approx 18.6$ months. The hazard rate of negative productivity shocks $\delta = 0.9874$, together with the R&D and learning hazard rates for a firm investing \$15 million, give a hazard of a productivity change equal to $\phi_\omega = 5.1$, or a productivity change every 2.4 months on average.

The parameters of the cost function $(\hat{c_0}, \hat{\beta}) = (15.4769, 0.7849)$ give the cost schedule in Figure 1.3. A firm with the lowest productivity level produces at a cost of \$15.48 per watt, and a firm at the top of the productivity ladder does it at \$1.5 per watt.

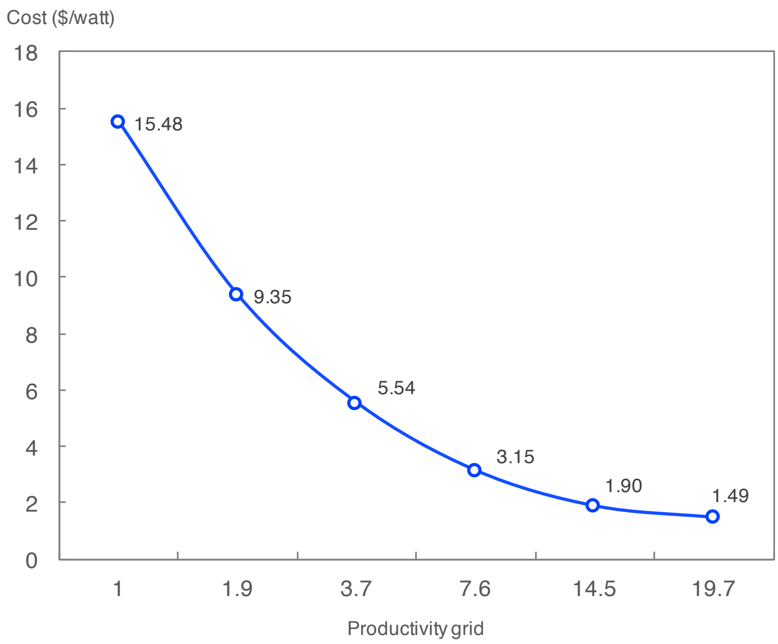


Figure 1.3. Estimated cost function, $c(\omega; \hat{c_0}, \hat{\beta})$.

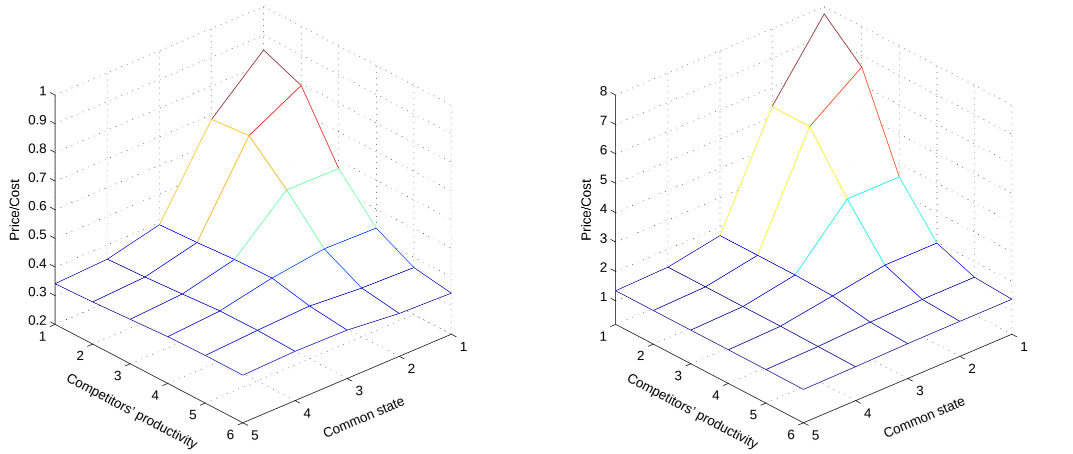
Entry and exit hazards λ_e and λ imply that opportunities to enter the industry arrive once every 5.3 months and opportunities to liquidate and exit once every 3.5 months. Since firms cannot influence the time of arrival of these opportunities, the model needs them to arrive often so that firms can take them when they find it profitable and generate the entry and exit rates we observe, conditional on entry costs and scrap values. Despite these high frequencies, in the model firms do not enter nor exit the industry much.

To understand the implications of these estimates for pricing and investment, Figures 1.4 and 1.5 present equilibrium price-cost margins and R&D investment for a firm facing four competitors, all of which are at the same productivity level (“equal competitors"). The model generates a wide range of price-cost margins. In Figure 1.4 (a), the margin for a low productivity firm (at $\omega = \omega_1$) facing four low-productivity incumbents ranges from 0.34 to 0.85, depending on the imported variety's price and the level of domestic competition. Low productivity firms price below current marginal cost due to learning effects (recall equation (1.13)). The higher the productivity of its competitors, the lower below marginal cost it will have to price in order to win market share and experience learning. At the highest level of foreign competition (i.e. when the common state is at $\varsigma = \varsigma_5$), however, the market is mostly dominated by imports so changes in incumbents' productivity have small effects on market shares and quantities; hence, the price-cost margin is virtually constant with the level of competitors' productivity. The same effect is present when all competitors are very productive: changes in the foreign variety's price do not have a effect on the margin.

The model can generate very high margins (as high as 7.7 in Figure 1.4) for a high productivity firm facing an environment with inefficient competitors and low foreign competition, but the margin falls rapidly with competitors' productivity. Recall that, even if a firm at the highest productivity level cannot learn any more (by design), as long as its competitors can the firm takes into account its effect on other firms' learning hazards and will then have an incentive to price aggressively (see equation (1.13)). In an environment with 4 competitors at medium productivity ($\omega = \omega_3$), a decrease of the imported variety's price from \$3 to \$1.2 lowers a high productivity firm's margin 19%, from 1.7 to 1.4.

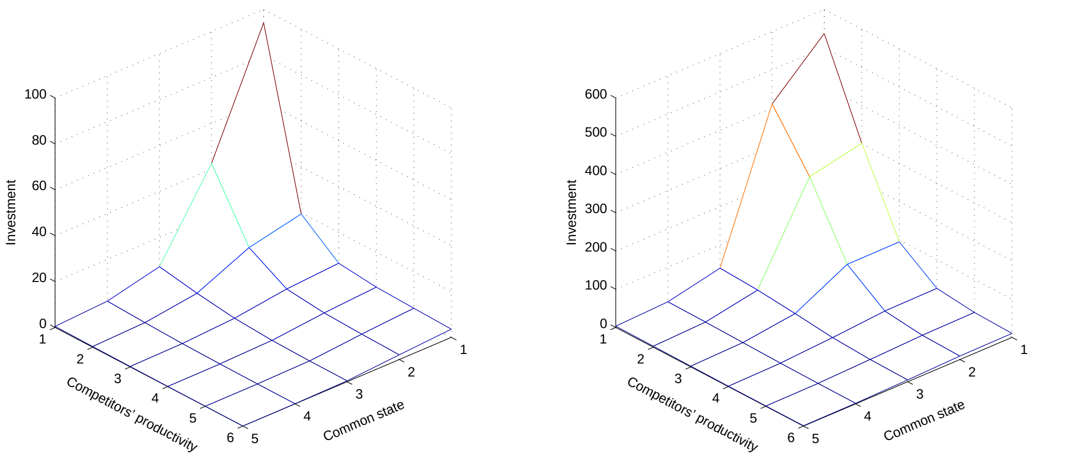
Turning to equilibrium R&D investment, its return is higher when competition is low, so investment levels are increasing in import prices and decreasing in competitors' productivity. For a low productivity firm facing four identical competitors at medium productivity ($\omega = \omega_3$), R&D investment ranges from US\$0.17 million to US\$6.5 million. While, as mentioned above, at estimated parameters learning by doing does not seem to be as important as R&D in absolute terms, productivity improvements for low productivity firms are, compared to those of higher productivity firms, relatively *less* likely to come as a result of R&D rather than learning. Conditional on a productivity change, the probability of an increase due to learning by doing for a low productivity firm facing four identical competitors at medium productivity is 16% and the probability of an increase due to R&D is 57% . For a medium productivity firm in the same environment these probabilities are

7% and 82%, respectively.



(a) Firm with the lowest productivity level ω_1. (b) Firm with the highest productivity level, ω_5.

Figure 1.4. Price-cost margins for a firm facing four equal competitors.



(a) Firm with the lowest productivity level ω_1. (b) Firm with medium productivity level, ω_3.

Figure 1.5. R&D investment for a firm facing four equal competitors.

1.6.2 Typical industry evolution

We can gain more insight about the implications of the model with respect to the evolution of the industry by looking at a typical 11-year simulation generated by the model in Figure 1.6. The industry is initialized as described above, i.e. with four active firms at productivity levels $(\omega^1, \omega^2, \omega^3, \omega^4) = (\omega_1, \omega_1, \omega_1, \omega_2)$ and the foreign price at its highest possible level.

A total of eight firms are observed during the 11-year period. Four firms pay the sunk cost of entry and enter during the first year, and all firms remain in the market for the rest of the period. Since the number of firms reaches the maximum allowed in the first period and there is no subsequent exit, no firms are allowed to enter. Even if this simulation reflects the bound imposed on the number of firms, the evolution of this set of firms helps to see the mechanisms of the model at work.

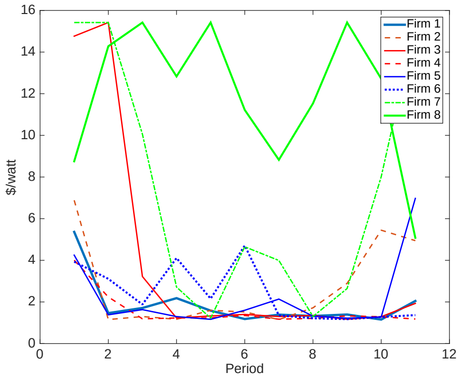
Marginal cost decreases during the first years for most firms as a result of R&D investment and learning, and fluctuations occur due to negative productivity shocks. Selling prices respond smoothly to movements in marginal costs and mark-ups, as they are pushed down by the evolution of the foreign price. Prices tend to be below marginal cost until firms reach the top of the productivity ladder and they loose incentives to price below marginal cost. After that point prices remain essentially flat. Dynamic effects generally result in lower prices than what we would observe in a static setting. Even if η_3 and η_4 give a low value of ϕ'_q, dynamic effects play a substantial role when firm productivity is low. Firm 8, for example, which has low productivity throughout the period, prices at an average of \$7 below the static price.

Note also that profits are negative or close to zero initially for some firms, even before start-up costs are considered, as a result of high R&D investment. Most firms then go on to make positive profits, with the exception of firm 8, who has negative net-of-R&D profits for the whole period. Variability in profits is naturally affected by firm-specific negative productivity shocks, but, as Figure 1.6 shows, variation in the foreign price generates correlation across firms.

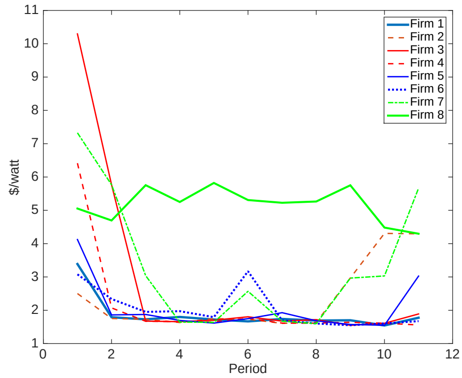
The foreign price trajectory is successful in capturing the data. As the price of the foreign variety decreases, imports consistently gain market share, from 3% in year 6 to 81% by the end of the period.

1.7 Counterfactual analysis

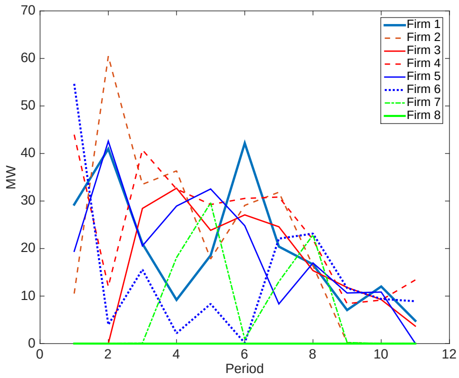
On October 2012, the U.S Department of Commerce announced a final affirmative determination in anti-dumping and countervailing duty investigations of imports of crystalline solar cells and modules from China. The investigation determined dumping margins of 18.32% and 31.73% for two major exporters and 249.96 % for wide-entity exporters. The International Trade Commission backed the decision in November that year by an anonymous ruling and anti-dumping and countervailing duty orders were issued. In December 2013 Solar World filed another petition destined to close some remaining loopholes. The



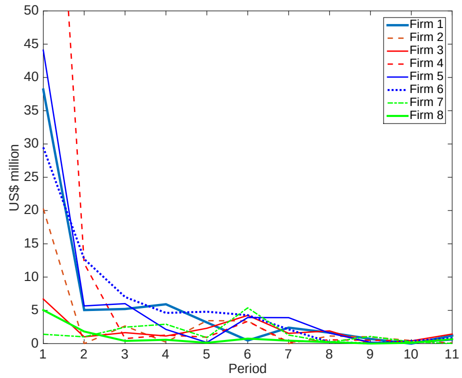
(a) Marginal cost.



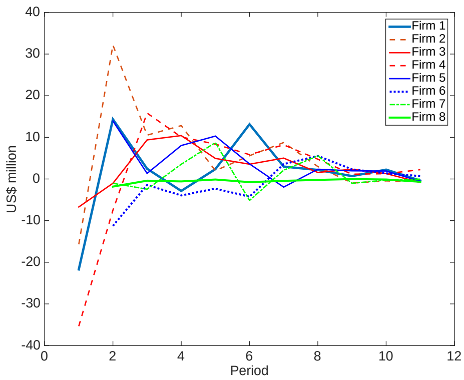
(b) Average selling price.



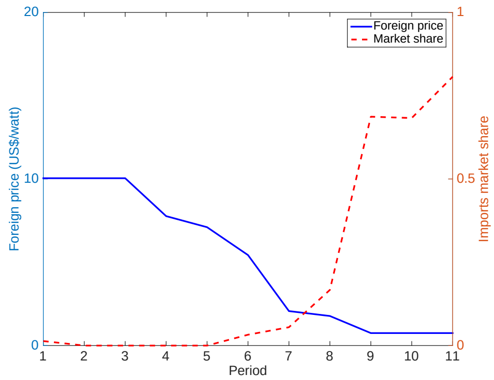
(c) Shipments.



(d) R&D investment.



(e) Operating profits net of R&D investment.



(f) Foreign price and imports market share.

Figure 1.6. Typical 11-year simulation.

Department of Commerce reached an affirmative final determination in December 2014 and established dumping margins of between 26.71% and 165.04%. In January 2015 the ITC made affirmative final determinations that the U.S. industry was materially injured by imports and the Department of Commerce issued AD and CVD orders.[47]

Inspired by this trade policy event, in this section I use the model to study the effects of a 30% increase in the foreign price of panels. I run the model for 11 years under the parametrization in Table 1.5, starting the industry at the initial condition described above, and increase the value of τ form 0 to 0.3 at the beginning of period 12 for 10 years, assuming firms do not anticipate the shock. Random draws are kept constant for both set of simulations, so that the differences between trajectories come only from the change in τ.

Before turning to the results, I mention three mechanisms that I abstract from and that could have been at work and are present in the dumping literature. First, I do not address the timing of the policy and the model omits any political economy mechanisms through which the tariff could arise endogenously in response to increased foreign competition. Second, I abstract from anticipation effects which could be present in anti-dumping episodes of the type experienced by the solar industry during this period. Third, I do not model the potential response of foreign exporters to the U.S., who could have increased prices to avoid duties.[48]

Figure 1.7 presents the average of 500 21-years simulations of key variables. The solid line represents the evolution of variables that would have been observed without the tariff and the dotted line the counterfactual evolution with the 30% duty.

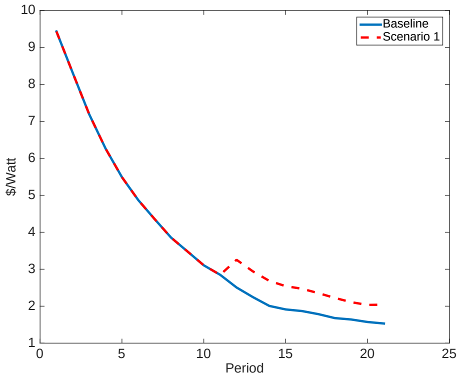
With the application of the duty the foreign variety's price increases in period 12 and the market share of imports drops from 55% to 46%, 13 percentage points lower than baseline. Imports' share gradually recovers over time and reaches 55% after 10 periods, 22 percentage points lower than baseline.

Despite facing lower competition from abroad, domestic firms set *lower* prices. The average selling price falls 1.4% initially and is $/W 0.18 lower than baseline after 10 years (-7.4%). Lower prices by domestic firms are the result of higher productivity, which in turn comes from higher R&D investments. R&D expenditures increase 73% at the time of the imposition of the duty and are around 40% higher than baseline, on average, in every period after the shock. This leads to higher productivity, as shown in panel (e) of Figure 1.7. In fact, productivity jumps due to R&D are about 30% higher than baseline in every period. Interestingly, although domestic firms sell more than in the baseline scenario, learning by doing events are less frequent and jumps due to learning are about 9% lower.

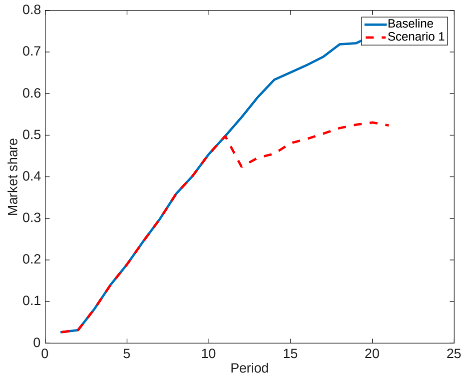
Although there are practically no differences in entry rates, the exit rate decreases as domestic firms are more profitable and face lower competition from abroad. As a result, after 10 years there is one more firm than in the baseline scenario. Even with more firms,

[47]The complete report can be accessed at `https://www.usitc.gov/publications/701_731/pub4519.pdf`.

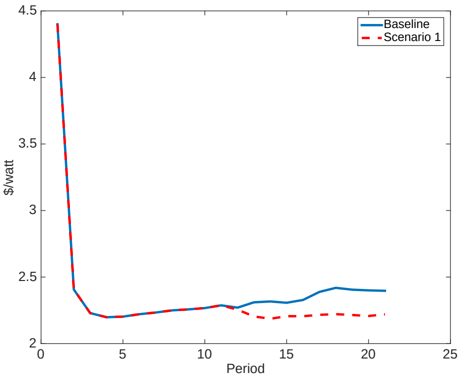
[48]See Staiger and Wolak (1994). Bloningen and Prusa (2016) present a thorough review of the literature on dumping and antidumping activity.



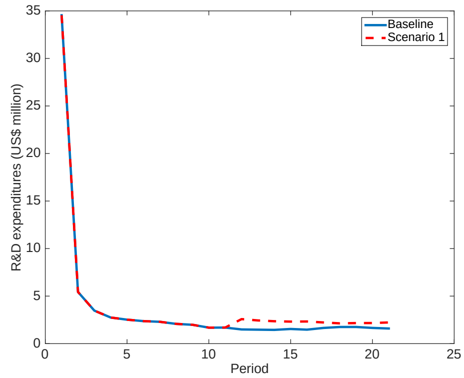
(a) Foreign price.



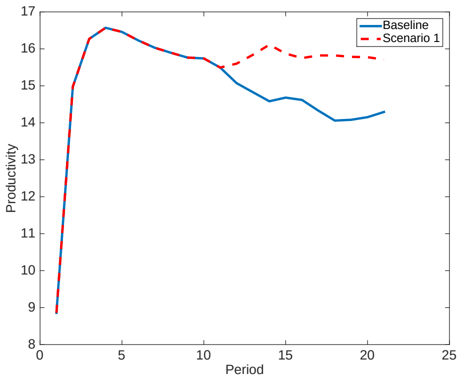
(b) Market share of imports.



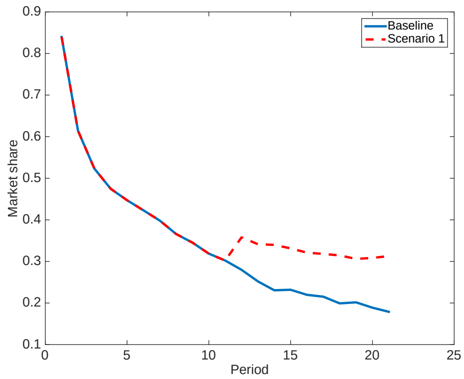
(c) Average selling price of domestic firms.



(d) Average R&D expenditures.



(e) Average productivity.



(f) C2 concentration index.

Figure 1.7. Counterfactual experiment: 30% increase in the foreign price of panels.

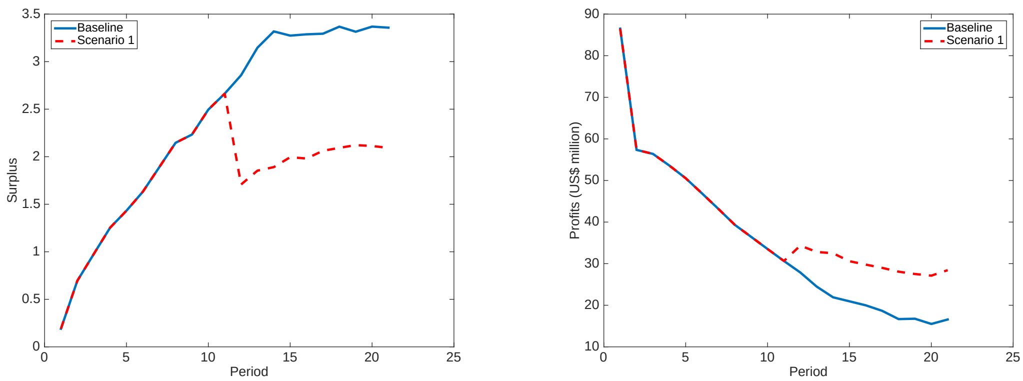
lower competition from abroad allows high productivity firms to capture a larger share of the market. Concentration therefore increases and the share of the two largest firms (the C2 index) increases 13 percentage points above baseline, reaching 31%, after 10 periods.

These changes imply changes in consumer surplus and profits, which determine the welfare loss or gain of the policy. The specification of consumer preferences above allows us to measure consumer surplus (CS) as

$$CS_t = -\frac{D_t}{\alpha} \log \left[\sum_{j=0}^{J} \exp(-\alpha p_{jt}) \right]. \tag{1.21}$$

Profits are computed from equation (1.5), net of R&D expenditures.

Figure 1.8 shows the evolution of consumer surplus and net aggregate profits. Even if prices of domestic varieties are lower than in the baseline scenario, consumer surplus decreases as a result of higher prices of the imported variety. The cumulative discounted fall in consumer surplus is \$3.6 million. Profits, on the other hand, are higher as domestic firms have a higher market share and are more productive on average. The present discounted value of net profits is \$28.8 million higher in the counterfactual scenario, more than compensating for the fall in consumer surplus. If we also take into account scrap values at exit and entry costs during the 10 year simulation in which the policy is in place, the net result of the policy is instead negative. The reason is that, because exit is less frequent in the counterfactual, the total scrap value generated by exit is lower. In fact, because firms decide to stay in the market when duties are applied, total scrap value is \$42.8 million lower. Together with entry costs (which are almost equal), the total welfare loss amounts to \$18.7 million.



(a) Consumer surplus.

(b) Aggregate profits.

Figure 1.8. Aggregate profits and consumer surplus after a 30% increase in the foreign price of panels.

1.8 Summary

The solar panel industry has emerged as a strategic industry in the U.S., the focus of major trade policies in recent years. The treatment of the industry and its response to policy shocks in the economics literature has been disproportionately scant, however. In this paper I try to fill this gap by developing a computable dynamic model of the industry that incorporates key aspects that characterize it, and using it to evaluate a trade policy counterfactual. The model features imperfect competition, investment in research and development, learning by doing, and import competition in continuos time.

I fit the model using a minimum distance method to estimate its main parameters, and am able to replicate several moments of the data. In turn, the estimates allow me to quantify important mechanisms that shape industry dynamics. I find that R&D is more important than learning by doing in driving productivity improvements, and that import competition discourages domestic firms from investing in R&D, rendering them less competitive and more prone to exit the market.

In a counterfactual experiment where I apply a 30% duty to imports of solar panels, the model generates a downward price response from domestic firms, as R&D expenditures, and hence productivity, increase. Concentration increases, as more productive firms gain market share to the imported variety and less productive firms. Even if the average selling price charged by domestic firms decreases in the counterfactual, more expensive imports imply a loss in consumer surplus. This is more than compensated by higher aggregate profits, however. When I further incorporate the effect of fewer firms exiting who do not receive a scrap value for their assets, there is a total welfare loss of applying duties.

Chapter 2
Born to Export: Understanding Export Growth in Bangladesh's Apparel and Textiles Industry

2.1 Introduction

Standard thinking about firms entering export markets is that they have already developed a strong position at home. Both static and dynamic models of trade with heterogeneous firms imply that exporters will always produce for and sell in the domestic market. Conditional on a firm's productivity, variable profits in the domestic market are always positive and fixed production costs have already been incurred upon making the decision to export. Hence, exporters will always sell in the domestic market. These types of models also imply that firms export a relatively low share of output and that changes in total exports arise either through the expansion of exports by incumbent exporters or by entry into exporting by established domestic firms.[1]

Evidence from Bangladesh suggests that these patterns do not apply to the rapid expansion of its apparel and textiles exports during the period 1983-2010: exporting firms emerged *de novo* and sold considerable amounts to new foreign markets without selling much or anything at home. To exploit the combination of cheap labour and non-binding MFA quotas, most Bangladeshi apparel and textiles producers were established to export. Foreign sales by these firms far exceeded what they sold domestically Mostafa and Klepper

[1] The standard static framework is essentially developed in Melitz (2003). Impullitti et al. (2013) provide an extension to a dynamic setting, allowing for time-varying productivity and sunk costs of creating firms and exporting. In general, firms enter foreign markets only after surpassing a given size (productivity) threshold. Even if this occurs at birth, firms will also sell in the domestic market.

(2009). As a consequence, firms that sold substantial amounts in foreign markets were not particularly large sellers at home, if they had any presence there at all. They were "born to export".

The Bangladeshi experience with apparel and textiles is not an isolated case of an export-oriented emerging industry. Rather, this seems to be a common feature of expanding exporting sectors in many developing countries. During their industrialization stage, by the end of the 1970s, Taiwan and Korea exported 80% and 70% of their electronics production, respectively Matthews (2006). In Malaysia, export oriented firms were responsible for the first wave of electronics growth Rasiah (2006).[2] The Colombian fresh cut-flower industry was conceived for export markets and, consequently, has exported the majority of its production (from 70% to 95%) since its inception Méndez (1991); Arbeláez et al. (2012), as did the same industry in Ethiopia Gebreeyesus and Iizuka (2010). Lu (2010) has documented that around 40% of Chinese exporters sell more than 90% of their production abroad.[3] McWilliams and Verma (2012), using the World Bank's Business Environment and Enterprise Performance Survey (BEEPS), find that 28% of firms in a sample of 95 low and middle-income countries were pure (and direct) exporters.

These observations are in contrast with what has been observed in developed countries, where, typically, firms export a small share of their production.[4]Since export-oriented industrialization has been key for productivity growth in developing countries, understanding born to export phenomena is important to shed light on the behavior of firms as they enter foreign markets.

A common feature among the cases of export emergence cited above is that born to export (BTE) firms have emerged in industries for which there is little or no domestic demand in the exporting country. We will refer to such industries as "orphan industries." The presence of orphan industries means that few incumbent firms exist, and, in the event that entrepreneurs become aware of exporting opportunities, they must create new establishments to exploit them. When they do, most of their production will be dedicated to foreign sales. The importance of sunk and fixed costs of foreign market entry has been well documented in the international trade literature Roberts and Tybout (1997); Das et al. (2007); Cherkashin et al. (forthcoming). We should expect these costs to be specially

[2]Multinational firms in export processing zones were key in generating this pattern in Malaysia. While the government discouraged multinationals from selling in the domestic market, Rasiah (2006) notes that "the domestic market was too small to affect most of the firms." We address the importance of export processing zones in Bangladesh below.

[3]Dai et al. (2012) have noted that firms engaged in processing trade are pervasive in China. We address the issue of processing trade below and still find that a significant fraction of non-processing exporters exports most of its output.

[4]See Bernard and Jensen (1995) and Bernard et al. (2003) for the U.S.; Bernard and Wagner (1997) for Germany; and Eaton et al. (2011, 2004) for France. Most firms in these studies usually ship less than 15% of the value of their output to foreign countries.

binding in orphan industries since, in addition to the costs of establishing products in a foreign market, entrepreneurs face the presumably much larger costs of creating new establishments and training managers and workers.[5] These extra costs are likely to generate export dynamics quite distinct from those generated by firms that are created initially to serve domestic consumers. For one thing, since these much larger start-up costs must be amortized over a relatively lengthy period, the current period pay-offs of exporting will matter relatively less than expectations about future payoffs in driving exporting decisions. Moreover, a large sunk cost creates a large option value of remaining in an export market once this cost is incurred. Thus, BTE firms are more likely than other firms to remain in foreign markets once they enter.

In this paper we use novel firm-level data sets from Bangladesh to assess the importance of BTE firms there and compare it to export dynamics in other countries for which we have the necessary data: China, Colombia, and Taiwan. Using micro data from these four countries we first document different patterns of export growth. In particular, we explore whether entrants represent a major dimension of export growth, how they behave over time and whether they can be characterized as BTE. Since export processing zones (EPZs) have been suggested to generate BTE-like patterns by design, we also discuss their role in generating the patterns we observe in Bangladesh. Finally, we employ a simpler version of the search and learning model of export dynamics developed in **?** (henceforth EEJKT) to show it can characterize the distinctive features of export dynamics when firms are born to export.

The rest of the paper is organized as follows. In the next section we present our empirical exercises and show that Bangladesh exporters are starkly different in key dimensions of the data. Section 2.3 contains a discussion of the role of EPZs in Bangladesh. Section 2.4 develops a model of BTE dynamics. Section 2.5 concludes.

2.2 Patterns of export participation and growth

We first discuss some features of export growth in the individual countries we examine and then turn to a description of our firm-level datasets. Since textiles and apparel represent more than 90% of exports in Bangladesh, we concentrate on this industry for all countries, commenting on other industries where appropriate. Our findings can be summarized as follows: exports from Colombia and Taiwan adhere to patterns of export dynamics implied by standard models: (1) export growth is primarily driven by expansion of exports on

[5] Artopoulos et al. (2013) have recently emphasized that firms in developing countries intending to export differentiated products to developed countries must adopt business practices significantly different from those implemented at home.

the part of incumbent exporters; (2) new exporters sell much less than incumbents and are much more likely to exit foreign markets; (3) the average age of a firm when it starts to export is over ten years. Bangladesh is the opposite in each dimension: (1) looking over a six-year horizon, net entry accounts for over half of export expansion; (2) firms that start exporting sell almost as much as incumbents and are more likely to survive than their Colombian and Taiwanese counterparts; (3) the mean age of an exporting firm is under two years and the median new exporter has never sold before. The picture for China is mixed: (1) entry makes an even more important contribution to growth than in Bangladesh; (2) new exporters sell only negligibly less than incumbents and are more likely to survive; but (3) the average new exporter is nearly seven years old.

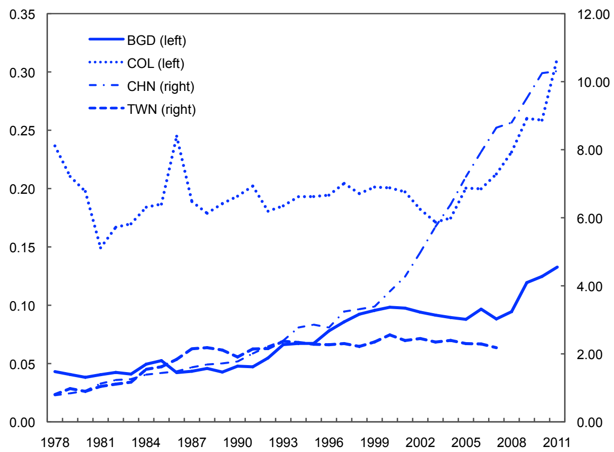
2.2.1 Countries studied: main aggregate trends

We study apparel and textiles producers in four countries: Bangladesh, China, Colombia, and Taiwan. Figures 2.1 and 2.2 summarize the main features about total and apparel and textiles exports over the last three decades.[6] All have gained market share in world manufacturing exports, although none as spectacularly as China, and most manufacturing exports have gone to high income countries. For all countries except Taiwan from the 1990s on, apparel and textiles exports have continued growing. Apparel and textiles were a significant share of exports in the mid 1970s (above 30%), more even so for Bangladesh, which was almost completely specialized in these industries. As China, Colombia and Taiwan developed a wider manufacturing base, the share of apparel and textiles has declined in general and, even for China, stands at below 20% of total manufacturing exports. Bangladesh, on the other hand, has not been able to diversify into other industries and apparel and textiles have remained at 90% or more of total exports.[7] Before turning to firm-level data, we briefly describe each country's background.

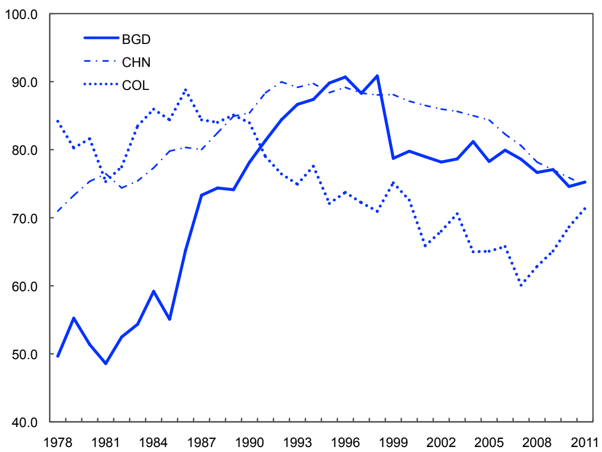
2.2.1.0.4 Bangladesh The emergence of the Bangladeshi apparel exporting sector is well known in development policy circles Rhee and Belot (1990); Hausmann and Rodrik (2003); Mostafa and Klepper (2009). It began in 1979 when Daewoo Corporation of South

[6]Aggregate merchandise exports are from The World Bank (Bangladesh, China and Colombia) and Feenstra et al. (2005) (Taiwan). Apparel and textiles exports are from Feenstra et al. (2005) and include exports in the following SITC two-digit industries: 26 (Textile fibers and their wastes), 61 (Leather and dressed furskins), 65 (Textile yarn, fabrics, and related products), 84 (Articles of apparel and clothing) and 85 (Footwear). We thank Robert Feenstra for providing us with more recent data.

[7]The composition of exports in Bangladesh at a more disaggregate level has, however, changed significantly since the 1970s. When looking at the four-digit SITC level, for example, those sub-industries included in "Articles of apparel and clothing" (SITC84) started to dominate the list of top-20 selling sub-industries in the mid 1980s. These tend to include more sophisticated products (shirts, jerseys, pullovers, undergarments) than were produced by Bangladesh in the 1970s (jute, textile fabrics).



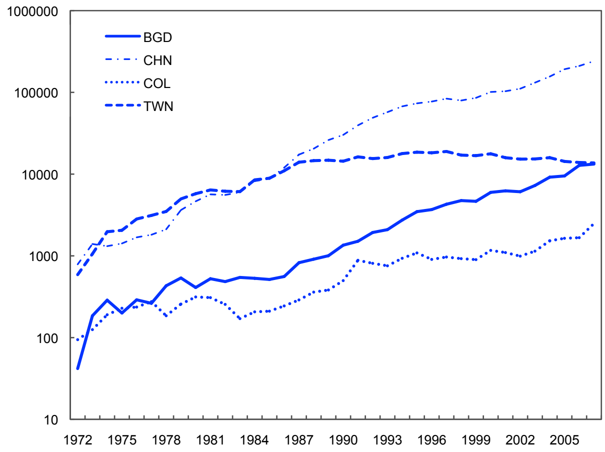
(a) Share in world merchandise exports (%).



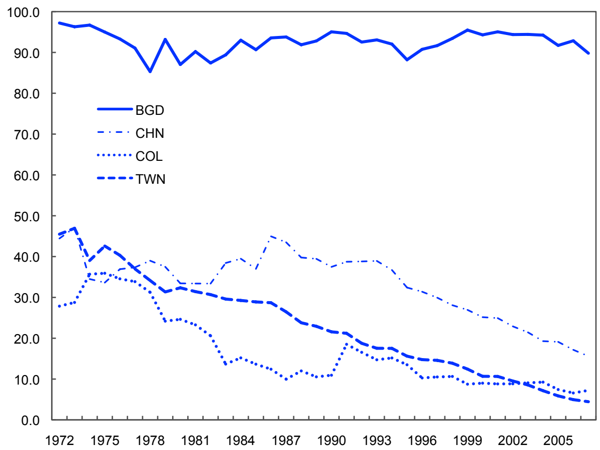
(b) Share exported to high income economies (% of total merchandise exports).

Figure 2.1. Aggregate exports: Bangladesh, China, Colombia and Taiwan, 1978-2011.

Korea, a company with considerable experience in apparel exports, signed a collaborative agreement with a Bangladeshi firm (Desh) with the intention of circumventing import quotas to the United States and European markets imposed by the Multi-Fiber Agreement (MFA). At that time, Bangladesh was not restricted by quotas. Bangladeshi apparel producers had so far produced garments for the local market, such as sarees and lungis, and had very low exports of Western-style apparel covered under the MFA. As part of the Daewoo-Desh agreement, about a 130 Bangladeshi workers were sent to Korea for training in technology, quality control, and management. Daewoo also helped Desh absorb key management and marketing techniques for garment exporting. Once Desh succeeded, many of its workers left to start up other firms, spurring the growth of the industry. As was mentioned above, apparel remains the overwhelmingly dominant export of Bangladesh.



(a) Log of total exports (US$ million).



(b) Share in manufacturing exports (%).

Figure 2.2. Apparel and textile exports: Bangladesh, China, Colombia and Taiwan, 1972-2007.

Interestingly, at least to our knowledge, the government does not seem to have played a major role in stimulating this particular industry in its early phase.[8]

2.2.1.0.5 China Like Bangladesh, China experienced a dramatic growth in apparel exports. However, the industry already served a relatively large domestic market and several policy reforms did play a major role. First, China initiated key market-oriented reforms in 1992 which improved the efficiency of the apparel sector (China Textile University and Harvard Center of Textile and Apparel Research, 1999). Second, after fifteen years of negotiations, China joined the World Trade Organization (WTO) in 2001. In doing so it benefitted from the phase-out of the MFA product- and country-specific quotas on

[8]There was only one EPZ established in the 1980s, and, as we show below, EPZs have not been substantial contributors to apparel export growth.

textiles, yarn, and apparel, which was completed by 2005.[9] As a member of the WTO, China also obtained Most Favored Nation (MFN) status (so that Chinese exporters to any WTO-member destination faced the lowest tariff applied to any exporter there).[10] Finally, under the terms of its accession to the WTO, China agreed to remove domestic restrictions on direct exporting. These restrictions, which were lifted in a series of reforms between 1999 and 2004, prevented firms (other than large producers and intermediaries, state-owned enterprises, and foreign firms) from exporting directly; they had to go through other firms or intermediaries who were permitted to export.[11]

Apparel exports have grown extremely rapidly, especially since 1992, and China now has the largest apparel sector in the world. Furthermore, most apparel exporters are strongly oriented toward foreign markets and ship well over half of their output abroad Lu (2010). China's apparel boom would have been even larger if the China Containment Agreements (CCAs) had not been implemented under China's WTO accession agreements of 2001. Under the CCAs, China agreed to constrain import surges voluntarily until 2013. The U.S. invoked the CCAs in mid 2005, after the phase-out of the MFA triggered a surge in its Chinese apparel imports. The E.U. followed suit in the fall of 2005 and since then a host of other countries have done so as well, including Canada, Mexico, Turkey, and some lower income countries.[12]

2.2.1.0.6 Colombia Colombia has managed to expand its apparel exports over the past 30 years successfully, albeit much more gradually than China and Bangladesh. Also, unlike Bangladesh, its export growth was largely driven by the re-orientation of its established apparel sector toward foreign markets. Colombia is, after Mexico, one of the largest employers of apparel and textiles in Latin America and enjoys the highest average unit values of apparel exports to the U.S. among Central and Latin American countries. This reflects Colombia's advantages in design and adoption of ISO quality standards over other countries in the region Condo et al. (2004). The sector has, like all Colombian manufacturing sectors, been influenced by government trade-induced policies to soften

[9] See Brambilla et al. (2010) for a historical discussion of the MFA and its precursor, the Agreement on Textiles and Clothing (ATC). These authors argue that China was more constrained by such quotas than other suppliers, resulting in the surge in Chinese exports post MFA. Khandelwal et al. (2013) estimate that removal of inefficient licensing among exporters of textiles and clothing accounted for almost three quarters of the productivity gain experienced by China after quotas were removed.

[10] However, most Chinese exports already had de facto MFN status.

[11] Bai and Krishna (2013) use the variation in time and space of these reforms to argue that these reforms were responsible for a good part of the surge in exports. Bai et al. (2013) suggest (based on estimates from a dynamic structural model) that the inability to export directly adversely affected such firms.

[12] The growth rate of the CCA quotas is higher than that of MFA quotas they replaced, though the coverage is similar or even greater in some cases. See Dayarathna-Banda and Whalley (2007) for more on this matter.

the cycles in world demand. After a first wave of tariff reductions in the 1970s, policy became increasingly protectionist in the beginning of the 1980s and turned more liberal again in the mid 1980s. For the 1977-1985 period, Roberts (1996) reports that apparel and textiles producers' entry rates were among the highest of Colombian manufacturing industries. Differently from other textiles-exporting countries in the region (Nicaragua, Mexico, Dominican Republic), Colombia hasn't been so dependent on preferential access to the U.S. market. However, it did benefit from the implementation of the Andean Trade Promotion and Drug Eradication Act of 2002, as it allowed it to increase value added of apparel and textiles exports to the U.S. Condo et al. (2004).

2.2.1.0.7 Taiwan Finally, Taiwan combined elements of Chinese and Colombian experiences. After implementing export subsidies and other industrial policies in the early 1960s, this country enjoyed a period of rapid growth in apparel exports. However, these exports peaked at 9.5% of total Taiwanese exports in 1986, and by 2004 their share had declined to less than 0.8%. Like their Colombian counterparts, most Taiwanese apparel producers who continue to export derive the majority of their revenue from domestic sales.[13]

2.2.2 Firm-level analysis

We base our empirical analysis on several firm-level data sets. To document producer-level patterns of export market participation, we rely on transactions-level data for the universe of exporting producers in Bangladesh, Colombia, and China (no such data are available for Taiwan). These data are collected from customs declarations in each country. For each shipment, we observe an exporter's ID, date of the customs declaration, product code of the item being shipped, values and quantities shipped, and destination country.

To study the relationship between firms' birth and their participation in export markets we augment customs records with additional information. For Bangladesh these extra data come from tax registries, which provide tax IDs and a tax registration date. Since tax IDs also appear in the customs declarations, the registration date allows us to construct a measure of exporter's age. Additionally, tax registries allow us to distinguish firms by activity. For each exporter in the tax registries we observe whether it belongs to any combination of the following five activities: manufacturer, exporter, importer, trader, or service renderer.

For Colombia, China and Taiwan, comprehensive tax registries are unavailable. However, we have access to annual manufacturing survey data that cover essentially all

[13]Establishment-level data from 2000-2004 show that, among Taiwanese apparel exporters, roughly 80% of production has been directed to the domestic market.

establishments with at least 10 workers and provide standard information on age of the plant or firm inputs, production and value of sales by destination (home versus foreign markets). Confidentiality constraints prevent us from linking these establishment data with customs data. Nonetheless, since industrial survey data include information on foreign sales and year of birth, we are able to infer firms' age when they enter export markets.

Importantly, while the data from Colombia and China are for firms, for Bangladesh and Taiwan are for establishments. We use "firm" to apply to all countries, but this distinction should be kept in mind. The appendix contains additional information on the sources of data.

2.2.2.1 Margins of growth

We begin our descriptive analysis by using transactions-level data from Bangladesh, China, and Colombia to study the margins of export growth. Specifically, following Eaton et al. (2008) (henceforth EEKT), we decompose the growth of total exports into the contribution of pairwise continuing, entering, and exiting firms. Letting X_t denote aggregate exports in period t and x_{jt} denote exports by firm j in period t, we use the following decomposition:

$$\begin{aligned}\frac{X_t - X_{t-1}}{(X_t + X_{t-1})/2} = {} & \frac{\sum_{j\in C_{t-1,t}}(x_{jt-1} + x_{jt})/2}{(X_t + X_{t-1})/2} \times \frac{\sum_{j\in C_{t-1,t}}(x_{jt} - x_{jt-1})}{\sum_{j\in C_{t-1,t}}(x_{jt} + x_{jt-1})/2} \\ & + \frac{N^{EN}_{t-1,t}\bar{x}_{t-1}}{(X_t + X_{t-1})/2} + \frac{\sum_{j\in EN_{t-1,t}}[x_{jt} - \bar{x}_{t-1}]}{(X_t + X_{t-1})/2} \\ & - \frac{N^{EX}_{t-1,t}\bar{x}_{t-1}}{(X_t + X_{t-1})/2} - \frac{\sum_{j\in EX_{t-1,t}}(x_{jt-1} - \bar{x}_{t-1})}{(X_t + X_{t-1})/2},\end{aligned} \tag{2.1}$$

where the set $C_{t-1,t}$ includes all firms that exported in $t-1$, and t (pairwise continuing), the set $EN_{t-1,t}$ those that exported in t but not $t-1$ (pairwise entering), and the set $EX_{t-1,t}$ those that exported in $t-1$ and not in t (pairwise exiting). The term N_t^Y represents the number of firms in set $Y \in \{C_{t-1,t}, EN_{t-1,t}, EX_{t-1,t}\}$ in period t. The term $\bar{x}_{t-1}$ indicates average firm export sales in period $t-1$.

The decomposition works as follows. The left-hand side measures the growth in the value of total exports between year $t-1$ and t. The first line of the right-hand side represents the contribution to growth of pairwise continuing firms, decomposed into the share of those firms in total sales in $t-1$ and the growth in their sales. The second line decomposes the contribution of entrants as the sum of two terms: the increase in exports by entering firms if entering firms had sold the same as the average firm in period $t-1$, and the sum of the differences between exports of entrants and that of the average exporter in $t-1$. The final line computes the contribution of exiting firms in a similar way, as the sum of the decrease in exports if exiting firms had exported the same as the average firm in period $t-1$ and a term that adjusts for the differences in sales between exiting firms and the average firm. The decompositions thus separate the contribution of entry and exit purely through the number of different firm categories from differences in the mean size of categories.

Table 2.1 applies the growth decomposition to apparel and textiles exports for Bangladesh (2004-2009), Colombia (2000-2012) and China (2000-2006). It reports cross-year averages of year-to-year growth rates, and cumulative growth rates between the first and last years of the sample. For example, in the case of Bangladesh, our cumulative growth figures take $t-1 = 2004$ and $t = 2009$. The column labeled “Contribution" reports the figures for each line in the right-hand side of equation (2.1) for each country. In all countries data limitations force us to miss the early years of rapid export growth. Nonetheless, since differences in domestic markets persisted within each country, patterns of apparel exports presumably continued to reflect each country’s distinctive circumstances.

Table 2.1: Contribution of pairwise entry and exit to the growth of exports between t and $t-1$.

		Pairwise continuing			Pairwise entering			Pairwise exiting		
Year (t)	Growth	Share in $t-1$	Growth	Contribution	Added firms	Rel. exports	Contribution	Dropped firms	Rel. exports	Contribution
	(1)	(2)	(3)	(2)×(3)/(1)	(5)	(6)	[(5) + (6)]/(1)	(8)	(9)	[(8) + (9)]/(1)
Bangladesh										
Annual Average	15.0	96.6	11.1	72.8	25.4	-19.8	38.6	-16.4	15.1	-11.4
2004-2009	71.9	70.8	44.7	44.7	63.5	-14.2	68.6	-25.9	16.8	-12.6
Colombia										
Annual Average	3.1	94.2	3.6	81.3	38.9	-33.4	47.7	-38.8	33.5	-29.0
2000-2012	36.4	66.5	55.4	101.2	65.5	-32.2	91.6	-66.6	32.8	-92.7
China										
Annual average	25.8	91.8	16.6	58.5	38.7	-25.2	56.8	-15.1	12.2	-15.4
2000-2006	130.4	30.1	44.5	10.3	131.4	-3.0	98.5	-19.2	7.8	-8.8

Note: Pairwise continuing firms in year t are those that exported in $t-1$ and t. Pairwise entering firms in t are those that exported in t but not in $t-1$. Pairwise exiting firms in t are those that exported in $t-1$ but not in t. Percentage contribution of each group to the growth of total exports is reported in columns 4, 7 and 10. All computations use values in USD.

The results in Table 2.1 highlight the role of entrants in explaining growth patterns in Bangladesh and China relative to Colombia. Net foreign market entry, given by the sum of columns 8 and 10, accounted for $38.6 - 11.4 = 27.2\%$ of export growth per year on average in Bangladesh, and $56.8 - 15.4 = 41.4\%$ of net export growth in China. In Colombia, in contrast, this margin was only $47.7 - 29.0 = 18.7\%$. New exporter arrival, on the other hand, had a lower relative importance in Bangladesh when compared to Colombia and China: new exporters accounted for approximately 40% of all exporters in Colombia and China, but only 25% in Bangladesh (see column 5). The large role of entry in driving Bangladeshi export growth reflected two facts: entrants' shipments relative to incumbents' shipments were much larger in Bangladesh than in Colombia and to a lesser extent China (column 6), and the exporter exit rate was much lower in Bangladesh than in Colombia (column 8). The Chinese exit rate was actually lower than Bangladesh's. These effects were only partly offset by the fact that exiting firms were relatively small in Colombia (refer to column 9 and recall that this figure is the negative of relative size).

A clearer picture emerges when we look at the contribution of continuing, entering and exiting firms to overall growth between the first and last years of our samples. While in Colombia almost all net growth is explained by continuing firms (the positive contribution of entering firms is almost exactly offset by the negative contribution of exiting firms), in Bangladesh and China the largest contribution is that of net entry (56% and 89.7%, respectively).

2.2.2.2 Export intensity and specialization

Why are shipments of new entrants relatively larger in Bangladesh? Part of the answer lies in the fact that, like incumbents, new exporters devote most or all of their productive capacity to foreign sales. In Bangladesh, not only exports are concentrated in a few products, but firms also specialize in serving either the domestic or the foreign market.

Using industrial survey data for Bangladesh in 2005 we can compute export intensity patterns at the product level. Table 2.2 lists top-10 products according to their share in Bangladesh's total foreign sales and total domestic sales. Garment producers reaped more than 99% of total sales revenues from exports in 2005, and this sector alone accounted for 63% of total exports. In contrast, domestic demand for this sector was almost inexistent: garments represented only 0.4% of total domestic sales, less than one third the share of newspapers. Similar comments apply to producers of woolen jumpers, who were entirely oriented to foreign markets and accounted for an additional 4% of exports. Dhoties and sarees, traditional apparel products in Bangladesh, were among the top selling products in the domestic market (2.3% of total sales) but producers were entirely domestically-oriented. Only cotton yarn and fabrics producers sold a significant share of output in the domestic

Table 2.2: Product specialization (selected products), Bangladesh (2005).

Product description	Export intensity	Share of exports	Share of domestic sales
Top-10 products by share of exports			
Garments, all types	99.40	62.83	0.41
Woolen jumpers	100.00	3.67	0.00
Jute yarn and twist	94.22	1.93	0.13
Cloth and cotton fabrics	40.67	1.42	2.21
Cotton yarn (all counts)	30.82	0.94	2.26
Finished leather	95.08	0.85	0.05
Leather and cow hides	97.91	0.72	0.02
Woven fabrics (nec)	100.00	0.72	0.00
Silk fabrics	67.88	0.66	0.33
Cotton yarn (up to 10 counts)	43.45	0.42	0.58
Top-10 products by share of domestic sales			
Iron and steel rods and bars	0.00	0.00	9.13
Motorcycles	0.00	0.00	8.63
Brick (ordinary)	0.01	0.00	6.54
Cigarettes	1.69	0.10	6.24
Cement	0.58	0.03	5.06
Leather boots and shoes (gents)	8.32	0.23	2.68
Dhoties and sarees	0.00	0.00	2.28
Cotton yarn (all counts)	30.82	0.94	2.26
Cloth and cotton fabrics	40.67	1.42	2.21
Iron and steel sheets (nec)	2.23	0.04	1.73
Newspapers (Bengali)	0.05	0	1.51

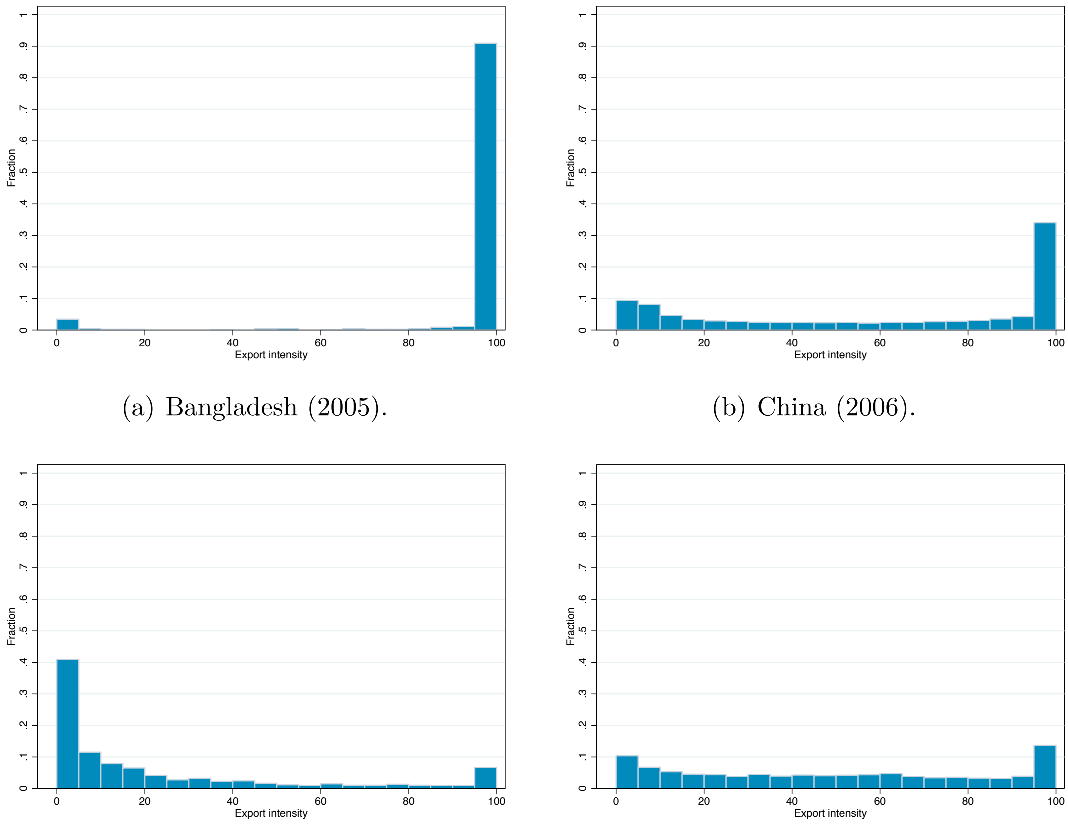
Note: based on survey data from the Bangladesh Bureau of Statistics, applying firms sample weights to construct aggregate figures. Export intensity is defined as the share of exports in total sales for a particular product. Products are 6-digit Bangladesh Standard Industrial Classification (BSIC) codes. Food commodities are excluded (frozen fish, rice, etc.).

and foreign markets, but their combined share in total exports was less than 3%. Thus, as argued above, apparel exporters in Bangladesh can be characterized as operating in orphan industries for which domestic demand is essentially missing.

Now turning to firm patterns, Figure 2.3 contrasts the cross-firm distribution of export intensities in Bangladesh with export intensity distributions in other countries. All graphs are based on industrial survey data and exclude non-exporters. Clearly, the dominance of pure exporting firms in Bangladesh is extraordinary, with more than 90% of exporters selling more than 90% of their sales abroad. China also shows an unusual concentration of firms that specialize in exports, as previously noted by Lu (2010), although not as high as in Bangladesh.[14] On the other hand, Taiwan, and especially Colombia, show a pattern similar to developed countries, where exporting firms generate most of their sales from

[14] Dai et al. (2012) have noted that not distinguishing exporters engaged in processing trade can lead to a misleading interpretation of the data. Hence, we exclude Chinese firms that are engaged in processing trade. Including these firms increases, but not significantly, the share of firms that specialize in exports.

domestic markets. Iacovone and Javorcik (2010) also show that Mexican exporters sell around 12% of their sales abroad during their first year of exporting, increasing to near 20% after five years.



(a) Bangladesh (2005). (b) China (2006).

(c) Colombia (1989). (d) Taiwan (2004).

Figure 2.3. Histograms of exporters' export intensities.

One concern with Figure 2.3 is that the export intensities we observe for Bangladesh could be the result of the prevalence of trading houses or intermediaries that are not actually manufacturers.[15] This is unlikely since the data comes from an industrial survey that reports on manufacturing establishments. Still, to have a sense of how prevalent trading is in Bangladesh, we use customs data to look at the composition of exporters by activity. For each exporter that we can match to a tax registry we observe whether it also performs any combination of the following four activities: manufacturer, importer, trader or service renderer. As Table 2.3 shows, although the number of traders and/or

[15]Manufacturers in Bangladesh can sell to foreign buyers directly, to local offices of foreign brands or to local buying houses (intermediaries), which are usually owned by foreign entrepreneurs (Indian, Thai, etc.). In a personal interview with one of the authors in Dhaka in 2011, the director of a large manufacturing group owning three plants in Bangladesh (around 650 workers) stated that it was not the case that administrative costs of selling through intermediaries were lower than exporting directly. Rather, he stressed diversification (selling to one brand only can be risky) and access to a larger pool of contacts.

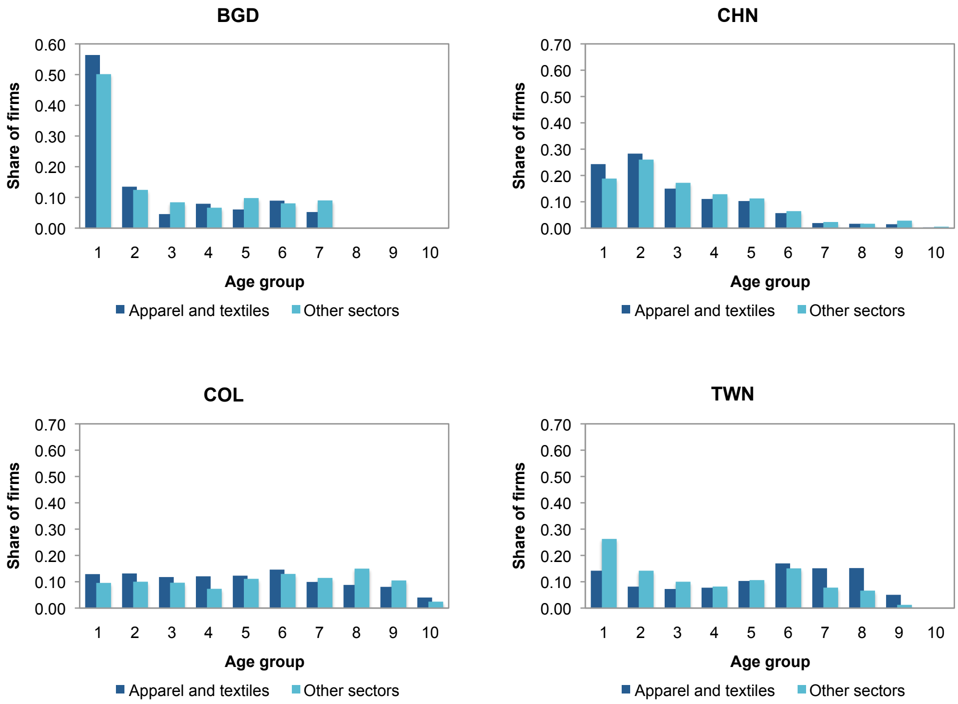


Figure 2.4. Fraction of total firms in an entering cohort by firm age group .

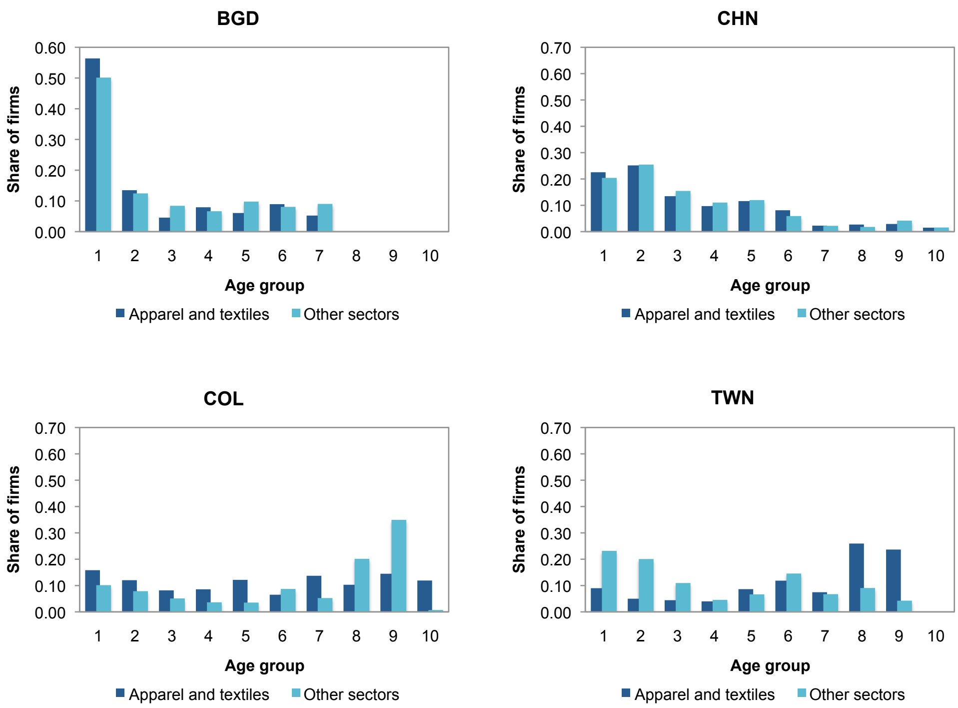


Figure 2.5. Share of total exports in an entering cohort by firm-age group.

non-manufacturer exporters increases throughout the period, their share in apparel and textiles exports remains less than 2%. The export intensities that we see in Bangladesh, therefore, can hardly be explained by the presence of traders and intermediaries.

Table 2.3: Exports and exporters by activity of the plant, Bangladesh (apparel and textiles).

	2004	2005	2006	2007	2008	2009
A. Exports as % of total apparel and textiles exports						
Manufacturer and exporter	98.0	97.9	98.1	97.5	97.7	97.3
Traders and other activity	0.9	1.0	1.1	1.3	1.1	1.3
Other exporters	1.2	1.1	0.9	1.2	1.2	1.4
B. Number of exporters						
Manufacturer and exporter	2,595	2,723	2,926	3,272	3,509	3,548
Traders and other activity	217	295	347	537	569	664
Other exporters	385	466	505	715	802	864

Note: only plants in the apparel and textiles sector are included. Based on customs and tax data from Bangladesh's National Board of Revenue.

2.2.2.3 Cohort survival

The high cumulative contribution of entrants to export growth in Bangladesh and China suggests that new exporters managed to survive at a relatively high rate in these countries. Further details on survival patterns are clearer when we organize exporting firms according to the number of years they have been exporting and examine their survival rates in export markets as they age.

Following EEKT, we can chronicle the progress of different cohorts of exporters from Bangladesh, China and Colombia (Tables 2.4-2.6). They are arranged with the year of entry in the column and the year of participation in the row. The top panel reports the number of firms from that cohort in that year, the second panel total exports of that cohort in that year, and the third panel exports per firm (i.e. the second panel divided by the first). Since we do not have data before the first year, the first "cohort" is simply all firms exporting in the first year regardless of when they entered.[16]

The top panels of Tables 2.4-2.6 show that, on average for apparel and textiles, Bangladeshi firms had a 68% chance of lasting past their first year as exporters and new Chinese exporters had a 79% chance of surviving their first year in foreign markets. In contrast, Colombian firms had only a 39% chance. The gap in survival rates between

[16]A cohort is defined by the first year of a foreign sale in our data; firms that quit exporting and re-enter foreign markets later switch cohorts. Changing the definition so that firms do not switch cohort does not alter the results significantly (with the disadvantage that it can generate survival rates above one).

Bangladesh and China narrows considerably for firms with at least two years of exporting experience, but that between these and Colombia is still significant even for firms with five years in foreign markets. It seems that the early shakedown period typical of firms after their first year of selling abroad is simply missing in Bangladesh and China.

Table 2.4: Firms by initial export year cohorts. Apparel and textiles, Bangladesh.

Year	Cohort						Total
	2004	2005	2006	2007	2008	2009	
			A. Number of firms				
2004	3,197						3,197
2005	2,654	830					3,484
2006	2,334	563	881				3,778
2007	2,098	446	639	1,341			4,524
2008	1,903	359	508	921	1,189		4,880
2009	1,705	301	420	699	757	1194	5,076
			B. Value of exports (US$ million)				
2004	6,660						6,660
2005	7,797	999					8,796
2006	8,510	865	402				9,777
2007	8,997	1,030	1,052	474			11,553
2008	9,322	1,108	1,281	1,236	433		13,380
2009	8,800	1,102	1,373	1,498	949	413	14,135
			C. Exports per firm (US$ million)				
2004	2.1						2.1
2005	2.9	1.2					2.5
2006	3.6	1.5	0.5				2.6
2007	4.3	2.3	1.6	0.4			2.6
2008	4.9	3.1	2.5	1.3	0.4		2.7
2009	5.2	3.7	3.3	2.1	1.3	0.3	2.8

Note: a firm is classified as belonging to cohort x if the firm first reported exporting in year x. If a cohort x firm exits in a given year t and re-enters in some future period $x + n$, it is treated as belonging to cohort $x + n$ (i.e. it switches cohorts).

The lower rows of the second panel reveal an equally remarkable difference between Bangladesh and China, on the one hand, and Colombia, on the other. If we consider total exports five years into our samples, for Colombia 80% of total exports (in the last column) were from firms that were there at the beginning of the period (the first column). The figure for Bangladesh is 62% and for China 30%. This means, in line with the findings above, that in Bangladesh and China new cohorts quickly gain market over incumbent exporters, while in Colombia it is established exporters who dominate foreign sales.

The third panel reveals another striking difference between new exporters in the two sets of countries. Not surprisingly, in all cases younger firms are usually smaller than

Table 2.5: Firms by initial export year cohorts. Apparel and textiles, China.

Year	Cohort 2000	2001	2002	2003	2004	2005	2006	Total
				A. Number of firms				
2000	13,644							13,644
2001	11,040	4,177						15,217
2002	9,475	3,195	6,393					19,063
2003	8,507	2,804	5,299	8,790				25,400
2004	7,630	2,462	4,649	7,154	13,539			35,434
2005	6,852	2,242	4,183	6,090	10,368	14,981		44,716
2006	6,114	1,991	3,803	5,334	8,745	11,566	20,063	57,616
				B. Value of exports (US$ million)				
2000	25,672							25,672
2001	26,128	2,103						28,231
2002	25,490	4,807	3,842					34,139
2003	26,611	5,831	9,238	6,059				47,739
2004	27,172	6,159	10,634	13,398	9,012			66,375
2005	26,919	6,385	11,972	15,844	18,508	9,501		89,129
2006	27,095	6,822	13,005	16,529	20,357	20,061	17,923	121,791
				C. Exports per firm (US$ million)				
2000	1.9							1.9
2001	2.4	0.5						1.9
2002	2.7	1.5	0.6					1.8
2003	3.1	2.1	1.7	0.7				1.9
2004	3.6	2.5	2.3	1.9	0.7			1.9
2005	3.9	2.8	2.9	2.6	1.8	0.6		2.0
2006	4.4	3.4	3.4	3.1	2.3	1.7	0.9	2.1

Note: a firm is classified as belonging to cohort x if the firm first reported exporting in year x. If a cohort x firm exits in a given year t and re-enters in some future period $x+n$, it is treated as belonging to cohort $x+n$ (i.e. it switches cohorts).

older ones, and exports per firm tend to grow as a cohort ages (through a combination of firm growth and the exit of smaller firms). But in Colombia the size disadvantage of new exporters is enormous. In 2006, for example, those firms that had always exported remained more than four times larger than those firms that entered in 2001, and almost twenty times larger than firms that entered in 2005, the previous year. For Bangladesh and China, on the other hand, new firms are not nearly as small relative to older ones, even in the first or second year of exporting.

To summarize, apparel export growth in Bangladesh and China was derived largely from firms that entered foreign markets on a large scale and, once in, tended to survive. These patterns contrast with those found in Colombia, where entry into export markets was frequent but mostly done on a small scale and relatively unimportant for cumulative

Table 2.6: Firms by initial export year cohorts. Apparel and textiles, Colombia.

Year	Cohort													Total
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	
	A. Number of firms													
2000	2,079													2,079
2001	1,331	1,147												2,478
2002	1,035	474	1,080											2,589
2003	863	297	433	1,362										2,955
2004	768	222	290	463	1,917									3,660
2005	591	133	160	227	417	1,388								2,916
2006	530	111	126	170	273	715	927							2,852
2007	487	96	105	131	210	475	417	1,067						2,988
2008	448	82	85	101	164	332	239	478	975					2,904
2009	396	68	60	71	127	235	147	253	407	971				2,735
2010	352	56	51	55	92	173	93	138	167	266	678			2,121
2011	320	49	45	47	76	139	62	100	105	137	288	723		2,091
2012	291	44	38	39	62	109	53	76	72	98	194	297	679	2,052
	B. Value of exports (US$ million)													
2000	893													893
2001	894	54												948
2002	750	40	27											817
2003	843	39	36	36										954
2004	1,024	70	49	57	97									1,297
2005	1,117	67	51	62	56	51								1,404
2006	1,150	55	51	43	78	79	35							1,491
2007	1,415	122	50	65	129	162	114	183						2,240
2008	1,337	118	42	58	109	198	93	200	233					2,388
2009	797	61	24	25	33	103	48	63	131	116				1,401
2010	810	43	28	33	33	44	40	22	31	24	81			1,189
2011	908	51	21	22	24	39	49	26	24	36	25	46		1,271
2012	891	53	15	21	20	34	56	25	21	38	29	55	33	1,291
	C. Exports per firm (US$ million)													
2000	0.43													0.43
2001	0.67	0.05												0.38
2002	0.72	0.08	0.03											0.32
2003	0.98	0.13	0.08	0.03										0.32
2004	1.33	0.32	0.17	0.12	0.05									0.35
2005	1.89	0.50	0.32	0.27	0.13	0.04								0.48
2006	2.17	0.50	0.40	0.25	0.29	0.11	0.04							0.52
2007	2.91	1.27	0.48	0.50	0.61	0.34	0.27	0.17						0.75
2008	2.98	1.44	0.49	0.57	0.66	0.60	0.39	0.42	0.24					0.82
2009	2.01	0.90	0.40	0.35	0.26	0.44	0.33	0.25	0.32	0.12				0.51
2010	2.30	0.77	0.55	0.60	0.36	0.25	0.43	0.16	0.19	0.09	0.12			0.56
2011	2.84	1.04	0.47	0.47	0.32	0.28	0.79	0.26	0.23	0.26	0.09	0.06		0.61
2012	3.06	1.20	0.39	0.54	0.32	0.31	1.06	0.33	0.29	0.39	0.15	0.19	0.05	0.63

Note: a firm is classified as belonging to cohort x if the firm first reported exporting in year x. If a cohort x firm exits in a given year t and re-enters in some future period $x + n$, it is treated as belonging to cohort $x + n$ (i.e. it switches cohorts).

export growth. Our findings for Bangladesh and China also contrast with what Amador and Opromolla (2013) report for Portugal. Using transactions data similar to those that we use here, their reported figures imply Portuguese manufacturing exporters had a 53% chance of surviving their first year between 1997 and 2005. Also, new exporters showed a significant size disadvantage vis à vis continuing exporters: in 2005, for example, firms that had always exported were eight times larger than those that entered in 2004.

The findings in this section together with the growth decomposition presented above suggest that, in orphan industries, a substantial portion of export growth comes from firms that are immediately committed to export markets, while firms that simply "test the waters" abroad are relatively less common. Firms in Bangladesh (and China) start big, not small, and their relationships with foreign buyers are long-lived. Viewed through the lens of theories that stress the importance of uncertainty in buyer-seller partnerships as determinants of international trade flows Rauch and Watson (2003), born to export firms seem to operate in environments where, from the buyers' side, some informational asymmetries have been resolved since exporters in orphan industries are specialized in adapting products for foreign markets.

2.2.2.4 Are firms born to export?

One explanation for the large role of entry in Bangladesh and China relative to Colombia is that, in the first two countries, entry into exporting was by newly-created, export-oriented firms, while in Colombia new exporters were existing, domestically-oriented firms testing out foreign markets. This interpretation seems to accord with Bangladeshi experiences. The domestic market for western apparel was limited in this country, and most entrepreneurs who started to export apparel could not do so by re-orienting production capacity in existing varieties toward foreign consumers. They needed to create new establishments, train workers and adapt to business practices not implemented at home.[17] As we show in this section, the BTE explanation fits the Bangladeshi experience very well. For China, however, the evidence is mixed.

To explore the prevalence of BTE firms, we turn to firms' ages at the time they begin exporting. For Bangladesh, we compute each exporter's age by using the date at which it registered its tax ID and we identify its entry into export markets using our shipment-level data. All firms at least 20 years old are assigned an age of 19 years since the tax registration date in our data is truncated at July 1st 1991. To calculate age in Colombia and China we

[17] Mostafa and Klepper (2009) report that, in 1978, there were only "a handful of garment producers," while the number in 2009 was over 4,000. Their Figure 1 shows how the number of garment factories in Bangladesh closely tracked total exports, suggesting that these factories weren't producing much for the domestic market.

Table 2.7: Age when entering foreign markets.

	Apparel and textiles		Other sectors	
	Mean	Median	Mean	Median
Bangladesh	2.0	0.4	2.6	0.8
China	5.0	3.0	6.1	3.7
Colombia	11.5	8.1	14.6	10.5
Taiwan	11.9	10.7	7.2	4.7

Note: figures are annual averages as follows: Bangladesh (2005-2009), China (2001-2006), Colombia (1983-1989) and Taiwan (2002-2004). Age at entry for an exporter is determined by the year it entered an export cohort and the date of tax registration (for Bangladesh) or firm start up (for Colombia, China and Taiwan).

use annual establishment survey data which show both the foundation date for the plant and the value of exports, year by year.[18] Finally, since we also have establishment survey data for Taiwan, we include figures for this country to broaden the basis for comparison.

Table 2.7 shows the main patterns. Note that in Colombia and Taiwan, the median age of an establishment in the apparel and textiles industry at the time of its first sale abroad is 8 years or more. In Bangladesh, however, the median age does not exceed one year. China is in between, with a median age of 3. Figure 2.4 provides more details on the distribution of exporters' ages in Bangladesh. It shows the histogram of the across-year average firm age the year of entry into export markets. We classify firms into ten age groups, with the first group being composed of firms one year old or less.[19] If exporters are born to export, we should expect to see that entrants are young. Indeed, Figure 2.4 shows that the age distribution at entry is remarkably skewed for Bangladesh. This pattern contrasts sharply with those observed in China, Colombia, and Taiwan, where the distribution of firm age at entry is far less skewed, if at all.

The fact that young Bangladeshi exporters are numerous and export substantial volumes suggests that a large fraction of total sales is supplied by newly created firms. Figure 2.5, which shows total exports by age group of the exporting firm, confirms this. Most exports in Bangladesh originate from firms less than five years old. But in China, Colombia and Taiwan, the older, established exporters are the dominant source of foreign sales.

[18]It should be noted that the establishment survey data only cover plants with at least 10 workers, so they miss very small exporters, which are also likely to be very young.

[19]The rest of the groups are as follows: (1,3] years old, (3,5], (5,7], (7,10], (10,15], (15,20], (20,30], (30,50] and more than 50 years old.

2.3 Export Processing Zones in Bangladesh

One possible explanation is that Bangladesh's distinctive exporting dynamics, and in particular the prevalence of BTE firms and the finding that exporters tend to sell very little in the domestic market, is an artifact of the Export Processing Zone (EPZ) regime: if this regime provides large benefits to exporters but prevents them by law from selling a significant share of their output in the domestic market, then the BTE phenomenon is bound to arise for firms located in EPZs. We examine this possibility in this section.

Bangladesh has eight operating export processing zones located in different districts in four divisions: Dhaka, Chittagong, Khulna and Rajshahi. Only one of them, the Chittagong EPZ, has been in operation since the 1980s. The Dhaka EPZ was opened in 1993 and the remaining 6 were opened between 2001 and 2007. There are fiscal benefits of opening a plant in an EPZ, as well as benefits in access to water, gas and electricity, together with warehouses and dormitories for workers.[20]

Exports from EPZs grew 172% between 2000 and 2010, but their overall role in Bangladesh's export boom is surprisingly small. Their share in total exports was 18% in 2010, down from a peak of 21% in 2005. Employment located in these zones remains low at 0.7% of total manufacturing employment in 2005.[21]

Both our customs and survey data sets give further evidence on the role of EPZs. Customs data provide more accurate information on the location of plants, while survey data allow us to investigate employment, export intensity and other characteristics of plants located in EPZ districts.

Table 2.8 summarizes what the customs data indicate about where total exports and apparel exports originated during 2004-2009. Overall, foreign sales from EPZs averaged only 10.9% of total exports during this period. Moreover, the share did not change much: exports originated inside and outside EPZs slightly more than doubled over the five year period. Inside EPZs export growth occurred much more on the extensive rather than the intensive margin. While the number of plants increased from 146 in 2004 to 238 in 2009, exports per firm rose only 26%, from US$5.3 million to US$6.7 million. Outside EPZs growth was more evenly balanced between the two margins. We also see little difference in the importance of apparel exports. Table 2.8 indicates an apparel share of EPZ exports hovering between 90% and 95%, in line with apparel's share in overall exports shown in

[20]See Aggarwal (2005) for a thorough description of the development of export processing zones in Bangladesh, and how it compares with those in India and Sri Lanka. He argues that plants located in EPZs are at a huge advantage both in terms of fiscal and non-fiscal incentives compared to units outside them. Also, Bangladesh seems to offer greater fiscal incentives relative to India and Sri Lanka. See the appendix for an extended description of EPZs in Bangladesh and the sources of data.

[21]We take total manufacturing employment from the Survey of Manufacturing Industries 2005-06 Bangladesh Bureau of Statistics (undated).

Figure 2.2.

Table 2.8: Exporters in export processing zones (EPZ), Bangladesh, 2004-2009.

	2004	2005	2006	2007	2008	2009
			Plants in EPZs			
Exports (US$ million)	775	1,551	1,099	1,277	1,422	1,594
Apparel and textiles	698	1,466	1,009	1,182	1,340	1,500
Number of plants	146	169	168	210	213	238
Apparel and textiles	94	110	122	151	153	163
Number of products	338	340	360	378	389	418
Number of destinations	88	82	93	87	98	96
Exports per plant (US$ million)	5.3	9.2	6.5	6.1	6.7	6.7
Apparel and textiles	7.4	13.3	8.3	7.8	8.8	9.2
			Plants outside EPZs			
Exports (US$ million)	6,865	8,329	9,839	11,832	13,360	14,035
Number of plants	4,542	4,960	5,034	5,827	6,257	6,469
Number of products	1,334	1,425	1,459	1,400	1,449	1,532
Number of destinations	172	171	178	186	182	185
Exports per plant (US$ million)	1.5	1.7	2.0	2.0	2.1	2.2
EPZ exports (% of total)	10.1	15.7	10.0	9.7	9.6	10.2
Data as % of BEPZA	50.0	84.5	53.3	52.6	55.1	56.5

Notes: source is Bangladesh customs and tax registration data. Location in an EPZ is determined by the address of the plant. Last row computes EPZ exports in our data (the one to last row) as a percentage of total EPZ exports as reported by BEPZA.

The most notable difference we do find between plants inside and outside EPZs has to do with size. Exports per EPZ plant were about three times higher than from plants outside EPZs. Moreover, within EPZs, apparel and textiles producers were larger than other producers, as measured by exports per plant. This is not surprising, as the fixed and sunk costs of establishing a plant in an EPZ are probably higher than those of opening up a plant outside an EPZ.[22]

Finally, we look at plant age to investigate whether EPZs have a distinctive role in explaining the BTE phenomenon. Table 2.9 shows that there are no significant differences in plant age in and out of EPZs. In 2009 plants in EPZs were around one year older than their counterparts not in EPZs, irrespective of whether they belonged to the apparel and textiles sector.[23] Table 2.9 also shows that there were no significant age differences on average between plants in and out of EPZs at the moment of entering export markets

[22]Firms in EPZs also tend to be foreign owned, or joint ventures between Bangladeshi and foreign firms. As of 2009, 75% of firms in EPZs were in either of these ownership categories. See the appendix.

[23]A t-test for the difference in means cannot reject the hypothesis that plants in EPZs were older than plants outside EPZs, but the difference in mean age is less than a year. This result holds even if we control for apparel and textiles producers in EPZs.

in 2009.[24] That the median plant age in EPZs was one year is not surprising, however, given that firms who want to operate in an EPZ must open a new plant there, usually registering a new plant ID.

Table 2.9: Plant age by EPZ status, Bangladesh, 2009.

	Age		Age at entry	
	Mean	Median	Mean	Median
		Apparel and textiles		
Non-EPZ	6.74	5.09	2.00	1
	(0.08)		(0.13)	
EPZ	7.41	6.03	1.92	1
	(0.37)		(0.57)	
		Other		
Non-EPZ	6.39	4.81	1.94	0
	(0.13)		(0.17)	
EPZ	7.29	6.50	2.00	1
	(0.47)		(0.75)	

Notes: source is Bangladesh customs and tax registration data. Location in an EPZ is determined by the address of the firm. Apparel and textiles sector are HS 2-digit codes 42, 43 and 50-65. Standard errors between parenthesis.

This evidence strongly suggests that BTE plants are not something exclusive of EPZs. In fact, if we define a BTE plant as one that entered the foreign market within one year of start-up, Table 2.10 shows that, if anything, the share of born to export plants is higher outside EPZs. Moreover, the share of total exports accounted for by BTE plants is lower in EPZs than in non-EPZs (23% compared to 31% in 2009), and the percentage of exports by BTE plants that are apparel and textiles is roughly similar for EPZ and non-EPZ plants.

In summary, while EPZ's have played some role in Bangladesh's export boom, they were not the central factor.[25] They account for a relatively small share of total exports, which has remained fairly constant over the period we look at. Moreover, we cannot find significant differences in their role in the born-to-export phenomenon. In the appendix we present some evidence that exporters located in districts where there is an EPZ (not necessarily *within* an EPZ) seem to be younger than those located outside EPZ districts

[24]When we pool all years, a t-test for the difference in mean age rejects the hypothesis that mean plant age is different in and out of EPZs.

[25]Kee (2015) studies the effect of FDI (mostly located in EPZs) on Bangladeshi garment firms' performance through shared supplier spillovers. She finds that the expansion of FDI firms led to better performance of domestic firms that shared suppliers with them.

Table 2.10: Born to export plants by EPZ status, 2004-2009.

	2004	2005	2006	2007	2008	2009
			Plants in EPZs			
No. of BTE plants	39	54	52	80	81	98
% of total	26.7	32.0	31.0	38.1	38.0	41.2
Exports (US$ million)	37.4	725.1	114.7	196.8	311.3	370.0
% of total	4.8	46.8	10.4	15.4	21.9	23.2
% apparel and textiles	55.2	97.8	90.2	88.7	92.7	94.4
			Plants outside EPZs			
No. of BTE plants	1,093	1,601	1,907	2,542	2,922	3,179
% of total	24.1	32.3	37.9	43.6	46.7	49.1
Exports (US$ million)	601.5	1,295.1	2,078.8	2,895.5	3,684.6	4,311.2
% of total	8.8	15.5	21.1	24.5	27.6	30.7
% apparel and textiles	84.3	86.4	91.1	90.0	93.0	91.2

Notes: source is Bangladesh customs and tax registration data. Location in an EPZ is determined by the address of the firm. Born to export (BTE) plants are defined as plants that began to export within 1 year or less from start-up. Apparel and textiles sector are HS 2-digit codes 42, 43 and 50-65.

(although this difference is absent for non-exporters). Since the quality of the data is not as good as the customs data, we do not consider this piece of evidence as conclusive.

Given the apparent benefits of locating in an EPZ, a puzzle is why more plants haven't located in them. We speculate that, for many plants, the administrative fees or price of land in EPZ's offset these benefits. The one significant difference that we do observe, that plants in EPZ's are about four times larger, is consistent with a fixed cost of locating in one that only larger plants can recover.

2.4 Export dynamics with born to export firms

Among the four countries we have examined, new exporters account for a large part of export growth in Bangladesh and China, and in Bangladesh these new exporters tend to be BTE firms. In this section we suggest a model that captures key features of BTE firms, namely the absence of a domestic market and the existence of large sunk costs associated with the decision to start exporting.

As discussed in the introduction, an entrepreneur who starts up a BTE firm must not only incur the fixed and sunk costs of exporting, but the presumably much larger start-up costs of the establishing a new business. This much higher cost has several implications for export dynamics. Relatively larger start-up costs make firms' exporting decisions relatively more forward-looking, given that a significant fraction of these costs are sunk and must be covered in expected value by a substantial stream of future export profits. Furthermore, when entrepreneurs lack experience in their home market, they face more uncertainty about their prospects for profits abroad. This uncertainty makes their entry decisions and subsequent efforts to meet foreign clients strongly depend upon whatever signals are available about foreign market conditions. Also, once they have created a firm, they are relatively more committed to remaining in foreign markets.

To numerically explore these distinctive features of born to export firms, we now adapt the search and learning model of export dynamics developed in EEJKT.[26] The EEJKT model assumes that firms experience ongoing, serially-correlated shocks to their own productivity which are independent across firms. Moreover, firms experience common shocks to aggregate demand at home and abroad, exchange rate shocks being incorporated in the foreign demand shock. In order to search for buyers in their domestic and foreign markets, firms pay a per-period fixed cost. While a firm knows the popularity of its product in the home country, it is initially uncertain about its popularity abroad. Taking stock of their acceptance rates among home market buyers and foreign buyers they have met (if any), firms formulate beliefs about their products' popularity abroad. As they update their beliefs, firms adjust their search intensity for foreign clients, and drop foreign clients when the expected operating profits from the match fall below the fixed costs of maintaining the relationship.

We modify these assumptions in two ways. First, we eliminate the home market and thus force entrepreneurs to make their initial exporting decisions without any prior information about the appeal of their products. Second, we assume that, before an entrepreneur can begin exporting, she must incur a fixed cost of setting up a firm, and this investment is only partially recoverable if the firm shuts down.

Firms choose how intensively to search for potential clients in each market where they wish to generate sales. If they wish to meet a client with probability $\lambda \in [0,1]$ during the next time interval, they must incur costs $c(\lambda)$, where $c(0) = 0$ and $c(\cdot)$ is increasing and convex in λ. Depending on search intensity, these costs might include the expenses of maintaining a web site in a foreign language, attending trade fairs, researching and contacting potential buyers on the internet, and/or maintaining a foreign sales office.

Simplifying EEJKT, we assume that some fraction $\theta_j \in [0,1]$ of the buyers in foreign markets are willing to do business with firm j, where θ_j is distributed beta with parameters (α, β) across potential exporters. Firms that have not yet exported know only the distribution from which their θ_j values are drawn, but they learn about their particular θ_j types as they meet new clients abroad and update their beliefs according to Bayes'

[26]Nguyen (2012) and Albornoz et al. (2012) also look at the implications of learning about markets for the pattern of exports.

rule.[27] Updating yields a posterior distribution for θ_j that depends upon the number of potential clients firm j has met (n_j), and the number of these meetings that resulted in successful business relationships (a_j), as well as the parameters (α, β). Specifically, firm j's perceived success count after having met n_j clients and established a_j successful business relationship is given by a draw from the conditional binomial distribution:

$$q(a_j|n_j, \theta_j) = \begin{pmatrix} n_j \\ a_j \end{pmatrix} \theta_j^{a_j}(1-\theta_j)^{n_j - a_j}. \tag{2.2}$$

Correspondingly, the posterior beliefs about the firm's product appeal θ_j are distributed according to

$$p(\theta_j|n_j, a_j) = \frac{q(a_j|n_j, \theta_j) \cdot h(\theta_j|\alpha, \beta)}{\int_0^1 q(a_j|n_j, \theta_j) \cdot h(\theta_j|\alpha, \beta) d\theta_j}, \tag{2.3}$$

where $h(\theta_j|\alpha, \beta)$ is the density of θ_j (derived from the beta distribution). The mean of this posterior distribution, which the firm uses to assess the value of continuing to search, is given by

$$\hat{\theta}_j(n_j, a_j) = \int_0^1 \theta_j p(\theta_j|n_j, \theta_j) d\theta_j. \tag{2.4}$$

If firm j chooses search intensity λ_{jt} during period t, the probability it will establish a new successful business relationship abroad is $\lambda_{jt}\theta_j$. Supposing this relationship is with client i, it generates period t profits of:

$$\pi(x_t, \varphi_{jt}, y_{ijt}) = x_t \varphi_{jt}^{\sigma-1} y_{ijt}, \tag{2.5}$$

where x_t captures market wide demand shocks (inclusive of exchange rate effects), φ_{jt} is a firm-specific productivity shock, and y_{ijt} is a shock specific to the match between buyer i and seller j. Here $\sigma > 1$ is the elasticity of substitution, and we assume that the seller sets a price equal to the Dixit-Stiglitz markup $\sigma/(\sigma-1)$ over its unit cost.

Successful matches endure until the buyer and seller are separated by an exogenous shock or until the seller determines it is not worth the fixed cost of maintaining the business relationship. Accordingly, the expected value of the profit stream associated with client i is:

$$\tilde{\pi}(x_t, \varphi_{jt}, y_{ijt}) = x_t \varphi_{jt}^{\sigma-1} y_{ijt} + \frac{1-\delta}{1+r} \max \left\{ \int_{x'} \int_{\varphi'} \int_{y'} \tilde{\pi}(x', \varphi', y') dG(x', \varphi', y'|x_t, \varphi_{jt}, y_{ijt}) - F, 0 \right\}, \tag{2.6}$$

where δ is a per-period probability that a successful match will break up for exogenous reasons, r is the rate of time preference and F is the fixed cost incurred by a firm to

[27] In EEJKT, a firm j also faces a fraction θ_j^h of domestic buyers that will be willing to do business with it, and it is assumed that firms have learned their θ_j^h.

maintain the relationship, and $G(x', \varphi', y'|x_t, \varphi_{jt}, y_{ijt})$ is the joint transition distribution for the model's exogenous stochastic variables. Of course, firms don't know *ex ante* with whom they will match next, so when choosing its search intensity in period t, firm j considers the expected payoff to a successful match to be:

$$\tilde{\pi}_0(x_t, \varphi_{jt}) = \int_y \tilde{\pi}(x_t, \varphi_{jt}, y) dG_0(y|x_t), \tag{2.7}$$

where $G_0(y|x_t)$ is the distribution of buyer types when market-wide conditions are x_t.

We are now ready to characterize a firm's exporting decisions when it has no experience in its domestic market. Suppose an up-front investment of K is required to create a firm, and upon shutting a firm down one can recoup some fraction $\psi \in [0, 1)$ of the initial investment. Then, suppressing firm and time subscripts, the value of an incumbent firm that has had n encounters, a of which were successful, is:

$$\begin{aligned} V_I(\varphi, x, a, n) = &\max_{\lambda} \; -c(\lambda) + \lambda\hat{\theta}(a, n)\Big[\tilde{\pi}_0(\varphi, X) + \rho E \max\{V_I(\varphi', x', a+1, n+1), \psi K\}\Big] \\ &+ \lambda\Big[1 - \hat{\theta}(a, n)\Big]\rho E \max\{V_I(\varphi', x', a, n+1), \psi K\} \\ &+ (1-\lambda)\,\rho E \max\{V_I(\varphi', x', a, n), \psi K\}, \end{aligned} \tag{2.8}$$

where $\rho \equiv 1/(1+r)$ is the discount factor and expectations are taken over next period's realizations of (φ', x') given (φ, x). The first line of equation (2.8) computes the expected value of a successful match, the second line computes the expected value of an unsuccessful match, and the third line the expected value value of not finding a buyer, all net of search costs. We specify the cost function $c(\lambda)$ as

$$c(\lambda) = \frac{\gamma\lambda}{1-\lambda} + F_\lambda \cdot \mathbb{1}_{\{\lambda>0\}}, \tag{2.9}$$

where γ is a parameter and F_λ represents fixed costs of searching. Solving the maximization problem in (2.8) determines the optimal search and exit policies of incumbent firms.[28]

Given that potential entrepreneurs know the macro state x and their initial productivity φ_0, they will view the value of an entry opportunity as:

$$V_E(\varphi_0, x) = \max\{V_I(\varphi_0, x, 0, 0) - K, 0\}. \tag{2.10}$$

Equation (2.10) determines the entry policy of potential exporters.

[28]Note that we require that exiting firms are able to "sell" their current business relationships to other firms at full value. Relaxing this assumption would have little effect on the behavior of the model but would require us to keep track of ongoing business relationships when the exit decision is characterized.

Table 2.11: Calibrated parameter values.

Parameter	Description	Value
Model		
α	Beta distribution parameter	3
β	Beta distribution parameter	6
σ	Elasticity of substitution	5
r	Rate of time preference	0.05
δ	Exogenous match separation rate	0.3298
γ	Cost function parameter	38.5289
F	Fixed cost of maintaining a relationship	34.1008
F_λ	Fixed cost of searching	0.1891
Stochastic processes		
$\overline{\varphi}$	Mean of productivity process	0
ρ_φ	Root of productivity process	0.7724
$\sigma_{\epsilon_\varphi}$	Std. dev. of innovation, productivity process	0.4344
$\overline{x}$	Mean of foreign shock process	0
ρ_φ	Root of foreign shock process	0.953
σ_{ϵ_x}	Std. dev. of innovation, foreign shock process	0.052
$\overline{y}$	Mean of match-specific shock process	0
ρ_φ	Root of match-specific shock process	0.6033
σ_{ϵ_y}	Std. dev. of innovation, match-specific shock process	0.8913
Discretization		
$\#(\theta)$	Number of discretized values, product appeal	100
$\#(\varphi)$	Number of discretized values, productivity shock	30
$\#(x)$	Number of discretized values, foreign shock	15
$\#(y)$	Number of discretized values, match-specific shock	30
$\#(n)$	Max. number of signals per firm	50

2.4.1 Calibration

To explore the role of firm entry costs in driving export dynamics, we now implement a quantitative version of the model. To do so we follow EEJKT in assuming that $dG(x', \varphi', y' | x_t, \varphi_{jt}, y_{ijt})$ is characterized by a first-order vector autoregression with mutually independent variables, and we take the estimated values for this VAR from that paper. Given that our data is very limited, we adopt the EEJKT calibration of the remaining model parameters. This calibration is based on various cross-sectional and dynamic features of the micro data on Colombian-U.S. trade relationships. Parameters that govern search intensity are identified by the relative frequency of firms with one foreign buyer, two foreign buyers, etc., and by the rates at which firms transit across numbers of buyers in foreign markets. The exogenous match failure rate δ and the fixed costs of maintaining a match F are identified by the rates at which buyer-seller relationships fail as a function of the age of the relationship. Parameters of the beta distribution for θ_j are identified by dispersions in log export volumes, conditioning on firm-level productivity, as well as cross-firm correlations in log sales. Table 2.11 summarizes our calibrated parametrization.

For our base-case simulations, we choose the start-up capital investment to be $K = 3,000$. This figure implies a capital-output ratio of three for the average firm, which is similar to what we can find in establishment level survey data. For comparison we also generate results under the assumption that $K = 0$, implicitly assuming that all potential exporters have already established their productive capacity. Finally, we experiment with several values of ψ to explore the role of scrap values. The smaller is ψ, the less entrepreneurs recover by liquidating their firms, and the more incentive they have to remain in export markets once they have entered.

2.4.2 Experiments

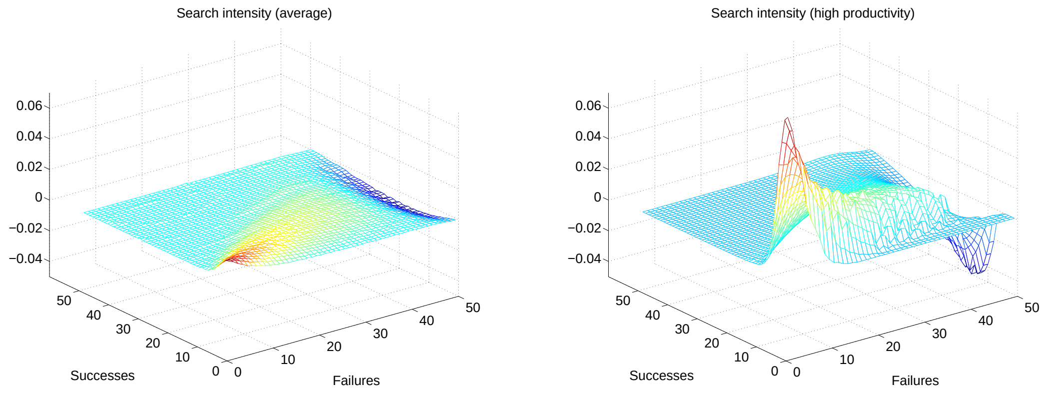
Our primary interest is in the effect of K and ψ on export dynamics. When K is large and ψ is small, we expect that firms will abstain from casual explorations of export markets, entering only when the expected long run profit stream more than covers the sunk costs of creating a firm. Also, once firms have committed to export markets, we expect them to stay in with high probability, since exiting and re-entering is costly.

To quantify these effects we look at search, entry and exit decisions for different specifications of (K, ψ). We do this first assuming that $K = 0$, then we introduce sunk start-up costs by assuming $K = 3,000$ and $\psi = 0.3$, and, finally, we examine the case of $K = 3,000$ and $\psi = 0$, which further discourages entry but also eliminates any incentive firms have to leave export markets once they have entered.

2.4.2.1 Policy functions

2.4.2.1.1 Incumbent search intensity We begin by looking at the effects of sunk start-up costs on firms' optimal search intensity, taking as given that they are already in the export market. Figure 2.6 presents the *change* in the search policy function $\lambda(\varphi, x, a, n)$ when we go from $K = 0$ to $K = 3,000$ and $\psi = 0.3$. The left panel takes expectations over all (φ, x) realizations, whereas the right panels characterizes $\lambda(\cdot)$ for an average value of x and a high value of φ, since high-productivity firms account for most exports. All panels take the cumulative number of successful matches (a) and cumulative number of unsuccessful matches $(n - a)$ as horizontal axes.

Figure 2.6 confirms that sunk entry costs increase the sensitivity of firms' search intensities to the arrival of information, especially among high-productivity firms. In particular, firms that receive negative signals about the fraction of potential buyers who like their product react more dramatically when scrap values are present. This result reflects the fact that meeting potential clients generates information about θ_j, and information



(a) (b)

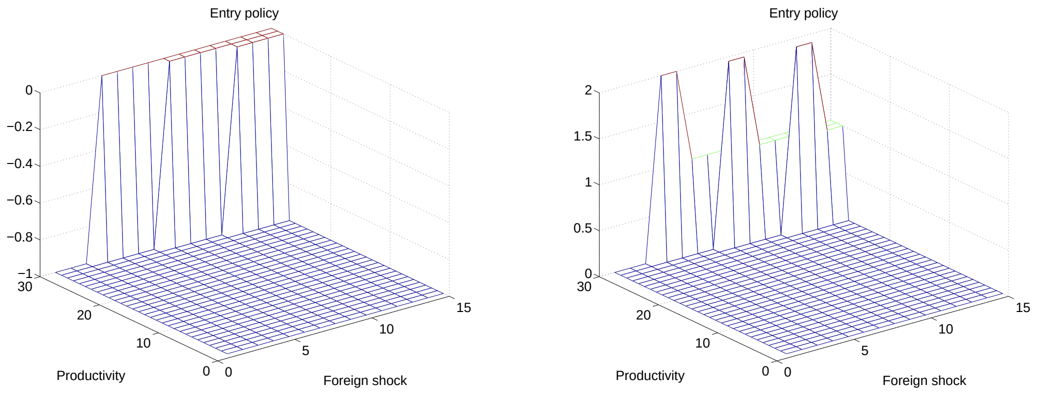
Figure 2.6. Differences in search policies, $\Delta\lambda(\cdot)$.

is particularly valuable when sunk costs create an option value to sticking around. Note that the biggest effects of sunk costs obtain for high productivity firms that have not yet acquired much experience in foreign markets.

2.4.2.1.2 Sunk costs and entry Let $\chi_e(\varphi_0, x; K, \psi) = \mathbb{1}_{\{V_I(\varphi_0,x,0,0)-K>0\}}$ be the entry policy function associated to equation (2.10). Figure 2.7 presents the change in χ_e when start-up costs and scrap values change, i.e. $\Delta\chi_e = \chi_e(\,\cdot\,;K',\psi') - \chi_e(\,\cdot\,;K,\psi)$. Since potential entrants have not yet experienced successes or failures in foreign markets ($n = a = 0$), we focus here on the relationship between initial profit determinants (φ_0, x) and entry decisions. Panel (a) plots $\Delta\chi_e$ when sunk costs increase from $K = 0$ to $K' = 3,000$, keeping fixed $\psi = 0.3$. If sunk costs deter entry, we should expect to see $\Delta\chi_e = -1$; $\Delta\chi_e = 0$ results if entry decisions are not affected. In fact, figure 2.7 (a) shows that, when K increases to 3,000, only the highest productivity firms keep entering. Further, sufficiently poor market-wide conditions (low values of x) keep even these firms out. Figure 2.7 (b) confirms that reducing the scrap value of firms to zero ($\psi' = 0$) further discourages entry of high productivity firms by reducing the expected value of creating a new firm.[29]

2.4.2.1.3 Sunk costs and continuation A similar graph can be constructed to demonstrate the effect of sunk costs on persistence in export markets. Define the continuation policy function implicit in equation (2.8) to be $\chi_c(\varphi, x, a, n; K, \psi) = \mathbb{1}_{\{V_I(\varphi,x,a,n)>\psi K\}}$. Figure 2.8 shows how this function changes when we go from an environment in which

[29]Figure 2.7 (b) plots $\Delta\chi_e = 2\chi_e(\,\cdot\,;3000, 0.3) - \chi_e(\,\cdot\,;3000, 0)$. A value of $\Delta\chi_e = 2$ indicates firms that are discouraged when there are no scrap values. $\Delta\chi_e = 1$ and $\Delta\chi_e = 0$ represent, respectively, firms that enter under both cases and firms that never enter with $K = 3000$ (irrespective of ψ).



(a) $\chi_e(\varphi_0, x; 3000, 0.3) - \chi_e(\varphi_0, x; 0, 0.3)$ (b) $\chi_e(\varphi_0, x; 3000, 0.3) - \chi_e(\varphi_0, x; 3000, 0)$

Figure 2.7. Market entry with and without sunk costs and scrap values.

$K = 0$ to an environment in which $K = 3,000$ and $\psi = 0.3$. Like in Figure 2.7, productivity φ and market-wide demand x are on the horizontal axes. However, since a different surface obtains for each a, n combination, we focus here on firms with products that are not well-loved in foreign markets: $a = 1$, $n - a = 10$. The message is simple. Firms with unpopular products have a reason to stop searching altogether and exit when their scrap value is positive. Only those with exceptionally high productivity find it worth their while to slog onward. Of course, even when K is large, this exit incentive goes away if $\psi = 0$. Thus orphan industry firms that face thin secondary markets for their capital stocks are likely to soldier onward in foreign markets, even when their profits are small.

Another way to visualize the effect of entry costs on export market participation is to ask: over what range of (φ, x) values would non-exporters refrain from entering, yet incumbent exporters refrain from exiting? This is the hysteresis band discussed in Dixit (1989) and Baldwin and Krugman (1989). This question can be answered by graphing the difference between the continuation policy function and the entry policy function: $\Delta\chi(\varphi, x; K, \psi) \equiv \chi_c(\varphi, x, 0, 0; K, \psi) - \chi_e(\varphi, x; K, \psi)$. Note that, in this exercise, sunk costs and scrap values remained unchanged. Figure 2.9 presents the case $\Delta\chi(\varphi, x; 3000, 0.3)$. It shows that, while very favorable conditions are required to induce entrepreneurs to create firms (recall Figure 2.7), incumbent exporters may experience large deteriorations in their productivity or in market-wide demand before they are induced to liquidate them.[30]

[30] Here we consider only firms that have yet to meet any potential buyers. Learning will of course change the shape of the hysteresis band.

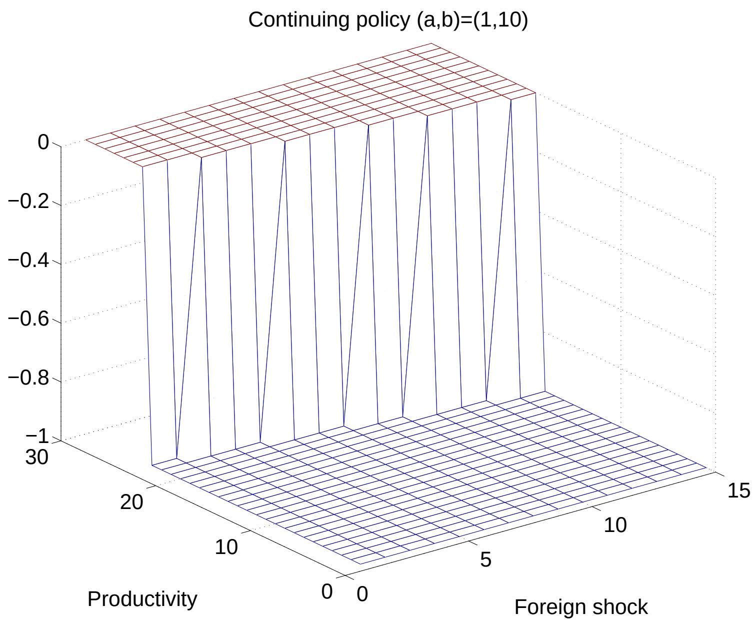


Figure 2.8. Persistence in export markets with and without sunk costs and scrap values.

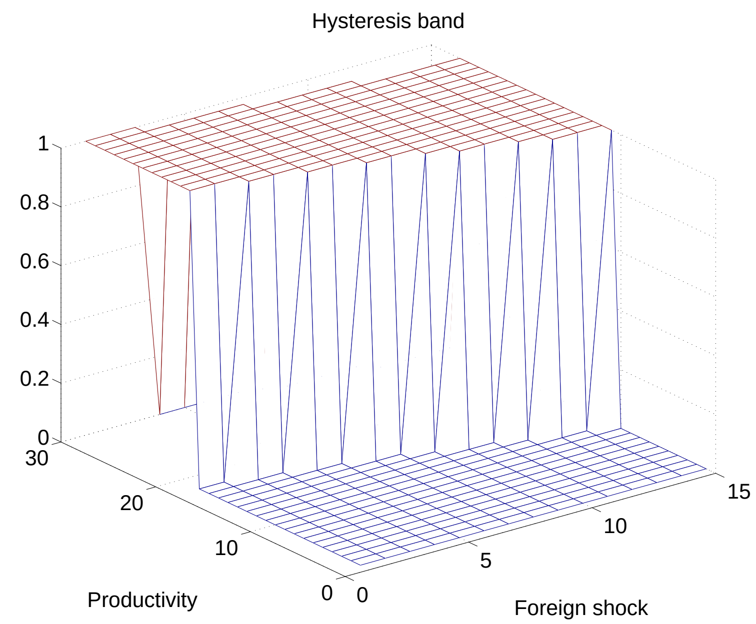


Figure 2.9. The shape of the hysteresis band, $\Delta\chi(\varphi, x; 3000, 0.3)$.

2.4.2.2 Export trajectories

Having characterized policy functions, we are ready to explore the effects of sunk entry costs on aggregate export trajectories. To do so we simulate aggregate matching patterns (successful and unsuccessful), aggregate export trajectories, and the aggregate number of exporters for a hypothetical population of 2,000 potential exporters over a 50 year period.

In the first set of simulations (case 1) we set sunk entry costs and scrap values to zero. In the second set (case 2) we assume $K = 3,000$ and $\psi = 0.3$, so that sunk entry costs are important, but relatively unprofitable exporters have an incentive to liquidate their firms. Finally, in the third set (case 3) we assume $K = 3,000$ and $\psi = 0$, thereby eliminating any incentive to exit foreign markets, once in.

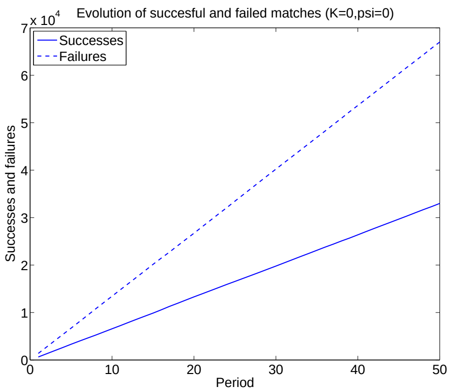
All three sets of trajectories are constructed using the same set of simulated realizations on $\{x_t, \varphi_{jt}, y_{ijt}\}$, which in turn is generated using the estimated transition distribution $G(x', \varphi', y'|x_t, \varphi_{jt}, y_{ijt})$ from EEJKT. Time-invariant θ_js are also common to the two sets of trajectories. These are drawn from the calibrated beta distributions discussed above and randomly assigned to entrepreneurs. Thus, comparing cases, the only sources of difference in outcomes are differences in K and/or in ψ.

By assumption, entrepreneurs always know their current-period φ realization and the current macro state, x, regardless of whether they are currently operating a firm. But entrepreneurs do not know their θ_j draws ex ante; these they learn about through their foreign market experiences. Further, to highlight the role of learning, all entrepreneurs are assumed to hold pessimistic priors about the foreign market. Specifically although the θ_js are drawn from a beta distribution with expected value of $\alpha/(\alpha + \beta)$, entrepreneurs with no experience in export markets assume that the θ_j's are drawn from a beta distribution with mean $0.5\alpha/(\alpha + \beta)$.

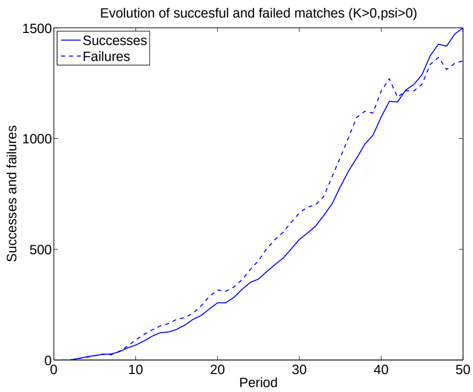
Period 0 is the first period in which exporting opportunities arise, either because of policy reforms (as in China) or because new technologies become known to domestic entrepreneurs (as in Bangladesh). Our simulations therefore begin from zero exports and characterize the emerge of a new exporting sector. Period by period, each entrepreneur endogenously creates or shuts down exporting firms as innovations in the $\{x_t, \varphi_{jt}, y_{ijt}\}$ process arrive, choosing optimal search intensities and updating her beliefs about her success rate (θ_j) as matches occur.

2.4.2.2.1 Selection and search intensity Figure 2.10 shows the aggregate number of successful and unsuccessful matches, $\sum_j a_{jt}$ and $\sum_j (n_{jt} - a_{jt})$, through time, for the three cases described above. Not surprisingly, experience accumulates in the foreign market much more slowly in cases 2 and 3, when start-up costs are present (note the units on the vertical axes in these graphs.) But more interestingly, the gap between unsuccessful (green line) and successful (blue line) matches is much smaller in case 2 ($K = 3,000$, $\psi = 0.3$) than in case 1 ($K = 0$). The reason is that entry costs generate selection effects. That is, as exporters with low success rates (modest θ_j values) learn their type through experience, they discover it is best to drop out and collect ψK. For this reason, as learning takes place, the population of exporters is increasingly dominated by high productivity firms that export relatively large volumes. Case 3 ($K = 3,000$, $\psi = 0$) is different still because no exporter ever liquidates her firm when scrap values are 0. Thus although there is strong selection on productivity when entry occurs, there is no selection on product appeal (θ_j) once new firms are created. This means the gap between failure rates and success rates evolves in a manner similar to case 1.

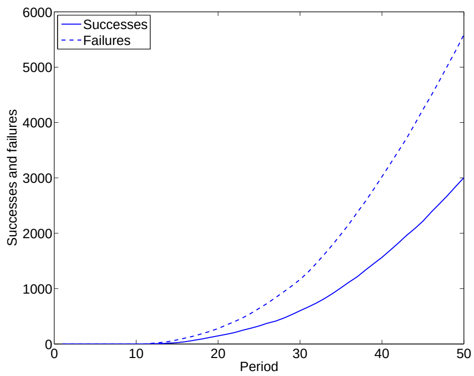
The fact that the trajectories for cases 2 and 3 are concave upward implies that aggregate experiences accumulate at an increasing rate when sunk costs are present. In turn, this reflects the fact that the number of exporters ramps up gradually when sunk costs are present.



(a) $K = 0, \psi = 0$



(b) $K = 3000, \psi = 0.3$



(c) $K = 3000, \psi = 0$

Figure 2.10. Aggregate successes and failures.

2.4.2.2.2 Total number of exporters Figure 2.11 shows the associated trajectories for total number of exporters. It also shows the simulated time series for market-wide shocks, x, which happens to start below its long run expected value and evolve upward over the early sample years. Notice that without sunk start-up costs (case 1), the number of exporters is immediately close to its long-run average of around 150. However, sunk entry costs cause far fewer firms to participate initially (recall the difference in entry policies discussed above). And rapid entry takes place as market-wide demand improves, especially in case 3, where *no one* enters at all until period 15.

Here, then, is one sense in which the need to create productive capacity can affect export dynamics and entry. When incumbent producers already exist (case 1), they participate in foreign markets even when foreign demand is limited. But when sunk entry costs are important, and productive capacity has not been created, such participation is limited (case 2) or missing altogether (case 3).

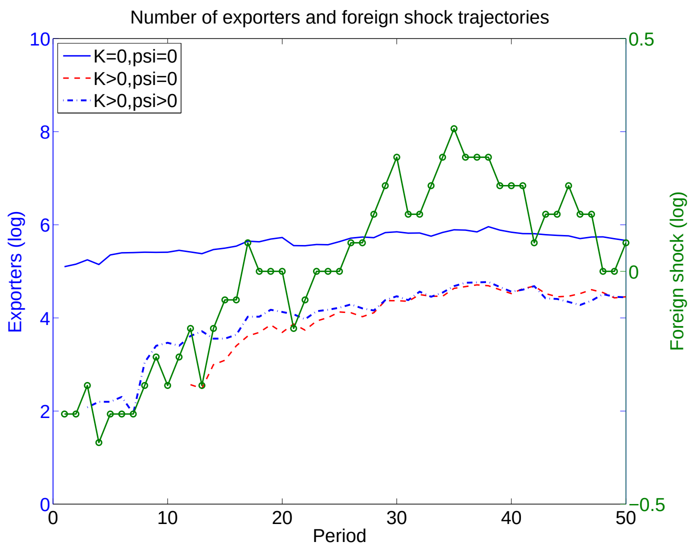


Figure 2.11. (Log of) Total exporters and foreign shock trajectories.

2.4.2.2.3 Aggregate exports Figure 2.12 brings the margins of response discussed above together, and shows how they translate into aggregate export trajectories for our three cases. The simulated trajectory for our market-wide demand index x is also presented.

Focussing on the first 20 years of simulated exports, note that when $K = 0$ (case 1), total exports are substantial from the beginning and they grow by about 250% by over the next 20 years. But when $K = 3,000$ and $\psi = 0.3$ (case 2), exports don't really take off until year 3, and thereafter grow about 200% over a 17 year period. The boom phase is even more dramatic when $K = 3,000$ and $\psi = 0$, since exports begin from 0 in year 16, and reach the same aggregate levels attained in cases 1 and 2 over a 4 year period. The simple message is that start-up costs can lead to export booms driven by born-to-export firms, especially when scrap values are low.

A number of forces lie behind these patterns. As seen in Figure 2.11, when $K = 0$ the number of exporters is immediately near its long run average. Accordingly, the only reasons

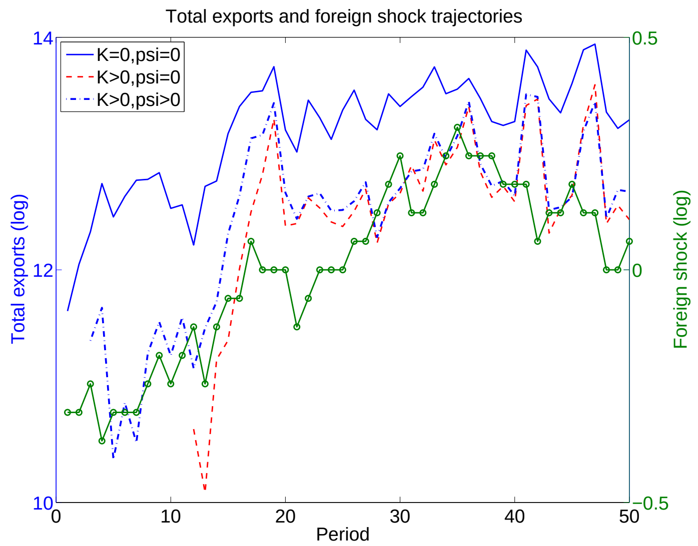


Figure 2.12. (Log of) Total exports and foreign shock trajectories.

exports grow during the early years are that x is improving and new exporters are building up their client bases. In contrast, when $K = 3,000$ and $\psi = 0.3$ low values of x during the early years discourage participation. As x improves, firms are drawn in, and those that come in are firms with relatively high productivity, so each contributes significantly to export volumes. Further, those exporters whose productivity deteriorates after entry continue to participate in foreign markets, reflecting the hysteresis effects summarized by Figure 2.9. Finally, sunk entry costs make the value of information relatively high, and thus induce new exporters to search for clients relatively intensively (Figure 2.6). All of these effects are stronger when scrap values are negligible (case 3 versus case 2) because the lack of an exit payoff makes selection on initial productivity stronger, eliminates incentives to liquidate firms, and increases the role of information by increasing the option value of staying in foreign markets.

2.5 Concluding remarks

Trade economists usually think about growth in manufactured exports as coming from established firms that diversify into foreign markets, starting with low export volumes and gradually increasing the share of output they ship abroad. But this pattern does not describe Bangladeshi and other developing countries' experiences, where new exporters have typically been new firms that were born to export. In Bangladesh these firms have entered big, not small, and survived in export markets at relatively high rates. Most of them sold all of their output abroad. We document these patterns using data on the universe of exporting firms in Bangladesh and a smaller sample of manufacturing establishments. We also show that similar but less-striking patterns appear in Chinese data, and that these features seem to be missing in Taiwan and Colombia, which accord with other typical cases of established exporters described in the literature.

We interpret these dynamics as being explained by the fact that exports come from “orphan industries" with very limited domestic markets. Thus, when profitable exporting opportunities arise, entrepreneurs are unable to exploit them by simply re-directing existing productive capacity toward foreign customers. Rather, they need to create whole new businesses. Furthermore, we argue that this phenomenon is not a consequence of the fact that export processing zones require firms to specialize in foreign sales (most Bangladeshi exports do not originate in EPZs).

Using a variant of the model in **?**, we show precisely how start-up costs can influence exporting patterns. First, when entrepreneurs must create productive capacity in order to export, only those producers who expect to sustain large export volumes are likely to enter. That is, sunk entry costs make Melitz-type selection effects relatively strong. Second, new exporters are relatively likely to survive in foreign markets. This hysteresis effect obtains because firms in orphan industries cannot reorient their production to domestic consumers when they experience negative shocks to their export profits, nor can they completely recoup their investment in productive capacity by shutting down. Third, it can take an exceptionally large market-wide shock to expected exporting profits before there is much of an export response. But once such a shock has occurred, rapid export growth may follow. This last result obtains partly because potential exporters face similar entry hurdles and, without any domestic market experience, they hold similar expectations about the scope of the market for their products. Thus they are likely to enter in large numbers, if at all. It also reflects the fact that once orphan industry exporters appear, they tend to survive, devoting their entire productive capacity to foreign sales.

A limitation of our approach is that we have not tried to link patterns of firm export participation to firm-level productivity. Although the model developed in section 2.4 relies on productivity differences across firms to generate entry and exit, the quality of our data prevents us from estimating a measure of productivity for Bangladeshi exporters.[31] We leave for future research a complete description of the channels between firm-productivity, orphan industries and born to export firms.

Throughout the paper we have been silent about policy issues. By itself, the BTE phenomenon that we document in Bangladesh is not indicative of a market failure in need of a particular policy response. However, in what follows we venture into three dimensions along which policy implications could be assessed: lack of existing manufacturing capacity,

[31]Recall that we are not able to merge customs data with industrial survey data.

uncertainty about profitability of new business opportunities and homogeneity of beliefs among entrepreneurs.

The lack of a domestic market, and, more generally, the absence of a developed manufacturing base, makes orphan industry exporting a particularly risky enterprise. First, entrepreneurs must sink substantial investments in productive capacity in order to export, rather than simply experiment by re-directing existing production toward foreign markets. Second, they must commit these resources without the benefit of production experience or feedback from domestic consumers about the appeal of their products. Thus, efforts to promote risk-pooling or venture capital markets may encourage this type of exporting.

Lacking idiosyncratic experiences in domestic markets, all potential orphan industry entrepreneurs are likely to hold similar beliefs about their prospects in export markets. Thus they are likely to move as a herd –or not at all– in response to market-wide shocks, be they informational (e.g. signals generated by pioneer firms) or economic (e.g. changes in trade barriers). When they do move, orphan industry entrants commit their entire capacity to foreign sales. These industries can generate dramatic export surges, but they can also be stubbornly unresponsive to modest export stimuli.

Finally, the fact that potential entrants are uniformly inexperienced makes them particularly sensitive to signals about market potential and best practices. As Hausmann and Rodrik (2003) have argued, this can create a coordination failure in which no entrepreneur wishes to generate information spillovers by being the pioneer entrant in an orphan industry. In the case of Bangladeshi apparel, this problem was surmounted by a joint venture between the Korean multinational Daewoo and the Bangladeshi firm Desh, which demonstrated the viability of exports and familiarized many Bangladeshi managers with production techniques and business practices. But the fact that Bangladesh has failed to diversify away from apparel suggests that it is difficult to replicate these conditions in other industries. It should be kept in mind that the single most successful story of industrial development in Bangladesh emerged not from a particular policy of industrial or export promotion, but from private agents that exploited a business opportunity.

Chapter 3
Productivity and Exporting: Selection, Learning by Exporting and Preparing to Export

3.1 Introduction

An extensive literature in international trade has studied the relationship between productivity and exporting, documenting significant productivity differences between exporters and non-exporters. In thinking about the sources of these differences, the productivity advantage of exporters has been attributed to (1) more productive firms self-selecting into exporting[1] and (2) exporters becoming more productive by learning by exporting[2] Distinguishing between these two, potentially complementary, hypothesis amounts to being able to sort out the direction of causality: does productivity cause exporting or the other way around? Furthermore, the discussion about causality has evolved to studying the determinants underlying productivity differences. In particular, researchers have tried to distinguish between exogenous selection (i.e. differences driven by stochastic productivity shocks) and endogenous selection (i.e. conscious actions by firms in order to increase efficiency). Thus, the links productivity and exporting literature could be classified into three hypothesis: (i) the (exogenous) self-selection hypothesis, (ii) the learning-by-exporting hypothesis, and (iii) the preparing to export hypothesis.

Recent papers have studied the links between firms investment decisions, export participation and productivity evolution in an empirical setting. Aw et al. (2007), Verhoogen (2008), Bustos (2011), Lileeva and Trefler (2010), and Aw et al. (2008) have found that

[1] See, among others, Aw and Hwang (1995), Bernard and Jensen (1999), Chen and Tang (1987), Tybout and Westbrook (1995), Roberts et al. (1995) and Alvarez and López (2005).

[2] See Clerides et al. (1998), Bernard and Jensen (1999), Baldwin and Gu (2003) and Alvarez and López (2005).

that access to foreign markets leads firms to improve performance by investing in R&D, technology or quality upgrading. Iacovone and Javorcik (2012) and Muendler and Molina (2013) have suggested that firms actively engage in activities that improve their performance with the purpose of entering export markets in the future, i.e. they "prepare to export". Artopoulos et al. (2013) have documented that successful Argentine pioneers went through a period of adapting domestic business practices to foreign ones before starting to export. Despite this large body of work, the relative quantitative importance of each channel within the same study hasn't been assessed. Apart from the variety of countries and periods, comparison is complicated due to the different measures used to identify firm performance.

In this paper, we study the links between productivity and exporting among Chinese manufacturing firms following China's accession to the WTO during 2000-2006. Rather than focusing on one hypothesis, we look at the evolution of firms' productivity over the whole period and decompose productivity growth before and after entering foreign markets. An advantage of the Chinese data is that they cover a period during which entry of new exporters was important, productivity increased dramatically and liberalization was gradual. Moreover, having many manufacturing industries allows us to study potential differences across industries with different degrees of export participation. Another feature of our data set is the availability of sales expenditures, which measure firms' efforts in building their marketing network, and revenue from newly introduced products, which is a result of past activities by firms to improve technology or introduce new products. These variables help to shed light on the particular ways in which firms can affect their productivity. We exploit the gradual liberalization of direct trading rights to try to assess whether productivity growth was associated to firms anticipating future improved access to foreign markets.

We first examine the path of firm productivity across types of firms with different export trajectories. Specifically, we compare the evolution of average productivity for always exporters, domestic firms who never exported, successful entrants into exporting and unsuccessful exporters. We find that future exporters are more productive than their domestic counterparts even three periods before they enter foreign markets. Productivity of successful entrants grows steadily before and after entry and catches up with always exporters after entry, but unsuccessful exporters' productivity decreases after exiting foreign markets. These findings are consistent with both selection and learning by exporting and suggest preparation to export.

In order to better understand and separate the effects of these channels, we then decompose the productivity growth into growth before and after entry. This decomposition shows that successful exporters experience most of their productivity growth after the entry, while the pattern is reversed for other exporters. Average annual productivity growth, however, is higher prior to entry for both groups. This is also true when compared to both non-exporters and continuous exporters. This suggests a period of intensive productivity growth leading to export, followed by a relatively longer period with lower average growth rates after entry. We then look at firms' behavior before exporting to detect possible productivity-enhancing activities. We find that future exporters enjoy a growth advantage of sales expenditures and revenue from new products for relative to other firms before and at the time of entry.

Finally, we use the events associated with China's gradual and anticipated liberalization of direct trading rights following its accession to the WTO to study other ways in which firms could have reacted to anticipated exporting opportunities. Our results suggest that, in addition to making cost- and demand-enhancing investments, Chinese firms invested with the specific purpose of acquiring direct trading rights.

The rest of the paper is organized as follows. In the following section we describe the data. In section 3.3 we present our strategy for recovering firm productivity and study productivity evolution across firms with different export trajectories. Section 3.4 uses data on sales expenditures and revenue from new products to link productivity growth to firms' actions prior to exporting. Section 3.5 exploits the gradual relaxation of trading rights to investigate firms' investment and exporting decisions during trade liberalization. We conclude with section 3.6.

3.2 Data

We use two Chinese datasets in our analysis. Our main dataset is comprised of firm-level data from the Annual Survey of Industrial Production (henceforth "survey data") from 1998 through 2006, conducted by the Chinese government's National Bureau of Statistics. Survey data includes all of the state-owned enterprises (SOEs) and non-SOEs with annual sales over RMB 5 million (about US$ 0.6 million). The data contain information on firms' 4-digit industry, ownership, age, employment, capital stock, wages, materials, revenue as well as firms' domestic and foreign sales. We combine survey data with Chinese customs transaction-level data (henceforth "customs data"), which has been collected and made available by the Chinese Customs Office. We observe the universe of Chinese firms that participated in international trade transactions over the 2000-2006 period. We match firms in both datasets and use customs data to distinguish direct and indirect exporters in the survey data.[3]

[3]Matching was on based on firm name, region code, address, legal person, and other firm characteristics. About 15.3% of exports were unmatched among producing exporters. For example, in 2004, intermediary

Our data include firms' levels of registered capital, which were used to determine whether firms were eligible for direct trading rights or not.[4] Restrictions on trading rights applied only to domestically owned firms, while foreign firms automatically had direct trading rights.[5] As an important commitment to eliminate trade barriers and expand market access, in 1997 the Chinese government agreed to liberalize trading rights as part of China's accession to the WTO. In 1998, the State Council approved the issuing of direct trading rights to domestic private firms and research institutes above certain sizes. The size requirements were lowered gradually over the years until 2004, when an amendment to the Foreign Trade Law lifted all requirements on direct trading rights.[6]

Table 3.1 below describes our sample after removing data with negative values for relevant variables and firms with gaps in the sequence of years (intermittent inclusion in the survey). There was significant entry of new exporters during the period and the gradual nature of the liberalization process is clear. The percentage of firms failing the eligibility criterion fell from 50% in 2000 to 31% in 2001 and only 5% in 2003.

Table 3.1: Total number of firms, exporters and eligible firms.

Year	N	Eligible firms (%)	Exporters		
			Indirect (%)	Direct (%)	Entry rate (%)
2000	128,180	48.2	13.7	11.2	-
2001	136,637	65.1	13.5	12.2	11.2
2002	148,234	68.0	13.5	13.4	10.2
2003	165,086	94.2	13.2	14.0	8.7
2004	232,559	100.0	11.9	16.6	12.8
2005	229,845	100.0	12.4	15.8	16.1
2006	255,556	100.0	11.3	15.2	7.8

Notes: the entry rate in year t is defined as the number of firms entering export markets in year t as a share of the total number of exporters in t.

firms accounted for 25.6% of total exported value and matched producers (producing exporters) accounted for 62.9%. Among unmatched firms and firms not surveyed, small manufacturing firms (with sales below 5 million Chinese Yuan) accounted for only 2% of exports, which leaves 9.5% accounted for by unmatched surveyed producers. See Bai et al. (2013) for additional details on the matching process.

[4] Registered capital, or authorized share capital, is the maximum value of securities that a company can legally issue. This number can be changed at the Administration for Industry and Commerce with shareholders' approval and capital verification certificates. Registered capital may be divided into (1) issued capital: par value of shares actually issued; (2) paid-up capital: money received from shareholders in exchange for shares; and (3) uncalled capital: money remaining unpaid by shareholders for shares they have bought.

[5] A firm is considered foreign owned if it has 25% or more foreign capital.

[6] See Bai et al. (2013) for a detailed description of the requirements for direct trading rights and the timing of size thresholds changes during the liberalization period.

3.3 Productivity evolution

3.3.1 Measuring productivity

In order to make statements about exporting and productivity, we first need a measure of firm-level productivity. Following a now long tradition in industrial organization, we recover firm-specific productivity by estimating a Cobb-Douglas production function in the spirit of Olley and Pakes (1996). Our empirical model assumes the following production function for firm i at time t generating output y_{it} from labor l_{it} and capital k_{it} (in logs) at productivity level ω_{it}

$$y_{it} = a + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it}, \tag{3.1}$$

where a is a constant intended to capture time, ownership and province average effects, and ϵ_{it} is the the standard i.i.d. error term capturing measurement error and unanticipated shocks to production. A key step in identifying ω_{it} is the specification of its law of motion. We follow the approach proposed in Aw et al. (2008) and DeLoecker (2013) and explicitly allow the evolution of productivity to depend on previous export experience. Specifically, exporting behavior is allowed to affect productivity in the following way:

$$\omega_{it+1} = g(\omega_{it}, e_{it}) + \xi_{it} \tag{3.2}$$

where e_{it} indicates firm i's export activity. In our implementation we use twos indicator variables that take the value of one if i is a direct exporter and zero otherwise, and one if i is an indirect exporter and zero otherwise. Bai et al. (2013) show that distinguishing export modes can have significant effects on estimated productivity.[7] In general, allowing for past export experience is important for the exercises we perform below. DeLoecker (2013) has shown that failing to control for past export experience can lead to biases in the estimates of the production function coefficients if a firm's factor usage (capital and labor) is correlated with its export status. This, in turn, can underestimate any learning by exporting effects.

The rest of our empirical implementation closely follows Olley and Pakes (1996) and Levinsohn and Petrin (2003). In the first stage regression, we use intermediate inputs m_{it} as proxy variables and estimate predicted output $\phi(m_{it}, l_{it}, k_{it}, e_{it})$ from $y_{it} = \phi(m_{it}, l_{it}, k_{it}, e_{it}) + \epsilon_{it}$, where $\phi(m_{it}, l_{it}, k_{it}, e_{it}) = \beta_l l_{it} + \beta_k k_{it} + h(m_{it}, k_{it}, e_{it})$, and $h(\cdot)$ is a proxy for productivity.

We use firm data on deflated values of firm revenue, book value of capital and labor employment from 2000 to 2006 to estimate (3.1) industry by industry for all two-digit

[7] In robustness checks we also consider other measures of export activity.

ISIC manufacturing industries. As a result, the measure of productivity we recover reflects sales per unit input at the firm level and, importantly, not only does it capture differences in the efficiency of production processes but also differences in profitability coming from firms' demand side.

3.3.2 Productivity evolution

During the period we study productivity increased dramatically in Chinese manufacturing. In our sample, the share-weighted average of productivity for all manufacturing firms increased 56.7% between 2000 and 2006. In this section we study the evolution of productivity for different groups of firms based on their export status and trajectories. We start by showing that the patterns observed in China during this period are consistent with all three hypothesis of exporting and productivity and then move on to quantify the relative importance of each.

3.3.2.1 Export trajectories and firm productivity

We are interested in understanding the relationship between the evolution of productivity and the timing of the export participation decision. Following Clerides et al. (1998) and Alvarez and López (2005), we start by looking at the path of productivity across firms with different export trajectories and the timing of entry into and exit from exporting. We isolate firm-specific productivity by running an OLS regression on the equation

$$\tilde{\omega}_{it} = \mathbf{D}_{it}\beta^D + \omega_{it}, \tag{3.3}$$

where $\mathbf{D}_{it}$ is a matrix including four-digit ISIC industry and year dummies. We use the residuals $\hat{\omega}_{it}$ to examine productivity evolution across exporters with different export participation patterns.[8]

We classify firms into five groups: (1) firms that exported in every year they are included in our sample ("always exporters"), (2) firms that never exported ("domestic"), (3) firms that began exporting at time $t > 2000$ for the first time in our sample and remain in export markets until they exit the sample (or until the last year in it)[9], (4) exporters that stopped exporting at some point during the period and remained domestic ("exiting exporters"), and (5) a residual groups that includes firms that enter and exit foreign markets without a clear pattern ("switchers"). We concentrate in groups (1)-(4) and exclude switchers for the time being. For groups (3) and (4) we normalize time

[8]For ease of notation we continue to denote these residuals ω_{it} throughout the rest of the paper.

[9]Exporters that are observed exporting in their first year in the sample and whose age is greater than one are not included in this group.

according to their date of entry or exit, $t^E = 0$, and track the average of the idiosyncratic component of productivity between $t^E - 3$ and $t^E + 3$. For groups (1) and (2) we set $t^E = 2003$. Since our emphasis is in changes over time for particular groups of firms, we keep a balanced panel and abstract from entry and exit.[10] Later in the paper we return to using the whole sample.

Figure 3.1 shows the paths of average idiosyncratic productivity for each group of firms. The patterns confirm the widely documented fact that exporters are more productive than non exporters and suggests that future exporters increase their productivity in the periods preceding entry into export markets. Future exporters are more productive than their domestic counterparts (that will never export) even three periods before they start exporting. Interestingly, exiting, unsuccessful exporters' productivity decreases steadily after they exit foreign markets (although it remains above that of domestic firms), but does not deteriorate before exiting. Successful exporters' productivity grows steadily since two periods before exporting, although at a lower growth rate after entry. These new entrants seem to catch up with permanent exporters quite fast, and after two periods their average productivity is equal to that of always exporters.

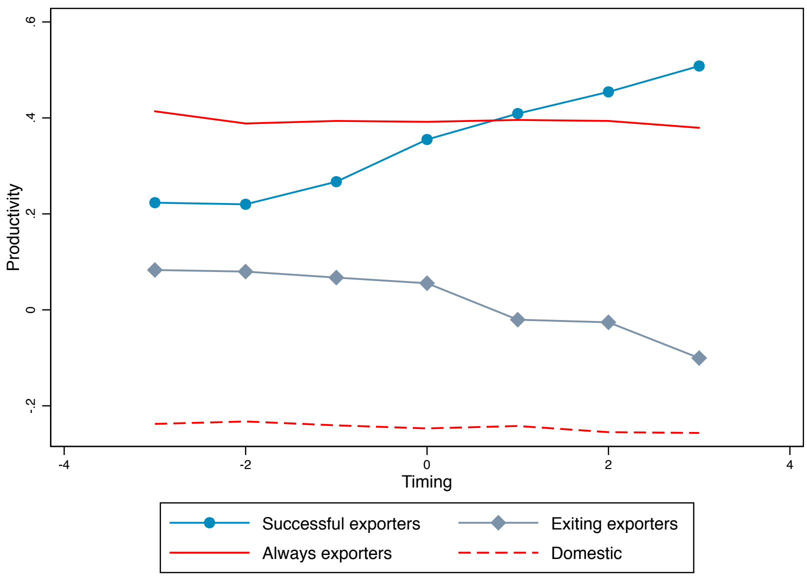


Figure 3.1. Exporting and productivity trajectories.

These findings, while suggestive, are consistent with both the selection and the learning by exporting hypotheses but do not, in principle, favor any of them exclusively. Even if productivity increased after entry and decreased after exit, the differences between exporters and non-exporters in Figure 3.1 could be due to persistent productivity shocks

[10]Our results are very similar if we consider the whole sample.

unrelated to the decision to export. Moreover, while future exporters could be purposely preparing to export by improving their productivity before entry, it could be that these firms received positive shocks that allowed them to become exporters.

As a robustness check, in the appendix we include trajectories for average variable costs and output per worker, two commonly used measures of firm efficiency. Using these variables we confirm that exporters were more efficient than non-exporters (showed lower average costs and higher output per worker). As to the timing of entry and exit, only successful exporters exhibit a fall in average variable the year the start exporting, but no significant decline after entry. We refer the reader to the appendix for additional details.

3.3.2.2 Productivity growth differences before and after entry

Figure 3.1 confounded across firms and over time variation in productivity. In this section we look at the variation of productivity along these two margins closely. We start by asking how much of a firm's productivity growth occurs before and after entering export markets. We answer this question by decomposing productivity growth into growth before and after a firm starts to export. Specifically, we apply the following exact decomposition:

$$\begin{aligned} \Delta\omega_{iT} = \omega_{iT} - \omega_{i0} &= \omega_{iT} - \omega_{it^E-1} + \omega_{it^E-1} - \omega_{i0} \\ &= \Delta\omega_{iA} + \Delta\omega_{iB}, \end{aligned} \tag{3.4}$$

where, for firm i, 0, T and t^E correspond to the first year in the sample, the last year in the sample and the year in which it started exporting (its export cohort), respectively. We restrict the sample to include those firms that change status during our sample and that are present at least two periods before and after entry. Moreover, within entrants, we distinguish successful entrants, as defined above, from the rest of exporters. We compute averages $(1/N_C)\sum_{i\in C}\Delta\omega_{it}$, for $C = \{\text{Successful exporters}, \text{Other exporters}\}$ and $t = T, A, B$. This decomposition offers a very simple test on the relative importance of preparing to export and learning by doing on the overall evolution of firm productivity over time. Moreover, if export success is positively associated to productivity before and after entry, comparing firms with different degrees of success in foreign markets gives another dimension along which we can measure the relative importance of learning and preparing to export. For instance, if learning by exporting is positively associated with export success, we should expect successful exporters to experience relatively higher productivity growth after rather than before entry compared with other exporters.

Table 3.2 presents the results for $\Delta\omega_{iT}$, $\Delta\omega_{iA}$, and $\Delta\omega_{iB}$. As previewed in Figure 3.1, successful exporters had higher productivity growth than other exporters (36.4% vs. 17.7%). However, for successful exporters 60.7% of the increase in productivity was realized after entry, while for other exporters only 33.8% of productivity growth occurred after entry. Notwithstanding these differences across exporters, *average* annual growth was higher before entry for both groups: 9.5% and 6.9% for successful and other exporters before entry, compared to 6.0% and 1.7%, respectively, after entry.

Table 3.2: Before and after export entry productivity growth decomposition.

	Entire period ($\Delta\omega_{iT}$)	Before entry ($\Delta\omega_{iB}$)		After entry ($\Delta\omega_{iA}$)	
A. Successful exporters					
Total growth	0.364	0.143	39.3%	0.221	60.7%
Annual average growth	0.068	0.095		0.060	
B. Other exporters					
Total growth	0.177	0.117	66.2%	0.060	33.8%
Annual average growth	0.034	0.069		0.017	

Notes: this table reports a before/after entry decomposition of productivity growth rates for entrants and successful entrants during 2000-2006. Sample is restricted to entrants that are in the sample at least two periods before and after entry. Reported figures are unweighted means over each group.

Total productivity growth was therefore strongly associated with success in foreign markets for Chinese exporters. Still, however different in their productivity growth patterns, exporting firms experienced at least on third of total productivity growth during their lowest contributing period, and average annual growth was higher on their way to foreign markets. As we will see below, most of the productivity growth after entry occurred the first year in foreign markets, possibly reflecting the fact that revenues increased sharply as a result of enlarging the market, without a corresponding adjustment in labor and/or capital during the first year as exporters.

We now turn to differences in productivity growth between successful exporters and other control groups at different windows before and after entry. In lack of more neutral terms, we define the average preparing to export effects (PTE) and average learning by exporting effects (LBE) s periods before and after starting to export as[11]

$$PTE_s = \frac{1}{N}\left(\sum_{i\in E}\Delta\omega_{is}^{-} - \sum_{i\in C}\Delta\omega_{is}^{-}\right), \tag{3.5}$$

$$LBE_s = \frac{1}{N}\left(\sum_{i\in E}\Delta\omega_{is}^{+} - \sum_{i\in C}\Delta\omega_{is}^{+}\right), \tag{3.6}$$

[11]The LBE effect is defined by DeLoecker (2013). We extend De Loecker's methodology to consider changes before entry.

where $\Delta x_{is}^{+} \equiv x_{it+s} - x_{it-1}$, $\Delta x_{is}^{-} \equiv x_{it-s} - x_{i0}$, $s = 0, 1, 2, ..., S$ ($S \leq t$ for Δx_{is}^{-}), E and C are the set of successful entrants and the control set, respectively, and N is the number of observations. For entrants we fix t to be the year they start to export, i.e. $t = t^{E}$. We consider $C = \{\text{Domestic firms}, \text{Always exporters}, \text{Other exporters}\}$ including year and four-digit ISIC industry dummies.

Table 3.3 shows that future (successful) exporters had an advantage of 7.4% in productivity growth over those firms that would remain domestic even four years before becoming exporters. This difference dropped to 6.9% the year before entering and jumped to 21.1% in the year of entry. Since our methodology for estimating productivity relies on both cost and demand variation, this sharp increase is most likely due to an increase in revenues for exporters as a result of enlarging their market. The productivity advantage of successful exporters over always exporters was also significant, although lower in magnitude: 5% four years before starting to export and 20% the entry year. Successful entrants and other new exporters did not differ significantly in their productivity growth trajectories on their way to becoming exporters. Only on the entry year successful exporters enjoy a 11.7% difference.

Table 3.3: Productivity of successful exporters before exporting.

Control group	Periods before entry				
	s=0	s=1	s=2	s=3	s=4
Domestic	0.211*	0.069*	0.089*	0.094*	0.074*
	(0.005)	(0.005)	(0.006)	(0.008)	(0.010)
N	840,718	840,095	830,677	826,460	824,539
Always exporters	0.200*	0.048*	0.061*	0.068*	0.050*
	(0.004)	(0.004)	(0.006)	(0.008)	(0.010)
N	254,596	253,973	244,555	240,338	238,417
Other Exporters	0.117*	0.009	0.009	0.007	0.015
	(0.006)	(0.006)	(0.009)	(0.011)	(0.012)
N	51,630	29,655	15,132	8,783	5,509

Notes: this table reports the results from a regression of $\Delta\omega_{is}^{-}$ on X_i^E and a set of controls, where X_i^E is an indicator variable that takes the value of 1 if i is a successful exporter and 0 if it belongs to the control group, and s are periods before entry into exporting. Controls include year and four-digit ISIC industry dummies. Standard errors in parenthesis. *,** and $^{+}$ indicate significance at the 1%, 5% and 10% level, respectively.

Once they entered foreign markets, successful exporters kept increasing their productivity differences with firms with other exporting status. As table 3.4 shows, four years after entry the productivity of entrants had grown 28.8% more than domestic firms, 24.7% more than always exporters and 23.9% higher than other, unsuccessful exporters. Furthermore,

Table 3.4: Productivity of successful exporters after starting to export.

Control group	Periods after entry				
	s=0	s=1	s=2	s=3	s=4
Domestic	0.153*	0.239*	0.251*	0.301*	0.288*
	(0.004)	(0.006)	(0.010)	(0.015)	(0.020)
N	$549,516$	$359,368$	$208,854$	$123,873$	$69,175$
Always exporters	0.157*	0.235*	0.230*	0.262*	0.247*
	(0.004)	(0.006)	(0.009)	(0.013)	(0.018)
N	$184,184$	$128,886$	$80,660$	$51,167$	$30,026$
Other Exporters	0.015^+	0.123*	0.188*	0.222*	0.239*
	(0.008)	(0.010)	(0.014)	(0.020)	(0.027)
N	$29,655$	$22,959$	$13,478$	$7,124$	$4,463$

Notes: this table reports the results from a regression of $\Delta\omega_{is}^{+}$ on X_i^E and a set of controls, where X_i^E is an indicator variable that takes the value of 1 if i is a successful exporter and 0 if it belongs to the control group, and s are periods before entry into exporting. Controls include year and four-digit ISIC industry dummies. Standard errors in parenthesis. *,** and $^{+}$ indicate significance at the 1%, 5% and 10% level, respectively.

most of the differences in growth were experienced during the first two years in export markets. In particular, when compared with other exporters, the learning by exporting effect of successful exporters, which was small at entry (1.5%), increased by more than 10 percentage points to 12.3% one year after entry, suggesting that experience during the first year in foreign markets was an important factor explaining productivity growth differences among new exporters.

To summarize, most of the productivity growth of new exporters occurred after entering export markets, rather than before, but annual growth was higher during the years prior to exporting. This suggests a period of intensive productivity growth leading to export, followed by a relatively longer period with lower average growth rates after entry. When explaining the cross-sectional growth differences between firms with different export status in China, it was at and after entry that successful exporters stood apart from the rest.

3.4 Preparing to export through demand and supply

In the last section we quantified the productivity differences across firms and over time before and after exporting. New exporters, and in particular future successful exporters, had a productivity growth advantage over domestic firms and permanent exporters. In this section we look at two particular variables that could shed light on the sources behind the advantages in productivity growth for new exporters. The first is sales expenditures, which is recorded as the expenditure each firm spent on marketing its products. This includes the cost of establishing and running its marketing network, such as packaging, shipping, loading and insurance. The second variable is revenue from new products, and is defined as sales from newly introduced products. Products are considered newly introduced if they are produced with newly invented or recently improved production technology, and have been introduced by the firm within one to three years for consumer goods and within two to four years for intermediate goods.

We view these variables as capturing conscious actions by firms aimed at improving both demand and cost stochastic processes, which in turn affect our measure of productivity. By spending more resources on packaging, reducing shipping times or extending insurance, firms can improve the quality of their products and business relationships with their distribution network. Higher revenue from new products reflects firms past expenditures in developing or applying newer technologies, presumably allowing them to lower average costs, and past efforts to introduce new products to expand their consumer base. These dimensions have been receiving increased attention as important determinants of export success in developing countries. Artopoulos et al. (2013) found that a key feature of consistent Argentine exporters to developed countries was their ability to adopt new business practices, different from those employed by domestic producers, in order to enter foreign markets. These new business models include both new marketing and product practices, which intend to upgrade technology and strengthen ties with foreign distributors.

We measure growth differences in sales expenditures and revenue from new products as a share of total revenue across firms by computing the PTE_s defined in section 3.3.2.2 replacing productivity with sales expenditures and revenue from new products. Table 3.5 presents the growth advantage of successful exporters relative to different control groups. The difference in growth rates of sales expenditures of successful exporters vis-à-vis domestic firms is relatively constant two and three periods before entry, but increases one period before and, specially, the period new exporters start to export. Growth rates in revenue from new products between future exporters and domestic firms do not appear to be significantly different from zero two or more periods before exporting, but, as with sales expenditures, they are significantly higher one period before and during the entry period. These patterns are qualitatively similar when compared to other exporters, but lower in magnitude. Growth in sales expenditures is significantly higher for successful exporters only during the entry period when compared to always exporters and other entrants, and the growth advantage in revenue from new products shows up one period before exporting, increasing at entry.

We should be careful when interpreting these results since, unfortunately, we cannot

Table 3.5: Performance of successful exporters before exporting.

	Periods before entry				
	s=0	s=1	s=2	s=3	s=4
A. Control group: domestic firms					
Sales expenditures	0.234*	0.094*	0.061*	0.060*	0.038
	(0.012)	(0.012)	(0.017)	(0.023)	(0.028)
N	841,994	841,371	831,952	827,728	825,806
New products revenue	0.963*	0.633*	0.028	−0.038+	−0.019
	(0.013)	(0.013)	(0.017)	(0.023)	(0.028)
N	842,106	841,483	832,064	827,839	825,917
B. Control group: always exporters					
Sales expenditures	0.107*	−0.009	−0.017	0.020	0.028
	(0.012)	(0.011)	(0.016)	(0.021)	(0.026)
N	254,541	253,918	244,499	240,275	238,353
New products revenue	0.723*	0.461*	−0.036	−0.050	−0.027
	(0.019)	(0.018)	(0.025)	(0.033)	(0.041)
N	254,633	254,010	244,591	240,366	238,444
C. Control group: other exporters					
Sales expenditures	0.119*	0.023	−0.000	0.010	−0.035
	(0.017)	(0.018)	(0.025)	(0.029)	(0.031)
N	51,648	29,664	15,140	8,784	5,508
New products revenue	0.236*	0.072**	−0.011	−0.062	−0.008
	(0.028)	(0.030)	(0.035)	(0.044)	(0.045)
N	51,652	29,667	15,143	8,786	5,510

Notes: this table reports the results from a regression of Δy_{is}^{-} on X_i^E and a set of controls, where X_i^E is an indicator variable that takes the value of 1 if i is a successful exporter and 0 if it belongs to the control group, and s are periods before entry into exporting. Controls include year and four-digit ISIC industry dummies. Standard errors in parenthesis. *,** and + indicate significance at the 1%, 5% and 10% level, respectively.

observe sales expenditures and new products revenue differently for the domestic and foreign markets. For instance, it could be that successful exporters introduce new products to serve the domestic market instead of foreign markets. In fact, the definition of new products includes products introduced in the last one to three years. Iacovone and Javorcik (2010) find that, following trade liberalization, new Mexican exporters start exporting varieties that were previously selling at home. Still, this could be interpreted as future exporters introducing new varieties for export but experimenting with them at home before selling them abroad. The fact that growth in new product revenue for successful entrants is higher than for other firms only during the entry period and one year before is suggestive of this pattern. Our data, however, does not allow us to test this hypothesis.

3.5 Liberalization of trading rights

Our sample includes a period during which China underwent significant trade liberalization. From 2000 to 2004 capital requirements for acquisition of direct trading rights were gradually relaxed, lowering fixed costs of direct exporting for those firms that were ineligible in the past. Between 22% and 27% of constrained firms increased registered capital each year between 2000 and 2003, while between 14% and 4% decreased it during that period. In this section we study the effects of the removal of direct trading restrictions on firms' investment behavior and export participation.

3.5.1 Investment behavior

During the liberalization period firms differed in their expected opportunities to access foreign markets. On the one hand, firms were heterogeneous in their registered capital levels, κ_{it}. On the other hand, they also faced different liberalization time tables.[12] This may have induced heterogeneous responses across firms related to their export decisions. Consider Figure 3.2, which depicts the evolution of capital requirements κ^*_{it} for a particular group of firms. Firms above the capital requirement (group 1) were unconstrained and hence did not need to increase registered capital in order to export. For firms below the threshold at t we can distinguish two groups. Group 2 is composed of firms expecting to become eligible at $t+1$ because the capital requirement is expected to decrease. Since there was some uncertainty with respect to the exact reduction in requirements, depending on their distance to the threshold, firms in this group would have different incentives to increase registered capital relative to group 1. Firms very close to period t's threshold intending to export directly, for example, would have few incentives to increase registered capital, since at their current registered capital level they would most likely become eligible next period. Firms farther from the required level would be more likely to increase registered capital if they are uncertain of the exact level of the future requirement. Firms in group 3 that wanted to obtain direct trading right at $t+1$, instead, would be more likely to increase registered capital than those in other groups, since otherwise they would remain below the $t+1$ threshold and remain ineligible.

We can test whether firms were behaving in a manner consistent with the story in the previous paragraph by estimating the effects of belonging to one of the eligibility groups

[12] Refer to the description of capital requirements in the appendix.

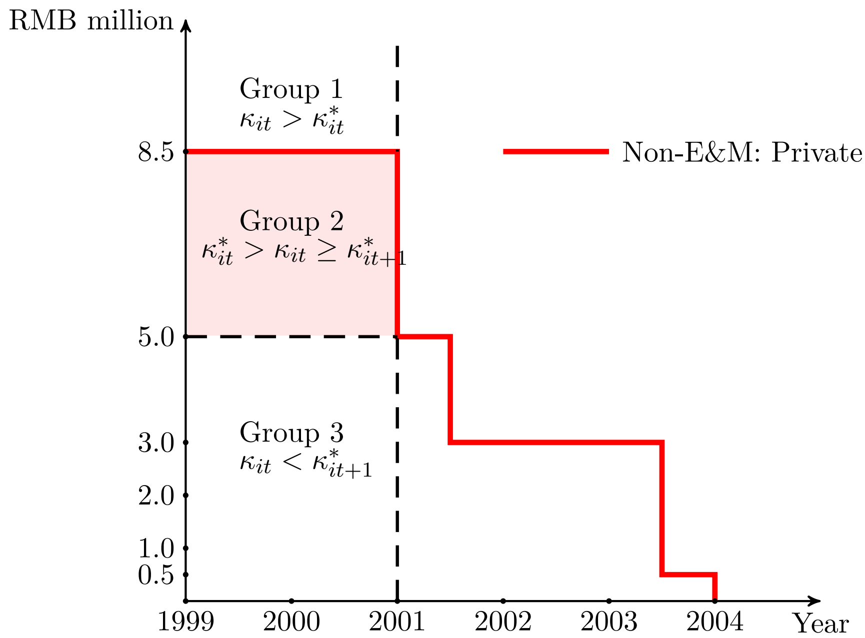


Figure 3.2. Direct trading eligibility groups.

in Figure 3.2 on the probability of changing registered capital. To this end, we estimate the following probit model for the probability of increasing registered capital:

$$\Pr\Big(\Delta\kappa_{t+1} > 0|\mathbf{D}^G_{it}, \mathbf{z}_{it}\Big) = \Phi\left(\mathbf{D}^G_{it}\beta^G + \mathbf{z}_{it}\beta^Z\right), \tag{3.7}$$

where, Φ is the standard normal cumulative distribution function, $\Delta x_{t+1} \equiv x_{t+1} - x_t$, $\mathbf{D}^G_{it}$ is a vector of indicator variables for whether firm i belong to groups 2 or 3 (the excluded category is group 1) and $\mathbf{z}_{it}$ is a vector of controls that includes year, four-digit ISIC industry, ownership, and province dummies; and firm i's capital stock, employment, revenue, productivity and an indicator function for whether firm i expanded its capital stock. We also control for the effect of increasing competition as more firms became eligible for direct trading overtime.[13] We restrict the sample to those firms that were not foreign owned at the beginning of the sample.

The results in Table 3.6 confirm the intuition outlined above. Firms in group 2 were more likely to increase registered capital relative to those in group 1, and those in group 3 were even more likely to do so.[14]

[13]For firm i, we use the revenue-adjusted share of eligible firms that were similar to i in terms of productivity, registered capital, ownership, industry and province as a proxy for the competition effect. As the policy changes applied to different groups of firms at the same time, the group indicator variables which represent firm i's eligibility are correlated with other firms obtaining eligibility, and thus correlated with the effect of increasing competition, which would otherwise be left in the error term. Not controlling for this effect would bias our estimates of the coefficients on $\mathbf{D}^G_{it}$.

[14]According to our logic, firms in group 3 at t in a neighborhood of period $t+1$'s threshold intending

Firms bound by the size thresholds who found direct exporting sufficiently profitable may have invested in registered capital to obtain direct trading rights. As the government gradually lowered the size thresholds, firms that had invested in registered capital just for the sake of eligibility may have found it optimal to dis-invest and re-allocate resources. To investigate this channel, we re-estimate model (3.7) replacing the components of vector $\mathbf{D}_{it}^{G}$ with indicator variables for the timing of eligibility (i.e. if firm i became eligible, has been eligible for some time, or will become eligible in the future).

Table 3.7 indicates that becoming eligible at period t makes it less likely for firms to increase their registered capital and more likely to decrease it. Remaining eligible for the following one or two periods has the same, significant negative effect on the probability that a firm increases registered capital. Past the period in which they acquired trading rights, firms tended to keep their registered capital levels constant. Export status does not seem to have driven the probability of firms changing their registered capital levels. This evidence is consistent with our conjecture that firms consciously invested in registered capital in order to obtain direct trading rights and, once obtained or once the requirement was relaxed, they stopped investing or decreased registered capital.

Table 3.6: Registered capital and and eligibility status.

	$\Pr(\Delta\kappa_{t+1} > 0)$	$\Pr(\Delta\kappa_{t+1} < 0)$
Group 2	0.216*	−0.314*
	(0.009)	(0.009)
Group 3	0.349*	−0.514*
	(0.009)	(0.009)
N	793,791	793,791

Notes: probit regression for the probability of increasing and decreasing registered capital κ. Standard errors in parenthesis. *,** and $^{+}$ indicate significance at the 1%, 5% and 10% level, respectively.

3.5.2 Eligibility and export participation

In this section we study how the timing of liberalization effected the probability of entry into export markets. If direct trading rights were not binding because more productive firms were already above the thresholds, we shouldn't see any effect of becoming eligible on the probability of exporting. On the other hand, since firms could choose to invest and acquire rights, if firms invested with the objective of exporting in the future we should

to become direct exporters would be even more likely to increase registered capital, since a small increase would render them eligible. In results available upon request, adding an indicator variable for firms in this group rejects this hypothesis, even when we interact it with firms that were also indirect exporters.

Table 3.7: Registered capital and and eligibility status.

	$\Pr(\Delta\kappa_{t+1} > 0)$	$\Pr(\Delta\kappa_{t+1} < 0)$
Becoming eligible	-0.084^{*}	0.097^{*}
	(0.007)	(0.007)
Eligible since $t-1$	-0.022^{*}	-0.001
	(0.004)	(0.005)
Eligible since $t-2$	-0.060^{*}	0.006
	(0.005)	(0.006)
Indirect exporter	-0.026^{*}	-0.013^{**}
	(0.006)	(0.006)
Direct exporter	-0.050^{*}	-0.097^{*}
	(0.008)	(0.009)
N	$702,344$	$702,344$

Notes: probit regression for the probability of increasing and decreasing registered capital κ. Standard errors in parenthesis. *,** and $^{+}$ indicate significance at the 1%, 5% and 10% level, respectively.

observe a higher probability of starting to export for those firms who satisfied the capital requirement "endogenously" (i.e. by investing). As before, then, we first classify firms according to whether they became eligible in the current period, became eligible last period or became eligible two periods ago. Additionally, we identify those firms that obtained rights because they increased their registered capital. These firms would have remained below the capital requirement had they not invested. We estimate model (3.7) for the probability of exporting using these groups indicators, as well as export status indicators for direct and indirect exporters, in vector $\mathbf{D}_{it}^{G}$. Vector $\mathbf{z}_{it}$ includes firm i's lagged capital, employment, wage, revenue and productivity. We restrict the sample to those firms that were not foreign owned at the beginning of the sample.

First we estimate the probability of starting to export, conditional on not exporting the period before. Table **??** presents the results. Becoming eligible in the current period, as well as one and two periods before, are positively and significantly associated with a higher probability of starting to export. The coefficient on one-period lagged change in eligibility being the highest, moreover, suggests that it took some time for firms to start exporting once they were eligible.

New exporters could be direct or indirect exporters. Since the liberalization of capital constraints was especially related to direct exporting, we then look at the probability of staring to export directly, conditional on not being a direct exporter the period before. There are two patterns of interest that come out from the results. First, becoming eligible in the current period is no longer a predictor of direct exporting. The coefficient is negative and significant. Instead, the results suggest that it took one or two periods in order to start exporting directly, consistent with firms having to prepare to do so. Second, indirect exporters, as could be expected, were much more likely to become direct exporters than non-exporters. These firms had already covered some of the sunk costs of exporting and had more experience in testing their products foreign markets through intermediaries. In this sense, indirect exporting could be seen as preparation to export directly. In column three we include an indicator variable for those firms that endogenously became eligible. The coefficient is positive, high and significant, and decreases the effect of becoming eligible (independently of the reason) to twice the original coefficient (in column 2). It seems, then, that firms' investment behavior with respect to capital requirements was significantly associated to the decision to export.

Columns 3 and 4 repeat the exercise for the probability of exporting as an indirect exporter, conditional on no exports the period before. To further examine whether firms export indirectly as a preparation to export directly, we estimate the probability of starting to export indirectly, conditional on not exporting the period before. The results are similar to those for direct exporters, with the difference that becoming eligible did have an positive, significant effect on the probability of starting to export. As before, though, this effect was higher for those firms that invested to overcome the capital constraint.

The results in this section point out that registered capital restrictions were not neutral with respect to the entry decisions among Chinese firms. In particular, our results suggest that constrained firms that invested to overcome the constraint did so with the purpose of acquiring rights and begin to export. Moreover, for indirect exporters, relaxing capital constraints had a positive on the probability of exporting. Lower requirements could have decreased the costs of exporting for these firms, as they now had access to a larger pool of exporters through which they could sell their products abroad.

3.6 Conclusion

In this paper, we study the links between productivity and export behavior and try to disentangle the export-productivity correlation that has been documented thoroughly in the international trade literature. Using unique features of Chinese firm-level data, we focus on the entire evolution of productivity of Chinese firms before and after they enter export markets.

We find evidence of all three channels of the export-productivity correlation among Chinese exporters. Particularly, exporters are more productive than non-exporters, which is consistent with selection. Future exporters' productivity grows steadily before and after they enter the foreign market. Most of this growth accrues after entry for successful exporters, while the pattern is reversed for unsuccessful exporters. Average annual productivity growth, however, is higher prior to entry for all exporters. This is consistent with both the learning-by-exporting and preparing to export. Finally, sales expenditures and revenue from new products increase more for successful exporters than for other firms before and when they start exporting, indicating that firms do involve in productivity enhancing activities before starting to export. We also exploit China's gradual and anticipated liberalization of direct trading rights following its accession to the WTO. Our results suggest that, in addition to making cost- and demand-enhancing investments, Chinese firms invested with the specific purpose of acquiring direct trading rights.

Throughout the paper we are careful when making causal statements about the correlations we find between productivity and export participation. We consider that developing a structural of model that includes details of firms' export and productivity-enhancing investment decisions is a fundamental step for elucidating the directions of causality between exporting and productivity. We plan to continue along this line of research in our future work.

Appendix A
Estimation of conversion efficiency

I construct a measure of average firm-level conversion efficiency using Photon's Solar Module Database. Photon's database has information about over 1,200 firms (module suppliers) and 48,000 varieties (module types). Among other variables, for each variety the database reports the country of origin, cell technology, conversion efficiency, the year it started being produced, and the year production ceased. In general, during any given period firms produce different models with different conversion efficiencies, so that each firm can be associated to more than one conversion efficiency value. To assign a single conversion efficiency value for each firm-year pair in my sample, I therefore identify all module varieties that were being produced by the firm that year, irrespective of origin, and compute the maximum over all module conversion efficiencies. In doing this, I drop all observations for which either the start or the stop period are missing.

The choice of the maximum rather than the average (or other moment) rests in the assumption that the maximum efficiency offered by the firm represents the relevant technological frontier of the firm, and the one the firm will advertise and be better known for.

The resulting sample shows variability over time and firms, with efficiency ranging from a minimum of 2.5% to a maximum of 19.6%. As one would expect, (maximum) module efficiency tends to increase over time for all firms, although some do show decreases for some periods. On average, maximum conversion efficiency increases 3% per year in the sample. The sample, however, has missing years for many firms, especially in the earlier period. The EIA survey has conversion efficiency figures only for 2007-2009, so I cannot use these data to fill in missing years in the earlier period. I therefore take the average conversion efficiency for each firm, which I then use in the demand estimation stage.

Appendix B
Estimation of an Ornstein-Uhlenbeck process

The dynamics of an Ornstein-Uhlenbeck (OU) process is described by the stochastic differential equation $dy_t = \lambda_y(\bar{y} - y_t)dt + \sigma dW_t$, where W_t is a Wiener process and $\bar{y}$ is the long-run mean. The parameters of the discretized Ehrenfest process and the associated OU process are related as $\gamma_y = n\lambda_y$ and $\Delta = \sigma/\sqrt{n\lambda_y}$. σ and λ_y can be estimated as follows. The differential equation describing the OU process can be approximated by the stochastic difference equation

$$y_{t+1} = y_t e^{-\lambda_y \delta} + \bar{y}(1 - e^{-\lambda_y \delta}) + \sigma\sqrt{\frac{1 - e^{-2\lambda_y \delta}}{2\lambda_y}} N_{0,1},$$

where δ is the time step (i.e. $\delta = 1$ for annual data) and $N_{0,1}$ is a normal random variable. Given a time series $\{y_t\}_{t=0}^{T}$, one can recover the parameters $(\bar{y}, \lambda_y, \sigma)$ by estimating the parameters of an autoregressive process $y_{t+1} = ay_t + b + \epsilon_t$ and computing

$$\begin{aligned} \lambda_y &= -\log(a)/\delta, \\ \bar{y} &= b/(1-a), \\ \sigma &= sd(\epsilon_t)\sqrt{\frac{-2\log(a)}{\delta(1-a^2)}}. \end{aligned}$$

Appendix C
The Simulated Minimum Distance Estimator

The exposition here closely follows Hall and Rust (2003) and Goettler and Gordon (2011). To apply the SMD estimator the model needs to be solved and simulated for each guess of parameter θ, starting at an initial condition (ω_0, ς_0). Since the model is set in continuous time, a typical simulation generates N jumps at times $\{t_n\}_{n=1}^N$, $t_n < t_{n+1}$ with $N = \max\{n : t_n < T\}$, for some number of discrete periods T. Variables change values at times t_n, when a jump occurs, and remain constant until there is a new jump, so that if variable y is an outcome of the model, it can be summarized as $\{y(t_n)\}_{n=0}^N$, where $t_0 = 0$ indexes the initial condition and the dependence of $y(t_n)$ on $(\omega_{t_n}, \varsigma_{t_n})$ is implicit. Variables are then discretized by integrating their values (i.e. computing their weighted sum) within discrete periods. To be precise, y_t, $t \in \mathbb{N}$, is given by

$$y_t = (t_{\underline{n}} - t + 1)y(t_{\underline{n}-1}) + \sum_{i=\underline{n}}^{\overline{n}} (t_{i+1} - t_i)y(t_i) + (t - t_{\overline{n}})y(t_{\overline{n}}),$$

where $\underline{n} = \min\{n : t_n \geq t - 1\}$ and $\overline{n} = \max\{n : t_n \leq t\}$. Discounting is applied when necessary (e.g. when computing discounted profits). Jump arrival times are stochastic outcomes that depend on the hazard rates specified by the model. Each simulation s then needs a (different) set of i.i.d. uniform random draws to generate these jump arrival times, denoted $\{U_n^s\}_{n=1}^N$. These numbers are drawn once at the beginning of the estimation exercise for each s and held fixed throughout so that continuity of the estimator's objective function is preserved. I run S simulations of T discrete periods each, and denote the set of simulated, discretized industry outcomes $\{\{\mu_{st}(\theta, \theta^{1\text{st}}, U_{<t}^s, \omega_0, \varsigma_0)\}_{t=1}^T\}_{s=1}^S$, where the notation $U_{<t}^s$ indicates that μ_{st} depends only on the first n ($t_n < t$) realizations of $\{U_n^s\}_{n=1}^N$ and not on subsequent realized values (i.e. the simulated process is adapted to $\{\{U_n^s\}_{n=1}^N\}_{s=1}^S$).

Let the $M \times 1$ vector of moments using actual data be $\mathbf{m}_T = m(\{\mu_t^{\text{data}}\}_{t=1}^T)$. Moments computed using the simulated data are

$$\mathbf{m}_{ST}(\theta) = \frac{1}{S}\sum_{s=1}^{S} m(\{\mu_{st}(\theta, \hat{\theta}^{1\text{st}}, U_{<t}^s, \omega_0, \varsigma_0)\}_{t=1}^T).$$

The SMD estimator is defined by

$$\hat{\theta}_T = \underset{\theta\in\Theta}{\arg\min}\, [\mathbf{m}_{ST}(\theta) - \mathbf{m}_T]' \, W_T \, [\mathbf{m}_{ST}(\theta) - \mathbf{m}_T] \,, \tag{C.1}$$

where W_T is a weighting matrix. Let $\mu_t \equiv \{\omega_t, \varsigma_t, p_t, x_t, \chi_t, \chi_{et}\}$ be the stochastic Markov process that results from the model, where $\{p_t, x_t, \chi_t\}$ are the vectors of firm decisions, i.e. $\{(p_{jt})_{j=1}^J, (x_{jt})_{j=1}^J, (\chi_{jt})_{j=1}^J\}$, and let f_μ be its transition probability. I assume the following:

Assumption 1 For any θ, $\{\mu_{st}(\theta^*, \theta^{1\text{st}}, U_{<t}^s, \omega_0, \varsigma_0)\}$ is ergodic with a unique invariant density $\Psi(\mu|\theta)$ given by

$$\Psi(\mu'|\theta) = \int f_\mu(\mu'|\mu, \theta) d\Psi(\mu|\theta)$$

Assumption 2 The model is correctly specified, i.e. there exists θ^* such that the simulated series $\{\mu_{st}(\theta^*, \theta^{1\text{st}}, U_{<t}^s, \omega_0, \varsigma_0)\}$ has the same probability distribution as the observed series $\{\mu_t^{\text{data}}\}$.

Assumption 3 θ^* is identified, i.e. if $\tilde{\theta} \neq \theta^*$,

$$\text{E}[m(\{\mu_{st}\}_{t=1}^T)|\tilde{\theta}] \neq \text{E}[m(\mu_{st})|\theta^*] = E[m(\{\mu_t^{\text{data}}\}_{t=1}^T)],$$

where $\text{E}[m(\mu)|\theta] = \int m(\mu) d\Psi(\mu|\theta)$. Additionally, $\text{rank}(\nabla\text{E}(m|\theta) = K$, where K is the number of components of θ; $\nabla\text{E}(m|\theta) \equiv \frac{\partial}{\partial\theta}\int m(\mu)d\Psi(\mu|\theta)$; and $\lim_{T\to\infty} W_T = W$, where W is a $M \times M$ positive definite matrix.

Under assumptions 1-3, the minimum distance estimator $\hat{\theta}_T$ is consistent and its asymptotic distribution is given by:

$$\sqrt{T}(\hat{\theta}_T - \theta^*) \to N(0, (1 + 1/S)\Lambda_1^{-1}\Lambda_2\Lambda_1^{-1}),$$

where

$$\Lambda_1 = \nabla\text{E}(m|\theta)' W \nabla\text{E}(m|\theta),$$
$$\Lambda_2 = \nabla\text{E}(m|\theta)' W \mathcal{V}(m|\theta^*) W \nabla\text{E}(m|\theta),$$

$$\mathcal{V}(m|\theta^*) = \mathrm{E}\{\{m(\mu) - \mathrm{E}[m(\mu)]\}\{m(\mu) - \mathrm{E}[m(\mu)]\}\}.$$

A consistent estimate of the optimal weighting matrix $\mathcal{V}(m|\theta^*)^{-1}$ is the inverse of covariance matrix of the moments computed using the actual data, $W_T = [\mathrm{Cov}(m_T)]^{-1}$. To estimate $\nabla \mathrm{E}(m|\theta)$, I follow Dix-Carneiro (2014) and compute it as follows. For each parameter θ_k in θ, I sample 20 points $\hat{\theta}_T + \varepsilon_k e_k$, where $|\varepsilon_k|$ is a small number and e_k is a vector of zeros with a one in the kth position, and compute $\mathbf{m}_{ST,k}(\hat{\theta}_T + \varepsilon_k e_k)$. Then I fit a second-order polynomial of $\mathbf{m}_{ST,k}$ on $(\hat{\theta}_T + \varepsilon_k e_k)$. Finally, I obtain an approximation for $\partial m/\partial\theta|_{\theta=\hat{\theta}_T}$ by computing the derivative of the polynomial at $\hat{\theta}_{T,k}$.

Appendix D
Country data sources

D.1 Bangladesh

We employ three data sets: plants' exports shipments data from customs declarations, tax registration data and industrial survey data.

Plants' exports shipments data come from customs declarations at Bangladesh's National Board of Revenue (NBR) compiled using UNCTAD's ASYCUDA++ system.[1,2] The database contains information on international trade shipments by individual exporters form 2004 to 2009 in daily frequency at the 8-digit HS code level. Each observation corresponds to a declared item, so that a single exporter could be identified with more than one observation in the sample. For each shipment in the data we observe exporter ID, destination country, item's HS code (plus three description fields),[3] gross weight, net weight, units, declared value, delivery terms (FOB, CFR, CIF, etc.), mode of transport and terms of payment, among other variables. The data set is augmented by including daily time series for the Taka/USD nominal exchange rate from the Central Bank of Bangladesh to convert values reported in domestic currency. For 2009, the data comprises 7,324 exporters, 1,800 products and 187 destinations. For every year in our sample the data account for more than 95% of aggregate exports as reported by official statistics.

Tax registration data for exporters comes from the NBR. For plants in this data set we obtain a tax ID (specifically, a "business identification number" —BIN) and a tax registration date. The latter allows us to construct a measure of exporter's age. Since

[1]ASYCUDA++ is an automatic system created by UNCTAD to assist developing countries in the compilation of foreign trade statistics.

[2]We are grateful to Chris Woodruff and Rocco Macchiavello for providing us with missing observations for 2006.

[3]For example: HS 52081100, Unbleached plain woven fabrics of cotton W, ith>=85% cotton, =<100g/M2, 100% cotton canvas W 58/59 =7000 YDS. Note, however, that although the HS at the 8 digit level is country-specific, most of the codes in Bangladesh end in 00, so that 8 digit codes map almost one to one to 6 digit codes, which are universal and can be compared across countries.

exporters in the customs data are also identified by BINs, we can merge tax registries with customs records. We can match between 85% and 90% of exporters and more than 90% of exports in any year.

Industrial survey data come from the Survey of Manufacturing Industries (SMI), conducted by the Bangladesh Bureau of Statistics (BBS). The BBS has conducted the SMI regularly since 1973. We have access to data containing information from the last three editions of the SMI: 1999-2001, 2001-2002 and 2005-2006. The SMI covers manufacturing establishments with 10 or more workers, irrespective of whether they use power or not. We only have specific information about the details of how the 2005-2006 survey was conducted. From the "Report on Survey of Manufacturing Industries 2005-2006" Bangladesh Bureau of Statistics (undated) we know that the survey was based on the 2001-2003 economic census, covering only 18.5 % of establishments. We do not know how these establishments were selected, however.

The information collected by the SMI is classified into 4-digit manufacturing industries following the Bangladesh Standard Industrial Classification (BSIC).[4] The survey collects data on a number of production variables such as employment, labor costs, fixed assets, raw materials used in production, domestic sales and foreign sales. An important drawback of our survey data is that establishments' IDs are survey edition-specific and hence establishments cannot be tracked over time nor linked to other plant-level data we use.

D.2 China, Colombia and Taiwan

For both China and Colombia we are able to employ export shipments from customs and industrial survey data (although for confidentiality reasons we are not allowed to use merged datasets). For China, export shipments data were collected by the Chinese Custom's Office and cover the 2000-2006 period.[5] For Colombia, our data set includes all export transactions by Colombian firms between 2000 and 2012 and comes from the Colombian Bureau of Statistics (Departamento Administrativo Nacional de Estadística, DANE). See Eaton et al. (2008) for details.[6]

The Chinese industrial survey data we use are firm-level data from Annual Surveys of Industrial Production from 1998 to 2007. These surveys are made by the Chinese National Bureau of Statistics and include all of the state-owned enterprises (SOE) and non-SOEs with sales over 5 million RMB (USD0.6 million in 2000). See Bai et al. (2013)

[4]The current BSIC classification, implemented in 2001, is adapted from the ISIC rev. 3 classification. Before 2001, the BSIC 1996 was in use. A concordance between BSIC 1996 and BSIC 2001 is available.

[5]See Bai et al. (2013) for details. We are grateful to Jiandong Ju and Hong Ma for allowing us access to the Chinese data.

[6]We thank Marcela Eslava for providing access to a more recent version of these data.

for additional details. The Colombian industrial data are annual plant-level data originally collected by DANE, covering all plants with 10 or more employees. (Roberts and Tybout, eds, 1996, Ch. 10) provide a detailed description of the data set.

Finally, the Taiwanese data was collected by the Ministry of Economic Affairs (MOEA) in Taiwan for the years 2000 and 2002-2004.[7] The data set is an unbalanced panel of plants that were in operation in all four sample years and that reported information on domestic and export sales, capital stocks and R&D expenditure. While the survey is conducted at the plant level, the distinction between plant and firm is not important as the bulk of firms in the Taiwanese manufacturing sector own only a single plant.[8]

[7] The survey was not conducted in 2001. In that year a manufacturing sector census was conducted by the Directorate General of Budget, Accounting, and Statistics. This cannot be merged at the plant level with the MOEA survey data for the other years.

[8] Over the period 2000-2004, 92.8 percent of the manufacturing plants were owned by single-plant firms.

Appendix E
Export processing zones

E.1 Additional characteristics of export processing zones in Bangladesh

Fiscal incentives provided to firms locating in EPZs consist of a 10-year holiday for firms established before January 1, 2012, while for firms established after December 31, 2011 the tax holiday schedule is 100% for the first 2 years, 50% for the next 2 years and 25% for the following (fifth) year. Additional fiscal incentives include duty free import of construction materials, machineries, office equipment, raw materials and finished goods, and exemption from dividend, municipal and regional taxes. Further non-fiscal incentives include allowance of 100% foreign ownership, full repatriation of capital and dividends and off-shore banking for foreign owned and joint-venture firms. Plants in EPZs also enjoy higher quality of governance relative to plants outside EPZs in terms of issue of trade licenses, security and access to utilities. Moreover, specific labor regulations apply in EPZs. Minimum wages and benefits for workers are established by law, formation of labor unions is forbidden and strikes are prohibited. This is a big deal in Bangladesh where strikes are common and costly.[1]

Bangladesh's tax registration data allow us to observe exporter plants' addresses, which indicate when a plant is located in an EPZ.[2] Looking at plants' addresses we are able to identify which plants were in an EPZ at the moment of entering the tax registration database. Given the nature of tax registration data, however, we cannot identify exporters moving in and out of EPZs over time. The number of plants in EPZs changes in our data

[1] The government has allowed the formation of Workers Welfare Committees (WWC), however. In a WWC, workers and management representatives meet to discuss workplace related issues. In a survey of manufacturing plants, Rahman et al. (2008) found that 21 out of 38 EPZ factories had WWC in 2006.

[2] This is indicated directly, so we do not have to infer an EPZ location by the plant's zip code, say. For example, consider the following address of a plant located in the Adamjee EPZ: "Plot-38 & 55 Aadamjee EPZ."

as firms enter or exit from exporting altogether.[3]

The 2008-2009 report of the Bangladesh Export Processing Zones Authority (BEPZA) identifies 305 firms operating in EPZs, of which 185 (60%) were 100% foreign owned, 48 (15%) were joint ventures and 74 (25%) were 100% local ventures. The number of exporters whose address is in an EPZ in our tax records is 460. When we merge these records with customs data we are left with 287 firms that were in an EPZ in at least one year. We are able to account for between 50% and 85% of total EPZ exports.[4]

Survey data prevent us from identifying exactly which firms are located in an EPZ. However, since we see the zip code for each manufacturing establishment in the survey, we can identify which plants are in districts where an EPZ is located. Table E.1 presents some summary statistics. By 2005, 45% of surveyed plants (2,367) were located in EPZ districts, and they accounted for 67% of total employment. Of these, 628 were exporters and accounted for 74% of total exports. In contrast, in non-EPZ districts there were only 154 exporters out of 2,850 plants in 2005. Plants in EPZ districts tend to be larger, as total sales per plant were US$2.0 million compared to US$1.2 million for plants located in non-EPZ districts.

To further compare producers in EPZ districts with those in non-EPZ districts, we compute differences in plant characteristics within the same four-digit BSIC industry pooling all years. Table E.2 reports that, on average, establishments in EPZ districts pay higher wages, sell more and employ more workers. Being located in an EPZ district does not appear to be significantly associated with differences in variable cost and labor productivity.[5] However, exporters located in an EPZ district do show higher labor productivity.

Since in our EPZ districts we include two main industrial regions, Dhaka and Chittagong, where factors other than proximity to an EPZ can affect plant characteristics, we compute differences in plant characteristics excluding plants located in these two districts. The results are presented in the last three columns of Table E.2. The results do not differ qualitatively, but now being an exporter in an EPZ district is more strongly associated to a lower age.

Table E.1 also shows that EPZ districts export 77% of what is sold, compared to 58%

[3] As an example, consider a firm that was set up in 2000, then applied for a VAT in 2005 and started exporting that same year, but was not in an EPZ. Then its address in the VAT registration data would indicate the firm is not in an EPZ. We have no way of telling whether the firm moved to an EPZ in 2007, say, and continued to export.

[4] We take total EPZ exports from BEPZA official data as of 2010. Reports and data from BEPZA are available at http://www.epzbangladesh.org.bd.

[5] We define variable cost as expenditures in raw materials, energy use and employment cost divided by gross output. Labor productivity is defined as gross output over number of workers. Both variables are constructed only for 1999 and 2005 since we do not have data on gross output for 2001.

Table E.1: Characteristics of EPZ districts, by survey year.

	1999	2001	2005
	Plants in EPZs districts		
Number of plants	1,247	1,583	2,367
Number of exporters	750	824	628
Exports (US$ million)	1,833.8	1,688.2	2,402.6
Total sales	3,021.3	2,843.0	4,790.0
Employment	514,345	470,185	600,917
Exports/Total sales (%)	60.7	59.4	50.2
Sales per plant (US$ million)	2.4	1.8	2.0
	Plants outside EPZs districts		
Number of plants	2,464	2,864	2,850
Number of exporters	90	128	154
Exports (US$ million)	298.5	461.9	1,688.3
Total sales (US$ million)	976.9	1,228.8	3,357.2
Employment	232,449	222,188	300,171
Exports/Total sales (%)	30.6	37.6	50.3
Sales per plant (US$ million)	0.4	0.4	1.2
EPZ exports (% of total)	91.0	86.0	73.9
EPZ employment (% of total)	68.9	67.9	66.7

Notes: EPZ districts are those districts in which there is an EPZ. It is not necessarily the case that all establishments in these districts are in fact located in an EPZ.

Table E.2: Establishment characteristics among EPZ and non-EPZ districts.

	All districts			Dhaka & Chittagong excluded		
Plant characteristic	EPZ	Exporter and EPZ	Observations	EPZ	Exporter and EPZ	Observatio
Variable cost	−0.011	0.033	8,906	0.019	−0.012	6,095
	(−0.023)	(−0.037)		(−0.034)	(−0.098)	
Labor productivity	−0.023	0.437*	8,904	−0.212*	0.696*	6,094
	(−0.035)	(−0.057)		(−0.049)	(−0.138)	
Employment	0.119*	0.660*	13,371	−0.012	0.641*	9,141
	(−0.024)	(−0.039)		(−0.034)	(−0.085)	
Total sales	0.163*	0.923*	12,650	−0.072	1.149*	8,659
	(−0.040)	(−0.066)		(−0.053)	(−0.133)	
Wage	0.081*	−0.002	13,330	0.024	0.045	9,101
	(−0.018)	(−0.028)		(−0.024)	(−0.060)	
Fixed assets	−0.136*	0.901*	13,356	−0.304*	1.221*	9,136
	(−0.042)	(−0.067)		(−0.056)	(−0.141)	

Notes: standard errors in parenthesis. Differences are obtained from a regression of the form $\ln Y_{ij} = \beta_0 + \beta_1 EPZ_{ij}$ $\beta_2 EX_{ij}^{EPZ} + I_j + \varepsilon_{ij}$, where i indexes plants, j indexes four-digit BSIC industries; EPZ are plants in EPZ districts, a EX^{EPZ} are exporters in EPZ districts; I are industry dummies and Y is the plant characteristic. *,** and $^{+}$ indica significance at the 1%, 5% and 10% level, respectively.

for non-EPZ districts. Table E.3 further shows that individual exporters in EPZ districts are almost fully devoted to exporting. Mean export intensity in EPZ districts is greater than 95% in any year of the survey. Export intensity in districts with no EPZs is lower, but still high, with plants selling 87% of their sales abroad in 2005. Moreover, around 95% of plants in EPZ districts sold more than 95% of their sales abroad in 2005, while 75% of plants in other districts did so in 2005.

Table E.3: Export intensity (X/Y) for exporters in EPZ districts.

	Mean X/Y			% with $X/Y \geq 95\%$		
	1999	2001	2005	1999	2001	2005
Non-EPZ	82.3	75.9	87.1	66.7	58.6	75.3
EPZ	97.0	97.0	96.4	94.1	94.1	94.8

Note: Export intensity is defined as exports as a share of total sales.

The age profile of establishments in EPZ and non-EPZ districts for 2005 is described in Table E.4.[6] Non-exporting establishments in EPZ districts do not seem to be significantly younger than their counterparts in non-EPZ districts. This is also the case if we focus on apparel and textiles producers, although these are 6 year older on average than establishments producing other products. However, exporters in EPZ districts are 7 and 8 years younger on average than exporters in non-EPZ districts, respectively. A simple regression of age on EPZ districts location and exporter indicators confirms that being in an EPZ district and exporting is strongly associated to a lower establishment age (see Table E.5).

Table E.4: Age of establishments in and out of EPZ districts and by export status.

	Non-exporters		Exporters	
	Mean	Median	Mean	Median
	Apparel and textiles producers			
Non-EPZ	19.3	13	17.1	10.5
EPZ	18.9	18	9.1	8
	Non-apparel and textiles producers			
Non-EPZ	13.2	10	19.5	14.5
EPZ	13.1	9	12.5	6

Note: Age is computed using the year of start of operations.

[6]2005 is the only survey year for which we have the year of start-up, from which we compute establishment age.

Table E.5: Establishment age differences between EPZ and non-EPZ districts.

	All districts	Dhaka & Chittagong excluded
Located in EPZ district	0.236	0.905
	(-0.670)	(-0.876)
Exporter	5.563^{*}	5.794^{*}
	(-1.765)	(-1.983)
Exporter in an EPZ district	-5.173^{**}	-14.207^{*}
	(-2.080)	(-4.368)
Constant	27.764^{**}	27.095^{**}
	(-12.99)	(-13.348)
Observations	$3,086$	$2,592$

Notes: standard errors in parenthesis. Age differences are obtained from a regression of the form $A_{ij} = \beta_0 + \beta_1 EPZ_{ij} + \beta_2 EX_{ij} + \beta_3 EX_{ij}^{EPZ} + I_j + \varepsilon_{ij}$, where i indexes plants, j indexes four-digit BSIC industries; EPZ are plants in EPZ districts, EX are exporters, and EX^{EPZ} are exporters in EPZ districts; I are industry dummies and A is establishment age. *,** and $^{+}$ indicate significance at the 1%, 5% and 10% level, respectively.

Appendix F
Other efficiency measures for Chinese firms

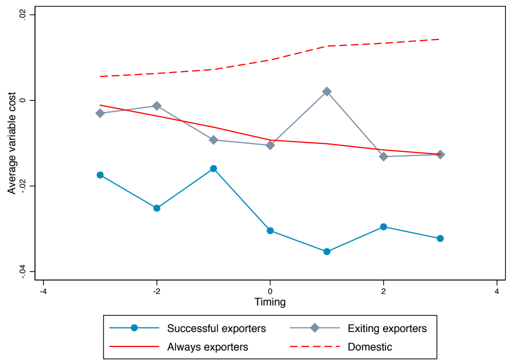
Firm productivity should be affected by cost and demand factors. As a robustness check, we examine two other raw measures of efficiency that do not rely on our strategy for recovering firm productivity but are indicative of cost and demand performance. We consider average variable costs AVC and real revenue per worker RPW. We isolate these measures from industry and time effects, by running OLS regressions on

$$\ln Y_{it} = \mathbf{D}_{it}\beta^D + \epsilon_{it}^Y, \tag{F.1}$$

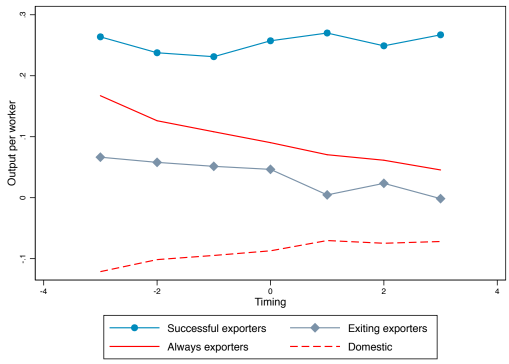
for $Y = AVC, RPW$, where a and k are age and capital (in logs), respectively. We look at residuals $\hat{\epsilon}_{it}^{AVC}$ and $\hat{\epsilon}_{it}^{RPW}$ in the same fashion as for productivity above.

Figure F.1 shows that average cost tends to be lower for exporters than for domestic firms, and even more so for successful exporters. Exporters show a slightly decreasing trend as opposed to domestic firms, which seem to experience increasing variable costs. Successful exporters do show a decrease in average cost at entry, but no clear trend afterward.

For revenue per worker the rankings among firm types are similar. Although, as before, exporters perform better than non-exporters, there is a downward trend for continuous and exiting exporters, absent for successful exporters, whose labor productivity tends to remain fairly constant before and after entering export markets.



(a) Average variable cost.



(b) Revenue per worker.

Figure F.1. Alternative efficiency measures.

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WORKING PAPERS

1. Diaz de Astarloa, B. (2017). "Trade Policy and Industry Dynamics in U.S. Solar PV Manufacturing", Working Paper.
2. Diaz de Astarloa, B., J. Eaton, K. Krishna, B. Roberts, A. Rodríguez Clare and J. R. Tybout (2015). "Born to Export: Understanding Export Growth in Bangladesh's Apparel and Textiles Industry", Working Paper.
3. Diaz de Astarloa, B., X. Bai and K. Krishna (2013). "Productivity and Exporting in China: Selection, Learning by Exporting and Preparing to Export", Working Paper.
4. Anós-Casero, P. and B. Diaz de Astarloa (2010). "Estimating the Import Content of Argentine Exports", *Policy Research Working Paper Series* 5225, The World Bank.

OTHER PUBLICATIONS

5. Mustafaoglu, Z., A. Coppola and B. Diaz de Astarloa (2015). "Informe General: Un nuevo rumbo", in World Bank, *Argentina - Notas de políticas públicas para el desarrollo*. Washington, D.C.: The World Bank Group.

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PEER REVIEW

Reviewer for *Journal of International Economics* (2).