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New Importer Dynamics and the Effects of Trade Shocks

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Abstract

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New importers increase their conditional survival rate and import share over time. However, a model of multi-input firms with an import entry cost and stochastic import costs cannot replicate these dynamics. I show that an extended model can be reconciled with the data. I calibrate both models and use them to identify the effects of trade shocks. The simulations show that a decrease in import prices with the new importer dynamics generates lower productivity gains, but these gains are more widespread across firms.

Keywords: importer dynamics, trade shocks, gains from trade
JELs: F12, F13, L11

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1 Introduction

The international trade literature has developed a growing interest in intermediate inputs trade. One of the reasons for this interest is that better access to foreign intermediate inputs has been shown to increase firms' productivity.[1] Empirical work on the link between trade shocks and productivity is backed by models explaining the cross-sectional patterns in the data. A natural question to ask is whether these models can also explain the dynamics of importing firms, including firms' entry into and exit from importing.

The class of models used to study the effect of importing on productivity and welfare features a multi-input firm deciding how many intermediate inputs to import. Prominent papers using these models are, for example, Goldberg et al. (2010), Gopinath and Neiman (2014), and Halpern et al. (2015). The main mechanism of these models is that firms trade off a decrease in marginal cost from having access to foreign intermediate inputs against the payment of import costs. The entry of firms into importing, when explicitly modeled, is assumed to involve a sunk entry cost and a per-period cost, as in Kasahara and Lapham (2013), Ramanarayanan (2017), and Brooks and Dovis (2020), among others. This *sunk-cost* model implies that only a small share of firms import, and their productivity is positively correlated with the number of intermediate inputs they import. Both implications are in line with the cross-sectional facts in the data.

However, a model explaining the link between imports and productivity should also be able to explain the dynamics of new importers present in the data. Two of the most salient facts about firms' entry into importing are the growth in (i) the conditional survival rate and in (ii) the import share, which slowly converge to the values of established importers. I document these facts in Figure 1 using plant-level data from Colombian manufacturers.

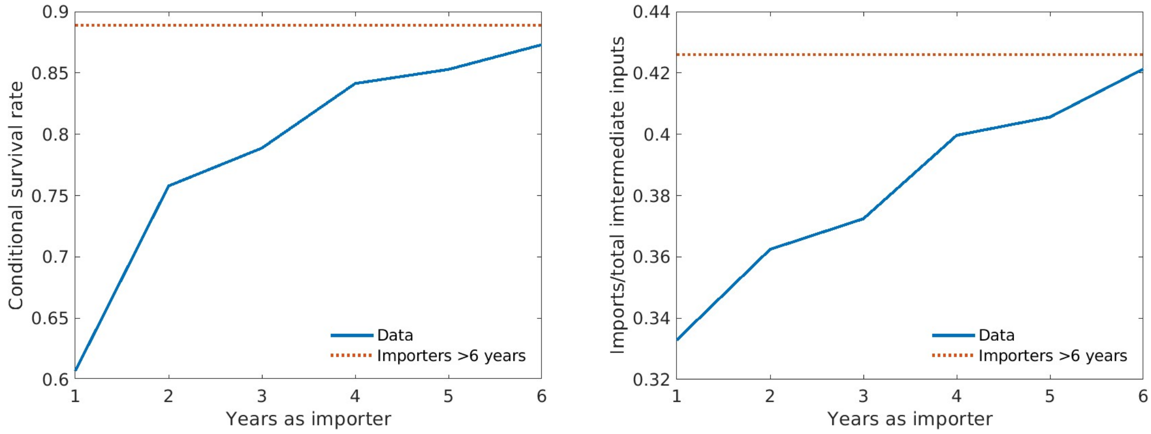
In this paper, I offer three contributions. First, after calibrating the sunk-cost model to match the plant-level data on Colombian manufacturers, I show that it fails to reproduce the dynamics in Figure 1. Second, I extend the model to rationalize these dynamics. Finally, I show that the effect of trade shocks, defined alternatively as a decrease in import costs, a decrease in the price of imported intermediate inputs, or a trade disruption, is different in the sunk-cost model and the extended model.

The failure of the sunk-cost model to reproduce these dynamics is due to a large import

[1] See, e.g., Amiti and Konings (2007), Kasahara and Rodrigue (2008), Topalova and Khandelwal (2011).

Figure 1: Dynamics of new importers

(a) Conditional survival rate (b) Import share



Note: Conditional survival rate calculated as the share of firms at time t that are still importing at time $t + 1$. Import share calculated as the value of imported intermediate inputs over the overall expenditure on intermediate inputs.

entry cost, which makes entry into importing only profitable (in expectations) for highly efficient firms. Adding stochastic import costs, as in Das et al. (2007) and Ruhl and Willis (2017), allows the model to match these dynamics during the first year. However, beyond the first year, the remaining importers exhibit an excessively high import share. As their efficiency decreases over time, their import share also decreases. To reconcile the model with the dynamics of new importers, I extend the model by incorporating two dynamic import costs. First, the per-period fixed cost increases over time, forcing increasingly low-efficiency firms to stop importing after entry. Second, the fixed cost per imported input declines over time, allowing surviving importers to expand their import share. Both extensions can be interpreted as outcomes of search and matching models[2] and together they generate the increasing conditional survival rate and import share observed in the data.

To highlight the importance of incorporating this extension into importer models when drawing policy implications, I explore the effects of these shocks in the sunk-cost and extended models: a 1% reduction in import prices, a 1% reduction in import costs, and a trade disruption that forces all importers to restart importing. The results show that, as in Das et al. (2007), there are larger effects when import prices decrease than when import costs decrease. Furthermore, the long-term effects are larger in the sunk-cost model than in the extended model. Specifically, the long-run productivity increase associated with a

[2]For example, as in Heise (2024) or Eaton et al. (2025), among others.

1% reduction in import prices is 2.1% in the sunk-cost model and 2% in the extended model. In the event of a trade disruption, the long-run productivity decreases are the same in both models, but the short-run decline is greater in the extended model (1.5%) than in the sunk-cost model (1.3%).

When looking at the effects by efficiency decile, both models predict, unsurprisingly, that the reduction in import prices increases the productivity of all firms. The largest difference between models is in how the gains are distributed across the efficiency distribution, with the extended model predicting the benefits being more widespread across firms: smaller gains in the upper half of the efficiency distribution but larger gains in the lower half. The reason for this discrepancy is the smaller import entry cost and per-period import cost in the extended model. Hence, in the extended model, there is a larger mix of smaller and larger importing firms that can increase their imports. This also helps explain the larger aggregate effects predicted by the sunk-cost model: the aggregate effects are dominated by the larger firms, which have larger gains in the sunk-cost model.

This paper relates to two strands of the literature. First, it relates to the literature on firm behavior in international markets. Part of this literature investigates how incorporating firm dynamics, including firm entry and exit, has implications for aggregated trade flows, and how these trade flows react to trade liberalizations and other trade shocks. However, although the behavior of exporters has been widely documented in Das et al. (2007), Albornoz et al. (2012), Békés and Muraközy (2012), Albornoz et al. (2016), Kohn et al. (2016), and Ruhl and Willis (2017), the behavior of importers has drawn much less attention. In a recent paper, Ramanarayanan (2017) shows that adding irreversibilities to import decisions is important to match observed aggregated trade flows. However, he does not consider the dynamics of new importers and focuses instead on cross-sectional measures. My contribution to this literature is to show that understanding the dynamics of new importers is relevant to predicting changes in trade flows and aggregated productivity after trade shocks.

Second, it is related to a large body of empirical and theoretical work studying the role of importing intermediate inputs on firms' productivity. This literature has documented that firms using foreign intermediate inputs can increase their productivity: Amiti and Konings (2007) for Indonesia, Kasahara and Rodrigue (2008) and Kasahara and Lapham (2013) for Chile, Goldberg et al. (2010) and Topalova and Khandelwal (2011) for India, and Halpern et al. (2015) for Hungary. More recently, Gopinath and Neiman (2014), Halpern et al. (2015), Blaum et al. (2018), and Ramanarayanan (2020) have shown that accounting for importer heterogeneity is important to understand the effect of importing on productivity, but none of them include firms' entry into and exit from importing. My contribution is to show that the productivity gains from improved access to foreign intermediate inputs are smaller when including the dynamics of new importers in these theoretical models, but the gains extend to a broader range of firms.

The remainder of this paper is structured as follows. Section 2 describes the data. Section 3 introduces the sunk-cost model. Section 4 calibrates and estimates the model. The simulation results for the sunk-cost model are in Section 5. I introduce and calibrate the extended model in Section 6. Section 7 describes the different effects of trade shocks in the sunk-cost model and the extended model. Section 8 concludes.

2 Data

The data used in this paper are from the Colombian Annual Manufacturing Survey (AMS), a plant-level survey that includes all plants with more than 10 employees or with revenues exceeding a certain threshold.[3] This dataset is similar to that in Das et al. (2007) and Ruhl and Willis (2017), who also use the AMS, but my data covers the period from 2004 to 2018.[4] For each plant-year, the AMS registers revenues, total wages paid, expenditure on inputs, expenditure on imported inputs, and employment, among others. All values are deflated and expressed in 2015 Colombian pesos. The cleaning of the data can be seen in section A of the Appendix.

The summary statistics for the relevant variables used in this paper are in Table 1. The average firm has around 13 million pesos in sales per year, while spending seven million pesos on intermediate inputs and employing 62 workers. However, there is a large gap between importers and non-importers, with importers having six times more sales, five times more expenditures, and employing 3.5 times more workers. Importing firms make up 17% of the observations, but there is a large amount of entry and exit into importing. Starting firms (firms that were importers in year t but not in year $t-1$) make

[3] To guarantee data consistency, whenever a plant enters the sample one year, it is followed in every subsequent survey, until its dissolution. This avoids firms entering and leaving the sample by moving over and below the threshold.

[4] Das et al. (2007) and Ruhl and Willis (2017) use the data from 1981 to 1991.

Table 1: Summary Statistics

Variable	Full Sample Mean	Full Sample Std.Dev.	Importers Mean	Importers Std.Dev.	Non-Importers Mean	Non-Importers Std.Dev.
Sales (Millions)	13.53	81.37	43.58	172.42	7.33	40.34
Expenditure (Millions)	7.29	50.74	22.44	102.59	4.17	29.61
Employment	62.03	120.17	153.12	217.36	43.23	74.86
Importer	0.17	0.38	1.00	0.00	0.00	0.00
Starter	0.05	0.22	0.31	0.46	0.00	0.00
Stopper	0.03	0.18	0.20	0.40	0.00	0.00
Import Share	0.07	0.22	0.42	0.36	0.00	0.00
Observations	96,588		16,525		80,063	

Note: Expenditure refers to expenditure on intermediate inputs. Importer, starter, and stopper are dummy variables that take the value of one if the firm at time t is importing, started importing, or stopped importing. Values in millions of 2015 Colombian pesos. Import share calculated as the value of imported intermediate inputs over the overall expenditure on intermediate inputs.

up 5% of the firm-year observations. In turn, stopping firms (firms that were importers in year t but not in year $t+1$) make up 3% of the firm-year observations. When looking only at the subsample of importing firms in an average year, starters make up 31% of all importers, and stoppers make up 20%. Finally, import share, defined as the value of imported intermediate inputs over overall expenditure on intermediate inputs, is around 42% among importing firms. This means that importing firms spend, on average, 42% of their intermediate input expenditure on imported intermediate inputs, and the other 58% on domestic intermediate inputs. Overall, the import share is higher than the ones documented in Argentina (17%) by Gopinath and Neiman (2014) and in Hungary (27%) by Halpern et al. (2015). This is probably due to the share of importing firms in Colombia (17%) being lower than in Hungary (39%), such that only relatively larger Colombian firms are importers.

New Importer Dynamics - The empirical facts central to this paper are those introduced in Figure 1: the conditional survival rate and the import share of new importers. The conditional survival rate is calculated as the share of firms at time t that are still importing at time $t+1$, and the import share is calculated as explained above.

Among Colombian firms, the conditional survival rate of importers is low in the first year, 60.7%, but increases every year, converging to that of firms importing for at least six years (88.9%). The average conditional survival rate of the whole sample is 73.8%.

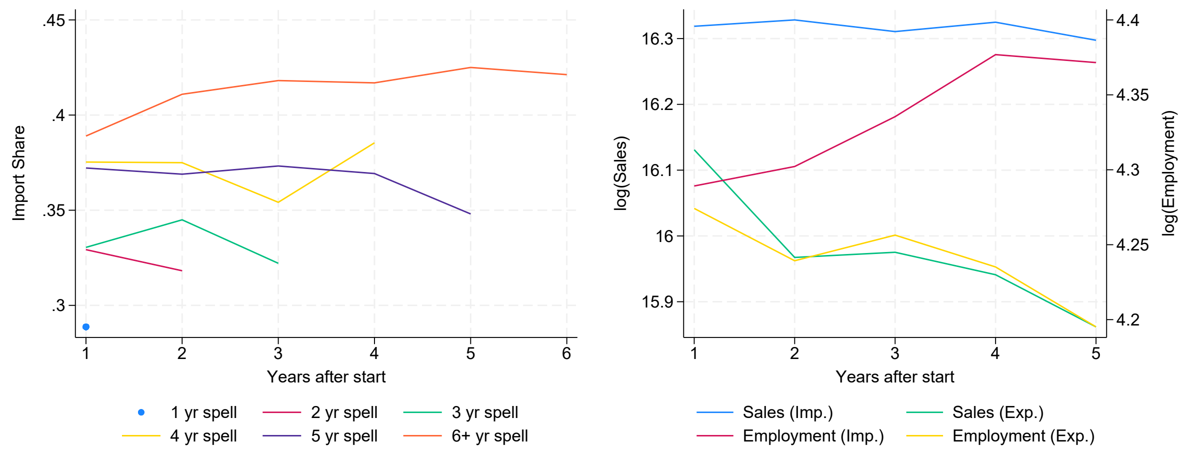
These values are very similar to the findings on the conditional survival rate of exporters in Kohn et al. (2016) (75% the first year) and Ruhl and Willis (2017) (63% the first year). The speed of convergence is, however, slower in my data, with importers reaching 88% conditional survival rate only after six years, compared to between two and four years in Kohn et al. (2016) and Ruhl and Willis (2017). New importers start with an import share of 33.3% and need around six years to reach the average share of firms importing at least six years (42.6%). The long time needed to converge can also be seen in Ruhl and Willis (2017) for the case of exporters, where new exporters need four years to reach the sample average of the ratio of exports to total sales. These dynamics hint at one important distinction between new importer dynamics and the new exporter dynamics documented before in the literature: importers tend to grow their conditional survival rate and import share over a longer period of time.

Note that firm selection is an important driver of the import share growth in Figure 1b. Specifically, Figure 1b can be partially explained by the fact that firms that drop after just one year tend to import less than firms that keep importing. To account for selection, Figure 2a displays the import share over time, considering the spell length of importers, i.e., the number of years the importer will continue importing before stopping. As expected, firms with shorter spell lengths have a smaller import share at any point than firms with longer spell lengths, although this ranking is not as clear among firms with four and five-year spells. Importantly, the import share paths tend to be flat or even growing in the case of firms with spells lasting longer than six years. This indicates that the growing path in Figure 1b is rather a combination of both, firm selection and firm growth. In this paper, however, I am interested in replicating the growing path, independently of the source of this growth. Hence, in all simulations, I allow for selection to be the driving force of import share growth.

Finally, it is worth noting that new importer dynamics differ from those of new exporters. In that regard, Figure 2b shows that while the size of exporters in terms of sales and employment tends to decrease after their first year exporting, importers grow their employment and maintain their sales level. Another potential concern is that new importer dynamics are just a mirror image of new exporter dynamics because they are two sides of the same relationship. That would, however, require that a non-importer be matched to a non-exporter, and neither of them adds additional relationships over time. That is highly unlikely based on the two-sided trade literature: Bernard et al. (2018a) shows that there is a large churning in Colombian importers, with 77% of the importers adding at least one new exporter, 76% dropping at least one exporter, and 66% doing both. Only 13% of the importers go on for one year without changing their exporter mix. Furthermore, Bernard et al. (2018b) shows that there is negative degree assortativity among importers and exporters. That is, small (new) importers tend to match with large (established) exporters, which makes it hard to explain the new importer dynamics as just a mirror of the new importer dynamics. These facts, together with the slower convergence of the import share relative to the export share, indicate that there are important differences between new importer dynamics and new exporter dynamics, not only related to the theoretical framework used to study them, but also in the data.

Figure 2: Dynamics of new importers

(a) Import share by spell length (b) Size of importers and exporters



Note: Import share calculated as the value of imported intermediate inputs over the overall expenditure on intermediate inputs. Spell length refers to the years the firm kept importing, with "6+" being six or more years.

Given the differences between new and established importers in the data, I move next to introduce the sunk-cost model used for modeling importing firms and to test whether this model can account for these differences.

3 The Sunk-cost Model

In this section, I present the sunk-cost model with firm entry into importing.[5] In the model, the world consists of two countries: Home and Foreign. All firms located in Home produce a unique variety of the final good, which they sell to domestic consumers. There are no exports. To produce their variety, firms use domestic labor and intermediate inputs with a given level of efficiency. Additionally, each firm can gain access to imported intermediate inputs by incurring a one-time entry cost, which cannot be recovered and is therefore "sunk", and some per-period cost. Moreover, firms face uncertainty in their future efficiency.

Production technology - The production technology of the firms is given by

$$Y_{it} = Z_{it} L_{it}^{\alpha_L} X_{it}^{\alpha_X}, \tag{1}$$

where the efficiency of the firm i in time t is denoted by Z_{it}. L_{it} is the amount of labor used in production and X_{it} is the intermediate input bundle. For simplicity, I assume constant returns to scale, i.e. $\alpha_L + \alpha_X = 1$. Moreover, X_{it} can be produced using domestic and imported intermediate inputs according to the following CES aggregator:

$$X_{it} = \left[\int_{j \in \Gamma} x_{ijt}^{\frac{\sigma^I - 1}{\sigma^I}} dj + M_{it} \int_{k \in \Omega_{it}} x_{ikt}^{\frac{\sigma^I - 1}{\sigma^I}} dk \right]^{\frac{\sigma^I}{\sigma^I - 1}}, \tag{2}$$

where $\sigma^I > 1$ is the elasticity of substitution between intermediate inputs. The quantity of each intermediate input used in the production of X_{it} is given by x, the set of intermediate inputs used in production, from Home and Foreign, is given by Γ and Ω_{it}, respectively, and M_{it} is a variable indicating whether the firm is importing ($M_{it} = 1$) or not ($M_{it} = 0$). There is roundabout production, such that each firm's output is used to produce a final good g and an intermediate input x, which all the firms in Home use:

$$Y_{it} = g_{it} + \int_{j \in \Gamma} x_{jit} dj. \tag{3}$$

[5] This model is similar to those in Goldberg et al. (2010), Topalova and Khandelwal (2011), Kasahara and Lapham (2013), Gopinath and Neiman (2014), Halpern et al. (2015), and Blaum et al. (2018), among others.

Denoting the wage by w and the intermediate input price index of the firm (i.e., the effective cost of X_{it}) by q_{it}, the firm's unit cost function resulting from cost minimization is

$$\mathcal{C}_{it} = \frac{1}{Z_{it}} \left(\frac{w}{\alpha_L}\right)^{\alpha_L} \left(\frac{q_{it}}{\alpha_X}\right)^{\alpha_X}. \tag{4}$$

Without loss of generality, I assume that domestic intermediate inputs can be sourced without any fixed cost. There is a fixed cost for imported intermediate inputs, denoted by $f_k(|\Omega_{it}|)$, that firms must pay and depends on the number of intermediate inputs sourced. This cost is fixed in the sense that it does not depend on the quantity of each imported intermediate input but rather on the number of imported intermediate inputs. This fixed cost can be interpreted as fixed transport costs or the cost of maintaining a relationship with the intermediate input supplier, as in Bernard et al. (2018b). The specific form of the function $f_k(|\Omega_{it}|)$ is simply:

$$f_k(|\Omega_{it}|) = f_c \times |\Omega_{it}|^2, \tag{5}$$

where f_c is a parameter that scales the fixed cost.

The expression for the intermediate input price index of the firm i, decomposed into the domestic and the imported part, is

$$q_{it}^{1-\sigma^I} = q_{\Gamma t} + M_{it} q_{\Omega it} \tag{6}$$

$$q_{\Gamma t} = \int_{j \in \Gamma} p_{jt}^{1-\sigma^I} dj \tag{7}$$

$$q_{\Omega it} = \int_{k \in \Omega_{it}} p_k^{1-\sigma^I} dk \tag{8}$$

where $q_{\Gamma t}$ indicates the domestic intermediate input price index, which is equal for all firms since the fixed cost of sourcing domestic intermediate inputs is zero. However, the imported intermediate input price index ($q_{\Omega it}$) differs across firms because the set of imported intermediate inputs (Ω_{it}) is firm-specific. As can be seen in equation (6), becoming an importer implies a decrease in the intermediate input price index and hence a decrease in the unit cost in equation (4).

Demand - Consumers in Home share identical preferences, given by a CES utility function over the traded (G) and non-traded (H) goods:

$$U_t = \left(\kappa G_t^{\frac{\phi-1}{\phi}} + (1-\kappa) H_t^{\frac{\phi-1}{\phi}} \right)^{\frac{\phi}{\phi-1}}, \tag{9}$$

where $\kappa \in (0,1)$ is the relative weight of the traded good in the utility function of consumers and $\phi > 1$ is the elasticity of substitution between the traded and the non-traded good. The traded good is a CES bundle containing all varieties of the final good produced in Home:

$$G_t = \left[\int g_{it}^{\frac{\sigma^F-1}{\sigma^F}} di \right]^{\frac{\sigma^F}{\sigma^F-1}}, \tag{10}$$

where $\sigma^F > 1$ is the elasticity of substitution between varieties of the final good and g_{it} the consumption of the final good variety from firm i at time t. Given the utility function in equation (9), the demand for each of the varieties and the price index Q_t for final goods in the domestic market are given by

$$g_{it} = \frac{E_G}{Q_t} \left(\frac{P_{it}}{Q_t} \right)^{-\sigma^F} \tag{11}$$

$$Q_t = \left[\int P_{it}^{1-\sigma^F} di \right]^{\frac{1}{1-\sigma^F}} \tag{12}$$

where E_G is the total expenditure by consumers on the traded good.

Firm's static problem - Each firm i maximizes its profit each period t by choosing L_{it} and the vector of intermediate input consumption $\{x\}$ given the wage w, the vector of intermediate input prices $\{p\}$ and its importing status M_{it}. The per-period profit maximization problem of the firm is therefore:

$$\Pi_{it}(Z_{it}, M_{it}) = \underset{L_{it},\{x\}}{max} \{P_{it}Y_{it} - \mathcal{C}_{it}Y_{it}\}. \tag{13}$$

From the profit maximization problem in equation (13), the optimal choice of labor, the domestic and imported intermediate inputs, and the corresponding expenditures on wages and intermediate inputs are given by:

$$L_{it} = \frac{Y_{it}}{Z_{it}} \left(\frac{\alpha_L}{\alpha_X} \frac{q_{it}}{w} \right)^{\alpha_X} \tag{14}$$

$$X_{it} = \frac{Y_{it}}{Z_{it}} \left(\frac{\alpha_X}{\alpha_L} \frac{w}{q_{it}} \right)^{\alpha_L} \tag{15}$$

$$x_{ijt} = \frac{1}{q_{it}} \left(\frac{p_j}{q_{it}} \right)^{-\sigma^I} X_{it} \tag{16}$$

$$x_{ikt} = \frac{1}{q_{it}} \left(\frac{p_k}{q_{it}} \right)^{-\sigma^I} X_{it} \quad \text{if } k \in \Omega_{it} \tag{17}$$

$$wL_{it} = \alpha_L \mathcal{C}_{it} Y_{it} \tag{18}$$

$$q_{it} X_{it} = \alpha_X \mathcal{C}_{it} Y_{it} \tag{19}$$

Given the heterogeneity in the demand of imported intermediate inputs arising from p_k in equation (17), the benefit of including each intermediate input k in Ω_{it} is different across intermediate inputs. To take this into account, I order foreign intermediate inputs such that the price is increasing in k:

$$p_1 \leq p_2 \leq ... \leq p_K$$

where K is the total amount of intermediate inputs in Foreign, i.e., the maximum amount of intermediate inputs that a firm in Home can import. This implies $|\Omega_{it}| \leq K$ for all firms.

Hence, firms choose the number of imported intermediate inputs used in production, $|\Omega_{it}|$, such that they maximize their profits (Π_{it}) after deducting the corresponding input fixed cost, f_k:

$$|\Omega_{it}| = arg \max_{|\Omega_{it}|} \{\Pi_{it} - f_k(|\Omega_{it}|)\} \tag{20}$$

Finally, given the monopolistic competition nature of the final good market, the price that each firm sets is the well-known constant markup over its marginal costs:

$$P_{it} = \frac{\sigma^F}{\sigma^F - 1} \mathcal{C}_{it} \tag{21}$$

Firm's dynamic problem - In the dynamic problem, the firms consider the import decision under an import entry cost, a per-period cost of importing, and the uncertainty about its future efficiency. The presence of an entry cost causes the decision of entry into and exit from importing to be a dynamic choice. Specifically, non-importing firms need to weigh the expected value of the future increase in profits derived from entry into importing against the entry cost. Similarly, an importing firm has to consider the possibility of having to incur the entry cost again if it stops importing and wants to start importing at some later period.

I model the efficiency process of the firms as a stationary AR(1), similar to Das et al. (2007), Alessandria and Choi (2014), and Ruhl and Willis (2017) among others,

$$ln\ Z_{it} = (1-\rho_Z)\mu_Z + \rho_Z ln\ Z_{it-1} + \epsilon_{it} \quad \text{with} \quad \epsilon_{it} \sim N(0, \sigma_Z^2). \tag{22}$$

The Bellman equation of the firm's dynamic problem is then

$$V(Z_{it}, M_{it-1}) = \max_{M_{it}} \{\Pi(Z_{it}, M_{it}) - f_M(M_{it}, M_{it-1}) + \delta E_t[V(Z_{it+1}, M_{it})|Z_{it}]\} \tag{23}$$

with the present efficiency and the import status in the previous period as state variables and the decision about present import status as the only control variable available to the firm. The discount factor over future profits is given by $\delta < 1$. The term $f_M(M_{it}, M_{it-1})$ is the importing cost, defined as:

$$f_M(M_{it}, M_{it-1}) = f_0 I(M_{it} = 1|M_{it-1} = 0) + f_1 I(M_{it} = 1|M_{it-1} = 1)$$

where f_0 is the entry cost and f_1 is the per-period cost of importing.

The binary nature of the decision implies that the decision rule is a discrete choice between importing in the present period or not. Therefore, the Bellman equation in (23) can be solved as in Das et al. (2007) and Ruhl and Willis (2017) by iterating the value function, which results in the following decision rule for non-importing firms:

$$M_{it}(Z_{it}, 0) = \begin{cases} 1 & \text{if } \Pi(Z_{it}, 1) - \Pi(Z_{it}, 0) + \delta E_t[V(Z_{it+1}, 1) - V(Z_{it+1}, 0)|Z_{it}] \geq f_0 \\ 0 & \text{otherwise.} \end{cases} \tag{24}$$

Intuitively, the firm decides to enter if the increase in profits this period $(\Pi(Z_{it}, 1) - \Pi(Z_{it}, 0))$ and in the discounted expected continuation value $(\delta E[V(Z_{it+1}, 1) - V(Z_{it+1}, 0)|Z_{it}])$ is equal or larger than the entry cost required to start importing (f_0). If, conversely, the entry cost is larger, the firm decides to remain domestic in the next period. The decision rule for importing firms follows the same logic and is

$$M_{it}(Z_{it}, 1) = \begin{cases} 0 & \text{if } \Pi(Z_{it}, 0) - \Pi(Z_{it}, 1) + \delta E_t[V(Z_{it+1}, 0) - V(Z_{it+1}, 1)|Z_{it}] \geq f_1 \\ 1 & \text{otherwise.} \end{cases} \tag{25}$$

Stochastic import cost - The literature has aimed at reducing the survival rate on entry by allowing firms with lower efficiency levels to start importing and exit soon after. Following Das et al. (2007), Kohn et al. (2016), and Ruhl and Willis (2017), I add a stochastic component to the cost of entry and the fixed cost of importing to allow firms with lower efficiency to start importing. More specifically, I assume that every period each firm has, with probability η, an entry cost of $f_0\lambda$ and a fixed cost of importing of f_1/λ. With probability $1 - \eta$, the costs are just f_0 and f_1, respectively.

With $\lambda < 1$, firms hit by the stochastic import cost face a lower entry cost but a higher fixed cost of importing. With the lower entry cost, these firms start importing even with lower efficiency levels. Once they start importing, the higher fixed cost makes them more likely to stop importing for any efficiency level. As the firms with lower efficiency tend to have smaller import shares, introducing the stochastic fixed cost creates shorter importing spells with smaller import shares.

Equilibrium - The model is in partial equilibrium as wages are fixed. Hence, the equilibrium is defined as the set of prices and import choices that, for a given wage level, satisfy the final demand in equation (11) and the first-order conditions in equations (13) and (23).

With the solution to the maximization problem in equation (13) and the decision rule in equations (24) and (25), I turn now to calibrate and simulate the model to see if it can replicate the dynamics in Figure 1.

4 Simulation

The objective of this section is to parameterize the sunk-cost model and to compare the dynamics of new importers in the model with the dynamics of new importers in the data. For this, I first normalize and calibrate the relevant parameters of the model. The calibration is done through values available in the literature and by estimating (directly and indirectly) parameters using the data. Following Ruhl and Willis (2017), I define a period in the simulation as one quarter, which implies that firms' decisions are taken with a quarterly frequency. To compare the simulated data and the data in the AMS, which is collected annually, I aggregate the simulated data to create an annual panel. This mitigates the issue of partial-year effects, which are known to artificially decrease the import share of first-year importers in the data.[6] Wages are considered fixed in all simulations.

Calibration - As a first step in the calibration, I used several parameter values from the literature. I set the yearly discount factor δ to 0.9, which is comparable to other papers like Alessandria and Choi (2014) for the US (0.96) and Das et al. (2007) and Ruhl and Willis (2017) for Colombia (0.9 and 0.891, respectively). Kohn et al. (2016) estimates a value between 0.83 and 0.98 using data from Chile. As to the elasticities of substitution between varieties and between intermediate inputs, I set both equal to 5 ($\sigma^F = \sigma^I = 5$), the standard value used in the literature.[7] Further, I set the elasticity of substitution between the traded and non-traded sectors, ϕ, also equal to 5.

Next, I make normalization assumptions concerning parameters in the model that have no direct link with the data. Specifically, I assume that the price of imported intermediate inputs is $p_k = 0.5 \; \forall \; k$. The efficiency parameter μ_Z is normalized such that the mean efficiency is equal to one, i.e. $\mu_Z = -\frac{\sigma_Z^2}{2(1-\rho_Z^2)}$. I set K, the number of foreign intermediate inputs present in the economy, to 200, ensuring sufficient variation in the number of imported intermediate inputs to generate a heterogeneous import share across importers. This number is similar to, for example, Halpern et al. (2015), who use 150 foreign intermediate inputs.

Finally, other parameters can be estimated directly from the data. This includes the labor and intermediate inputs exponents in the production function, α_L and α_X. I calculate α_L and α_X as the share of expenditure in labor and intermediate inputs in the data, respectively. This delivers the values $\alpha_L = 0.38$ and $\alpha_X = 0.62$. The value for α_X is very close to the 0.66 reported by Gopinath and Neiman (2014). Following Gopinath

[6]See Bernard et al. (2017) for further information on the partial-year effect.

[7]For example, Alessandria and Choi (2014), Kohn et al. (2016), and Ruhl and Willis (2017), use a elasticity of substitution of 5.

and Neiman (2014), I chose the price index in the non-traded sector (Q_N), the wage level (w), and the relative weight of the traded sector in the utility function (κ) such that, in equilibrium, the share of the manufacturing sector in the final consumption spending is around 15%, the weight of manufacturing on value added in Colombia in 2010. This implies $Q_N = 0.5$, $w = 2$, and $\kappa = 0.2$. The parameter values taken from the literature and the parameters directly estimated, which are common across models, are listed in Table 2.

Table 2: Common parameters

Parameter	δ	κ	ϕ	Q_N	p_k	K	μ_Z	σ^F	σ^I	α_L	α_X	w
Value	0.9	0.2	5	0.5	0.5 $\forall k$	200	$-\frac{\sigma_Z^2}{2(1-\rho_Z^2)}$	5	5	0.38	0.62	2

I estimate the rest of the model's parameters using the simulated method of moments (SMM). This includes the entry cost and the per-period cost related to importing (f_0 and f_1), the input fixed cost parameter (f_c), the two parameters of the firm's efficiency process in equation (22), ρ_Z and σ_Z, and the parameters of the stochastic import cost η and λ.

To estimate these parameters, I simulate a panel of 1,000 firms over 120 quarters. I drop the first 60 quarters and aggregate the last 60 quarters to create a 15-year panel, the same length as the AMS, which I use to compute the simulated moments. Note that the optimal moments and parameters depend on the specific draws of the random generator. To address this issue, I repeat the simulation 50 times, each with a different random generator seed. I always show the average value across the 50 simulations.

I then define the following expression that measures the deviation between moments in the data and in the simulation

$$g(\theta) = m_d - m_s(\theta)$$

where m_d is a vector with moments from the data, m_s is the same moments measured in the simulation and $\theta = (f_0, f_1, f_c, \rho_Z, \sigma_Z, \eta, \lambda)$ is the vector of parameters to be estimated.

The optimal parameters are those that minimize the distance between the moments in the data and the moments in the simulation

$$\hat{\theta} = arg \ \min_{\theta}\{g(\theta)'\mathbf{W}g(\theta)\} \tag{26}$$

where $\mathbf{W}$ is defined as the weighting matrix. The weighting matrix is the inverse of the estimated variance-covariance matrix of the moments in the data.[8] I solve the minimization problem in equation (26) numerically.

Identification - To identify the parameters in θ, I have chosen the moments to be matched in equation (26) such that they capture Colombian firms' importing behavior while following the existing literature on importers and exporters. My objective is to characterize the stationary equilibrium and the behavior of importers during their first year, specifically their import share and survival rate. The dynamics of new importers after the first year are to be determined by the simulation. The moments are calculated as the average over the whole sample, when applicable.

First, I use the share of non-importing firms that start importing each year and the share of importing firms that stop importing each year. These two moments capture the decision of the firms when facing the importing choice in equation (23) of the model. Specifically, they are relevant to identify the sunk cost (f_0) and the fixed cost of importing (f_1). Next, I include the average import share of importers to identify the input fixed cost (f_c). The objective of including this moment is to capture the number of imported intermediate inputs that firms optimally choose ($|\Omega_{it}|$), conditional on being an importer. The corresponding decision of firms in the model is given by equation (20).

Then, the coefficient of variation of log employment and the autocorrelation of log sales. Both moments are intended to identify the efficiency process in equation (22) rather than firm decisions. Specifically, the autocorrelation of efficiency shocks (ρ_Z) and their standard deviation (δ_Z). I measure the autocorrelation of log sales as the coefficient β_Y in

$$\log Y_{it} = \beta_Y \log Y_{it-1} + \mu_i + \mu_t + \epsilon_{it},$$

where I regress the log value of sales each year on its lag, including plant and time fixed effects.

The last two moments are the first-year importers' import share and survival rate. Both moments have been used extensively in the literature to approximate firm entry dynamics. These moments are influenced by the stochastic entry cost parameters, η and

[8] I estimate $\mathbf{W}$ using the following bootstrap procedure. First, I resampled 1,000 times with replacement 5,000 plants from the data. Then, I calculated the vector of moments m_d for each sample. Finally, I calculated $\mathbf{W}$ as the variance-covariance matrix of the moments estimated in all the samples.

λ. Specifically, as η increases and λ decreases, more and smaller firms start importing, reducing the import share and survival rate, especially among the first-year importers.

It is important to note that all parameters affect all the moments, and the identification of a parameter cannot be entirely attributed to a specific moment. For example, increasing the entry cost decreases importers' stopper rate, because firms are more hesitant to stop importing and require lower efficiency levels to stop importing. But it also decreases the import share because those firms that are importing are, on average, less efficient and import less.[9]

5 Results

Model fit - The fit of the moments in the simulation to their data counterparts is shown in table 3. Note that a firm in the theoretical model corresponds to a plant in the Colombian data. As seen in the table, the model matches all moments very closely. To assess the fit outside of the targeted moments, I report the importer size premium, measured as (i) the mean expenditure on domestic intermediate inputs of importers relative to non-importers, (ii) the mean sales of importers relative to non-importers, and (iii) the mean sales of importers relative to non-importers by sales quintile. The fit of the importer size premium provides a measure of the general fit of the model to the data because it indicates the size dispersion between non-importing and importing firms. The importer size premium in terms of expenditure on domestic intermediate inputs and sales is 3.06 and 5.92 in the data, compared to 2.67 and 5.45 in the simulation. The size distribution of importers in the model is similar to that in the data. However, the importers in the model are larger than in the data in the smaller four quintiles, while it delivers smaller importers in the largest quintile.

The model does not perform well in matching other dynamic non-targeted moments, such as the probability of re-entry after exit and import growth, as shown in Figure C.1 of Appendix C. While the probability of re-entry in the data decreases in the years following exit, the model predicts a constant probability throughout time. Similarly, while import growth in the data decreases only slightly over time, the model generates very low growth

[9]This might seem counter-intuitive since the average efficiency of entrants increases. As shown in Albornoz et al. (2016) for the case of exporters, the relevant parameter for survival is the ratio of entry to per-period costs, and higher survival implies less efficient firms remain active.

Table 3: Moments in data and simulation

Moments	Data	Sunk-cost
Starter rate	0.064	0.062 (0.001)
Stopper rate	0.219	0.219 (0.001)
Import share	0.434	0.434 (0.005)
CV log employment	0.345	0.346 (0.002)
Correlation log sales	0.457	0.452 (0.013)
Import share, 1st year	0.333	0.333 (0.006)
Survival rate, 1st year	0.607	0.604 (0.006)
Imp. premium (Dom. Exp.)	3.064	2.667* (0.104)
Imp. premium (Sales)	5.924	5.446* (0.231)
Imp. premium (Sales), Q1	0.225	0.494* (0.030)
Imp. premium (Sales), Q2	0.729	1.541* (0.092)
Imp. premium (Sales), Q3	1.694	3.267* (0.167)
Imp. premium (Sales), Q4	4.024	6.237* (0.294)
Imp. premium (Sales), Q5	22.950	15.691* (0.657)

*Moment not targeted.

in the first two years and higher growth thereafter.

The estimated parameters, reported in table 4, indicate an estimated entry cost of about 232.5% of the expenditure on intermediate inputs of the median firm, while the per-period cost of importing during one year is around 27.2%, almost 9 times smaller. Note that the fixed cost per input is increasing in the number of inputs, and therefore, f_c is not informative about the actual costs. To build some intuition, if a firm imports half of the intermediate inputs (100) during one year, the overall fixed cost per input amounts to 67% of the expenditure on intermediate inputs of the median firm.

New importers - After calibrating the model, I turn now to the variables of interest. Figures 3a and 3b show the conditional survival rate and the import share for new importers in the data and in the simulation. Despite the good fit of the model to the characteristics of importers as a whole, the model does a poor fit of the dynamics of importers after the first year. The moments in the first year can be matched because the stochastic import cost allows small firms to enter with smaller import shares and survival rates. The model replicates the growing path of the conditional survival rate also in the second year and stabilizes around 86% after the third. In the case of import shares, the partial-year effect also plays a role in suppressing the import share during the first year. But as most small firms exit during the first year, the import share increases faster

Table 4: Estimated parameters

Parameters	Sunk-cost
f_0	2.325 (0.094)
f_1	0.272 (0.011)
f_c	0.67 (0.035)
ρ_Z	0.789 (0.002)
σ_Z	0.196 (0.007)
η	0.325 (0.009)
λ	0.164 (0.006)

Costs measured as a fraction of the median firm's expenditure. f_1 is measured as annual costs. f_c is measured as the annual cost of importing 100 intermediate inputs.

than in the data, in part due to the end of the partial-year effect,[10] and reaching close to 50% in the second year. Furthermore, while the import share is increasing in the data, it starts dropping after the second year in the simulation as the positive efficiency shock that induced firm entry into importing fades away.

The reason for this discrepancy between the sunk-cost model and the data is that, even with the inclusion of the stochastic import cost, firms in the model only start importing after their efficiency is high enough to make incurring the entry cost profitable in expectations. Note that this fact represents well the observations in the data, with importing firms being more efficient than non-importing firms. However, zooming in on the first years of a firm as an importer reveals a downward trend in the import share. Given that the firms paying the entry cost have high efficiency, they have large import shares. Because of their high efficiency, they are likely to decrease their efficiency once the positive efficiency shock fades away. As their average efficiency decreases, so does their import share. This is a characteristic of models featuring an entry cost and the analogue of what has been observed for the case of exporters in Kohn et al. (2016) and Ruhl and Willis (2017).

Robustness - I explore next whether the failure of the model to match the moments in the data is due to the assumptions related to the efficiency process. Specifically, it could be that the efficiency shocks of new importers are highly correlated, explaining the import

[10]Note that the partial-year effect still reduces to some extent the import share in all years, as exiting firms might only import for a part of their final year.

Figure 3: Dynamics of new importers in the sunk-cost model

(a) Conditional survival rate (b) Import share

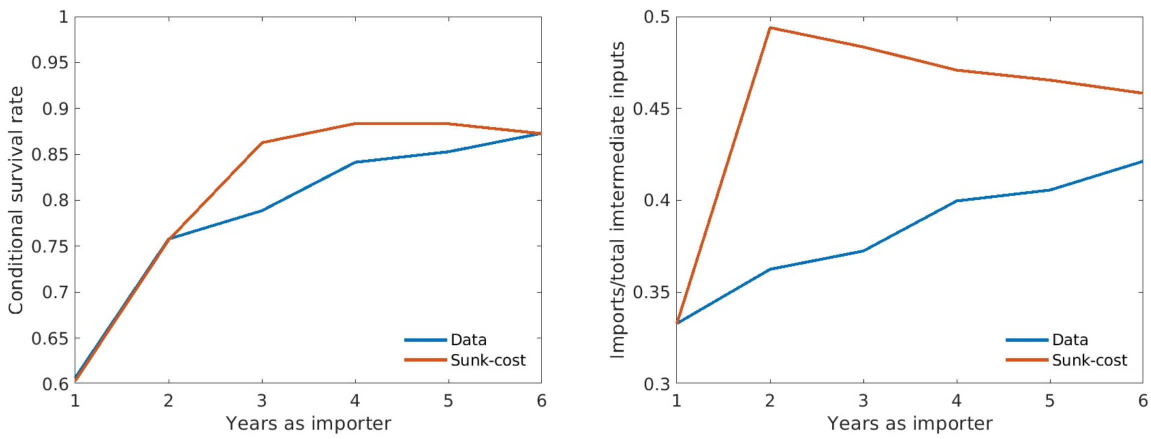


Table 5: Moments in data and simulation if $\rho = 0.95$

Moments	Data	Sunk-cost
Starter rate	0.064	0.064 (0.003)
Stopper rate	0.219	0.220 (0.001)
Import share	0.434	0.371 (0.022)
CV log employment	0.345	0.304 (0.004)
Correlation log sales	0.457	0.750* (0.006)
Import share, 1st year	0.333	0.311 (0.022)
Survival rate, 1st year	0.607	0.707 (0.013)

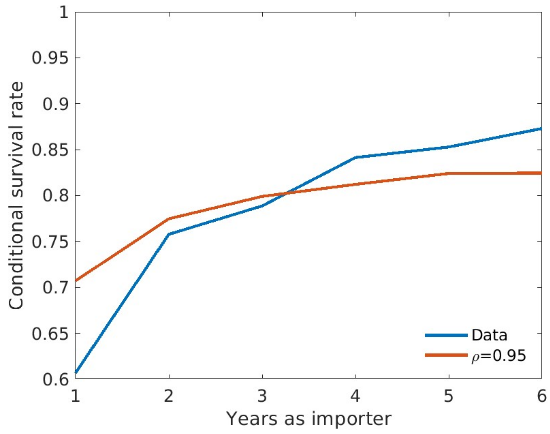
*Moment not targeted.

share growth during the first years. I set then $\rho_Z = 0.95$ and remove the correlation of log sales from the targeted moments. Figure 4 shows that in this case, the model features a growing conditional survival rate and import share. However, the match of the conditional survival rate is now worse. Furthermore, as shown in Table 5, the model also performs poorly when matching the CV of log employment, which falls from 0.345 to 0.304, and the import share (from 43.4% to 37.1%). The estimated parameters are in Table C.1 of Appendix C.

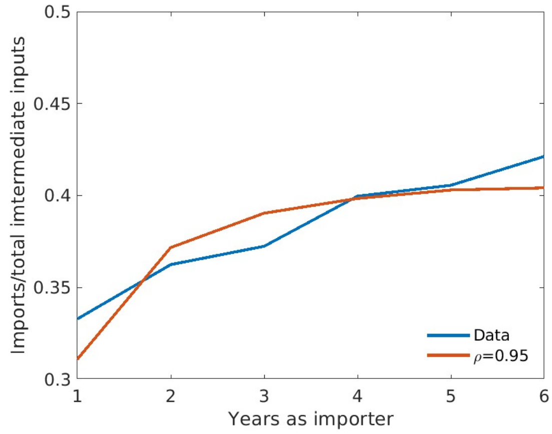
In sum, a different efficiency process does not seem to match the data better, as the improvement in the matching of the import share dynamics comes at the cost of worsening the match in the conditional survival rate dynamics and most of the cross-sectional moments.

Figure 4: Dynamics of new importers in if $\rho = 0.95$

(a) Conditional survival rate



(b) Import share



6 Model Extension

In light of the failure of the sunk-cost model to match the dynamics of new importers, I present an extended model with modifications aimed at solving that shortcoming. Specifically, the extension should help the model match the conditional survival rate and the import share of new importers. The main idea of the extended model is that importers face time-dependent import costs, rather than just the stochastic import cost often used in the literature. That is, the per-period import cost and the fixed cost per input depend on how long the firm has been an importer.

Varying per-period fixed cost - The first modification affects the per-period fixed cost. The per-period fixed cost is now a function of the number of quarters that the firm is importing l and the baseline per-period fixed cost parameter f_1:

$$f_a(l) = \nu^{l-1} f_1, \tag{27}$$

where $l = 1, 2, ..., 24$ is the number of quarters that the firm has been importing. As a result, the per-period fixed cost changes during the first 6 years after entry.

Varying fixed cost per input - The second modification is that the fixed cost per input changes by ψ each quarter that the firm is importing. Hence, the fixed cost per input also depends on how long the firm has been an importer:

$$f_k(|\Omega_{it}|, l) = \psi^{l-1} f_c |\Omega_{it}|^2 \tag{28}$$

.

That is, the first quarter that the firm is importing, both costs are f_1 and $f_c|\Omega_{it}|^2$, the second quarter νf_1 and $\psi f_c|\Omega_{it}|^2$, and so on. The intuition behind these two modifications is that, over time, the cost structure of importers changes. For example, as firms gain experience in importing, they can reduce some import costs, such as filling out customs forms or dealing with transport firms. However, other costs might increase, such as maintaining a large international supplier network. Each cost could increase or decrease over time, as there is no restriction on either parameter being above or below one.

Intuition - These two parameters could be understood as just a way of bringing the model closer to the data. However, an increasing per-period fixed cost and a decreasing fixed cost per input could be the outcome of search and matching models, such as Benguria (2021), Heise (2024), Gimenez-Perales (2024), and Eaton et al. (2025), among others. In these models, firms choose each period their search intensity.[11] Higher search intensities are costly, but offer the possibility of larger profits by matching with a better partner. More importantly, in some models, firms adjust their search intensity over time, either due to diminishing returns on investment (Gimenez-Perales, 2024) or due to learning (Eaton et al., 2025). Search and matching models of this type could explain an increasing per-period fixed cost and a decreasing fixed cost per input. After entry, firms that decide to keep importing choose, on average, to increase their search intensity, which translates in the extended model to an increase in per-period fixed cost. As a result of the increase in search intensity, firms find better partners, which translates into a lower fixed cost per input.

New Bellman equation - Equations (27) and (28) imply that the number of quarters that a firm has been an importer affects the profitability of importing. Hence, l is a new state variable in the dynamic problem of the firm. The associated Bellman equation to

[11] Benguria (2021) is a static model, and firms choose their search intensity only once.

the firm's decision is now the following:

$$V(Z_{it}, M_{it-1}, l) = \underset{M_{it}}{max} \{\Pi(Z_{it}, M_{it}, l) - f_M(M_{it}, M_{it-1}, l) \\ + \delta E_t[V(Z_{it+1}, M_{it}, l+1)|Z_{it}]\} \tag{29}$$

where the term $f_M(M_{it}, M_{it-1}, l)$ is now defined as:

$$f_M(M_{it}, M_{it-1}, l) = f_0 I(M_{it} = 1 | M_{it-1} = 0) + f_a(l) I(M_{it} = 1 | M_{it-1} = 1)$$

where f_0 is the entry cost and f_1 is the per-period cost of importing.

The nature of the problem in equation (29) is the same as in equation (23): the firm must decide over a one-time payment in the present against an uncertain increase in future profits. The decision rule for import status remains the same as in equation (24), and the decision rule for the number of imported intermediate inputs is very similar.

Calibration - Next, I calibrate the model with the two additional parameters included in the extension: the varying per-period fixed cost parameter (ν) and the varying input fixed costs parameter (ψ). For this, I expand the technique of the simulated method of moments in the sunk-cost model and include ν and ψ as parameters to be estimated together with two additional moments. Given that the objective of this extension is to bring the model closer to the pattern of growing import share and conditional survival rate observed in the data, the additional moments I choose to match are the import share and the survival rate among second-year importers.

As can be seen in table 6, the simulation of the extended model can bring the import share and the survival rate of importers during the second year closer to the values observed in the data. The non-targeted moments in the extended model, the importer premium in terms of domestic expenditure and sales, as well as the size distribution of importers, are very similar to the moments in the sunk-cost model. The dynamic non-targeted moments, i.e., the probability of re-entry after exit and imports growth in Figure C.1 in Appendix C, are also very close to the moments in the sunk cost model.

As for the estimated parameters in table 7, the efficiency-related parameters are very similar across models. This is because the efficiency parameters are not strongly affected by changes in the importing side of the model. With respect to the importing costs, the

Table 6: Moments in data and in simulation

Moments	Data	Sunk-cost	Extended
Starter rate	0.064	0.062 (0.001)	0.063 (0.001)
Stopper rate	0.219	0.219 (0.001)	0.220 (0.002)
Import share	0.434	0.434 (0.005)	0.418 (0.004)
CV log employment	0.345	0.346 (0.002)	0.347 (0.002)
Correlation log sales	0.457	0.452 (0.013)	0.447 (0.01)
Import share, 1st year	0.333	0.333 (0.006)	0.313 (0.007)
Import share, 2nd year	0.362	0.494* (0.01)	0.399 (0.008)
Survival rate, 1st year	0.607	0.604 (0.006)	0.625 (0.013)
Survival rate, 2nd year	0.758	0.747* (0.02)	0.768 (0.013)
Imp. premium (Dom. Exp.)	3.064	2.667* (0.104)	2.822* (0.089)
Imp. premium (Sales)	5.924	5.446* (0.231)	5.426* (0.168)
Imp. premium (Sales), Q1	0.225	0.494* (0.030)	0.546* (0.034)
Imp. premium (Sales), Q2	0.729	1.541* (0.092)	1.604* (0.074)
Imp. premium (Sales), Q3	1.694	3.267* (0.167)	3.290* (0.122)
Imp. premium (Sales), Q4	4.024	6.237* (0.294)	6.126* (0.197)
Imp. premium (Sales), Q5	22.950	15.691* (0.657)	15.566* (0.542)

Standard errors in parentheses. *Moment not targeted.

size of the parameters shows a few important differences. First, the entry cost is just 64.5% of the median firm's expenditure, a large reduction relative entry cost in the sunk-cost model. The per-period cost is also much lower in the extended model, at just 8% of the median firm's expenditure. These reductions are somewhat offset by an increase in the fixed cost per input, which increases to more than twice the cost in the sunk-cost model, from 67% to 150.4%. The estimated ν and ψ parameters imply that the per-period cost increases over time and the fixed cost per input decreases. After six years, these costs are 40% and 0.06%, respectively.

The parameters governing the stochastic import costs, η and λ, are similar in both models. Specifically, in the extended model, firms are slightly less likely to receive the possibility of a discounted entry (31.9% instead of 32.5%), but the discount is somewhat larger, with firms only required to pay 14.8% of the import entry cost instead of 16.4% in the sunk-cost model.

New importers - As can be seen in Figure 5, the extended model performs better than the sunk-cost model in the matching of the first years of importing firms. In the extended model, the conditional survival rate starts very low and grows in the following years, as it does in the data and the sunk-cost model. However, as in the sunk-cost model, years 3-6

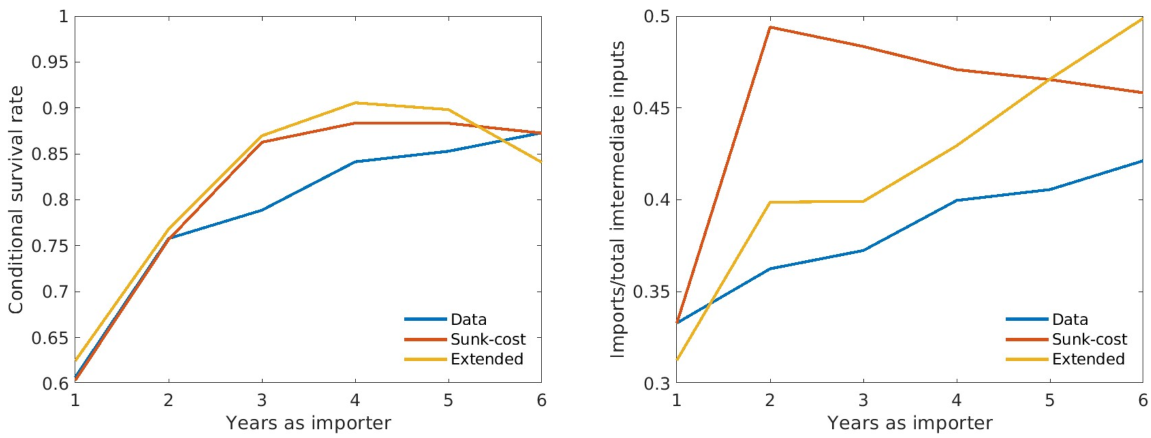
Table 7: Estimated parameters

Parameters	Sunk-cost	Extended
f_0	2.325 (0.094)	0.645 (0.027)
f_1	0.272 (0.011)	0.079 (0.003)
f_c	0.67 (0.035)	1.504 (0.066)
ρ_Z	0.789 (0.002)	0.789 (005)
σ_Z	0.196 (0.007)	0.199 (0.002)
η	0.325 (0.009)	0.319 (0.009)
λ	0.164 (0.006)	0.148 (0.006)
ν		1.07 (0.002)
ψ		0.875 (0.007)

Costs measured as a fraction of the median firm's expenditure. f_1 is measured as annual costs. f_c is measured as the annual cost of importing 100 intermediate inputs.

Figure 5: Dynamics of new importers across models

(a) Conditional survival rate (b) Import share



are not part of the calibration, and the model overshoots the conditional survival rate in the third and fourth years, and returns to the survival rate in the data after that.

The import share in the extended model is now growing over time, as observed in the data, and in the first years, firms have a lower import share than established importers. The model accomplishes this by increasing the per-period fixed cost over time ($\nu > 1$), such that larger firms exit every quarter: a firm that would just keep importing in the second year would drop in the third year due to the higher per-period fixed cost, everything else constant. In addition, the decreasing fixed cost per input ($\psi < 1$) allows surviving firms to increase their import share, even for the same efficiency levels. The combination of both effects creates a growing average import share over time.

Mechanism - I now explore how the extended model creates the growing import share path of new exporters. For this, I plot in Figure 6 the mean efficiency in the exit quarter and the mean import share in the last quarter as an importer. To make both models comparable, I select only those firms that started importing without the reduction in import costs, i.e., that were not hit by the stochastic import cost η.

The mean efficiency in the exit quarter is a good approximation of the efficiency threshold below which an importing firm decides to stop importing. In the sunk-cost model, efficiency at exit is constant over time, fluctuating between 0.55 and 0.6, while the mean efficiency in the data is 1. Only in the first quarter is efficiency slightly higher, at 0.65, reflecting the higher average efficiency of firms immediately after starting to import. The extended model, however, creates a very different pattern. Efficiency at exit starts higher and declines over the first 16 quarters, from an average of 0.75 to 0.53. This decline is driven by a larger fixed cost per input, which forces firms to exit at higher efficiency levels during the early quarters. After entry, however, firms start to benefit from the decreasing fixed cost per input, reducing their efficiency at exit. After 16 quarters, efficiency at exit starts to increase again as the increase in per-period fixed costs offsets the reduction in the fixed cost per input. Finally, after 24 quarters, efficiency at exit stabilizes around 0.6, higher than in the sunk-cost model.

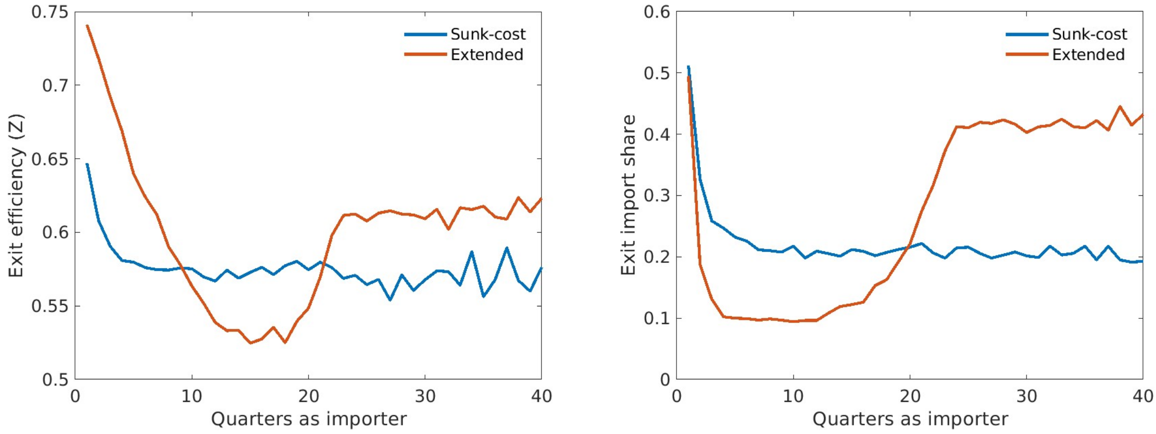
The mean import share at exit follows a similar pattern. Both show the same peak in the first two quarters, as new importers have a relatively high efficiency. After that, in the sunk-cost model, the import share at exit is 20% and almost constant over time. In the extended model, however, the import share at exit starts at around 10% and after 12 quarters, due to the increase in per-period fixed cost, it reaches 40% after 24 quarters. Comparing the dynamics in Figure 6b to Figure 2a, the extended model comes closer to replicating the growing path of import share by exiting firms in the data.

7 Policy Analysis

In the previous section, I showed that the extended model features the growing conditional survival rate and import share observed in the data. In this section, I show that the different new importer dynamics in the sunk-cost and the extended model result in different predictions after a trade shock. In particular, I look at the effects of three shocks: a

Figure 6: Mechanism

(a) Mean efficiency at exit (b) Mean import share at exit



Note: Subsample of importers that started to import without the reduction in import costs.

permanent 1% decrease in import prices, a permanent 1% decrease in import costs, and a one-time disruption to importers. As in the previous simulations, wages are held constant before and after the shocks. A central motivation for this analysis is to compare the changes in productivity and import shares in both models relative to a benchmark.

As in the calibration, I simulate 50 times a panel of 1,000 firms over 120 quarters. The first 60 quarters are simulated as in the previous sections, i.e., without trade shocks, and then dropped. The last 60 quarters are simulated once for the case without trade shocks (as a benchmark) and once for the case with trade shocks. The benchmark in each model is the case without trade shocks: the same set of firms with the same efficiency shocks. The only difference between the simulations is the trade shocks.

For every quarter, I calculate the price index for final goods (Q_t) as in equation (12), and the demand for each firm is adjusted following equation (11). Given the change in the firm's demand, some firms change their importing decision and their final price, which in turn affects Q_t. I iterate every period until Q_t converges, i.e., until firms do not adjust their prices anymore. The overall expenditure is held constant throughout all simulations.

7.1 Variables

Before showing the results of the simulations, I define in this subsection the key variables used. All changes (Δ) are relative to the benchmark.

Productivity - To measure the firm-level productivity increase (ΔPR_{it}), I use, similarly to Basu and Fernald (2002) and Gopinath and Neiman (2014), the Solow residual:

$$\Delta \log PR_{it} = \Delta \log Y_{it}^{V} - \frac{s_{Li}}{1 - s_{Xi}} \Delta \log L_{it}, \tag{30}$$

where $\Delta \log Y_{it}^{V}$ and $\Delta \log L_{it}$ denote the increase in value-added and labor of the firm in the case of trade shocks relative to the benchmark, and $s_X = (q_{it} X_{it})/(P_{it} Y_{it})$ and $s_L = (wL_{it})/(P_{it} Y_{it})$ are the expenditure, as a share of total revenues, on intermediate inputs and labor, respectively.

The measure of value-added increase is the Divisia index:

$$\Delta \log Y_{it}^{V} = \frac{\Delta \log Y_{it} - s_X \Delta \log X_{it}}{1 - s_X}, \tag{31}$$

and finally, I calculate the economy-level productivity by aggregating firm-level productivity using value-added weights:

$$\Delta \log PR_t = \sum_i w_{it}^{V} \Delta \log PR_{it} \tag{32}$$

where $w_{it}^{V} = (P_{it} Y_{it})/(P_t Y_t)$ is the firm's share of value-added.

Most importantly, note that, as in Basu and Fernald (2002) and Gopinath and Neiman (2014), this is the welfare-relevant measure of productivity in manufacturing in the model.

Labor productivity - Given that this economy is producing goods using only intermediate inputs and labor, labor productivity is a relevant measure of overall productivity in the economy. Labor productivity change in the economy is measured as follows:

$$\Delta \log LP_t = \sum_i w_{it}^{L} \Delta \log LP_{it} \tag{33}$$

where $w_{it}^{L} = L_{it}/L_t$ is the firm's share of labor and $LP_{it} = Y_{it}/L_{it}$ is the number of final good units produced by one unit of labor.

Since the efficiency shocks did not change relative to the benchmark, both measures capture different effects. The Solow residual productivity captures the impact of scale effects on productivity due to the presence of markups, as shown in Gopinath and Neiman

(2014). Labor productivity measures how the increase in the usage of intermediate inputs affects the number of units of the final good that one worker can produce.

Import share - I compute the import share as the ratio of the expenditure on imported intermediate inputs over the total expenditure on intermediate inputs. The change in import share is therefore defined as:

$$\Delta IS_t = \Delta \frac{\sum_i \sum_k p_k x_{ikt}}{\sum_i q_{it} X_{it}}, \tag{34}$$

where $\sum_k p_k x_{ikt}$ is the expenditure on imported intermediate inputs of firm i in period t and $q_{it} X_{it}$ its total expenditure on intermediate inputs.

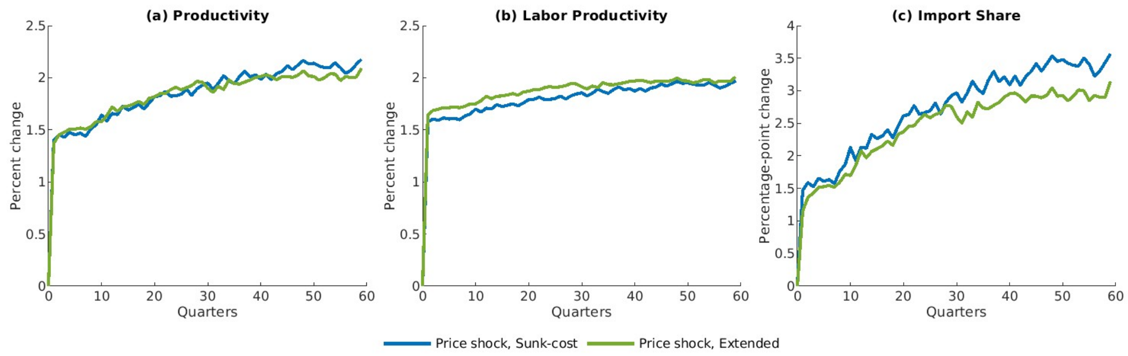
7.2 Import Price Decrease

I analyze here a permanent 1% decrease in import prices, which could be associated with a decrease in import tariffs.

Aggregate dynamics - The changes in productivity, labor productivity, and import share in the sunk-cost and extended models relative to the benchmark are shown in Figure 7. The increases in productivity and labor productivity are similar in both models during the first few quarters, around 1.5%. Ten years after the shock, the productivity increase is slightly higher in the sunk-cost model (2.1%) than in the extended model (2%), whereas the increase in labor productivity is slightly higher in the extended model during the first 10 years. To put these magnitudes in perspective, Amiti and Konings (2007) estimated for Indonesia that a 10% decrease in input tariffs leads to an increase in productivity of 12% for importing firms, a very similar effect to the 1.5% immediate increase shown in Figure 7. Topalova and Khandelwal (2011), on the other hand, find a smaller effect for India, with a 4.8% increase in productivity from a 10% decrease in input tariffs. The larger effect in the model can be due to the model accounting for roundabout production: every firm is affected by the import price decrease, as it also lowers the cost of domestic intermediate inputs.

The import share increases immediately after the shock by 1.5 percentage points in the sunk-cost model, while the increase is slightly lower in the extended model, of 1.2 percentage points. 15 years after the decrease in import prices, the import share increases

Figure 7: Aggregate effects, import price decrease

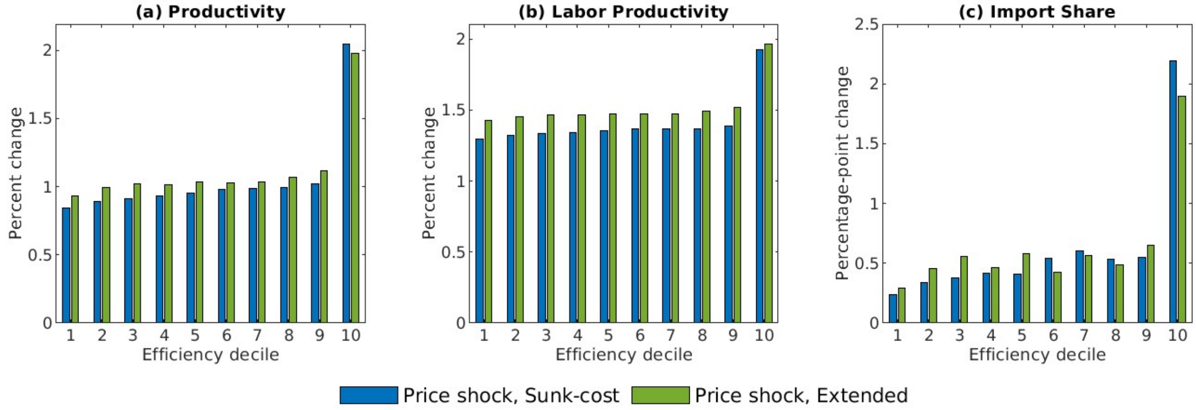


by 3.5 percentage points in the extended model and by 3 percentage points in the sunk-cost model.

Effect by efficiency decile - To understand the reasons behind the differences in the speed of adjustment as well as in the degree to which each variable is affected, I show now the heterogeneity of the effect by efficiency decile, in Figures 8 and 9. The first efficiency decile compresses the 10% least efficient firms and the tenth efficiency decile the 10% most efficient firms.

Figure 8 shows the effect of the shock after one year. In both models, following a decrease in import prices, a clear difference emerges between the most efficient firms (the 10th efficiency decile) and the rest. Specifically, the increase in productivity (Figure 8a) for firms in the 10th efficiency decile is twice the size in all other efficiency deciles. The difference is smaller in terms of labor productivity due to roundabout production. That is, while firms in the 10th efficiency decile directly benefit by increasing their import share, the other firms benefit from the reduction in their domestic intermediate inputs. Because firms in the 10th efficiency decile benefit disproportionately from the decrease in import prices, they extract market share from smaller firms, which leads to an increase in productivity measured by the Solow residual.

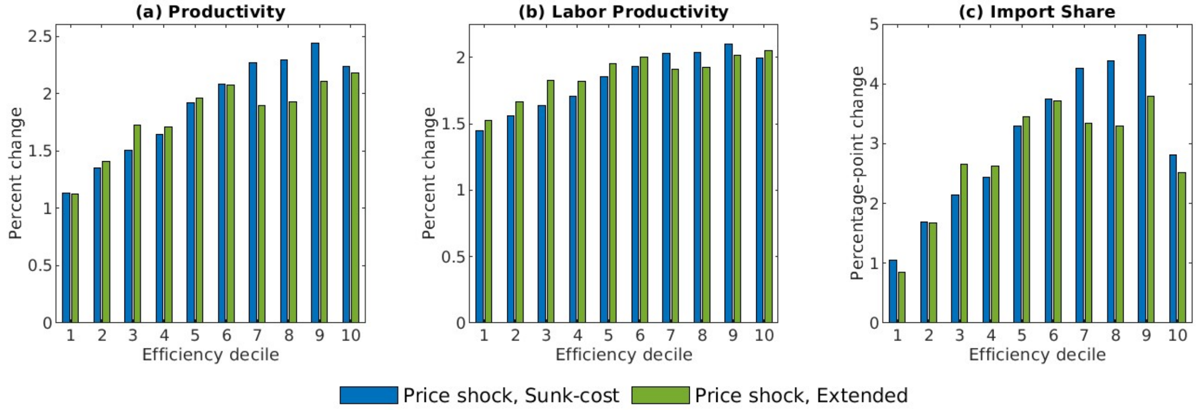
Figure 8: Changes by efficiency decile after one year, import price decrease



The effects in both models show important differences. In the sunk-cost model, the effects are more concentrated in the 10th decile, while in the extended model, the gains are more widespread, with larger productivity gains in all other efficiency deciles. This difference is due to the dynamic import costs present in the extended model: the lower entry and per-period import costs cause smaller firms to start importing immediately after the shock.

There are large differences in the effects when comparing the changes in labor productivity and import share after one year (Figure 8) and after 15 years (Figure 9). After 15 years, gains spread to the firms in the upper half of the productivity distribution. In the case of the sunk-cost model, these gains are larger, especially around the 7th to 9th efficiency decile, because these are the marginal firms in the sunk-cost model. The extended model shows again a different picture: the gains are more equal throughout the 3rd to 10th deciles. Relative to the sunk-cost model, the extended model delivers lower gains in the 7th to 10th deciles and larger gains in the 3rd to 5th deciles.

Figure 9: Changes by efficiency decile after 15 years, import price decrease



In both models, the immediate effect is concentrated in the 10th decile, while over time, the gains extend to the rest of the upper half of the efficiency distribution. Since the firms in the 10th decile dominate the aggregate dynamics, this explains the large immediate effects in Figure 7. The distribution of gains in Figure 9 explains why the long-term aggregate gains are larger in the sunk-cost model than in the extended model: in the sunk-cost model, the gains are larger in the 7th to 10th deciles, while in the extended model, the gains are larger in the lower deciles. Due to the importance of large firms in aggregate dynamics, the sunk-cost model predicts larger gains than the extended model.

7.3 Import Cost Decrease

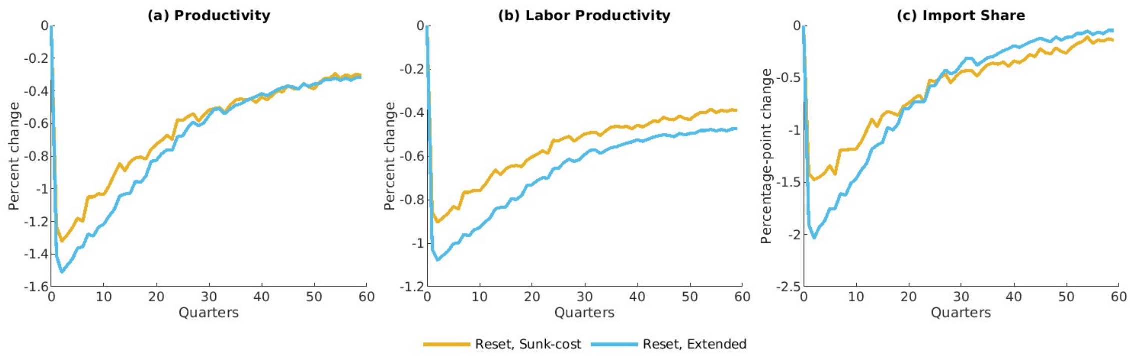
Next, I analyze the effect of a permanent 1% decrease in import costs, that is, a 1% reduction in f_0, f_1, and f_c. Overall, the effects are smaller in the case of a 1% decrease in import costs than in the case of a 1% decrease in import prices. This finding mirrors the one in Das et al. (2007) for exporters. Specifically, labor productivity increases by 0.5% in the sunk-cost model and 0.6% in the extended model. The effects of the import cost decrease are otherwise similar to the effects of the import price decrease, and they are shown in Appendix D.

7.4 Trade Disruption

Finally, I analyze the effect of a large trade disruption. For this, I remove the importing status for all firms at quarter 0, that is, I set $M_{i0} = 0$. All firms have the option of starting to import again, but for that, they need to pay the entry cost.

Aggregate dynamics - After the trade disruption, productivity decreases by 1.3% in the sunk-cost model and by 1.5% in the extended model. The decrease in productivity is due to the loss in import shares, which is also larger in the extended model (2 percentage points) than in the sunk-cost model (1.5 percentage points). The reason for this discrepancy between the models is the different new importer dynamics. New importers start with high import shares in the sunk-cost model, such that the reduction in the aggregate import share is only due to the time needed for firms to start importing again, that is, due to the high entry cost. In the extended model, however, firms need time to increase their import shares, causing a larger reduction in the aggregate import share as well as in productivity and labor productivity.

Figure 10: Aggregate effects, trade disruption



Over time, however, the extended model recovers faster than the sunk-cost model. After 5 years, both models show a reduction of 0.75% in the aggregate import share. The decreases in productivity and labor productivity are also persistent over time: after 15 years, productivity is still 0.3% lower in both models relative to the benchmark, and labor productivity is 0.4% lower in the sunk-cost model (0.5% in the extended model).

Effect by efficiency decile - The heterogeneity of the effect by efficiency decile during the first year, in Figure 11, shows that firms in the extremes of the efficiency distribution are affected the least. Low-efficiency firms are less affected because they do not use imported intermediate inputs, while high-efficiency firms can start importing immediately after the shock. The most affected are the firms in the 7th, 8th, and 9th efficiency deciles, because many of these firms were importing but did not enter immediately after the shock. In the extended model, the effect is larger for all efficiency deciles except for the 7th.

Figure 11: Changes by efficiency decile after one year, trade disruption

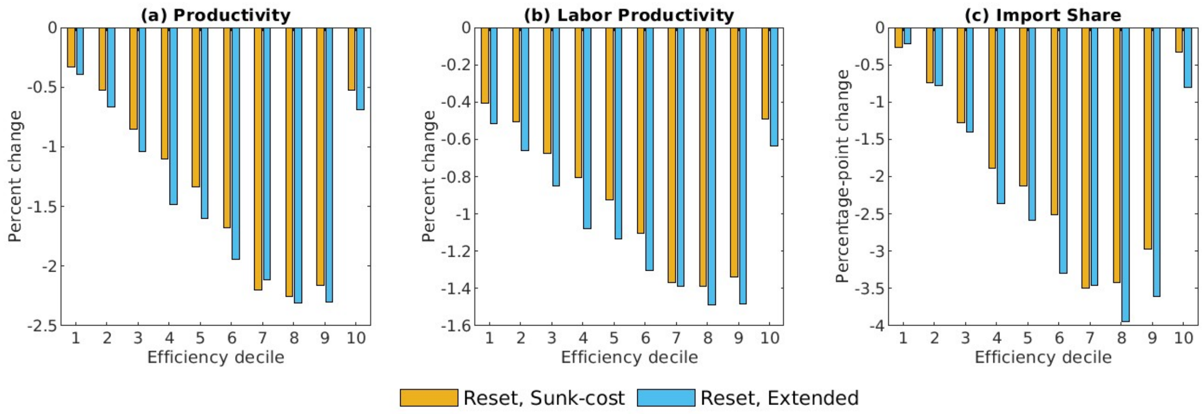
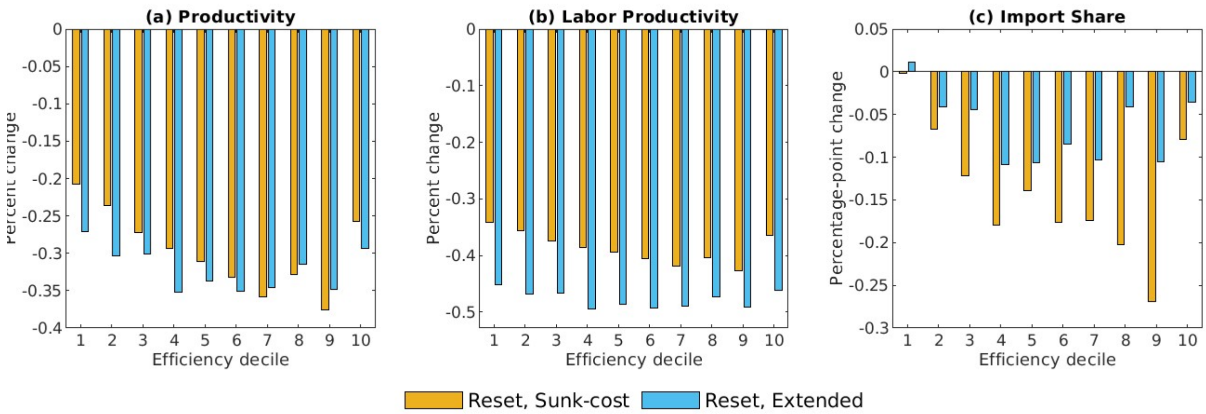


Figure 12 shows that, after 15 years, the size of the effect has decreased for all efficiency deciles. The import shares are almost back to the level in the benchmark case for both models, but it is still relatively smaller in the sunk-cost model. The effect becomes more homogeneous across efficiency deciles, as firms with higher efficiency start to import again. However, the differences between the sunk-cost model and the extended model remain, with firms in all efficiency deciles in the extended model facing a larger decrease in their labor productivity.

Figure 12: Changes by efficiency decile after 15 years, trade disruption



Overall, these results are in line with the findings in Monarch and Schmidt-Eisenlohr (2023) and Eaton et al. (2025), who show that trade disruptions have a large effect on trade, and they tend to impact young importers more than old ones.

8 Conclusion

In this paper, I study the ability of the sunk-cost model to reproduce the growth of new importers in terms of conditional survival rates and import share over time. I also develop an extended model capable of generating these new importer dynamics and examine the implications of trade shocks in both the sunk-cost and extended models.

I find that the sunk-cost model cannot reproduce the observed behavior of new importers. This limitation mirrors findings in similar studies of new exporters: firms begin importing only when their efficiency is high enough to make the payment of the entry cost profitable in expectation. While adding stochastic import costs allows the model to match the conditional survival rate and import share during the first year, new importers exhibit a declining import share during the following years because their efficiency decreases over time.

To correct this mismatch between the sunk-cost model and the data, I propose an extended model with dynamic import costs. Specifically, the per-period fixed cost increases over time, while the fixed cost per input decreases. This extended model can qualitatively replicate the growing conditional survival rate and import share in new importers observed in the data. The mechanism that causes the import share to grow is that the increasing per-period fixed cost causes low-efficiency importers to stop importing, while the decreasing fixed cost per input causes the remaining importers to increase their import share.

Capturing these dynamics has important implications for the predicted effects of trade shocks on productivity, labor productivity, and import share. In the sunk-cost model, gains are larger following import price reductions but smaller following reductions in import costs. Furthermore, under a trade disruption that forces all importers to restart importing, the extended model predicts a larger negative shock. Moreover, the models differ in which firms are most affected: in the sunk-cost model, effects concentrate among the upper half of the efficiency distribution, whereas the extended model predicts productivity effects more evenly distributed across all efficiency deciles.

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A Data

For the cleaning of the data, I exclude all observations with zero, one, or missing expenditure on inputs, wages paid, or sales. Also, I exclude those observations with fewer than 10 employees. Next, drop all plants that have any gaps between two reporting years. That is, I allow plants to enter and exit the sample, but if a plant exits the sample and then re-enters, I drop the plant. The final dataset contains an unbalanced panel of 12,521 plants over 15 years. I have observations for all years for 2,050 of the plants, and each plant is included for an average of 7.7 years.

B Theory

Unit cost function - Start with the cost minimization problem:

$$\underset{L_{it},X_{it}}{min} \quad wL_{it} + q_{it}X_{it}$$
$$\text{subject to } \; Y_{it} = Z_{it}L_{it}^{\alpha_L}X_{it}^{\alpha_X},$$

with $\alpha_L + \alpha_X = 1$.

Set up the Lagrangian:

$$\mathcal{L} = wL_{it} + q_{it}X_{it} + \mu\left(Y_{it} - Z_{it}L_{it}^{\alpha_L}X_{it}^{\alpha_X}\right).$$

First Order Conditions:

$$\frac{\partial \mathcal{L}}{\partial L_{it}} = w - \mu\alpha_L Z_{it}L_{it}^{\alpha_L - 1}X_{it}^{\alpha_X} \stackrel{!}{=} 0 \rightarrow w = \mu\alpha_L Z_{it}L_{it}^{\alpha_L - 1}X_{it}^{\alpha_X}, \tag{35}$$
$$\frac{\partial \mathcal{L}}{\partial X_{it}} = q_{it} - \mu\alpha_X Z_{it}L_{it}^{\alpha_L}X_{it}^{\alpha_X - 1} \stackrel{!}{=} 0 \rightarrow q_{it} = \mu\alpha_X Z_{it}L_{it}^{\alpha_L}X_{it}^{\alpha_X - 1}. \tag{36}$$

Dividing (36) over (35):

$$\frac{q_{it}}{w} = \frac{\mu\alpha_X Z_{it}L_{it}^{\alpha_L}X_{it}^{\alpha_X - 1}}{\mu\alpha_L Z_{it}L_{it}^{\alpha_L - 1}X_{it}^{\alpha_X}} = \frac{\alpha_X}{\alpha_L}\frac{L_{it}}{X_{it}}$$
$$L_{it} = \frac{\alpha_L}{\alpha_X}\frac{q_{it}}{w}X_{it}. \tag{37}$$

Substitute (37) in the production function:

$$
\begin{aligned}
Y_{it} &= Z_{it} L_{it}^{\alpha_L} X_{it}^{\alpha_X} = Z_{it} \left(\frac{\alpha_L}{\alpha_X} \frac{q_{it}}{w} \right)^{\alpha_L} X_{it} \\
X_{it} &= \frac{Y_{it}}{Z_{it}} \left(\frac{\alpha_X}{\alpha_L} \frac{w}{q_{it}} \right)^{\alpha_L}.
\end{aligned}
$$

Substitute X_{it} in (37):

$$
L_{it} = \frac{Y_{it}}{Z_{it}} \left(\frac{\alpha_L}{\alpha_X} \frac{q_{it}}{w} \right)^{\alpha_X}.
$$

Substitute X_{it} and L_{it} in the objective function and divide by Y_{it} to get the unit cost ($\mathcal{C}_{it}$):

$$
\begin{aligned}
\mathcal{C}_{it} &= w \frac{1}{Z_{it}} \left(\frac{\alpha_L}{\alpha_X} \frac{q_{it}}{w} \right)^{\alpha_X} + q_{it} \frac{1}{Z_{it}} \left(\frac{\alpha_X}{\alpha_L} \frac{w}{q_{it}} \right)^{\alpha_L} \\
&= \frac{1}{Z_{it}} \left(\frac{w}{\alpha_L} \right)^{\alpha_L} \left(\frac{q_{it}}{\alpha_X} \right)^{\alpha_X}.
\end{aligned}
$$

Expenditure shares:

$$
\begin{aligned}
q_{it} X_{it} &= q_{it} \frac{Y_{it}}{Z_{it}} \left(\frac{\alpha_X}{\alpha_L} \frac{w}{q_{it}} \right)^{\alpha_L} = \alpha_X \mathcal{C}_{it} Y_{it} \\
w L_{it} &= w \frac{Y_{it}}{Z_{it}} \left(\frac{\alpha_L}{\alpha_X} \frac{q_{it}}{w} \right)^{\alpha_X} = \alpha_L \mathcal{C}_{it} Y_{it}.
\end{aligned}
$$

Demand for domestic and foreign intermediate inputs - Start with the cost minimization problem for intermediate inputs:

$$
\begin{aligned}
&\min_{\{x_{ij}\},\{x_{ik}\}} \quad \int_j p_{ij} x_{ij} dj + M_{it} \int_{k \in \Omega_{it}} p_{ik} x_{ik} dk \\
&\text{subject to } \; X_{it} = \left[\int_j x_{ij}^{\frac{\sigma^I - 1}{\sigma^I}} dj + M_{it} \int_{k \in \Omega_{it}} x_{ik}^{\frac{\sigma^I - 1}{\sigma^I}} dk \right]^{\frac{\sigma^I}{\sigma^I - 1}}.
\end{aligned}
$$

Set up the Lagrangian:

$$
\mathcal{L} = \int_j p_{ij} x_{ij} dj + M_{it} \int_{k \in \Omega_{it}} p_{ik} x_{ik} dk + \lambda \left(X_{it} - \left[\int_j x_{ij}^{\frac{\sigma^I - 1}{\sigma^I}} dj + M_{it} \int_{k \in \Omega_{it}} x_{ik}^{\frac{\sigma^I - 1}{\sigma^I}} dk \right]^{\frac{\sigma^I}{\sigma^I - 1}} \right).
$$

First Order Condition:

$$\frac{\partial \mathcal{L}}{\partial x_{i1}} = p_{i1} - \lambda \frac{\sigma^I - 1}{\sigma^I} \left[\int_j x_{ij}^{\frac{\sigma^I-1}{\sigma^I}} dj + M_{it} \int_{k\in\Omega_{it}} x_{ik}^{\frac{\sigma^I-1}{\sigma^I}} dk \right]^{\frac{\sigma^I}{\sigma^I-1}-1} \frac{\sigma^I}{\sigma^I - 1} M_{it} x_{i1}^{\frac{\sigma^I-1}{\sigma^I}-1} \overset{!}{=} 0.$$

Rearranging:

$$x_{i1} = M_{it}^{\sigma^I} \frac{1}{(\lambda p_{i1})^{\sigma^I}} \left[\int_j x_{ij}^{\frac{\sigma^I-1}{\sigma^I}} dj + M_{it} \int_{k\in\Omega_{it}} x_{ik}^{\frac{\sigma^I-1}{\sigma^I}} dk \right]^{\frac{\sigma^I}{\sigma^I-1}}.$$

Relative intermediate input demand:

$$\frac{x_{i1}}{x_{i2}} = \left(\frac{p_{i2}}{p_{i1}} \right)^{\sigma^I}.$$

In the intermediate input bundle:

$$\begin{aligned}
X_{it} &= \int_j p_{ij} x_{i2} \left(\frac{p_{i2}}{p_{ij}} \right)^{\sigma^I} dj + M_{it} \int_{k\in\Omega_{it}} p_{ik} x_{i2} \left(\frac{p_{i2}}{p_{ik}} \right)^{\sigma^I} dk \\
&= x_{i2} p_{i2}^{\sigma^I} \int_j p_{ij}^{1-\sigma^I} dj + M_{it} \int_{k\in\Omega_{it}} p_{ik}^{1-\sigma^I} dk \\
x_{i2} &= \frac{1}{p_{i2}^{\sigma^I}} \frac{X_{it}}{\int_j p_{ij}^{1-\sigma^I} dj + M_{it} \int_{k\in\Omega_{it}} p_{ik}^{1-\sigma^I} dk}.
\end{aligned}$$

Defining the intermediate input price index as $q_{it}^{1-\sigma^I} = \int_j p_{ij}^{1-\sigma^I} dj + M_{it} \int_{k\in\Omega_{it}} p_{ik}^{1-\sigma^I} dk$, then:

$$\begin{aligned}
x_{ij} &= \frac{1}{q_i} \left(\frac{p_j}{q_i} \right)^{-\sigma^I} X_{it} \\
x_{ik} &= \frac{1}{q_i} \left(\frac{p_k}{q_i} \right)^{-\sigma^I} X_{it}.
\end{aligned}$$

C Other Results

Figure C.1: Other non-targeted moments

(a) Re-entry Probability (b) Imports growth

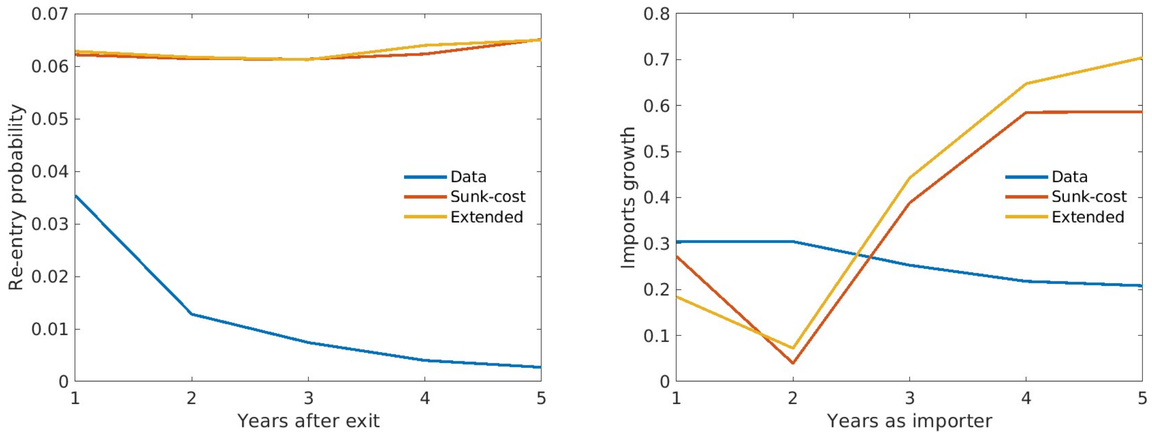

Table C.1: Estimated parameters if $\rho = 0.95$

Parameters	Sunk-cost
f_0	0.776 (0.063)
f_1	0.342 (0.028)
f_c	≈ 0 (≈ 0)
ρ_Z	0.95
σ_Z	0.121 (0.002)
η	0.895 (0.012)
λ	0.298 (0.009)

Costs measured as a fraction of the median firm's expenditure. f_1 is measured as annual costs.

D Policy Analysis: import cost decrease

Figure D.1: Aggregate effects, import cost decrease

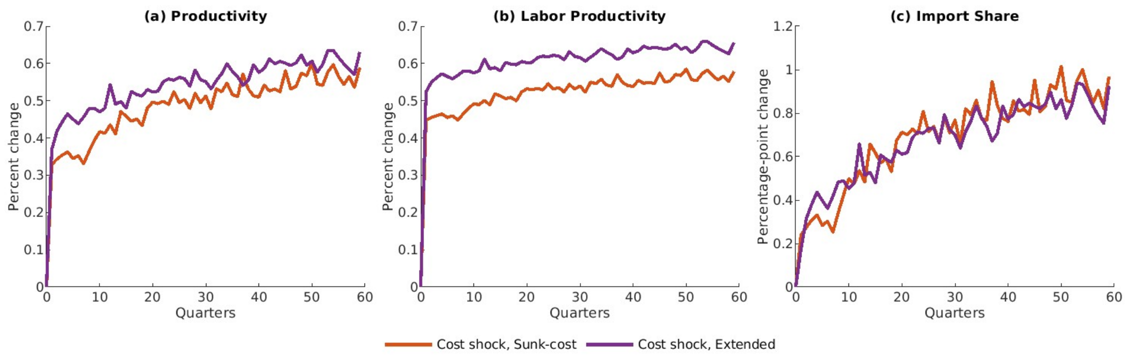

Figure D.2: Changes by efficiency decile after one year, import cost decrease

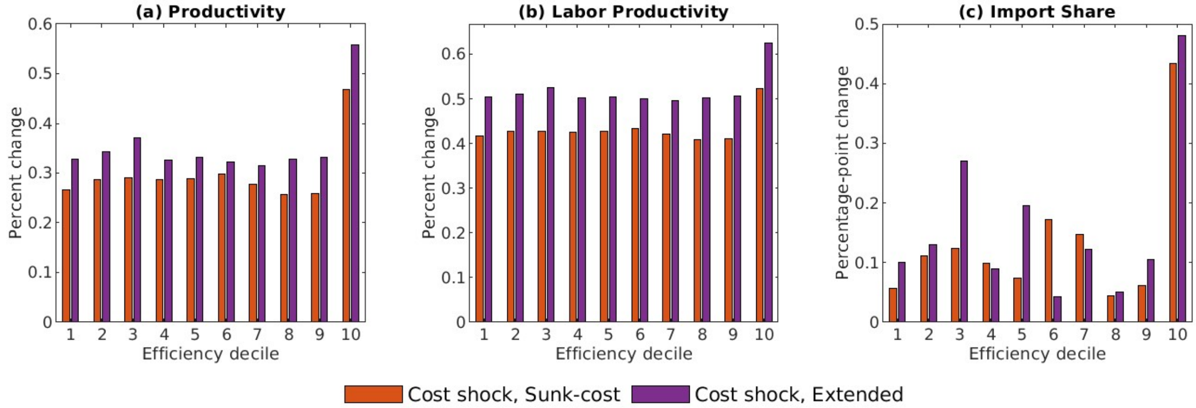

Figure D.3: Changes by efficiency decile after 15 years, import cost decrease