PARIS SCHOOL OF ECONOMICS
ÉCOLE D'ÉCONOMIE DE PARIS

WORKING PAPER N° 2007 - 09

Trade integration and within-plant productivity evolution in Chile

Maria Bas

Ivan Ledezma

JEL Codes : F1, F4, O1
Keywords : trade barriers, plant productivity, firm heterogeneity, plant-level data

PARIS-JOURDAN SCIENCES ECONOMIQUES
LABORATOIRE D'ECONOMIE APPLIQUÉE - INRA

48, BD JOURDAN – E.N.S. – 75014 PARIS
TÉL. : 33(0) 1 43 13 63 00 – FAX : 33 (0) 1 43 13 63 10
www.pse.ens.fr

CENTRE NATIONAL DE LA RECHERCHE SCIENTIFIQUE – ÉCOLE DES HAUTES ÉTUDES EN SCIENCES SOCIALES
ÉCOLE NATIONALE DES PONTS ET CHAUSSÉES – ÉCOLE NORMALE SUPÉRIEURE

Trade Integration and Within-Plant Productivity Evolution in Chile*

Maria BAS† and Ivan LEDEZMA‡

October 2008

Abstract

We study the impact of trade on productivity using Chilean plant-level data (1982-1999). Our contribution is to disentangle the impact of export and import barriers. Firstly, we estimate the production functions to obtain plant TFP. Secondly, we estimate trade barriers (border effects) between Chile and its trading partners at the industry level and over time. Finally, we test the impact of trade barriers by regressing productivity on border effect estimates. A fall in export barriers improves productivity in traded sectors, while the reduction of import barriers might foster productivity in export industries but it hurts firms in import-competing ones.

Keywords: Trade barriers, plant productivity, firm heterogeneity, plant-level data.

JEL Classification: F1, F4 and O1.

*We are grateful to Pol Antras, Jose Miguel Benavente, Gene Grossman, Thierry Mayer, Jacques Mairesse, Nina Pavcnik, Andrea Repetto and James Tybout for helpful comments.

†Paris School of Economics & London School of Economics (Centre for Economic Performance). Email: bas@pse.ens.fr

‡Paris School of Economics & Université Paris 1 Panthéon-Sorbonne (Centre d'Economie de la Sorbonne). Email: ledezma@pse.ens.fr

1 Introduction

Trade liberalization was at the core of reform packages carried out in many developing economies during the 1980s. In this paper we revisit the case of Chile, one of the earliest and most radical examples of trade liberalization. We aim at testing the link between trade integration and productivity in Chilean manufacturing plants. At the micro level, the impact of trade reforms is generally studied from a unilateral perspective through direct measures of trade costs or aggregate trade ratios that might neglect several features of trade integration. The novelty of this paper is to estimate trade barriers in a multilateral context to disentangle within a unique framework the effect of export- and import-oriented policies on plant productivity.

By differentiating export and import trade barriers, we emphasize different channels by which trade integration affects plant productivity. The reduction of import barriers increases foreign competition, which is often viewed as a positive engine of productivity (Pavcnik, 2002; Amiti and Konings, 2007). It pushes the least productive firms to cease production and surviving ones to trim down their inefficiencies. On the other hand, the presence of increasing returns to scale and imperfect competition may modify the relationship between import competition and plant productivity (Devarajan and Rodrik, 1989; Rodrik, 1988). One consequence of scale economies is precisely that average cost falls as output increases. In this case, foreign competition reduces domestic sales restricting the possibility to exploit scale economies.

Import-oriented policies also determine the extent of foreign technology transmissions. In developing countries, the access to high-quality imported capital equipment or intermediate goods enables firms to reduce their marginal costs and to raise their productivity level. Using plant-level data, Schor (2004) for Brazil, and Amiti and Konings (2007) for Indonesia show that input tariff reductions boost productivity gains.[1]

On the other hand, export promotion policies allow more firms to benefit from positive spillovers stemming from foreign markets. The literature suggests learning-by-exporting

[1]Kasahara and Rodriguez (2008) for Chile, find that imported inputs foster plant productivity.

as a plausible mechanism to explain a positive impact of trade liberalization on plant productivity. There is some evidence on ex-post productivity gains arising from knowledge and expertise gained in the export process (Kraay (2002) on China, Alvarez and Lopez (2005) on Chile, De Loecker (2007) on Slovenia).

These different mechanisms of trade liberalization call for further analysis on the multiple dimensions of trade. We carry out three empirical exercises. Firstly, we obtain estimates of plant TFP and address simultaneity issues thanks to the Levinsohn and Petrin (2003) methodology. These estimates draw on plant-level data (1979-1999) from the annual industry survey ENIA (Encuesta Nacional Industrial Anual) of the Chilean manufacturing sector provided by the INE (Instituto Nacional de Estadisticas). Secondly, we use specific data on destination markets for bilateral trade flows of Chile and its main trade partners at the industry level to capture (a) the barriers faced by Chilean partners to reach the domestic market (import barriers) and (b) those barriers faced by Chilean exporters to access foreign markets (export barriers). To estimate these barriers we rely on the border effect methodology developed by Fontagné et al. (2005) and use the Trade and Production database provided by the CEPII (Centre d'Etudes Prospecives et d'Information Internationales). This strategy enables us to obtain time-varying measures of trade integration at the industry level. Unlike Chilean tariff rates, these measures do present heterogeneity across industries. Finally, we estimate the impact of import and export barriers on plant productivity by combining the results of the first two steps. In this third step, we regress plant productivity on border effect estimates.

We carried out several robustness checks. We use alternative measures of productivity, different specifications dealing with potential mark-ups bias and dynamic concerns of the persistence of plant productivity over time. In the different empirical stages we deal with the potential risk of reversal causality between trade barriers and plant productivity. This is done by purging productivity effects in the gravity specification, by using a four-year rolling horizon in step 2 and by treating trade barriers as endogenous in GMM estimations. We also test two possible mechanisms by which trade affects plant productivity, namely the presence of IRS and foreign technology transmission.

Based on specific trade barrier measures, the paper yields new findings on trade policy implications. Considering productivity gains relative to non traded sectors, our regressions suggest three main results: (i) a reduction in export barriers fosters plant productivity gains in export-oriented and import-competing industries; (ii) the impact of import barriers depends on trade orientation. A decrease in import barriers has a negative effect on plant productivity in import-competing industries. Interestingly, production function estimates suggest the presence of increasing returns to scale (IRS) in these industries. Foreign competition may have dampened domestic sales and thereby, reduced the possibility to exploit scale economies. Concerning export-oriented industries, a fall in import barriers fosters plant productivity. This result is present in different static specifications. However, once we control for past productivity levels in the dynamic model, foreign competition might also reduce productivity gains in these industries; (iii) a reduction in import barriers on machinery improves plant productivity of both export-oriented and import-competing industries.

Our findings contribute with new evidence on trade liberalization and plant productivity in Chile. The identification setting has been chosen to allow for a close comparison with previous results obtained by Pavcnik (2002) and Bergoeing et al. (2006).[2] Both studies show the presence of time-varying firm heterogeneity and deal with the effects of trade integration on productivity gains in a similar and comparable indentification strategy. Using plant-level data, Pavcnik (2002) estimates the impact of trade on plant productivity in Chile during the period 1979-1986. By the means of a difference-in-difference framework, Pavcnik (2002) concludes that trade liberalization induces the growth of within-plant productivity in import-competing industries. Productivity improvements in export-oriented industries are observed only for initial years.[3] Using our sample, we are able to repro-

[2]Several works have investigated the relationship between Chilean market-oriented reforms and plant productivity. See Liu and Tybout, 1996; Pavcnik, 2002; Bergoeing et al., 2002; Bergoeing et al., 2004; Alvarez and Lopez, 2005; Bergoeing et al., 2006.

[3]Pavcnik (2002) also performs the Olley and Pakes (1996) aggregate productivity decomposition and shows that, in the period, aggregate productivity growth is mainly explained by the exit of the least productive firms and the reallocation of market shares towards most productive ones.

duce these results. However, contrary to what the difference-in-difference specification assumes, trade exposure in Chile does not increase continuously during Pavcnik's sample period. In the context of the 1982 debt crisis, the government raises import tariffs from 15% in 1982 up to 26% in 1985.

Chilean trade reforms have been recently revisited by Bergoeing et al. (2006). They study the impact of the financial and trade reforms on productivity gains in Chile during a longer period (1980-2001). The authors show that if one uses effective tariffs instead of year dummies to capture trade liberalization, plant productivity advantages in export-oriented industries are not significant and, similar to our results, productivity gains of plants belonging to import-competing industries fall after trade liberalization.

Nevertheless, both studies suffer from the lack of cross-section variance on the right-hand side of regressions. Indeed, the identification of trade liberalization effects can be problematic since the reduction in import tariffs was almost homogeneous across industries and remained constant during the 1990s. The radical drop in the average nominal tariff rate from 98% in 1973 to 10% in 1979 came along with the homogenization of tariff rates among industries. Even their rise in early 1980s, during the debt crisis, was uniform. This homogeneous tariff reduction is probably the reason why Pavcnik (2002) is constrained to use time dummy indicators and Bergoeing et al.(2006) can not get enough variance for their estimates concerning export-oriented industries.

Considering direct measures of trade policy such as import tariffs also neglects two important features of trade integration. First, a unilateral import tariff reduction does not necessarily imply a symmetric response across trade partners. Second, several direct and indirect trade barriers might be omitted (Anderson and van Wincoop, 2004). Among them, one finds not only non-tariff barriers and fixed export costs, but also bilateral agreements, institutional arrangements, infrastructure and even political efforts. For instance, while the evolution of tariffs in Chile remains flat during the 1990s, in order to promote exports the government signed several trade agreements with different countries and also developped an important agenda of political integration.

By estimating the evolution of trade integration between Chile and its trading partners, we are able to capture this type of missing information. This strategy also allows us to address the lack of cross-section variance of standard trade measures and to capture the multiple channels of trade integration. These are the main contributions relative to previous works.

The rest of the paper is structured as follows. Section 2 presents the estimation strategy of our empirical exercises. Section 3 shows the results and, finally, section 4 presents a brief conclusion.

2 Estimation strategy

The estimation strategy consists of three steps. In the first one, we estimate the production function using OLS, fixed-effect specification and the LP methodology to obtain plant TFP as a residual. In the second step, we construct the measure of trade liberalization by estimating border effects between partners following Fontagné et al. (2005). Finally, in the third step, we estimate the impact of trade barriers by regressing productivity on border effect estimates. Within this methodology, we address simultaneity issues in the estimation of TFP (step 1) and reversal causality between productivity and trade flows (step 2 and 3).

2.1 Step 1: Production function

We estimate the following specification of a Cobb-Douglas production function at the two-digit industry level:

$$y_{pt} = \beta_0 + \beta_x x_{pt} + \beta_k k_{pt} + \varepsilon_{pt} \tag{1}$$

Where all variables are expressed in natural logs, y_{pt} is the value added of plant p at time t, which is explained by short-term adjustable inputs x_{pt} (i.e. skilled and unskilled labor) and capital stock k_{pt}. The error term can be decomposed into an intrinsical "transmitted" component ω_{pt} (productivity shock) and an i.i.d. component χ_{pt}. Consequently, plant TFP a_{pt} is calculated as the residual given by the difference between the observed output and the predicted factor contribution:

$$\widehat{a}_{pt} = y_{pt} - \widehat{\beta}_x x_{pt} - \widehat{\beta}_k k_{pt} \tag{2}$$

When estimating production functions using firm panel data, eventual problems concerning simultaneity and selection should be considered. Simultaneity arises because input demand and unobserved productivity are positively correlated. Firm specific productivity is known by the firm but not by the econometrician. If a firm expects a high productivity shock it will anticipate an increase in its final good demand and, consequently, it will purchase more inputs. OLS will tend to provide upwardly biased estimates of the labor elasticity and downwardly biased estimates of the capital one[4]. Selection problems are likely to be present because the unobserved productivity influences the exit decision of the firm and we can only observe those firms that stay in the market. On the other hand, if capital is positively correlated with profits, firms with larger capital stock will decide to stay in the market even for low realizations of productivity shocks. This implies a potential source of negative correlation in the sample between productivity shocks and capital stock, which translates into a downward bias in capital elasticity estimates.

Olley and Pakes (1996) (henceforth OP) propose a three-stage methodology to control for the unobserved firm productivity. They deal explicitly with exit and investment behavior. The rationale is to reveal the unobserved productivity through the investment behavior of the firm, which in turns depends, theoretically, on capital and productivity. Selection issues are taken into account by inferring that firms that stay in the market have decided to do it accordingly to their capital stock and their expectations of productivity. By the means of this theoretical exit rule, OP estimate survival probabilities conditional on firm's available information. These probabilities are then used in the productivity

[4]OLS elasticities can be stated as $\hat{\beta}_x = \beta_x + \frac{\hat{\sigma}_{kk}\hat{\sigma}_{x\varepsilon} - \hat{\sigma}_{xk}\hat{\sigma}_{k\varepsilon}}{\hat{\sigma}_{xx}\hat{\sigma}_{kk} - \hat{\sigma}^2_{xk}}$ and $\hat{\beta}_k = \beta_k + \frac{\hat{\sigma}_{xx}\hat{\sigma}_{k\varepsilon} - \hat{\sigma}_{xk}\hat{\sigma}_{x\varepsilon}}{\hat{\sigma}_{xx}\hat{\sigma}_{kk} - \hat{\sigma}^2_{xk}}$. Where $\hat{\sigma}_{rs}$ is the covariance between variables r and s in the sample. If capital is positively correlated with labor and labor's correlation with the productivity shock is higher than capital one (which is the realistic case) then the coefficient of capital $\hat{\beta}_k$ will be underestimated and the one of labor $\hat{\beta}_x$ upward biased.

estimation.

Levinsohn and Petrin (2003) (henceforth LP) extend the OP idea, by noting that some inputs, such as electricity or materials, can be better proxies than investment to control for the unobserved firm productivity when one deals with simultaneity. Inputs adjust in a more flexible way, so they are more responsive to productivity shocks. Moreover, inputs usually have more non-zero observations than investment, a property that has consequences on estimation efficiency. In the case of the ENIA survey this property is important. Thus, in order to maximize sample size we keep the LP strategy and use electricity as a proxy for unobserved productivity.[5]

There are some advantages of OP-LP methodologies. Firstly, they perform better than fixed-effect specifications because the unobserved individual effect (productivity) is not constrained to be constant over time. Secondly, approaches based on instrumental variables can be limited by the instruments availability. Finally, OP-LP do not assume restrictions on the parameters. For instance, an alternative approach is the one developed by Katayama et al.(2005) who show how misleading can be the use of sale revenues to measure productivity. Factor prices and mark-ups can produce important distortions if they are not homogeneous. However, their methodology assumes constant returns to scale and neglect entry-exit process to facilitate likelihood estimates. Again both assumptions are not neutral in the case of the ENIA. In the third step, we allow for plant's individual fixed effects and control for market concentration at a disaggregated industry level in order to reduce the potential risk of mark-up bias.

2.2 Step 2: Border effects

It is well known that the reduction of tariffs in Chile was homogeneous across industries. As a consequence, tariff rates do not provide enough cross-section variance. On the other hand, tariffs are not the only measure that matters to capture trade costs. One should also

[5] Besides technical concerns, a key difference between LP and OP is that the former does not directly take into account selection. However, as LP show, the risk of selection biases are significantly reduced by considering an unbalanced panel.

consider bilateral agreements, asymmetries between export and import costs and indirect difficulties to trade.[6] Considering all these features of trade, we do obtain heterogeneity in both industrial and time dimensions.

To do so, we apply a border effect methodology. This type of empirical strategy provides an assessment of the level of trade integration by estimating a gravity-like model that considers, as a very intuitive benchmark, the market access of domestic producers reaching domestic (intra-border) destinations. [7]

2.2.1 The Methodology

The identification strategy of Fontagné et al.(2005) builds on Head and Mayer (2000) gravity model derivation. This strategy seems suitable to measure Chilean trade integration as it corrects for the lack of theoretical foundations of earlier works and keeps the idea of using intra-national trade as a benchmark of trade integration. Moreover, it allows for asymmetries in the identification of trade barriers among partners, one of the main focus of this paper. Fontagné et al.'s (2005) theoretical foundation builds on a static monopolistic competition setting with increasing returns to scale for one-sector economies. Consider an instantaneous CES utility function in which the representative consumer of country i has specific preferences a^s_{ijt} for each variety h depending on the exporter country j (for the sake of clarity in the exposition of our empirical implementation, we indicate explicitly both industry s and time t specificity):

$$U^s_{it} = \left[\sum_{j=1}^{N^s_t} \sum_{h=1}^{M^s_{jt}} \left(a^s_{ijt} c^s_{ijht} \right)^{\frac{\sigma_t \; -1}{\sigma_t}} \right]^{\frac{\sigma_t}{\sigma_t \; -1}} \tag{3}$$

Thus, varieties belonging to the same country share the same weight in the utility

[6]Theoretically, these indirect difficulties include a large list of country specificities, namely bias of consumption towards home goods and the like. As long as they can be interpreted, at least in part, as the outcome of history and political efforts, we consider them as a part of the measure of trade integration.

[7]McCallum (1995) applies this methodology to study market access between Canada and the US. Despite the high expected trade integration, trade between US and Canada is found to be around 22 times more difficult than Canadian intra-national trade. Anderson and van Wincoop (2003) reestimate McCallum's (1995) model, correcting for multilateral price bias, and the assessment still remains striking (11%).

function. Imports $m^s_{ijt}(= c^s_{ijt}p^s_{ijt})$ of country i from country j are valuated at the point of consumption (c.i.f) $p^s_{ijt} = p^s_{jt}\tau^s_{ijt}$. This includes the producer price (f.o.b.) p^s_{jt} augmented of all trade cost τ^s_{ijt}, modeled as iceberg costs. Total expenditure for the industry $Y^s_{it} = \sum_{j'=1}^{N^s_t} m^s_{ij't}$ considers all imports, including intra-national ones m^s_{iit}. For symmetric varieties, this utility function (3) with constant elasticity σ_t leads to the well known demands:

$$m^s_{ijt} = \left(\frac{p^s_{jt}\tau^s_{ijt}}{a^s_{ijt}P^s_{it}}\right)^{1-\sigma_t} M^s_{jt}Y^s_{it} \tag{4}$$

In this gravity-like equation (4), $P^s_{it} = \left[\sum_{j'=1}^{N_t}\left(\frac{p_{ij't}}{a_{ij't}}\right)^{1-\sigma_t} M^s_{j't}\right]^{\frac{1}{1-\sigma_t}}$ is the consumer price of all varieties in the industry. This index takes into account differences in price setting across countries. If omitted, not only a multilateral control is missing but also a bias is induced between the error term and the partners dummies (border effect). Anderson and van Wincoop (2003) argue that the omission of multilateral price effects (what they call "multilateral resistances") explains the upward bias in border effects of Canada vis-à-vis the US estimated by McCallum (1995).[8]

One might mention four possible strategies to consistently estimate a gravity equation including price effects. The first one is to use price index data. Baier and Bergstrand (2001) follow this strategy measuring prices with GDP deflators. However, as highlighted by Anderson and van Wincoop (2004), empirical counterparts of P^s_{it} such as CPIs measures neglect changes in the true set of varieties and do not accurately reflect non tariff barriers and indirect trade policies. The second strategy is the one followed by Anderson and van Wincoop (2003). They develop a two-step methodology in which border effect estimates are used to measure multilateral price effects. Besides practical difficulties of implementation, one crucial limitation for our purposes is the assumption of symmetry in bilateral trade costs. A third alternative approach uses fixed effect specification to control for unobservable prices. The effect of price indexes is captured by the coefficients of individual fixed effects related to country source and destination (Harrigan, 1996). Feenstra (2003) shows that the coefficients of fixed effect estimation are consistent and

[8]See previous footnote

reports values very similar to the non-linear least squares estimation of Anderson and van Wincoop (2003). Redding and Venables (2004) construct market access measures to explain cross-country differences in per capita income. Their market access estimation relies on fixed country effects to capture exporting and importing country characteristics. These country indicators take into account unobserved economic variables associated with supply and market capacity.

If the economic and geographic determinants captured by fixed effects vary over time, a useful strategy consists in eliminating the price index in the CES demand setting by expressing inter-national imports relative to intra-national ones. This is what Head and Mayer (2000) do. We follow this solution and divide equation (4) by m^s_{iit}:

$$\frac{m^s_{ijt}}{m^s_{iit}} = \left(\frac{a^s_{ijt}}{a^s_{iit}}\right)^{\sigma_t - 1} \left(\frac{p^s_{jt}}{p^s_{it}}\right)^{-\sigma_t} \left(\frac{\tau^s_{ijt}}{\tau^s_{iit}}\right)^{1-\sigma_t} \left(\frac{v^s_{jt}}{v^s_{it}}\right) \tag{5}$$

Where $\frac{v^s_{jt}}{v^s_{it}}$ is the relative value added at industry level between both countries (i and j).The relative value added captures the relative number of symmetric varieties within a model of monopolistic competition. To obtain an empirical counterpart of equation (5), we assume, as Fontagné et al. (2005), that trade costs (τ^s_{ijt}) are composed of transport cost (captured by distance d_{ij}), ad-valorem tariffs (t^s_{ijt}) and "tariff equivalent" (NTB^s_{ijt}) of non tariff barriers: $\tau^s_{ijt} \equiv (d_{ij})^{\delta t} \left(1 + t^s_{ijt}\right) \left(1 + NTB^s_{ijt}\right)$.

Protection (tariffs and non tariff barriers) varies across all partner pairs and depends on the direction of the flow for a given pair. To capture this, a dummy structure is defined to take into account flows' direction. Taking the example of the US and Chile as trade partners we define $\left(1 + t^s_{ij}\right) \left(1 + NTB^s_{ijt}\right) \equiv \exp\left[\eta^s_t US\_CHL^s_{ijt} + \gamma^s_t CHL\_US^s_{ijt}\right]$, where $US\_CHL^s_{ijt}$ is a dummy variable set equal to 1 when Chile is the exporter country j and the US the importer country i. Similarly, $CHL\_US^s_{ijt}$ is a dummy variable set equal to 1 when the US is the exporter country j and Chile the importer country i.

Preferences a^s_{ijt} are supposed to have a random component e^s_{ijt} and a systematic bias β^s_{it} for goods produced in the home country i. This "'home market bias"' is reduced when countries i and j share the same language and are contiguous. The dummies L_{ij} and C_{ij}

are defined to capture each situation, respectively. Under these assumptions preferences can be written as $a^s_{ijt} \equiv \exp\left[e^s_{ijt} - \left(\beta^s_{it} - \lambda_{Lt} L_{ij} - \lambda_{Ct} C_{ij}\right)\left(US\_CHL^s_{ijt} + CHL\_US^s_{ijt}\right)\right]$, where λ_{Lt} and λ_{Ct} represent the extent to which the home market bias is mitigated by common language and contiguity. Taking into account these assumptions, equation (5), for the example of the US and Chile, can be written as:

$$\begin{aligned}\ln\left(\frac{m^s_{ijt}}{m^s_{iit}}\right) &= \ln\left(\frac{v^s_{jt}}{v^s_{it}}\right) - (\sigma_t - 1)\,\delta_t \ln\left(\frac{d_{ij}}{d_{ii}}\right) - (\sigma_t - 1)\,\lambda_{Lt} L_{ij} - (\sigma_t - 1)\,\lambda_{Ct} C_{ij} \\ &\quad -\sigma_t \ln\left(\frac{p^s_{jt}}{p^s_{it}}\right) - (\sigma_t - 1)\left(\beta^s_{it} + \eta^s_t\right) US\_CHL^s_{ijt} - (\sigma_t - 1)\left(\beta^s_{it} + \gamma^s_t\right) CHL\_US^s_{ijt} \\ &\quad + (\sigma_t - 1)\left(e^s_{ijt} - e^s_{iit}\right)\end{aligned} \tag{6}$$

2.2.2 Empirical specification

The number of observations in our international sample does not allow to split the sample by each year and 2-digit industry. In order to consistently estimate equation (6), we run pooled regressions in a four-years rolling window for each industry. This allows us to obtain time-varying elasticities. Our estimable equation can be written as:

$$\begin{aligned}\ln\left(\frac{m^s_{ijt}}{m^s_{iit}}\right) &= \alpha_{1t'} \ln\left(\frac{v^s_{jt}}{v^s_{it}}\right) + \alpha_{2t'} \ln\left(\frac{d_{ij}}{d_{ii}}\right) + \alpha_{3t'} L_{ij} + \alpha_{4t'} C_{ij} + \alpha_{5t'} \ln\left(\frac{p^s_{jt}}{p^s_{it}}\right) \\ &\quad + \alpha_{6t'} US\_CHL^s_{ijt} + \alpha_{7t'} CHL\_US^s_{ijt} + \epsilon_{ijt}\end{aligned} \tag{7}$$

Where the theoretical counterparts of each $\alpha_{1t'}, \alpha_{2t'}, .., \alpha_{7t'}$ are given by equation (6). We split the sample by each 2-digit industry and sample periods $t = t' - 3$ to t' , where t' runs from 1982 to 1999. In this sense, $\alpha_{6t'}$ and $\alpha_{7t'}$ will capture the average border effects of exports of Chile to the US and imports of Chile from the US, respectively (i.e. $-(\sigma_t - 1)\left(\beta^s_{it} + \eta^s_t\right)$ and $-(\sigma_t - 1)\left(\beta^s_{it} + \gamma^s_t\right)$) during the period $t' - 4$ to t'. In the regressions, we drop the constant and incorporate all dummy variables to capture the partners in each trade flow direction (i.e. $US\_CHL^s_{ijt}$ and $CHL\_US^s_{ijt}$ in our example of Chile and the US). Thus, $\alpha_{6t'}$ can be directly interpreted as the export border effect

(Chilean exports to the US) and $\alpha_{7t'}$ as the import border effect (US imports to Chile). We run OLS regressions and, due to the form of the error term, $\epsilon_{ij} = (\sigma - 1)(e_{ij} - e_{ii})$, we use Hubert and White corrected standard errors clustered at the importer-industry-year level to control for the expected correlation. In equation (7) we do not impose $\alpha_{1t'} = 1$, as the theoretical equation (6) suggests, and allow for its empirical estimation.

Note that a potential endogeneity problem exits in the estimation of equation (7). In a monopolistic competition framework, prices and output are determined simultaneously. Fontagné et al. (2005) use aggregate prices (instead of industry-level ones). The underlying assumption is that prices at the national level are less correlated with profit maximization at the firm level. In our estimation, we adopt a different approach and use relative wages at the industry level. This choice is motivated by the potential reverse causality in Step 3. As previously mentioned, we will use the border effect estimates to test the impact of trade liberalization on plant productivity for different industries. Most productive industries (or those producing high quality goods) will tend to increase their trade flows and induce a downward bias in the border effect estimates (Step 2). Our assumption is that relative wages capture potential asymmetries in technology or efficiency and thereby they help to remove productivity concerns from the border effect estimates.[9] Additionally, due to the four-year rolling horizon the border effect estimates include past values of trade flows, which allows for a lagged effect of the change in trade barriers. This also contributes to reduce the risk of reversal causality in Step 3.

From these industry-level estimations, we obtain the border effects from the dummy coefficients corresponding to each combination of partners and trade flows direction ($\alpha_{6t'}$ and $\alpha_{7t'}$). In our regressions we consider bilateral trade flows of all main trade partners of Chile. The list includes the US, 9 European countries (EU) and 7 Latin American countries (LA) including Chile (See section 3). Border effects are captured by the bilateral dummies indicating all combination of flows between the EU, LA, the US and Chile. This structure also captures the difference between trade barriers among partners belonging

[9] In non-reported regression we have used relative aggregate prices and also the lag of relative aggregate prices and relative wages. The resulting border-effect estimates are very close to those used in what follows.

to the same region.[10] Finally, our proxies of export and import barriers are constructed for each industry as the weighted average of the border effects estimated for all partners. Weights are given by the part of the import (export) flow on total imports (exports) of Chile.

2.3 Step 3: The impact of trade policy on plant TFP

In this final step, we use the previous estimates of trade barriers to measure the impact of trade liberalization on plant productivity across export-oriented and import-competing industries relative to non-traded ones. The following reduced equation is estimated, analogous to the difference-in-difference framework implemented by Pavcnik (2002):

$$\widehat{a}_{pt} = \theta_0 + \beta\ B_{pt} + \zeta\ T_p + \delta\ B_{pt} \cdot T_p + \varphi\ Z_{pt} + \xi_{pt} \tag{8}$$

Where θ_0 is the constant and ξ_{pt} the error term. $\widehat{a}_{pt}$ is the log of TFP of plant p at time t estimated by the LP strategy. B_{pt} is a vector of trade barriers estimates (import and export border effects) for the 2-digit industry in which the plant operates. T_p is a vector of trade orientation dummies indicating if the plant belongs to export-oriented or import-competing industries. Similar to Pavcnik (2002), we classify industries by trade orientation at the 3-digit industry level (See Appendix). Plants are classified as export-oriented if they belong to a 3-digit industry which has more than 15% of exports over total production and as import-competing if the industry has more than 15% of imports over total production. The rest are considered as non-traded. [11] Our classification concerns the initial period of 1980-1986. The initial sample classification also helps to avoid endogeneity

[10]Following our notation the set of dummies for the European Union (EU), Latina America (LA), Chile (CHL) and the US (US) is: $EU\_CHL^s_{ijt}, CHL\_EU^s_{ijt}, US\_CHL^s_{ijt}, CHL\_US^s_{ijt}, EU\_EU^s_{ijt}, LA\_CHL^s_{ijt}, CHL\_LA^s_{ijt}, LA\_LA^s_{ijt}, EU\_LA^s_{ijt}, LA\_UE^s_{ijt}, LA\_US^s_{ijt}, US\_LA^s_{ijt}, EU\_US^s_{ijt}, US\_EU^s_{ijt}$.

[11]There are only two industries (351 and 384) that matched up to both categories. Nevertheless, the industry 351 (384) presents an export-output ratio of 0.82 (0.21) and an import-output ratio of 1.32 (2.01). Therefore these industries were classified as import competing. Our results remain unchanged if we consider a fourth category of export-import competing for industries 351 and 384 (See the technical appendix).

problems arising from the classification. As Pavcnik (2002) notes, classification at 3- or 4-digit does not change significantly. Neither does it when considering the pre-sample period.

Z_{pt} is a vector of plant characteristics: industry affiliation at 2-digit [12], indicators of entry and exit and plant characteristics that may change over time, namely the use of imported inputs and credit constraints. Similar to Bergoeing et al. (2006), we identify plants that may face liquidity constraints using as a proxy a loan tax payment at the plant-level. In Chile, financial credits are subject to this tax. "'Credit"' is a dummy variable equals to one if the plant reports having paid this tax in a given year. This information is used as a signal that the plant has not been financial constraint. We also introduce year indicators to control for other macroeconomic shocks. The excluded categories are non-traded industries, the year 1982 and the industry 38. As a robustness check we use alternative measures of plant productivity and also control for variable mark-ups.

We are mainly interested in the estimates of the vector coefficient δ of the interaction terms ($B_{pt} \cdot T_p$). Negative and significant coefficients mean that a reduction of trade barriers has a positive effect on productivity in traded industries (export-oriented and import-competing) relative to non-traded ones. The full set of interaction terms enables us to measure separately the effect of import and export barriers, depending on trade orientation.

2.4 Data

In the first step, we use plant-level data from the ENIA survey, which is provided by the Chilean institute of statistics INE (*Instituto Nacional de Estadisticas*). This survey is a manufacturing census of Chilean plants with more than 10 employees. Our data covers the period 1979-1999 and contains information of added value, materials, labor, investment

[12] We introduce industry indicators in order to control for specific characteristics of industries. In order to avoid possible colinearity issues, following Pavcnik (2002), the industry affiliation dummies are defined at the 2 digit industry level, while trade orientation dummies are defined at the 3 digit industry level.

and exports (only available from 1990).[13] We used different specific deflators at the 3-digit level (ISIC Rev-2) and year base 1992 for added value, exports, materials and investment. For the latter, specific deflators are considered for infrastructure, vehicles and machinery. Capital series were constructed using the methodology of Bergoeing et al. (2006).[14] Table 7 (Appendix) shows a description of the variables and Table 8 (Appendix) reports general descriptive statistics of the plant-level sample.

In the second step we use data from the "'Trade and Production Database"' constructed by CEPII (*Centre d'Etudes Prospecives et d'Information Internationales*). This is an extension of the data collected by Nicita and Olarreaga (2001) at the World Bank. The CEPII has filled many missing values for production variables using UNIDO and OECD-STAN (for OECD members). It has also completed trade data with the international trade database BACI of CEPII. The final bilateral trade data covers the period 1976-1999 for 67 developing and developed countries. It provides information on value added, export and import trade flows, origin and destination countries, wages and labor at the 3-digit industry level (ISIC Rev-2).

Detailed intra-national trade flows for our sample of countries are not available. Intra-national trade is computed as output minus exports. This requires an appropriate measure of internal distance that should take into account economic activity to weight internal regions (Head and Mayer, 2000). For distance variables, contiguity and common language, we also used the CEPII database of internal and external distances. The CEPII uses specific city-level data in order to compute a matrix of distance including the geographic population density for each country. Distance between two countries is measured based on bilateral distance between cities weighted by the share of the city in the overall country's population.

At the end, bilateral trade data is available for nine members of the European Union throughout the whole period 1979-1999 (Germany, France, Great Britain, Italy, Belgium, Luxembourg, Ireland, Netherlands and Denmark), the United States and seven Latin-

[13]The ENIA survey has been used in previous studies such as Pavcnik (2002), Liu and Tybout (1996), Levinsohn and Petrin (2003) and Bergoeing et al. (2006) for different sample periods.

[14]We thank the authors for providing us with their Stata routine for capital series.

American countries (Argentina, Brazil, Bolivia, Chile, Mexico, Uruguay and Venezuela).

3 Results

3.1 Results of step 1: plant TFP estimates

In this step we estimate the Cobb-Douglas production function in equation (1) at the 2-digit industry level using simple OLS, fixed effects (FE) and the LP methodology. Table 1 shows the results. As expected, LP estimates of unskilled labor elasticities are generally the lowest and those of capital elasticities the highest. This means that the bias induced by the larger responsiveness of unskilled labor relative to capital is addressed. Considering the production function estimates by LP, we can not reject at 5% the null hypothesis of constant returns to scale in the Wald test in five export-oriented industries (Food (31); Wood (33); Non-metallic minerals (36) and Basic metals (37)). On the other hand, industries with increasing returns are mainly import-competing (Textile (32), Paper (34), Chemicals (35) and Machinery(38)). Thus, in these industries market size can affect the cost structure of firms.

[Table 1 about here]

After estimating production function elasticities, we calculate plant TFP as a residual. Figure 1 (Appendix) presents the average evolution of different measures of plant productivity: fixed effects (tfp_fe), LP (tfp_lp), OLS (tfp_ols) and labor productivity (lnproductivity).

As a first robustness check of our productivity measures, the figure shows that labor productivity and all TFP measures depict similar evolutions. Although FE and LP elasticities exhibit some differences, the TFP path illustrated by both measures is very similar. [15]

[15] Thus, even if the assumption of fixed effects may overestimate the capital elasticity and underestimate labor one, after computing all factors contribution, the evolution of the residual is not drastically affected.

3.2 Results of step 2: Border effect estimates

In the second step, we construct market access measures by estimating equation (7) at the 2-digit industry level. This estimation captures the heterogeneity of trade barriers across industries. Figure 2 (Appendix) plots the weighted average of export and import border effect estimates across trade partners. Weights are based on each country export (import) share over total exports (imports) of Chile. All coefficients are significant at least at 5%. The solid line depicts export border effects and the dashed line those corresponding to import.

Difficulties of Chilean exporters to access foreign markets (export border effect) were relatively constant at the beginning of the eighties. Reflecting the active trade agreement agenda, most industries switch to a downward trend at the end of the 1980s. This becomes specially pronounced during the 1990s. This is the case of Wood, Textiles, Plastics and Machinery. Two important export-oriented industries, Basic metals and Food, show an evolution of export border effect almost flat. The former, however, is the most traditional export-oriented industry and in this industry trade barriers were already low at the beginning of the period. On the other hand, the rather flat evolution of export barriers on Food industry might be explained by quality controls set by EU and the US. Home biases are also likely to be present in this type of industry. Once again one observes the extent to which direct trade measures such as import tariffs do not capture all dimensions of trade integration: export barriers have considerably diminished in all industries during the 1990s, even if import tariffs were already low.

Figure 2 also shows the evolution of the weighted measure of industry-level barriers faced by EU, LA and the US to access the Chilean market (import border effect). In many industries, import barriers increased during the first half of the 1980s (Food, Textiles, Wood, Non-metallics and Machinery). This is consistent with the raise in import tariffs during this period and also with other discretionary policy measures set to control the current account deficit during the debt crisis. Since we use a moving average of border effects, this tendency is observed even in the late 1980s as a lagged effect of protection.

During the 1990s import border effects fall in almost all industries except in Basic metals. This reduction and convergence of import border effects seem also consistent with the new trade integration agenda of Chile based on bilateral and multilateral trade agreements.

3.3 Results of step 3: The impact of trade barriers on plant TFP

The final step consists in identifying the influence of each type of trade barrier on the evolution of plant productivity. Equation (8) disentangles the variation in productivity due to changes in trade barriers depending on trade orientation. We are interested in the vector coefficient δ of the interaction terms between trade orientation indicators and our border effect estimates.

3.3.1 Reproducing Pavcnik's (2002) results

In order to provide a baseline estimation, we start by reproducing Pavcnik's (2002) regressions for our full sample period. We use within group estimates in a difference-in-difference framework. In this specification, year indicators capture trade liberalization effects. These estimates are illustrated in Figure 3 (Appendix). We obtain similar results to Pavcnik (2002). Once controlling for exit and plant specific characteristics, trade liberalization (captured by time dummies) has a positive impact on plant productivity in traded industries (export-oriented and import-competing) relative to non-traded ones. Interestingly, considering only the period 1980-1986, Pavcnik (2002) highlights that plant productivity gains in export-oriented industries are minor. Using the full sample period, this trend changes after the 1990s.

3.3.2 Disentangling the effects of export and import barriers

In this section, we employ the weighted average border effects estimated in step 2. As previously mentioned, we use a four-year rolling window for each industry. Hence, the border effect measures capture not only the current but also the lagged effect of trade integration on plant TFP. This implies the loss of initial years in the sample (1979-1981). On the other hand, these lagged measures of border effects and the controls introduced in step 2 to address asymmetric technologies reduce the risk of potential endogeneity between our measure of trade barriers and productivity. Additionally, in robustness check of dynamic specification we treat border effects as endogenous regressors in GMM estimations.

Table 2 reports the results using the plant TFP measured by the LP methodology (TFP_LP). After controlling for industry specific effects (2-digit industry indicators) and macroeconomic shocks (year indicators), the coefficients of the other variables should only capture the effects of within-industry productivity variation. We consider plant-fixed effects and use Huber-White standard errors in all estimations. In the last column, these errors are corrected for clustering at the plant level.

The first column presents the baseline estimation. In this specification we include the indicators for export-oriented (Export) and import-competing (Import) industries, the measures of import border effects (BM) and export border effects (BX) and their interactions (Export*BX, Import*BX, Export*BM, Import*BM). In this difference-in-difference framework we interpret the coefficients of interaction terms relative to non-traded industries (the omitted category). Export border effects interacted with both export-oriented (Export*BX) and import-competing (Import*BX) indicators present a negative and significant coefficient. This suggest a positive and significant impact of export barrier *reductions* on plant productivity in both traded industries. This result can be related to learning-by-exporting and international knowledge spillovers (Kraay (2002) on China, Alvarez and Lopez (2005) on Chile and De Loecker (2007) on Slovenia). In the case of plants belonging to import-competing industries, the positive effect of export barrier reductions on their productivity could be driven by new-exporters within these industries. Bergoeing et al.(2005) show that, even if with a small aggregate export share, a number of plants entered the export market during the nineties in those Chilean industries.

The impact of import barriers depends on trade orientation. We find evidence of a negative effect of import barrier reductions on productivity of plants belonging to import-competing industries (Import*BM). Therefore, contrary to Pavcnik's (2002) results, in our regressions foreign competition appears to dampen plant productivity in those industries. The production function estimates (step 1) show that import-competing industries (Textile, Paper, Chemicals and Machinery) operate under increasing returns to scale (IRS). In this case, import competition reduces market shares of domestic firms shrinking the opportunities to exploit scale economies. This possible explanation has also been emphasized by Bergoeing et al. (2006) for different production function estimates and data treatment.

[Table 2 about here]

On the other hand, the reduction of import barriers has a positive impact on plant productivity in export-oriented industries (Export*BM). While import competition does not affect export sales, exporters also sell in the domestic markets and have to face foreign competitors. Hence, this category of exporters may help to isolate the "trimming fat" effect of foreign competition, since economies of scale are guaranteed for these firms by the access to international markets. The positive effect of the reduction of import barriers on plant productivity in export-oriented industries, in these static regressions, might come from innovative strategies implemented to improve domestic competitiveness. However, if one might expect a positive and a negative effect of foreign competition, for plants belonging to import-competing industries the effect of market size reduction is negative enough to offset a positive outcome of import barrier reductions.

The above results (interaction terms) remain almost unchanged after the progressive inclusion of several controls. [16] As expected, the exit indicator (Exit ind) has a negative coefficient (column (2)). Exiting plants are on average 14% less productive than surviving plants. The entry indicator (Entry ind) coefficient is also negative showing that new-entrants are roughly 6% less productive than incumbents (column (3)). The use of imported inputs (Imported input) also appears to be positively correlated with produc-

[16] It is well documented in plant level studies that multinationals are relatively productive, technology-intensive, and trade-intensive. Unfortunately, in our database, plant foreign status is only available since 1993.

tivity (column (4)). The last column introduces a financial indicator (Credit). Although the coefficient is small, it has the expected positive sign (column (5)). Column 6 reports the results correcting for clustering at the plant level. Our estimates are still significant if one controls for intra group correlation.

3.3.3 Robustness checks

Alternative measures of productivity gains. The previous results remain robust using alternative measures of plant productivity. First, we use the estimates of the production function using an individual fixed effect specification (within-group estimates) instead of LP strategy to obtain the plant TFP in step 1. The first two columns of Table 3 report the results using this alternative measure of TFP (TFP_FE). Columns 3 and 4 show the results using labor productivity (Labor pr), measured as (deflated) value added per worker, and controlling for capital intensity (deflated capital stock over total labor). In both cases, the sign and the magnitude of the coefficients of the interaction terms between trade barriers and trade orientation indicators are very similar to those obtained in the previous specification (Table 2). Export barrier reductions improve plant productivity of firms in export-oriented and import-competing industries, while the fall in import barriers has only a positive impact on export-oriented industries and a negative effect on import-competing ones. These findings confirm the previous results using plant TFP estimated by LP strategy.

[Table 3 about here]

Industry concentration and mark-ups. As is common to the empirical literature on plant TFP estimations, this productivity measure is likely to be sensitive to mark-ups variations. It is difficult to disentangle real (physical) productivity improvements from variations in value added arising from market power and price setting. In order to control for mark-up concerns, which are not captured by the individual fixed effects included in our previous regressions, we add the Herfindahl index of market concentration. This index is computed as the sum of the squared market shares in each 3-digit industry. Columns 5 of Table 3 shows these results. Once we introduce the Herfindahl index the magnitude of the coefficients of the interaction terms between trade barriers and trade orientation remain entirely unchanged (see column 6 of Table 2). Market concentration is negatively correlated with plant productivity in these regressions.

If productivity improvements due to trade barrier reductions reflect variations in market power, this effect should be more important for firms producing in concentrated industries. Similar to previous works (Amiti and Konings, 2007) we compute an additional robustness check introducing an interaction term between an industry concentration indicator, trade barriers and trade orientation indicators (Export*BX*concentration, Import*BX*concentration, Export*BM*concentration, Import*BM*concentration). The industry concentration dummy indicator is equal to one if the average of the Herfindahl index in the pre-sample period (1979-1981) is higher than 0.22, which corresponds to the 75th percentile.[17] The interaction terms of this concentration indicator with trade barriers and trade orientation indicators are not significant (column 6 of Table 3). This suggests that there is no significant difference in productivity gains between low and high concentrated industries. Moreover, the coefficients of our key interaction terms between trade barriers and trade orientation indicators are not altered by the introduction of these controls.

Dynamic specification. In this section, we perform a dynamic specification of equation (8) in which plant productivity depends on its past values. This implies the following auto-regressive multivariate model:

$$\widehat{a}_{pt} = \theta_0 + \theta_1\ \widehat{a}_{pt-1} + \zeta\ B_{pt} + \gamma\ T_p + \delta\ B_{pt} \cdot T_p + \varphi\ Z_{pt} + \xi_{pt} \tag{9}$$

If we believe that the error term contains a specific time-invariant unobserved heterogeneity ($\xi_{pt} = \upsilon_p + \mu_{pt}$), the lagged value of TFP, $\widehat{a}_{pt-1}$, is then endogenous to the

[17] We use the pre-sample period due to the difference-in-difference framework and also in order to avoid endogenous changes in the Herfindahl index.

error term (as it also contains υ_p). Econometric literature provides well-known strategies for this dynamic issue. These strategies exploit moment conditions of exogeneity of the lags of the endogenous dependent variable. Here we use the GMM estimator of Arellano and Bond (1991). We include OLS and within-group (WG) estimators to identify an interval within which a consistent estimate of the autoregressive coefficient θ_1 should lie (Bond, 2002). The first column of Table 4 reports the OLS results, the second one the within-group estimates and finally, column 3 shows the GMM results. As expected, the coefficient of the auto-regressive term (tfp_lp(t-1)) is higher when using OLS than in the case of within-group regressions. This is a signal of a consistent dynamic specification, which means that the number of TFP lags on the right-hand side is correct. The set of instruments used in GMM estimation is composed of deep lags of border effect measures and TFP. Both set of variables are treated as endogenous. This provides an additional robustness check on the potential endogeneity issue between border effects and productivity mentioned in the step 2. The Hansen and Sargan tests validate our instrument choice. The number of individuals relative to the number of instruments is reassuring as regards any possible bias in the test when using a large number of instruments (Windmeijer, 2005). We focus on GMM and within-group results. Dynamic regressions confirm the existence of plant productivity improvements after a reduction of export barriers in both traded industries. The positive sign in the interaction between import barriers and the import-competing indicator (Import*BM), also resists the dynamic control in GMM regressions. In the case of a within-group estimates this effect fails to be significant, though the autoregressive coefficient seems clearly downward biased.

[Table 4 about here]

On the contrary, the positive impact of import barrier reductions on plant productivity in export-oriented industries depends on the method. Within-group estimations confirm this finding (column 2), while in GMM regressions (column 3) the coefficient of the interaction between import barriers and the export-oriented indicator (Export*BM) becomes positive and significant. If GMM addresses the dynamic panel bias as it is expected, this result means that, once we control for the persistence of plant productivity series, foreign competition might also dampen domestic sales and plant productivity in export-oriented industries. Their high productivity trend overwhelms this effect in a static specification or in the case of a panel data bias in the within-group estimation.

3.3.4 Trade liberalization channels

Increasing returns to scale. One of the novel findings in previous regressions is the negative impact of import barrier reductions on productivity gains of firms producing in import-competing industries. This result is robust to alternative measures of productivity and to controls of market power. In this subsection we provide additional evidence on the mechanism by which import competition might affect plant productivity.

As previously mentioned, the production function estimates in the first step reveal IRS in industries classified as import-competing. Hence, one possible explanation is that foreign competition reduces market shares of all firms and hampers the possibility to exploit economies of scale in import-competing industries. To illustrate this argument we provide regressions interacting trade barriers and a dummy indicating whether the plant operates in an industry under IRS (Increasing).[18])

Table 5 presents these results. Firms producing in industries operating under IRS have a lower productivity level than other firms (column (1)). The interaction term between import barriers and the indicator of increasing returns to scale is positive and significant (column (2)). This means that firms producing in industries under IRS suffer from foreign competition. As expected, the interaction term between export barriers and the indicator of increasing returns to scale is negative and significant. The reduction of export barriers increases market potential and enlarges the possibility to exploit scale economies (column (2)). These results remain robust when we control for market concentration (column (3)) and standard errors corrected for clustering at the plant level (column (4)).

[Table 5 about here]

[18]The production function estimates show that industries operating under Increasing returns are Textile (32), Paper (34), Chemicals (35) and Machinery (38).

The better access to foreign technology. In a developing country like Chile, the access to new technologies embodied in high-quality imported inputs and capital equipment may have a major role on productivity enhancements. This channel is present in our data. First, in previous regressions we find that firms producing with imported inputs have a higher TFP than those that only use domestic inputs. Second, in this subsection instead of using the import border effect at the 2-digit industry level for each industry, we only use the one corresponding to Machinery (BK_M) as a proxy of import barriers on capital equipment. The interaction term of this specific import border effect with the trade orientation dummies captures the extent to which plant productivity reacts to a better access to foreign capital goods. Table 6 reports the results of these regressions. Relative to non-traded industries, firms belonging to traded industries enhance their productivity after a reduction of import barriers on machinery industry. Moreover, productivity gains are significantly higher for plants in export-oriented industries (Export*BK_M) than in import-competing ones (Import*BK_M).

[Table 6 about here]

4 Conclusion

The main contribution of the paper is to construct specific measures of trade barriers at the industry-level in order to disentangle the impact of the reduction of export and import barriers on plant productivity. This distinction introduces new results. First, the reduction of export barriers improves productivity of plants belonging to both traded industries. As the export costs fall, more firms are able to export increasing their size and probably benefiting from knowledge spillovers stemming from international markets. This encouraging result is robust to all robustness checks and specifications. Second, in all static specifications the reduction of import barriers shows a positive impact on the evolution of plant productivity in export-oriented industries relative to non-traded. However, this is not the case for plants belonging to import-competing industries producing with increasing returns to scale. The reduction of import barriers may prevent local firms to exploit economies of scale since they must share the local market with foreign competitors. Moreover, exporters' productivity also appears to have a negative reaction to foreign competition when a dynamic setting is considered.

References

[1] Alvarez, R., and R. Lopez (2005). Exporting and Performance: Evidence from Chilean Plants. Canadian Journal of Economics 38 (4): 1384-1400.

[2] Amiti, M., and J. Konings (2007). Trade liberalization, intermediate inputs, and productivity: Evidence from Indonesia. American Economic Review 97 (5): 1611-1638.

[3] Anderson, J. E., and E. van Wincoop (2003). Gravity with Gravitas : a Solution to the Border Puzzle. American Economic Review 93 (3): 170-192.

[4] Anderson, J. E., and E. van Wincoop (2004). Trade Costs. Journal of Economic Literature 42 (1): 691-751.

[5] Arellano, M., and S. Bond (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. Review of Economic Studies 58 (1): 277-297.

[6] Baier, S. L., and Jeffrey H. Bergstrand (2001). The Growth of World Trade: Tariffs, Transport Costs and Income Similarity. Journal of International Economics 53(1): 1-27.

[7] Bond, S. (2002). Dynamic Panel Data Models: a Guide to Micro Data Methods and Practice. Portuguese Economic Journal 1: 141-162.

[8] Bergoeing, R., P. J. Kehoe, T. J. Kehoe, and R. Soto (2002). Policy-Driven Productivity in Chile and Mexico in the 1980s and 1990s. American Economic Association 92(2): 16-21.

[9] Bergoeing, R., N. Loayza and A. Repetto (2004). Slow Recoveries. Journal of Development Economics 75, 473-506.

[10] Bergoeing, R., A. Hernando and A. Repetto (2006). Market Reforms and Efficiency Gains in Chile. Working Paper CEA, University of Chile.

[11] Bergoeing, R. , A. Micco and A. Repetto (2005). Dissecting the Chilean Export Boom. Working Paper CEA, Universidad de Chile.

[12] De Loecker, J. (2007). Do exports generate higher productivity? Evidence from Slovenia. Journal of International Economics 73(1): 69-98.

[13] Devarajan, S. and D. Rodrik (1989). Trade Liberalization in Developing Countries: Do Imperfect Competition and Scale Economies Matter?. The American Economic Review 79(2): 283-287.

[14] Feenstra, R. C. (2003). Advanced International Trade: Theory and Evidence. Princeton University Press.

[15] Fontagné, L., T. Mayer and S. Zignago (2005). Trade in the Triad: How Easy is the Access to Large Markets?. Canadian Journal of Economics 38(4): 1402-1430.

[16] Harrigan, J. (1996). Openness to Trade in Manufactures in the OECD. Journal of International Economics 40(1-2): 23-39.

[17] Head, K., and T. Mayer (2000). Non-Europe : The Magnitude and Causes of Market Fragmentation in Europe. Weltwirschaftliches Archiv 136 (2): 285-314.

[18] Kasahara, H., and J. Rodriguez (2008). Does the Use of Imported Intermediates Increase Productivity? Plant-Level Evidence. Journal of Development Economics 87: 106-118.

[19] Katayama, H. , S. Lu and J. Tybout (2005). Firm-Level Productivity Studies: Illusions and a Solution. NBER Working Paper No. 9617.

[20] Kraay, A. (2002). Exports and Economic Performance: Evidence from a Panel of Chinese Firms. In M. F. Renard (Ed.). China and its Regions, Economic Growth and Reform in Chinese Provinces. Cheltenham : Edward Elgar. 278-299.

[21] Levinsohn, J., and A. Petrin (2003). Estimating Production Functions Using Inputs to Control for Unobservables. Review of Economic Studies 70(2): pp. 317-341.

[22] Liu, L., and J. Tybout (1996). Productivity Growth in Colombia and Chile: Panel-Based Evidence on the Role of Entry, Exit and Learning. In M. Roberts and J. Tybout (eds.), Industrial Evolution in Developing Countries. New York : Oxford University Press.

[23] McCallum, J. (1995). National Borders Matter. American Economic Review 85 (3): 615-23.

[24] Nicita, A., and M. Olarreaga (2001). Trade and Production, 1976-99. Policy Research Working Paper Series 2701, The World Bank.

[25] Olley, S., and A. Pakes (1996). The Dynamics of Productivity in the Telecommunication Equipment Industry. Econometrica 64(6): 1263-1298.

[26] Pavcnik, N. (2002). Trade Liberalisation, Exit and Productivity Improvement: Evidence from Chilean Plants. Review of Economic Studies 69: 245-276.

[27] Redding, S., and A. Venables (2004). Economic Geography and International Inequality. Journal of International Economics 62(1): 53-82.

[28] Rodrik, D. (1988). Closing the Technology gap: Does Trade Liberalization Really Help?. NBER working paper No. 2654.

[29] Schor, A. (2004). Heterogeneous productivity response to tariff reduction: evidence from Brazilian manufacturing firms. Journal of Development Economics 75(2) :373-396.

[30] Windmeijer, F. (2005). A Finite Sample Correction for the Variance of Linear Eficient Two-Step GMM Estimators. Journal of Econometrics 126(1): 25-51.

Table 1: *Production Function Estimates*

Industry	**Factors**[a]	**OLS**	**S.E.**	**Fixed effects**	**S.E.**	**LP**[b]	**S.E.**
Food and	U	0.815	(0.010)	0.627	(0.012)	0.570	(0.024)
beverage [31]	S	0.359	(0.009)	0.159	(0.008)	0.212	(0.015)
obs: 18559	K	0.250	(0.005)	0.083	(0.007)	0.208	(0.046)
Textile [32]	U	0.833	(0.011)	0.777	(0.014)	0.710	(0.024)
	S	0.202	(0.010)	0.165	(0.009)	0.174	(0.018)
obs: 11063	K	0.206	(0.005)	0.102	(0.008)	0.249	(0.034)
Wood [33]	U	0.865	(0.017)	0.849	(0.021)	0.681	(0.034)
	S	0.208	(0.015)	0.095	(0.014)	0.131	(0.021)
obs: 5711	K	0.209	(0.009)	0.104	(0.013)	0.275	(0.040)
Paper [34]	U	0.763	(0.018)	0.539	(0.024)	0.692	(0.044)
	S	0.252	(0.014)	0.175	(0.015)	0.207	(0.025)
obs: 3175	K	0.229	(0.010)	0.182	(0.014)	0.299	(0.055)
Chemicals [35]	U	0.604	(0.016)	0.639	(0.017)	0.528	(0.045)
	S	0.337	(0.015)	0.168	(0.013)	0.266	(0.028)
obs: 6588	K	0.294	(0.008)	0.149	(0.011)	0.354	(0.057)
Non metalic	U	0.780	(0.028)	0.797	(0.031)	0.577	(0.074)
products [36]	S	0.241	(0.026)	0.130	(0.025)	0.103	(0.049)
obs: 2153	K	0.244	(0.013)	0.136	(0.018)	0.281	(0.074)
Basic metals [37]	U	0.280	(0.070)	0.346	(0.061)	0.217	(0.104)
	S	0.485	(0.063)	0.161	(0.045)	0.263	(0.094)
obs: 640	K	0.412	(0.042)	0.059	(0.049)	0.290	(0.189)
Machinery [38]	U	0.897	(0.012)	0.766	(0.015)	0.767	(0.033)
	S	0.242	(0.011)	0.204	(0.011)	0.178	(0.022)
obs: 8524	K	0.164	(0.006)	0.111	(0.010)	0.236	(0.058)

Standard errors (S.E.) in perentheses

[a] U: unskilled labor (production workers); S: skilled labor (non-production workers); K: capital stock

[b] Levinsohn and Petrin (2003) methdology using electricity to control for the unobserved plant heterogeneity. 250 replications are used for bootstrap. The Wald test of constant returns to scale is rejected for Textile (32), Paper (34), Chemicals (35) and Machinery (38) industries

Table 2: *The Impact of Trade Barriers on Plant TFP (LP measure)*

	1	**2**	**3**	**4**	**5**	**6**[a]
Export	0.636***	0.633***	0.633***	0.638***	0.635***	0.635***
	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)	(0.111)
Import	0.283***	0.290***	0.291***	0.288***	0.291***	0.291***
	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)	(0.090)
Export*BX	-0.023***	-0.024***	-0.023***	-0.025***	-0.025***	-0.025**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)
Import*BX	-0.063***	-0.062***	-0.062***	-0.062***	-0.062***	-0.062***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)
Export*BM	-0.103***	-0.101***	-0.101***	-0.101***	-0.100***	-0.100***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.015)
Import*BM	0.040***	0.038***	0.038***	0.039***	0.039***	0.039**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.016)
BX	0.095***	0.095***	0.095***	0.095***	0.095***	0.095***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)
BM	0.083***	0.083***	0.083***	0.081***	0.081***	0.081***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.014)
Exit indicator		-0.134***	-0.139***	-0.137***	-0.137***	-0.137***
		(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Entry indicator			-0.063***	-0.063***	-0.063***	-0.063***
			(0.016)	(0.016)	(0.016)	(0.016)
Imported Inputs				0.051***	0.050***	0.050***
				(0.010)	(0.010)	(0.012)
Credit					0.024***	0.024**
					(0.009)	(0.011)
Constant	5.284***	5.275***	5.280***	5.259***	5.249***	5.249***
	(0.107)	(0.108)	(0.107)	(0.107)	(0.107)	(0.136)
Plant, ISIC 2 and Year Ind	YES	YES	YES	YES	YES	YES
Number of Obs	46894	46894	46894	46894	46894	46894
Adjusted R-Sq.	0.220	0.228	0.229	0.238	0.241	0.241

Huber White standard errors in parentheses. ***, **, * denote significance at 1%,5%, and 10%, respectively.

[a] Standard errors corrected for clustering at the plant level.

Table 3: *Alternative Measures of Productivity and Controls for Mark-up*

	TFP FE	**TFP FE**[a]	**Labor pr.**	**Labor pr.**[b]	**TFP LP**	**TFP LP**[c]
Export	0.524***	0.520***	0.489***	0.540***	0.617***	0.798***
	(0.074)	(0.105)	(0.063)	(0.098)	(0.111)	(0.162)
Import	0.227***	0.232***	0.296***	0.291***	0.304***	0.358***
	(0.062)	(0.082)	(0.058)	(0.083)	(0.092)	(0.097)
Export*BX	-0.019***	-0.020*	-0.020***	-0.022**	-0.024**	-0.024**
	(0.007)	(0.010)	(0.006)	(0.010)	(0.011)	(0.011)
Import*BX	-0.059***	-0.059***	-0.067***	-0.066***	-0.062***	-0.064***
	(0.007)	(0.010)	(0.006)	(0.009)	(0.010)	(0.010)
Export*BM	-0.090***	-0.090***	-0.083***	-0.090***	-0.099***	-0.104***
	(0.011)	(0.015)	(0.010)	(0.014)	(0.015)	(0.015)
Import*BM	0.051***	0.050***	0.048***	0.051***	0.039**	0.040**
	(0.012)	(0.016)	(0.011)	(0.015)	(0.016)	(0.017)
BX	0.092***	0.092***	0.078***	0.081***	0.095***	0.095***
	(0.007)	(0.010)	(0.006)	(0.010)	(0.011)	(0.011)
BM	0.062***	0.063***	0.069***	0.075***	0.080***	0.086***
	(0.010)	(0.014)	(0.010)	(0.014)	(0.014)	(0.015)
Exit indicator	-0.146***	-0.145***	-0.146***	-0.150***	-0.136***	-0.137***
	(0.013)	(0.013)	(0.010)	(0.013)	(0.013)	(0.013)
Entry indicator	-0.067***	-0.066***	-0.027***	-0.049***	-0.062***	-0.063***
	(0.015)	(0.016)	(0.010)	(0.015)	(0.016)	(0.016)
Imported Inputs	0.064***	0.063***	0.065***	0.058***	0.050***	0.050***
	(0.010)	(0.012)	(0.009)	(0.012)	(0.012)	(0.012)
Credit		0.032***		0.030***	0.025**	0.024**
		(0.010)		(0.010)	(0.011)	(0.011)
Capital Intensity				0.081***		
				(0.007)		
Herfindahl					-0.218*	
					(0.129)	
Export*BX*Concentration						0.047
						(0.047)
Import*BX*Concentration						0.044
						(0.042)
Export*BM*Concentration						-0.058
						(0.059)
Import*BM*Concentration						-0.094
						(0.064)
Concentration						-0.178
						(0.192)
Constant	6.660***	6.647***	7.152***	6.567***	5.253***	5.151***
	(0.106)	(0.130)	(0.090)	(0.137)	(0.135)	(0.140)
Number of Obs	46894	46894	65068	49001	46894	46894
Adjusted R-Sq.	0.207	0.214	0.106	0.235	0.241	0.234
Plant, ISIC 2 and Year Ind	YES	YES	YES	YES	YES	YES
Number of Obs	46894	46894	65068	49001	46894	46894
Adjusted R-Sq.	0.207	0.214	0.106	0.235	0.241	0.235

Huber White standard errors in parentheses. ***, **, * denote significance at 1%,5%, and 10%, respectively. Fixed effect TFP (TFP FE) and labor productivity (Labor pr.) are considered as alternative measures of the LP TFP. The last two columns address potential markup bias concerns by adding the Concentration dummy, which indicates if the average Herfindahl index in the pre-sample period is in the 75th percentile.
[a],[b],[c] Standard errors corrected for clustering at the plant level.

Table 4: *Dynamic specification*

	1	**2**[a]	**3**[b]
TFP(t-1)	0.822***	0.482***	0.741***
	(0.005)	(0.009)	(0.091)
Export	0.233***	0.400***	-1.853
	(0.044)	(0.101)	(2.221)
Import	0.021	0.137*	-1.061
	(0.037)	(0.081)	(1.731)
Export*BX	-0.016***	-0.020**	-0.233***
	(0.006)	(0.008)	(0.067)
Import*BX	-0.016***	-0.034***	-0.343***
	(0.005)	(0.008)	(0.110)
Export*BM	-0.030***	-0.052***	0.358***
	(0.008)	(0.012)	(0.098)
Import*BM	0.015*	0.019	0.515***
	(0.008)	(0.013)	(0.154)
BX	0.043***	0.066***	0.220**
	(0.006)	((0.008)	(0.086)
BM	-0.009	0.030***	-0.346***
	(0.008)	(0.011)	(0.113)
Herfindahl	-0.008	0.099	0.593
	(0.065)	(0.109)	(0.811)
Exit indicator	-0.148***	-0.115***	-0.262***
	(0.012)	(0.014)	(0.039)
Entry indicator	0.000	0.000	
	(0.000)	(0.000)	
Credit	0.041***	0.013	0.604**
	(0.006)	(0.009)	(0.266)
Imported Inputs	0.081***	0.035***	0.077
	(0.006)	(0.010)	(0.137)
Constant	0.722***	2.672***	
	(0.049)	(0.134)	
Plant, ISIC 2 and Year Ind	YES	YES	YES
Number of Obs	35117	35117	31853
Adjusted R-Sq.	0.757	0.287	
Sargan p			0.160
Hansen p			0.248
AR(2)p			0.002[c]
AR(3)p			0.810
instruments			85
individuals		5392	4911

Huber White standard errors in parentheses.
***, **, * denote significance at 1%,5%, and 10%, respectively.
[a] Standard errors corrected for clustering at the plant level.
[b] The set of instruments is composed of lagged values of border effect and plant TFP. Both are treated as endogenous vairables. As usual, we use industry and year indicators as exogenous instruments. Orthogonal transformations are used to maximize sample size.
[c] Since the Arellano-Bond test of autocorrelation reveals that the disturbance might be in itself auto-correlated of order-1, but not further, we take lags between t - 4 and t -6.

Table 5: *Foreign Competition and Increasing Returns to Scale*

	1	**2**	**3**	**4**[a]
Increasing	-0.505**	-0.953***	-0.949***	-0.949***
	(0.211)	(0.216)	(0.216)	(0.243)
BX	0.060***	0.083***	0.083***	0.083***
	(0.006)	(0.007)	(0.007)	(0.011)
BM	0.040***	-0.005	-0.006	-0.006
	(0.008)	(0.009)	(0.009)	(0.011)
Exit indicator	-0.140***	-0.136***	-0.136***	-0.136***
	(0.013)	(0.013)	(0.013)	(0.013)
Entry indicator	-0.061***	-0.062***	-0.062***	-0.062***
	(0.016)	(0.016)	(0.016)	(0.016)
Imported Inputs	0.047***	0.049***	0.049***	0.049***
	(0.010)	(0.010)	(0.010)	(0.012)
Credit	0.028***	0.025***	0.025***	0.025**
	(0.009)	(0.009)	(0.009)	(0.011)
Increasing*BM		0.125***	0.124***	0.124***
		(0.010)	(0.010)	(0.013)
Increasing*BX		-0.030***	-0.030***	-0.030***
		(0.006)	(0.006)	(0.009)
Herfindahl			-0.226**	-0.226*
			(0.097)	(0.125)
Constant	6.245***	6.387***	6.401***	6.401***
	(0.147)	(0.151)	(0.151)	(0.173)
Plant, ISIC 2 and Year Ind	YES	YES	YES	YES
Number of Obs	46894	46894	46894	46894
Adjusted R-Sq.	0.232	0.233	0.232	0.232

Huber White standard errors in parentheses.
***, **, * denote significance at 1%,5%, and 10%, respectively.
[a] Standard errors corrected for clustering at the plant level.

Table 6: *Import Barriers on Machinery and Productivity (TFP LP)*

	1	**2**	**3**	**4**	**5**	**6**[a]
Export	0.950***	0.950***	0.929***	0.928***	0.925***	0.925***
	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.108)
Import	0.482***	0.491***	0.504***	0.502***	0.505***	0.505***
	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.095)
Export*BK_M	-0.264***	-0.263***	-0.259***	-0.259***	-0.259***	-0.259***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.020)
Import*BK_M	-0.105***	-0.107***	-0.105***	-0.104***	-0.104***	-0.104***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.020)
BK_M	-0.103***	-0.143***	-0.147***	-0.149***	-0.149***	-0.149***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.022)
Exit indicator		-0.141***	-0.140***	-0.139***	-0.138***	-0.138***
		(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Entry indicator		-0.059***	-0.059***	-0.060***	-0.059***	-0.059***
		(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Herfindahl			-0.250**	-0.251**	-0.252**	-0.252**
			(0.100)	(0.100)	(0.100)	(0.127)
Imported Inputs				0.051***	0.050***	0.050***
				(0.010)	(0.010)	(0.012)
Credit					0.024***	0.024**
					(0.009)	(0.011)
Constant	6.593***	6.740***	6.749***	6.729***	6.720***	6.720***
	(0.114)	(0.114)	(0.114)	(0.113)	(0.113)	(0.137)
Plant, ISIC 2 and Year Ind	YES	YES	YES	YES	YES	YES
Number of Obs	46894	46894	46894	46894	46894	46894
Adjusted R-Sq.	0.116	0.120	0.120	0.121	0.121	0.121

Huber White standard errors in parentheses. ***, **, * denote significance at 1%,5%, and 10%, respectively.
[a] Standard errors corrected for clustering at the plant level.

A Appendix

Export oriented industries: 311, 312, 331, 341, 372.

Import competing industries: 321, 322, 351, 354, 355, 361, 362, 381, 382, 383, 384, 385, 390.

Non traded industries: 313, 323, 324, 332, 342, 352, 353, 356, 369, 371.

Table 7: *Variables description*

	Variable	Data
Export Border Effect	BX	Export barriers at 2 digit industry level estimated by a gravity model in step 2.
Import Border Effect	BM	Import barriers at 2 digit industry level estimated by a gravity model in step 2.
Export oriented sector	Export	Dummy variable equal to one if the firm belongs to a 3 digit industry with more than 15% of exports over output
Import competing sector	Import	Dummy variable equal to one if the firm belongs to a 3 digit industry with more than 15% of import over output
Market concentration	Herfindahl	Herfindahl index of market concentration at 3 digit industry level
Pre-sample Concentration	Concentration	Dummy variable equal if the average Herfindahl index in the pre-sample period is in the 75th percentile
Imported Inputs	Imported Inputs	Dummy variable equal to one if the plant reports having used imported inputs
Credit Indicator	Credit	Dummy variable equal to one if the plant reports having paid a loan tax in year "'t"'

Table 8: Summary Statistics by Industry (2-digit ISIC Rev-2)

	Labor pr.	Δ Labor pr.	S/L	K/L	Exports share
Food (31)	5108	0.10	0.13	3420	0.09
	(10204)	(0.66)	(0.11)	(10709)	(0.2)
Textile (32)	3828	0.07	0.13	2198	0.02
	(3770)	(0.5)	(0.10)	(8676)	(0.09)
Wood (33)	4099	0.11	0.11	2192	0.07
	(6428)	(0.93)	(0.10)	(4143)	(0.18)
Paper (34)	7119	0.02	0.17	4775	0.03
	(9492)	(0.42)	(0.15)	(14877)	(0.12)
Chemicals (35)	10832	0.07	0.16	4793	0.04
	(23366)	(0.57)	(0.11)	(10573)	(0.13)
Non metallic (36)	8130	0.09	0.13	5356	0.01
	(14480)	(0.59)	(0.10)	(16133)	(0.06)
Basic metals (37)	34409	0.13	0.19	7826	0.18
	(93787)	(0.71)	(0.14)	(12033)	(0.31)
Machinery (38)	5375	0.10	0.16	3122	0.02
	(5987)	(0.68)	(0.13)	(6519)	(0.07)

Mean of variables reported; standar deviation in parentheses
Labor pr.: labor productivity, Δ Labor pr.: Labor productivity growth, S/L: skill intensity, K/L: capital intensity

Figure 1: Evolution of TFP estimates.

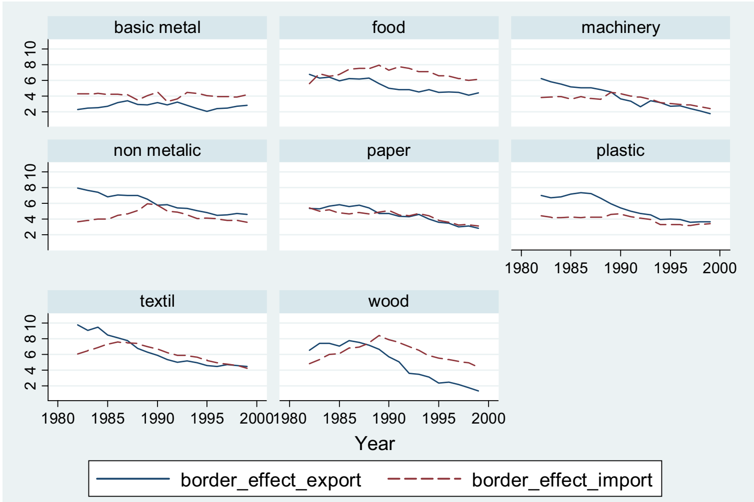

Figure 2: Border effect estimates.

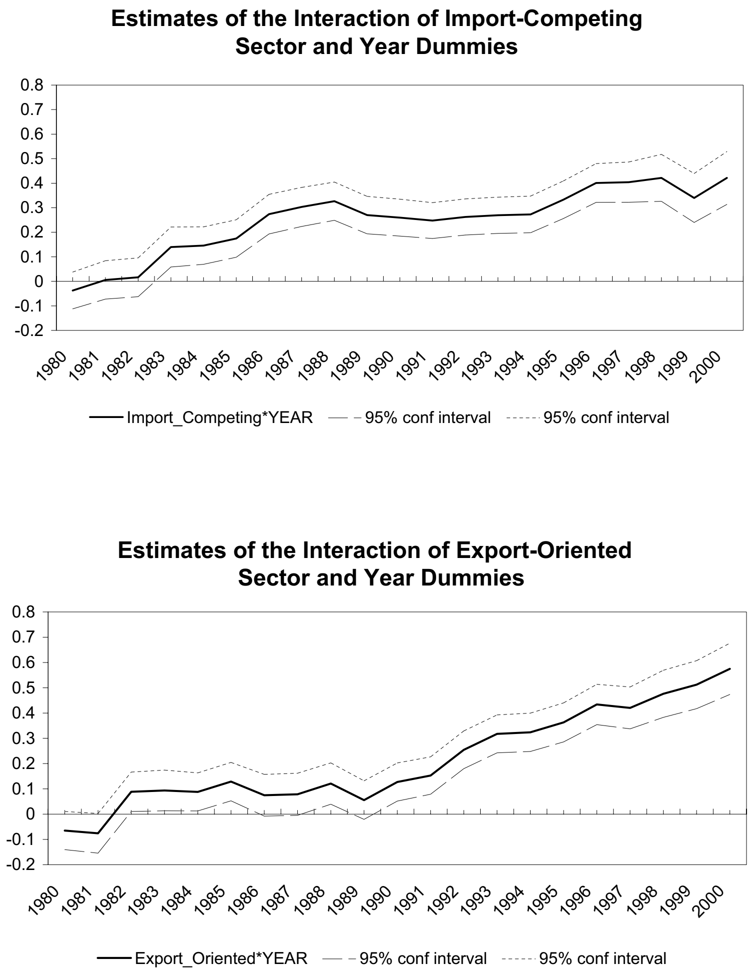

Figure 3: Reproducing Pavcnik's (2002) results

B Technical appendix

We classify industries by trade orientation at the 3-digit industry level similar to Pavcnik (2002)(Table 1.B). Plants are classified as export-oriented if they belong to a 3-digit industry which has more than 15% of exports over total production (Export-Output ratio) and as import-competing if the industry has more than 15% of imports over total production (Import-Output ratio). The rest are considered as non-traded. There are only two industries (351 and 384) that matched up to both categories. Nevertheless, the industry 351 (384) presents an export-output ratio of 0.82 (0.21) and an import-output ratio of 1.32 (2.01). Therefore these industries were classified as import competing in the paper. Our results remain unchanged if we consider a fourth category of export-import competing (Export-Import) for industries 351 and 384. Table 2.B and 3.B report the results with this classification (Export-oriented, Import-competing and Export-Import). The interaction terms between trade barriers and trade orientation status (Export*BX,Import*BX, Export*BM and Import*BM) are very similar to the previous results with the original classification that considers industries 351 and 384 as import-competing (Table 2 and 3 in main text of the paper).

Table 1.B.: Trade orientation classification

Import competing industries	**Export-Output ratio**	**Import-Output ratio**
321	0.006	0.271
322	0.004	0.174
354	0.019	0.262
355	0.040	0.296
361	0.092	0.716
362	0.017	0.318
381	0.097	0.255
382	0.053	2.141
383	0.036	1.649
385	0.089	7.381
Import competing	**or Export-Import**	
351	0.824	1.326
384	0.210	2.010
Export oriented		
311	0.212	0.104
312	0.174	0.078
331	0.254	0.019
341	0.418	0.096
372	0.733	0.012
Non traded		
313	0.046	0.045
323	0.008	0.135
324	0.004	0.097
332	0.016	0.089
342	0.023	0.062
352	0.002	0.113
353	0.029	0.114
356	0.002	0.102

Note: All reported figures are averages over 1980-1986. Source: Pavcnik (2002)

Table 2.B.: The impact of trade barriers on plant productivity (TFP LP)

	1	**2**	**3**	**4**	**5**	**6**
Export	0.633***	0.629***	0.630***	0.634***	0.630***	0.630***
	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)	(0.111)
Import	0.380***	0.387***	0.389***	0.381***	0.384***	0.384***
	(0.073)	(0.072)	(0.072)	(0.072)	(0.072)	(0.098)
Export Import	-0.464***	-0.446***	-0.446***	-0.444***	-0.446***	-0.446**
	(0.141)	(0.140)	(0.140)	(0.140)	(0.140)	(0.188)
Export*BX	-0.022***	-0.023***	-0.022***	-0.024***	-0.024***	-0.024**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)
Import*BX	-0.067***	-0.067***	-0.067***	-0.067***	-0.067***	-0.067***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)
Export*BM	-0.104***	-0.102***	-0.102***	-0.102***	-0.102***	-0.102***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.015)
Import*BM	0.036***	0.035***	0.035***	0.036***	0.035***	0.035**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.017)
Export Import*BX	-0.020	-0.021	-0.020	-0.019	-0.019	-0.019
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.028)
Export Import*BM	0.151***	0.148***	0.147***	0.148***	0.149***	0.149***
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.048)
BX	0.095***	0.094***	0.095***	0.095***	0.095***	0.095***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)
BM	0.088***	0.088***	0.088***	0.086***	0.087***	0.087***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.014)
Exit indicator		-0.133***	-0.138***	-0.137***	-0.136***	-0.136***
		(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Entry indicator			-0.064***	-0.064***	-0.064***	-0.064***
			(0.016)	(0.016)	(0.016)	(0.016)
Imported Inputs				0.049***	0.048***	0.048***
				(0.010)	(0.010)	(0.012)
Credit					0.025***	0.025**
					(0.009)	(0.011)
Constant	5.243***	5.234***	5.238***	5.221***	5.211***	5.211***
	(0.108)	(0.109)	(0.109)	(0.108)	(0.108)	(0.137)
Plant, ISIC 2 and Year Ind	YES	YES	YES	YES	YES	YES
Number of Obs	46894	46894	46894	46894	46894	46894
Adjusted R-Sq.	0.220	0.228	0.230	0.238	0.241	0.241

Note: Huber White Standard errors in parentheses.
Errors corrected for clustering at the plant level in the last column.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3.B.: Robutness checks

	TFP FE	**TFP FE**	**VA_L**	**VA_L**	**TFP LP**	**TFP LP**
Export	0.523***	0.518***	0.493***	0.538***	0.616***	0.794***
	(0.074)	(0.105)	(0.064)	(0.098)	(0.111)	(0.163)
Import	0.330***	0.335***	0.401***	0.384***	0.392***	0.472***
	(0.069)	(0.091)	(0.062)	(0.091)	(0.098)	(0.109)
Export Import	-0.400***	-0.403**	-0.160	-0.308*	-0.427**	-0.364*
	(0.134)	(0.173)	(0.121)	(0.171)	(0.189)	(0.193)
Export*BX	-0.019***	-0.019*	-0.019***	-0.021**	-0.024**	-0.023**
	(0.007)	(0.010)	(0.006)	(0.010)	(0.011)	(0.011)
Import*BX	-0.062***	-0.061***	-0.067***	-0.068***	-0.066***	-0.068***
	(0.007)	(0.010)	(0.006)	(0.010)	(0.010)	(0.010)
Export*BM	-0.091***	-0.091***	-0.084***	-0.091***	-0.100***	-0.106***
	(0.011)	(0.015)	(0.010)	(0.014)	(0.015)	(0.015)
Import*BM	0.046***	0.045***	0.042***	0.046***	0.036**	0.037**
	(0.012)	(0.016)	(0.011)	(0.016)	(0.017)	(0.017)
Export Import*BX	-0.038*	-0.038	-0.071***	-0.045*	-0.019	-0.021
	(0.020)	(0.026)	(0.018)	(0.025)	(0.028)	(0.028)
Export Import*BM	0.158***	0.160***	0.141***	0.153***	0.148***	0.145***
	(0.040)	(0.046)	(0.036)	(0.047)	(0.048)	(0.048)
BX	0.091***	0.091***	0.077***	0.081***	0.095***	0.096***
	(0.007)	(0.010)	(0.006)	(0.010)	(0.011)	(0.011)
BM	0.066***	0.067***	0.073***	0.079***	0.085***	0.091***
	(0.010)	(0.014)	(0.010)	(0.014)	(0.014)	(0.015)
Exit indicator	-0.146***	-0.145***	-0.146***	-0.150***	-0.136***	-0.136***
	(0.013)	(0.013)	(0.010)	(0.013)	(0.013)	(0.013)
Entry indicator	-0.068***	-0.067***	-0.028***	-0.050***	-0.064***	-0.064***
	(0.015)	(0.016)	(0.010)	(0.015)	(0.016)	(0.016)
Imported Inputs	0.063***	0.061***	0.062***	0.056***	0.048***	0.048***
	(0.010)	(0.012)	(0.009)	(0.012)	(0.012)	(0.012)
Credit		0.033***		0.030***	0.025**	0.025**
		(0.010)		(0.010)	(0.011)	(0.011)
lnK_L				0.081***		
				(0.007)		
Herfindahl					-0.178	
					(0.128)	
Export*BX*concentration						0.045
						(0.047)
Import*BX*concentration						0.046
						(0.042)
Export*BM*concentration						-0.052
						(0.060)
Import*BM*concentration						-0.103
						(0.064)
Export Import*BX*concentration						0.000
						(0.000)
Export Import*BX*concentration						0.000
						(0.000)
concentration						-0.195
						(0.194)
Constant	6.614***	6.601***	7.102***	6.524***	5.216***	5.095***
	(0.107)	(0.132)	(0.091)	(0.138)	(0.137)	(0.144)
Number of Obs	46894	46894	65068	49001	46894	46894
Adjusted R-Sq.	0.206	0.213	0.102	0.229	0.241	0.234

Note: Huber White Standard errors in parentheses.
Errors corrected for clustering at the plant level in column 2, 4, 5 and 6.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$