The Pro-Competitive Effects of Importing Intermediates*

Malte Thie

Université Paris Dauphine–PSL & CEPII

Job Market Paper

June 2026

Abstract

Firms increase markups following a decrease in import prices because of imperfect cost pass-through. This paper analyzes an understudied, countervailing effect: as more firms are induced to import (extensive margin), each individual firm is forced to pass through more of their cost reductions in order to retain their market position. I introduce a partial equilibrium model of monopolistic competition under non-CES demand, in which firms choose to either import an intermediate or to source it domestically. The model reveals the theoretical link between the extensive margin and pass-through, and yields a simple way to estimate the relevant parameters in the data. I then quantify the extensive margin for French firms, using detailed product-level price data on both the output and input side. Results show that the extensive margin is sizable, a 10% increase in the marginal cost savings potential from sourcing from abroad increase the share of firms importing by 3.9%. A quantitative exercise using a sufficient statistics approach and parametrizing a Kimball demand system suggests that the extensive margin can explain around 16% of the decrease of the aggregate price index following a 10% reduction in foreign prices.

JEL Classification: F1, F61, F62, L11

Keywords: Intermediate Imports, Pass-Through, Markups, Competition

*I would like to thank Gianluca Orefice for precious advice and guidance. I'm also indebted to Joachim Jarreau and Jiancong Liu for valuable discussions, as well as Axelle Arquié, Thomas Chaney, Jonathan Dingel, Juan Herreño, Thierry Mayer, Isabelle Méjean, Monica Morlacco, Noémie Pinardon-Touati, Ariell Reshef, Farid Toubal, Fabian Trottner and Peio Villanueva for their feedback. I would also like to thank participants at the LEDa Doctoral Retreat, the LEDa PhD Seminar, the Columbia ITS Colloquium, UCSD, ETSG, CEPII and the Doctorissimes conference for their comments.

1. Introduction

Trade liberalization is thought to have mainly positive welfare effects through price reductions. While a decrease in tariffs on final goods decreases prices due to pro-competitive forces, trade liberalization on the input side decreases prices through its effects on marginal costs. One of the key questions in assessing the welfare effects of the latter relates to the degree to which firms' prices react to a change in their marginal costs. There exists wide empirical evidence suggesting that firms absorb a significant portion of international price variations in their markups through imperfect pass-through. In that sense, borrowing the term from Arkolakis, Costinot, Donaldson, and Rodríguez-Clare (2018), the welfare gains of input trade liberalization are "elusive".

However, lower input prices could also induce more firms to source intermediates from abroad. This increases the share of firms affected by the foreign shock, limiting the cost-advantage of incumbent importers through competitive forces: if more firms are affected by the shock, each individual firm is forced to pass through a greater share of its change in costs to keep its share of the market. Thus, the propensity of firms to opt into the importing market following a change in relative prices between home and abroad will determine the degree to which firms are able to (not) pass through cost reductions into output prices, directly affecting the efficiency of trade policy. In this sense, the extensive margin works as a pro-competitive counterbalance for the relative welfare losses due to imperfect pass-through.

The change in the share of importers – in the following called the extensive margin of importing – has been mainly overlooked in the literature.[1] In this paper, I explicitly incorporate the extensive margin of importing in the analysis of the markup effects of changes in trade policy. I start by providing reduced-form empirical evidence on the reaction of both prices and the share of importing firms in France following the adoption

[1] Weinberger (2020) for instance relies on the sufficient statistic result by Blaum, Lelarge, and Peters (2018) that firm size and markups can be directly connected to the share of inputs sourced from abroad to analyze the markup effect of exchange rate changes. He explicitly refrains from modeling the importing decision of firms, stating that it affects results only quantitatively but not qualitatively. The present paper, in contrast, shows the importance of the extensive margin.

of new trade agreements. As one would expect, on aggregate, the share of importing firms increases, while prices decrease (though only marginally). More interestingly, looking at the heterogeneous effect for more and less concentrated sectors reveals that aggregate effects are mainly driven by the lower half of the distribution: for the most concentrated sectors, effects are almost entirely absent. This paper argues that these two findings are intrinsically linked: a larger increase in the share of importing firms will lead to a higher pass-through of marginal cost reductions into prices.

Motivated by the reduced-form evidence, I set up a simple partial-equilibrium model, which shows the sourcing decision of firms in a non-CES setting with variable markups and imperfect pass-through. In the model, firms adjust prices as a reaction to changes in their own marginal costs, and as a reaction to price changes by competitors (demand complementarities). Each firm faces the choice of importing or sourcing a given intermediate input from the domestic market. Importing intermediate inputs incurs a fixed cost. Firms maximize profits, and, hence, choose to import a given intermediate according to its potential to reduce marginal costs. Under non-CES, the reaction of profits depends on two channels: the reaction of demand (increase in quantity sold), and the reaction of per-unit profits (increase in markup). Aggregating across firms at the sectoral level, and calculating the share of importers as the share of firms that are above the cutoff productivity needed for importing, the model then predicts that the number of importers for a given intermediate is a function of the associated marginal cost reduction, the fixed costs, the demand structure and the industry-wide heterogeneity between firms with respect to productivity (Pareto shape). This last result implies that the extensive margin of importing is less pronounced in *ex-ante* more concentrated sectors. Because the size of the extensive margin will directly affect the pass-through of importers through demand complementarities, this will have important implications for the *ex-ante* evaluation of the welfare gains from input trade liberalization: ignoring the heterogeneity in the extensive margin could lead, in certain sectors, to mis-specifying the welfare gains from trade liberalization.

I then show that, given the demand system, the relative price at the importing cutoff is a sufficient statistic to quantify the effect of the extensive margin on the aggregate price index. Guided by theory, I develop an empirical methodology to obtain the relative price at the cutoff for each input-output pair: regressing the (log) change in the share of importing firms on the (log) change in the marginal-cost advantage when sourcing from abroad identifies a parameter composed of the Pareto-shape parameter and the elasticity of demand at the cutoff. I estimate this relationship using French firm-product-level data. The output data is comprised of information on the products that firms sell. This can be matched to customs data, which I use to obtain information on the input side. By using single-product importers, I determine the inputs needed for producing a given output and construct the input expenditure shares. Results show that the extensive margin is sizable: a 10% increase in the marginal cost advantage from abroad increases the share of importing firms by around 3.9%. The results are robust to a battery of checks.

Using the results of the empirical exercise, I then simulate the effect of the extensive margin on the aggregate price index, in order to assess the counterfactual welfare gains from trade. Employing standard production function estimation techniques to obtain the Pareto shape parameters, I recover the cutoff demand elasticities at the detailed input-output level. Calibrating a Kimball (1995) demand system, using the functional form by Klenow and Willis (2016) and product-level distributions of pass-through, I then simulate different trade liberalization scenarios. The results of the counterfactual exercise suggest that, following a 10% decrease in foreign prices, the aggregate price index decreases by around an additional 16% when the extensive margin is present. Further, the size of the extensive margin effect depends on the size of the shock: a larger decrease of foreign prices will lead to a larger increase in the number of the firms sourcing from abroad, and therefore to a larger impact of the extensive margin. A 20% decrease in foreign prices, for instance, increases the average effect of the extensive margin to 24.2%.

These average results mask important heterogeneities between products. For around 50% of products, the reduction in the cutoff productivity implied by a 10% decrease in foreign prices is not big enough to induce new firms to import. Concentrating solely on the products where the extensive margin was "activated", the share of price decreases explained by the extensive margin increases to around 25%. Further, in line with the motivational evidence and theory, products produced by firms in the most concentrated sectors display a significantly *lower* effect of the extensive margin on the aggregate price index. Less concentrated sectors show an additional reduction of prices by 0.4 percentage points when taking into consideration the extensive margin, around two times larger than the effect for the most concentrated sectors. This relative difference between more and less concentrated sectors is similar for a 20% decrease, where prices decrease by an additional 1.2 percentage points for the bottom half of the concentration distribution, compared to only 0.6 percentage points for the upper half.

These results combine two ways in which the extensive margin affects the aggregate price index: the number of firms that are affected by the import shock and the larger pass-through due to demand complementarities. To isolate the latter, I analyze the markup adjustment of incumbent importers that did not change their sourcing strategy following input trade liberalization. Results suggest that, for the 10% liberalization scenario, markups for these firms increase by 5% less when allowing for the extensive margin. This number climbs to 10% for the 20% scenario.

The findings of this paper have important implications for policy makers. Namely, in order to limit the welfare losses due to markup increases, and to activate the virtuous effect of the extensive margin, input trade liberalization will be more effective in less concentrated sectors. This paper provides a tool of analysis to identify these sectors *ex-ante*. Further, for more concentrated sectors, combining trade policy with a pro-competitive industrial policy is likely to increase the efficiency of the former. Enabling more firms to reap the benefits of importing will contribute to higher welfare gains through larger decreases in the price index.

Related literature This paper contributes to multiple strands of the literature. First, on the theoretical side this paper is related to a list of papers that develop models of importing under heterogeneous markups. Amiti, Itskhoki, and Konings (2014) develop an oligopolistic competition model with a firm's choice of importing intermediate inputs, which combines the insights by Atkeson and Burstein (2008) and Halpern, Koren, and Szeidl (2015). Firms are heterogeneous in productivity and their importing intensity, and charge different markups. Their paper reveals an important heterogeneity in the exchange rate pass-through, with firms engaged in international trade showing a smaller pass-through than purely domestic firms. Weinberger (2020) develops a model of monopolistic competition with importing, looking at the effect of an exchange rate shock on allocative efficiency, showing that differential markup adjustment following global shocks leads to changes in allocative efficiency. Compared to these contributions, my paper explicitly models the importing decision in a non-CES monopolistic competition setting, highlighting the potential importance of the extensive margin of selection into importing for aggregate markup adjustments. By integrating the extensive margin, and showing its heterogeneity depending on sectoral concentration, this paper provides a tool to *ex ante* analyze the aggregate response of markups in different sectors. The results of the simulation suggest that not incorporating the extensive margin would, on average, underestimate the price decreases following input trade liberalization by around 15%.

Moreover, this paper also relates to the empirical literature on the effect of (input) trade liberalization on markups. De Loecker, Goldberg, Khandelwal, and Pavcnik (2016) analyze the effect of input trade liberalization on markups for Indian firms, finding substantial increases of pricing over marginal costs. These markup increases more than outweigh the pro-competitive effects of trade liberalization in final goods, leading to an overall increase in markups following trade liberalization. Closer to the present paper is the study by Amiti, Itskhoki, and Konings (2019). Their paper uses Belgian data to analyze the reaction of a firm's price to exchange rate shocks, both through its own marginal costs, as well as through reductions in the price of competitors (what they call "strategic complementarities"). I add to this literature by providing robust empirical evidence of the extensive margin, which acts as a pro-competitive force through strategic complementarities. To a lesser extent, by analyzing the potential markup increases stemming from input trade liberalization, this paper is also related to the literature on the pro-competitive effect of trade liberalization (Feenstra & Weinstein, 2017; Arkolakis et al., 2018; Crowley, Han, & Prayer, 2024).

By showing the importance of international trade for markups, this paper also contributes to the literature on increases in markups that has emerged in recent years. The increases in markups have been shown for the US by De Loecker, Eeckhout, and Unger

(2020) and for a larger panel of countries by De Loecker and Eeckhout (2018). To explain this phenomenon, the literature has mainly focused on the emergence of superstar firms (Autor, Dorn, Katz, Patterson, & Van Reenen, 2020), a reduction in the effectiveness of antitrust reglementation (Gutiérrez & Philippon, 2017) and the growing importance of intangible investment (De Ridder, 2024). By showing the importance of input trade on aggregate markups, this paper aims to add another dimension which played a role in the increase of markups.

The rest of this paper is organized as follows: section 2 shows some reduced form motivational evidence; section 3 introduces the partial equilibrium model; section 4 describes the data used for the empirical application; section 5 presents the empirical strategies with which I test the main conclusions of the theoretical model; section 6 displays the results of the empirical exercise; section 7 contains the quantitative counterfactual exercise, using Kimball demand. Finally, section 8 concludes the paper.

2. Motivational Evidence

In this section, I establish two reduced-form facts: following the adoption of a preferential trade agreement (PTA), less concentrated sectors experience (i) a larger increase in the share of firms importing from the partner country, and (ii) a more important decrease in prices. As I will argue in the following theory part of this paper, these two patterns are intrinsically linked: increasing the number of firms importing from abroad works as a pro-competitive counterforce to potential welfare drains from market power.

In order to show these differential evolutions, I conduct an event study on the 28 trade agreements signed by the EU during the period 2009-2019.[2] This setup lends itself to a differences-in-differences design with staggered adoption. I will use these agreements as an exogenous shock to the trade environment in order to show the evolution of the share of firms importing (industry-level) and the evolution of prices (firm-product level) following (provisional) adoption of the agreement. For the analysis, I will rely on confi-

[2]Due to the common trade policy of EU member countries, all of these agreements effectively represent a trade liberalization for France. For a complete list of these agreements, refer to Table A.1.

dential firm-level data on the universe of French firms for the import margin, and on a survey of manufacturing firms for price dynamics. The trade data covers the universe of yearly import values at the firm×origin×product dimension, while data on output prices shows the yearly unit values of products produced by a sample of large manufacturing firms. For a detailed description of the data used, refer to section 4.

2.1. Importing firms following trade liberalization

To analyze the importing decision of firms following the adoption of PTAs, I employ a two-way fixed effects specification at the industry×product×origin level (Jio):

$$y_{Jiot} = \alpha_{Jiot} + \sum_{h=-4}^{-2} \beta_h \times T_{Jiot} + \sum_{h=0}^{7} \beta_h \times T_{Jiot} + \eta_{Jio} + \eta_t + \epsilon_{Jiot},$$

where y_{Jiot} is the (log) share of firms in industry J importing good i from country o at time t. Products are defined as the combination of a 8-digit Prodcom code and the unit of account. The same definition will be applied throughout this paper for both outputs and inputs. An industry is defined at the 5-digit level of the French industry classification (*nomenclature d'activités française* – NAF). Treatment is defined as the provisional adoption of a PTA at the origin level. I only retain manufacturing industries and drop all agricultural products.[3]

Figure 1a shows the average effect of the adoption of a PTA on the share of firms importing a given product from a given origin.[4] While there is little movement on impact and in the first year following adoption, there seems to be a gradual uptake in the share of firms importing from abroad. Overall, the effect stabilizes after three years, with a peak at 17.6% after five years. Let's now look at the heterogeneity of the effect in two different sub-samples: firms in sectors with a high or low normalized HHI.[5] I define concentrated

[3]Manufacturing products are defined as 2-digit Prodcom codes between 10 and 34. Agricultural products are defined as 2-digit CN8 codes below 25.

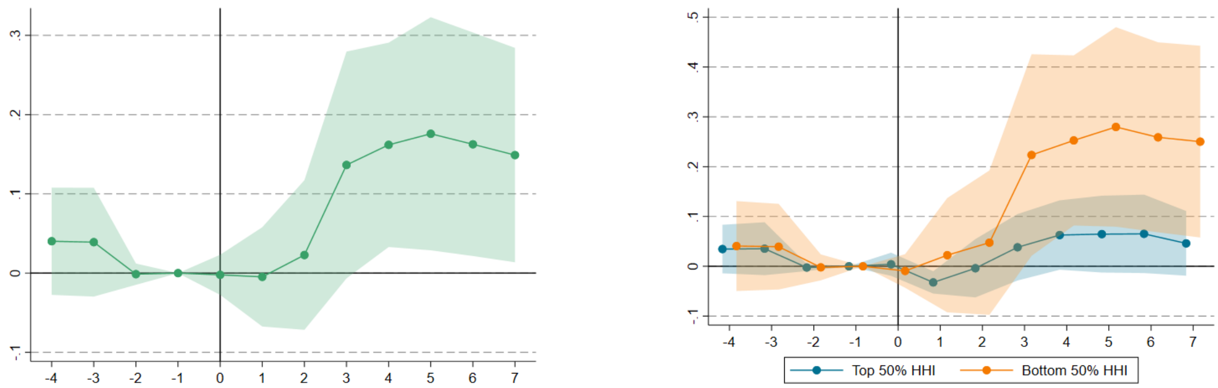
[4]Confidence intervals are calculated using standard errors clustered by origin country. The full regression results can be found in Appendix Table A.2.

[5]Using balance sheet information, I calculate the ranking on *all* manufacturing industries and not just the industries for which I have firms with price information. I calculate the normalized HHI using the classical formula: $HHI = (\sum_{i=1}^{N}(\text{market-share})^2 - 1/N)/(1 - 1/N)$.

Figure 1: Event-study on share of firms importing

(a) Overall effect of trade agreement

(b) Heterogeneous effect of trade agreement



Note: Bands around solid lines denote 95% confidence intervals.

sectors as being in the upper half of the distribution. To avoid any effects of trade liberalization on the HHI over my sample period, I fix the ranking in the first year of analysis (2009). Figure 1b shows the difference in the effect between high- and low-concentrated sectors. Results suggest that the overall positive effect is almost exclusively driven by the least concentrated sectors. Following the adoption of a trade agreement, the share of firms importing a given product from a given origin increases by over 28% in these sectors after five years. On the other side, there is only a small and only slightly significant effect for the most concentrated sectors, with a maximum increase of the share of importing firms of around 6.5% after three years.

2.2. Prices following trade liberalization

I will again employ a dynamic two-way fixed effects specification at the firm×output level (fj):

$$y_{fjt} = \alpha_{fjt} + \sum_{h=-4}^{-2} \beta_h \times T_{fjt} + \sum_{h=0}^{7} \beta_h \times T_{fjt} + \eta_{fj} + \eta_t + \epsilon_{fjt},$$

where η_{fj} and η_t denote fixed effects at the firm×output and year level, respectively, where y_{fjt} will be the (log) unit value of product j charged by firm f in year t, and where T_{fjt} denotes a treatment dummy. As before, products are defined as the combination of a 8-digit Prodcom code and the unit of account. Treatment is defined at the firm level according to three criteria: (a) firms need to have imported from the partner country in the year prior to the adoption of the PTA, (b) the partner country represented at least 10% of total imports of the firm, and (c) imports from the partner country represented at least 10% of total expenditure on variable costs.[6] As before, I only consider non-agricultural imports and restrict the sample of output products to manufacturing goods. In this setting, firms are potentially treated multiple times. In these cases I define treatment as the first treatment that occurred. To account for potential biases stemming from attrition in the product mix of firms, I will only retain products for which we have information in all years in which a firm was present. Further, to account for outliers, I only keep products for which the ratio between contemporary and lagged prices does not fall below 1/3 and does not exceed 3. The pre-trend assumption here posits that, absent the signing of the trade agreement, output prices of importers and non-importers would have evolved in the same way. Similarly, the parallel trend assumption for the heterogeneity exercise assumes that prices for importers and non-importers would have evolved similarly *within* sample splits.

Figure 2a shows the event-study plot of this exercise.[7] Following the adoption of a trade agreement, prices of treated firms drop up to almost 15%. However, the coefficients are quite noisy, the effect being only slightly significant in certain years. Figure 2b shows the heterogeneity according to the same categorization into high and low concentration as in the prior subsection. While prices in less concentrated sectors significantly decrease by 21.9% seven years after the adoption of the PTA, prices in the most concentrated sectors, though very noisy, show very little effect after the signing of a trade agreement. In the following, I will argue that this difference in price responses is a direct result of the differential response in the share of firms importing: a larger increase in the share of firms importing plays a pro-competitive role, forcing firms to pass-through a higher share of marginal cost reductions into output prices.

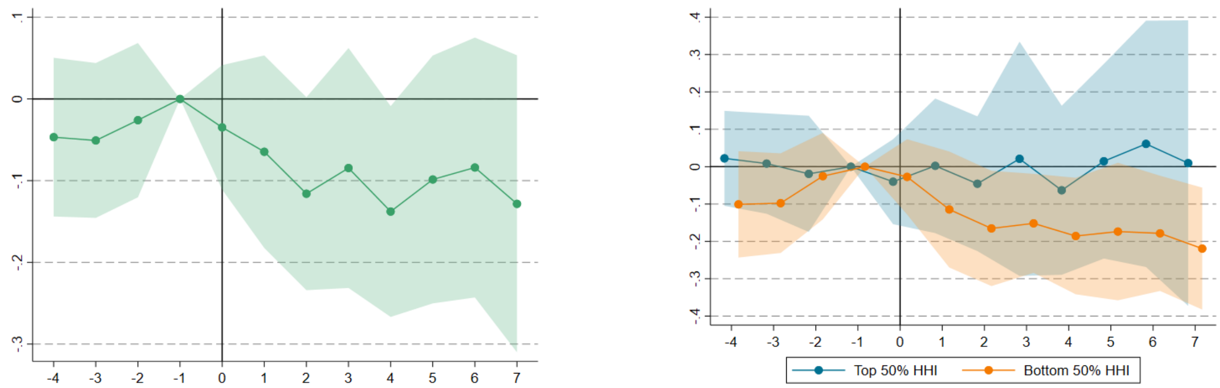
[6]As a sensitivity check, in Appendix A I change the definition of treatment using 1% (5%) of total imports of the firm and similarly using 1% (5%) of total expenditure on variable costs.

[7]Confidence intervals are calculated using robust standard errors. The full regression results can be found in Appendix Table A.3.

Figure 2: Event-study on prices

(a) Overall effect of trade agreement

(b) Heterogeneous effect of trade agreement



Note: Bands around solid lines denote 95% confidence intervals.

3. Theory

3.1. Demand and pass-through

Consider the following general system of demand drawn from Arkolakis et al. (2018) and Arkolakis and Morlacco (2017): all consumers have the same preferences and the same income (think of a representative consumer). As a convention I will write all aggregate variables in capital and firm-level variables in small letters.

Goods within the economy are differentiated between firms. Consumers face the price schedule $p \equiv \{p_j\}_{j \in J}$. J here denotes an industry. To ease the exposition, I will drop all J subscripts. The Marshallian demand for any differentiated good j is

$$q_j(p_j, P, Q) = QD(p_j/P), \tag{1}$$

where $D(\cdot)$ is the demand function and strictly decreasing ($D'(\cdot) < 0$). Demand for variety j depends on its relative price p_j/P. Q and P denote aggregate demand shifters that are exogenously and jointly determined through utility maximization constraints.[8] These

[8]The aggregate demand shifters are jointly determined through the following system of two equations: $\int_{j \in \Omega} [H(p_j/P)]^{\beta} [p_j QD(p_j/P)]^{1-\beta} dj = y^{1-\beta}$ and $Q^{1-\beta} \left[\int_{j \in \Omega} p_j QD(p_j/P) dj\right]^{\beta} = y^{\beta}$, where y denotes the revenue of a given firm. As shown in Arkolakis et al. (2018), this general demand system includes a variety of different demand functions, depending on the value of the parameter β.

demand shifters can be thought of as general equilibrium conditions on aggregate prices and demand. The form of the demand function $D(\cdot)$ is restricted by (i) the presence of a choke price p^* that drives demand for a given variety j to zero for all prices above p^*, i.e. $D(p/P) = 0, \forall p \geq p^*$, and (ii) the assumption that demand elasticity decreases with the relative price, thus satisfying "Marshall's Second Law of Demand" (Arkolakis et al., 2018).[9] Finally, for variable markups to exist on the market, the own-price elasticity $\partial \ln D(p_j/P)/\partial \ln p_j$ is allowed to vary with prices, meaning that the response of demand to changes in prices depends on the level of said prices.

Pricing by firms and pass-through Firms on the final-goods market act under monopolistic competition. Each variety j is produced by an individual firm, thus also indexed by j. Taking into consideration demand q_j as defined in Equation 1, each firm will choose the price of its variety p_j so as to maximize its profits π_j:

$$\pi_j(c_j, Q, P) = \max_{p_j}\{(p_j - c_j(\upsilon))q_j(p_j, Q, P)\}, \tag{2}$$

where c_j denotes the (firm-specific) marginal cost depending on a cost-shifter υ, such as transportation costs or tariffs.

In equilibrium, firms set prices as a markup over marginal cost. I will define the partial elasticity of demand with respect to the price of variety j as $\varepsilon_j \equiv -\partial \ln q_j/\partial \ln p_j$. Using this definition, from the first order condition of Equation 2 we can derive the equilibrium price as:

$$p_j = \frac{\varepsilon_j}{\varepsilon_j - 1} \cdot c_j(\upsilon) = \mu_j \cdot c_j(\upsilon), \tag{3}$$

where $\mu_j = \varepsilon_j/(\varepsilon_j - 1)$ denotes the markup. Assuming non-negative markups, it follows that $\varepsilon_j > 1$.

From Equation 1 follows that demand is a function of the relative price of a variety with respect to the aggregate price, p_j/P. Thus, we can write the partial elasticity of

[9]The assumption that demand elasticity decreases in the relative price is also empirically relevant. First, under a monotonically decreasing demand function more productive firms, displaying lower prices, have higher markups because $\varepsilon_j^{'} = \frac{\partial \ln \varepsilon(p_j/P)}{\partial \ln p_j/P} > 0$. Second, if "Marshall's Second Law of Demand" is satisfied, pass-through is incomplete, a real-world feature that is very salient in the literature (De Loecker et al., 2016; Amiti et al., 2019), and that can also be found in French data (see Appendix I). Between-firm heterogeneity with respect to pass-through will depend on the curvature of the derivative of the demand elasticity, i.e. on the second derivative of the demand elasticity with respect to the relative price.

demand as $\varepsilon_j = \varepsilon(p_j/P)$ and markups as $\mu_j = \mu(p_j/P)$, showing that both are a function of the relative price. Using this, we can rewrite Equation 3 in log-form and take log differences to obtain:

$$d \ln p_j = -\Gamma_j (d \ln p_j - d \ln P) + \rho_\upsilon d \ln \upsilon, \tag{4}$$

where $\rho_\upsilon = \partial \ln c / \partial \ln \upsilon$ denotes the partial-elasticity of the marginal cost to a shock to the cost-shifter υ, which for simplicity can be assumed to be equal to one, i.e. positive shocks to the cost-shifter are entirely translated into an increase in the marginal costs. Γ_j denotes the markup elasticity with respect to the relative price of a variety j:

$$\Gamma_j \equiv -\frac{\partial \ln \mu_j}{\partial \ln (p_j/P)}.$$

In other words, Γ_j shows the response of the markup following a change in the relative price of a variety j: the higher Γ_j, the more the markup will increase when the relative price decreases. Intuitively, depending on the demand-elasticity for its product, a profit-maximizing firm chooses a higher markup when its price decreases relative to the price of its competitors as this leads to higher profits.

I can now rewrite Equation 4 in order to analyze the movement of firm-specific prices to a shock to the cost-shifter υ:

$$\Theta_j \equiv \frac{d \ln p_j}{d \ln \upsilon} = \frac{1}{1 + \Gamma_j} + \frac{\Gamma_j}{1 + \Gamma_j} \frac{d \ln P}{d \ln \upsilon}, \tag{5}$$

where the first term denotes the direct effect of a shock to the cost-shifter on a firm's price (*direct pass-through*) and the second term denotes the reaction to the changes in prices by competitors as in Amiti et al. (2019) (*demand complementarities*).[10] Thus, as long as there is incomplete pass-through of cost shocks into prices (i.e. $\Gamma_j > 0$), a decrease in marginal costs will not translate into a one-to-one decrease in prices and will, in turn, lead to higher markups.[11] I will define *direct* pass-through as $\Psi_j \equiv \frac{1}{1+\Gamma_j}$, while *total* pass-through is denoted by Θ_j.

[10]While the term *strategic complementarities* has gained traction due to the paper by Amiti et al. (2019), the correct term to be used in the context of monopolistic competition, as the authors note, is *demand complementarities*.

[11]Note here that $\Gamma_j = 0$ represents the CES case of complete pass-through and constant markups. The result that $\Gamma_j = 0$ for CES comes from the fact that for CES, the elasticity is constant (equal to the elasticity of substitution) and, thus, does not depend on the relative price p_j/P.

3.2. Marginal costs and the sourcing decision

Marginal costs After having determined the demand-side of the model and a firm's profit-maximization behavior, I now turn to production. I assume that each firm uses a set of intermediate inputs in their production technology. Specifically, a firm produces its output using a Cobb-Douglas production function that takes the following form:

$$q_j = \varphi_j l^{\gamma_l} \prod_{i=1}^{n} v_i^{\gamma_i}, \tag{6}$$

where l denotes labor, v_i denotes the quantity of a given intermediate input i, and φ_j represents productivity of firm j. The production technology is well-behaved, i.e. $q_j(\cdot)$ is twice differentiable with respect to its arguments. The assumption of Cobb-Douglas implies a unit-elasticity of substitution and constant cost shares γ. I assume there to be constant returns to scale, i.e. $\gamma_l + \sum_i \gamma_i = 1$.[12]

Firms are heterogeneous with respect to their productivity φ_j. As is standard in the literature (Melitz, 2003; Chaney, 2008; Antràs, Fort, & Tintelnot, 2017), I assume that firms draw their productivity from a Pareto distribution $g(\varphi)$, with an associated cumulative distribution $G(\varphi) \equiv 1 - \varphi_j^{-a}$, where a is an inverse measure of firms heterogeneity.

Marginal costs can be derived from a standard cost minimization problem, and are thus given by:

$$c_j = \varphi_j^{-1} \left(\frac{w}{\gamma_l}\right)^{\gamma_l} \prod_{i=1}^{n} \left(\frac{p_i}{\gamma_i}\right)^{\gamma_i}, \tag{7}$$

where w denotes the wage and p_i denotes the price of intermediate i.

For each intermediate input i a firm faces the same choice of sourcing: she can either source the input from home or from abroad. Opposite to the modeling in other papers (Halpern et al., 2015; Morlacco, 2021), this assumption entails that intermediates, whether sourced from home or from abroad, are substitutes and not complements. The assumption that intermediates from home and abroad are perfect substitutes is in line with the empirical strategy in section 5 which is conducted using products at a very fine-grained level (8-digit Prodcom × unit level). When deciding to source intermediates from abroad,

[12] I relax this assumption in Appendix H.

the firm needs to pay a fixed cost of importing, f^m.[13] I assume these fixed costs to be equal for all intermediates and to be independent of the quantity shipped.[14]

Firms minimize costs, hence the main motivation for firms to source intermediates from abroad is the lower price abroad (including iceberg trade costs τ associated with importing) which will lead to lower marginal costs of production. The price for a given intermediate input i can, thus, be written as:

$$p_i = \begin{cases} \tau p_i^F \\ p_i^D \end{cases}, \tag{8}$$

where p_i^F and p_i^D denote the foreign and domestic price of i, respectively.

Sourcing decision Let us now turn to the sourcing decision of a given firm. The profit maximizing nature of firms means that a firm will choose to source intermediates from abroad if the positive effect of the price differential in terms of profits offsets the fixed cost. Hence, the sourcing decision depends on how profits react to a change in marginal costs. Replacing p_j in the profit Equation 2 by the equilibrium price given in Equation 3, we can rewrite profits as:

$$\pi^*(c_j(\upsilon), Q, P) = (\mu_j - 1)c_j(\upsilon)q_j(p_j, Q, P). \tag{9}$$

Then, as before, we can rewrite profits in log-form, take log differences and rearrange to obtain the change in profits following a change in the cost-shifter υ:

$$\frac{d\ln \pi_j}{d\ln \upsilon} = 1 - \Lambda_j \cdot \Psi_j - \varepsilon_j^* \cdot \Psi_j + \underbrace{\left(\Lambda_j \cdot \Psi_j + \varepsilon_j^* \cdot \Psi_j\right) \frac{d\ln P}{d\ln \upsilon}}_{\text{GE}}, \tag{10}$$

where $\Lambda_j \equiv -\frac{\partial \ln(\mu_j - 1)}{\partial \ln(p_j/P)}$ denotes the elasticity of the *per-unit profit margin* to the relative price, which – assuming that Marshall's Second Law of Demand is satisfied – is a negative

[13] This fixed cost reflects for instance the cost of setting up contracts or the cost incurred by searching for cheaper suppliers.

[14] As the focus of this paper is on the importing of intermediates, *regardless* of the origin country, I abstract here from any heterogeneity in fixed costs. This assumption is somewhat restrictive. As shown by Antràs et al. (2017), the fixed costs of importing depend on the country from which a firms decides to source its intermediates. Fixed costs increase in distance and are lower for countries with a common language.

relation. Further, $\varepsilon_j^* \equiv -\frac{\partial \ln q_j}{\partial \ln(p_j/P)}$ denotes the *realized* demand elasticity, i.e. the change in demand following a change in the *relative* price.

Under monopolistic competition, firms do not take into account their effect on aggregate prices. we will thus concentrate on the direct partial equilibrium effects for a firm, i.e. the change in profits given changes in the aggregate price index P:

$$\left.\frac{d \ln \pi_j}{d \ln \upsilon}\right|_P = 1 - \Lambda_j \cdot \Psi_j - \varepsilon_j^* \cdot \Psi_j. \tag{11}$$

A firm's profits (directly) react to a change in the cost-shifter υ along two distinct lines: a change in demand and a change in the markup that stem from a reduced relative price. First, the term $-\Lambda_j \cdot \Psi_j$ reflects the change in the per-unit profit margin $(\mu_j - 1)$ following a shift in the relative price, multiplied by pass-through, thus, reflecting the response of profits that is due to the response of markups resulting from a change in the cost-shifter. Second, the term $-\varepsilon_j^* \cdot \Psi_j$ denotes the according change in demand.

Now, profit maximization implies that a firm will choose to import intermediates from abroad if the potential gains in terms of profits offset the fixed cost needed for setting up the importing relation. Thus, again concentrating on the partial equilibrium of a firm, we can use Equation 10 to obtain the change in profits that stems from a change in marginal costs. As Equation 10 is in elasticity-form, we can multiply it by the percentage change of marginal costs and scale up using (pre-importing) profits $(\pi_{j,0})$ to bring it into levels and to make it comparable to fixed costs. The potential savings of marginal costs for firm j from importing a given input i are:

$$\chi_i \equiv \frac{c^{i^D} - c^{i^F}}{c^{i^D}} = 1 - \left(\frac{p_i^F}{p_i^D}\right)^{\gamma_i}, \tag{12}$$

where c^{i^D} and c^{i^F} denote the marginal costs when sourcing intermediate i from home and from abroad, respectively. I can then write the sourcing condition for a given firm and a given intermediate input as follows:[15]

$$\left(\Lambda_j \cdot \Psi_j + \varepsilon_j^* \cdot \Psi_j - 1\right) \chi_i \pi_{j,0} \geq f^m, \tag{13}$$

[15] Remember that Equation 10 shows the percentage change in profits following a percentage *increase* in marginal costs. As the sourcing from abroad constitutes a negative marginal cost shock, written here as a positive term (i.e. as marginal cost saving, $\chi > 0$), the elasticity of profits with regard to the cost-shifter needs to have an inverted sign.

where I have assumed (as before) that a change in the cost-shifter υ translates one-to-one into a change in marginal costs (i.e. $\rho_\upsilon = \partial \ln c / \partial \ln \upsilon = 1$). [16]

In the spirit of Melitz (2003), one can now determine the cutoff productivity $\underline{\varphi}_i$ at which firms are indifferent between sourcing a given intermediate input i from abroad or sourcing it from home:

Proposition 1. *The cutoff productivity to import a given intermediate input i is given by the following fixed-point equation:*

$$\underline{\varphi}_i = \underline{e}_0 \left(\frac{f^m}{\chi_i \mathcal{S}(\underline{\varphi}_i, \Phi_J, Q)} \right)^{\frac{1}{\underline{\varepsilon}_i - 1}}, \tag{14}$$

where $\underline{e}_0$ denotes the per-unit expenditure on inputs by the cutoff firm before importing, $\underline{\varepsilon}_i$ denotes the demand elasticity of a firm with cutoff productivity $\underline{\varphi}_i$, and $\mathcal{S}(\underline{\varphi}_i, \Phi_J, Q)$ represents a function of the demand-driven changes in profits resulting from a change in costs, depending on aggregate productivity Φ_J and the demand shifter Q.

The proof is given in Appendix B and I here only proceed to a quick discussion of the mechanisms underlying Equation 14. The cutoff productivity needed to import intermediate i intuitively depends positively on the fixed costs of importing f^m: the higher these fixed costs, the higher the productivity needed to still reap benefits from importing. Conversely, $\underline{\varphi}_i$ decreases with an increase in the potential marginal cost savings from importing (χ_i) and with an increase in the demand-driven change in profits due to a decrease in marginal costs ($\mathcal{S}$).[17] $\mathcal{S}$ here reflects the domestic market potential. Finally, the

[16]To be transparent, the modeling of marginal cost savings as χ_i relies on some important assumptions. First, I assume that all firms face the same production function and hence employ the same intermediate inputs. This is of course only (approximately) consistent if one compares firms within a given sector. Second, I assume that firms face the same vector of foreign prices for intermediate inputs, i.e. they are input price takers. That is, I abstract here from the potentially important dimension of buyer market power, described for French firms in Morlacco (2021). Finally, I assume that there is a single foreign price for a given intermediate input. Hence, I do not model the potentially important extensive margin of sourcing decisions as in Antràs et al. (2017). In essence, I assume that due to profit-maximizing behavior a firm will choose the first origin-country for which Equation 13 is fulfilled, irrespective of their sourcing choices for other products. Due to differential fixed costs as in Antràs et al. (2017) there might be a shift in the optimality of origin countries, depending on a firm's productivity.

[17]The model implies an implicit perfect ranking of intermediate inputs according to their marginal cost savings potential. In Appendix Appendix E I test this hypothesis empirically using French data.

pre-importing per-unit expenditure on inputs ($\underline{e}_0$) works as a scalar: larger costs of producing imply a higher price, and therefore lower demand. Hence, in order to pay the fixed cost of importing, firms need to have a higher productivity φ_j.

3.3. Impact on aggregate price index P

A change in the cutoff productivity implies a change in the number of firms importing following input trade liberalization. This in turn implies that more firms will be able to profit from the concurrent marginal cost reductions, leading to a stronger reduction in the aggregate price index.

As shown by Amiti et al. (2019) for homothetic demand systems, using Shephard's Lemma, the change in the aggregate price index following a shock to the cost-shifter υ is a sales-weighted average of pass-throughs Θ_j from Equation 5. Hence (in continuous form over all j):

$$\frac{d\ln P}{d\ln \upsilon} = \int_{\varphi^{\text{min}}}^{\infty} \text{ms}_j \Theta_j dG(\varphi_j),$$

where each firm j is identified by φ_j and where ms_j denotes the market share of firm j.[18]

In line with the theory section displayed above, we can decompose the change in the aggregate price index into three components: (i) the effect stemming from incumbent imports, (ii) the effect from new importers (the extensive margin), and (iii) the effect of remaining domestically sourcing firms. Thus, the following equation summarizes the total effect of an input trade liberalization with the extensive margin:

$$\frac{d\ln P}{d\ln \upsilon} = \int_{i=1}^{n} \left[\int_{\underline{\varphi}_i}^{\infty} \text{ms}_j \Theta_j dG(\varphi_j) + \underbrace{\int_{\underline{\varphi}'_i}^{\underline{\varphi}_i} \text{ms}_j \Theta_j dG(\varphi_j)}_{\text{Extensive margin}} + \int_{\varphi^{\text{min}}}^{\underline{\varphi}'_i} \text{ms}_j \Theta_j dG(\varphi_j) \right] di. \tag{15}$$

Here, the first term denotes the effect on the aggregate price from *ex ante* importers. The second term represents the main theoretical contribution of the present paper: as foreign prices drop following input trade liberalization, the cutoff productivity for importing shifts downwards (from $\underline{\varphi}_i$ to $\underline{\varphi}'_i$), inducing more firms to source intermediates from abroad. These new importers are now exposed to the same cost-reducing shock as the *ex*

[18] Appendix D in Amiti et al. (2019) shows that this aggregation holds as a first-order approximation for a Kimball demand system as it will be used in the simulation exercise in section 7.

ante importers, passing through part of their marginal cost reduction into output prices and reacting to the aggregate price index through demand complementarities. The last term denotes *ex ante* and *ex post* non-importers, which only display demand complementarities as they are not directly affected by the input trade liberalization.

3.4. A sufficient statistics result

Concentrating on the second term in the last equation, we can see that the effect of changes in the extensive margin on the aggregate price index is determined by a limited number of variables: the market share of j (ms_j), total pass-through (Θ_j), as well as the cutoff productivity before and after the shock ($\underline{\varphi}_i$ and $\underline{\varphi}_j^{i'}$). In this subsection, I will show that all of these variables are simply a function of the relative price, and that, thus, given the demand system, the relative price at cutoff is a sufficient statistic to assess the effect of the extensive margin on the aggregate price index.

First, consider the general definition of relative demand for the good by firm j from Equation 1. Multiplying it by the relative price, we obtain the market share ms_j:

$$\text{ms}_j = \frac{q_j}{Q}\frac{p_j}{P} = D\left(\frac{p_j}{P}\right)\frac{p_j}{P}, \tag{16}$$

which shows that the market share ms_j is directly determined by the relative price.

Second, re-consider the definition of pass-through in Equation 5. Using the definition of Ψ_j, we can write:

$$\Theta_j = \Psi_j + (1 - \Psi_j)\frac{d\ln P}{d\ln \upsilon}, \tag{17}$$

where, $\Psi_j = \frac{1}{1+\Gamma_j} = \frac{1}{1-\frac{\partial \ln \mu_j}{\partial \ln(p_j/P)}}$ and $\mu_j = \varepsilon_j/(\varepsilon_j - 1)$. As the demand elasticity ε_j is simply a function of the relative price, we can rewrite $\Theta_j(p_j/P)$.

Third, take the optimal price given in Equation 3. Dividing by the price index P, writing in logs and re-arranging yields an expression of log productivity:

$$\ln \varphi_j = \ln \mu_j + \sum_{i=1}^{n} \gamma_i (\ln p_i - \ln \gamma_i) - \ln(p_j/P) - \ln P, \tag{18}$$

where γ_i is obtained as described below (subsection 5.2), where input price indices p_i can be constructed from data, and where the output price index P depends on the demand system. Thus, because the markup is a direct function of the relative price, knowing the relative price at cutoff allows us to construct the cutoff productivity $\underline{\varphi}^i_j$.

Finally, from the definition of the cutoff productivity in Equation 14 we can derive the following elasticity of the cutoff productivity $\underline{\varphi}_i$ with respect to a change in χ_i:

$$\frac{\partial \ln \underline{\varphi}_i}{\partial \ln \chi_i} = -\frac{1}{\underline{\varepsilon}_i - 1}. \tag{19}$$

This shows that the elasticity of the cutoff productivity for importing i with respect to a change in relative prices is fully determined by the demand elasticity at the cutoff, itself a direct function of the relative price.

Taken together, equations (16)–(19) show that the relative price at cutoff is a sufficient statistic to determine the effect of the extensive margin on the aggregate price index. In Appendix J I derive all of these elements when assuming a Kimball (1995) demand system with the functional form introduced by Klenow and Willis (2016).

3.5. Identifying $\underline{p}_j/P$

I will now propose a method to empirically identify the relative price at the cutoff. Using the definition of the Pareto distribution of productivities and inserting the cutoff productivity from Equation 14, we obtain the following share of firms importing i:

$$s^F_i = \underline{e}_0^{-a} \left(\frac{\chi_i \mathcal{S}(\underline{\varphi}_i, \Phi_J, Q)}{f^m} \right)^{\frac{a}{\underline{\varepsilon}_i - 1}}. \tag{20}$$

Let us now introduce a time dimension t to Equation 20. Note that we have assumed that fixed costs are time-invariant. Hence, taking logs and first differences, we can rewrite the prior equation as:

$$\Delta \ln s^F_{it} = \frac{a}{\underline{\varepsilon}_i - 1} \Delta \ln \chi_{it} + \frac{a}{\underline{\varepsilon}_i - 1} \Delta \ln \mathcal{S}(\underline{\varphi}_{it}, \Phi_{Jt}, Q) + \varepsilon_{it}. \tag{21}$$

This last equation implies that regressing the log change in the share of firms importing i on the change in log χ_i identifies a coefficient composed of a and $\underline{\varepsilon}_i$. I include output-time and input fixed effects to control for changes in the output-market potential as represented by the term $\frac{a}{\underline{\varepsilon}_i - 1} \Delta \ln \mathcal{S}(\underline{\varphi}_{it}, \Phi_{Jt}, Q)$. Then, using measures of a, obtained independently from Equation 21, we can back out $\underline{\varepsilon}_i$, and, thus, the relative price at cut-off $\underline{p}/P$. The estimation of Equation 21 constitutes the core of the empirical strategy in section 5.

4. Data

4.1. French firm data

For the empirical identification of the relevant structural parameters described in the theoretical model, I will rely on multiple datasets. In this section I will describe the main datasources and some basic cleaning steps. For additional details, such as descriptive statistics or the treatment of firm groups, refer to Appendix C.

Product-level information for French firms is taken from a survey on manufacturing firms, the *Enquête Annuelle de Production* (EAP), collected by the French national statistics bureau INSEE, which covers a sample of large manufacturing firms. According to INSEE, the survey includes over 90% of total manufacturing sales. EAP stretches over the period 2009 to 2019. The database contains information on both quantity and value of goods sold at the product level, allowing to construct unit values of output sold. Products are defined using the European Prodcom classification. I concentrate on all manufacturing products, produced by the firm itself. Firm-product level information is supplemented with firm-level balance sheet information from the *Fichier Approché des Résultats d'ESANE* (FARE) database.

Finally, I obtain firm×product×origin-level information on exports and imports from French customs data. Customs reports annual value and quantities of imports and exports for products reported in Eurostat's combined nomenclature at the 8-digit level (CN8), which can be converted to the Prodcom nomenclature. I use the customs dataset to construct series of average annual import unit values for intermediate inputs at the firm level. I further use exports in order to concentrate on domestic sales only.

4.2. Other data

To construct the instrumental variable (see below) I will use the *Base d'Analyse du Commerce International* (BACI) database, provided by CEPII. BACI provides data on both sales and quantity of all annual trade flows in the HS6 nomenclature, allowing to construct disaggregated series of unit values.

5. Empirical Strategy

In this section I will describe the empirical strategy used to estimate Equation 21. I will start by describing the estimated equation, before explaining the construction of the variables used in the equation. This section will finish by discussing the identification strategy and describing the instruments used. Note that in this section, as before i denotes inputs, but now j represents a product, J denotes a 5-digit industry, and f is a firm.

5.1. Estimation equation

As has been eluded to in the theoretical section above, I will use equation Equation 21 to identify the relative price at the cutoff. Concretely, I will estimate the following equation:

$$\Delta \ln s_{ijt} = \beta \Delta \ln \chi_{ijt} + \eta_{jt} + \eta_t + \epsilon_{ijt}, \tag{22}$$

where s_{ijt} denotes the share of j-producing firms that import input i at time t, where χ_{ijt} is constructed in line with theory (see below), and where η_{jt} and η_i denote output-year and input fixed effects, respectively. According to theory, we know that β identifies the Pareto-distribution shape parameter (a) and the demand elasticity at the importing cutoff ($\underline{\varepsilon}_i$) according to:

$$\beta = \frac{a}{\underline{\varepsilon}_i - 1}.$$

5.2. Construction of χ_{ijt}

I will follow theory and construct χ_{ijt} according to Equation 12:

$$\chi_{ijt} \equiv 1 - \left(\frac{p_{it}^F}{p_{it}^D} \right)^{\gamma_{ij}},$$

where p_{it}^F and p_{it}^D denote the foreign and domestic price of input i, respectively, and where γ_{ij} denotes the Cobb-Douglas parameter of input i in the production of good j.

In line with the assumed Cobb-Douglas production function, I will construct prices p_{it}^F and p_{it}^D as Cobb-Douglas aggregators:

$$p_{it}^D = \prod_{f=1}^{N} \left(p_{ift}^D\right)^{s_{ift-1}} \qquad\qquad p_{it}^F = \sum_{o^*} w_{io^*t-1} \times \prod_{f=1}^{N} \left(p_{ifo^*t}^F\right)^{s_{ifo^*t-1}}.$$

For the construction of domestic price indices, I rely on the information in EAP. p_{ift}^D therefore denotes the price charged by i-producing firm f in year t. Aggregating across all f gives the Cobb-Douglas price index, where s_{ift-1} denotes the market share of firm f in the sales of good i at $t-1$.[19] I follow Amiti et al. (2019) and clean micro prices by dropping all observations with a contemporaneous-to-lag-price ratio of above 3 or below 1/3.

For foreign price indices, I start by constructing price indices at the origin level o, where p_{ifot}^F is defined as EAP-firm f, importing i from o in year t. While the model assumes a single representative foreign origin, the real world of course consists of n different origins. To consistently link theory and data, I will aggregate across origins to obtain a single importer price index. I start by aggregating across all importing firms, again according to lagged market shares s_{ifot-1}, which yields country-level price indices for each input i.[20] I then clean the set of origins in two ways: (i) in order to abstract from the potential confounding effect of small and relatively unimportant origins, I only retain origins that represented at least 1% of imports of i between 2009 and 2019; (ii) as theory dictates that firms only source goods when $p_{it}^F < p_{it}^D$, I restrict the set of countries o to countries that in fact display a lower price for input i than the domestic firms.[21] To obtain one price for foreign goods, I then construct a lagged-sales-weighted average of the price indices across all remaining origins o^*, with sales-shares denoted by w_{io^*t-1}. Together, this yields

[19]A fully consistent construction of Cobb-Douglas price indices would be $p_{it}^D = \prod_{f=1}^{N} \left(\frac{p_{ift}^D}{s_{ift-1}}\right)^{s_{ift-1}}$. However, in this case the number of products for which foreign prices are below domestic prices is drastically reduced by more than half. I include this exercise as a robustness check in Table F.1.1. The IV coefficients are higher and still slightly significant, however the F-Stat is very low.

[20]I again dropped micro price observations with price-to-lag-price ratios above 3 or below 1/3.

[21]As a robustness check, I will also run the same exercise without restricting the set of countries. See Table F.1.1 for the results. Additionally, I also construct the vector of χ using the top 5, top 10 and top 20 origin countries. See subsection F.8 for the results

the expression for p_{it}^F displayed above.

Finally, the construction of χ_{ijt} necessitates a measure of input weights γ_{ij}. Lacking information on domestic purchases at the micro-level, I will rely on import information by single-product firms to determine a vector of γ_{ij}. Concretely, I first identify firms that only reported a single product in a given year.[22] I then construct the share of input i in total imports from j-producing firms:

$$\mathcal{I}_{ij} = \frac{\sum_{ft} v_{ijft}}{\sum_{ift} v_{ijft}}.$$

Next, I drop all inputs for which $\mathcal{I}_{ij} < 1\%$ and re-weight to ensure that $\sum_i \mathcal{I}_{ij} = 1$. I then construct a measure of the input share γ_{ij} by multiplying $\mathcal{I}_{ij}$ with the share of intermediate inputs in total variable costs (including labor). Hence,

$$\gamma_{ij} = \frac{\sum_{ft} \text{intermediates}_{ijft}}{\sum_{ft} \text{variable cost}_{ijft}} \times \tilde{\mathcal{I}}_{ij},$$

where $\tilde{\mathcal{I}}_{ij}$ denotes the re-weighted $\mathcal{I}_{ij}$.

Table 1 shows the 10 largest output products in terms of total domestic sales over the period 2009-2019 for which at least one observation was retained, together with their largest input and the according input share γ_{ij}. The final vector of γ_{ij} includes information for 1,868 output products. While the number of individual output-products for which we have input information represents only about 57.5% of all individual codes, these codes account for the majority of total domestic sales reported in EAP (83.6%).[23] In appendix D, I propose a method to test the representativeness of using single-product firms to predict the input coefficients of multi-product firms. Overall, single-product firms seem to be a good predictor of input shares of multi-product firms.

[22] In order to avoid any bias stemming from firms potentially only reporting their main product, I drop all firms for which the sum of sales in a given year was below 75% of the according information in their balance sheet (taken from Fare).

[23] This number is calculated on the restricted sample.

Table 1: Summary statistics on extensive margin (10 largest products w.r.t. sales)

Prodcom output code	Prodcom output name	Output unit	Dom. sales (M€)	Avg. nb. firms	Prodcom max input code	Prodcom max input name	Input unit	γ_{ij}
30.30.40.00	Spacecraft, satellites and launch vehicles, for civil use	Pieces	43,367	9	26.70.11.00	Mounted objective lenses, of any material	Number	0.002
29.10.23.10	Motor vehicles with a diesel or semi-diesel engine $\leq$ 1,500 cm^3	Pieces	37,962	7	29.32.30.20	Brakes and servo-brakes and their parts	Kgs	0.555
23.63.10.00	Ready-mix concrete	m^3	37,363	358	23.51.12.10	Portland cement	Kgs	0.425
29.10.21.00	Vehicles with spark-ignition engine ($\leq$1,500cm^3, new)	Pieces	32,873	9	22.11.11.00	New pneumatic rubber tyres for motor cars	Pieces	0.076
17.21.13.00	Cartons, Boxes and cases, of corrugated paper or paperboard	Kgs	30,560	173	17.21.11.00	Corrugated paper and paperboard in rolls or sheets	Kgs	0.135
20.42.11.70	Toilet waters (excl. after-share lotions, deodorants and hair lotions)	Litres	25,514	73	20.53.10.79	Mixtures of odoriferous substances	Kgs	0.262
25.12.10.50	Aluminium doors, thresholds for doors, windows and their frames	Pieces	24,327	656	24.42.22.50	Aluminium alloy bars, rods, profiles and hollow profiles	Kgs	0.499
25.11.23.50	Structures and parts of structures, of iron and steel, solely or principally of sheet: others	Kgs	24,055	1,481	24.10.32.30	Flat-rolled products of iron or non-alloy steel, of a width < 600mm	Kgs	0.091
30.30.16.00	Parts of turbo-jets or turbo-propellers, for use in civil aircraft	Number	22,251	11	25.72.14.60	Other base metal mountings, fittings and similar articles	Kgs	0.090
29.32.30.33	Gear boxes and their parts	Pieces	20,009	19	28.12.14.50	Valves for the control of oleohydraulic power transmission	Kgs	0.037

5.3. Construction of s_{ijt}

The dependent variable s_{ijt} is defined as the share of j-producing firms that import i. In line with the construction of χ_{ijt}, I define s_{ijt} as the share of firms that import input i from country o^*, where o^* is the same sample as before (i.e. for which $p^F_{io^*t} > p^D_{it}$). Hence, a firm is defined as an importer at time t if it imports an intermediate i from at least one country in o^*.

5.4. Identification

The threats to identification regard the two sub-components of $\Delta \ln \chi_{ijt}$: import and domestic prices. First, French import prices are potentially endogenous to the change in the share of importers due to an issue of reverse causality: an increase in the share of French firms that import i, due for example to a positive sector-wide productivity shock, constitutes a positive demand shock, which in turn will increase the price of i. This would represent a downward bias, blurring the expected positive effect of $\Delta \ln \chi_{ijt}$ on the (log) change in the share of importers.

Second, domestic prices are reacting to foreign prices through a channel of import competition. When import prices decrease, domestic prices will, to a certain degree, decrease as well, depending on the elasticity of firms' own prices to the price index (*demand complementarities*).[24] This dynamic again constitutes a downward bias of the tested mechanism.

5.4.1. Instruments

In order to circumvent the threats to identification described above, we want to have purely supply-driven changes in prices. To that end, I will construct an instrument based on two components: import price changes in other countries and average cost changes of domestic producers.

[24] In Appendix I I implement an empirical strategy akin to Amiti et al. (2019) to test for imperfect pass-through and demand complementarities.

Prices in other countries In order to abstract from demand effects on import prices, one has to assure that price changes are indeed supply-driven. To that end, I will use the average of the price changes of i in other countries to instrument French import price changes, a strategy widely used in the literature (Autor, Dorn, & Hanson, 2013; Dauth, Findeisen, & Suedekum, 2014; Acemoglu, Akcigit, & Kerr, 2016; Malgouyres, 2016).[25] The data is taken from BACI. The use of other countries relies on the identification strategy that demand shocks in France are not correlated with their own demand shocks.[26]

For each pair of destination country d and input i, $\Delta \ln P_{i,d}^{F,IV}$ is constructed as the weighted average of the (log) change in import prices of i across origin countries, using (lagged) import shares of origin country o^* in total imports of i by destination country d. Thus, $\Delta \ln p_{i,d}^{IV}$ is constructed as follows:

$$\Delta \ln P_{idt}^{F,IV} = \sum_{o^*} \frac{m_{ido^*t-1}}{\sum_{o^*} m_{ido^*t-1}} \Delta \ln P_{ido^*t}, \tag{23}$$

where m_{ido^*t-1} denotes the imports of input i from origin o^* by firms in destination d in year $t-1$. I then take the average of $\Delta \ln P_{idt}^{F,IV}$ across all destination countries to obtain $\Delta \ln \bar{P}_{it}^{F,IV}$. As before, I drop all observations that displayed a ratio of contemporaneous to lag prices of above 3 or below 1/3.

Average costs To isolate domestic price adjustments that are not related to strategic complementarities or demand shocks (i.e. that are supply driven), I will instrument domestic prices by changes in average costs, constructed at the firm-level using the methodology introduced in Amiti et al. (2019). Accordingly, average costs are given by:

$$\begin{aligned}\Delta \ln ac_{ft} &= \Delta \ln vc_{ft} - \Delta \ln y_{ft} \\ &= \Delta \ln vc_{ft} - (\Delta \ln r_{ft} - \Delta \ln p_{ft}),\end{aligned}$$

[25]The final sample for the instrument is a mixture of the countries used by Dauth et al. (2014) for Germany and Malgouyres (2016) for France, and includes the following countries: Argentina, Australia, Canada, Chile, Denmark, Japan, Mexico, New Zealand, Norway, Singapore, South Korea, Sweden and the United Kingdom.

[26]The exclusion restriction here states that average price changes in other countries do not have a direct effect on the share of firms importing, other than the supply driven changes embodied in French price changes.

where vc_{ft} denotes firm f's expenditures on variable costs, r_{ft} represents its revenue (both taken from balance sheets) and $\Delta \ln p_{ft}$ is a firm-level output-price index, constructed as a sales-weighted aggregation of output prices (irrespective of domestic or export sales). I use lagged sales for the construction of weights. The identification relies on the assumption that the average cost of domestic producers does not react to a change in the prices of foreign competitors.[27]

These firm-level average cost measures will then be aggregated at the output level i as a weighted average across all producers, using (lagged) sales as weights. Thus, the variable takes the following form:

$$\Delta \ln AC_{it}^{IV} = \sum_f \frac{x_{fit-1}}{\sum_f x_{fit-1}} \Delta \ln ac_{ft}, \tag{24}$$

where x_{fit-1} denotes sales of product i by firm f at time $t-1$.

Final instrument The final instrument then combines the two components as:

$$\mathcal{Z}_{it} = -\left(\Delta \ln \bar{P}_{it}^{F,IV} - \Delta \ln AC_{it}^{IV}\right).$$

5.5. Summary statistics

The table below shows summary statistics for some relevant variables used in the empirical strategy.

[27] For this instrument, the exclusion restriction posits that the average change in production costs for i-producing firms does not directly affect the change in the share of j-producing firms that import i, other than it's effect through the domestic price of i.

Table 2: Extensive margin - Summary statistics

	N	Mean	P5	P10	P25	P50	P75	P90	P95
Import share									
s_{ijt}^{Imp}	77,782	0.162	0.000	0.000	0.000	0.071	0.250	0.500	0.625
$\Delta \ln(s_{ijt}^{Imp})$	36,051	-0.016	-0.780	-0.595	-0.212	0.000	0.182	0.560	0.734
Input requirements									
γ_{ij}	77,761	0.066	0.007	0.008	0.012	0.024	0.063	0.168	0.287
Prices									
P^F	77,782	145.07	0.59	0.89	1.73	3.78	9.39	24.53	60.60
P^D	72,504	578.44	0.88	1.25	2.70	6.50	20.23	61.08	197.76
$\Delta \ln \chi_{ijt}$	60,094	-0.005	-1.182	-0.766	-0.302	-0.010	0.303	0.794	1.155

Note: Table reports summary statistics on different variables of interest for the extensive margin estimation. P5, P25, P50, P75 and P95 denote the 5th, 25th, 50th, 75th and 95th percentile, respectively.

6. Results

6.1. Baseline

Results of estimating Equation 22 are shown in Table 3, where columns 1 to 3 show the OLS results and columns 4 to 6 show the 2SLS results. I further include reduced form results in tables 7 to 9. I include three different sets of fixed effects, dictated by theory. The first column of each subset of columns only includes year fixed effects. The second and third column then include output×year, and the third columns additionally includes input fixed effects. In order to deal with outliers, all variables are winsorized yearly at the 1%-level. Standard errors are clustered at the HS6-level.

Comparing OLS to 2SLS results, we indeed find the predicted downward bias, which is quite sizable: the coefficient jumps from 0.056 to around 0.39. Results in columns (4), (5) and (6) suggest that an increase of 10% in the marginal cost saving potential from abroad increases the share of importing firms by 3.5% to 3.9%. Knowing that the average share of importing firms for this sample is around 25%, this translates into an average increase in the share of importing firms of around 0.975 percentage points. These results are roughly

Table 3: Extensive margin

	OLS			2SLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln \chi_{ijt}$	0.056***	0.056***	0.051***	0.351***	0.383***	0.393***			
	(0.012)	(0.013)	(0.014)	(0.076)	(0.075)	(0.072)			
$\mathcal{Z}_{it}$							0.149***	0.176***	0.201***
							(0.025)	(0.025)	(0.027)
t FE	✓			✓			✓		
$j \times t$ FE		✓	✓		✓	✓		✓	✓
i FE			✓			✓			✓
KP F-Stat				29.7	46.1	47.1			
First stage coeff.				0.424***	0.460***	0.510***			
Obs	32,042	29,233	29,181	32,042	29,233	29,181	32,042	29,233	29,181

* p<0.1, ** p<0.05, *** p<0.01

HS6-clustered standard errors in parentheses. The dependent variable is the (log) change in the share of j-producing firms importing i in year t. $\Delta \ln \chi_{ijt}$ is constructed as described in the text. $\mathcal{Z}_{it}$ denotes the instrument, constructed as described in the text. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

in the same ball park as other contributions in the literature.[28]

6.2. Robustness

In this subsection, I will test the robustness of the empirical results using a battery of different checks. For the sake of brevity, I here only quickly name the robustness check and report the main result. Table 4 shows the results of all robustness checks for the 2SLS specification with output×year and input fixed effects. A detailed description of the different robustness checks, as well as tables with all specifications are relegated to

[28]Results on the extensive margin of importing firms are astonishingly scarce. The most comparable study is Bas and Berthou (2017), who estimate the according margin for Indian firms, studying the trade liberalization episode in the early 1990s. Their results suggest that the probability for an Indian firm to import a capital good increases by 1.5% following a 10% decrease in tariffs. Note, that a proper comparison between their and my results is hard, because of the non-linear relation between χ_{ij} and tariffs. However, the fact that their coefficient is roughly in the same ball park as mine is reassuring. Less comparable, Imbruno and Ketterer (2018), in the Indonesian context, show that a tariff decrease by 10 percentage points increases the number of imported inputs by 2.84%. Looking at exports, Fontagné, Orefice, Piermartini, and Rocha (2015) show that a tariff increase by 10% decreases the number of firm-products exported towards that destination by 2.4%, again in the same ballpark as my estimates.

Appendix F.[29]

I test for the sensitivity of the results to the following changes: column (1) in Table 4 reports the result when using the "true" definition of $\Delta \ln \chi_{ijt}$ (i.e. using prices constructed as $p_{it} = \prod_{f=1}^{N} \left(\frac{p_{ift}}{s_{ift-1}}\right)^{s_{ift-1}}$); column (2) uses a definition of importing above €10,000; (3) restricts the sample to firms present in $t-1$; (4) defines $\Delta \ln s_{ijt}$ as $\Delta \ln(1+s_{ijt})$; (5) similarly defines $\Delta \ln s_{ijt}$ as $\Delta \ln \text{arcsin}(s_{ijt})$; (6) only uses products with at least 4 firms on average;[30] (7) uses a version of the instrument that excludes all EU countries (Denmark, Sweden and the UK); (8) uses all countries in the construction of $\Delta \ln \chi_{ijt}$ and the instrument; column (9) shows the result when using the top 5 origin countries;[31] finally, column (10) reports the result when restricting domestic prices to be a maximum of three times as large as foreign prices.

Table 4: Extensive margin - Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta \ln \chi_{ijt}$	1.350	0.311***	0.366***	0.060***	0.069***	0.429***	0.402***	0.050**	0.235***	0.474***
	(1.010)	(0.063)	(0.072)	(0.018)	(0.020)	(0.084)	(0.079)	(0.023)	(0.064)	(0.089)
$j \times t$ FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
i FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
KP F-Stat	2.1	53.4	48.1	28.2	28.2	41.1	37.5	75.7	16.7	41.0
First stage coeff.	0.149	0.539***	0.508***	0.437***	0.437***	0.497***	0.430***	1.177***	0.569***	0.423***
Obs	11,658	24,526	27,685	55,849	55,849	26,056	29,106	12,727	14,320	29,181

* p<0.1, ** p<0.05, *** p<0.01

HS6-clustered standard errors in parentheses. Column (1) in Table 4 reports the result when using prices constructed as $p_{it} = \prod_{f=1}^{N} \left(\frac{p_{ift}}{s_{ift-1}}\right)^{s_{ift-1}}$ when constructing $\Delta \ln \chi_{ijt}$; column (2) uses a definition of importing above €10,000; column (3) restricts the sample to firms present in $t-1$; column (4) defines $\Delta \ln s_{ijt}$ as $\Delta \ln(1+s_{ijt})$; column (5) defines $\Delta \ln s_{ijt}$ as $\Delta \ln \text{arcsin}(s_{ijt})$; column (6) only uses products with at least 4 firms on average; column (7) uses a version of the instrument that excludes all EU countries; column (8) uses all countries in the construction of $\Delta \ln \chi_{ijt}$ and the instrument; column (9) uses the top 5 origin countries in the construction of $\Delta \ln \chi_{ijt}$ and the instrument; column (10) reports the result when restricting domestic prices to be a maximum of three times as large as foreign prices. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

The results in Table 4 show that overall, the results seem robust to these different changes. Nonetheless, there is the some heterogeneity in the size of the coefficient and the F-Stat. The only specification that is not significant in the robustness checks is the expression when using the "true" $\Delta \ln \chi_{ijt}$, as it largely reduces the sample size and has

[29]Appendix F also includes a heterogeneity exercise when interacting $\Delta \ln \chi_{ijt}$ with a dummy for the most concentrated sectors, in line with the motivational evidence.

[30]In Appendix F, I also include a specification for products with at least 10 firms on average.

[31]In Appendix F, I additionally include specifications with the top 10 and top 20 countries.

a very low F-Stat. However, Table F.1.1 shows that results are still (slightly) significant when using specifications with only year or output-year fixed effects.

7. Implications for aggregate prices and pass-through

Armed with the empirical results from the extensive margin, I will now simulate the effect of the extensive margin on the aggregate price index and pass-through. In essence, I will quantify the effect of a trade liberalization shock on Equation 15. To that end, I start by estimating production functions to obtain measures of a. The production function estimation is based on Burstein, Carvalho, and Grassi (2025). See Appendix G for more details. Using the vector of a, I will back-out the elasticity of demand at the cutoff from the empirical estimates of $\beta = \frac{a}{\varepsilon_i - 1}$. In simulations, I will assume a Kimball (1995) demand system with the functional form introduced by Klenow and Willis (2016), described in appendix J. This type of demand system is widely used in the literature on pass-through (e.g. Burstein and Gopinath (2014) and Amiti et al. (2019)) and has the advantage of being very tractable.

The calibration of the quantitative model under Klenow and Willis (2016) preferences necessitates a stance on the elasticity and the superelasticity in a symmetric equilibrium. As shown by Baqaee, Farhi, and Sangani (2023), one can derive these from the estimation of pass-through rates at different instances of the size distribution. To see this, consider the definition of pass-through with respect to the relative quantity, derived in appendix J:

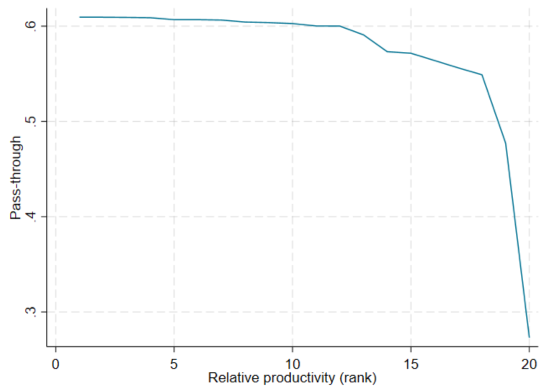
$$\Psi_j = \frac{1}{1 + \Gamma_j} = \frac{1}{1 + \frac{\bar{\sigma}}{\bar{\varepsilon}} \mu_j}. \tag{25}$$

This formula implies that, at the bottom of the distribution (i.e. for $q_j/Q = 0$ or $\mu_j = 1$), the pass-through is given by $\Psi_j^{\min} = 1/(1 + \bar{\sigma}/\bar{\varepsilon})$ such that $\bar{\sigma}/\bar{\varepsilon} = 1/\Psi_j^{\min} - 1$. I will set $\bar{\varepsilon}$ to a standard CES value that is used in the literature ($\bar{\varepsilon} = 5$) and derive $\bar{\sigma}$ to respect the ratio implied by the distribution of pass-throughs. I will use the estimates of pass-through regressions in the spirit of Amiti et al. (2019), described in Appendix I, as measures of Ψ_j.[32]

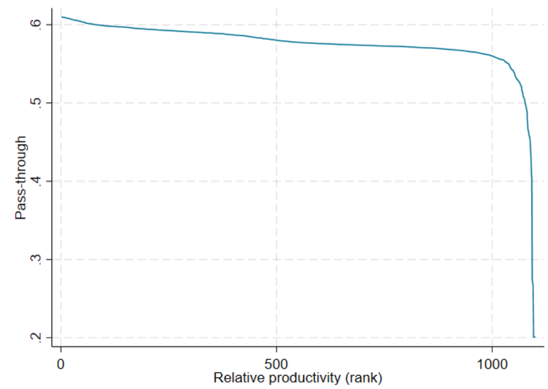
[32]The baseline pass-through regression *à la* Amiti et al. (2019) consists of regressing the log change in unit values on the log change in a measure of average costs and the log change in the prices by competitors. Average costs are constructed as the difference between the log change of total variable costs and the log

Figure 3: Pass-through by relative productivity

(a) "Gear boxes and their parts"



(b) "Structures of iron and steel, principally of sheet: other"



Interacting their measure of log change in marginal costs with relative productivity across the period yields, for each product, a distribution of pass-through rates. In line with the assumption of monopolistic competition, in the simulation I only retain products with at least 20 firms across the years of my sample. The final sample of simulation includes 310 output products j with a little under 25,000 firm×product observations. Figure 3 below shows the pass-through distribution for the two largest products of the final sample in terms of sales ("Gear boxes and their parts") and in terms of the number of firms ("Structures principally of sheet: other"). Further details on the parametrization of the model, such as the distribution of cutoff demand elasticities, are relegated to Appendix J.

Depending on their sourcing strategy, firms will be differently exposed to foreign price changes: firms with a productivity above the cutoff for all inputs will source every input —with the exception of labor— from abroad and thus reap the full benefits of the shock in terms of marginal cost reduction. Meanwhile, firms with productivity below the cutoff for the lowest-cutoff-input will source all of their inputs from home. Marginal costs are calculated in line with the theory section of the paper, using relative domestic and foreign prices and product-specific per-unit wage rates as the numeraire.[33]

change of a quantity indicator. The latter is constructed as the difference between the log change of firm-level revenue and the weighted average of firm×product-level log changes of unit values.

[33]To avoid the effect of outliers, in the counterfactual exercise I restrict domestic prices to be a maximum of three times the foreign price. As shown in Appendix Table F.9.1, the extensive margin is robust to using

I then simulate three different scenarios: a reduction in the price of all foreign goods by (i) 5%, (ii) 10%, and (iii) 20%. This reduction in foreign prices will reduce marginal costs of incumbent importers, depending on their sourcing strategy. The marginal costs of non-importers remain unchanged.[34] However, through its effect on χ_{ij}, the reduction in foreign prices also activates the extensive margin, shifting the productivity cutoff downward. Depending on the gap in productivities between the last incumbent importer and the next non-importer, the change in $\underline{\varphi}_i$, given by Equation 19, includes more or less firms.[35] One can then compare the change in the (log) aggregate price index, given by Equation 15 with and without the extensive margin.

Figure 4a shows the results of the baseline simulation exercise. The outcome variable here is the average change in the (log) price index across all products included in the simulation sample. Overall, a 5% decrease in foreign prices decreases the overall price index by a little under 1%, of which 10.6% can be explained by the extensive margin. However, increasing the size of the shock increases the size of the distribution of the extensive margin: around 16.1% of the average aggregate price decreases are explained by the extensive margin for the 10% scenario; for the 20% scenario this ratio climbs to 24.2%. The intuition here is that the extensive margin is "activated" more with larger shocks, as more and more firms find it profitable to import from abroad. This in turn increases the competitive pressure on incumbent importers to pass-through a higher share of costs into their prices due to demand complementarities. Together with the direct price effect of trade liberalization on a larger number of firms, this can explain the larger aggregate price decreases.

---

this set of prices, with a slightly higher coefficient. I then further restrict the per-unit wage rate to be a maximum of three times and a minimum of 1/3 of the domestic price.

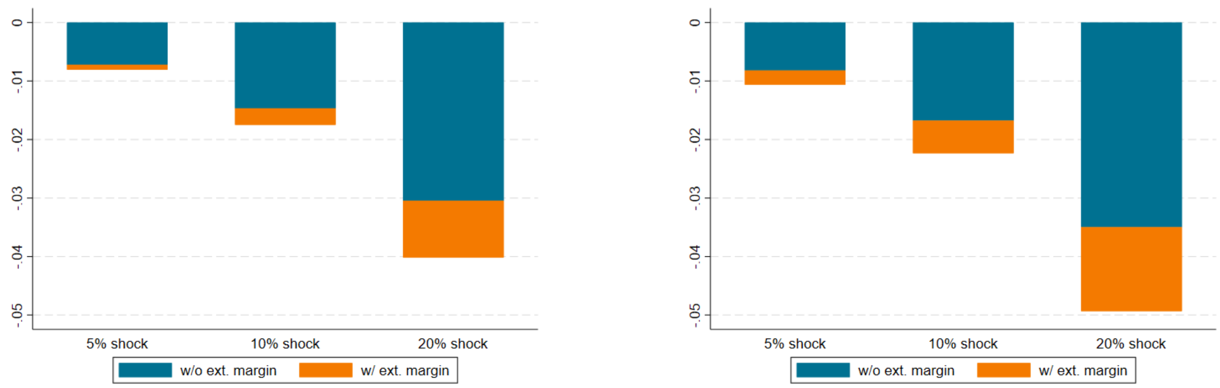
[34]Note that, because of demand complementarities and their own marginal cost reductions, domestic firms in the real world are likely to react to tariff cuts by lowering their own price. A full-fledged general equilibrium model that incorporates variable markups and the full input-output structure of the economy does, to the best of my knowledge, not exist and should be own of the focal points of future research.

[35]Note, as will be the case in many instances, that the shift in $\underline{\varphi}_j$ might not be large enough to include any new firms.

Figure 4: Contribution of extensive margin to $\Delta \ln P$

(a) With zeros

(b) Without zeros



These average numbers, however, mask a large heterogeneity in the extent to which the extensive margin is activated. For example, for almost half of products in the 10% scenario there are no new firms opting into importing. Therefore, in Figure 4b I display the results only for those products where the extensive margin was activated. The extensive margin now explains around 22.7%, 25% and 29.1% of the decline in the aggregate price index, for the 5%, 10% and 20% scenarios, respectively. Overall, these results suggest that the extensive margin, when activated, can play an important role in increasing the welfare gains from input trade liberalization.

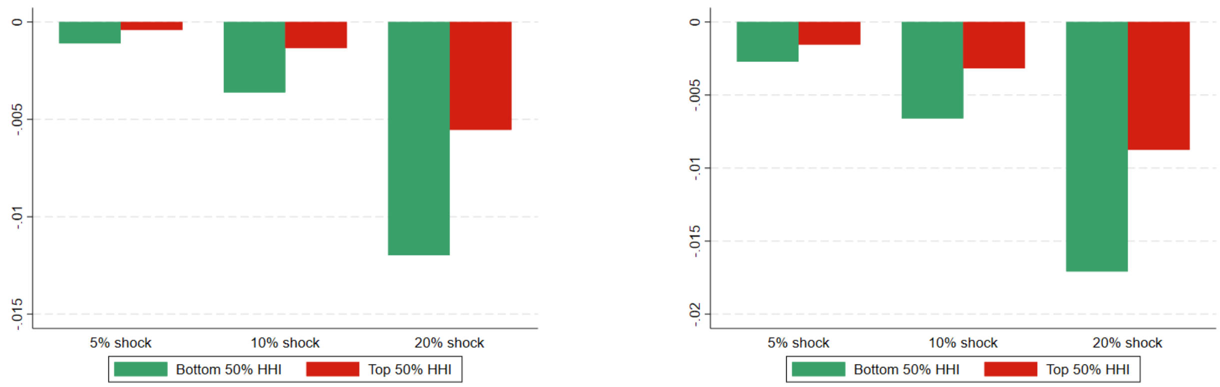
7.1. Heterogeneity by concentration

The motivational evidence in section 2 showed the differential response in prices and import shares for the most concentrated and the least concentrated sectors. Creating an indicator for products produced mainly by firms in highly concentrated industries, using the same ranking of industries as in section 2, we can now look at the heterogeneity in the contribution of the extensive margin to the average aggregate price index. As shown in Figure 5 and in line with the motivational evidence, the extensive margin is significantly larger in less concentrated sectors. Across the different scenarios, the contribution of the extensive margin on average is around twice as high in the least concentrated sectors than in the most concentrated sectors. These findings are consistent with the motivational evidence in section 2 that the increase in the import share for the least concentrated sectors was four times higher than the increase of the most concentrated sectors.

Figure 5: Heterogeneity by concentration

(a) With zeros

(b) Without zeros



7.2. The role of demand complementarities

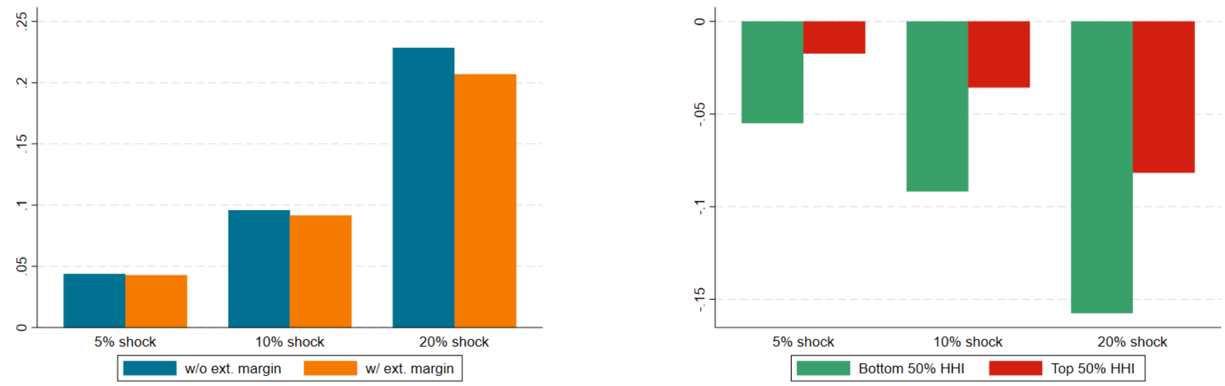
The simulation results on the size of the extensive margin effect displayed above incorporate both the effects coming from a larger number of firms having negative marginal cost shocks and the effect that is due to demand complementarities. To isolate the latter, we can look at the average markup increases of incumbent importers, *that did not change their sourcing strategy*, with and without the extensive margin. The left-hand graph in Figure 6 shows the result of this simulation exercise: for the 10% shock, the average markup of incumbent importers that did not change their sourcing strategy increased by a little under 5% less when allowing for the extensive margin. Looking at the 20% shock, the extensive margin reduced markup increases by almost 10%.

As before, we can also look at the heterogeneity between more and less concentrated sectors. The right-hand graph in Figure 6 plots the average contribution of the extensive margin on markups — equal to the relative difference between the two bars in the left-hand figure for each firm — for firms in the most and in the least concentrated sectors. As before, we again find a significantly higher contribution of the extensive margin in the least concentrated sectors, in line with theory and the motivational evidence: for the least concentrated sectors and the 10% shock, the extensive margin reduces the average markup increases by almost 10%, and by over 15% for the 20% shock.

Figure 6: Changes in markups

(a) $\Delta\bar{\mu}$ incumbent importers

(b) Contribution ext. mar. by HHI



8. Conclusion

In this paper, I analyze the interplay between the extensive margin of the share of importing firms and the pass-through of marginal cost changes into prices. Motivated by reduced-form evidence on the differential impact of trade agreements on prices and the share of firms importing in more and less concentrated sectors, I introduce a simple theoretical model, able to mimic these empirical patterns. In the model, firms act under monopolistic competition with non-CES demand, giving rise to variable markups and imperfect pass-through. When producing, firms face the choice of sourcing intermediate inputs domestically or on international markets. Aggregating across firms, the model predicts that the share of firms importing ("extensive margin") will react more in sectors that are marked by less heterogeneity with respect to productivity. Changes in the number of firms importing will have a direct effect on the competitive environment, and, therefore, impact the pass-through of marginal cost changes into prices. This, ultimately, affects the markup responses following input trade liberalization at both the firm- and the sector-level.

Guided by the theoretical model, I use a sufficient statistic approach to identify the necessary structural parameters, needed to estimate the impact of the extensive margin on markups. The empirical strategy relies on the identification of input requirements from single-product firms. I then use confidential French data on both firm-level imports and outputs to implement the strategy and estimate the parameters.

The results of the analysis suggest that the extensive margin is both statistically significant and economically relevant. Following a 10% increase in the marginal cost savings potential from importing a given intermediate, the share of firms importing this intermediate increases by around 3.9%. This result is robust to a battery of alternative specifications.

Finally, using the estimates of the extensive margin I identify the demand elasticity at cutoff. Calibrating a Kimball demand system *à la* Klenow and Willis (2016), I then use these estimates of cutoff elasticities in order to identify importing and domestic firms at the very detailed input-output level. I run multiple different counterfactual scenarios of input trade liberalization to quantify the effect of the extensive margin on the change in the aggregate price index. The simulations show that the size of the shock matters in activating the virtue of the extensive margin, and that, on average, the extensive margin can explain around 16% of aggregate price decreases following a 10% reduction in foreign prices. Re-running the same heterogeneity exercises as before shows that the extensive margin plays a significantly bigger role in the least concentrated sectors — a finding that is in line with both the motivational evidence and the estimates for the extensive margin. Moreover, isolating the effect for incumbent importers that did not change their sourcing strategy highlights the importance of demand complementarities: when allowing for the extensive margin, the markup increases for these firms are 5% lower for the 10% liberalization scenario.

By highlighting the role of the extensive margin, this article points towards an effective policy tool to increase the welfare gains from input trade liberalization: import incentives/subsidies. By increasing the number of firms profiting from the marginal cost decreases, one can importantly increase the welfare gains from trade. Future research should try to strengthen the economic model by developing an input-output model with various markups and demand complementarities in order to assess the full effect of an input trade liberalization on prices and welfare.

References

Acemoglu, D., Akcigit, U., & Kerr, W. (2016). Networks and the macroeconomy: An empirical exploration. *NBER Macroeconomics Annual*, *30*(1), 273–335.

Ackerberg, D. A., Caves, K., & Frazer, G. (2015). Identification Properties of Recent Production Function Estimators. *Econometrica*, *83*(6), 2411–2451.

Amiti, M., Itskhoki, O., & Konings, J. (2014). Importers, exporters, and exchange rate disconnect. *American Economic Review*, *104*(7), 1942-78.

Amiti, M., Itskhoki, O., & Konings, J. (2019). International Shocks, Variable Markups, and Domestic Prices. *The Review of Economic Studies*, *86*(6), 2356–2402.

Antràs, P., Fort, T. C., & Tintelnot, F. (2017). The Margins of Global Sourcing: Theory and Evidence from US Firms. *American Economic Review*, *107*(9), 2514–2564.

Arkolakis, C., Costinot, A., Donaldson, D., & Rodríguez-Clare, A. (2018). The Elusive Pro-Competitive Effects of Trade. *The Review of Economic Studies*.

Arkolakis, C., & Morlacco, M. (2017). Variable Demand Elasticity, Markups, and Pass-Through. *mimeo*, 36.

Atkeson, A., & Burstein, A. (2008). Pricing-to-Market, Trade Costs, and International Relative Prices. *American Economic Review*, *98*(5), 1998–2031.

Autor, D., Dorn, D., & Hanson, G. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, *103*(6), 2121–2168.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The Fall of the Labor Share and the Rise of Superstar Firms. *The Quarterly Journal of Economics*, *135*(2), 645–709.

Baqaee, D. R., Farhi, E., & Sangani, K. (2023). The Darwinian Returns to Scale. *Review of Economic Studies*, *91*(3), 1373–1405.

Barrows, G., Ollivier, H., & Reshef, A. (2025). *Production Function Estimation with Multi-Destination Firms* (Tech. Rep.). mimeo.

Bas, M., & Berthou, A. (2017). Does Input-Trade Liberalization Affect Firms' Foreign Technology Choices? *The World Bank Economic Review*, *31*(2), lhw062.

Blaum, J., Lelarge, C., & Peters, M. (2018). The Gains from Input Trade with Heterogeneous Importers. *American Economic Journal: Macroeconomics*, *10*(4), 77–127.

Burstein, A., Carvalho, V. M., & Grassi, B. (2025). Bottom-Up Markup Fluctuations. *The Quarterly Journal of Economics*, *140*(4), 2619–2684.

Burstein, A., & Gopinath, G. (2014). International Prices and Exchange Rates. In *Handbook of International Economics* (pp. 391–451). Elsevier.

Bustos, P. (2011). Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms. *American Economic Review*, *101*(1), 304–340.

Chaney, T. (2008). Distorted Gravity: The Intensive and Extensive Margins of International Trade. *American Economic Review*, *98*(4), 1707–1721.

Crowley, M. A., Han, L., & Prayer, T. (2024). The pro-competitive effects of trade agreements. *Journal of International Economics*, *150*, 103936.

Dauth, W., Findeisen, S., & Suedekum, J. (2014). The Rise of the East and the Far East: German Labor Markets and Trade Integration. *Journal of the European Economic Association*, *12*(6), 1643–1675.

De Loecker, J., Goldberg, P. K., Khandelwal, A. K., & Pavcnik, N. (2016). Prices, Markups, and Trade Reform. *Econometrica*, *84*(2), 445-510.

De Loecker, J. (2007). Do exports generate higher productivity? Evidence from Slovenia. *Journal of International Economics*, *73*(1), 69–98.

De Loecker, J., & Eeckhout, J. (2018). *Global Market Power* (NBER Working Paper No. 24768). Cambridge, MA.

De Loecker, J., Eeckhout, J., & Unger, G. (2020). The Rise of Market Power and the Macroeconomic Implications. *The Quarterly Journal of Economics*, *135*(2), 561–644.

De Ridder, M. (2024). Market Power and Innovation in the Intangible Economy. *American Economic Review*, *114*(1), 199–251.

Feenstra, R. C., & Weinstein, D. E. (2017). Globalization, Markups, and US Welfare. *Journal of Political Economy*, *125*(4), 35.

Fontagné, L., Orefice, G., Piermartini, R., & Rocha, N. (2015, September). Product standards and margins of trade: Firm-level evidence. *Journal of International Economics*, *97*(1), 29–44.

Gabaix, X., & Ibragimov, R. (2011). Rank – 1/2: A Simple Way to Improve the OLS Estimation of Tail Exponents. *Journal of Business & Economic Statistics*, *29*(1), 24–39.

Gutiérrez, G., & Philippon, T. (2017). *Declining Competition and Investment in the U.S.* (Tech. Rep.).

Halpern, L., Koren, M., & Szeidl, A. (2015). Imported Inputs and Productivity. *American Economic Review*, *105*(12), 3660–3703.

Imbruno, M., & Ketterer, T. D. (2018, November). Energy efficiency gains from importing intermediate inputs: Firm-level evidence from Indonesia. *Journal of Development Economics*, *135*, 117–141.

Kimball, M. S. (1995). The Quantitative Analytics of the Basic Neomonetarist Model. *Journal of Money, Credit and Banking*, *27*(4), 1241.

Klenow, P. J., & Willis, J. L. (2016). Real Rigidities and Nominal Price Changes. *Economica*, *83*(331), 443–472.

Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *Review of Economic Studies*, *70*(2), 317–341.

Malgouyres, C. (2016). The Impact of Chinese Import Competition on the Local Structure of Employment and Wages: Evidence from France. *Journal of Regional Science*, *57*(3), 411–441.

Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica*, *71*(6), 1695–1725.

Morlacco, M. (2021). *Market Power in Input Markets: Theory and Evidence from French Manufacturing* (mimeo).

Olley, G. S., & Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, *64*(6), 1263.

Weinberger, A. (2020). Markups and Misallocation with Evidence from Exchange Rate Shocks. *Journal of Development Economics*, *146*, 102494.

A. Additional material on motivational evidence

Table A.1: List of PTAs signed by EU – 2009-2019

Partner	Type of Agreement	Larger Group	Year
South Korea	FTA		2011
Iraq	PCA		2012
Madagascar	EPA	ESA	2012
Mauritius	EPA	ESA	2012
Seychelles	EPA	ESA	2012
Zimbabwe	EPA	ESA	2012
Costa Rica	AA	Central America	2013
El Salvador	AA	Central America	2013
Guatemala	AA	Central America	2013
Honduras	AA	Central America	2013
Nicaragua	AA	Central America	2013
Panama	AA	Central America	2013
Colombia	TA	Colombia, Peru & Ecuador	2013
Peru	TA	Colombia, Peru & Ecuador	2013
Cameroon	Interim EPA	Central Africa	2014
Fiji	IPA	Pacific	2014
Papua New Guinea	IPA	Pacific	2014
Georgia	AA		2014
Moldova	AA		2014
Ukraine	AA		2014
Botswana	EPA	SADC	2016
Eswatini	EPA	SADC	2016
Lesotho	EPA	SADC	2016
Canada	FTA		2017
Ecuador	TA	Colombia, Peru & Ecuador	2017
Mozambique	EPA	SADC	2018
Samoa	IPA	Pacific	2018
Japan	GA		2019
Singapore	FTA		2019

Abbreviations Type of Agreement: FTA - Free Trade Agreement; PCA - Partnership & Cooperation Agreement; EPA - Economic Partnership Agreement; AA - Association Agreement; TA - Trade Agreement; IPA - Interim Partnership Agreement; GA - Global Agreement

Abbreviations Larger Group: ESA - Eastern & Southern Africa; SADC - Southern African Development Community

A.1. Importing firms following trade liberalization

Table A.2: Coefficients underlying Figure 1a & Figure 1b

	All	Top 50%	Bottom 50%
	(1)	(2)	(3)
$t = -4$	0.040	0.035	0.041
	(0.034)	(0.025)	(0.046)
$t = -3$	0.039	0.035	0.039
	(0.035)	(0.027)	(0.044)
$t = -2$	-0.001	-0.002	-0.002
	(0.007)	(0.004)	(0.013)
$t = -1$	0.000	0.000	0.000
	(.)	(.)	(.)
$t = 0$	-0.002	0.004	-0.009
	(0.013)	(0.012)	(0.017)
$t = 1$	-0.005	-0.032***	0.022
	(0.032)	(0.011)	(0.058)
$t = 2$	0.023	-0.004	0.048
	(0.048)	(0.030)	(0.073)
$t = 3$	0.137*	0.038	0.223**
	(0.073)	(0.034)	(0.103)
$t = 4$	0.162**	0.063*	0.253***
	(0.065)	(0.035)	(0.087)
$t = 5$	0.176**	0.065*	0.280***
	(0.075)	(0.039)	(0.102)
$t = 6$	0.163**	0.065	0.259***
	(0.072)	(0.040)	(0.097)
$t = 7$	0.149**	0.046	0.250**
	(0.069)	(0.033)	(0.098)
Constant	-5.373***	-4.658***	-6.160***
	(0.000)	(0.000)	(0.001)
Year FE	✓	✓	✓
Industry× FE	✓	✓	✓
R^2	0.941	0.926	0.909
Obs	3,312,242	1,736,223	1,576,018

* p<0.1, ** p<0.05, *** p<0.01

Standard errors clustered at the origin-country level in parentheses. The dependent variable is the log share of firms in industry i importing CN8-product p from country o in year t. $t = 0$ denotes the year of (provisional) adoption of a preferential trade agreement. Column (1) shows the entire sample, while columns (2) and (3) show the result for industries in the top 50 and bottom 50 percentile of the distribution of normalized HHI in 2009, respectively.

A.2. Prices

Table A.3: Coefficients underlying Figure 2a & Figure 2b

	All	Top 50%	Bottom 50%
	(1)	(2)	(3)
$t = -4$	-0.047	0.022	-0.101
	(0.050)	(0.065)	(0.073)
$t = -3$	-0.051	0.008	-0.098
	(0.048)	(0.069)	(0.068)
$t = -2$	-0.026	-0.019	-0.025
	(0.048)	(0.079)	(0.059)
$t = -1$	0.000	0.000	0.000
	(.)	(.)	(.)
$t = 0$	-0.035	-0.040	-0.027
	(0.039)	(0.058)	(0.051)
$t = 1$	-0.065	0.002	-0.115
	(0.060)	(0.092)	(0.079)
$t = 2$	-0.116*	-0.046	-0.165**
	(0.060)	(0.092)	(0.079)
$t = 3$	-0.085	0.021	-0.152**
	(0.075)	(0.160)	(0.068)
$t = 4$	-0.138**	-0.063	-0.186**
	(0.066)	(0.115)	(0.080)
$t = 5$	-0.099	0.015	-0.174*
	(0.077)	(0.133)	(0.094)
$t = 6$	-0.084	0.061	-0.178**
	(0.081)	(0.168)	(0.079)
$t = 7$	-0.128	0.010	-0.219***
	(0.093)	(0.195)	(0.083)
Year FE	✓	✓	✓
Firm × Product FE	✓	✓	✓
R^2	0.977	0.974	0.978
Obs	242,565	64,254	178,309

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Robust standard errors in parentheses. The dependent variable is log domestic price of product j, sold by firm f in year t. $t = 0$ denotes the year of (provisional) adoption of a preferential trade agreement. Column (1) shows the entire sample, while columns (2) and (3) show the result for firms in the top 50 and bottom 50 percentile of the distribution of normalized HHI in 2009, respectively. The sample only includes products that are present in all years in which the firm is observed.

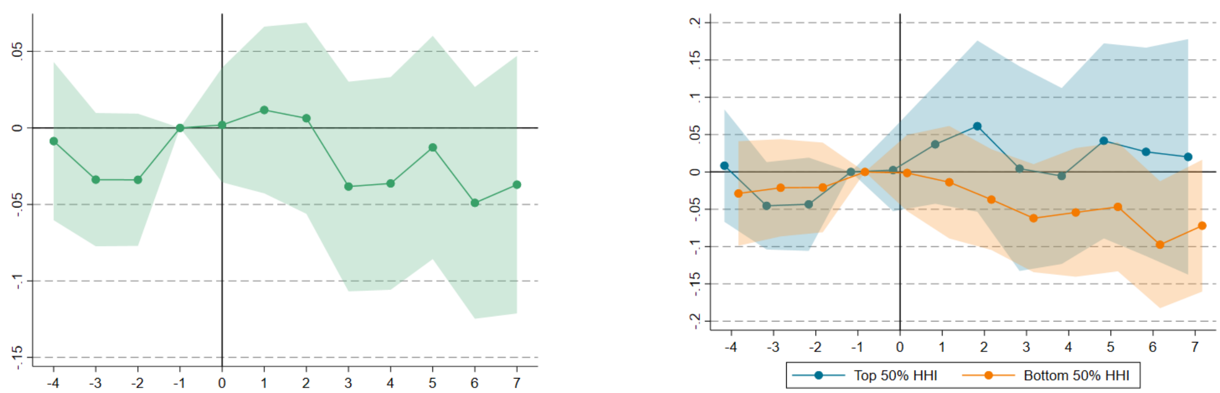
A.3. Sensitivity: Prices with 1% criteria

This section presents the results for the motivational evidence on prices when defining treatment at the firm level according to the following criteria: (a) firms need to have imported from the partner country in the year prior to the adoption of the PTA, (b) the partner country represented at least 1% (instead of 10% as in baseline) of total imports of the firm, and (c) imports from the partner country represented at least 1% (instead of 10% as in baseline) of total expenditure on variable costs.

Figure A.1: Event-study on prices with 1%

(a) Overall effect of trade agreement

(b) Heterogeneous effect of trade agreement



Note: Bands around solid lines denote 95% confidence intervals.

Table A.4: Coefficients underlying Figure A.1a & Figure A.1b

	All	Top 50%	Bottom 50%
	(1)	(2)	(3)
$t = -4$	-0.009	0.008	-0.029
	(0.026)	(0.038)	(0.036)
$t = -3$	-0.034	-0.045	-0.021
	(0.022)	(0.030)	(0.033)
$t = -2$	-0.034	-0.043	-0.021
	(0.022)	(0.032)	(0.031)
$t = -1$	0.000	0.000	0.000
	(.)	(.)	(.)
$t = 0$	0.002	0.002	-0.001
	(0.019)	(0.028)	(0.026)
$t = 1$	0.012	0.037	-0.014
	(0.028)	(0.041)	(0.038)
$t = 2$	0.006	0.061	-0.037
	(0.032)	(0.059)	(0.034)
$t = 3$	-0.038	0.004	-0.062*
	(0.035)	(0.070)	(0.037)
$t = 4$	-0.036	-0.005	-0.054
	(0.035)	(0.060)	(0.044)
$t = 5$	-0.013	0.042	-0.047
	(0.037)	(0.067)	(0.044)
$t = 6$	-0.049	0.027	-0.098**
	(0.039)	(0.071)	(0.043)
$t = 7$	-0.037	0.020	-0.072
	(0.043)	(0.081)	(0.045)
Year FE	✓	✓	✓
Firm × Product FE	✓	✓	✓
R^2	0.978	0.975	0.979
Obs	240,191	62,927	177,262

* p<0.1, ** p<0.05, *** p<0.01

Robust standard errors in parentheses. The dependent variable is log domestic price of product j, sold by firm f in year t. $t = 0$ denotes the year of (provisional) adoption of a preferential trade agreement. Column (1) shows the entire sample, while columns (2) and (3) show the result for firms in the top 50 and bottom 50 percentile of the distribution of normalized HHI in 2009, respectively. The sample only includes products that are present in all years in which the firm is observed.

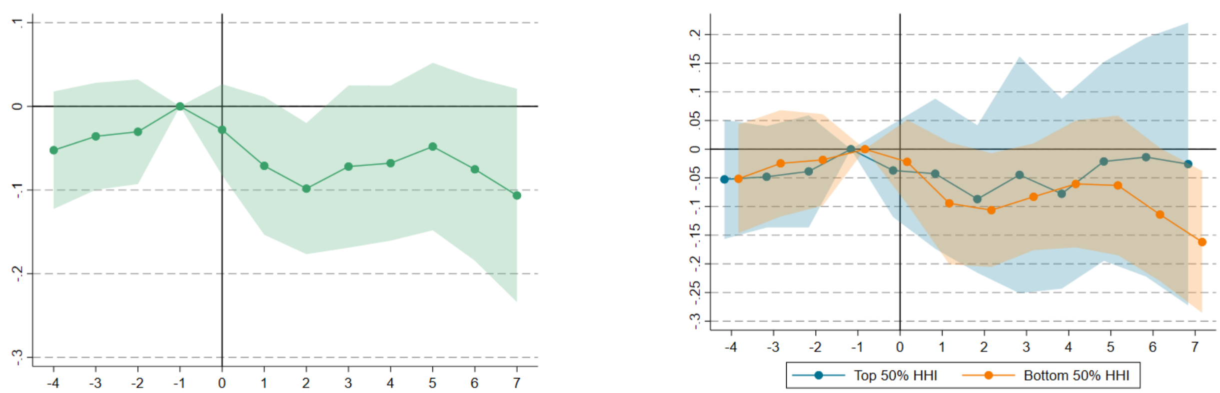
A.4. Sensitivity: Prices with 5% criteria

This section presents the results for the motivational evidence on prices when defining treatment at the firm level according to the following criteria: (a) firms need to have imported from the partner country in the year prior to the adoption of the PTA, (b) the partner country represented at least 5% (instead of 10% as in baseline) of total imports of the firm, and (c) imports from the partner country represented at least 5% (instead of 10% as in baseline) of total expenditure on variable costs.

Figure A.2: Event-study on prices with 5%

(a) Overall effect of trade agreement

(b) Heterogeneous effect of trade agreement



Note: Bands around solid lines denote 95% confidence intervals.

Table A.5: Coefficients underlying Figure A.2a & Figure A.2b

	All	Top 50%	Bottom 50%
	(1)	(2)	(3)
$t = -4$	-0.052	-0.053	-0.052
	(0.036)	(0.053)	(0.048)
$t = -3$	-0.036	-0.048	-0.025
	(0.033)	(0.045)	(0.047)
$t = -2$	-0.030	-0.039	-0.019
	(0.032)	(0.050)	(0.041)
$t = -1$	0.000	0.000	0.000
	(.)	(.)	(.)
$t = 0$	-0.028	-0.037	-0.022
	(0.028)	(0.041)	(0.037)
$t = 1$	-0.071*	-0.043	-0.094*
	(0.042)	(0.067)	(0.054)
$t = 2$	-0.098**	-0.087	-0.106**
	(0.040)	(0.066)	(0.051)
$t = 3$	-0.072	-0.045	-0.083*
	(0.049)	(0.105)	(0.047)
$t = 4$	-0.068	-0.078	-0.061
	(0.047)	(0.084)	(0.056)
$t = 5$	-0.048	-0.021	-0.063
	(0.051)	(0.089)	(0.062)
$t = 6$	-0.075	-0.014	-0.114*
	(0.056)	(0.106)	(0.059)
$t = 7$	-0.106	-0.026	-0.162**
	(0.065)	(0.126)	(0.063)
Year FE	✓	✓	✓
Firm × Product FE	✓	✓	✓
R^2	0.977	0.974	0.978
Obs	241,868	63,855	178,011

* p<0.1, ** p<0.05, *** p<0.01

Robust standard errors in parentheses. The dependent variable is log domestic price of product j, sold by firm f in year t. $t = 0$ denotes the year of (provisional) adoption of a preferential trade agreement. Column (1) shows the entire sample, while columns (2) and (3) show the result for firms in the top 50 and bottom 50 percentile of the distribution of normalized HHI in 2009, respectively. The sample only includes products that are present in all years in which the firm is observed.

B. Proofs

Proof of Proposition 1. Inserting the optimal *pre-importing* profits from Equation 9 together with marginal costs c_j from Equation 7 into the sourcing condition in Equation 13 gives:

$$\left(\Lambda_j \cdot \Psi_j + \varepsilon_j^* \cdot \Psi_j - 1\right) \frac{e_0}{\underline{\varphi}_i} \chi_i(\mu_j - 1) q_j(\underline{\varphi}_i) = f^m,$$

where $e_0 \equiv \prod_{i=1}^{n} \left(\frac{p_i}{\gamma_i}\right)^{\gamma_i}$ denotes the per-unit expenditure on inputs by firm j (including labor). Note here that the per-unit expenditure on inputs by firm j will be the same for all firms that do not import.

Now, in order to avoid negative markups, I have defined that $\varepsilon_j \equiv -\partial \ln q_j / \partial \ln p_j > 1$. This definition implies a first-order approximation of the demand curve as:

$$q_j(\varphi_j) \approx B p_j^{-\varepsilon_j},$$

where B incorporates all (aggregate) variables related to the demand function, such as the demand shifters Q and P. Knowing the optimal price from Equation 3 and combining it with marginal costs from Equation 7, the residual demand function of firm j can be written as:

$$q_j(\varphi_j) = B \varphi_j^{\varepsilon_j} \left(\mu_j e_{j,0}\right)^{-\varepsilon_j} = \hat{B}_j e_{j,0}^{-\varepsilon_j} \varphi_j^{\varepsilon_j},$$

where $\hat{B}_j$ now also includes the (demand-driven) markup μ_j, therefore incorporating all demand-related variables other than productivity φ_j and the pre-importing per-unit expenditure on inputs $e_{j,0}$.

We can now plug the general form for q_j into the cutoff sourcing condition to obtain:

$$\underline{\varphi}_i = e_0 \left(\frac{f^m}{\chi_i \left(\underline{\Lambda} \cdot \underline{\Psi} + \underline{\varepsilon}^* \cdot \underline{\Psi} - 1\right) (\mu_j - 1) \hat{B}} \right)^{\frac{1}{\varepsilon_i - 1}}.$$

Finally, we know that $\underline{\Lambda}$, $\underline{\Psi}$, $\underline{\varepsilon}^*$, $\underline{\mu}$ and $\underline{\hat{B}}$ are all function of the firm-level productivity $\underline{\varphi}$, relative to an aggregation of productivity across firms Φ_J, and function of the aggregate demand-shifter Q, therefore $\underline{\Lambda}(\underline{\varphi}, \Phi_J, Q)$, $\underline{\Psi}(\underline{\varphi}, \Phi_J, Q)$, $\underline{\varepsilon}^*(\underline{\varphi}, \Phi_J, Q)$, $\underline{\mu}(\underline{\varphi}, \Phi_J, Q)$ and $\underline{\hat{B}}(\underline{\varphi}, \Phi_J, Q)$. Hence, we can gather all demand-related terms in the function $\mathcal{S}$ and write:

$$\underline{\varphi}_i = \underline{e}_0 \left(\frac{f^m}{\chi_i \mathcal{S}(\underline{\varphi}_i, \Phi_J, Q)} \right)^{\frac{1}{\varepsilon_i - 1}}.$$

Note here that the impact of $\underline{e}_0$ is driven primarily by demand: because firms with larger expenditures on inputs have larger prices, the demand for their products is lower. Therefore the necessary productivity for importing increases with larger $\underline{e}_0$. ■

C. Notes on data and data treatment

C.1. EAP

The *Enquête Annuelle de Production* (EAP), collected by the French national statistics bureau INSEE, covers all manufacturing firms with either more than 20 employees or more than a certain industry-specific cutoff level in sales revenue in a given year. Starting in 2016, the cutoff is harmonized for all sectors and set at 5 million €. This is amended by a random sample of smaller firms by industry. Overall, the survey covers between 35,000 and 40,000 legal units per year. EAP stretches over the period 2009 to 2022. However, I omit the last three years to avoid any confounding effects due to the Covid-19 crisis. Each firm is identified by its official identifier (*SIREN*). EAP gives information on both quantity and value of goods sold at the product level, with products defined using the European Prodcom classification. The raw data is provided in the slightly more detailed Prodfra classification, a French classification that builds on the Prodcom nomenclature, adding two additional figures at the end of the code, the first eight representing the corresponding Prodcom code. I transform all codes into the Prodcom classification. Moreover, I use concordance tables provided by Eurostat to ensure coherence across time. I drop all non-manufacturing products (4.4% of observations). EAP includes products produced according to different modes of production, including for instance goods fabricated by subcontractors. In the empirical exercise I only retain products produced by the firm itself. This is designated by the codes *VF1* for values and *VQ1C* for quantities. Finally, data cleaning required a mild homogenization of units, such as for instance the conversion of tons to kilograms.

C.2. Fare

Firm-product level information is supplemented by balance sheet information from the *Fichier Approché des Résultats d'ESANE* (FARE) database. FARE is constructed by the INSEE and contains balance sheets for the universe of French firms. The data is based on fiscal, and survey data. As in all French datasets used in this paper, each firm is identified through its *SIREN*. From FARE I retain information on the number of employees, wagebills, purchases of raw and other materials, variation in stock of materials, as well as revenue.

C.3. Customs

The customs dataset provides the annual value and volume of the imports and exports of a French firm by product code at Eurostat's combined nomenclature at the 8-digit level (CN8) and by origin/destination country. The CN8 product classification is built on the harmonized system (HS) by the World Customs Organization at the 6-digit level, adding two additional digits. Compared to the HS nomenclature, the CN8 classification changes each year, such that one needs to harmonize product codes across all years of the empirical exercise in order to obtain coherent product codes. The concordance tables are provided by Eurostat. I use the customs dataset to construct series of average annual import prices for intermediate inputs at the firm level. I rely on the BEC classification to identify intermediate goods. The conversion of CN8 to BEC is taken from Eurostat's Comext database. Moreover, I only retain observations which consisted of an actual transfer of ownership of the good. All observations need to be transformed from CN8 to Prodcom, again using conversion tables provided by Eurostat. I first transform all codes into 2009 codes for both CN8 and Prodcom. Subsequently, I then use the yearly conversion tables to obtain a consistent mapping of CN8 to Prodcom codes. It should be noted that Eurostat does not provide a CN8 to Prodcom conversion table for the year 2009, such that I assumed there to be no change between the 2009 and 2010 conversion, using the 2010 conversion for 2009. See below for more details on this. Exports are then subtracted from overall sales in EAP in order to concentrate on domestic sales only. Finally, the transformation from CN8 to Prodcom ensures that we can obtain series for both domestic and import price (needed for χ_i), and that we can coherently include imports in the construction of the competitors' price index (as in Amiti et al. (2019); see Appendix I).

C.4. Other data

Base d'Analyse du Commerce International (BACI) database, provided by CEPII, includes all annual global trade flows. Trade flows are provided in the HS6 nomenclature. I build a concordance between HS6 and Prodcom, based on the CN8 to Prodcom conversion.

C.5. Data treatment

Homogenization of CN8 and Prodcom codes across time To assure consistency of CN8 and Prodcom codes across time, I use concordance tables provided by Eurostat to convert both series into 2009 codes. A large problem when converting codes back into prior nomenclatures are codes for which we have multiple observations in prior years, i.e. that were bunched together. I call this the "m:1" issue. One possibility to handle this problem consists of bunching together these codes into one "generic" code throughout years. However, this will lead to some cases where many codes are bunched together which, arguably, are in reality not the same product (nor even very similar products). Due to this last issue, I opted to simply drop all products that were marked by at least one instance of "m:1" through the years 2009-2019.

Concordance CN8 to Prodcom I convert CN8 to Prodcom codes, based on concordance tables provided by Eurostat. To assure a deterministic concordance, i.e. that no CN8 codes is contained in multiple Prodcom codes, I first drop all instance in which this condition is violated. I then subsequently convert both CN8 and Prodcom codes to their 2009 version and establish the conversion of CN8 to Prodcom codes based on the 2010 concordance, as the 2009 conversion is not provided by Eurostat.

Concordance HS6 to Prodcom As mentioned in the main text, I convert HS6 codes to Prodcom codes, based on the concordance between CN8 and Prodcom codes. While the CN8-Prodcom conversion assures that each individual CN8 code is assigned to a single Prodcom code, the more aggregate HS6 classification violates this condition in some instances. However, as the HS6 will be only used as an instrument, I refrain from dropping these instances. This decision comes at the cost of a more precise first stage.

Treatment of groups One particular issue in the French datasets used in this paper pertains to aggregate groups of firms. These *groupes historiques* are historical groups of different firms, representing very large firms with many subsidiaries. These groups are identified by a pseudo *SIREN*, starting with the letter "P". The INSEE provides a mapping of individual subsidiaries to larger groups. While Customs provide disaggregate information for each subsidiary, and Fare includes both group and subsidiary observations, EAP uses the pseudo *SIREN* for 13 historical groups. However, the inclusion of groups is not consistent across years in EAP: groups are only included starting in 2012, and some of the groups are found as disaggregate *SIREN* in later years.

Hence, to assure a coherent treatment of groups across datasets and years, a lot of individual treatments were needed. I start by identifying subsidiaries that are present in any year of EAP. I then analyze the consistency of the product mix, sales and individual prices for these individual subsidiaries in EAP compared to the years where the group is represented by the pseudo *SIREN*. If products, sales and prices were consistent, I aggregate the subsidiaries which were present in EAP in all datasets and years in order to obtain consistent information on sales, imports, exports and balance sheets.

If product mix, sales and prices were, however, not consistent, I keep group and subsidiary codes separate and aggregate all subsidiaires *except* the one included in EAP. If no subsidiary is found in EAP, we aggregate all affiliated subsidiaries in Fare and customs, assuming that each subsidiary is represented in EAP sales.

Moreover, there were four groups for which Fare only contained relatively sparse information on subsidiaries, i.e. aggregating across subsidiaries present in Fare only gave a fraction of the sales and expenditure from the aggregate observation. For these groups, in Fare we used the aggregate observation and aggregate across all subsidiaries linked to the group in the customs data.

C.6. Summary statistics

The final EAP dataset includes 39,186 individual firms and 3,349 individual output products. Table C.1 shows the distribution of relevant firm-level variables. On average, firms in EAP earn around 80% of their revenue from domestic sales, with a yearly average of

Table C.1: Firm-level summary statistics

	N	Mean	P5	P25	P50	P75	P95
Number products	252,345	1.652	1	1	1	2	4
Number imported intermediates	252,345	7.072	0	0	0	5	37
Total sales (EAP, €M)	252,345	13.558	0.041	0.285	1.211	4.804	38.861
Total domestic sales (EAP, €M)	252,345	10.752	0.030	0.263	1.119	4.352	31.658
Total imports (Customs, €M)	252,345	3.961	0.000	0.000	0.000	0.370	9.314
Total raw material expenses (Fare, €M)	232,517	12.986	0.019	0.157	0.689	3.042	28.775
Total variable costs, incl. labor (Fare, €M)	234,077	17.038	0.073	0.394	1.390	4.898	41.006
Share imports in raw material expenses	230,603	0.399	0.000	0.000	0.000	0.182	0.730
Share imports in variable costs, incl. labor	233,743	0.148	0.000	0.000	0.000	0.102	0.476

Note: Table reports summary statistics on different firm-level variables of interest. P5, P25, P50, P75 and P95 denote the 5th, 25th, 50th, 75th and 95th percentile, respectively.

10.75 Million €. On average, firms report slightly less than 2 products per year, with a large part of firms reporting to be single-product firms. Further, on average firms import around 7 products per year, with many, however, reporting no imports at all. Imports represent an average of 39.9% of raw materials expenditure, and 14.8% of total variable costs.

Units In the table below, I list all individual units present in the EAP and customs datasets.

Table C.2: Units in EAP and customs

Unit	Code	Nb. obs. EAP	Nb. obs. Customs
Carats	P1	0	359
Cubic metres	S2	6,461	18,028
Gross tonnage	GT	348	0
Kilograms	P4	209,276	3,296,211
Kilograms of drymatter	Y9	78	4,102
Kilograms of sulfuric acid	YA	67	0
Kilowatt	E2	144	0
Litres	V1	2,037	2,308
Megawatt hours	E5	0	1
Metres	L2	1,662	2,445
Number	N6	193	0
Number of pairs	N3	2,615	272
Pieces	N4	181,572	89,673
Square metres	S1	8,404	123,429
Square metres of wool	L3	5	0
Tons of active matter	ZC	2,167	0
Tons of chlorhydric acid	ZI	156	0
Tons of chlorine	ZG	102	0
Tons of dialuminium trioxide	ZD	51	0
Tons of diboron trioxide	ZF	6	0
Tons of fluorine	ZH	20	0
Tons of hydrofluoric acid	ZJ	38	0
Tons of hydrogen peroxide	ZK	57	525
Tons of nitrogen	Z3	686	2,447
Tons of phosphorous pentoxide	Z5	177	1,673
Tons of potassium hydroxide	ZL	57	534
Tons of potassium oxide	Z4	107	1,197
Tons of silicon dioxide	W1	114	0
Tons of sodium carbonate	ZO	23	0
Tons of sodium hydroxide	ZN	136	1,561
Tons of sodium metabisulfite	ZP	23	0
Tons of suplhor dioxide	ZR	72	0
Tons of titanium dioxide	ZH	129	0

D. Representativeness of SPF for MPF

How representative are single-product firms to predict the production function of multi-product firms? To test the validity of the method described in subsection 5.2, I regress the *actual* input share of input i on its *predicted* input share for multi-product firms. That is, to construct the predicted input share of i for firm f, I will take the sales-weighted average of i's input share across all final products that are assigned i as an input from single-product importers:

$$\hat{\mathcal{I}}_{if}^{MPF} = \sum_j w_{jf}^{MPF} \mathcal{I}_{ij}^{SPF}, \tag{D.1}$$

where

$$w_{jf}^{MPF} = \frac{q_{jf}^{MPF}}{\sum_j q_{jf}^{MPF}} \tag{D.2}$$

represents the share of product j in total sales of firm f, where total sales also include products for which we don't have input information. This implies that the sum of the weights at the firm-level does not equal 1. Further, note here that $\hat{\mathcal{I}}_{if}^{MPF}$ is constructed across years, in line with the way I construct input shares from single-product importers.

By regressing the actual share of i in total imports of firm f across years on $\hat{\mathcal{I}}_{if}^{MPF}$, one can then analyze the potential bias that stems from using single-product firms to construct input shares. I run the following regression:

$$\mathcal{I}_{if}^{MPF} = \beta_1 \hat{\mathcal{I}}_{if}^{MPF} + \beta_2 \sum_j w_{jf}^{MPF} + \eta_f + \eta_i + \varepsilon_{if}, \tag{D.3}$$

where η_f and η_i are firm and input fixed effects, respectively, and where I control for the sum of shares $\sum_j w_{jf}^{MPF}$. Additionally, I also include a version of input shares where, instead of defining $\mathcal{I}_{ij}^{SPF}$ as the share of i in total imports, I define it as the share of i in total variable costs. If input shares from single-product firms are indeed a good proxy for input shares for all firms, we would expect β to be highly significant and, in the best case, close to 1.

Results in Table D.1 below are for input codes restricted to $\mathcal{I}_{ij} \geq 0.01$, and the vector of $\mathcal{I}_{ij}$ was not re-weighted. I include different sets of fixed effects (only input, and both input and firm). As we can see, the predicted share of i always significantly correlates to the actually observed share. A caveat, however, is that the coefficient is consistently below 1. Moreover, we see that the share of i in total variable costs is significantly higher if we use the predicted shares than the actual shares, suggesting that the individual product i represents a higher share in total variable costs for single-product firms than for multi-product firms.

Additionally, in Figure D.1 I also show binscatter plots for the relation between predicted and observed input shares, both when dividing by total imports and when dividing by total variable costs. I include either product fixed effects or firm fixed effects.

Table D.1: Regressing observed input share ($\mathcal{I}_{ij}^{MPF}$) on predicted input share ($\hat{\mathcal{I}}_{ij}^{MPF}$)

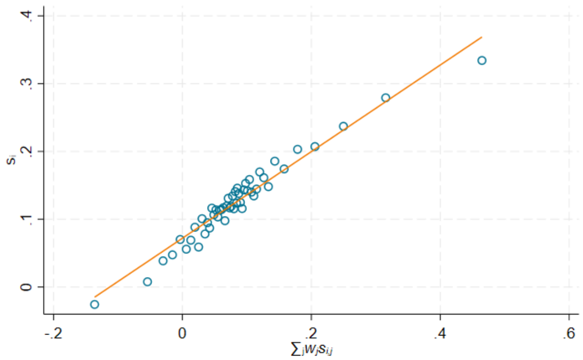
	Imports			Variable costs		
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{s}_{ijf}^{SPF}$	0.756***	0.639***	0.613***	0.166***	0.134***	0.117***
	(0.012)	(0.016)	(0.016)	(0.009)	(0.013)	(0.015)
Product FE		✓	✓		✓	✓
Firm FE			✓			✓
R^2	0.176	0.269	0.447	0.044	0.198	0.658
Obs	20,712	18,203	17,381	8,154	6,901	5,556

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

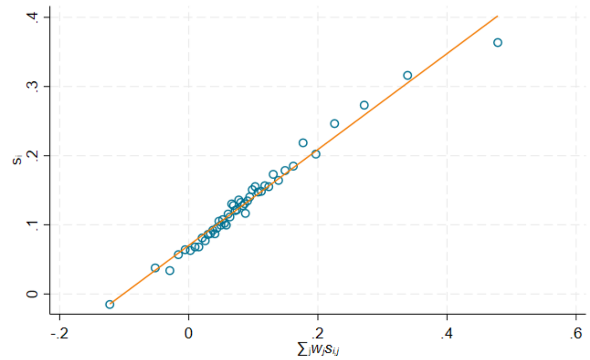
Standard errors in parentheses. The dependent variable is the *observed* input share of input i for the production of output p, calculated across all years ($\mathcal{I}_{ij}^{MPF}$). $\hat{\mathcal{I}}_{ij}^{MPF}$ denotes the according *predicted* shares, constructed based on input shares $\mathcal{I}_{ij}$ from single-product importers (see text). Sample is restricted to $\mathcal{I}_{ij} > 0.01$.

Figure D.1: Regressing observed input share ($\mathcal{I}_{ij}^{MPF}$) on predicted input share ($\hat{\mathcal{I}}_{ij}^{MPF}$)

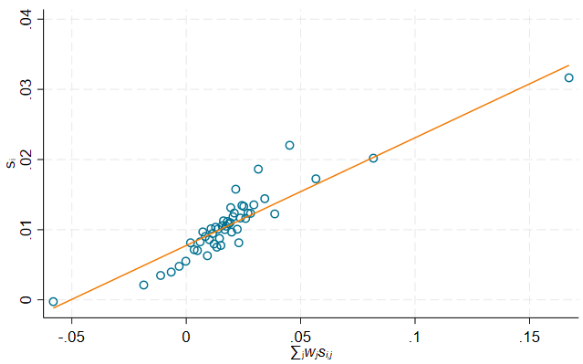
(a) Import share - Product FE



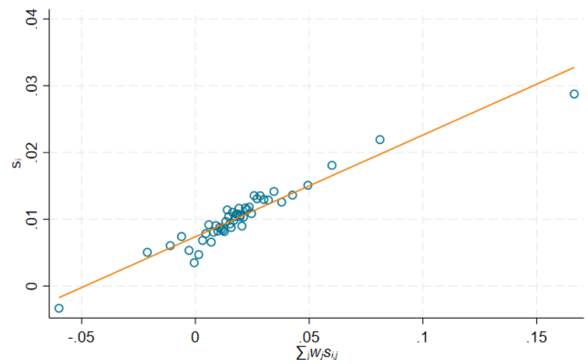
(b) Import share - Firm FE



(c) Variable cost share - Product FE



(d) Variable cost share - Firm FE



E. Testing the hypothesis of χ-ranked inputs

This section empirically tests the hypothesis that firms, when deciding on their importing strategy, rank inputs according to their marginal cost savings potential χ_{ij}. To validate this assumption, I employ tests at both the aggregate output j level, and at the disaggregate firm level.

E.1. Output level

The modeling choice of a perfect ranking of intermediates according to χ_{ij} implies that the share of firms producing a given output j and importing a given intermediate i increases with χ_{ij}, as shown by Equation 20 in the main text, re-written here for ease of exposition:

$$s_i^F = \underline{e}_0^{-a} \left(\frac{\chi_i \mathcal{S}(\underline{\varphi}_i, \Phi_J, Q)}{f^m} \right)^{\frac{a}{\varepsilon_i - 1}}.$$

To test this hypothesis at the aggregate output level, I will rely on the vector of χ_{ijt}'s constructed as described in the main text. For each output j and year t, I then construct the rank of each intermediate input by ordering them according to their marginal cost savings potential. To take into account that we have more input information for some outputs, I will use the *relative* rank of an each intermediate, instead of using the rank in levels. Regressing the share of firms importing on the relative rank of each intermediate ($\mathcal{R}_{ijt}$) then reveals the additional share of firms importing when moving up by one rank. I thus run the following regression:

$$s_{ijt}^F = \beta_1 \mathcal{R}_{ijt} + \eta_{jt} + \varepsilon_{ij},$$

where η_{jt} denotes output-year fixed effects. I run the regression both on the share of firms importing in logs and in levels.

Table E.1 shows the result of this empirical exercise. As we can see moving from the bottom to the top ranked intermediate, increases the share of firms importing by 50% or around 10 percentage points. In columns (2) and (5) I restrict the sample to outputs with at least 10 inputs. In columns (3) and (6) I only retain outputs with at least 10 firms on average.

Table E.1: Share-rank regression

	Logs			Levels		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathcal{R}_{ijt}$	0.507***	0.602***	0.656***	0.095***	0.091***	0.096***
	(0.031)	(0.051)	(0.043)	(0.006)	(0.010)	(0.007)
$j \times t$ FE	✓	✓	✓	✓	✓	✓
Sample	All	Nb $i \geq 10$	Nb $f \geq 10$	All	Nb $i \geq 10$	Nb $f \geq 10$
R^2	0.750	0.719	0.656	0.736	0.662	0.521
Obs	42,021	14,673	26,137	42,021	14,673	26,137

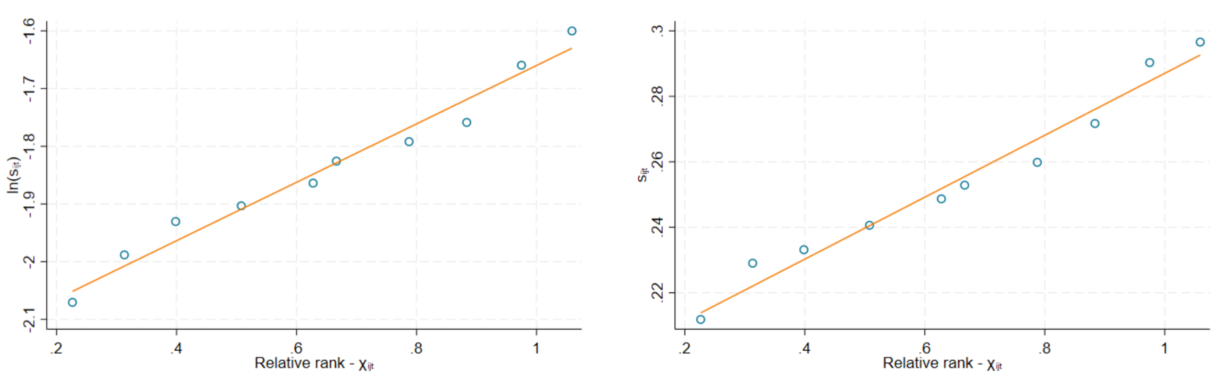
* p<0.1, ** p<0.05, *** p<0.01

The dependent variable is the share of firms producing j and importing i at time t. $\mathcal{R}_{ijt}$ denotes the relative rank of input i for output j at time t, ordered with respect to χ_{ijt}.

To expose the linear relation between the share of firms importing and the ranking of intermediates as it is assumed by theory, Figure E.1 shows binscatter plots of columns (1) and (4) from Table E.1. The clear linear and increasing relation between the share of firms importing and the rank of i confirms, at the aggregate product level, the assumption made in the theoretical section of the paper.

Figure E.1: Share-rank binscatter plots

(a) Logs (b) Levels



E.2. Firm level

Similarly to the aggregate test of the perfect rank assumption, we can also test this hypothesis at the firm level. As shown by the expression of the cutoff productivity of importing in Equation 14, a higher χ_{ij} decreases the necessary cutoff productivity of importing, and therefore, as productivity is fixed, increases the probability for a given firm to import an intermediate input i. To test this hypothesis, I merge firm-level import data with the rank vector from the aggregate exercise described in the prior subsection, based on a firm's output mix. I then regress an import dummy that takes the value 1 if a firm imports a given intermediate on the rank of an intermediate input i, hence employing the following equation:

$$\mathbb{1}_{fijt} = \beta_1 \mathcal{R}_{ijt} + \eta_{fjt} + \eta_i + \varepsilon_{fijt}, \tag{E.1}$$

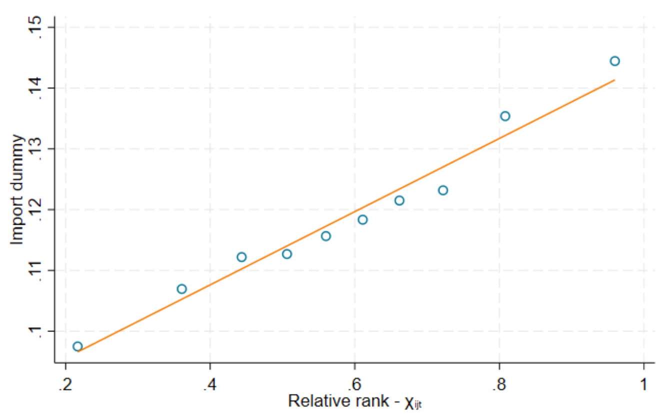
where η_{fjt} denotes firm-output-year fixed effects and η_i denotes input fixed effects.

The table below shows the results of this regression, while the graph shows the binscatter plot for column (2). The result suggests that going from the bottom to the top of the ranking distribution increases the probability to import by 6 percentage poitns.

	All firms	
	(1)	(2)
$\mathcal{R}_{ijt}$	0.045***	0.060***
	(0.006)	(0.005)
$f \times j \times t$ FE	✓	✓
i FE		✓
Obs	1,846,997	1,846,995

* p<0.1, ** p<0.05, *** p<0.01

The dependent variable is a dummy variable, indicating whether firm f, producing j, is importing i at time t. $\mathcal{R}_{ijt}$ denotes the relative rank of input i for output j at time t, ordered with respect to χ_{ijt}.



One concern with estimating Equation E.1 on the entire sample of firms is that χ_{ij} is constructed using the vector of input requirements obtained from single product firms' imports. To alleviate these concerns, columns (1) and (2) in Table E.2 show the relative rank regression when using only multi-product firms. Additionally, columns (3) and (4) show the results when estimating the regression as a logit specification, and columns (5) and (6) when estimating it in PPML, both estimated on the sample of multi-product firms. Considering a baseline probability to import of 37.6%, the logit estimation in column (4) suggests that the probability to import increases by 23.9 percentage points when going from the bottom- to top-ranked input. As before, I visualize the results for multi-product firms using binscatter plots in Figure E.2. We observe a similar linearly increase as before, giving evidence on the validity of the perfect χ-rank assumption.

Table E.2: Share-rank regression

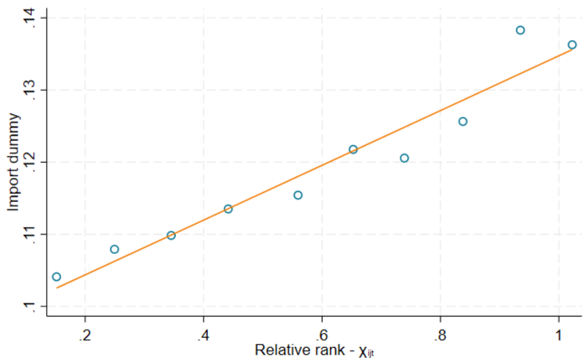
	MPF		Logit		PPML	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathcal{R}_{ijt}$	0.038***	0.051***	0.695***	0.635***	0.385***	0.391***
	(0.006)	(0.006)	(0.026)	(0.025)	(0.014)	(0.014)
$f \times j$ FE			✓		✓	
$f \times j \times t$ FE	✓	✓		✓		✓
i FE		✓			✓	✓
Obs	1,291,702	1,291,699	464,796	347,919	473,613	367,649

* p<0.1, ** p<0.05, *** p<0.01

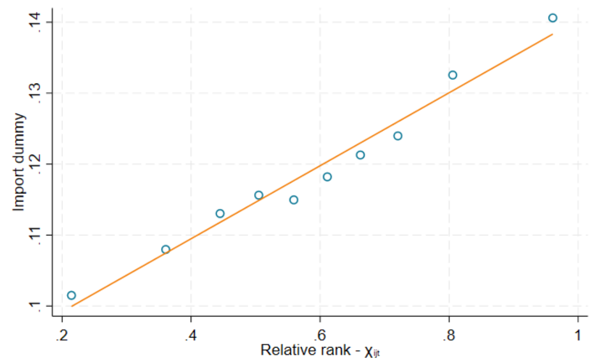
The dependent variable is a dummy variable, indicating whether firm f, producing j, is importing i at time t. $\mathcal{R}_{ijt}$ denotes the relative rank of input i for output j at time t, ordered with respect to χ_{ijt}.

Figure E.2: Firm-level share-rank binscatter plots – MPF

(a) Column (1)



(b) Column (2)



F. Robustness and heterogeneity of extensive margin

F.1. "True" χ_{ijt}

As discussed in the main text, I use a slightly transformed version of the Cobb-Douglas price indices. That is, instead of using $p_{it} = \prod_{f=1}^{N}\left(\frac{p_{ift}}{s_{ift}}\right)^{s_{ift}}$ for foreign and domestic prices, I omit the division by s_{ift} in order to increase the number of products for which the condition $p_{it}^F < p_{it}^D$ is satisfied. In Table F.1.1 I use the "true" form for χ_{ijt}. While the 2SLS results are still slightly significant without industry fixed effects and display a larger coefficient than before, the F-stat of the first stage is very low, leading to a weak-instrument problem. When including industry fixed effects, the F-Stat becomes even lower and the coefficient becomes insignificant. Further, the OLS results are highly significant, but in the *opposite* direction that one would expect.

Table F.1.1: Extensive margin with "true" χ_{ijt}

	OLS			2SLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln \chi_{ijt}$	-0.033***	-0.037***	-0.038**	0.610*	0.899*	1.350			
	(0.011)	(0.013)	(0.015)	(0.320)	(0.524)	(1.010)			
$\mathcal{Z}_{it}$							0.132***	0.159***	0.201***
							(0.035)	(0.035)	(0.040)
t FE	✓			✓			✓		
$j \times t$ FE		✓	✓		✓	✓		✓	✓
i FE			✓			✓			✓
KP F-Stat				5.8	3.9	2.1	.	.	.
First stage coeff.				0.216**	0.177**	0.149			
Obs	15,197	11,727	11,658	15,197	11,727	11,658	15,197	11,727	11,658

* p<0.1, ** p<0.05, *** p<0.01

HS6-clustered standard errors in parentheses. The dependent variable is the (log) change in the share of j-producing firms importing i in year t. $\Delta \ln \chi_{ijt}$ is constructed using the true formula for CD-indices, i.e. $p_{it} = \prod_{f=1}^{N}\left(\frac{p_{ift}}{s_{ift}}\right)^{s_{ift}}$. $\mathcal{Z}_{it}$ denotes the instrument, constructed as described in the text. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

F.2. Defining importing as above €10.000

Many observations in the customs data are imports of very small amounts. Arguably, imports of such small value do not represent actual importing activity in the sense of the theory described above. To check whether results might be driven by these small events, I re-define a firm as importing if it imports at least €10,000 of input i from a country from the set of valid origins o^*. Table F.2.1 shows that results are not driven by the definition of imports. The coefficients are smaller than before, but still highly significant. The F-stat of the first stage is even slightly higher compared to before.

Table F.2.1: Extensive margin with importing defined as above €10,000

	OLS			2SLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln \chi_{ijt}$	0.050***	0.050***	0.046***	0.278***	0.265***	0.311***			
	(0.012)	(0.014)	(0.015)	(0.065)	(0.060)	(0.060)			
$\mathcal{Z}_{it}$							0.124***	0.149***	0.168***
							(0.023)	(0.025)	(0.027)
t FE	✓			✓			✓		
$j \times t$ FE		✓	✓		✓	✓		✓	✓
i FE			✓			✓			✓
KP F-Stat				34.6	36.8	53.4			
First stage coeff.				0.446***	0.469***	0.539***			
Obs	27,474	24,587	24,526	27,474	27,345	24,526	27,474	24,587	24,526

* p<0.1, ** p<0.05, *** p<0.01

HS6-clustered standard errors in parentheses. The dependent variable is the (log) change in the share of j-producing firms importing i in year t, where importing is defined as importing at least €10,000 from a country o^*. $\Delta \ln \chi_{ijt}$ is constructed as described in the text. $\mathcal{Z}_{it}$ denotes the instrument, constructed as described in the text. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

F.3. Restricting sample to firms present in $t-1$

A confounding effect might come from the entry/exit of firms, naturally affecting the share of firms importing. To account for this, I restrict the sample to firms present in both t and $t-1$ before calculating the share of firms importing. Table F.3.1 shows the results of this exercise. Coefficients remain highly significant, with the point estimate slightly smaller. The F-Stat is very similar to the baseline.

Table F.3.1: Extensive margin with only firms present in t and $t-1$

	OLS			2SLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln \chi_{ijt}$	0.051***	0.052***	0.048***	0.332***	0.369***	0.366***			
	(0.012)	(0.013)	(0.014)	(0.076)	(0.076)	(0.072)			
$\mathcal{Z}_{it}$							0.141***	0.168***	0.186***
							(0.025)	(0.025)	(0.027)
t FE	✓			✓			✓		
$j \times t$ FE		✓	✓		✓	✓		✓	✓
i FE			✓			✓			✓
KP F-Stat				30.1	46.6	48.1			
First stage coeff.				0.425***	0.455***	0.508***			
Obs	30,496	27,740	27,685	30,496	27,740	27,685	30,496	27,740	27,685

* p<0.1, ** p<0.05, *** p<0.01

HS6-clustered standard errors in parentheses. The dependent variable is the (log) change in the share of j-producing firms importing i in year t. The dependent variable only includes firms present in both t and $t-1$. $\Delta \ln \chi_{ijt}$ is constructed as described in the text. $\mathcal{Z}_{it}$ denotes the instrument, constructed as described in the text. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

F.4. Defining $\Delta \ln s_{ijt}$ as $\Delta \ln(1 + s_{ijt})$ or $\Delta \ln \textbf{arcsin}(s_{ijt})$

A potential bias might come from the fact that the use of $\Delta \ln s_{ijt}$ automatically drops all observations for which $s_{ijt} = 0$. To check whether this drives the results, I use a slight transformation of $\Delta \ln s_{ijt}$ as $\Delta \ln(1+s_{ijt})$ or, alternatively, as $\Delta \ln \text{arcsin}(s_{ijt})$.[36] Note that results from this do not allow for a structural interpretation. Results are shown in Table F.4.1 and Table F.4.2. The number of observations nearly doubles in both tables. The coefficients are drastically reduced in both cases, but remain highly significant. The F-Stat is lower than in the baseline estimation.

Table F.4.1: Extensive margin with $\Delta \ln(1 + s_{ijt})$

	OLS			2SLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln \chi_{ijt}$	0.006***	0.005**	0.004*	0.060***	0.060***	0.060***			
	(0.002)	(0.002)	(0.002)	(0.019)	(0.017)	(0.018)			
$\mathcal{Z}_{it}$							0.024***	0.024***	0.026***
							(0.007)	(0.006)	(0.006)
t FE	✓			✓			✓		
$j \times t$ FE		✓	✓		✓	✓		✓	✓
i FE			✓			✓			✓
KP F-Stat				25.7	29.3	28.2			
First stage coeff.				0.397***	0.404***	0.437***			
Obs	57,795	55,863	55,849	57,795	55,863	55,849	57,795	55,863	55,849

* p<0.1, ** p<0.05, *** p<0.01

HS6-clustered standard errors in parentheses. The dependent variable is constructed as the (log) change in the share of j-producing firms importing i in year t, augmented by $+1$ in order to include observations with zero-shares. $\Delta \ln \chi_{ijt}$ is constructed as described in the text. $\mathcal{Z}_{it}$ denotes the instrument, constructed as described in the text. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

[36] The formula for $\text{arcsin}(s_{ijt})$ is $\text{arcsin}(s_{ijt}) = s_{ijt} + \sqrt{1 + s_{ijt}^2}$.

Table F.4.2: Extensive margin with $\Delta \ln \text{arcsin}(s_{ijt})$

	OLS			2SLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln \chi_{ijt}$	0.007***	0.006**	0.005*	0.071***	0.069***	0.069***			
	(0.003)	(0.002)	(0.003)	(0.022)	(0.020)	(0.020)			
$\mathcal{Z}_{it}$							0.028***	0.028***	0.030***
							(0.008)	(0.007)	(0.007)
t FE	✓			✓			✓		
$j \times t$ FE		✓	✓		✓	✓		✓	✓
i FE			✓			✓			✓
KP F-Stat				25.7	29.3	28.2			
First stage coeff.				0.397***	0.404***	0.437***			
Obs	57,795	55,863	55,849	57,795	55,863	55,849	57,795	55,863	55,849

* p<0.1, ** p<0.05, *** p<0.01

HS6-clustered standard errors in parentheses. The dependent variable is constructed as the (log) change in the *arcsin* of the share of j-producing firms importing i in year t (see text for exact formula of *arcsin*). $\Delta \ln \chi_{ijt}$ is constructed as described in the text. $\mathcal{Z}_{it}$ denotes the instrument, constructed as described in the text. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

F.5. Using only products with at least 4 (10) firms on average

A potential biasing factor might be jumps in the share of importing firms for products with a small number of producing firms. Take the example of a product which is produced by only two firms, one importing, the other not. If the second firm starts to import, the data would show a 100% increase in the share of firms importing, when in reality only one firm started to import. To control for this, in Table F.5.1 I restrict the sample to products with, on average, at least 4 firms. In Table F.5.2, I restrict the sample even further to, on average, at least 10 firms. Results are robust to this restriction. In both cases, the coefficients are bigger than in the baseline, while the F-stat of the first stage is smaller.

Table F.5.1: Extensive margin with only products with at least 4 firms on average

	OLS			2SLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln \chi_{ijt}$	0.059***	0.058***	0.054***	0.393***	0.419***	0.429***			
	(0.013)	(0.014)	(0.015)	(0.088)	(0.087)	(0.084)			
$\mathcal{Z}_{it}$							0.165***	0.189***	0.213***
							(0.027)	(0.027)	(0.029)
t FE	✓			✓			✓		
$j \times t$ FE		✓	✓		✓	✓		✓	✓
i FE			✓			✓			✓
KP F-Stat				28.3	41.1	41.1			
First stage coeff.				0.421***	0.451***	0.497***			
Obs	28,196	26,106	26,056	28,196	26,106	26,056	28,196	26,106	26,056

* p<0.1, ** p<0.05, *** p<0.01

HS6-clustered standard errors in parentheses. The dependent variable is constructed as the (log) change in the share of j-producing firms importing i in year t. $\Delta \ln \chi_{ijt}$ is constructed as described in the text. $\mathcal{Z}_{it}$ denotes the instrument, constructed as described in the text. The sample is restricted to output products with at least 4 firms on average. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

Table F.5.2: Extensive margin with only products with at least 10 firms on average

	OLS			2SLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln \chi_{ijt}$	0.064***	0.061***	0.056***	0.412***	0.424***	0.425***			
	(0.016)	(0.017)	(0.018)	(0.103)	(0.102)	(0.096)			
$\mathcal{Z}_{it}$							0.178***	0.193***	0.217***
							(0.033)	(0.033)	(0.035)
t FE	✓			✓			✓		
$j \times t$ FE		✓	✓		✓	✓		✓	✓
i FE			✓			✓			✓
KP F-Stat				28.4	35.0	35.9			
First stage coeff.				0.432***	0.455***	0.510***			
Obs	19,779	18,836	18,780	19,779	18,836	18,780	19,779	18,836	18,780

* p<0.1, ** p<0.05, *** p<0.01

HS6-clustered standard errors in parentheses. The dependent variable is constructed as the (log) change in the share of j-producing firms importing i in year t. $\Delta \ln \chi_{ijt}$ is constructed as described in the text. $\mathcal{Z}_{it}$ denotes the instrument, constructed as described in the text. The sample is restricted to output products with at least 10 firms on average. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

F.6. IV without EU countries

A potential violation of the exclusion restriction might come from the fact that I include some EU countries in the construction of the instrument, namely Denmark, Sweden and the United Kingdom. Due to the integrated EU market, this might introduce a relatively large correlation between French demand and demand in these countries. To check for this, in Table F.6.1 I drop EU countries from the sample of countries that I use in the construction of the instrument. The coefficients are slightly higher than in the baseline, the F-Stat is lower.

Table F.6.1: Extensive margin without EU countries in IV

	OLS			2SLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln \chi_{ijt}$	0.057***	0.056***	0.052***	0.364***	0.388***	0.402***			
	(0.012)	(0.013)	(0.014)	(0.089)	(0.079)	(0.079)			
$\mathcal{Z}_{it}$							0.129***	0.150***	0.173***
							(0.024)	(0.024)	(0.026)
t FE	✓			✓			✓		
$j \times t$ FE		✓	✓		✓	✓		✓	✓
i FE			✓			✓			✓
KP F-Stat				22.9	37.3	37.5			
First stage coeff.				0.354***	0.387***	0.430***			
Obs	31,978	29,158	29,106	31,978	29,158	29,106	31,978	29,158	29,106

* p<0.1, ** p<0.05, *** p<0.01

HS6-clustered standard errors in parentheses. The dependent variable is constructed as the (log) change in the share of j-producing firms importing i in year t. $\Delta \ln \chi_{ijt}$ is constructed as described in the text. $\mathcal{Z}_{it}$ denotes the instrument, constructed as described in the text. The sample of countries for the construction of $\mathcal{Z}_{it}$ only includes non-EU countries. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

F.7. Using all countries

In the construction of prices and import shares, I restricted the sample of origin countries o^* to countries that represented at least 1% of all imports of input i by j-producing firms, and to countries for which the Cobb-Douglas price index was lower than the domestic prices index. As a robustness check, in Table F.7.1 I include all countries, irrespective of their share in total imports or whether the import price index was below the domestic prices index. I also restrict the sample to input-output pairs for which both foreign and domestic prices could be found in all years. In this case, the number of observations is drastically reduced, so are the coefficients. Point estimates remain significant, but at a lower level of confidence. The F-Stat is higher than in the baseline.

Table F.7.1: Extensive margin with *all* countries

	OLS			2SLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln \chi_{ijt}$	0.003	0.004	0.003	0.046**	0.044*	0.050**			
	(0.004)	(0.004)	(0.005)	(0.019)	(0.022)	(0.023)			
$\mathcal{Z}_{it}$							0.050**	0.048**	0.059**
							(0.020)	(0.024)	(0.026)
t FE	✓			✓			✓		
$j \times t$ FE		✓	✓		✓	✓		✓	✓
i FE			✓			✓			✓
KP F-Stat				50.0	59.5	75.7			
First stage coeff.				1.091***	1.093***	1.177***			
Obs	15,786	12,750	12,727	15,786	12,750	12,727	15,786	12,750	12,727

* p<0.1, ** p<0.05, *** p<0.01

HS6-clustered standard errors in parentheses. The dependent variable is constructed as the (log) change in the share of j-producing firms importing i in year t. $\Delta \ln \chi_{ijt}$ is constructed as described in the text. $\mathcal{Z}_{it}$ denotes the instrument, constructed as described in the text. The sample of origin countries for all variables includes *all* countries. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

F.8. Using top n origin countries

As another robustness check, in Table F.8.1 I include the top 5 origin countries in terms of import value by French firms over the period 2009-2019. To check for sensitivity, in Table F.8.2 and Table F.8.3 I use the top 10 and top 20 origins, respectively. Compared to the baseline specification, in all three specifications the number of observations are significantly reduced, so are the coefficients. Point estimates, however, remain highly significant. The F-Stat is again high enough to avoid any problems related to weak instruments.

Table F.8.1: Extensive margin with top 5 origin countries

	OLS			2SLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln \chi_{ijt}$	0.051***	0.053***	0.051***	0.153***	0.201***	0.235***			
	(0.007)	(0.007)	(0.008)	(0.046)	(0.052)	(0.064)			
$\mathcal{Z}_{it}$							0.091***	0.117***	0.134***
							(0.023)	(0.023)	(0.028)
t FE	✓			✓			✓		
$j \times t$ FE		✓	✓		✓	✓		✓	✓
i FE			✓			✓			✓
KP F-Stat				17.9	19.1	16.7			
First stage coeff.				0.595***	0.582***	0.569***			
Obs	17,753	14,361	14,320	17,753	14,361	14,320	17,753	14,361	14,320

* p<0.1, ** p<0.05, *** p<0.01

HS6-clustered standard errors in parentheses. The dependent variable is constructed as the (log) change in the share of j-producing firms importing i in year t. $\Delta \ln \chi_{ijt}$ is constructed as described in the text. $\mathcal{Z}_{it}$ denotes the instrument, constructed as described in the text. The sample of origin countries for all variables includes the top 5 origin countries. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

Table F.8.2: Extensive margin with top 10 origin countries

	OLS			2SLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln \chi_{ijt}$	0.040***	0.045***	0.046***	0.107***	0.128***	0.149***			
	(0.007)	(0.007)	(0.008)	(0.037)	(0.038)	(0.045)			
$\mathcal{Z}_{it}$							0.072***	0.086***	0.103***
							(0.023)	(0.024)	(0.030)
t FE	✓			✓			✓		
$j \times t$ FE		✓	✓		✓	✓		✓	✓
i FE			✓			✓			✓
KP F-Stat				19.7	24.0	24.2			
First stage coeff.				0.675***	0.669***	0.690***			
Obs	15,760	12,327	12,286	15,760	12,327	12,286	15,760	12,327	12,286

* p<0.1, ** p<0.05, *** p<0.01

HS6-clustered standard errors in parentheses. The dependent variable is constructed as the (log) change in the share of j-producing firms importing i in year t. $\Delta \ln \chi_{ijt}$ is constructed as described in the text. $\mathcal{Z}_{it}$ denotes the instrument, constructed as described in the text. The sample of origin countries for all variables includes the top 10 origin countries. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

Table F.8.3: Extensive margin with top 20 origin countries

	OLS			2SLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln \chi_{ijt}$	0.040***	0.041***	0.040***	0.079**	0.112***	0.122***			
	(0.005)	(0.006)	(0.007)	(0.037)	(0.041)	(0.044)			
$\mathcal{Z}_{it}$							0.053**	0.073***	0.089***
							(0.025)	(0.025)	(0.031)
t FE	✓			✓			✓		
$j \times t$ FE		✓	✓		✓	✓		✓	✓
i FE			✓			✓			✓
KP F-Stat				17.7	23.0	23.1			
First stage coeff.				0.671***	0.650***	0.735***			
Obs	14,533	11,093	11,046	14,533	11,093	11,046	14,533	11,093	11,046

* p<0.1, ** p<0.05, *** p<0.01

HS6-clustered standard errors in parentheses. The dependent variable is constructed as the (log) change in the share of j-producing firms importing i in year t. $\Delta \ln \chi_{ijt}$ is constructed as described in the text. $\mathcal{Z}_{it}$ denotes the instrument, constructed as described in the text. The sample of origin countries for all variables includes the top 20 origin countries. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

F.9. Synthetic domestic prices

The difference between foreign and domestic prices can, at times, be very large. To control for whether baseline results are driven by these outliers, in Table F.9.1 I artificially restrict domestic prices to be a maximum of three times their foreign counterpart. The coefficient is now larger than in the baseline table, suggesting that very low outliers in terms of domestic prices are driving the extensive margin down. The F-Stat is lower than in baseline.

Table F.9.1: Extensive margin with synthetic domestic prices ($p_{it}^D <= 3 \times p_{it}^F$)

	OLS			2SLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln \chi_{ijt}$	0.059***	0.057***	0.052***	0.440***	0.464***	0.474***			
	(0.013)	(0.014)	(0.015)	(0.096)	(0.092)	(0.089)			
$\mathcal{Z}\_it$							0.149***	0.176***	0.201***
							(0.025)	(0.025)	(0.027)
t FE	✓			✓			✓		
$j \times t$ FE		✓	✓		✓	✓		✓	✓
i FE			✓			✓			✓
KP F-Stat				25.1	39.7	41.0			
First stage coeff.				0.338***	0.380***	0.423***			
Obs	32,042	29,233	29,181	32,042	29,233	29,181	32,042	29,233	29,181

* p<0.1, ** p<0.05, *** p<0.01

HS6-clustered standard errors in parentheses. The dependent variable is constructed as the (log) change in the share of j-producing firms importing i in year t. $\Delta \ln \chi_{ijt}$ is constructed as described in the text, with domestic prices restricted to be a maximum of 3 times foreign prices. $\mathcal{Z}_{it}$ denotes the instrument, constructed as described in the text. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

G. Production function estimation

The estimation of productivities at the firm-level relies on standard methodologies of production function estimation. In particular, in order to estimate production elasticities I will rely on the procedure by Ackerberg, Caves, and Frazer (2015), which itself builds on Olley and Pakes (1996) and Levinsohn and Petrin (2003). In this section I will first describe the methodology employed to estimate production functions. I will then describe how I construct industry-level input deflators and how I use firm-level productivities to estimate the Pareto-shape parameters. Finally, I will show the main results of the estimation.

G.1. Methodology

In line with the theoretical part of this paper, I will estimate a Cobb-Douglas production function composed of intermediates, labor, and capital. For comparison, I also estimate a translog production function. The main challenges in estimating production functions are the presence of both a simultaneity and a selection bias due to unobserved productivity. The former designates the fact that producers' input choices are likely to be correlated with their productivity levels, which leads to a correlation between the explanatory variables (factor input) and the error term (productivity). The latter describes the bias that arises due to the exit of low-productivity firms. Both biases will be addressed in the methodology.

We start by writing the production function in log form:

$$q_{jt} = f_j(x_{jt}; \beta) + \varphi_{jt} + \epsilon_{jt}, \tag{G.1}$$

where φ_{jt} denotes firm-level productivity and ϵ_{jt} denotes a standard error term. The variables q_{jt} and x_{jt} denote output and inputs, respectively, all of which are written in terms of quantities. Following the procedure by Burstein et al. (2025), I construct firm-level quantities by deflating firm-level revenue by a firm-level price index. Because multi-product firms produce products in different units, they construct a revenue-weighted average of standardized prices, consisting of dividing firm-level prices by the quantity-weighted average price of the same product across all firms in the same year. This procedure addresses the often voiced concerns regarding not observed quantities (Barrows, Ollivier, & Reshef, 2025). To obtain input quantities, I deflate balance sheet values by 5-digit industry-specific deflators. The construction of the deflators is described below.[37]

The main challenge, giving rise to the afore-mentioned biases, is related to the (by the econometrician) unobserved productivity. To deal with this issue, I follow the literature and adopt a control function approach, based on a static input demand equation. Consider the following materials demand function:

$$m_{jt} = m_j \left(\varphi_{jt}, k_{jt}, l_{jt}, \mathbf{ms}_{jt}, \text{EXP}_{jt}\right), \tag{G.2}$$

where $\mathbf{ms}_{jt}$ denotes a set of market shares, and where EXP_{jt} denotes the export status of a firm. I will use both a firm's overall market share in year t, and its industry-specific market share. The idea behind Equation G.2 is that the demand for materials will depend on productivity φ_{jt}, the demand for the other factors of production k_{jt} and l_{jt}, and on a set of materials demand shifters, such as a firm's market share and its export status. Finally, inverting Equation G.2, we obtain the control function for productivity as:

$$\varphi_{jt} = h_j \left(m_{jt}, k_{jt}, l_{jt}, \mathbf{ms}_{jt}, \text{EXP}_{jt}\right). \tag{G.3}$$

Finally, the identification of input elasticities relies on a GMM procedure. Moments are based on the law of motion in productivity, which takes the form of an AR(1)-process:

$$\varphi_{jt} = g\left(\omega_{jt-1}, EXP_{jt-1}\right) + \xi_{jt}, \tag{G.4}$$

implying that productivity depends on its lag and on the lagged export status of the firm, reflecting the idea that exporting enhances productivity (De Loecker, 2007; Bustos, 2011). Plugging the expression for unobserved productivity into the production function, we obtain

$$q_{jt} = \phi_t \left(m_{jt}, k_{jt}, l_{jt}, \mathbf{ms}_{jt}, \text{EXP}_{jt}\right) + \epsilon_{jt}. \tag{G.5}$$

[37]I choose to deflate balance sheet values because of two reasons: (i) while I do observe physical output quantities for *EAP*-firms, I do not observe physical input quantities, and (ii) as production function estimations often necessitate a lot of statistical power, I rely on *Fare* to estimate production functions at the 5-digit industry level.

By non-parametrically computing q_{jt} on the arguments of $\phi_t(\cdot)$ in a first stage, we can purge output quantities from unanticipated shocks and/or measurement error.

Output elasticities are then obtained by constructing moments of the productivity shock. Specifically, we assume the following moment conditions:

$$E\left(\xi_{jt}(\beta)\begin{pmatrix} v_{jt-1} \\ k_{jt} \\ l_{jt} \\ \mathbf{ms}_{jt-1} \\ \text{EXP}_{jt-1} \end{pmatrix}\right) = 0, \tag{G.6}$$

i.e. the shock in productivity is uncorrelated with the dynamic inputs (capital and labor) at time t, with the lagged static input (materials), and with lagged market shares and export dummies.

After the estimation of input coefficients using the GMM method, we can construct the *predicted* output based on the production function estimates. Firm-level productivity will then simply be defined as the ratio between actual output (purged of ϵ_{jt}) and predicted output:

$$\varphi_{jt} = \frac{\hat{\phi}_{jt}}{\tilde{q}_{jt}}, \tag{G.7}$$

where $\hat{\phi}_{jt}$ denotes the output purged from measurement error (first stage) and $\tilde{q}_{jt}$ denotes the predicted output based on input coefficients. I take the average of φ_{jt} across years to obtain a single firm-level estimate of productivity.

G.2. Construction of input deflators

I construct input deflators based on domestic prices series, import price series, the product mix of a given industry, and the input requirements $\mathcal{I}_{ij}$. To construct domestic and import prices, I start from the product-specific series of sales-weighted average (log) prices changes ($\Delta \ln P^D_{it}$). Specifically, $\Delta \ln P^D_{it}$ is constructed as the weighted average (log) price change of domestic producers of i, with weights constructed using lagged sales, and where sales-share$_{jft}$ is the share of output j in total sales of firm f. Import prices ($\Delta \ln P^F_{it}$) are constructed accordingly, using sales-weighted average import prices and where each product×origin×year triplet denotes an individual observation. I only retain products with information in all years. The domestic and import deflators for input i at time t and with base year 2009 is defined as:

$$\mathcal{P}^D_{i;t,2009} = \frac{P^D_{i,t}}{P^D_{i,2009}} \qquad \mathcal{P}^F_{j;t,2009} = \frac{P^F_{i,t}}{P^F_{i,2009}}.$$

Re-writing in logs, it becomes evident that $\mathcal{P}^D_{i;t,2009}$ and $\mathcal{P}^F_{i;t,2009}$ for any given year can be obtained from the sum of year-on-year changes between t and 2009, i.e. from the following formula:

$$\mathcal{P}^D_{i;t,2009} = e^{\sum_{t=2009}^{T-1} \Delta \ln P^D_{i,t+1,t}} \qquad \mathcal{P}^F_{i;t,2009} = e^{\sum_{t=2009}^{T-1} \Delta \ln P^F_{i,t+1,t}}.$$

Note that this only works for products present in all years. Finally, taking the share of product j in the sales of firms in industry J, we can construct an industry-specific deflator as the weighted average of $\mathcal{P}^{Output}_{j;t,2009}$ across all j within J, with weights summing to 1.

To construct deflator series for both domestic and foreign inputs at the output level, I calculate the weighted average of $\mathcal{P}^D_{i;t,2009}$ and $\mathcal{P}^{Import}_{i;t,2009}$, using input requirements $\mathcal{I}_{ij}$ as weights. For a given output product j, both components are thus constructed as:

$$\mathcal{P}^{Input,D}_{j;t,2009} = \sum_i \mathcal{I}_{ij} \mathcal{P}^D_{i;t,2009} \qquad \mathcal{P}^F_{j;t,2009} = \sum_i \mathcal{I}_{ij} \mathcal{P}^{Import}_{i;t,2009}.$$

Note that, by construction, $\sum_i \mathcal{I}_{ij} = 1$. To obtain input price deflators at the 5-digit industry level, I aggregate across the outputs of firms within industry J, using again a sales-weighted average.

Using balance sheet information, I construct the overall share of imports in the expenditure on intermediates for firms in industry J across years. The final input deflator will then simply be the weighted average between the domestic and foreign input deflators, where weights are the overall share of imports and domestic input expenditure of firms in a given industry.

G.3. Obtaining a

Armed with firm-level productivities, I follow Gabaix and Ibragimov (2011) to estimate the Pareto-shape parameters a by 5-digit industry. Their procedure builds on the classical log-log rank-size equations, suggesting that the bias resulting from small samples can be corrected by a simple correction that consists of using $\log(\text{Rank} - 1/2)$. Hence, I will estimate the following equation by 5-digit industries J:

$$\log(\text{Rank} - 1/2) = c + a\log(\varphi_j). \tag{G.8}$$

G.4. Results

Figure G.1 shows the distribution of the estimated a parameters, when using either a Cobb-Douglas production function or a translog. Table G.4.1 shows the underlying estimates of the production function.

Figure G.1: Distribution of a

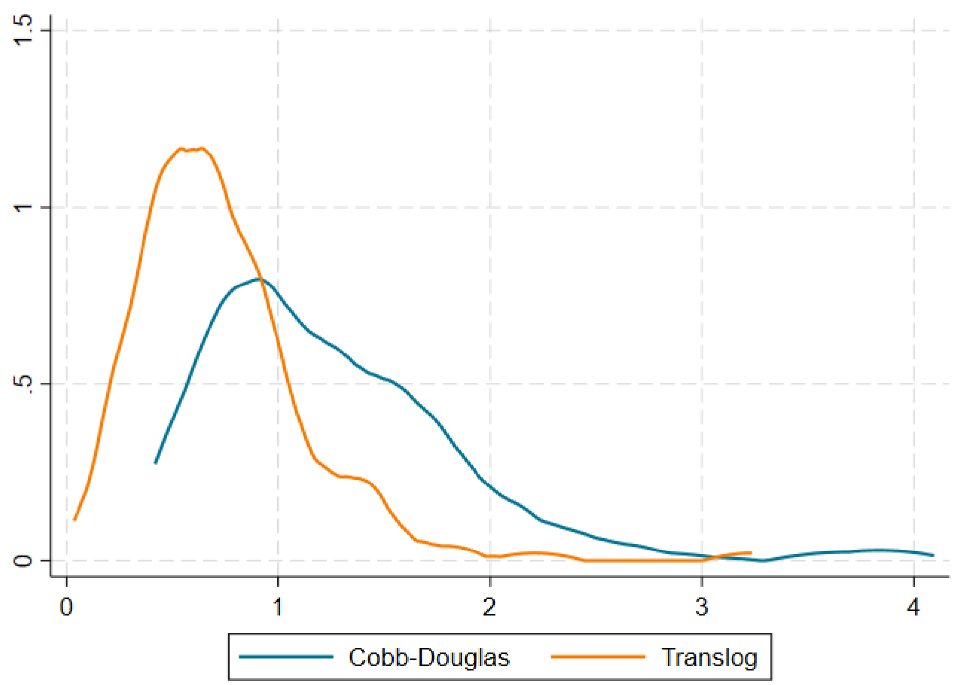


Table G.4.1: Production function estimates

Cobb-Douglas						
	Nb. obs.	Mean	25th per.	50th per.	75th per.	95th per.
Elast. Materials	149	0.494	0.386	0.488	0.584	0.845
Elast. Capital	149	0.093	0.031	0.098	0.172	0.351
Elast. Labor	149	0.404	0.319	0.435	0.517	0.730
Returns to scale	149	0.990	0.941	0.989	1.043	1.152
Translog						
	Nb. obs.	Mean	25th per.	50th per.	75th per.	95th per.
Elast. Materials	159,014	0.462	0.364	0.453	0.555	0.822
Elast. Capital	159,014	0.119	0.012	0.100	0.181	0.379
Elast. Labor	159,014	0.423	0.272	0.419	0.538	0.887
Returns to scale	159,014	1.004	0.879	0.969	1.059	1.300

H. Extension: Non-constant returns to scale

H.1. Marginal cost under non-constant returns to scale

The theoretical model in section 3 assumes constant returns to scale in the Cobb-Douglas production function. In this section I will relax that assumption to allow for arbitrary returns to scale. Under non-constant returns to scale, marginal costs become:

$$c_j = \varphi_j^{-\frac{1}{\kappa}} q_j^{\frac{1-\kappa}{\kappa}} \left(\frac{w}{\gamma_l}\right)^{\frac{\gamma_l}{\kappa}} \prod_{i=1}^{n} \left(\frac{p_i}{\gamma_i}\right)^{\frac{\gamma_i}{\kappa}} \tag{H.1}$$

where $\kappa = \sum_i \gamma_i$ indicates the returns to scale parameter. As before, we can derive the marginal cost savings potential of importing as

$$\chi_i^{RTS} = 1 - \left(\frac{p_i^F}{p_i^D}\right)^{\frac{\gamma_i}{\kappa}}. \tag{H.2}$$

The rest of the model is unaffected by the returns to scale parameter, i.e. all insights apply up to the change in χ_i.

H.2. Implementation and results

To test the implications of non-constant returns to scale, I will augment the baseline measure of χ_i — constructed as described in section 5 — using the industry-specific returns-to-scale parameter from the production function estimation, described above. I then implement the same procedure as before to estimate the extensive margin and to obtain the demand elasticity at cutoff.

The result of the extensive margin estimation with non-constant returns to scale is given in Table H.2.1 below. It appears that the introduction of non-constant returns to scale slightly increases the coefficient, with a very similar F-Stat. Overall, these results suggest that non-constant returns to scale only have a very limited impact on the extensive margin in the French context.

Table H.2.1: Extensive margin with non-constant returns to scale

	OLS			2SLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln \chi_{ijt}^{RTS}$	0.060***	0.058***	0.054***	0.365***	0.387***	0.402***			
	(0.012)	(0.014)	(0.015)	(0.081)	(0.077)	(0.075)			
$\mathcal{Z}\_it$							0.156***	0.182***	0.208***
							(0.027)	(0.027)	(0.029)
t FE	✓			✓			✓		
$j \times t$ FE		✓	✓		✓	✓		✓	✓
i FE			✓			✓			✓
KP F-Stat				28.9	45.8	45.3			
First stage coeff.				0.427***	0.472***	0.519***			
Obs	29,308	26,930	26,865	29,308	26,930	26,865	29,308	26,930	26,865

* p<0.1, ** p<0.05, *** p<0.01

HS6-clustered standard errors in parentheses. The dependent variable is constructed as the (log) change in the share of j-producing firms importing i in year t. $\Delta \ln \chi_{ijt}^{RTS}$ is constructed as described in the text, with non-constant returns to scale. $\mathcal{Z}_{it}$ denotes the instrument, constructed as described in the text. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

I. Pass-through regressions

The estimation of the pass-through coefficients relies on a shift-share IV strategy akin to Amiti et al. (2019). In the following I will first describe the construction of the different variables (marginal costs and competitors' prices), then describe the estimation equation employed to analyze the data, and finally introduce the instrument and discuss identification.

I.1. Average costs

Firm-level average costs, used here as a proxy for marginal costs, are constructed using the same method described in the main text (subsubsection 5.4.1), i.e. as:

$$\begin{aligned}\Delta \ln ac_{ft} &= \Delta \ln vc_{ft} - \Delta \ln y_{ft} \\ &= \Delta \ln vc_{ft} - \left(\Delta \ln r_{ft} - \Delta \ln p_{ft}\right),\end{aligned}$$

where vc_{ft} denotes firm f's expenditures on variable costs, r_{ft} represents its revenue (both taken from balance sheets) and $\Delta \ln p_{ft}$ is a firm-level output-price index, constructed as a sales-weighted aggregation of output prices (irrespective of domestic or export sales). I use lagged sales for the construction of weights.

I.2. Competitors' prices

As shown in the theory section, firms not only react to their own marginal costs, but also to the price changes of their competitors. To account for this, I construct an index of the price changes of competitors including both domestic and foreign competitors. Competitors prices for output j are aggregated using market shares as weights, again using lagged sales. The competitor price index for firm f selling good j is, thus, constructed as:

$$\Delta P_{jft} = \sum_{k \in D_j} \frac{s_{kt}}{1 - s_{ft}} \Delta \ln p_{kt} + \sum_{k \in F_j} \frac{s_{kt}}{1 - s_{ft}} \Delta \ln p_{kt}, \tag{I.1}$$

where D_j and F_j denote the set of domestic and foreign competitors of firm f producing good j, respectively. The entire universe of domestically active firms selling good j can thus be written as $A_j = \{D_j, F_j, f\}$. Moreover, s_{kt} denotes the (lagged) market shares of a firm k.[38]

I.3. Estimation equation

I will employ the following equation to test the intensive margin on French manufacturers:

$$\Delta \ln p_{jft} = \beta_1 \Delta \ln ac_{ft} + \beta_2 \Delta P_{jft} + \eta_J + \eta_t + \varepsilon_{fjt}, \tag{I.2}$$

where $\Delta \ln p_{jft}$ denotes the (log) change in the price of output j by firm f, where $\Delta \ln ac_f$ and ΔP_{jft} denote the variables as described above, and where η_J, η_t denote industry j and year t fixed effects, respectively.

I.4. Instruments and identification

Average costs A potential issue of endogeneity related to the empirical setup is due to unobserved market power: changes in market power could explain both lower input prices and larger increases in markups. For instance, Morlacco (2021) reveals the importance of input market power for French firms. This input market power could, intuitively, be highly correlated to output market power and, thus, affect both the price at which a firm buys its intermediate imports and the markup it charges on its products, biasing regressions.

Thus, to ensure the identification of pass-through, I construct two instrumental variables for the average costs: the domestic and the foreign component. For the domestic component, I construct an instrument based on the re-weighted input coefficients $\tilde{\mathcal{I}}_{ij}$ defined above. The instrument takes the following form:

$$\Delta \ln ac_{ft}^{IV,D} = \sum_j \text{sales-share}_{jft} \times \left(\sum_i \tilde{\mathcal{I}}_{ij} \times \Delta \ln P_{it}^D \right),$$

where $\Delta \ln P_{it}^D$ denotes the weighted average (log) price change of domestic producers of i, with weights constructed using lagged sales, and where sales-share_{jft} is the share of

[38] To treat outliers, I follow Amiti et al. (2019) and only include firm-products (including imports) for which the ratio of prices to their lags did not exceed 3 and was not lower than $1/3$.

output j in total sales of firm f (as in Appendix G). I use lagged values when constructing sales-share$_{jft}$.The final instrument is multiplied by the share of raw materials in total variable costs for firm f.

For the instrument of the foreign component of marginal costs, I rely on firm-level customs data. In practice, I construct a weighted sum of aggregate (log) price changes across all imported inputs. The instrument is, hence, constructed as:

$$\Delta \ln ac_{ft}^{IV,F} = \sum_{io} \text{import-share}_{ioft} \times \Delta \ln P_{iot}^{F},$$

where $\Delta \ln P_{iot}^{F}$ denotes the weighted average (log) price change of input i, imported from origin o across all French imports, and where import-share$_{ioft}$ denotes the share of an $i \times o$-pair in total imports of firm f at time t. I again use lag import values in the construction of the variable import-share$_{ioft}$. The final instrument is again re-weighted by the share of raw materials in total variable costs for firm f.

Competitors' prices There might also be an endogeneity problem concerning the price index of competitors due to reverse causality: because of demand complementarities, competitor firms will react to the price adjustment of firm f in t in the same way that f reacts to the prices of competitors. Hence, to assure the exogeneity of the competitors' price index, I construct the weighted average of marginal costs of domestic competitors, using the same weights as for the price index:

$$\Delta \ln AC_{-fi}^{IV} = \sum_{k \in D_j} \frac{s_{kt}}{1 - s_{kt}} \Delta \ln ac_k$$

The identification relies on the assumption that price changes by f do not induce changes in marginal costs by its competitors.

I.5. Regressing marginal costs component on $\Delta \ln ac_{ft}$

To assess to what extent $\Delta \ln ac_{ft}$ represents actual marginal costs, I project $\Delta \ln ac_{ft}$ on the foreign marginal cost instrument $\Delta \ln ac_{ft}^{IV,F}$, arguably a much more precise measure of marginal costs. Columns (1) and (2) in Table I.5.1 show the results when using the raw measure of $\Delta \ln ac_{ft}^{IV,F}$. Columns (3) to (6) then re-weight $\Delta \ln ac_{ft}$ first by the share of imports in raw material expenses, and then by the share of raw materials in total variable costs. I winsorize the re-weighted share at either the 1% or the 5% yearly level. I include either year, or both year and input fixed effects. The highly significant coefficient, close to 1 in the last two columns, suggests that $\Delta \ln ac_{ft}$ is indeed a fairly good representation of marginal costs. However, the quite poor R^2 suggests that import prices only explain a fraction of the variation in $\Delta \ln ac_{ft}$.

Table I.5.1: Project $\Delta \ln ac_{ft}$ on $\Delta \ln ac_{ft}^{IV,F}$

	Raw variable		Re-wght, wins. 1%		Re-wght, wins. 5%	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln ac_{ft}^{IV,F}$	0.147***	0.146***	0.852***	0.839***	1.088***	1.071***
	(0.012)	(0.012)	(0.051)	(0.051)	(0.070)	(0.071)
t FE	✓	✓	✓	✓	✓	✓
Ind. FE		✓		✓		✓
R^2	0.010	0.014	0.013	0.016	0.012	0.015
Obs	82,447	82,447	82,447	82,447	82,447	82,447

* p<0.1, ** p<0.05, *** p<0.01

Output-clustered standard errors in parentheses. The dependent variable is $\Delta \ln ac_{ft}$, constructed as described in the text. $\Delta \ln ac_{ft}^{IV,F}$ denotes the foreign component of marginal cost changes. Again refer to the text for details on construction.

Moreover, having established that $\Delta \ln ac_{ft}$ is a viable representation of marginal costs, we can assess the accuracy of the domestic marginal costs component $\Delta \ln ac_{ft}^{IV,D}$. Remember, while the foreign marginal cost component relies on directly observable import information at the firm level, the domestic marginal cost shifter is constructed based only on output information, paired with constructed input coefficients γ_{ij}. As before, columns (1) and (2) in Table I.5.2 show the results when using the raw measure of $\Delta \ln ac_{ft}^{IV,D}$, while columns (3) to (6) use a winsorized and re-weighted (as above, but with domestic share instead of the import share) version of the domestic instrument. The coefficient in column (5) and (6), close to 1 and highly significant, suggests that the instrument $\Delta \ln ac_{ft}^{IV,D}$ indeed captures well changes in the domestic marginal costs component. Nonetheless, the poor R^2, as before, suggests that $\Delta \ln ac_{ft}$ is influenced my many other factors.

Table I.5.2: Project $\Delta \ln ac_{ft}$ on $\Delta \ln ac_{ft}^{IV,D}$

	Raw variable		Re-wght, wins. 1%		Re-wght, wins. 5%	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln ac_{ft}^{IV,D}$	0.307***	0.309***	0.763***	0.770***	1.045***	1.054***
	(0.060)	(0.058)	(0.154)	(0.149)	(0.219)	(0.216)
t FE	✓	✓	✓	✓	✓	✓
Ind. FE		✓		✓		✓
R^2	0.010	0.014	0.011	0.014	0.011	0.015
Obs	151,837	151,837	151,837	151,837	151,837	151,837

* p<0.1, ** p<0.05, *** p<0.01

Output-clustered standard errors in parentheses. The dependent variable is $\Delta \ln ac_{ft}$, constructed as described in the text. $\Delta \ln ac_{ft}^{IV,F}$ denotes the domestic component of marginal cost changes. Again refer to the text for details on construction.

I.6. Results of pass-through regressions

I start by showing the results for the intensive margin in Table I.6.1. Columns 1 and 2 report the OLS results, while the IV results are shown in columns 3 and 4. For completeness I also report the reduced form results in columns 5 and 6. As indicated in the table, regressions include either only year, or both year and industry fixed effects. All regressions are weighted by the lag of the log of firm-product level real domestic sales. Standard errors are clustered at the output-level. The corresponding first stage results are displayed in Table I.6.2.

As we can see, firms react significantly to both their own foreign marginal cost shock and to the price changes by their competitors. Importantly, the coefficient on marginal cost changes is significantly lower than one, suggesting imperfect pass-through: following a 10% decrease in marginal costs, prices only decrease by 5.6%, translating into an increase in the firms' markup. Moreover, firms not only adjust prices following reductions in their own marginal costs but also following price adjustments by competitors (themselves stemming from marginal cost reductions). Results in column (4) suggest that firms reduce their own price by 5.1% following a 10% decrease in the price of competitors.

Table I.6.1: Pass-through regression - Second stage

	OLS		2SLS		Reduced form	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln ac_{ft}$	0.568***	0.568***	0.556***	0.564***		
	(0.010)	(0.010)	(0.064)	(0.065)		
$\Delta \ln P_{it}$	0.420***	0.421***	0.515***	0.513***		
	(0.030)	(0.030)	(0.056)	(0.057)		
$\Delta \ln ac_{ft}^{IV,D}$					0.158***	0.158***
					(0.030)	(0.030)
$\Delta \ln ac_{ft}^{IV,F}$					0.022	0.022
					(0.015)	(0.016)
$\Delta \ln AC_{-ft}^{IV}$					0.643***	0.643***
					(0.058)	(0.057)
t FE	✓	✓	✓	✓	✓	✓
Ind. FE		✓		✓		✓
KP F-Stat			58.2	58.9		
Obs	146,655	146,655	146,655	146,655	146,655	146,655

* p<0.1, ** p<0.05, *** p<0.01

Output-clustered standard errors in parentheses. The dependent variable is the log price change of product j, sold by firm f at time t ($\Delta \ln p_{jft}$). $\Delta \ln ac_{ft}$ denotes the (log) changes of average costs, constructed as described in the text. ΔP_{jft} denotes the change in the competitors' price index. $\Delta \ln ac_{ft}^{IV,D}$, $\Delta \ln ac_{ft}^{IV,F}$ and $\Delta \ln AC_{-fi}^{IV}$ are the instruments, and denote the change in the domestic marginal cost component, the foreign marginal cost component, and the sales-weighted average of competitors' marginal cost changes, respectively. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1% level. Regressions are weighted by log real domestic sales.

Table I.6.2: Pass-through regression - First stage

	AC		P	
	(1)	(2)	(3)	(4)
$\Delta \ln ac_{ft}^{IV,D}$	0.185***	0.189***	0.009	0.009
	(0.030)	(0.031)	(0.021)	(0.019)
$\Delta \ln ac_{ft}^{IV,F}$	0.145***	0.140***	0.002	0.000
	(0.014)	(0.014)	(0.009)	(0.010)
$\Delta \ln AC_{-ft}^{IV}$	0.517***	0.512***	0.695***	0.693***
	(0.042)	(0.042)	(0.046)	(0.046)
t FE	✓	✓	✓	✓
Ind. FE		✓		✓
SW F-Stat	92.2	92.6	89.6	90.1
Obs	146,655	146,655	146,655	146,655

* p<0.1, ** p<0.05, *** p<0.01

Output-clustered standard errors in parentheses. The dependent variable in columns (1) and (2) is $\Delta \ln ac_{ft}$, constructed as described in the text. For columns (3) and (4), the dependent variables is the change in the competitors' price index (ΔP_{jft}). $\Delta \ln ac_{ft}^{IV,D}$, $\Delta \ln ac_{ft}^{IV,F}$ and $\Delta \ln AC_{-fi}^{IV}$ are the instruments, and denote the change in the domestic marginal cost component, the foreign marginal cost component, and the sales-weighted average of competitors' marginal cost changes, respectively. The F-Stat denotes the Sanderson-Windmeijer conditional F-stat. All variables are winsorized at the 1% level. Regressions are weighted by log real domestic sales.

I.7. Heterogeneous pass-through

Similar to Amiti et al. (2019), I will test for heterogeneity in pass-through rates. In contrast, however, instead of concentrating on the size distribution, I will, in line with theory, look at the pass-through rates along the productivity distribution. Productivities are estimated as described in Appendix G. Specifically, I will implement an interaction between the relative productivity of firm f producing good j ($\tilde{\varphi}_{fj} = \varphi_f/\bar{\varphi}_j$) and the log change in average costs in Equation I.2:

$$\Delta \ln p_{jft} = \beta_1 \Delta \ln ac_{ft} + \beta_2 \Delta \ln ac_{ft} \times \tilde{\varphi}_{fj} + \beta_3 \ln \tilde{\varphi}_{fj} + \beta_4 \Delta P_{jft} + \eta_J + \eta_t + \varepsilon_{fjt}. \tag{I.3}$$

Note that for multi-product firm we thus have multiple relative productivities, depending on which product we consider. The vector of $\tilde{\varphi}_{fj}$ is very mildly winsorized at the top (0.05%). Results are given in Table I.7.1 below. The first stage results are given in Table I.7.2.

Table I.7.1: Heterogeneous pass-through by productivity

	OLS		2SLS	
	(1)	(2)	(3)	(4)
$\Delta \ln ac_{ft}$	0.579***	0.579***	0.602***	0.610***
	(0.011)	(0.011)	(0.064)	(0.065)
$\Delta \ln ac_{ft} \times \tilde{\varphi}_{fj}$	-0.012***	-0.012***	-0.039***	-0.038***
	(0.005)	(0.005)	(0.015)	(0.015)
$\Delta \ln P_{it}$	0.419***	0.421***	0.504***	0.502***
	(0.030)	(0.030)	(0.055)	(0.056)
t FE	✓	✓	✓	✓
Ind. FE		✓		✓
KP F-Stat			35.1	35.4
Obs	146,655	146,655	146,655	146,655

* p<0.1, ** p<0.05, *** p<0.01

Output-clustered standard errors in parentheses. The dependent variable is the log price change of product j, sold by firm f at time t ($\Delta \ln p_{jft}$). $\Delta \ln ac_{ft}$ denotes the (log) changes of average costs, constructed as described in the text. ΔP_{jft} denotes the change in the competitors' price index. $\Delta \ln ac_{ft}^{IV,D}$, $\Delta \ln ac_{ft}^{IV,F}$ and $\Delta \ln AC_{-fi}^{IV}$ are the instruments, and denote the change in the domestic marginal cost component, the foreign marginal cost component, and the sales-weighted average of competitors' marginal cost changes, respectively. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1% level. Regressions are weighted by log real domestic sales.

I will use these heterogeneity results paired with the distribution of relative productivities to obtain pass-through rates at different points of the productivity distribution for

Table I.7.2: Heterogeneous pass-through by productivity - First stage

	AC		AC $\times\tilde{\varphi}$		P	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln ac_{ft}^{IV,D}$	0.189***	0.193***	-0.297**	-0.297**	0.001	0.001
	(0.034)	(0.035)	(0.141)	(0.142)	(0.020)	(0.019)
$\Delta \ln ac_{ft}^{IV,D} \times \tilde{\varphi}_{fj}$	-0.004	-0.005	0.514***	0.517***	0.008*	0.008*
	(0.012)	(0.012)	(0.158)	(0.159)	(0.004)	(0.004)
$\Delta \ln ac_{ft}^{IV,F}$	0.139***	0.134***	-0.104	-0.110	-0.002	-0.003
	(0.016)	(0.016)	(0.185)	(0.185)	(0.010)	(0.010)
$\Delta \ln ac_{ft}^{IV,F} \times \tilde{\varphi}_{fj}$	0.007	0.007	0.258	0.257	0.004*	0.004*
	(0.008)	(0.008)	(0.213)	(0.213)	(0.002)	(0.002)
$\Delta \ln AC_{-ft}^{IV}$	0.517***	0.513***	0.421***	0.417***	0.695***	0.693***
	(0.042)	(0.042)	(0.050)	(0.050)	(0.046)	(0.046)
$\tilde{\varphi}_{fj}$	-0.002***	-0.001***	-0.009	-0.009	-0.000**	-0.000*
	(0.000)	(0.000)	(0.006)	(0.006)	(0.000)	(0.000)
t FE	✓	✓	✓	✓	✓	✓
Ind. FE		✓		✓		✓
SW F-Stat	62.7	63.0	7.9	8.0	60.1	60.3
Obs	146,655	146,655	146,655	146,655	146,655	146,655

* p<0.1, ** p<0.05, *** p<0.01

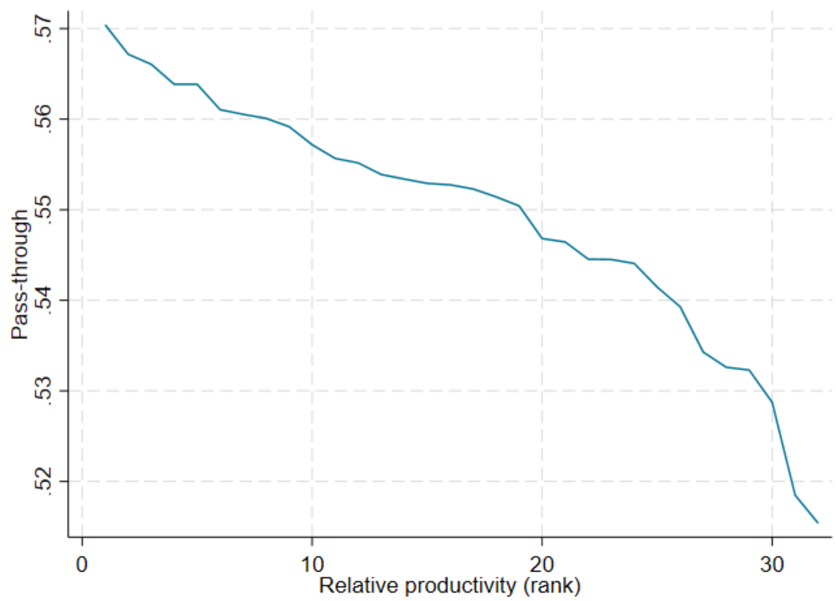
Output-clustered standard errors in parentheses. SW F-Stat denotes the Sanderson-Windmeijer conditional F-stat. All variables are winsorized at the 1% level. Regressions are weighted by log real domestic sales.

each individual product. The pass-through along the productivity distribution is simply calculated as $\beta_1 + \beta_2\tilde{\varphi}_{fj}$. Inspired by Baqaee et al. (2023), I will then use the resulting pass-through distribution to calibrate the Klenow-Willis demand system. To avoid non-sensible pass-through rates (i.e. $\Psi_j < 0$), I marginally winsorize the series of pass-through rates at the bottom 0.5% level.

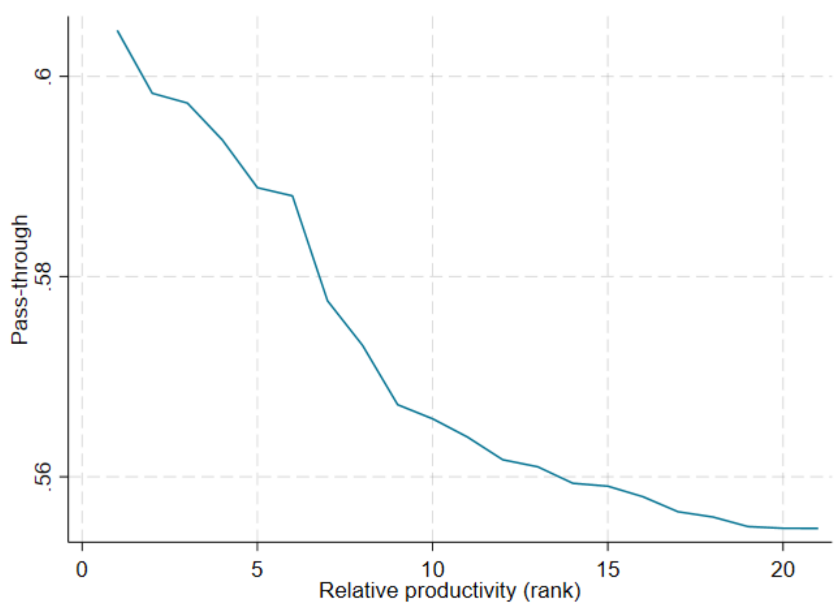
Figure 3 in the main text shows the distribution of pass-through along the product-wise distribution of relative productivities. Both graphs display a very steep and sudden decrease towards the end of the distribution, suggesting that these products are dominated by one or two very productive firms. As a counter example, below I show two other products that display a much more homogeneous distribution of productivities.

Figure I.1: Pass-through by relative productivity

(a) "Unglazed ceramic and stoneware flags and paving, hearth or wall tiles" (Prodcom: 23.31.10.50)



(b) "Wooden coffins" (Prodcom: 32.99.59.90)



J. Quantitative model with Kimball demand

J.1. Algebra

In this section I will show how the different components of the extensive margin are derived assuming a standard Kimball demand system, using the functional form introduced by Klenow and Willis (2016). Assume that there is a final good producer that assembles the goods in sector J according to a Kimball aggregator:

$$\int_0^1 \Upsilon\left(\frac{q_j}{Q}\right) dj = 1, \tag{J.1}$$

such that $\Upsilon(1) = 1$, $\Upsilon'(.) > 0$ and $\Upsilon''(.) < 0$. Final good producers are perfectly competitive, take prices as given and maximize $P^Q Q - \int_0^1 p_j q_j dj$. From the maximization problem of the final good producer we obtain the following first order conditions:

$$P^Q - \lambda_j \left(\int_0^1 \Upsilon'\left(\frac{q_j}{Q}\right)\frac{-q_j}{Q^2} dj\right) = 0$$
$$-p_j - \lambda_j \Upsilon'\left(\frac{q_j}{Q}\right)\frac{1}{Q} = 0$$

which can be used to derive:

$$p_j = \Upsilon'\left(\frac{q_j}{Q}\right)\frac{P^Q}{\int_0^1 \Upsilon'\left(\frac{q_j}{Q}\right)\frac{q_j}{Q} dj}$$

Define $D = \int_0^1 \Upsilon'\left(\frac{q_i}{Q_t}\right)\frac{q_j}{Q} dj$ and $\mathcal{P} = \frac{P^Q}{D}$ to obtain:

$$p_j = \Upsilon'\left(\frac{q_j}{Q}\right)\mathcal{P} \tag{J.2}$$

Because final good producers are perfectly competitive, we obtain:

$$\pi^{FG} = 0 \Rightarrow P^Q Q - \int_0^1 p_j q_j dj = 0$$

such that

$$P^Q = \int_0^1 p_j \frac{q_j}{Q} dj$$

From the FOC, we obtain the following demand function:

$$\frac{q_j}{Q} = \Theta\left(\frac{p_j}{\mathcal{P}}\right), \tag{J.3}$$

where $\Theta = \Upsilon'^{-1}$.

From this we can derive the price elasticity of demand as

$$\frac{\partial \ln q_j}{\partial \ln p_j} = \frac{p_j}{\mathcal{P}} \frac{1}{\Theta\left(\frac{p_j}{\mathcal{P}}\right)} \Theta'\left(\frac{p_j}{\mathcal{P}}\right). \tag{J.4}$$

Using $\Theta' = (\Upsilon'^{-1})' = \frac{1}{\Upsilon''(\Upsilon'^{-1})}$, and replacing $\frac{p_j}{\mathcal{P}} = \Upsilon'\left(\frac{q_j}{Q}\right)$ and $\Theta\left(\frac{p_j}{\mathcal{P}}\right) = \frac{q_j}{Q}$, we get:

$$\frac{\partial \ln q_j}{\partial \ln p_j} = \Upsilon'\left(\frac{q_j}{Q}\right) \frac{1}{\frac{q_j}{Q}} \frac{1}{\Upsilon''\left(\Upsilon'^{-1}\right)},$$

where $\Upsilon'^{-1}\left(\frac{p_j}{\mathcal{P}}\right) = \frac{q_j}{Q}$, such that:

$$\frac{\partial \ln q_j}{\partial \ln p_j} = \frac{\Upsilon'\left(\frac{q_j}{Q}\right)}{\frac{q_j}{Q}} \frac{1}{\Upsilon''\left(\Upsilon'^{-1}\right)} = -\theta\left(\frac{q_j}{Q}\right), \tag{J.5}$$

Klenow and Willis (2016) functional form In the following, we will assume the functional form for Υ by Klenow and Willis (2016):

$$\Upsilon(x) = 1 + (\bar{\varepsilon} - 1)\exp\left(\frac{1}{\bar{\sigma}}\right)\bar{\sigma}^{(\bar{\varepsilon}/\bar{\sigma})-1}\left(\Gamma\left(\frac{\bar{\varepsilon}}{\bar{\sigma}}, \frac{1}{\bar{\sigma}}\right) - \Gamma\left(\frac{\bar{\varepsilon}}{\bar{\sigma}}, \frac{x^{\bar{\sigma}/\bar{\varepsilon}}}{\bar{\sigma}}\right)\right), \tag{J.6}$$

where $\bar{\varepsilon}$ and $\bar{\sigma}$ are the parameters that will govern the demand system, and represent the values of the elasticity of demand and the superelasticity of demand at any symmetric equilibrium, respectively. Γ denotes the incomplete gamma function:

$$\Gamma(u, z) = \int_z^\infty s^{u-1} e^{-s} ds \tag{J.7}$$

Note, that in the original version by Klenow and Willis (2016) $\varepsilon = \theta$ and $\bar{\sigma} = \varepsilon$.

Using the properties of the Gamma function, i.e. that $\frac{\partial F}{\partial x} = -x^{u-1}e^{-x}$, we can derive

$$\begin{aligned}\Upsilon'(x) &= \frac{\bar{\varepsilon} - 1}{\bar{\varepsilon}} x^{\bar{\sigma}/\bar{\varepsilon}-1} \exp\left(\frac{1}{\bar{\sigma}}\right)\bar{\sigma}^{(\bar{\varepsilon}/\bar{\sigma})-1}\left(\frac{x^{\bar{\sigma}/\bar{\varepsilon}}}{\bar{\sigma}}\right)^{\frac{\bar{\varepsilon}}{\bar{\sigma}}-1}\exp\left(-\frac{x^{\bar{\sigma}/\bar{\varepsilon}}}{\bar{\sigma}}\right) \\ &= \frac{\bar{\varepsilon} - 1}{\bar{\varepsilon}} \exp\left(\frac{1 - x^{\bar{\sigma}/\bar{\varepsilon}}}{\bar{\sigma}}\right).\end{aligned}$$

The inverse of the derivative ($\Theta(x) = (\Upsilon')^{-1}$) can then be derived as:

$$\Theta(x) = \left(1 + \bar{\sigma}\ln\left(\frac{\bar{\varepsilon} - 1}{\bar{\varepsilon}x}\right)\right)^{\bar{\varepsilon}/\bar{\sigma}}$$

Replacing x by q_j/Q or $p_j/\mathcal{P}$, we obtain the following two terms:

$$\Upsilon'(q_j/Q) = \frac{\bar{\varepsilon}-1}{\bar{\varepsilon}} \exp\left(\frac{1-(q_j/Q)^{\bar{\sigma}/\bar{\varepsilon}}}{\bar{\sigma}}\right) \tag{J.8}$$

$$\Theta(p_j/\mathcal{P}) = \left(1+\bar{\sigma}\ln\left(\frac{\bar{\varepsilon}-1}{\bar{\varepsilon}(p_j/\mathcal{P})}\right)\right)^{\bar{\varepsilon}/\bar{\sigma}} \tag{J.9}$$

The demand elasticity is

$$-\varepsilon_j = \frac{\partial \ln q_j}{\partial \ln p_j} = \left(\frac{p_j}{\mathcal{P}}\right) \times \frac{\Theta'\left(p_j/\mathcal{P}\right)}{\Theta\left(p_j/\mathcal{P}\right)},$$

where

$$\Theta(p_j/\mathcal{P}) = \left(1+\bar{\sigma}\ln\left(\frac{\bar{\varepsilon}-1}{\bar{\varepsilon}(p_{jj}/\mathcal{P})}\right)\right)^{\bar{\varepsilon}/\bar{\sigma}};$$

$$\Theta'(p_j/\mathcal{P}) = -\frac{\bar{\varepsilon}\left(1+\bar{\sigma}\ln\left(\frac{\bar{\varepsilon}-1}{\bar{\varepsilon}(p_j/\mathcal{P})}\right)\right)^{\bar{\varepsilon}/\bar{\sigma}-1}}{p_j/\mathcal{P}},$$

such that

$$\varepsilon_j = \bar{\varepsilon}\left(1+\bar{\sigma}\ln\left(\frac{\bar{\varepsilon}-1}{\bar{\varepsilon}}\frac{1}{p_j/\mathcal{P}}\right)\right)^{-1},$$

and finally

$$\frac{p_j}{\mathcal{P}} = \left[\exp\left(\left(\frac{\bar{\varepsilon}}{\varepsilon_j}-1\right)\frac{1}{\bar{\sigma}}\right)\frac{\bar{\varepsilon}}{\bar{\varepsilon}-1}\right]^{-1}, \tag{J.10}$$

which shows that, conditional on knowing $\underline{\varepsilon}_j$, we can obtain the relative price at the cutoff.

Additionally, we can also derive the relative demand q_j/Q as a function of demand parameters and the demand elasticity. We know that

$$-\varepsilon_j = \frac{\partial \ln q_j}{\partial \ln p_j} = \frac{\Upsilon'\left(q_j/Q\right)}{\Upsilon''\left(q_j/Q\right)} \times \left(\frac{q_j}{Q}\right)^{-1} = -\theta\left(\frac{q_j}{Q}\right),$$

with

$$\Upsilon'(q_j/Q) = \frac{\bar{\varepsilon}-1}{\bar{\varepsilon}} \exp\left(\frac{1-(q_j/Q)^{\bar{\sigma}/\bar{\varepsilon}}}{\bar{\sigma}}\right);$$

$$\Upsilon''(q_j/Q) = -\frac{\bar{\varepsilon}-1}{\bar{\varepsilon}^2}(q_j/Q)^{\bar{\sigma}/\bar{\varepsilon}-1} \exp\left(\frac{1-(q_j/Q)^{\bar{\sigma}/\bar{\varepsilon}}}{\bar{\sigma}}\right).$$

The demand elasticity in terms of relative quantities is then

$$\varepsilon_j = \bar{\varepsilon}\left(\frac{q_j}{Q}\right)^{-\bar{\sigma}/\bar{\varepsilon}}, \tag{J.11}$$

such that we can derive the following expression for q_j/Q

$$\frac{q_j}{Q} = \left(\frac{\varepsilon_j}{\bar{\varepsilon}}\right)^{-\bar{\varepsilon}/\bar{\sigma}}. \tag{J.12}$$

Further, we can also determine the demand index D as a function of relative quantities:

$$D = \int_0^1 \Upsilon'\left(\frac{q_i}{Q_t}\right)\frac{q_j}{Q}dj = \int_0^1 \frac{\bar{\varepsilon}-1}{\bar{\varepsilon}}\exp\left(\frac{1-(q_j/Q)^{\bar{\sigma}/\bar{\varepsilon}}}{\bar{\sigma}}\right)\frac{q_j}{Q}dj. \tag{J.13}$$

Because q_j/Q is simply a function of the demand elasticity, we can write $D(\varepsilon_j)$.

Combining $\frac{p_j}{\mathcal{P}}$, $\frac{q_j}{Q}$ and D, we get the market share as a function of demand elasticity and demand parameters:

$$S_j = \frac{p_j}{P^Q}\frac{q_j}{Q} = \frac{\exp\left(\frac{1-\bar{\varepsilon}/\varepsilon_j}{\bar{\sigma}}\right)\left(\frac{\bar{\varepsilon}}{\varepsilon_j}\right)^{\frac{\bar{\varepsilon}}{\bar{\sigma}}}}{\int_0^1 \exp\left(\frac{1-\bar{\varepsilon}/\varepsilon_j}{\bar{\sigma}}\right)\left(\frac{\bar{\varepsilon}}{\varepsilon_j}\right)^{\frac{\bar{\varepsilon}}{\bar{\sigma}}}dj}, \tag{J.14}$$

which implies that $p_j q_j = \exp\left(\frac{1-\bar{\varepsilon}/\varepsilon_j}{\bar{\sigma}}\right)\left(\frac{\bar{\varepsilon}}{\varepsilon_j}\right)^{\frac{\bar{\varepsilon}}{\bar{\sigma}}}$ denotes the sales of firm j.

To derive pass-through, we start be determining the markup. The optimal markup is:

$$\mu_j = \frac{\varepsilon_j}{\varepsilon_j - 1} \tag{J.15}$$

Inserting the demand elasticity (both as a function of relative price and relative quantity), yields the following expressions for the markup:

$$\mu_j(p_j/\mathcal{P}) = \frac{\bar{\varepsilon}}{\bar{\varepsilon} - \left(1 + \bar{\sigma}\ln\left(\frac{\bar{\varepsilon}-1}{\bar{\varepsilon}}\frac{1}{p_j/\mathcal{P}}\right)\right)}, \tag{J.16}$$

$$\mu_j(q_j/Q) = \frac{1}{1 - \frac{1}{\bar{\varepsilon}}\left(\frac{q_j}{Q}\right)^{\frac{\bar{\sigma}}{\bar{\varepsilon}}}}. \tag{J.17}$$

Deriving the markup function with respect to the relative price yields:

$$-\Gamma_j = \frac{\partial \ln \mu_{it}}{\partial \ln(p_{it}/\mathcal{P}_t)} = -\frac{\bar{\sigma}}{\bar{\varepsilon}}\mu_j,$$

which implies the following direct pass-through:

$$\Psi_j = \frac{1}{1+\Gamma_j} = \frac{1}{1+\frac{\bar{\sigma}}{\bar{\varepsilon}}\mu_j}. \tag{J.18}$$

J.2. Parametrization

Super-elasticity $\bar{\sigma}$ As stated in the main text, I chose a standard CES value of 5 for the parameter $\bar{\varepsilon}$. The superelasticity of demand $\bar{\sigma}$ is then chosen to respect the equation $\bar{\sigma} = (1/\Psi_j^{\min} - 1) \times \bar{\varepsilon}$ as explained in the main text, and where $\Psi_j^{\min}$ denotes the minimum pass-through rate.

Cutoff elasticities To obtain the implied cutoff elasticities, I construct a counterfactual measure of $\ln \hat{s}_{ij}$, based on measures of $\ln \chi_{ij}$. The idea is based on the definition of the share of importing firms in Equation 20. Writing in logs, this yields:

$$\ln s_{ij}^F = \frac{a}{\underline{\varepsilon}_i - 1} \ln \chi_{ij} - a \ln \underline{e}_{j,0} + \frac{a_J}{\underline{\varepsilon}_i - 1} \ln \left(\frac{\mathcal{S}(\underline{\varphi}_{ji}, \Phi_J, Q)}{f^m} \right)$$

I use the baseline $\beta = \frac{a}{\underline{\varepsilon}_i - 1}$ from Table 3, such that $\ln \hat{s}_{ij}^F = \beta \times \ln \chi_{ij} + \eta_{ij} + \eta_t$. To obtain the correct fixed effects η_{ij} and η_t, I estimate Equation 22 in levels and extract the fixed effects.

Table J.2.1: Extensive margin with variables in levels

	OLS			2SLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\ln \chi_{ijt}$	0.170***	0.127***	0.134***	0.127	0.253*	0.477***			
	(0.011)	(0.009)	(0.008)	(0.221)	(0.131)	(0.149)			
$\mathcal{Z}_{it}$							0.026	0.073*	0.113***
							(0.050)	(0.038)	(0.025)
t FE	✓			✓			✓		
$j \times t$ FE		✓	✓		✓	✓		✓	✓
i FE			✓			✓			✓
KP F-Stat				2.9	13.0	12.1			
First stage coeff.				0.208*	0.282***	0.197***			
Obs	32,042	29,233	29,181	32,042	29,233	29,181	32,042	29,233	29,181

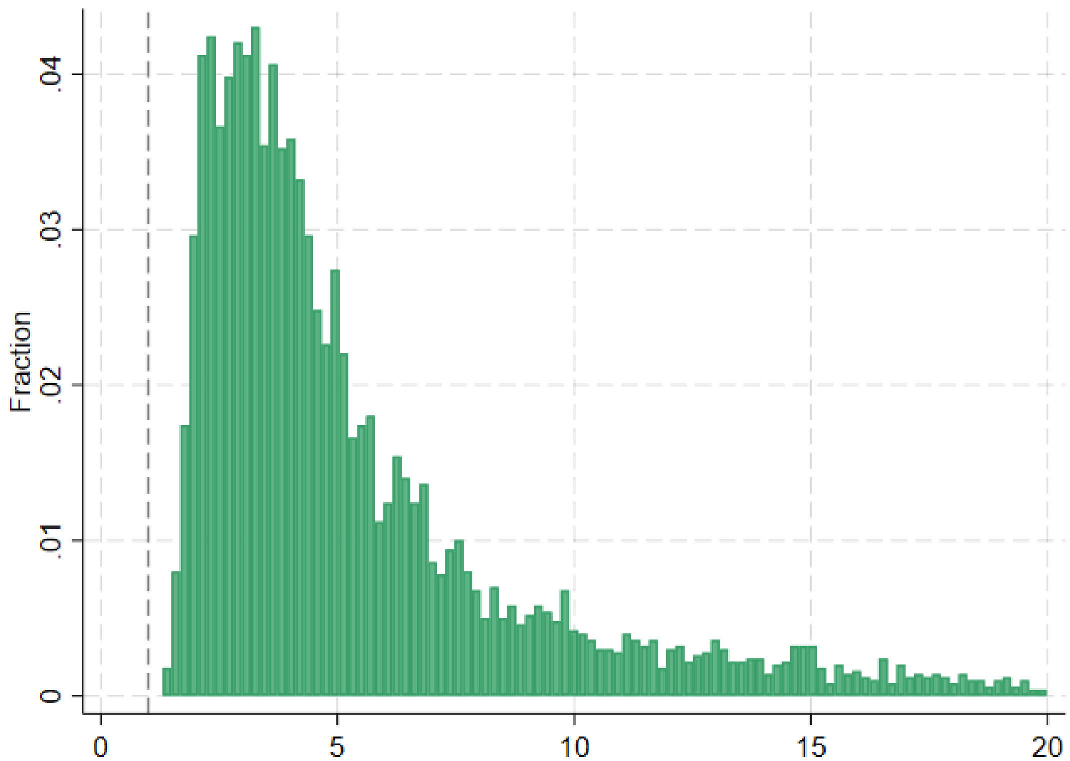
* p<0.1, ** p<0.05, *** p<0.01

Input-clustered standard errors in parentheses. The dependent variable is constructed as the (log) share of j-producing firms importing i in year t. $\ln \chi_{ijt}$ is constructed as described in the text. $\mathcal{Z}_{it}$ denotes the instrument, constructed as described in the main text. KP F-Stat denotes the Kleibergen-Paap F-Stat. All variables are winsorized at the 1%-level by year.

The results of the extensive margin in levels are displayed in Table J.2.1 above. Using the a estimated in Appendix G, we can then derive cutoff elasticities as $\underline{\varepsilon}_i = a \times \frac{\ln \chi_{ij}}{\ln \hat{s}_{ij}^F} - 1$.

The final calibration then takes the average $\underline{\varepsilon}_i$ for a given input-output pair ij. Figure J.1 below shows the distribution of the estimated cutoff elasticities with a value below 20 (98% of the distribution).

Figure J.1: Distribution of $\underline{\varepsilon}_i$



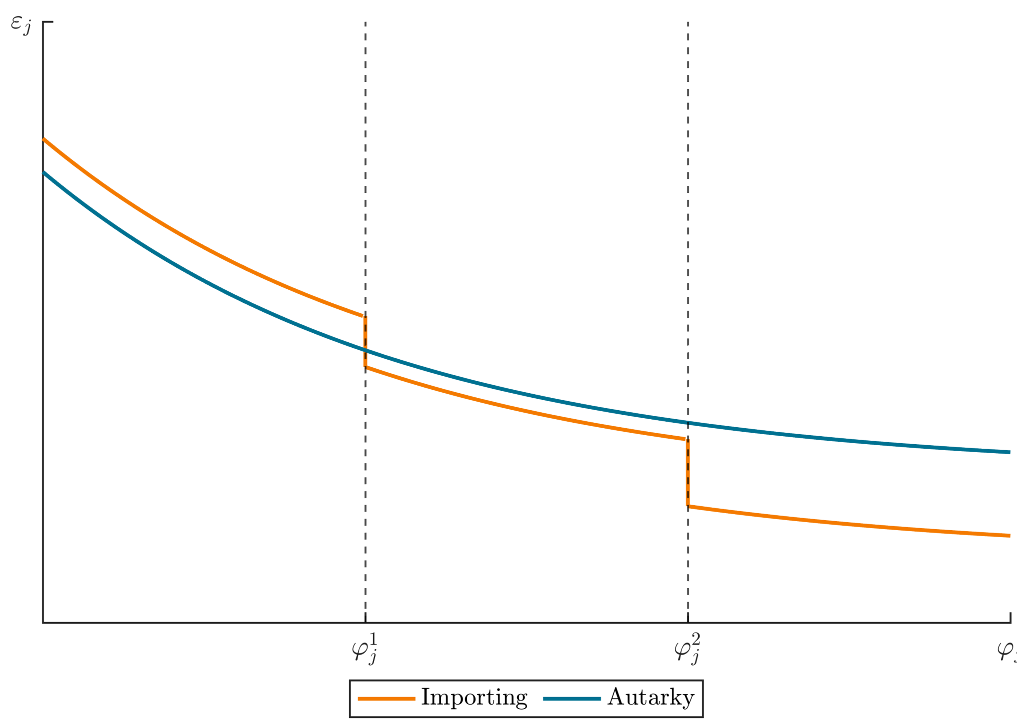
Productivities, elasticities and relative prices In order to obtain the right elasticity at cutoff $\underline{\varphi}_{ji}$, needed to estimate the effect of the extensive margin, I employ the formula for the optimal price in logs. Hence, the cutoff elasticity is identified as:

$$\ln \underline{\varphi}_{ji} = \ln \mu_j + \sum_{i=1}^{n} \gamma_{ij} \left(\ln p_i - \ln \gamma_{ij}\right) - \ln(p_j/P) - \ln P.$$

In autarky, all firms face the same unit expenditure on marginal costs, which is given by $\sum_{i=1}^{n} \gamma_{ij} \left(\ln p_i - \ln \gamma_{ij}\right)$ in the equation above. This implies a smooth relation between elasticity and productivity, as described above. Differences in firms' productivities are reflected solely by demand-related variables such as the relative price and the markup. In such a world, one can simply plug in a given demand elasticity and extract the associated productivity. Due to importing, however, this smooth relationship now displays kinks, because different firms face different marginal costs.

This idea is illustrated by Figure J.2 below. As firms above a certain productivity cutoff start to import, their marginal cost drops. This lowers their relative price and, therefore, lowers their demand elasticity. At the same time, non-importing firms are faced with a lower aggregate price index, which entails a higher relative price and, thus, a higher demand elasticity for them. Together, this means that for productivities below the cutoff, the associated demand elasticity is now higher than in autarky; and vice-versa for productivities above the cutoff.

Figure J.2: Linking ε_j to φ_j



To account for these distortions, and to correctly calibrate the cutoff productivity associated with a given demand elasticity, I will start from a hypothetical autarky world, in which the marginal cost of each firm is composed of domestic prices only. This gives a smooth mapping between demand elasticities and an implied productivity. I then use the cutoff elasticities, obtained as described above, and plug them into the distribution of elasticities in autarky, hence determining the firms that will import a given intermediate input. This gives, for a fraction of firms, a reduction in marginal costs. I then numerically solve the fixed point problem of setting the new price for each firm (given by Equation 15 in order to obtain the right relative price, price index and markup associated with a given elasticity and productivity. This gives the right correlation between elasticities and productivities.

In practice, the nature of the kinks described in Figure J.1 implies that there is no actual relative price associated with a given demand elasticity, and that we can thus not exactly determine the implied cutoff productivity. As a conservative choice, for each input I will thus use the productivity assigned to the first firm that imports as a measure of $\underline{\varphi}_{ji}$.

J.3. Model fit

How does the model compare to the real data? Figure J.3 and Figure J.4 below compare the distributions of the real and the counterfactual data for log market-shares at the firm-output level and for import-shares at the input-output level, respectively. Overall, the model displays roughly similar distributions for the three variables. Nonetheless, concerns about the fit of market shares remain. While we do approximately match the right tale of the market share distribution, market shares at the middle of the distribution seem to be larger than in real data. Counterfactual import shares match the real observed import shares reasonably well.

Figure J.3: Real market shares vs. KW market shares

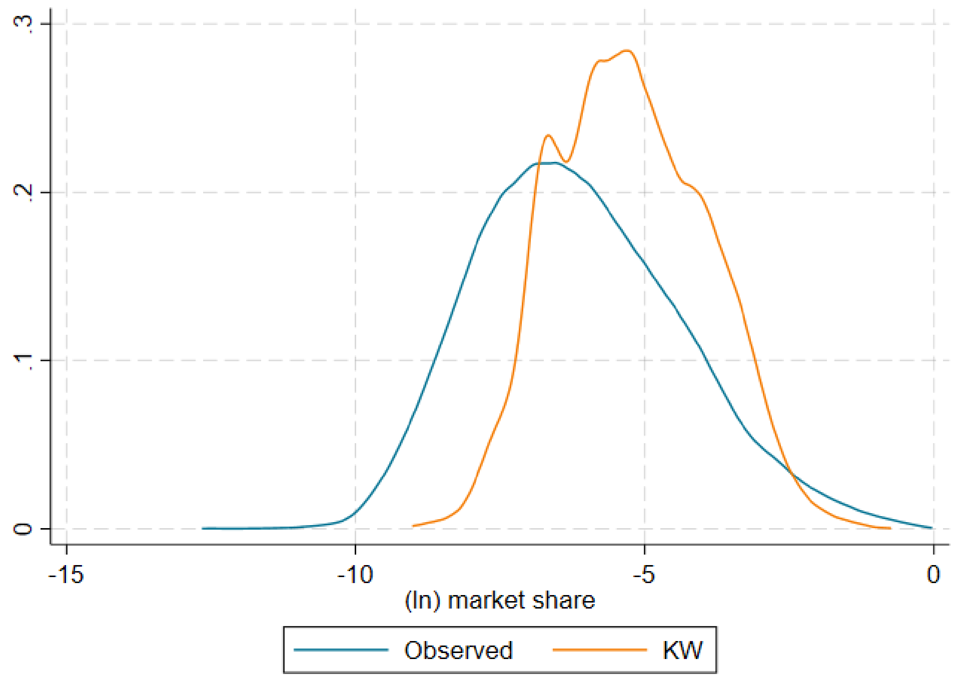


Figure J.4: Real import shares vs. KW import shares