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Estimating Production Function and Productivity Impact of Export Persistence in Presence of Market Imperfections*

Jaan Masso[†], Amaresh K Tiwari [‡]

Abstract

This paper develops a new method to estimate a production function and the total factor productivity (TFP) impact of persistence in exporting. Certain "proxy methods" for estimating the production function invert the demand for flexible inputs with respect to TFP to obtain a proxy for the unobserved TFP. When markets are imperfectly competitive, the demand for inputs depends on unobserved demand shifters (UDS), which violates the "scalar unobservability" required for inversion. We write the production function as a partially linear model, where the nonparametric part, the proxy for productivity, depends on the UDS. Identification rests on postulating (i) a law of motion for the UDS, which evolves endogenously, and (ii) distributional restrictions to control for the correlation between the UDS and the variables of interest. Output elasticities and productivity impact of endogenous treatments are identified. Using Estonian firm-level data, we find that revenue per employee and the amount, in physical units, of goods exported per employee generally increase with the number of years of exporting activities (NYrEx). However, we find limited evidence of the TFP impact of exporting, with only the most persistent of exporters experiencing such gains. In comparison, the estimated productivity impact of NYrEx from an alternative estimator, which assumes perfect competition, closely matches the way revenue per employee varies with the NYrEx. Finally, exporters charge lower markups than non-exporters, where the difference between the exporters' and the non-exporters' markups increases with NYrEx.

Keywords: Production Function Estimation, Imperfect Competition, Variable Markups, TFP, Unobserved Demand Shifters, Learning by Exporting

JEL Classifications: D24, F10, L10

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1 Introduction

This paper develops a new method to estimate a production function and the total factor productivity (TFP) impact of persistence in exporting. This is to provide evidence on learning by exporting (LBE), which refers to a variety of mechanisms, such as investing in marketing, upgrading product quality, innovating, or dealing with foreign buyers, that might induce productivity gains when firms start exporting (De Loecker, 2013). Since the TFP impact of exporting is likely to vary with the number of years of exporting, we study if and how the impact depends on how persistently a firm exports. Secondly, while it is postulated that opening up markets to foreign competition induces efficiency and reduces market distortions, papers such as De Loecker and Warzynski (2012) find evidence that exporting firms (more generally higher productivity firms) charge a higher markup over marginal cost than non-exporters. While exporting firms can gain from trade by charging higher markups, this could, as shown in Arkolakis, Costinot, Donaldson and Rodríguez-Clare (2019)(ACDR), reduce the welfare gained from the pro-competitive effects of trade liberalisation. We, therefore, in addition study how changes in markups are linked to export persistence.

To estimate the parameters of a production function and productivity, proxy methods – e.g., due to Levinsohn and Petrin (2003)(LP), where the demand for flexible/material inputs is inverted with respect TFP, ω_t, to obtain a proxy for ω_t – are commonly used. In imperfectly competitive markets, the demand for flexible inputs also depends on output prices and price elasticity of demand, ε_{YP}. Prices, however, depend on output – hence inputs and productivity – and observed and unobserved demand shifters, and ε_{YP} depends on prices and the demand shifters. The unobserved demand shifters capture heterogeneity in demand (e.g, quality and consumer taste). The proxy for ω_t, therefore, includes unobserved demand shifters as its argument. Without information on prices, we model the demand for firm output, to make explicit the role of unobserved demand shifters. In modelling demand, we also consider the role that shipping costs, as demand shifters, play.

The presence of unobserved demand shifters implies that the proxy for ω_t, which evolves endogenously, is not identified. The proposed method, however, is still able to identify the quantities of interest: the output elasticities and productivity impact of endogenous treatments such as exports and R&D. This is because, while the method borrows from the two-step proxy methods, it does not require construction of a proxy for ω_t using first step estimates before all the structural quantities are estimated. Instead, we treat the unobserved demand shifters as nonseparable errors in the proxy for ω_{t-1},[1] the nonparametric part of the output equation. Since the unobserved demand shifters, which are state variables, affect the choice of inputs and other endogenous variables in each period, they are likely correlated with the variables of interest, which include

[1]Given that TFP exhibits persistence, we, as is common, assume a controlled Markov process for the law of motion of TFP, where TFP in the current period, ω_t, depends on (i) TFP in the last period, ω_{t-1}, (ii) certain variables, $\mathbf{x}_{t-1}$, that endogenously affect the evolution of TFP, and (iii) ex-post shocks, ξ_t, to last period's TFP. This allows us to express TFP, ω_t, as a function of ω_{t-1}, $\mathbf{x}_{t-1}$, and ξ_t.

the dynamic inputs and export related variables. To obtain consistent estimates, our method relies on controlling for the confounding influence of the unobserved demand shifters.

Central to our identification strategy are (i) a specification for the law of motion of the unobserved demand shifters, and (ii) a set of reasonable distributional restrictions to account for the correlation between the unobserved demand shifters and the variables of interest. We assume that the unobserved demand shifters depend on current and past values of variables, such as investments in intangible assets and marketing expenses, and are subject to idiosyncratic shocks. This specification follows from the literature on customer accumulation (e.g. Fitzgerald, Haller and Yedid-Levi, 2023, (FHYL)), which emphasises that improvements in quality and appeal require costly investments in intangible assets, marketing, and advertisement. While we allow for certain persistence in the unobserved demand shifters, without costly investments these unobserved measures of quality and appeal depreciate.

Like most researchers we are faced with revenue and expenditures data, which introduce price errors into quantity measurements. This leads to an unobserved output-input price wedge in the production function. When markets are imperfectly competitive and products are quality-differentiated, the wedge, as has been shown in the influential works of De Loecker and Goldberg (2014)(DLG) and De Loecker, Goldberg, Khandelwal and Pavcnik (2016) (DLGKP), can lead to biased estimates of the output elasticities and of the TFP impact of endogenous treatment. To account for the unobserved wedge, we follow De Loecker, Eeckhout and Unger (2020)(DLEU), who employ variables, like market share, that govern this output-input price wedge. Besides, since we account of the unobserved demand shifter, the proposed method provides an additional set of controls that likely account for the wedge.

Now, exporting firms interact with a variety of customers and are exposed to competitors in the global market, and thus, compared to non-exporters, are more likely to learn about best-practice technology and business processes. The accumulation of such knowledge and technology from their activities in foreign markets is likely to help increase exporters' productivity. Besides, tougher competition in the global market incentivises exporters to reduce X-inefficiencies. As pointed out by De Loecker (2013), along with exporting, firms often simultaneously undertake other complementary activities to improve their performance. A non-exhaustive list of these other activities include quality upgrading (Verhoogen, 2008), R&D (Aw, Roberts and Xu, 2011, (ARX)), and technology adoption (Lileeva and Trefler, 2010; Bustos, 2011).

In their insightful work, Atkin, Khandelwal and Osman (2017) (AKO) use randomised control trial (RCT) to generate exogenous variation in the access to foreign markets. Using RCT, they establish that learning-by-exporting, which involves shifts in the production possibility frontier (PPF) and which includes transfers of knowledge from buyers to producers and learning-by-doing, occurs through improvements in technical efficiency (more output per input) as well as quality. Due to data limitations, we do not try to delineate the implications of such knowledge generated by exporting from the impact of any of the complementary activities listed above. Our estimates of the TFP impact of exports, therefore, likely include the resulting shifts in the PPF due to the unobserved complementary activities.

For the empirical part, we consider Estonia's manufacturing sector. To assess the TFP impact of export persistence, we use several measures of export persistence. We find that the persistence, at the extensive and intensive margins, is affected by the 2007-2008 Financial Crisis and the economic slowdown of Russia in 2014-2016 following sanctions and a sharp fall in oil prices. While these major economic shocks[2] to the Estonian economy, which saw the highest proportion of exits from export markets, have adverse productivity implications, generally, (a) the export revenue per employee, and (b) the amount of goods (in physical units) exported per employee increase with persistence. However, as far as the TFP impact of exports is concerned, we find some evidence that the most persistent of the exporters are able to increase their productivity by exporting. For estimating markups, we follow De Loecker and Warzynski (2012), who further develop the estimator of Hall (1986). We find that, on average, exporter markups are lower than those of non-exporters. Moreover, the more persistently a firm exports, the larger the markup difference compared to that of non-exporter. This indicates that the markets for products produced by exporters in the manufacturing sector are more competitive, which induces them to increase productivity and lower markups to remain competitive.

The rest of the paper proceeds as follows. In Section 2, we review related literature on export persistence. Section 3 describes the model of firm-level production in the presence of endogenous exports and our identification and estimation strategy. Data is discussed in Section 4. The results are discussed in Section 5 and Section 6 concludes.

2 Literature Review

In this section, we review some literature on export persistence, which forms the background for studying the productivity and markup impacts of export persistence. We do not intend the review to be exhaustive. For recent excellent reviews, see Redding (2011) on theoretical literature on heterogeneous firms and trade, and Alessandria, Arkolakis and Ruhl (2021) for a review on the dynamics of firms in foreign markets.

As fas as persistence in export status is concerned, Alessandria, Arkolakis and Ruhl (2021) list the following facts:

[2] In the following we refer to the two events simply as "major economic" shocks. Bems, Johnson and Yi (2013), who survey literature on the causes of the collapse in international trade during the 2008-2009 global recession, find demand shocks in the shape of a collapse in aggregate expenditure, concentrated on trade-intensive durable goods, to be the main driver of the trade collapse. Shocks to credit supply, which constrained export supply, further exacerbated the decline in trade. Juust (2023), who studies firm level responses of the Estonian firms to the 2014-2016 Russian trade shock, describes the trade shock as multifaceted that evolved in stages. It combined (a) an initial ban of food items from the EU by Russia, (b) a volley of sanctions and embargoes between the Western countries and Russia following the annexation of Crimea, and (c) the recession in the Russian economy following a sharp fall in oil prices and the devaluation of the Rouble.

Fact1. Past export participation is the main predictor of current export participation.

Fact2. Exporter exit rates fall with past export intensity and time in the export market.

Fact3. The exporter entry rate is low but is increasing in size and past export activity.

Although, a small fraction of firms enter export markets, most exporters are able to export for a few more periods. An important reason for this persistence is attributed to the relatively large sunk cost of entering export markets (see Das, Roberts and Tybout, 2007, who find large estimates for sunk costs). Those firms that enter, can continue to export by incurring small fixed costs and increasing their volumes at marginal production costs. Since re-entering would again involve incurring sunk costs, firms persist even if some incur losses in the short run. However, if the fixed costs to keep exporting are also high, then only the most productive of firms are likely to enter and persist in exporting.

Recent works, such as Timoshenko (2015) and Berman, Rebeyrol and Vicard (2019), suggest learning about demand as an alternative mechanism. The learning models posit that firms entering an export market are small, are uncertain about the demand their product faces, and learn as noisy information arrives in each period. Over time, as firms continue to export and observe sales realisations, they may grow large if they have a successful product or, if not, they shrink and may eventually exit the market. A firm that experiences higher demand than initially expected, revises upward its belief and expands production. A firm that experiences lower demand than expected cuts back on production, and may even find it optimal to exit the market. Timoshenko (2015) finds that once learning is controlled for, the role of sunk costs in generating export persistence is at most forty per cent of what was then the estimates in the literature.

Piveteau (2021) argues that while large entry costs are necessary to explain the persistence in export decisions, such large costs are incompatible with the fact that most new exporters start small and only a small fraction survive and expand in these foreign markets. One strand of the literature emphasises the accumulation of customers or habit formation in the export market(s) as a means to grow demand (Ruhl and Willis, 2017; Eaton, Eslava, Jinkins, Krizan and Tybout, 2021; Piveteau, 2021; Fitzgerald, Haller and Yedid-Levi, 2023). For inducing inertia in consumption choice, the costs incurred by entrants, who usually begin small, include costly search and investments for better future market access. As surviving firms accumulate consumers in foreign destination(s), their sales and profits increase, which further improves their chances of survival in the foreign destination. While Piveteau (2021) emphasises dynamic pricing to accumulate customers, FHYL emphasise investing in marketing and advertising activities.

On the supply side, as in Das, Roberts and Tybout (2007), Ruhl and Willis (2017) and others, export entry is driven by the arrival of a favourable shock to a firm's productivity, and persistence in export status is aided by the persistent stochastic shocks to the firm's productivity. That exporters are, on average, larger than non-exporters, which is known as the exporter size premium, is often cited in support of models in which firms are heterogeneous in productivity, and more productive firms are larger, more profitable and more likely to become exporters. While more productive firms are more likely to export, exporters also learn by exporting, which improves their productivity. As stated earlier, learning by exporting refers to a variety of mechanisms, which include externalities derived from exporting, that might improve productivity when firms start exporting. Exporting firms, if not all, undertake one or more of a variety of activities to improve productivity, especially if there is complementarity between exporting and the activity; for example, complementarity between exporting and R&D (ARX).

Since the influential work of Clerides, Lach and Tybout (1998), many papers using different frameworks have tried to establish whether firms learn by exporting; notable works include ARX and De Loecker (2013). While the evidence for learning by exporting is mixed, DLG and De Loecker and Syverson (2021) have emphasised that using revenue data to simultaneously estimate the production function and the TFP impact of endogenous decisions may not identify the impact of these decisions on productivity. This is because with revenue data one identifies the impact on firm performance, which depends not only on physical efficiency but also on prices, which reflect quality differentiation and markups. In addition, changes in firm performance are due to changes in product mix, investments and input costs.

To be able to use revenue data for the simultaneous estimation of the production function and the TFP impact of endogenous decisions, this paper develops a method which controls for prices and the demand side factors that affect revenue and the demand for material inputs. Using the method, we add to the literature by assessing how the TFP impact of exports depends on how persistently a firm exports.

ACDR, p. 46–80 pose the questions, "How large are the gains from trade liberalization? Does the fact that trade liberalization affects firm-level markups,..., make [the pro-competitive] gains [from trade] larger or smaller?" Markup of prices over marginal costs, a key variable in economics, affects, among others, the labour share of income, productivity, and resource allocation. Markups also serve as an important metric for market power. Melitz and Ottaviano (2008), who introduce endogenous markups in Melitz (2003) to explore the pro-competitive effects of trade in environments with firm-level heterogeneity, show that markups are lower in tougher markets; that is, in markets that are larger and where the average productivity of competing firms is higher.

However, as Mayer, Melitz and Ottaviano (2021) show, when the residual demand facing firms satisfies Marshal's Second Law of Demand, according to which demand becomes more inelastic with consumption, firms with lower marginal cost (higher productivity) charge higher markups. And, therefore, the reallocation of resources within firms towards more successful or core products – which incur a lower marginal cost when produced – in the face of tougher competition in export market(s) or in response to positive demand shocks raises the productivity of the inputs as well as the markups.

De Loecker and Warzynski (2012), however, using Slovenian data, find that exporters charge, on average, higher markups and that markups increase upon export entry. ACDR using US micro-level trade data find that the estimates of a quantity, which summarises the effects of the elasticity of markups with respect to firm productivity, is such that it implies that the gains (i.e., welfare) from trade liberalisation are lower than those predicted by models with constant markups. In their insightful paper, BCHR, using Chilean data, find that compared to non-exporters, exporters face flatter demand curves in the domestic and foreign markets (that is "thicker" domestic markets), which allows them to attract significantly more domestic customers for any price reduction (e.i., reductions in markups given marginal costs) than do non-exporters. On the other hand, given productivity, the demand for exporters' product exhibit a higher domestic willingness-to-pay, likely due to higher quality. This, they argue, could indicate why exporters' domestic markups are higher than those of the non-exporters.

The within sector aggregate difference between the exporters' markups and the non-exporters' markups is, however, unlikely to be uniform across countries. While we document the difference between exporters' and non-exporters' markups for the various manufacturing sectors in Estonia, we also add to the literature by studying on how this markup difference depends on how persistently firms export.

3 Conceptual Framework, Empirical Strategy, and Estimation

We assume that firm j's gross output production function is Cobb-Douglas[3]:

$$Y_{jt} = F(L_{jt}, K_{jt}, M_{jt})\Omega_{jt}\mathcal{E}_{jt} = L_{jt}^{\alpha_L} K_{jt}^{\alpha_K} M_{jt}^{\alpha_M} \exp(\omega_{jt} + \epsilon_{jt}), \tag{1}$$

where Y_{jt} is gross output, L_{jt} is labour, K_{jt} is capital stock, and M_{jt}, as stated below, is the aggregate of multiple material inputs. For multi-product firms, as discussed in Appendix B.1 , Y_{jt} is the aggregate, $Y_{jt} = Y(Y_{1,jt} \ldots Y_{\mathcal{Y}_j,jt})$, of quality-differentiated products, where the aggregator $Y(.)$ is a homogeneous function that suitably adjusts for quality and substitutability. *For the sake of exposition, though, unless we make it explicit, we will assume that firms produce a single commodity. All corresponding quantities, such as price elasticity of demand, for multi-product firms are derived in Appendix B.1 and Appendix B.2.* The term, $\omega_{jt} = \ln(\Omega_{jt})$, is the Hick's neutral total factor productivity and $\epsilon_{jt} = \ln(\mathcal{E}_{jt})$ is assumed to be log-additive measurement errors in reported output or unanticipated shocks to the production. With the latter interpretation of ϵ_{jt}, $Y_{jt}^* = F(L_{jt}, K_{jt}, M_{jt})\Omega_{jt}$ could be construed as the planned output (Doraszelski and Jaumandreu, 2021).

Firms combine multiple material inputs, $\{M_{1,jt}, \ldots, M_{\mathcal{M}_j,jt}\}$, through an aggregator

$$M_{jt} = M(M_{1,jt}, \ldots, M_{\mathcal{M}_j,jt}), \tag{2}$$

where $M(.)$ is a linearly homogeneous index function which summarises the contribution of all materials inputs in the production of Y_{jt}. Similarly, one can think of the capital

[3] Although, the strategy developed here applies for estimating the more general translog production function.

stock, K_{jt}, in (1) as the aggregate of the stocks of various fixed capital assets. The structure in (2) allows for differentiated material inputs to substitute for each other in an unknown manner.

Capital, K_{jt}, and labour, L_{jt} are subject to adjustment frictions (for example, time-to-install, hiring and training costs) and thus are quasi-fixed, whereas M_{jt} is freely varying. That is, M_{jt}, a static input, is optimally chosen in period t, whereas the dynamic inputs, K_{jt} and L_{jt}, are (pre)determined in period $t-1$. Both K_{jt} and L_{jt} are state variables with dynamic implications and follow their respective deterministic laws of motion:

$$K_{jt} = I_{j,t-1} + (1-\delta)K_{j,t-1} \text{ and } L_{jt} = H_{j,t-1} + L_{j,t-1} \tag{3}$$

where $I_{j,t-1}$, $H_{j,t-1}$ and δ are the gross investment, net hiring and the depreciation rate, respectively.

In the following, we denote a destination/country by d, $d \in \mathfrak{D}_{jt}$, where $\mathfrak{D}_{jt}$ is the set of countries where firm, j, sells its product. Let $o \in \mathfrak{D}_{jt}$ index the country of origin/home country. Let Y_{jdt} be the amount of good Y_{jt} exported by firm, j, to country, d. Let $X_{jdt} := \dfrac{Y_{jdt}}{Y_{jt}}$ be the export intensity with which firm, j, exports to country, d. If the firm does not export, then $X_{jot} = 1$. The revenue earned by the firm is

$$\sum_{d\in\mathfrak{D}_{jt}} P^{f}_{jdt} Y_{jdt} = (\sum_{d\in\mathfrak{D}_{jt}} P^{f}_{jdt} X_{jdt}) Y_{jt} = P_{jt} Y_{jt}, \tag{4}$$

where P^{f}_{jdt} is the Free on Board (FOB) price charged by the firm for goods that are exported to destination, d. The FOB prices can be the same or differ across destinations. The price paid by the consumers in destination, d, is denoted by P^{c}_{jdt}, which includes the costs of transportation, handling, freight and insurance. This is same as what is knowns as the CIF – cost, insurance, freight – prices. If only to mention, in the country of origin, $P^{c}_{jot} = P^{f}_{jot}$. We also allow the possibility for firms to have market power in each of the output markets or destinations. That is, firms' residual demand curves in the home and in foreign destinations may not be perfectly elastic, and that the firms' market shares in these destinations may not be negligible.

As in Malikov, Zhao and Kumbhakar (2020) (MZK), we assume that the endogenous decisions regarding export intensity and orientation, X_{jdt}, are made in period $t-1$. That is, it is assumed that

$$X_{jdt} = \mathcal{X}_{jd,t-1} + X_{jd,t-1}, \tag{5}$$

where $\mathcal{X}_{jd,t-1}$ represents the endogenous adjustment – a choice variable – in the firm's export intensity or orientation, X_{jdt}. The assumption is motivated by the fact that changes in the firm's export orientations are subject to adjustment costs, and therefore to delay. The adjustment costs associated with changes in export orientations, as pointed out by MZK, include (1) time for and cost of finding new intermediaries or buyers abroad, (2) contract (re)negotiations, (3) obtaining new permits, and (4) reconfiguring the production technology if products intended for sale abroad are distinct from those sold domestically etc. Besides, firms that are starting to export or those that are entering a new export market have to bear sunk costs of entry. In addition, all exporting firms have to bear certain fixed costs of exporting.[4] Though not made explicit, the adjustment costs, as in MZK, could be subject to stochastic variations.

The laws of motion of the state variables K_{jt}, L_{jt}, and $\mathbb{X}_{jt}$ are described in (3) and (5). We now describe the law of motion for the productivity term, $\omega_{jt} = \ln(\Omega_{jt})$, which brings us to the main objective of the paper: studying the role of learning by exporting in the evolution of firm productivity. Borrowing from De Loecker (2013), we model the evolution of firm productivity as a controlled first-order Markov process, whereby firms improve their future productivity via LBE and investments in capital. That is, we assume that ω_{jt} evolves according to the first order controlled Markov Process, $p(\omega_{jt}|\mathcal{I}_{j,t-1}) = p(\omega_{jt}|\omega_{j,t-1}, i_{j,t-1}, x_{j,t-1})$. The term, $x_{j,t-1}$, is any of the export-related variables that describe the exporting behaviour of firms, and $i_{j,t-1}$ is investments in fixed (tangible) capital. The distribution, $p(\omega_{jt}|\omega_{j,t-1}, i_{j,t-1}, x_{j,t-1})$, which is stochastically increasing in $\omega_{j,t-1}$, is known to the firm. The Markovian assumption implies that

$$\omega_{jt} = \mathbb{E}(\omega_{jt}|\omega_{j,t-1}, i_{j,t-1}, x_{j,t-1}) + \xi_{jt} = g(\omega_{j,t-1}, i_{j,t-1}, x_{j,t-1}) + \xi_{jt}, \tag{6}$$

where the innovation, ξ_{jt}, to productivity process is uncorrelated with all input choices *prior* to period t. As underscored by MZK, p. 462, the evolution process in the above equation "implicitly assumes that learning is a costly process, which is why the dependence of ω_{jt} on the export variable is lagged, implying that the export-driven improvements in firm productivity take a period to materialize." Such an assumption is implied in De Loecker (2013) and more generally in the "learning" literature. Capital expansion expenditures, $i_{j,t-1}$, are likely to capture expenditures on new technologies. It could also, as argued in De Loecker (2013), pick up the future productivity effects of a range of unobserved firm-level actions.

Since our objective is to assess the TFP impact of persistence in exporting, we use two measures for export persistence, x_{jt}: (a) a set of dummies that capture export persistence, and (b) number of years of exporting and its higher powers. These measures pick any non-linearity in the TFP impact of the number of years the firm has been in the export market(s).

We assume the firms do not have monopsony power in the material goods market. This, however, is a common assumption (e.g., Dobbelaere and Mairesse, 2013; Yeh, Macaluso and Hershbein, 2022). Among the reasons why such an assumption might be valid, Yeh, Macaluso and Hershbein (2022) point out that since material inputs include largely generic, primary goods which tend to be traded on open, often global, markets, it is unlikely that local firms have market power over their prices.

[4] The sunk costs of entry include costs of (1) establishing distribution channels, (2) designing a marketing strategy, (3) learning about exporting procedures, and (4) familiarisation with the institutional and policy characteristics of the foreign country etc. Other fixed costs of exporting, include (1) shipping and other port activities, (2) maintenance of an international division within the firm, and (3) handling and processing of the documents necessary for exporting.

Let $\mathbb{X}_{jt} := \{X_{jdt}\}_{d\in\mathfrak{D}_{jt}}$ be the set of export intensities. Let $D_{jt} := \{\zeta^{\mathrm{o}}_{jt}, \zeta^{\mathrm{u}}_{jt}\}$ denote a set of demand shifters, where ζ^{o}_{jt} are observed and ζ^{u}_{jt}, which denote quality and appeal of the firm's products are unobserved. Let $\mathbb{P}^M_{jt} := \{P^M_{1,jt}, \ldots, P^M_{\mathcal{M},jt}\}$, be the set of prices of material inputs. And let W_{jt} and R^K_{jt} be the wage and rental rates faced by the firm. Let $S_{jt} := \{K_{jt}, L_{jt}, \mathbb{X}_{jt}, \Omega_{jt}, \mathbb{P}^M_{jt}, W_{jt}, R^K_{jt}, D_{jt}\}$ be the set of state variables.

Given the state variables, firms minimise short-run costs with respect to the freely varying inputs, $\{M_{1,jt}, \ldots, M_{\mathcal{M}_j,jt}\}$:

$$C(Y^*) := \min_{M_1,\ldots,M_{\mathcal{M}_j}} \sum_{m=1}^{\mathcal{M}_j} P^M_{m,jt} M_{m,jt} \text{ subject to}$$
$$F(L_{jt}, K_{jt}, M(M_{1,jt}, \ldots, M_{\mathcal{M}_j,jt}))\Omega_{jt} \geq Y^*_{jt}. \tag{7}$$

where Y^*_{jt} is the planned output, and $C(Y^*)$ is the firm's cost function.

Now, the production function in equation (1) expressed in logarithmic terms is

$$y_{jt} = \alpha_L l_{jt} + \alpha_K k_{jt} + \alpha_M m_{jt} + \omega_{jt} + \epsilon_{jt}, \tag{8}$$

where the lower-case symbols, y_{jt}, k_{jt}, l_{jt}, and m_{jt} represent natural logs of quantities of output (Y_{jt}), capital stock (K_{jt}), number of employees (L_{jt}) and the amount of material inputs (M_{jt}) respectively.

From here on, unless necessary, we drop the firm and the time subscripts, j and t.

While production function in (8) is written in terms of quantities of inputs and output, we, as most researchers, observe monetary values of output and inputs:

$$R := \sum_{\kappa=1}^{\mathcal{Y}_j} Y_\kappa P_\kappa, \quad \widetilde{M} := \sum_{m=1}^{\mathcal{M}_j} P^M_m M_m, \quad \widetilde{K} := \sum_{k=1}^{\mathcal{K}_j} P^K_k K_k.$$

Linear homogeneity of $Y = Y(Y_1, \ldots, Y_{\mathcal{Y}_j})$, $M = M(M_1, \ldots, M_{\mathcal{M}_j})$ and $K = K(K_1, \ldots, K_{\mathcal{K}_j})$ in (1) implies that we write the revenue, R, and the expenditures, $\widetilde{M}$ and $\widetilde{K}$, as

$$R = PY, \quad \widetilde{M} = P^M M \text{ and } \widetilde{K} = P^K K, \tag{9}$$

where the price indices, P, P^M and P^K, respectively, are the unit costs of the composites, Y, M and K.

Let $p_i := \ln(P_I)$, $p^m_i := \ln(P^M_I)$ and $p^k_i := \ln(P^K_I)$ denote sector/industry, I, wise deflators for output, intermediate inputs, and capital. Let $\delta^y := p - p_i$, $\delta^m := p^m - p_i$, and $\delta^k := p^k - p^k_i$ respectively be the deflated prices of output, intermediate inputs, and capital. We can, therefore, write the revenue production function in logs as

$$r = y + \delta^y = \alpha_L l + \alpha_K \widetilde{k} + \alpha_M \widetilde{m} + \omega + \underbrace{\delta^y - \alpha_K \delta^k - \alpha_M \delta^m}_{\varrho} + \epsilon, \tag{10}$$

where $r = y + \delta^y$ is the log of deflated revenue, $R = Y\dfrac{P}{P_I}$, and

$$\widetilde{k} = k + \delta^k \text{ and } \widetilde{m} = m + \delta^m$$

are the log of the deflated values of capital and material inputs respectively.

In imperfectly competitive markets, because the prices and the quantities of flexible inputs and output are determined simultaneously, factor inputs are correlated with the unobserved prices, p. In other examples, as pointed out in De Ridder, Grassi and Morzenti (2024), when firms face downward sloping demand curves, a firm can increase demand by lowering the price, p. However, inputs have to increase to meet the demand if the returns to scale are decreasing or constant, causing a correlation between prices and inputs. Also, in the event of a positive demand shock, prices and inputs will be correlated if in response firms increase their output but the returns to scale are decreasing. DLG term the bias resulting from the correlation of inputs with the output prices as "output price bias".

On the other hand, DLGKP argue that if the quality of products varies across producers, then, because higher output quality requires high quality inputs, the quality of inputs is also likely to vary. Input price deflators then are unlikely to account for the input price variation across firms that quality-differentiated inputs introduce. The correlation between unobserved input prices, $\{p^k, p^m\}$, and inputs could potentially bias the estimates, which is termed an "input price bias". In the absence of perfect competition, DLG list conditions such that variations in input and output prices interact so that the output price bias exactly offsets the input price bias; that is, $\delta^y - \alpha_K\delta^k - \alpha_M\delta^m$ in (10) is zero.[5] These conditions are restrictive, and generally when output produced is quality-differentiated, output and input biases will only partially neutralise each other.

DLGKP argue that when the output produced is quality-differentiated, the prices of the inputs depend on the unobserved quality, $\zeta^{\mathrm{u}}_{\mathrm{q}} \in \zeta^{\mathrm{u}}$, of the outputs. This accounts for the fact that firms that produce quality-differentiated products are likely to use quality-differentiated inputs. They further argue that there is complementarity in input quality, where manufacturing high-quality products requires combining high-quality materials with high-quality labour and capital. This complementarity implies that the prices of all inputs facing a firm can be expressed as an increasing function of a single index of product quality.[6] So, any remaining variation in $\varrho = \delta^y - \alpha_M\delta^m - \alpha_K\delta^k$ after the output and input biases partially neutralise each other is due to the unobserved quality, $\zeta^{\mathrm{u}}_{\mathrm{q}}$. And, therefore, the unobserved wedge, ϱ, is likely to be correlated with the deflated expenditures, $\widetilde{k}$ and $\widetilde{m}$.

[5] The assumptions include: (1) in an industry characterised by monopolistic competition, where firms produce a horizontally differentiated product and face the same constant elasticity of substitution (CES) demand system, (2) production is characterised by constant returns to scale (CRS), and (3) input price variation (across firms and time) is input neutral.

[6] Accordingly, they use the variables (such as output price, market share, and product dummies) that act as proxies for output quality to control for the unobserved input prices.

Now, given that ω_t in (6) evolves according to a controlled Markov process, we can write (10) as

$$r_t = \alpha_L l_t + \alpha_K \widetilde{k}_t + \alpha_M \widetilde{m}_t + g(\omega_{t-1}, x_{t-1}, i_{t-1}) + \varrho_t + \xi_t + \epsilon_t, \tag{11}$$

where $\xi_t + \epsilon_t$, the sum of shocks to productivity and the ex-post shocks, ϵ_t, is orthogonal to all state variables, current and past, and the endogenous observables that are optimally chosen prior to period, t. *To ease notations, throughout we will suppress the investment term,* i_{t-1}.

To estimate the equation in (11), it would be required that the correlations between the endogenous variables of interest and the unobserved variables, ω_{t-1} in $g(\omega_{t-1}, x_{t-1})$ and ϱ_t, are controlled for. To account for correlations with the unobserved TFP, ω, we borrow from the insights of LP and De Loecker (2011), where, to construct a proxy for ω, it is required that the demand for material inputs, m, increase monotonically in productivity, ω. Formally, it is required that

$$\frac{\partial m(\mathcal{Z}, \omega)}{\partial \omega} > 0, \text{ where } m(\mathcal{Z}, \omega) := \underset{m}{\operatorname{argmin}} \exp(p^m + m) \text{ subject to } f(l, k, m) + \omega \geq y^*, \tag{12}$$

and where $f(l, k, m) + \omega = \ln(F(L, K, M)\Omega)$. The set, $\mathcal{Z}$, which we define below, includes state variables that affect the demand for material inputs. If the condition in (12) is satisfied, then one can invert the demand function for material inputs $m = m(\mathcal{Z}, \omega)$ to obtain $\omega = m^{-1}(\mathcal{Z}, m)$. LP show that this monotonicity condition holds when the markets are perfectly competitive. De Loecker (2011) shows that monotonicity is preserved under the monopolistic competition with CES preferences. In the proposition below we show that:

Proposition 1 *When productivity,* $\omega = \ln(\Omega)$, *is Hick's neutral then in the presence of market imperfection in the goods market,* $m(\mathcal{Z}, \omega)$ *monotonically increase with* ω *if the elasticity of markup,* μ, *with respect to productivity,* Ω, $\varepsilon_{\mu\Omega} := \frac{\partial \mu}{\partial \Omega}\frac{\Omega}{\mu} = \frac{\partial \ln(\mu)}{\partial \omega}$, *is less than* $\frac{1}{\mu}$.

Proof 1 *Given in appendix A.*

Since $0 < \frac{1}{\mu} \leq 1$, the requirement for monotonicity is that the markup elasticity of productivity be inelastic. Since more productive firms use fewer inputs to produce the same output as less productive firms, for the condition in the proposition to hold, more productive firms must therefore produce "sufficiently" more output than the less productive firms. This ensures that firms experiencing productivity growth use more inputs. Melitz (2000), who obtains a similar result, argues that this will be possible if firms that experience an increase in productivity – especially those with already high markups – do not set a disproportionately higher markup than those firms that do not experience an increase in productivity. An inordinate markup difference, as Levinsohn and Melitz (2006) argue, implies that a productivity increase leads a firm to increase its markup by such an amount that it eventually decreases its input usage. This they consider to be an extraordinary case and rule it out as a possibility, even though they note that the profit maximising assumptions of monopolistic competition automatically rules out this special case.

Expressing $g(\omega_{t-1}, x_{t-1})$ in (11) as $g(\mathcal{Z}_{t-1}, m_{t-1}, x_{t-1}) \coloneqq g(m^{-1}(\mathcal{Z}_{t-1}, m_{t-1}), x_{t-1})$, we can write equation (11) as:

$$r_t = \alpha_L l_t + \alpha_K \widetilde{k}_t + \alpha_M \widetilde{m}_t + g(\mathcal{Z}_{t-1}, m_{t-1}, x_{t-1}) + \varrho_t + \xi_t + \epsilon_t. \tag{13}$$

While it is possible to solve for m given $\{y^*, k, l, \omega, p^m\}$, y^* is unknown. To know y^* is to know the condition of demand. To see this, consider, for example, the profit maximisation objective of a monopolist,

$$\max_{Y^*} PY^* - C(Y^*), \tag{14}$$

where $C(Y^*)$ is the firm's cost function defined in (7). The FOC for obtaining the optimal, Y^*, is

$$P[1 + \varepsilon_{PY}] = C'(Y^*), \tag{15}$$

where ε_{PY} is the inverse of the price elasticity of demand and $C'(Y^*)$ is the marginal cost. Assuming that the constraint in (7) binds at the optimum, by substituting $P[1 + \varepsilon_{PY}]$ for λ in the FOC for cost minimisation in (A.2) in Appendix A.1, we get

$$\mathcal{L}_m = \alpha_L l + \alpha_K k + \omega + \ln(\alpha_M[\varepsilon_{PY} + 1]) + p - p^m - m(1 - \alpha_M) = 0. \tag{16}$$

where $\mathcal{L}$ denotes the Lagrangian for the cost minimisation problem.

Given absent information on prices, p, and elasticity, ε_{PY}, in subsection 3.1, we model the demand for firms' output to express p and ε_{PY} as:

$$\varepsilon_{PY} = \varepsilon_{PY}(p, D) \text{ and } p = p(y^*(l, k, m, \omega), D) = p(m, \omega, \mathcal{Z}), \tag{17}$$

where $y^*(l, k, m, \omega)$, the log of planned output, is a function of optimally chosen inputs and ω. The set D, as defined earlier, is the set of observed (ζ^{o}) and unobserved (ζ^{u}) demand shifters. The unobserved components, ζ^{u}, include output firm specific preference parameters, which capture heterogeneity in demand, and unobservable demand shocks that are known to the firm at the time of static optimisation. The set of state variables, $\mathcal{Z}$, in (13) thus includes dynamic inputs, l and k, the demand shifters, D, and the price of material inputs, p^m. This and the monotonicity condition in Proposition 1 then, as shown in (43), allow us to express ω as $\omega = m^{-1}(m, \mathcal{Z})$. The model of demand for firms' output entails certain assumptions regarding (i) consumer preferences, and (ii) market structure, which is assumed to be monopolistically competitive. We also highlight the role that shipping costs, as a demand shifter, play in shaping demand.

These assumptions allow us to derive closed form solutions for the elasticity, ε_{PY}, and the price, p, as functions of ω, m, and $\mathcal{Z}$.

Now, as discussed above, instead of m and k we observe the deflated values, $\widetilde{m} = m + \delta^m$ and $\widetilde{k} = k + \delta^k$, where the deflated prices (or the price residuals), δ^m and δ^k depend only on $\zeta^{\mathrm{u}}_{\mathrm{q}}$ and are monotone in $\zeta^{\mathrm{u}}_{\mathrm{q}}$. Also, since $p^m = p^m_i + \delta^m(\zeta^{\mathrm{u}}_{\mathrm{q}})$, we have

$$\begin{aligned}\omega = m^{-1}(m, l, k, p^m, \zeta^{\circ}, \zeta^{\mathrm{u}}) &= \omega(\widetilde{m}, \delta^m(\zeta^{\mathrm{u}}_{\mathrm{q}}), l, \delta^k(\zeta^{\mathrm{u}}_{\mathrm{q}}), \widetilde{k}, p^m_i, \zeta^{\circ}, \zeta^{\mathrm{u}}) \\ &= \omega(\widetilde{m}, l, \widetilde{k}, p^m_i, \zeta^{\circ}, \boldsymbol{\zeta}^{\mathbf{u}}), \end{aligned} \tag{18}$$

where $\boldsymbol{\zeta}^{\mathbf{u}} := \{\zeta^{\mathrm{u}}, \delta^m(\zeta^{\mathrm{u}}_{\mathrm{q}}), \delta^k(\zeta^{\mathrm{u}}_{\mathrm{q}})\}$. This allows us to write (13) as:

$$r_t = \alpha_L l_t + \alpha_K \widetilde{k}_t + \alpha_M \widetilde{m}_t + g(\mathbb{Z}_{t-1}, \boldsymbol{\zeta}^{\mathbf{u}}_{t-1}, x_{t-1}) + \varrho_t + \xi_t + \epsilon_t. \tag{19}$$

where $\mathbb{Z} := \{\widetilde{m}, l, \widetilde{k}, p^m_i, \zeta^{\circ}\}$ is the set of observed variables.

The object of our interest is the impact of export related variable, x_{t-1}, on future productivity, $\omega_t = g(\omega_{t-1}, x_{t-1}) + \xi_t$. This can be captured by estimating the average partial effect (APE):

$$\mathbb{E}_{\omega}\left[\frac{\partial g(\omega_{t-1}, x_{t-1})}{\partial x_{t-1}}\right].$$

For estimating the APE, we restrict the functional form of $g(\omega_{t-1}, x_{t-1})$, where

$$g(\omega_{t-1}, x_{t-1}) = h(\omega_{t-1}) + \chi(x_{t-1}), \text{ so that } \mathbb{E}_{\omega}\left[\frac{\partial g(\omega_{t-1}, x_{t-1})}{\partial x_{t-1}}\right] = \frac{\partial \chi(x_{t-1})}{\partial x_{t-1}}. \tag{20}$$

We can therefore write $g(\mathbb{Z}_{t-1}, \boldsymbol{\zeta}^{\mathbf{u}}_{t-1}, x_{t-1})$ in (19) as:

$$g(\mathbb{Z}_{t-1}, \boldsymbol{\zeta}^{\mathbf{u}}_{t-1}, x_{t-1}) = h(\mathbb{Z}_{t-1}, \boldsymbol{\zeta}^{\mathrm{u}}_{t-1}) + \chi(x_{t-1}).$$

Due to lack of common support, as discussed in Appendix B.3, it may not be possible to estimate the APE of x_{t-1} on productivity, ω_t, without the restriction in (20).

The unobserved demand shifters, ζ^{u}_t, which we interpret as quality and taste/appeal, are correlated with the inputs and the export related variables, as they determine the next period's choice of inputs and export orientation. For the demand system in subsection 3.1, $\zeta^{\mathrm{u}}_t := \{a_t, -b_t\}$. *To keep notation light, we will refer to a_t and $-b_t$ by the common notation, ζ^u_t.*

Since knowledge gained from buyers in the export market; that is, through LBE, could induce firms to improve quality, they are likely correlated with exporting activities in the past. We also assume that, as with productivity, improvements in appeal or quality require costly investments. Formally, we assume that

$$\zeta^{\mathrm{u}}_t = \zeta^{\mathrm{u}}_{t-1}(\mathbf{g}_{t-1}, \ldots, \mathbf{g}_1) + \tilde{\zeta}_t, \tag{21}$$

where $\mathbf{g}$ includes (1) investments in intangibles (including goodwill) per employee, and (2) marketing costs per employee. The term, $\tilde{\zeta}_t$, is the idiosyncratic term, which is exogenous (e.g., fashion trends affecting appeal). The assumption in (21), as discussed in the section on the related literature (Section 2), is motivated by studies, which emphasise accumulation of customers or habit formation as a means to grow demand. To induce inertia in consumption choice, certain costs, including investing in marketing and advertising activities, are incurred by the firms. Advertisements, as discussed in Ackerberg (2001), not only provide information on the product's "search" and "experience" (e.g. taste) characteristics, but may also stimulate demand by creating prestige; that is, consumers may also have a preference for "advertising characteristics." BCHR find that advertising/marketing expenditure is strongly positively correlated with the estimated components (slope "b" and location parameters "a" of the linear demand curve) of demand heterogeneity, which suggests that advertising affects demand through both prestige and information.[7] Importantly, the above also encompasses the assumption that without costly marketing activities at home and abroad, the scope for LBE, which also induces quality improvements, is reduced.

One could think of $\zeta(\mathbf{g}_t, \ldots, \mathbf{g}_1)$ as

$$\zeta_t^{\mathrm{u}}(\mathbf{g}_t, \ldots, \mathbf{g}_1) = f(\mathbf{g}_t, \mathbf{a}_t) + \delta_\zeta f(\mathbf{g}_{t-1}, \mathbf{a}_{t-1}) + \ldots + \delta_\zeta^{t-1}(f(\mathbf{g}_1, \mathbf{a}_1) + \delta_\zeta^t \zeta_0^{\mathrm{u}}),$$

where $\mathbf{a}_t$ is the age of the firm and $0 < \delta_\zeta < 1$ is the industry specific rate with which past improvements in ζ_t^{u} depreciates, and ζ_0^{u} is the quality/appeal in the initial period, which is random. We assume that $f(\mathbf{g}, \mathbf{a}) = 0$ if $\mathbf{g} = 0$ and that $f(\mathbf{g}, \mathbf{a})$ is an increasing but concave function of the elements of $\mathbf{g}$. Following FHYL, we also assume that $f_{\mathbf{g},\mathbf{a}} > 0$; that is, to increase product appeal and accumulate customers, much higher marketing and advertising expenses are required in the beginning. As the firm accumulates customers and ages, these expenses decline as a fraction of sales or per employee – as predicted in FHYL and which can be evinced in Figure 4f. Except for highly persistent exporters, as can be seen in Figure 4h, investments in intangible assets have also declined.

The above assumptions ensure that, given age, $\zeta_t^{\mathrm{u}}(0, \mathbf{g}_{t-1}, \ldots, \mathbf{g}_1) < \zeta_{t-1}^{\mathrm{u}}(\mathbf{g}_{t-1}, \ldots, \mathbf{g}_1)$.[8] In sum, if there are no new (and sufficient) investments to improve or maintain ζ_t^{u}, it will depreciate, or worse, risk obsolescence if there is a sequence of adverse realisation of $\tilde{\zeta}_t$. This places a mild restriction on firm type: it assumes that ζ_t^{u} for two firms in an industry are drawn from the same distribution if they are of the same age and their $\{\mathbf{g}_{t-1}, \ldots, \mathbf{g}_1\}$ are identical.

[7] Kugler and Verhoogen (2012) argue that the scope for quality differentiation, which gives more capable/productive plants relatively greater incentive to produce high-quality outputs, also captures the willingness of consumers to pay for product quality. They interpret R&D and advertising intensity as a proxy for the scope for quality differentiation based on the argument that firms invest in R&D and advertising only if it is possible to affect quality or appeal.

[8] One can also construct other values of $\mathbf{g}_t$, whose elements are less than those in $\mathbf{g}_{t-1}$, such that $\zeta_t^{\mathrm{u}}(\mathbf{g}_t, \mathbf{g}_{t-1}, \ldots, \mathbf{g}_1) \leq \zeta_{t-1}^{\mathrm{u}}(\mathbf{g}_{t-1}, \ldots, \mathbf{g}_1)$.

Now, the state variables, ζ_t^{u}, affect inputs and other dynamic variables in future periods. Due to persistence in ζ_t^{u}, they are likely to be correlated with the current and past levels of inputs and export related variables. Besides, due to LBE, ζ_t^{u} is likely to be correlated with exporting activities in the past. Our key identifying assumption is:

$$\widetilde{k}_t, l_t, \widetilde{m}_t, x_t \perp\!\!\!\perp \boldsymbol{\zeta}_t^{\mathbf{u}} | i_t, \mathbf{G}_t, \zeta_t^{\circ}, ms_t, \mathbf{a}_t, w_t \text{ and that} \tag{22a}$$

$$\widetilde{k}_{t+1}, l_{t+1}, \widetilde{m}_{t+1}, x_{t+1} \perp\!\!\!\perp \boldsymbol{\zeta}_t^{\mathbf{u}} | \widetilde{k}_t, l_t, \widetilde{m}_t, x_t, i_t, \mathbf{G}_t, \zeta_t^{\circ}, ms_t, \mathbf{a}_t, w_t \tag{22b}$$

According to (22a), conditional on $\mathbf{G}_t \equiv \{\mathbf{g}_{t-1}, \ldots, \mathbf{g}_1\}$ (the history till t of sources of change in ζ_t^{u}), i_t (current investments in fixed tangible assets), ζ_t° (current observed demand shifters, which includes CIF-FOB margins), ms_t (current market share), w_t, (log of average wage, which again is aggregated over a window of two time periods), and $\mathbf{a}_t$ (age of the firm), the dynamic variables, $\{k_t, l_t, x_t\}$, are independent of $\boldsymbol{\zeta}_t^{\mathbf{u}} := \{\zeta_t^u, \delta^m(\zeta_{\mathrm{q}t}^{\mathrm{u}}), \delta^k(\zeta_{\mathrm{q}t}^{\mathrm{u}})\}$. Since, given output, increases in a_t and $-b_t$, which are elements of ζ_t^{u}, increase the price, i.e., demand, and the market share of the firm, we include ms_t in the conditioning set. Since higher output quality requires high quality of all input – for example, due to complementarity in the quality of inputs, high-skill workers operating high-end machinery use high-quality material inputs – (DLGKP), aggregate wage as a proxy for proportion of skilled workers is likely to contain information regarding output quality. As discussed in section 4.3, the CIF-FOB margins are higher for more expensive higher quality products, and therefore these margins are also informative about ζ_t^{u}.

We believe that the assumption in (22a), reasonable as conditional on the history of $\mathbf{g}$ (the sources of change in $\boldsymbol{\zeta}_t^{\mathbf{u}}$), and a host of variables, including market share, CIF-FOB margins, and current investment in fixed capital, that are informative about $\boldsymbol{\zeta}_t^{\mathbf{u}}$, it is unlikely that $\boldsymbol{\zeta}_t^{\mathbf{u}}$ will be correlated with the current and past dynamic variables. In (22b), since the conditioning includes current investment in fixed capital and additionally, the current dynamic variables, the future dynamic variables are also likely to be independent of $\boldsymbol{\zeta}_t^{\mathbf{u}}$. This is plausible since ζ_t^{u} and the other state variables affect the dynamic variables, such as capital, in the next and subsequent periods, through investment. Therefore, investment and current dynamic variables along with other variables in the conditioning set should summarise the relevant information about $\boldsymbol{\zeta}_t^{\mathbf{u}}$.

According to lemma 4.3 in Dawid (1979), (22a) and (22b) imply that

$$\widetilde{k}_{t+1}, l_{t+1}, \widetilde{m}_{t+1}, x_{t+1}, \widetilde{k}_t, l_t, \widetilde{m}_t, x_t \perp\!\!\!\perp \boldsymbol{\zeta}_t^{\mathbf{u}} | i_t, \mathbf{G}_t, \zeta_t^{\circ}, ms_t, w_t, \mathbf{a}_t. \tag{23}$$

To sum up, (23) assumes that no information about $\{\widetilde{k}_{t+1}, l_{t+1}, \widetilde{m}_{t+1}, x_{t+1}, \widetilde{k}_t, l_t, \widetilde{m}_t, x_t\}$ is contained in $\boldsymbol{\zeta}_t^{\mathbf{u}}$ (and vice-versa) over and above that which is contained in $\mathcal{W}_t := \{i_t, \mathbf{G}_t, \zeta_t^{\circ}, ms_t, w_t, \mathbf{a}_t\}$.

To account for the variation in the price error wedge, $\varrho_t := \delta^y - \alpha_K \delta^k - \alpha_M \delta^m$, in (19), borrowing from DLGKP and DLEU, we assume that:

$$\widetilde{k}_t, l_t, \widetilde{m}_t, x_{t-1}, \perp\!\!\!\perp \varrho_t | ms_t, \widetilde{k}_{t-1}, l_{t-1}, \widetilde{m}_{t-1}, \mathcal{W}_{t-1}. \tag{24}$$

In the absence of perfect competition, DLG list conditions such that $\varrho_t = 0$. These conditions, as discussed earlier, are restrictive, and in general, output and input biases will only partially neutralise each other, as higher input prices are partially passed through to higher output prices. DLEU, based on DLGKP, argue that conditional on productivity, ms_t is the exact control that governs the output-input price wedge when demand is of the (nested) logit form. We in addition use $\mathcal{W}_{t-1}$ and lagged inputs as an additional set of controls to account for any remaining correlation between the wedge and the variables of interest.

Let $\mathbb{W}_t := \{\widetilde{k}_t, l_t, \widetilde{m}_t, \mathcal{W}_t\}$. Given the restriction in (20) and distributional assumption in (23) and (24), we write the conditional expectations of r_t given $\{\widetilde{k}_t, l_t, \widetilde{m}_t, x_{t-1}, ms_t, \mathbb{W}_{t-1}\}$ as:

$$\begin{aligned}\mathbb{E}[r_t|\widetilde{k}_t, l_t, \widetilde{m}_t, x_{t-1}, ms_t, \mathbb{W}_{t-1}] =& \alpha_L l_t + \alpha_K \widetilde{k}_t + \alpha_M \widetilde{m}_t + \chi(x_{t-1}) + \\ & \mathbb{E}[h(\mathbb{Z}_{t-1}, \boldsymbol{\zeta}^{\mathbf{u}}_{t-1}) + \varrho_t + \xi_t + \epsilon_t | \widetilde{k}_t, l_t, \widetilde{m}_t, x_{t-1}, ms_t, \mathbb{W}_{t-1}],\end{aligned} \tag{25}$$

where, because $\mathbb{Z}_{t-1} \subset \mathbb{W}_{t-1}$,

$$\begin{aligned}&\mathbb{E}[h(\mathbb{Z}_{t-1}, \boldsymbol{\zeta}^{\mathbf{u}}_{t-1})|\widetilde{k}_t, l_t, \widetilde{m}_t, x_{t-1}, ms_t, \mathbb{W}_{t-1}] = \mathbb{E}[h(\mathbb{Z}_{t-1}, \boldsymbol{\zeta}^{\mathbf{u}}_{t-1})|ms_t, \mathbb{W}_{t-1}] = \widetilde{h}(ms_t, \mathbb{W}_{t-1}) \\ &\mathbb{E}[\varrho_t|\widetilde{k}_t, l_t, \widetilde{m}_t, x_{t-1}, ms_t, \mathbb{W}_{t-1}] = \mathbb{E}[\varrho_t|ms_t, \mathbb{W}_{t-1}] = \widetilde{\varrho}(ms_t, \mathbb{W}_{t-1}) \text{ and} \\ &\mathbb{E}[\xi_t|\widetilde{k}_t, l_t, \widetilde{m}_t, x_{t-1}, ms_t, \mathbb{W}_{t-1}] = \mathbb{E}[\xi_t|ms_t, \widetilde{m}_t] \neq 0.\end{aligned} \tag{26}$$

The last conditional expectation in the above follows because unlike $\{\widetilde{k}_t, l_t, x_{t-1}, \mathbb{W}_{t-1}\}$, current market share, ms_t, and material inputs, $\widetilde{m}_t$, are correlated with ex-post shocks to productivity. To proceed further, for convenience we assume that:

$$\widetilde{h}(ms_t, \mathbb{W}_{t-1}) = \beta_h ms_t + \overline{h}(\mathbb{W}_{t-1}) \text{ and } \widetilde{\varrho}(ms_t, \mathbb{W}_{t-1}) = \beta_\varrho ms_t + \overline{\varrho}(\mathbb{W}_{t-1}). \tag{27}$$

While this assumption is strictly not necessary, it greatly simplifies the estimation.

The conditional expectations in (26) and the restrictions in (27) imply that we can write the firm revenue production function as

$$r_t = \alpha_L l_t + \alpha_K \widetilde{k}_t + \alpha_M \widetilde{m}_t + \chi(x_{t-1}) + \beta ms_t + \overline{g}(\mathbb{W}_{t-1}) + \underbrace{\xi_t + e_t + \epsilon_t}_{\eta_t} \tag{28}$$

where $\beta = \beta_h + \beta_\varrho$, $\overline{g}(\mathbb{W}_{t-1}) = \overline{h}(\mathbb{W}_{t-1}) + \overline{\varrho}(\mathbb{W}_{t-1})$, and $e_t = h(\mathbb{Z}_{t-1}, \boldsymbol{\zeta}^{\mathbf{u}}_{t-1}) + \varrho_t - \mathbb{E}[h(\mathbb{Z}_{t-1}, \boldsymbol{\zeta}^{\mathbf{u}}_{t-1}) + \varrho_t | ms_t, \mathbb{W}_{t-1}]$. The residual, e_t, is orthogonal to all variables in the conditioning set in (25).

To estimate the partially linear model in (28), we use the methodology developed by Chen, Linton and Van Keilegom (2003) (CLVK), who allow the parametric to be endogenous.[9] We use material inputs, $\widetilde{m}_{t-2}$ and market share, ms_{t-2}, from period $t-2$ to instrument $\widetilde{m}_t$ and ms_t. While CLVK assume that $\text{med}(\eta_t|\mathbb{W}_{t-1}, \widetilde{m}_{t-2}, ms_{t-2}) = 0$, we assume that $\mathbb{E}(\eta_t|\mathbb{W}_{t-1}, \widetilde{m}_{t-2}, ms_{t-2}) = 0$. We use polynomial sieves to approximate the nonparametric part, $\overline{g}(\mathbb{W}_t)$. Because powers of variables tend to be highly collinear, especially when the arguments of $\overline{g}(.)$ are limited to a small range, using polynomials of $\mathbb{W}_{t-1}$ to approximate $\overline{g}(.)$ can give rise to the problem of multicollinearity. The orthogonalisation of the polynomial function, as suggested in Newey (1997), can help reduce the problems associated with multicollinearity.

While it is possible to estimate analytical standard errors, the process is involved. CLVK show that a nonparametric bootstrap provides asymptotically correct confidence regions for the finite dimensional parameters (the output elasticities, $\{\alpha_L, \alpha_K, \alpha_M\}$, and the productivity impact of exports, $\dfrac{\partial \chi(x)}{\partial x}$ and β). The quantities of interest are computed for each of the bootstrapped samples, where the distribution of the estimates provides the bootstrap approximation to the true sampling distribution of the statistics. The resampling rule treats each set of firm-level observations together as an independent, identical draw from the overall population of firms. We sample with replacement and with equal probability from the sets of firm-level observations in the original sample.

Now, markups, μ_t, is obtained by writing the FOC for cost minimisation as $\mu_t = \dfrac{\alpha_M}{S_t^M \mathcal{E}_t}$, where $\mathcal{E}_t = \exp(\epsilon_t)$ is the ex-post shock. While α_M is obtained by estimating (28), to obtain the ex-post shocks, we write the FOC as:

$$\ln(S_t^M) = \ln(\alpha_M) + [1 + \varepsilon_{PY}(p_t, D_t)] - \epsilon_t \tag{29}$$

where $\varepsilon_{PY}(p_t, D_t)$, as stated in (17), is the inverse of the price elasticity of demand and $D_t := \{\zeta_t^{\circ}, \zeta_t^{\mathrm{u}}\}$ is the set of observed and unobserved demand shifters. Since $p_t = p(y(k_t, l_t, m_t, \omega_t), D_t)$ and since we observe deflated values, $\widetilde{m} = m + \delta^m$ and $\widetilde{k} = k + \delta^k$, we can write the above FOC as:

$$\ln(S_t^M) = \ln(\alpha_M) + \varepsilon(\omega_t, \widetilde{m}_t, l_t, \widetilde{k}_t, \zeta_t^{\circ}, \boldsymbol{\zeta}_t^{\mathbf{u}}) - \epsilon_t$$

where, as in (18), $\boldsymbol{\zeta}^{\mathbf{u}} := \{\zeta^{\mathrm{u}}, \delta^m(\zeta_{\mathrm{q}}^{\mathrm{u}}), \delta^k(\zeta_{\mathrm{q}}^{\mathrm{u}})\}$.

While given $\mathcal{W}_t$, $\{\widetilde{k}_t, l_t, \widetilde{m}_t, x_t\}$, according to the assumption in (23), is independent of $\boldsymbol{\zeta}_t^{\mathbf{u}}$, they are not independent of ω_t. And so, we have:

$$\mathbb{E}[\ln(S_t^M)|x_t, \mathbb{W}_t] = \ln(\alpha_M) + \widetilde{\varepsilon}(x_t, \mathbb{W}_t),$$

[9]Without the restrictions in (27), both the parametric and the nonparametric would contain endogenous variables. This could, as argued in Florens, Johannes and Bellegem (2012), give rise to the "ill-posed" problem if the nonparametric part does not lie in a compact set of function. For consistently estimating the parametric part, Florens, Johannes and Bellegem (2012) make use of a regularization method to overcome the problem.

which allows us to write the FOC as:

$$\ln(S_t^M) = \ln(\alpha_M) + \widetilde{\varepsilon}(x_t, \mathbb{W}_t) + \nu_t - \epsilon_t, \tag{30}$$

where $\nu_t := \varepsilon(\omega_t, \widetilde{m}_t, l_t, \widetilde{k}_t, \zeta_t^\circ, \boldsymbol{\zeta}_t^{\mathbf{u}}) - \widetilde{\varepsilon}(x_t, \mathbb{W}_t)$.

For $\mathcal{E}_t = \exp(\epsilon_t)$, required for estimating the markup, we use the residual, $-\tilde{\epsilon}_t = -\epsilon_t + \nu_t$, obtained after nonparametrically estimating $\ln(\alpha_M) + \widetilde{\varepsilon}(x_t, \mathbb{W}_t)$ in (30). A criticism against the use of residuals in the canonical proxy methods is that the "prediction error," ν_t, is likely to be correlated with some of the determinants, such as export status of price elasticity (i.e. markups) (Doraszelski and Jaumandreu, 2021). This is because the proxy methods do not include such variables in the conditioning set when estimating ϵ_t. Since in the proposed method, the conditioning set includes x_t and $\mathbb{W}_t$, which contains both the endogenous and exogenous variables, the prediction errors, ν_t, are unlikely to contain any information regarding export related variables and inputs.[10] We, therefore, interpret the residuals, $-\tilde{\epsilon}_t$, as a noisy measure of $-\epsilon_t$.

To estimate the signal, $-\epsilon_t$, from the noisy signal, $-\tilde{\epsilon}_t$ (or, more appropriately, to reduce the noise), we use the Empirical Bayes method (Gu and Koenker, 2017; Koenker and Gu, 2017). For convenience, we define $u_t := -\epsilon_t$ and $\tilde{u}_t := -\tilde{\epsilon}_t$. The Empirical Bayes or the expected a priori estimates of u_t are given by:

$$\mathbb{E}(u_t|\tilde{u} = \tilde{u}_t) = \hat{u}_t = \tilde{u}_t + \frac{f'_{\tilde{u}}(\tilde{u}_t)}{f_{\tilde{u}}(\tilde{u}_t)} \text{ where the density, } f_{\tilde{u}}(\tilde{u}_t) \text{, is } f_{\tilde{u}}(\tilde{u}_t) = \int f_\nu(\tilde{u}_t - u_t) f_u(u_t) du_t$$

and $f'_{\tilde{u}}(\tilde{u}_t)$ is its derivative. The marginal density, $f_\nu(\nu_t)$, of ν_t, which has a mean of zero and which is independent of u_t, is assumed to be Gaussian. To obtain the mixture density, $f_{\tilde{u}}(\tilde{u}_t)$, Koenker and Gu (2017) estimate the mixing density, $f_u(u_t)$, nonparametrically. The Empirical Bayes method, which "shrinks" the estimates, $\hat{u}_t$, towards the prior mean, 0, minimises the expected loss, $\mathbb{E}[(\hat{u} - u)^2]$. The ex-post shock, $\mathcal{E}_t$, is then estimated as $\hat{\mathcal{E}}_t = \exp(-\hat{u}_t)$.[11]

The estimation of ex-post shocks, ϵ_t, is not required if firms are assumed to have perfect foresight; that is, if $\epsilon_t = 0$. This, however, is not an uncommon assumption; for example, recent papers that maintain this assumption include Dobbelaere and Mairesse (2013) and Forlani, Martin, Mion and Muûls (2023). Also, if the price elasticity is independent of prices and $\zeta_t^{\mathbf{u}}$, $-\epsilon_t$ in (29) is estimated without the prediction error, ν_t. An example of this is oligopolistic competition with nested CES preferences studied in Appendix B.2, where price elasticity is a function of (a) export intensity weighted transportation costs to various destinations, and (b) export intensity weighted market share of the firm in various destinations. The framework presented here allows for a more general demand system, where price elasticity depends on prices and unobserved

[10] While ν_t is mean independent of x_t and $\mathbb{W}_t$, we further assume that ν_t is statistically independent of x_t and $\mathbb{W}_t$. This, however, is not an uncommon assumption; see, for example, Assumption 1 in Angrist (1997).

[11] The R package, REBayes, developed by Koenker and Gu (2017) can be used for estimating $\hat{u}_t$. Alternatively, STATA's EBREG developed by Armstrong, Kolesár and Plagborg-Møller (2022) to compute robust Empirical Bayes confidence intervals can be used.

demand shifters. While a rich set of control variables accounts for the correlation between the unobserved demand shifters and the endogenous variables in (19), the prediction errors, ν_t, as argued above, are likely to be independent of the variables that influence markups. Moreover, since we try to reduce the noise (prediction errors) in the estimates of ϵ_t, any resulting bias in the estimates of markups due to the noise is likely to be small.[12]

Remark 1 *Although we have borrowed from the two-step proxy methods, the proposed method does not require the construction of a proxy for ω_t using the results of the first stage before all the structural quantities are estimated. The method, therefore, does not rely on "scalar unobservability," and allows for unobserved factors, e.g. unobserved demand shifters, ζ_t^u, to affect the demand. While this implies that $g(\mathbb{Z}_{t-1}, x_{t-1}, \boldsymbol{\zeta}_{t-1}^{\boldsymbol{u}})$ in (19) contains correlated unobserved variables, there is also the possibility, as with the law of motion for ζ_t^u in (21) and certain distributional restrictions, of controlling their correlations with the variables of interest. So, while the proxy for TFP, $\omega_t = m^{-1}(m_t, \mathcal{Z}_t)$, may not be identified, the TFP impact of endogenous treatments, as we have shown, can still be identified.*

Remark 2 *When prices, p_t, and quantities, y_t, are observed, the proxy for TFP is given by $\omega_t = m^{-1}(\mathbb{Z}_t, p_t, \boldsymbol{\zeta}_t^{\boldsymbol{u}})$ and price elasticity is $\varepsilon_{PY}(p_t, D_t)$, where the set of demand shifters, D_t, includes the unobserved, ζ_t. So, even when prices are observed, due to the unobserved $\boldsymbol{\zeta}_t^{\boldsymbol{u}}$, the proxy for ω_t cannot be identified. The proposed method, which postulates a law of motion for ζ_t^u and distributional restrictions to control for the confounding influence of $\boldsymbol{\zeta}_t^{\boldsymbol{u}}$, is likely to be of relevance for proxy methods that use quantities and prices. Besides, when quantities of multiple products (and their prices) produced by multi-product firms are observed and one seeks to estimate a joint production function, aggregating products that vary by quality and attributes might not be straightforward. Using prices to aggregate, which would result in revenue as an aggregate measure, could be a potential solution. The proposed method, which identifies quantities of interest when the available data is on revenue, could be of relevance in this context as well.*

3.1 Modelling Demand

Here, we assume that firms produce a single product. All corresponding results for multi-product firms can be found in Appendix B.1. First, consider the inverse of the price elasticity of demand, ε_{PY}, in (16). In Proposition 2, we show that ε_{PY} is the weighted average of elasticities of the residual demand curves at various destinations.

Proposition 2 *The inverse of the price elasticity of demand, ε_{PY}, is the weighted sum, $\sum_{d \in \mathfrak{D}} s_d \varepsilon_{PY,d}$, where $\varepsilon_{PY,d}$ is the inverse of the elasticity with respect to producer/FOB price, P_d^f, of the residual demand that the firm faces in destination, d, and $s_d = \dfrac{P_d^f Y_d}{PY}$ is the share of revenue earned from destination, d.*

[12] Our results are found to be robust to using $\hat{\epsilon}_t$ or $\tilde{\epsilon}_t$ as proxies for ϵ_t. Assuming $\mathcal{E}_t = \exp(\epsilon_t = 0) = 1$, also had little effect on the estimated markups.

Proof 2 *Given in appendix A.*

Now, $\varepsilon_{PY,d}$ in the above proposition is given by:

$$\varepsilon_{PY,d} = \frac{dP_d^f}{dY_d}\frac{Y_d}{P_d^f} = \frac{d\ln(P_d^f)}{d\ln(P_d^c)}\frac{d\ln(P_d^c)}{d\ln(Y_d)}, \tag{31}$$

where P_d^c is the price paid by the consumer at destination, d. This price, which includes the cost of transporting such as freight costs and insurance charges, is the Cost, Insurance, Freight (CIF) price. Similar to that in Hummels and Skiba (2004) and Hummels (2007), we assume that:

$$P_d^c = P_d^f + \mathcal{T}_d = P_d^f(1 + M_d^{cf}), \tag{32}$$

where $\mathcal{T}_d$ is the additive, per unit, shipping cost and M_d^{cf} is the CIF-FOB margin. The specification in (32) is based on recent studies, such as by Bosker and Buringh (2020), that find that additive cost components account for the largest part of the transportation costs. Hummels (2007) states that studies examining customs data consistently find that transportation costs pose barriers to trade that are larger than tariffs. One reason, as argued, is that trade negotiations have been steadily reducing tariff rates across the globe.[13] [14] The CIF price as given in (32) implies that $\frac{d\ln(P_d^f)}{d\ln(P_d^c)}$ in (31) is:

$$\frac{d\ln(P_d^f)}{d\ln(P_d^c)} = \frac{P_d^c}{P_d^f} = 1 + \frac{\mathcal{T}_d}{P_d^f} = (1 + M_d^{cf}). \tag{33}$$

To account for the unobserved output prices, p, in (16) and the elasticity, $\frac{d\ln(P_d^c)}{d\ln(Y_d)}$, in (31), we assume that in country, d, the representative consumer's preference over different varieties, indexed j, in industry, I, is given by the "flexible nonsymmetric utility",

$$U = Y_{0d} + \sum_j a_j Y_{jd} - \sigma \sum_j \sum_{i>j} Y_{jd}Y_{id} - \frac{1}{2}\sum_j \tilde{b}_j Y_{jd}^2, \tag{34}$$

considered in Choné and Linnemer (2020). Y_{0d} is the numéraire good whose price is normalized to 1. A larger $\tilde{b}_j$ implies that additional units of good, j, are less valued which limits. The most popular products are those with large a_j and low $\tilde{b}_j$. The parameter, σ, along with $\tilde{b}_j$ capture complementarity and substitutability among the goods. Here, each firm, j, produces a uniquely differentiated good so that variety and

[13] Hummels and Skiba (2004) assumes that the price paid at the destination, d, is $P_d^c = P_d^f\tau_d + \mathcal{T}_d$, where where $\tau_d > 1$ is the multiplicative or ad valorem trade cost, usually the tariff rate. However, given recent evidence (Bosker and Buringh, 2020), the ad valorem trade costs, $P_d^f(\tau_d - 1)$, are likely to be much smaller compared to the additive component, $\mathcal{T}_d$.

[14] The CIF-FOB margin, as detailed in the section on data, is obtained form the International Transport and Insurance Cost (ITIC) of merchandise trade database constructed by the OECD (see Miao and Wegner, 2022, 2017).

firm are interchangeable. For multi-product firms, Y_{jd}, as discussed in Appendix B.1, is a unique composite of multiple products. *While the observable demand shifters derived below are industry-destination specific, to keep notation light, we do not use the industry script, I.*

Again, to ease notations here, for any country, d, we use P_{jd} to denote the price – be it the CIF prices of varieties imported or the prices of varieties produced domestically – of a product. The above quasilinear utility yields the following linear demand curve [15]:

$$P_{jd} = a_j - \tilde{b}_j Y_{jd} - \sigma Y_{-jd}$$

where $Y_{-jd} = \sum_{i \neq j} Y_{id}$ is the total output of firm j's competitors in market, d. Instead of imposing different underlying utility parameters across varieties, BCHR derive the heterogeneities, a_j and $\tilde{b}_j$, from different numbers of consumers demanding different varieties. They interpret $a_j - \sigma Y_{-jd}$ as the consumer's willingness to pay, and show that slope parameter, $\tilde{b}_j$, provides a measure of market thickness, where smaller values of $\tilde{b}_j$ correspond to thicker market. Accordingly, we interpret a_j as quality and/or appeal of firm j's output. For simplicity and little loss in generality, we assume that the preference parameters, $\{a_j, \tilde{b}_j, \sigma\}$, are identical in all destinations/markets. This would imply that products that are popular in the home country are also popular in foreign markets/destinations. Following the literature on customer accumulation, we have argued earlier that the heterogeneities, $\{a_j, \tilde{b}_j\}$, are influenced by a firm's investment in intangible assets and through marketing activities.

The above linear demand can be written as:

$$P_{jd} = a_j - b_j Y_{jd} - \sigma \overline{Y}_d \tag{35}$$

where $b_j = \tilde{b}_j - \sigma$ and $\overline{Y}_d$ is the total output of the industry in market d. For this linear demand, equation (33) implies that, for destination, d, the inverse of the price elasticity of demand with respect to the producer price, P_d^f, in (31), suppressing the script, j, is:

$$\varepsilon_{PY,d} = \frac{dP_d^f}{dY_d}\frac{Y_d}{P_d^f} = \frac{d\ln(P_d^f)}{d\ln(P_d^c)}\frac{d\ln(P_d^c)}{d\ln(Y_d)} = \frac{P_d^c}{P_d^f}\left[1 - \frac{a - \sigma\overline{Y}_d}{P_d^c}\right]. \tag{36}$$

Since in the country of origin, indexed $d = o$, no shipping costs are incurred for delivering the goods, the price elasticity, $\varepsilon_{PY,d}$, for goods not exported is:

$$\varepsilon_{PY,d} = \varepsilon_{PY,o} = \left[1 - \frac{a - \sigma\overline{Y}_o}{P_o^f}\right]. \tag{37}$$

[15] While the assumption of linearity is not without loss of generality, the implied elasticity, see (39) below, has a simple implementable solution. A linear demand curve implies an incomplete but a constant absolute pass-through for all firms (see Mrázová and Neary, 2020). However, firms can be heterogeneous in markups.

Since according to Proposition 2, $\varepsilon_{PY} = \sum_{d\in\mathfrak{D}} s_d\varepsilon_{PY,d}$, we have:

$$\varepsilon_{PY} = \sum_{d\in\mathfrak{D}} s_d\varepsilon_{PY,d} = \sum_{d\in\mathfrak{D}} s_d\frac{P^c_d}{P^f_d}\left[1-\frac{a-\sigma\overline{Y}_d}{P^c_d}\right] \quad = \sum_{d\in\mathfrak{D}} s_d(1+M^{cf}_d) - \sum_{d\in\mathfrak{D}} s_d\frac{a-\sigma\overline{Y}_d}{P^f_d}. \tag{38}$$

Since $s_d = X_dP^f_d/P$, where $X_d = Y_d/Y$, we can express ε_{PY} as:

$$\varepsilon_{PY} = \overline{M}^{cf} - \frac{a-\sigma\overline{\mathcal{D}}}{P}, \tag{39}$$

where $\overline{M}^{cf} = \sum_{d\in\mathfrak{D}} s_d(1+M^{cf}_d)$ is aggregate CIF-FOB margin and $\overline{\mathcal{D}} = \sum_{d\in\mathfrak{D}} X_d\overline{Y}_d$. Now, the quantity demanded at destination, d, is given by:

$$P^f_d(1+M^{cf}_d) = a - bY_d - \overline{Y}_d,$$

which implies that we can write the aggregate price P in (4) as

$$\begin{aligned} P &= \sum_{d\in\mathfrak{D}} X_dP^f_d = \sum_{d\in\mathfrak{D}} X_d(a-bY_d-\sigma\overline{Y}_d) - P\sum_{d\in\mathfrak{D}} s_dM^{cf}_d \\ \Rightarrow P &= \frac{1}{\overline{M}^{cf}}(a-bY\overline{X}-\sigma\overline{\mathcal{D}}) \end{aligned} \tag{40}$$

where $\overline{\mathcal{D}}$ and $\overline{M}^{cf}$ are defined above and $\overline{X} = \sum_{d\in\mathfrak{D}} X^2_d$. The linearity of demand in (35) implies that aggregate price and elasticity are written as functions of the aggregate CIF-FOB margin, $\overline{M}^{cf}$, and the aggregate of demand shifter, $\overline{\mathcal{D}}$. The CIF-FOB margins, $\overline{M}^{cf} > 1$, depresses demand in foreign destinations. Also, if the FOB prices are uniform across destinations, the above reduces to the familiar demand curve obtained by aggregating demand (at the common FOB price) across destinations. If only to mention, the optimization problem in (14) is the maximization of the short-run profit subject to the inverse demand function in (40). In our model, the export orientation, $\{X_d\}_{d\in\mathfrak{D}}$, as discussed earlier, is predetermined and known at the time of static optimization.

Since $Y = F(L,K,M)\Omega$, we can express P as:

$$\begin{aligned} &P = P\big(L,K,M,\Omega,\overline{M}^{cf},\overline{\mathcal{D}},\overline{X},a,b\big) \\ \Longleftrightarrow\ &p = p\big(l,k,m,\omega,\overline{M}^{cf},\widetilde{\mathcal{D}},\widetilde{X},a,b\big), \end{aligned} \tag{41}$$

where $\widetilde{\mathcal{D}} = \ln(\overline{\mathcal{D}})$ and $\widetilde{X} = \ln(\overline{X})$.

From the elasticity, $\ln[1+\varepsilon_{PY}] = \ln[1+\exp(\ln(\overline{M}^{cf} - \exp\big(\ln(a+\sigma\overline{\mathcal{D}})\big) - p)]$, in (39), and the price, p, in (41), it is clear that the set of state variables, $\mathcal{Z}$, defined in (12), that can help solve the demand for material inputs is:

$$\mathcal{Z} = \big\{l,k,\overline{M}^{cf},\widetilde{\mathcal{D}},\widetilde{X},p^m,a,b\big\}.$$

The unobserved demand shifters, $\zeta^{\text{u}} := \{a, -b\}$ correspond to product characteristics. These state variables, whose evolution we have discussed, affect the choice of inputs. However, as discussed, to the extent that we can control for the correlation of ζ^{u} with the inputs, we take it as given. Because the proposed method does not require the construction of a proxy for ω, as in the two-step methods, the "scalar unobservable" assumption of the two-step methods is not required here. The set, $\mathcal{Z}$, could also include any other observable demand shocks; for example, firm-specific quota protection rate and product dummies, as in De Loecker (2011), and industry and time dummies.

Given the set, $\mathcal{Z}$, we can write the FOC for material inputs in (16) as:

$$\mathcal{L}_m(\omega, m, \ln[\varepsilon_{PY}(p(\omega, m, \mathcal{Z}), \mathcal{Z}) + 1], p(\omega, m, \mathcal{Z}), \mathcal{Z}) = 0.$$

Let

$$m = m(\omega, \mathcal{Z}) \tag{42}$$

be the solution, if implicit, to the above FOC. As long as the condition in Proposition 1 holds true, we can invert the demand function for material inputs in (42) with respect to ω to express it in terms of m and $\mathcal{Z}$,

$$\omega = m^{-1}(\mathcal{Z}, m), \tag{43}$$

which allows us to derive (13).

Before we end this subsection, we list the assumptions made for modelling demand.

Assumption 1 The multiplicative or ad valorem trade costs are negligible compared to the additive per unit shipping costs, which comprise transportation, insurance, and freight costs.[16]

Assumption 2 Distribution and retail cost for a particular good is uniform across all countries, and is normalised to 0.[17]

Assumption 3 A quadratic utility function in the class of quasilinear utility is assumed.

Assumption 4 Market structure in all countries is assumed to be monopolistically competitive.

4 Data

For our study, we use administrative data, which includes balance sheet information of enterprises. The distinction between enterprise and firm is not important for this study,

[16] This assumption can be easily relaxed if product-destination ad valorem trade costs are available.
[17] This assumption, though unstated earlier, is implied in the above model of demand.

and so, we use the two terms interchangeably. In the following, we describe the data on transportation and insurance costs and the firm-level data set used for the estimations.

4.1 Export Related Data

The data on firm-level exports is taken from the International Goods dataset of Statistics Estonia (Eesti Statistika). The trade/customs data contain detailed information regarding goods (HS, 8-digit) exported and imported by the firms. The customs data records information on the volume shipped, both in terms of kilograms and number of units (pieces, pairs, litres, etc.), and the monetary value on the invoice for each transaction. This data is available from 1995 onwards.

After the accession of Baltic countries to the European Union in 2004, a threshold appears on export declaration. For intra-EU exports, only firms with total export turnover of at least 100,000 EUR are required to declare their shipment/transaction details. This reduced the number of exporters in 2004 by 22% from 2003, even though the total number of shipments saw an increase of 11%. Since the appearance of the threshold in 2004 is likely to artificially change the export status of many firms, we consider customs data from 2005 to 2019. We also drop those exporters from the data who entered export markets prior to 2005. This ensures that we have a consistent measure of the number of years of exporting.

As Estonia is a small open economy on the Baltic Sea in Northern Europe, a large fraction of the goods entering Estonia are subsequently re-exported to other countries. We drop those firms who re-exported the same products, identified by the 8-digit HS codes, that they imported in the same time period.

The distribution of current export status against the number of years of exporting and summary statistics of some export related variables are presented in Table 2. The distributions of current export status by the history of exporting activities for the three macro industries are based on 2005-2019 customs data.

Due to the legacy left behind by the former USSR, which specialised in chemical and mechanical engineering, the largest proportion of exporters, 8%, are in the material manufacturing sector. This is followed by consumer manufacturing, where 4% of firms have exported at least once. The corresponding figures for technological manufacturing is 5.5%.

[Table 2 about here]

As the table shows, the longer a firm exports, the more likely it is to maintain its status as an exporter. In panel (b), we describe how export intensity, as measured by the share of export revenue in total revenue, and export revenue per employee vary with number of years of exporting. While both export intensity and export revenue per employee increase with years of exporting, the distribution of the two quantities, which are skewed to the left during the initial years of exporting, becomes more symmetrical with additional years in the export market. This, as has been documented elsewhere, suggests that most firms begin by exporting small quantities, and over time, as they accumulate customers, gradually increase their export volume.

[**Figure 3 about here**]

[**Figure 4 about here**]

Even though the likelihood of exporting increases with the number of years in the export market, as can be see in Figure 3, the proportion of highly persistent exporters is very small. However, on average, with each additional year of exporting, firms increase the number of export destinations and the number of products that they export. Figure 3 also shows that the highest proportion of firms exited from export markets during the 2007-2008 financial crisis and during the 2014-2016 Russian trade shock.

In Figure 4, we find that aggregate measures of revenue productivity (market share weighted averages of revenue per employee and export revenue per employee) and aggregate export productivity have increased with the number of years in the export market. Export productivity is the number of pieces of the "core" product exported per employee. To make the products comparable, we weight their amounts by their prices relative to the year-industry price index. We compute the yearly price index for each NACE 5-digit industry as $\sum_j Y_j^c P_j / \sum_j Y_j^c$, where Y_j^c is the amount of core product exported by firm, j, and P_j is its FOB price. For aggregation, we sum using market share as weights. To determine the core product, we compare the exported volumes of different 8-digit HS codes. The product with the highest exported volume is assigned as the core product. When the exported amounts of different products are not comparable (e.g., when the volume of one product is recorded in kilograms and the volume of another in no. of pieces), we compare the values of the exported amount of different products.

4.2 Administrative Data

The financial data used in the paper has been taken from the Estonian Business Registry (Äriregister), available since 1995, that includes, in addition to the general information on companies (e.g., legal form, industry codes, etc.), their annual reports (balance sheets, profit and loss statements, cash flow statements). The Estonian Business Registry data has been complemented (to fill in the gaps in the time series of some variables) with the data from the Statistics Estonia's EKOMAR survey of structural business statistics.

For our study, though, we consider only the manufacturing sector for the period, 2005 to 2019. Within manufacturing, based on Eurostat classification, which uses NACE 2-digit industry codes, we consider (a) consumer manufacturing, (b) material manufacturing, and (c) technological manufacturing.[18]

[18] The following NACE 2-digits define each of the sectors:

In Table 4, we present summary statistics of suitably deflated variables from the administrative data. The statistics are presented by the number of years firms have been in export markets. Here, we do not distinguish between current exporters and non-exporters. If, for example, a firm exports just once then for all subsequent periods the dummy variable, "Exported 1 or 2 Years," takes value 1.

First, the size – as measured by the number of employees, the size (book value) of the capital stock, revenue, and market share[19] – of the firms that exported at least once are, on average, larger than the firms that have never exported. Besides, firm size increases with additional years in the export market. Also, compared to non-exporters, exporters have a larger share of labour and of material inputs.

[Table 4 about here]

For estimation, we also use marketing costs and investment in intangible assets. Marketing expenses per employee, as shown in Figure 4f, seem to decline with the no. of years of exporting activities. Intangible assets consists of valuations of goodwill, development expenses, computer software, patents, licences, trade marks, and other intangible assets. We regard the increase in the stock of intangible assets due to additions, acquisitions, and mergers as investment in intangibles. In Figure 4g and Figure 4h respectively we plot the stock of and investment in intangible assets against no. of years of exporting activity. The more persistent a firm is in its exporting activities, the higher is its stock of intangible assets. Except for the highly persistent exporters, the ratio of investments in intangible assets to the no. of employees seem to decline with the no. of years of exporting activities.

4.3 Data on Transportation and Insurance Costs

For transportation and insurance cost, we use the International Transport and Insurance Cost (ITIC) of merchandise trade database constructed by the OECD (see Miao and Wegner, 2022, 2017). It reports estimates of CIF-FOB margins, M_d^{cf}, for more than 180 countries and partners and for more than 1000 HS 4-digit products. The data covers the period, 1995 to 2020. The approach used by Miao and Wegner (2022) to develop the OECD database on ITIC is a two-step process. To estimate the CIF-FOB margins, Miao and Wegner (2022) use trade data in the first step, which contains CIF-FOB margins at HS 6-digit product level for 33 countries, to estimate a gravity-type model. The methodology is similar to that in Hummels and Skiba (2004). The gravity-type model takes into account the effects of distance, geographical situation (contiguous partners, partners on the same continent), infrastructure quality, oil prices, product unit values and time effect on the CIF-FOB margin. In the second step, the

Consumer manufacturing: 10 to 15, 18, and 31 to 32
Material manufacturing: 16 to 17 and 19 to 25
Technological manufacturing: 26 to 30 and 33

[19]The market share is the share of the firm's revenue within NACE 5-digit industry.

gravity-model coefficients are used to derive estimates for those countries which did not explicitly report CIF-FOB margins.

The CIF-FOB margins are available for more than 92% of the Year-Destination-Products (HS 4-digit). To obtain the CIF-FOB margins for the remaining 8% Year-Destination-Products, using the CIF-FOB margin from the OECD database, we first estimate the same gravity-type model as in Miao and Wegner (2022), though, instead of unit values of products (FOB prices), we include log transforms of (i) weight-per-unit of the goods shipped, $\mathcal{W}_{jk}$ and (ii) the value-to-weight ratio, $\mathcal{U}_{jk}$, in the specification. As argued by Lashkaripour (2020), heavier varieties of the same product are more costly to produce and exhibit a higher product appeal or quality. Importantly, heavier varieties are not only more costly to transport, but the cost of transportation rises more rapidly with physical weight than the cost of production itself. The additive costs, as in Hummels and Skiba (2004), also depend on value-to-weight ratio because more valuable goods are likely to require higher quality transportation services such as more insurance, greater care in handling, and more rapid delivery. However, as Lashkaripour (2020) shows, it is weight-per-unit of the goods that explains most of the variation in cost of transport. In the second step, using the estimates from the gravity model, we then predict the CIF-FOB margin for the remaining Year-Destination-Products.

5 Results

5.1 Output Elasticities and TFP impact of Persistence in Export Status

In this section, we discuss the results obtained from estimating (28). To be able to estimate it, as discussed in section 3.1, we have to control for the aggregate demand shifters, $\overline{\mathcal{D}} = \sum_{d\in\mathfrak{D}} X_d\overline{Y}_d$. The total output, $\overline{Y}_d$, of a NACE 2-digit industry at market/destination, d, is estimated as $\overline{Y}_d = \mathbb{R}_d/\mathbb{P}_d$, where $\mathbb{R}_d$ is the total revenue of NACE 2-digit industry at destination, d, and $\mathbb{P}_d$ is the NACE 2-digit producer price index.[20] Since we do not observe the total output of the firms, we approximate X_d according to the ratio of the value of exports for destination, d, to the total revenue of the firm; this, in effect, assumes that the FOB prices for all destinations are equal. We include year and industry dummies, which are likely to account for the two major economic shocks, the 2007-2008 financial crisis and the 2014-2016 Russian trade shock, that affected the demand (in particular the export demand) for firms' output.

[Table 5 about here]

[Table 6 about here]

[20] Eurostat's datasets, "sbs_na_ind_r2" and "sts_inppd_q," respectively provide official statistics for revenue (yearly data) and producer price index (PPI) (quarterly data) for the NACE 2-digit industries for EU member states. Yearly data on revenue for the NACE 2-digit industries for countries outside the EU is obtained from the United Nations Industrial Development Organization's (UNIDO) database. Since PPI by industry for destinations outside the EU was not available, for destinations outside the EU, we use the PPI for the manufacturing sector.

For the estimation, we orthogonalise the polynomial function that approximates the nonparametric part in (28).[21] The results in Tables 5 and 7 use data from 2005 to 2019. The results in Table 6 use data from 2009 to 2019, where only those exporters that entered the export markets after the financial crisis of 2007-2008 are considered.

First, in both the tables we find that except in technological manufacturing, where returns to scale is larger than one, production function in all other sectors exhibit constant returns to scale. Also, the output elasticities vary across sectors. Compared to consumer and material manufacturing, the output elasticity of labor is larger for the technological manufacturing, and, generally, the output elasticity of materials is the larger for the material and consumer manufacturing. Furthermore, the estimated output elasticities of material inputs, the flexible input, is found to be larger than the share of material inputs (see Table 4), which indicates that firms operate in imperfectly competitive markets.

To assess the TFP impact of export persistence, we use two measures of persistence: (a) a dummy variable for the 1st and 2nd year of exports, a dummy variable for 3rd and 4th year of exports, etc., and (b) the number of years of exporting. The second measure does not distinguish between current exporters and non-exporters. If, for example, a firm exports twice, then in the first year of exporting and for all subsequent periods until the second year of exporting, the variable for number of years of exporting takes the value 1. From the second year of exporting until the last period the variable takes the value 2. These measures allow us to assess (a) if, depending on the number of years of exporting activities, the TFP impact of exporting is heterogeneous, and (b) the TFP impact of an additional year of exporting.

As can be seen in Table 5 and Table 7, we do not find much evidence of a TFP impact of exporting. There is some evidence of a TFP impact of exports in the consumer manufacturing sector. However, the little evidence that we have indicates that it is the persistent exporters who realise productivity gains from exporting. Now, the "Great Trade Collapse" following the financial crisis of 2007-2008 saw the highest number of exits from the export market, as well as reductions in the export intensities. Even though we control for the financial crisis years, as a robustness check, in Table 6 we consider only those exporters – exporters with no history of exporting, at least in the customs data, prior to 2009 – who entered the export market after the financial crisis years. Similar to the results in Table 5, we find little evidence of a TFP impact of exporting.

These results may seem to be at odds with the plots in Figure 4, where various measures of productivity are plotted against the number of years of exporting. In Figure 4, we find that measures of revenue productivity (revenue per employee and export

[21] We use a modified Gram-Schmidt procedure to orthogonalise the polynomial functions. The raw and the orthogonalised polynomial carry the same information even as the orthogonalisation helps to reduce the problems associated with multicollinearity (see Newey, 1997, on the use of orthonormal polynomials of several variables for addressing the issue of multicollinearity in series regression). The nonparametric parts are not the objects of our interest. The only objective of the nonparametric parts is to control for the confounding effects of the unobserved variables.

revenue per employee) and export productivity (see section 4.1 for the definition of export productivity) have increased with the number of years in the export market. Firms' TFP can increase with the number of years of exporting for a variety of reasons. These include shifts in the PPF; for example, due to R&D or managerial innovation, which are not due to learning-by-exporting. Even within firm reallocation towards best performing or core product(s) in the face of tougher competition in export market(s) or in response to positive demand shocks improves over all productivity (Mayer, Melitz and Ottaviano, 2014).[22]

Our objective, however, is to control for current TFP, ω_t, and the TFP effects of other activities as captured by the investment variable, i_t, when assessing the impact of export persistence on future TFP, ω_{t+1}. Investments in fixed capital, as argued in De Loecker (2013), are likely to capture the productivity effect of expenditures on new technologies and upgrading existing production processes. And so, even if there is no learning-by-exporting, measures of productivity that are used in Figure 4 can increase with number of years of exporting due to any of the reasons discussed above.

Our results, which do not find a strong evidence of learning-by-exporting, could be due to the fact that we count small exporters – those who export only within the EU and whose export value is less than 100 thousand EUR – among non-exporters. Since most firms begin by exporting small quantities (Eaton, Kortum and Kramarz, 2011) and since most Estonian firms export within the EU (88% of firm-years export within the EU and 77% export only within the EU),[23] it is, therefore, quite likely that a significant fraction of the exporters has been in the export market for many years before appearing in customs data.[24] And therefore much of the learning is likely to have taken place before the exporting firms show up as exporters in our data.

Since, as mentioned earlier, we are unable to perfectly control for endogenous complementary activities, such as R&D for products and process innovations or the adoption of new technology, we are unable to separate the TFP implications of knowledge generated by exporting from the impact of any of the unobserved complementary activities.[25] Since quite likely most of the small exporters do not figure as exporters in our data, the

[22] In Mayer, Melitz and Ottaviano (2014), the core product is the product that, due to higher expertise in manufacturing it, involves low production costs and/or, given its appeal, has a higher demand. Therefore, shifting more resources to the production of the core product, say, in response to positive demand shocks, is likely to register as an improvement in TFP even without shifts in the PPF.

[23] Of the 88% of firm-years that export within the EU, 90% export within Northern Europe, which comprise Åland Islands, Bouvet Island, Denmark, Greenland, Iceland, Latvia, Lithuania, Norway, Svalbard and Jan Mayen, Sweden, and The Faroe Islands.

[24] We saw a 22% decline in the number of exporters in 2005 because after the accession of the Baltic countries to the European Union in 2004, only firms with total export turnover of at least 100 thousand EUR are required to declare their transactions details.

[25] While the objective to condition the evolution of TFP in equation (6) on past investments, i_{t-1}, is to control for the TFP effects of a "wide range of firm-level actions" (De Loecker, 2013), it is unlikely to control for the TFP effects of some of the unobserved endogenous complementary activities, such as innovation. Though, the TFP effects of non-complementary activities, through persistent shocks, ξ_{t-1}, to TFP, are captured by $\omega_{t-1} = g(\omega_{t-2}, x_{t-2}) + \xi_{t-1}$. The shocks, ξ_{t-1}, which represent the uncertainties naturally linked to productivity, as suggested in Doraszelski and Jaumandreu (2013), capture, among others, the absorption of techniques, modification of processes, and chance discoveries. Though it is debatable whether activities such as the absorption of new techniques are non-complementary and exogenously affect TFP growth.

little evidence that we find of the TFP impact of exporting is likely due to the impact of costly productivity enhancing investments, which are more likely to be undertaken by large and persistent exporters.

5.2 Comparing Estimates with the Estimates from an Alternative Estimator

In Table 7, we compare estimates obtained from the method developed here with the estimates obtained by using the method in Malikov and Zhao (2023) (MZ). In terms of assumed structures, it is the closest to our model, but unlike ours, their method requires the output markets to be perfectly competitive. Another reason for comparing our estimates with those obtained by the method in MZ is that it is the only method for estimating the parametric production function that we know of that avoids the critique by Gandhi, Navarro and Rivers (2020).[26]

[Table 7 about here]

To estimate using the method in MZ, the law of motion of productivity in (6)[27] is specified as

$$\omega_t = g(\omega_{t-1}, i_{t-1}, NYrEx_{t-1}) + \xi_t = f(\omega_{t-1}) + \gamma i_{t-1} + \chi(NYrEx_{t-1}) + \xi_t, \quad (44)$$

where $NYrEx$ is the number of years in export markets, $f(.)$ is a cubic function, and $X(.)$ is a fourth order polynomial. As in their baseline specification, we include year dummies to control for technical change.

When markets are imperfectly competitive, the coefficients of the inputs obtained from using the method in MZ are more appropriately thought of as the revenue elasticity of inputs. When markets are imperfect ($[1 + \varepsilon_{PY}] < 1$), revenue elasticity of materials, $\alpha_M^R = [1 + \varepsilon_{PY}]\alpha_M$, is smaller than output elasticity, α_M. As can be seen in Table 7, the elasticities of material inputs are smaller in comparison to ours. This suggests that using methods that assume perfect competition when markets are imperfectly competitive is likely to give erroneous results. Elasticity of labour, on the other hand, is larger compared to ours and does not vary much. The coefficients of capital are smaller compared to ours and with little variation across sectors.

We find that the method in MZ estimates the function, $\chi(NYrEx_{t-1})$, with precision. In Figure 1, we plot revenue productivity (Revenue/No. of Employees) and $\hat{\chi}(NYrEx_{t-1})$,[28] where $\hat{\chi}(NYrEx_{t-1})$ is the estimate of $X(NYrEx_{t-1})$ for the en-

[26] Gandhi, Navarro and Rivers (2020) argue that the proxy variable techniques, such as in LP, do not identify (or under-identify) the production function. They show that if there are no sources of variation in flexible input demand other than a panel of data on output and inputs, the gross output production function is non-identified under such approaches. They accordingly use a share of material inputs to estimate the output elasticity of material inputs.

[27] Equation (3.3) in MZ describes the law of motion of productivity and in equation (5.2) of their paper, the function, $h(.)$, in (44) is approximated by a polynomial function.

[28] The estimate of $\chi(NYrEx_{t-1})$ is $.181 \times NYrEx - .043 \times NYrEx^2 + .00406 \times NYrEx^3 - .00013 \times NYrEx^4$.

Figure 1: Revenue Productivity and Productivity Impact of Number of Years of Exporting as obtained from the MZ Method

tire manufacturing sector obtained using the method in MZ. Computing $\frac{\partial \chi(NYrEx)}{\partial NYrEx}$ would give estimates for the productivity impact of one additional year of exporting as a function of the number of years of exporting. As Figure 1 suggests, the estimate, $\hat{\chi}(NYrEx_{t-1})$, mimics the way revenue productivity changes with the number of years of exports. This suggests that with revenue data, the methods that do not control for prices and demand side factors are likely to identify the impacts on revenue based measures of productivity rather than the implications for TFP.

5.3 Markups and Persistence in Export Status

In Table 8 we study how markups are associated with export persistence. We estimate markups for each firm-year following the indirect or the production approach in De Loecker and Warzynski (2012), where markup, μ_t, is computed as

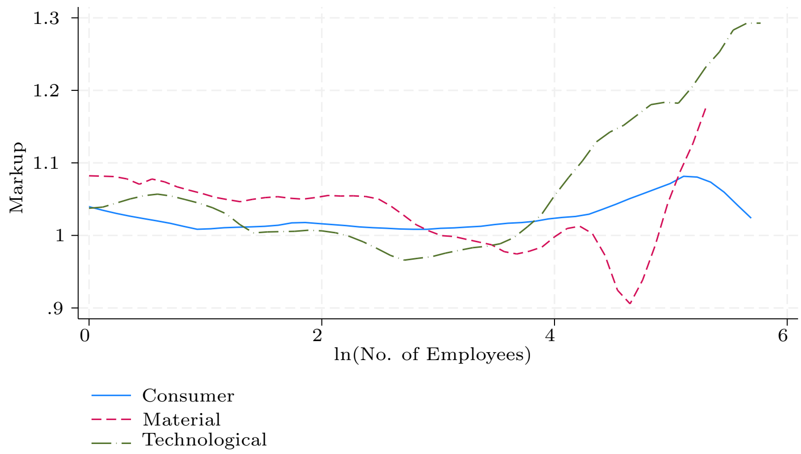
$$\mu_t = \frac{\alpha_M}{S_t^M \mathcal{E}_t},$$

where α_M is the output elasticity of material inputs and $S_t^M \mathcal{E}_t$ is the share of material inputs in the planned revenue of the firm. In perfectly competitive markets, markup is equal 1 and the output elasticity equals the input's share of revenue. When markets are imperfect, markups are greater than 1, which implies that the expenditure on materials as a fraction of planned revenue falls short of the output elasticity.

[Table 8 about here]

For estimating markups, we estimate output elasticities of material inputs for each year. Once markups are estimated, in Figure 2a we plot the nonparametric regression (for smoothing) of markup on log of number of employees. Since we are unable to estimate TFP, we use number of employees as a proxy for firm productivity. This is based on the well documented relationship between firm size and productivity. We

Figure 2: Markup and Price



(a) Markup and Firm Size

(b) ln(Price of the Core Product) and Firm Size

do not use revenue or value-added productivity as these measures are contaminated by prices, which are correlated with markups. We find that only in the technological manufacturing, which happen to be the smallest of the three, markups increase with firm size. This finding, which is limited mostly in one sector and only among large firms, is in line with the findings that larger firms face a less elastic demand.[29] For the large bulk of the manufacturing sector, markups either decline or remain unchanged with firm size.

[29]There could be various reasons why markups at the far end of the tail of the size distribution, especially in the technological sector, are relatively large. It could be that due Marshal's Second Law of Demand larger firms face a less elastic demand (Mayer *et al.*, 2021). It could be that larger firms produce more expensive quality differentiated goods. If high quality products feature a high willingness-to-pay, as suggested in BCHR, or if consumers of high quality products are price insensitive (Döpper, MacKay, Miller and Stiebale, 2024), it could lead to firms that produce higher quality goods charge a higher markup. It could also be because larger firms charge prices above marginal costs to cover fixed costs they might incur. It is however beyond the scope of this paper to investigate why markups increase quickly as large firms in the technological manufacturing become even larger.

Now, though we do not have prices for all the firms, customs data has information on the FOB prices of the exported products. In Figure (2b), we plot the aggregate of ln(Price) of the core products. That larger, more productive exporters are offering lower prices suggests efficiency sorting (Melitz and Ottaviano, 2008), where products are not quality differentiated and firms compete on prices to gain market share. However, if exporters are setting lower prices in export markets, which are larger, it is likely that, as the model in Melitz and Ottaviano (2008) implies, the prices in the home, too, are lowered to increase revenue and market share. The most productive firms charge lower prices, command a larger market share, earn higher revenues even as some of the larger ones have higher markups.

In Table 8 we regress the firm-level markups on a measures of export persistence.[30] We control for labor and capital, which capture differences in size and factor intensity, as well as year, industry, and firm fixed effects. We find that, except for the highly persistent exporter in the consumer and technological manufacturing sectors, exporters' markups, though lower, are not statistically different from that of the non-exporters'. Using Chilean data, BCHR estimate domestic as well as foreign markups for the Chilean exporters. They find that the exporters charge higher markups in the domestic market but smaller markups in the foreign markets, which is why, in the aggregate, exporters have higher markups than the non-exporters. They find that given productivity, the demand for exporters' product exhibit a higher domestic willingness-to-pay, likely due to higher quality. This, they argue, could indicate why exporters' domestic markups are higher than the non-exporters'. While this may as well be the case for Estonian exporters, in the aggregate, Estonian exporters' markups are lower than that of the non-exporters'. This finding also points toward efficiency sorting across Estonian exporters.

Under efficiency sorting, which as argued above is a more likely scenario for the Estonian exporters, tougher markets select firms with lower marginal costs (i.e., with higher productivity) and induce them to lower markup. The results therefore suggest that the highly persistent exporters export to destinations where competition is tougher, that is, destinations that have large market size, have higher income, are less remote and the are more central (network centrality:- a measure of country's position in the global trade network). To continue to remain competitive in these markets, exporter must lower their marginal costs by increasing productivity.

6 Concluding Remarks

This paper develops a novel strategy to estimate output elasticities and the total factor productivity (TFP) impact of endogenous treatments, such as the decision to export, in the presence of market imperfections. The method extends the "proxy/control function"

[30] The dummy variables used in Table 8 are different from the dummy variables used in Table 5. The dummy variables used in Table 8 are based on number of years of exporting, which does not distinguish between current exporters and non-exporters. If, for example, a firm exports twice, then in the first year of export and for all subsequent periods until the second year of export, the variable, number of years of exporting, takes value 1. From the second year of exporting until the last period the variable takes value 2.

method to account for imperfect competition. The proxy for TFP in certain control function methods is obtained by inverting the demand for flexible inputs. When markets are imperfectly competitive, the demand for material (flexible) inputs depends on output prices and the price elasticity of demand, which, among others, are functions of unobservable demand shifters. The proxy for TFP therefore depends on unobservable demand shifters, which implies that the proxy for TFP cannot be identified.

Our contribution lies in treating the unobserved demand shifters, which capture the quality and appeal of products, as non-separable errors in the proxy for TFP, the nonparametric part of the production function, and controlling for the confounding influence of the unobserved demand shifters. Central to our identification strategy are (i) a specification for the law of motion of the unobserved demand shifters, which borrows from the literature on customer accumulation, and (ii) a set of distributional restrictions to account for the correlation between the unobserved demand shifters and the variables of interest. These restrictions and other model specifications lead to a partially linear model with endogenous variables. An instrumental variable method for estimating a partially linear model is employed for the estimation.

In addition, like most researchers, we are faced with revenue and expenditures data, which leads to an unobserved output-input price wedge in the estimating equation. We provide an additional set of controls than is proposed in the literature to account for the confounding influence of the price wedge.

Using firm-level data for the Estonian manufacturing sector, we find limited evidence of the TFP impact of exports; that is, of learning-by-exporting (LBE). We attribute this weak evidence of LBE to small exporters – those whose intra-EU export value is less than 100 thousand EUR – being wrongly classified as non-exporters in the customs data. The limited evidence shows that it is the persistent exporters who are likely to improve their TFP by exporting. Since we are unable to perfectly control for complementary activities, such as innovation, it is possible that the TFP impact for large and persistent exporters is due to costly productivity enhancing complementary activities. Finally, exporters are found to charge lower markups than non-exporters and this markup difference increases with persistence in exporting. Our results suggest efficiency sorting across exporters. So, while firms with lower marginal costs are selected into tougher export markets, competition induces them to lower their markups. This is best achieved by persistent exporters, who happen to be among the most productive firms. We also show that using methods that assume perfectly competitive markets are likely to give erroneous results for the TFP impact of endogenous treatments. We also show that using methods that assume perfectly competitive markets are likely to give erroneous results for TFP impact of endogenous treatments.

References

Ackerberg, D. (2001). Empirically Distinguishing Informative and Prestige Effects of Advertising. *RAND Journal of Economics*, **32** (2), 316–33.

Alessandria, G., Arkolakis, C. and Ruhl, K. J. (2021). Firm Dynamics and Trade. *Annual Review of Economics*, **13** (1), 253–280.

Altonji, J. and Matzkin, R. (2005). Cross Section and Panel Data Estimators for Nonseparable Models with Endogenous Regressors. *Econometrica*, **73** (4), 1053–1102.

Angrist, J. D. (1997). Conditional Independence in Sample Selection Models. *Economics Letters*, **54** (2), 103–112.

Arkolakis, C., Costinot, A., Donaldson, D. and Rodríguez-Clare, A. (2019). The Elusive Pro-Competitive Effects of Trade. *Review of Economic Studies*, **86** (1), 46–80.

Armstrong, T. B., Kolesár, M. and Plagborg-Møller, M. (2022). Robust Empirical Bayes Confidence Intervals. *Econometrica*, **90** (6), 2567–2602.

Atkin, D., Khandelwal, A. K. and Osman, A. (2017). Exporting and Firm Performance: Evidence from a Randomized Experiment. *The Quarterly Journal of Economics*, **132** (2), 551–615.

Aw, B. Y., Roberts, M. J. and Xu, D. Y. (2011). R&D Investment, Exporting, and Productivity Dynamics. *American Economic Review*, **101** (4), 1312–1344.

Bems, R., Johnson, R. and Yi, K.-M. (2013). The Great Trade Collapse. *Annual Review of Economics*, **5** (1), 375–400.

Berman, N., Rebeyrol, V. and Vicard, V. (2019). Demand Learning and Firm Dynamics: Evidence from Exporters. *The Review of Economics and Statistics*, **101** (1), 91–106.

Blum, B. S., Claro, S., Horstmann, I. and Rivers, D. A. (2024). The ABCs of Firm Heterogeneity When Firms Sort into Markets: The Case of Exporters. *Journal of Political Economy*, **132** (4), 1162–1208.

Blundell, R. W. and Powell, J. L. (2004). Endogeneity in Semiparametric Binary Response Models. *The Review of Economic Studies*, **71** (3), 655–679.

Bosker, M. and Buringh, E. (2020). Ice(berg) Transport Costs. *The Economic Journal*, **130** (629), 1262–1287.

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.

Chen, X., Linton, O. and Van Keilegom, I. (2003). Estimation of semiparametric models when the criterion function is not smooth. *Econometrica*, **71** (5), 1591–1608.

Choné, P. and Linnemer, L. (2020). Linear Demand Systems for Differentiated Goods: Overview and User's Guide. *International Journal of Industrial Organization*, **73**, 102663.

Clerides, S., Lach, S. and Tybout, J. (1998). Is Learning by Exporting Important? Micro-Dynamic Evidence from Colombia, Mexico, and Morocco. *The Quarterly Journal of Economics*, **113** (3), 903–947.

Das, S., Roberts, M. J. and Tybout, J. R. (2007). Market Entry Costs, Producer Heterogeneity, and Export Dynamics. *Econometrica*, **75** (3), 837–873.

Dawid, A. P. (1979). Conditional Independence in Statistical Theory. *Journal of the Royal Statistical Society: Series B (Methodological)*, **41** (1), 1–15.

De Loecker, J. (2011). Product Differentiation, Multiproduct Firms, and Estimating the Impact of Trade Liberalization on Productivity. *Econometrica*, **79** (5), 1407–1451.

— (2013). Detecting Learning by Exporting. *American Economic Journal: Microeconomics*, **5** (3), 1–21.

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

— and Goldberg, P. K. (2014). Firm Performance in a Global Market. *Annual Review of Economics*, **6** (1), 201–227.

—, —, Khandelwal, A. K. and Pavcnik, N. (2016). Prices, Markups, and Trade Reform. *Econometrica*, **84**, 445–510.

— and Syverson, C. (2021). An Industrial Organization Perspective on Productivity. In K. Ho, A. Hortaçsu and A. Lizzeri (eds.), *Handbook of Industrial Organization, Volume 4*, *Handbook of Industrial Organization*, vol. 4, Elsevier, pp. 141–223.

— and Warzynski, F. (2012). Markups and Firm-Level Export Status. *American Economic Review*, **102** (6), 2437–2471.

De Ridder, M., Grassi, B. and Morzenti, G. (2024). *The Hitchhiker's Guide to Markup Estimation*. Discussion papers, Centre for Macroeconomics (CFM).

Dobbelaere, S. and Mairesse, J. (2013). Panel Data Estimates of the Production Function and Product and Labor Market Imperfections. *Journal of Applied Econometrics*, **28** (1), 1–46.

Döpper, H., MacKay, A., Miller, N. H. and Stiebale, J. (2024). *Rising Markups and the Role of Consumer Preferences*. Working Paper 32739, National Bureau of Economic Research.

Doraszelski, U. and Jaumandreu, J. (2013). R&D and Productivity: Estimating Endogenous Productivity. *The Review of Economic Studies*, **80** (4), 1338–1383.

— and — (2021). *Reexamining the De Loecker & Warzynski (2012) Method for Estimating Markups*. CEPR Discussion Papers, C.E.P.R.

Eaton, J., Eslava, M., Jinkins, D., Krizan, C. J. and Tybout, J. R. (2021). *A Search and Learning Model of Export Dynamics*. Working Paper 29100, National Bureau of Economic Research.

—, Kortum, S. and Kramarz, F. (2011). An Anatomy of International Trade: Evidence From French Firms. *Econometrica*, **79** (5), 1453–1498.

Eslava, M., Haltiwanger, J. and Urdaneta, N. (2023). The Size and Life-Cycle Growth of Plants: The Role of Productivity, Demand, and Wedges. *The Review of Economic Studies*.

Fitzgerald, D., Haller, S. and Yedid-Levi, Y. (2023). How Exporters Grow. *The Review of Economic Studies*, pp. 1–31.

Florens, J., Johannes, J. and Bellegem, S. V. (2012). Instrumental Regression in Partially Linear Models. *Econometrics Journal*, **15** (2), 304–324.

Forlani, E., Martin, R., Mion, G. and Muûls, M. (2023). Unraveling Firms: Demand, Productivity and Markups Heterogeneity. *The Economic Journal*, **133** (654), 2251–2302.

Gandhi, A., Navarro, S. and Rivers, D. (2020). On the Identification of Gross Output Production Functions. *Journal of Political Economy*, **128** (8), 2973–3016.

Gu, J. and Koenker, R. (2017). Unobserved Heterogeneity in Income Dynamics: An Empirical Bayes Perspective. *Journal of Business & Economic Statistics*, **35** (1), 1–16.

Hall, R. (1986). Market Structure and Macroeconomic Fluctuations. *Brookings Papers on Economic Activity*, **17** (2), 285–338.

Hottman, C. J., Redding, S. J. and Weinstein, D. E. (2016). Quantifying the Sources of Firm Heterogeneity. *The Quarterly Journal of Economics*, **131** (3), 1291–1364.

Hummels, D. (2007). Transportation Costs and International Trade in the Second Era of Globalization. *Journal of Economic Perspectives*, **21** (3), 131–154.

— and Skiba, A. (2004). Shipping the Good Apples Out? An Empirical Confirmation of the Alchian-Allen Conjecture. *Journal of Political Economy*, **112** (6), 1384–1402.

Juust, M. (2023). Trade Effects of a Negative Export Shock on Direct Exporters and Wholesalers. *Journal of Economic Studies*, **50** (5), 967–986.

Koenker, R. and Gu, J. (2017). REBayes: An R Package for Empirical Bayes Mixture Methods. *Journal of Statistical Software*, **82** (8), 1–26.

Kugler, M. and Verhoogen, E. (2012). Prices, Plant Size, and Product Quality. *The Review of Economic Studies*, **79** (1), 307–339.

Lashkaripour, A. (2020). Weight-based Quality Specialization. *Journal of International Economics*, **127**, 103380.

Levinsohn, J. and Petrin, A. (2003). Estimating Production Functions Using Inputs to Control for Unobservables. *The Review of Economic Studies*, **70** (2), 317–341.

Levinsohn, J. A. and Melitz, M. (2006). *Productivity in a Differentiated Products Market Equilibrium*. Working paper, Harvard University.

Lileeva, A. and Trefler, D. (2010). Improved Access to Foreign Markets Raises Plant-level Productivity For Some Plants. *The Quarterly Journal of Economics*, **125** (3), 1051–1099.

Liu, L., Poirier, A. and Shiu, J.-L. (2024). Identification and Estimation of Partial Effects in Nonlinear Semiparametric Panel Models.

Malikov, E. and Zhao, S. (2023). On the Estimation of Cross-Firm Productivity Spillovers with an Application to FDI. *The Review of Economics and Statistics*, **105** (5), 1207–1223.

—, — and Kumbhakar, S. C. (2020). Estimation of Firm-level Productivity in the Presence of Exports: Evidence from China's Manufacturing. *Journal of Applied Econometrics*, **35** (4), 457–480.

Matsuyama, K. (2023). Non-CES Aggregators: A Guided Tour. *Annual Review of Economics*, **15** (1), 235–265.

Mayer, T., Melitz, M. J. and Ottaviano, G. I. P. (2014). Market Size, Competition, and the Product Mix of Exporters. *American Economic Review*, **104** (2), 495–536.

—, — and — (2021). Product Mix and Firm Productivity Responses to Trade Competition. *The Review of Economics and Statistics*, **103** (5), 874–891.

Melitz, M. (2000). *Estimating Firm-Level Productivity in Differentiated Product Industries*. Working Paper 14404, Harvard University OpenScholar.

— and Ottaviano, G. (2008). Market Size, Trade, and Productivity. *Review of Economic Studies*, **75** (1), 295–316.

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

Miao, G. and Wegner, E. (2017). *Estimating Transport and Insurance Costs of International Trade*. Tech. rep., Organisation for Economic Co-operation and Development.

— and — (2022). *Recent Trends in Transport and Insurance Costs and Estimates at Disaggregated Product Level*. Tech. rep., Organisation for Economic Co-operation and Development.

Mrázová, M. and Neary, J. P. (2020). IO for Exports(s). *International Journal of Industrial Organization*, **70**, 102561.

Newey, W. K. (1997). Convergence rates and asymptotic normality for series estimators. *Journal of Econometrics*, **79** (1), 147–168.

Piveteau, P. (2021). An Empirical Dynamic Model of Trade with Consumer Accumulation. *American Economic Journal: Microeconomics*, **13** (4), 23–63.

Redding, S. (2011). Theories of Heterogeneous Firms and Trade. *Annual Review of Economics*, **3** (1), 77–105.

Roberts, M. J., Xu, D. Y., Fan, X. and Zhang, S. (2018). The Role of Firm Factors in Demand, Cost, and Export Market Selection for Chinese Footwear Producers. *Review of Economic Studies*, **85** (4), 2429–2461.

Ruhl, K. J. and Willis, J. L. (2017). New Exporter Dynamics. *International Economic Review*, **58** (3), 703–726.

Timoshenko, O. A. (2015). Learning Versus Sunk Costs Explanations of Export Persistence. *European Economic Review*, **79** (C), 113–128.

Valmari, N. (2023). Estimating Production Functions of Multiproduct Firms. *The Review of Economic Studies*, **90** (6), 3315–3342.

Verhoogen, E. (2008). Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector. *The Quarterly Journal of Economics*, **123** (2), 489–530.

Yeh, C., Macaluso, C. and Hershbein, B. (2022). Monopsony in the US Labor Market. *American Economic Review*, **112** (7), 2099–2138.

Appendices

Appendix A Proofs

A.1 Derivation of the First Order Condition

The firm j's short run cost minimisation problem is:

$$\min_{M_1,\ldots,M_{\mathcal{M}_j}} \sum_{m=1}^{\mathcal{M}_j} P_m^M M_m \text{ subject to } F(L,K,M(M_1,\ldots,M_{\mathcal{M}_j}))\Omega \geq Y^*$$

where $\{P_1^M \ldots, P_{\mathcal{M}_j}^M\}$ are the prices of the material inputs. The first order conditions (FOC) for the above problem are:

$$\lambda \frac{\partial F(L,K,M(M_1,\ldots,M_{\mathcal{M}_j}))\Omega}{\partial M} \frac{\partial M}{\partial M_m} = P_m^M, m = 1,\ldots,\mathcal{M}_j, \tag{A.1}$$

where λ is the Lagrange multiplier to the constraint in the cost minimisation problem. Multiplying the FOC for M_m in (A.1) throughout with M_m and summing over m, we obtain:

$$\lambda \frac{\partial F(L,K,M(M_1,\ldots,M_{\mathcal{M}_j}))\Omega}{\partial M} \sum_{m=1}^{\mathcal{M}_j} M_m \frac{\partial M}{\partial M_m} = \sum_{m=1}^{\mathcal{M}_j} P_m^M M_m = \widetilde{M}.$$

By Euler's Theorem, the linear homogeneity of $M(M_1,\ldots,M_{\mathcal{M}_j})$ implies that $\sum_{m=1}^{\mathcal{M}_j} M_m \frac{dM}{dM_m} = M$. And therefore, we can write the above as:

$$\lambda \frac{\partial F(L,K,M(M_1,\ldots,M_{\mathcal{M}_j}))\Omega}{\partial M} = \frac{\widetilde{M}}{M} = P^M,$$

where P^M, as stated in (9), is the price of M. Multiplying throughout by $\frac{M}{PY^*}$, where P, as stated in (9), is the price of output Y, we obtain

$$\frac{\lambda}{P}\alpha_M = \frac{P^M M}{PY^*}, \tag{A.2}$$

where α_M is the elasticity of output with respect to M and λ is the marginal cost of producing an extra unit of Y.

A.2 Condition for the Invertibility of the Material Input Demand Function

Proposition 1 *When productivity, Ω, is Hick's neutral then in the presence of market imperfection in the goods market, the demand for material inputs $\mathbb{M}(Z,\Omega)$ monotonically increase with Ω if the elasticity of markup, μ, with respect to productivity, Ω, $\varepsilon_{\mu\Omega} := \frac{\partial \mu}{\partial \Omega}\frac{\Omega}{\mu}$, is less than $\frac{1}{\mu}$.*

Proof of Proposition 1 *Let $\mathbb{M}(\Omega) := \text{argmin}_M P^M M$, such that $F(L,K,M)\Omega \geq Y^*$, denotes the demand for material inputs. Let $\mathcal{L}(M,\Omega)$ be the Lagrangian for the constrained minimisation problem, and write the FOC as:*

$$\frac{\partial \mathcal{L}(M,\Omega)}{\partial M}|_{M=\mathbb{M}(\Omega)} = 0.$$

Differentiating the FOC with respect to Ω, we get:

$$\begin{aligned}\frac{d}{d\Omega}\left(\frac{\partial \mathcal{L}(\mathbb{M}(\Omega),\Omega)}{\partial M}\right) &= \frac{\partial^2 \mathcal{L}(\mathbb{M}(\Omega),\Omega)}{\partial\Omega\partial M} + \frac{\partial^2 \mathcal{L}(\mathbb{M}(\Omega),\Omega)}{\partial M^2}\frac{\partial \mathbb{M}(\Omega)}{\partial \Omega} \\ &= \mathcal{L}_{\Omega M}(\mathbb{M}(\Omega),\Omega) + \mathcal{L}_{MM}(\mathbb{M}(\Omega),\Omega)\frac{\partial \mathbb{M}(\Omega)}{\partial\Omega} = 0.\end{aligned}$$

That is,

$$\frac{\partial \mathbb{M}(\Omega)}{\partial \Omega} = -\frac{\mathcal{L}_{\Omega M}(\mathbb{M}(\Omega),\Omega)}{\mathcal{L}_{MM}(\mathbb{M}(\Omega),\Omega)}, \tag{A.3}$$

Since according to the second order condition, $\mathcal{L}_{MM}(\mathbb{M}(\Omega), \Omega) < 0$, to derive the conditions under which $\frac{\partial \mathbb{M}(\Omega)}{\partial \Omega}$ in (A.3) is positive, we have to establish the conditions for which $\mathcal{L}_{\Omega M}(\mathbb{M}(\Omega), \Omega) > 0$. Now, we can write the FOC in (A.2) as:

$$\mathcal{L}_M(M, \Omega) = \frac{\partial F(L, K, M)\Omega}{\partial M}\frac{P}{\mu} - P^M,$$

where $\mathcal{L}_M(M, \Omega) := \frac{\partial \mathcal{L}(M, \Omega)}{\partial M}$ and $\mu := \left[\frac{dP}{dY}\frac{Y}{P} + 1\right]^{-1}$ is the markup over marginal cost that the firm charges, and $\frac{P}{\mu}$ is the marginal revenue. Differentiating $\mathcal{L}_M(M, \Omega)$ with respect to Ω, we get:

$$\begin{aligned}
\mathcal{L}_{\Omega M}(M, \Omega) &= \frac{\partial^2 Y}{\partial \Omega \partial M}\frac{P}{\mu} + \frac{\partial Y}{\partial M}\frac{\partial P}{\partial Y}\frac{\partial Y}{\partial \Omega}\frac{1}{\mu} - \frac{\partial Y}{\partial M}\frac{P}{\mu^2}\frac{\partial \mu}{\partial \Omega} \\
&= \frac{\partial Y}{\partial M}\frac{1}{\Omega}\frac{P}{\mu} + \frac{\partial Y}{\partial M}\frac{\partial P}{\partial Y}\frac{Y}{\Omega}\frac{1}{\mu} - \frac{\partial Y}{\partial M}\frac{P}{\mu^2}\frac{\partial \mu}{\partial \Omega} \\
&= \frac{\partial Y}{\partial M}\left[\frac{1}{\Omega\mu}\left[P + \frac{\partial P}{\partial Y}Y\right] - \frac{P}{\mu^2}\frac{\partial \mu}{\partial \Omega}\right] \\
&= \frac{\partial Y}{\partial M}\frac{P}{\Omega\mu}\left[\frac{1}{\mu} - \frac{\Omega}{\mu}\frac{\partial \mu}{\partial \Omega}\right] \\
&= \frac{\partial Y}{\partial M}\frac{P}{\Omega\mu}\left[\frac{1}{\mu} - \varepsilon_{\mu\Omega}\right],
\end{aligned} \tag{A.4}$$

where the second line follows from the Hick's neutrality of Ω, according to which $\frac{\partial^2 Y}{\partial \Omega \partial M} = \frac{\partial Y}{\partial M}\frac{1}{\Omega}$ and $\frac{\partial Y}{\partial \Omega} = \frac{Y}{\Omega}$. In the third line, we collect common terms, and the fourth line follows because $\left[P + \frac{\partial P}{\partial Y}Y\right] = \frac{P}{\mu}$.

Therefore, $\mathcal{L}_{\Omega M}(M, \Omega)|_{M=\mathbb{M}(\Omega)} > 0$, or equivalently $\frac{\partial \mathbb{M}(\Omega)}{\partial \Omega} > 0$, if $\varepsilon_{\mu\Omega} < \frac{1}{\mu}$.

A.3 Elasticity and Markup

Proposition 2 *(a) The inverse of price elasticity of demand, ε_{PY}, is the weighted sum, $\sum_{d \in \mathfrak{D}} s_d \varepsilon_{PY,d}$, where $\varepsilon_{PY,d}$ is the inverse of the elasticity with respect to producer/FOB price, P_d^f, of the residual demand that the firm faces in destination, d, and $s_d = \frac{P_d^f Y_d}{PY}$ is the share of revenue earned from destination, d.*

(b) The markup, $\mu = [\varepsilon_{PY} + 1]^{-1} = \left[\sum_{d \in \mathfrak{D}} \frac{s_d}{\mu_d}\right]^{-1}$, where $\mu_d = [\varepsilon_{PY,d} + 1]^{-1}$.

Proof of Proposition 2 *(a) Since the revenue earned by the firm is $\sum_{d \in \mathfrak{D}} P_d^f Y_d = (\sum_{d \in \mathfrak{D}} P_d^f X_d)Y = PY$ and $Y_d = X_d Y$, we have:*

$$\frac{dP}{dY} = \sum_{d \in \mathfrak{D}} \frac{\partial P}{\partial P_d^f}\frac{dP_d^f}{dY} = \sum_{d \in \mathfrak{D}} X_d \frac{dP_d^f}{dY} = \sum_{d \in \mathfrak{D}} X_d \frac{dP_d^f}{dY_d}\frac{dY_d}{dY} = \sum_{d \in \mathfrak{D}} \frac{dP_d^f}{dY_d} X_d^2. \tag{A.5}$$

The above result follows from the fact that the export orientation, $\{X_d = \frac{Y_d}{Y}\}_{d\in\mathfrak{D}}$*, is predetermined; that is, it is fixed at the time of static optimisation.*

Equation (A.5) and $Y_d = X_d Y$ *imply that*

$$\varepsilon_{PY} = \frac{dP}{dY}\frac{Y}{P} = \sum_{d\in\mathfrak{D}} \frac{dP_d^f}{dY_d} X_d^2 \frac{Y}{P} = \sum_{d\in\mathfrak{D}} \frac{dP_d^f}{dY_d} X_d^2 \frac{Y_d}{X_d P} = \sum_{d\in\mathfrak{D}} X_d \frac{P_d^f}{P}\frac{dP_d^f}{dY_d}\frac{Y_d}{P_d^f} = \sum_{d\in\mathfrak{D}} s_d \varepsilon_{PY,d}. \tag{A.6}$$

(b) Since $\mu = [\varepsilon_{PY} + 1]^{-1}$*, given (A.6), we can write* μ *as:*

$$\mu = [\varepsilon_{PY} + 1]^{-1} = [\sum_{d\in\mathfrak{D}} s_d \varepsilon_{PY,d} + 1]^{-1} = \left[\sum_{d\in\mathfrak{D}} s_d(\varepsilon_{PY,d} + 1)\right]^{-1} = \left[\sum_{d\in\mathfrak{D}} \frac{s_d}{\mu_d}\right]^{-1},$$

where the third equality follows from the fact that $\sum_{d\in\mathfrak{D}} s_d = 1$ *and the fourth because* $\mu_d = (\varepsilon_{PY,d} + 1)^{-1}$*.*

Appendix B Extensions

B.1 Multi-product Firms

Firms produce multiple products and face demand for each of the products that depends on their quality. As in Hottman, Redding and Weinstein (2016)(HRW) and Eslava, Haltiwanger and Urdaneta (2023)(EHU), we assume that for firms producing multiple products, the output, Y_j, in equations (1) and (35) is the aggregate of quality/appeal[31] weighted differentiated products:

$$Y_j = \left[\sum_{\kappa\in\Theta_j} (\varphi_{j\kappa} Y_{j\kappa})^{\frac{\sigma_j - 1}{\sigma_j}}\right]^{\frac{\sigma_j}{\sigma_j - 1}}. \tag{B.1}$$

The weights, $\varphi_{j\kappa}$, which denotes the quality/appeal of the product, $j\kappa$, adjusts the quantities, $Y_{j\kappa}$, of each quality-differentiated products for quality. The constant elasticity of substitution (CES), σ_j, aggregator in (B.1) also adjusts the quality-adjusted product, $\varphi_{j\kappa} Y_{j\kappa}$, for substitutability between the various products produced by the firm. We also assume that the set of products, Θ_j, produced by the firm belong to the same product category, v, which is not unique to the firm. Though, each product, $j\kappa$, and, therefore, Y_j are uniquely quality-differentiated.

HRW argue that if goods are imperfect substitutes (i.e. if $1 < \sigma_j < \infty$), then the real output of a multi-product firm is not equal to the sum of the outputs of each product. This is because if it assumed that the quantity demanded is the sum of the outputs of each product produced by the firms, then one implicitly assumes that either (a) firms produces a single product or (b) that the products of the firm are

[31] HRW find that higher appeal products are on average more costly to produce, which, they argue, is consistent with a quality interpretation.

perfect substitutes. Under these assumptions, the implied or the conventional price index ($\sum_{\kappa\in\Theta_j} Y_{j\kappa}P^f_{j\kappa}/\sum_{\kappa\in\Theta_j} Y_{j\kappa}$), which is the quantity-weighted average of prices, for multi-product firms is higher than the price index, P^f_j, in (B.3); we return to this point below. And, therefore, the conventional price index understates the "real" output of the firm, a bias which tend to rise as the number of products supplied by the firm increases.[32]

The index of real consumption, Y_j, in (B.1) is a CES nest in

$$U = Y_0 + \sum_j a_j Y_j - \gamma \sum_j \sum_{i>j} Y_j Y_i - \frac{1}{2}\sum_j \tilde{b}_j Y_j^2, \tag{B.2}$$

which, as in (34), is the representative consumer's utility. This is an aggregate of consumptions of aggregate bundles, Y_j, produced by a set of firms indexed, j.

If R_j is the amount spent on the goods produced by firm, j, then the demand for the quality-adjusted product, $j\kappa$, is given by

$$\varphi_{j\kappa}Y_{j\kappa} = \left[\frac{P^f_{j\kappa}}{\varphi_{j\kappa}}\frac{1}{P^f_j}\right]^{-\sigma_j}\frac{R_j}{P^f_j}, \text{ where } P^f_j = \left[\sum_{\kappa\in\Theta_j}\left(\frac{P^f_{j\kappa}}{\varphi_{j\kappa}}\right)^{1-\sigma_j}\right]^{\frac{1}{1-\sigma_j}} \text{is the FOB price index,} \tag{B.3}$$

and $\dfrac{P^f_{j\kappa}}{\varphi_{j\kappa}}$ is the quality-adjusted FOB price of product, $j\kappa$. Given the firm's revenue,

$$R_j = \sum_{\kappa\in\Theta_j} Y_{j\kappa}P^f_{j\kappa} = \sum_{\kappa\in\Theta_j}\Big(Y_{j\kappa}\varphi_{j\kappa}\Big)\left(\frac{P^f_{j\kappa}}{\varphi_{j\kappa}}\right), \tag{B.4}$$

linear homogeneity of the CES aggregator in (B.1) implies that

$$Y_j = \frac{R_j}{P^f_j}. \tag{B.5}$$

In other words, $\dfrac{R_j}{P^f_j}$ is the real output of the firm.

As discussed in HRW, for multi-product firms if the price index is to be economically informed then it must consider how the quality-differentiated products of the firm enter consumers' utility. This is because, assuming that the preferences are CES, only the price index, P_j, is sensitive to how differentiated its products are and how many products it supplies.

An alternative approach, such as in DLGKP and Valmari (2023), relies on treating products, instead of firms, as separate units. This approach entails imputing input shares for each product line, and requires knowledge of quantities and prices of each product produced. In Valmari (2023) information on prices of intermediate inputs, too,

[32] As stated in HRW, p. 1349, "for multiproduct firms, the concept of real output is not independent of the demand system, so all attempts to measure productivity based on a real output concept contain an implicit assumption about the structure of the demand system."

is used. Such detailed information, though, is not ordinarily available. EHU, on the other hand, who have product level information, instead of setting up product specific production functions, specify production structure directly at the establishment/firm level. EHU, p. 9 argue that "if one queried establishments (plants) to specify input costs (capital, labour, materials, and energy) on a product-specific basis, most would be unable to do so since multiple costs are shared across products (i.e. there is joint production). That is, an establishment is not simply a collection of separable lines of production. It is, in itself, an empirically relevant object." Besides, as pointed out by De Loecker and Syverson (2021), product specific production function rules out physical synergies across products as a source of economies of scope.

To obtain a measure of real output, EHU empirically construct the price index, P_j, which requires knowledge of within plant revenue shares of each product. Our approach does not require construction of such a measure. It, therefore, leaves open the possibility that the price index, P_j, is derived from a homothetic non-CES or a non-homothetic CES nest (see Matsuyama, 2023, for examples).

B.1.1 Demand and Elasticity for Multi-product Firms

The multi-product firm in the home country, whose demand and elasticity we seek to derive, is denoted by j. The amount of product, $j\kappa$, that it exports to destination, d, is denoted by $Y_{j\kappa d}$.

Here we make the following two assumptions:

Assumption A The preferences of the representative consumers at all destinations are identical.

Assumption B For a firm, j, in the home country, exporting in the year, t, the CIF-FOB margins for destination, d, are identical for all products, $\kappa \in \Theta$.

The preferences over the products, $\{Y_{j\kappa}\}_{\kappa \in \Theta_j}$, of the firm, j, is given by the utility function, Y_j, in (B.1), which is a CES nest in the aggregate utility in (B.2). According to **Assumption A**, the preferences — as denoted by quality/appeal parameters $\varphi_{j\kappa}$ in (B.1) and $\{a_j, b_j\}$ in (B.2) — for the outputs produces by the firm, j, are identical in all destinations.

Assumption B is based on the observation in Table 1.

Table 1: Distribution of Within Firm-Year-Destination Standard Deviation of CIF-FOB Margin

Percentile	5^{th}	10^{th}	20^{th}	30^{th}	40^{th}	50^{th}	60^{th}	70^{th}	80^{th}	90^{th}	95^{th}	Total Range
Std. Dev.	0	0	0	0	0	0	0	2.14	3	4.01	4.99	1 to 19

The CIF-FOB margins are expressed in percentage.

For more than 60 percent of the multi-product firms, there is no within firm-year-destination variation in the CIF-FOB margins. Even for firms for whom there is variation, the variation is small compared to total range of CIF-FOB margins. This also suggests that multi-product firms produce goods that are likely to be highly substitutable with each other. **Assumption B**, though, in line with Hummels (2007) and Lashkaripour (2020), allows for transportation costs to be higher for more expensive goods.

To ease notation, from here on we will suppress the weights, $\varphi_{j\kappa}$, and with a slight abuse of notations denote the quality-adjusted quantities, $\varphi_{j\kappa}Y_{j\kappa d}$, consumed at destination, d, by $Y_{j\kappa d}$. Also, the quality adjusted FOB prices, $\frac{P^f_{j\kappa d}}{\varphi_{j\kappa}}$, and the quality adjusted CIF prices, $\frac{P^c_{j\kappa d}}{\varphi_{j\kappa}}$, for destination, d, are respectively denoted by $P^f_{j\kappa d}$ and $P^c_{j\kappa d}$.[33]

Now, the revenue of the firm is

$$R_j = \sum_{\kappa\in\Theta_j}\sum_{d\in\mathfrak{D}_j} P^f_{j\kappa d}Y_{j\kappa d} = \sum_{\kappa\in\Theta_j}(\sum_{d\in\mathfrak{D}_j} P^f_{j\kappa d}X_{j\kappa d})Y_{j\kappa} = \sum_{\kappa\in\Theta_j} P^f_{j\kappa}Y_{j\kappa} = P^f_j Y_j, \tag{B.6}$$

where $X_{j\kappa d} = \frac{Y_{j\kappa d}}{Y_{j\kappa}}$ is the export intensity for product, κ, at destination, d. $P^f_{j\kappa} = \sum_{d\in\mathfrak{D}_j} P^f_{j\kappa d}X_{j\kappa d}$ is the export intensity weighted aggregate price of the product, κ. The last equality follows from (B.3), where $P^f_{j\kappa}$ and P^f_j are defined.

From here on, unless necessary, we will drop the firm subscript, j.

To derive an expression for the inverse price elasticity demand, ε_{P^fY}, for the aggregate ("real") good, Y, in (B.1), with respect to FOB price index, P^f, in (B.3) we have

$$\frac{dP^f}{dY} = \sum_{\kappa\in\Theta}\frac{\partial P^f}{\partial P^f_\kappa}\frac{dP^f_\kappa}{dY} = \sum_{\kappa\in\Theta}\frac{\frac{\partial P^f}{\partial P^f_\kappa}}{\sum_{\kappa'\in\Theta}\frac{\partial Y}{\partial Y_{\kappa'}}\frac{dY_{\kappa'}}{dP^f_\kappa}}.$$

From (B.3) it follows that $\frac{\partial P^f}{\partial P^f_\kappa} = S_\kappa\frac{P^f}{P^f_\kappa}$, where $S_\kappa = \frac{P^f_\kappa Y_\kappa}{P^fY}$ is the revenue/expenditure share of product κ, and $\frac{\partial Y}{\partial Y_\kappa} = \frac{P^f_\kappa}{P^f}$. These imply that

$$\varepsilon_{P^fY} = \frac{YdP^f}{P^fdY} = \sum_{\kappa\in\Theta}\frac{S_\kappa}{\sum_{\kappa'\in\Theta}\frac{S_{\kappa'}}{\varepsilon^{\kappa'\kappa}_{P^fY}}}, \tag{B.7}$$

where $\varepsilon^{\kappa'\kappa}_{P^fY}$ is the inverse of the price elasticity of demand of product κ' with respect to the price of product κ.

[33] We suppress the weights, $\varphi_{j\kappa}$, since in the CES framework, the price elasticities are independent of the weights, $\varphi_{j\kappa}$. That is, the price elasticity of quality-adjusted quantity, $\varphi_{j\kappa}Y_{j\kappa}$, of product, $j\kappa$, with respect to quality-adjusted price, $\frac{P_{j\kappa'}}{\varphi_{j\kappa'}}$, of product, $j\kappa'$, is same as the elasticity of unadjusted quantity, $Y_{j\kappa}$, with respect to the unadjusted price, $P_{j\kappa'}$.

Following Proposition 2, $\varepsilon^{\kappa'\kappa}_{P^fY}$ in (B.7) is written as the weighted average,

$$\varepsilon^{\kappa'\kappa}_{P^fY} = \sum_{d\in\mathfrak{D}} s_{\kappa d}\varepsilon^{\kappa'\kappa}_{P^fY,d},$$

where the weight, $s_{\kappa d} = \dfrac{P^f_{\kappa d}Y_{\kappa d}}{P^f_\kappa Y_\kappa}$, is the share of revenue in product, κ, accruing from destination, d, and $\varepsilon^{\kappa'\kappa}_{P^fY,d}$ the inverse of the price elasticity of demand at destination, d, for the product, κ', with respect to the FOB price, $P^f_{\kappa d}$. However, as shown in section 3.2.1 of the main text (equations (32) and (33)), the price elasticity of the firm's output with respect to its FOB price is the product of the elasticity of its CIF price with respect to its FOB price and the price elasticity of the output with respect to its CIF price:

$$\varepsilon^{\kappa'\kappa}_{P^fY,d} = \frac{\ln(P^f_{\kappa d})}{\ln(P^c_{\kappa d})}\varepsilon^{\kappa'\kappa}_{P^cY,d} \tag{B.8}$$

Since the CIF price, $P^c_{\kappa d}$, at destination, d, is the sum of FOB price and the transportation costs,

$$P^c_{\kappa d} = P^f_{\kappa d} + \mathcal{T}_{\kappa d},$$

(B.8) implies that $\varepsilon^{\kappa'\kappa}_{P^fY}$ in (B.7) is given by:

$$\varepsilon^{\kappa'\kappa}_{P^fY} = \sum_{d\in\mathfrak{D}} s_{\kappa d}\varepsilon^{\kappa'\kappa}_{P^fY,d} = \sum_{d\in\mathfrak{D}} s_{\kappa d}\left(\frac{P^c_{\kappa d}}{P^f_{\kappa d}}\right)\varepsilon^{\kappa'\kappa}_{P^cY,d} = \sum_{d\in\mathfrak{D}} W_{\kappa d}\varepsilon^{\kappa'\kappa}_{P^cY,d}. \tag{B.9}$$

And so, we can write ε_{P^fY} in (B.7) as

$$\varepsilon_{P^fY} = \frac{YdP^f}{P^fdY} = \sum_{\kappa\in\Theta} \frac{S_\kappa}{\sum\limits_{\kappa'\in\Theta} \dfrac{S_{\kappa'}}{\sum\limits_{d\in\mathfrak{D}} W_{\kappa d}\varepsilon^{\kappa'\kappa}_{P^cY,d}}}. \tag{B.10}$$

Let the consumption of the firm's "real" output, as given in (B.1), at destination, d, be Y_d. Then from (B.3) we know that the demand for product, κ, at destination, d, is given by

$$Y_{\kappa d} = \left[\frac{P^c_{\kappa d}}{P^c_d}\right]^{-\sigma} Y_d, \text{ where } P^c_d = \left[\sum_{\kappa\in\Theta}(P^c_{\kappa d})^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \tag{B.11}$$

is the CIF price index of the "real" output, Y_d, consumed at destination, d. Since the preference for Y_d is given by the utility function in (B.2), from equation (35) in the main text we know that the demand for Y_d is given by

$$Y_d = \frac{a - \gamma\mathbb{Y}_d - P^c_d}{b}.$$

This implies that the final demand for product, κ, at destination, d, is

$$Y_{\kappa d} = \left[\frac{P^c_{\kappa d}}{P^c_d}\right]^{-\sigma}\left[\frac{a - \gamma \mathbb{Y}_d - P^c_d}{b}\right]. \tag{B.12}$$

Using (B.12), we can therefore write $\varepsilon^{\kappa'\kappa}_{P^cY,d}$ in (B.10) as

$$\sigma\varepsilon^{\kappa'\kappa}_{P^cY,d} = \sigma\frac{d\ln(P^c_{\kappa d})}{d\ln(Y_{\kappa' d})} = -\frac{d\ln(Y_{\kappa d})}{d\ln(Y_{\kappa' d})} + \left(\sigma\frac{Y_{\kappa' d}}{P^c_d} - \frac{1}{b}\frac{Y_{\kappa' d}}{Y_d}\right)\left(\sum_{l\in\Theta}\frac{\partial P^c_d}{\partial P^c_{ld}}\frac{dP^c_{ld}}{dY_{\kappa' d}}\right). \tag{B.13}$$

In deriving the above, we have used the assumption that a monopolistic firm, since it is small compared to the size of the industry, cannot affect the aggregate demand shifter, $\mathbb{Y}_d$.

Before proceeding further, we state a Lemma.

Lemma 1 ***Assumption A*** *and* ***Assumption B*** *imply that (a) the relative prices of the products of any given firm are equal at all destinations and (b) expenditure shares of a product in the total revenue from a destination are equal for all destinations.*

That is, according to part (a) of the lemma, $\frac{P^c_{\kappa d}}{P^c_{\kappa' d}}$ is identical for all destinations. According to (b), for a product, κ, $\frac{P^c_{\kappa d}Y_{\kappa d}}{P^c_d Y_d}$ is identical for all destinations.

Proof of Lemma 1 *(a) Since by* ***Assumption B****, the CIF-FOB margins for any destination, d, are identical for all products, let M^{cf}_d, where $P^c_{\kappa d} = P^f_{\kappa d}(1 + M^{cf}_d) = P^f_{\kappa d} + \mathcal{T}_{\kappa d}$, be the common CIF-FOB margin — common for all goods — for destination, d. Then for destination, d, we have $\frac{P^c_{\kappa d}}{P^c_{\kappa' d}} = \frac{P^f_{\kappa d}}{P^f_{\kappa' d}}$. Similarly, for destination, d', we have $\frac{P^c_{\kappa d'}}{P^c_{\kappa' d'}} = \frac{P^f_{\kappa d'}}{P^f_{\kappa' d'}}$. So,*

$$\frac{P^c_{\kappa d}}{P^c_{\kappa' d}} = \frac{P^c_{\kappa d'}}{P^c_{\kappa' d'}} \text{ if } \frac{P^f_{\kappa d}}{P^f_{\kappa' d}} = \frac{P^f_{\kappa d'}}{P^f_{\kappa' d'}}. \tag{B.14}$$

However, since by ***Assumption A*** *preferences are identical in all countries, coupled with assumption* ***Assumption B****, which does not distort the relative prices of goods at the foreign destination, the firm has no incentive to set FOB price of good, κ, relative to that of κ' different for different destinations.*

(b) Since by ***Assumption B****, at the destination, d, $P^c_{\kappa d} = P^f_{\kappa d}(1 + M^{cf}_d)$, where M^{cf}_d is the common CIF-FOB margin, P^c_d in (B.11) and $Y_{\kappa d}$ in (B.12) are*

$$P^c_d = \left[\sum_{\kappa\in\Theta}(P^c_{\kappa d})^{1-\sigma}\right]^{\frac{1}{1-\sigma}} = \left[\sum_{\kappa\in\Theta}(P^f_{\kappa d})^{1-\sigma}\right]^{\frac{1}{1-\sigma}}(1 + M^{cf}_d) = P^f_d(1 + M^{cf}_d) \text{ and}$$

$$Y_{\kappa d} = \left[\frac{P^c_{\kappa d}}{P^c_d}\right]^{-\sigma} Y_d = \left[\frac{P^c_{\kappa d}}{P^c_d}\right]^{-\sigma}\left[\frac{a - \gamma\mathbb{Y}_d - P^c_d}{b}\right] = \left[\frac{P^f_{\kappa d}}{P^f_d}\right]^{-\sigma}\left[\frac{a - \gamma\mathbb{Y}_d - P^f_d(1 + M^{cf}_d)}{b}\right] \tag{B.15}$$

respectively. This implies that for a product, κ,

$$S_{\kappa d} := \frac{P^c_{\kappa d} Y_{\kappa d}}{P^c_d Y_d} = \frac{P^c_{\kappa d}\left[\frac{P^c_{\kappa d}}{P^c_d}\right]^{-\sigma} Y_d}{P^c_d Y_d} = \frac{P^f_{\kappa d}(1+M^{cf}_d)\left[\frac{P^f_{\kappa d}}{P^f_d}\right]^{-\sigma}}{P^f_d(1+M^{cf}_d)} = \frac{(P^f_{\kappa d})^{1-\sigma}}{\sum\limits_{\kappa\in\Theta}(P^f_{\kappa d})^{1-\sigma}}. \quad \text{(B.16)}$$

However, by part (a), it can be shown that $\frac{(P^f_{\kappa d})^{1-\sigma}}{\sum\limits_{\kappa\in\Theta}(P^f_{\kappa d})^{1-\sigma}}$ *in the above equation is identical for all destinations.*

Consider equation (B.13) again. In (B.13), $\frac{\partial P^c_d}{\partial P^c_{ld}} = \frac{P^c_d}{P^c_{ld}} S_{ld}$, where $S_{ld} := \frac{P^c_{ld} Y_{ld}}{Y_d P^c_d}$ is the expenditure share of good, l, in the total revenue, $Y_d P^c_d$, generated at destination, d. However, as shown in Lemma 1, S_{ld} is identical for all destinations. That is, $S_{ld} = S_l$ for all d. This also implies that S_{ld} in (B.16) is equal to S_l, where S_l, as defined in (B.7), is the revenue share of product l in the total revenue: $S_l = \frac{P^f_l Y_l}{P^f Y}$. *In other words, the share of revenue due to the product, κ, at a destination, d, in the total revenue generated at d is identical for all destinations, and is equal to the share of revenue due to the product, κ, in the total revenue of the firm.*

Equation (B.13) can, therefore, be written as

$$\sigma\varepsilon^{\kappa'\kappa}_{P^c Y,d} = -\frac{d\ln(Y_{\kappa d})}{d\ln(Y_{\kappa' d})} + \left(\sigma - \frac{1}{b}\frac{P^c_d}{Y_d}\right)\sum_{l\in\Theta} S_l \varepsilon^{\kappa' l}_{P^c Y,d} \text{ for each } \kappa\in\Theta\ . \quad \text{(B.17)}$$

By definition, $\varepsilon^{\kappa'\kappa'}_{Y,d} := \frac{d\ln(Y_{\kappa' d})}{d\ln(Y_{\kappa' d})} = 1$, and since by Lemma 1 the relative prices of the goods at all destinations are equal, $\varepsilon^{\kappa\kappa'}_{Y,d} := \frac{d\ln(Y_{\kappa d})}{d\ln(Y_{\kappa' d})}$ in the above is

$$\varepsilon^{\kappa\kappa'}_{Y,d} := \frac{d\ln(Y_{\kappa d})}{d\ln(Y_{\kappa' d})} = -\sigma\frac{d\ln(P^c_{\kappa d})}{d\ln(P^c_{\kappa' d})} = -\sigma\frac{d\ln(P^c_{\kappa d'})}{d\ln(P^c_{\kappa' d'})} = \frac{d\ln(Y_{\kappa d'})}{d\ln(Y_{\kappa' d'})} := \varepsilon^{\kappa\kappa'}_{Y,d'}.$$

In the rest, we denote $\varepsilon^{\kappa\kappa'}_{Y,d} = \varepsilon^{\kappa\kappa'}_{Y,d'}$ by $\varepsilon^{\kappa\kappa'}_{Y}$.

For each product, κ', and destination, d, (B.17) gives $K = |\Theta|$ equations, which can be solved to obtain the K elasticities, $\{\varepsilon^{\kappa' 1}_{P^c Y,d} \ldots \varepsilon^{\kappa'\kappa}_{P^c Y,d} \ldots \varepsilon^{\kappa' K}_{P^c Y,d}\}$, in terms of

$\{\varepsilon_Y^{1\kappa'} \dots \varepsilon_Y^{\kappa\kappa'} \dots \varepsilon_Y^{K\kappa'}\}$:

$$\varepsilon_{P^cY,d}^{\kappa' 1} = -\frac{\varepsilon_Y^{1\kappa'}}{\sigma} - \left(\frac{bY_d}{P_d^c} - \frac{1}{\sigma}\right) \sum_{\kappa \in \Theta} S_\kappa \varepsilon_Y^{\kappa\kappa'}$$

$$\vdots$$

$$\varepsilon_{P^cY,d}^{\kappa' \kappa} = -\frac{\varepsilon_Y^{\kappa\kappa'}}{\sigma} - \left(\frac{bY_d}{P_d^c} - \frac{1}{\sigma}\right) \sum_{\kappa \in \Theta} S_\kappa \varepsilon_Y^{\kappa\kappa'}$$

$$\vdots$$

$$\varepsilon_{P^cY,d}^{\kappa' K} = -\frac{\varepsilon_Y^{K\kappa'}}{\sigma} - \left(\frac{bY_d}{P_d^c} - \frac{1}{\sigma}\right) \sum_{\kappa \in \Theta} S_\kappa \varepsilon_Y^{\kappa\kappa'}, \text{ for any } \kappa' \in \Theta. \tag{B.18}$$

Since for any $\kappa' \in \Theta$,

$$\varepsilon_{P^cY,d}^{\kappa\kappa'} = \varepsilon_{P^cY,d}^{\kappa'\kappa'} \varepsilon_Y^{\kappa'\kappa}, \tag{B.19}$$

we can use it to write ε_{P^fY} in (B.10) as

$$\varepsilon_{P^fY} = \sum_{\kappa \in \Theta} S_\kappa \frac{\sum_{d \in \mathfrak{D}} W_{\kappa d} \varepsilon_{P^cY,d}^{\kappa\kappa}}{\sum_{\kappa' \in \Theta} S_{\kappa'} \varepsilon_Y^{\kappa'\kappa}}. \tag{B.20}$$

Plugging the values of $\varepsilon_{P^cY,d}^{\kappa\kappa}$ as derived in (B.18) in (B.20) and rearranging, we obtain

$$\varepsilon_{P^fY} = -\sum_{\kappa \in \Theta} S_\kappa \left(\sum_{d \in \mathfrak{D}} W_{\kappa d} \frac{bY_d}{P_d^c} \right) + \frac{1}{\sigma} \sum_{\kappa \in \Theta} S_\kappa \left(\sum_{d \in \mathfrak{D}} W_{\kappa d} \right) - \frac{1}{\sigma} \sum_{\kappa \in \Theta} S_\kappa \left(\frac{\sum_{d \in \mathfrak{D}} W_{\kappa d}}{\sum_{\kappa' \in \Theta} S_{\kappa'} \varepsilon_Y^{\kappa'\kappa}} \right). \tag{B.21}$$

Note, however, that for any destination, d, the weights, $\{W_{\kappa d}\}_{\kappa \in \Theta}$, defined in (B.9) are identical for all the products. To see this, consider the weights as defined in (B.9). For a product, κ, and destination, d,

$$W_{\kappa d} = s_{\kappa d} \frac{P_{\kappa d}^c}{P_{\kappa d}^f}, \tag{B.22}$$

where $s_{\kappa d} = \frac{P_{\kappa d}^f Y_{\kappa d}}{\sum_{d \in \mathcal{D}} P_{\kappa d}^f Y_{\kappa d}}$, is the destination's d share of revenue in the revenue due to product, κ. Now, since by **Assumption B**, the CIF-FOB margins for a destination, d, are identical for all products, the ratio, $\frac{P_{\kappa d}^c}{P_{\kappa d}^f}$, in (B.22) is same for all the products. From B.15, we know that demand for product, κ, at destination, d, is $Y_{\kappa d} = \left[\frac{P_{\kappa d}^f}{P_d^f}\right]^{-\sigma} Y_d$

where $Y_d = b - \mathbb{Y}_d \dfrac{P_d^f(1+M_d^{cf})}{a\mathbb{P}_d}$, and therefore

$$s_{\kappa d} = \frac{P_{\kappa d}^f \left[\frac{P_{\kappa d}^f}{P_d^f}\right]^{-\sigma} Y_d}{\sum\limits_{d\in\mathcal{D}} P_{\kappa d}^f \left[\frac{P_{\kappa d}^f}{P_d^f}\right]^{-\sigma} Y_d} = \frac{\left[\frac{P_{\kappa d}^f}{P_d^f}\right]^{1-\sigma} P_d^f Y_d}{\sum\limits_{d\in\mathcal{D}} \left[\frac{P_{\kappa d}^f}{P_d^f}\right]^{1-\sigma} P_d^f Y_d} = \frac{S_{\kappa d} P_d^f Y_d}{\sum\limits_{d\in\mathcal{D}} S_{\kappa d} P_d^f Y_d} = \frac{P_d^f Y_d}{\sum\limits_{d\in\mathcal{D}} P_d^f Y_d} := s_d, \tag{B.23}$$

where the third equality follows because $\left[\frac{P_{\kappa d}^f}{P_d^f}\right]^{1-\sigma} = S_{\kappa d}$, the revenue shares of a product, κ, in the total revenue from the destination, d. The fourth equality follows from part (b) of Lemma 1, according to which, $S_{\kappa d} = S_\kappa$.

Since for a given destination, d, the weights $\{W_{\kappa d}\}_{\kappa\in\Theta}$, as shown above, are identical, denoting by W_d the common destination specific weight, we can write

$$\frac{1}{\sigma}\sum_{\kappa\in\Theta} S_\kappa \left[\sum_{d\in\mathfrak{D}} W_{\kappa d} - \left(\frac{\sum\limits_{d\in\mathfrak{D}} W_{\kappa d}}{\sum\limits_{\kappa'\in\Theta} S_{\kappa'}\varepsilon_Y^{\kappa'\kappa}}\right)\right] \text{in (B.21) as } \frac{1}{\sigma}\left(\sum_{d\in\mathfrak{D}} W_d\right)\left[1 - \sum_{\kappa\in\Theta}\frac{S_\kappa}{\sum\limits_{\kappa'\in\Theta} S_{\kappa'}\varepsilon_Y^{\kappa'\kappa}}\right].$$

It can be shown that $\sum\limits_{\kappa\in\Theta}\frac{S_\kappa}{\sum\limits_{\kappa'\in\Theta} S_{\kappa'}\varepsilon_Y^{\kappa'\kappa}} = 1$,[34] which implies that ε_{PfY} in (B.21) is given by

$$\varepsilon_{PfY} = -\sum_{\kappa\in\Theta} S_\kappa \left(\sum_{d\in\mathfrak{D}} W_{\kappa d}\frac{bY_d}{P_d^c}\right), \tag{B.24}$$

which — given the demand for real output, Y, at destination, d, $Y_d = \dfrac{a - \gamma\mathbb{Y}_d - P_d^c}{b}$ — can be written as

$$\varepsilon_{PfY} = \sum_{\kappa\in\Theta}\sum_{d\in\mathfrak{D}} \mathbb{S}_{\kappa d}\frac{P_{\kappa d}^c}{P_{\kappa d}^f}\left[1 - \frac{a-\gamma\mathbb{Y}_d}{P_d^c}\right], \tag{B.25}$$

where $\mathbb{S}_{\kappa d} = S_\kappa s_d$, the revenue shares of a product, κ, from the destination, d, in the total revenue of the firm. The above reduces to (38) in the main text if the exporting firm produces a single product, and to (37) for firms that do not export.

[34] Suppose that the firm produces two products so that $\Theta = \{1,2\}$. In this case, $\sum\limits_{\kappa\in\Theta}\frac{S_\kappa}{\sum\limits_{\kappa'\in\Theta} S_{\kappa'}\varepsilon_Y^{\kappa'\kappa}}$ is given by

$\frac{S_1}{S_1\varepsilon_Y^{1,1} + S_2\varepsilon_Y^{2,1}} + \frac{S_2}{S_1\varepsilon_Y^{1,2} + S_2\varepsilon_Y^{2,2}}$. Multiplying and dividing $\frac{S_2}{S_1\varepsilon_Y^{1,2} + S_2\varepsilon_Y^{2,2}}$ by $\varepsilon_Y^{2,1}$, we get

$$\frac{S_1}{S_1\varepsilon_Y^{1,1} + S_2\varepsilon_Y^{2,1}} + \frac{S_2}{S_1\varepsilon_Y^{1,2} + S_2\varepsilon_Y^{2,2}} = \frac{S_1}{S_1\varepsilon_Y^{1,1} + S_2\varepsilon_Y^{2,1}} + \frac{S_2\varepsilon_Y^{2,1}}{S_1\varepsilon_Y^{1,1} + S_2\varepsilon_Y^{2,1}} = 1$$

We can write the elasticity, ε_{P^fY}, as

$$\begin{aligned}
\varepsilon_{P^fY} &= \sum_{\kappa\in\Theta}\sum_{d\in\mathfrak{D}} \frac{P^f_{\kappa d}Y_{\kappa d}}{P^fY}\frac{P^c_{\kappa d}}{P^f_{\kappa d}}\left[1-\frac{a-\gamma\mathbb{Y}_d}{P^c_d}\right] = \sum_{d\in\mathfrak{D}}\frac{1}{P^fY}\left(\sum_{\kappa\in\Theta}P^c_{\kappa d}Y_{\kappa d}\right)\left[1-\frac{a-\gamma\mathbb{Y}_d}{P^c_d}\right] \\
&= \sum_{d\in\mathfrak{D}}\frac{P^c_dY_d}{P^fY}\left[1-\frac{a-\gamma\mathbb{Y}_d}{P^c_d}\right] = \sum_{d\in\mathfrak{D}}s_d(1+MC^{cf}_d) - \frac{a-\sum\limits_{d\in\mathfrak{D}}X_d\mathbb{Y}_d}{P^f} \\
&= \overline{M}^{cf} - \frac{a-\overline{\mathcal{D}}}{P^f},
\end{aligned} \tag{B.26}$$

where the first equality follows because $\mathbb{S}_{\kappa d} = \frac{P^f_{\kappa d}Y_{\kappa d}}{P^fY}$. In the second, we aggregate over products, κ, to obtain $\sum\limits_{\kappa\in\Theta}P^c_{\kappa d}Y_{\kappa d} = P^c_dY_d$ in the third, where P^c_d is the CIF price of the "real" good, Y_d, exported to destination, d. This CIF price is $P^c_d = P^f_d(1+M^{cf}_d)$, where P^f_d is the FOB price of the "real" good, Y_d. The fourth follows because in **Assumption B** we have assumed that the CIF-FOB margins for a destination, d, are identical for all products. Also, in the fourth, X_d is the share of the real good, Y, that is exported to destination, d, and $s_d = \frac{P^f_dY_d}{P^fY}$ is the share of revenue earned by exporting to destination, d. In the fifth, $\overline{M}^{cf}$ is the aggregate CIF-FOB margin and $\overline{\mathcal{D}} = \sum\limits_{d\in\mathfrak{D}}X_d\mathbb{Y}_d$.

Now, we can write the revenue of a firm as

$$R = \sum_{\kappa\in\Theta_j}\sum_{d\in\mathfrak{D}_j}P^f_{j\kappa d}Y_{j\kappa d} = \sum_{d\in\mathfrak{D}}(\sum_{\kappa\in\Theta}P^f_{\kappa d}Y_{\kappa d}) = \sum_{d\in\mathfrak{D}}P^f_fY_d = P^fY, \tag{B.27}$$

where Y_d is the amount of real good exported to destination, d, and P^f_d is its FOB price. This allows us to write the price index, P_f, as the weighted average of FOB prices: $P^f = \sum\limits_{d\in\mathfrak{D}}P^f_f\frac{Y_d}{Y} = \sum\limits_{d\in\mathfrak{D}}P^f_fX_d$. As for the single product firm in the main text, we can write the aggregate demand function as

$$\begin{aligned}
P^f &= \sum_{d\in\mathfrak{D}}X_dP^f_d = \sum_{d\in\mathfrak{D}}X_d(a-bY_d-\gamma\mathbb{Y}_d) - P^f\sum_{d\in\mathfrak{D}}s_dM^{cf}_d \\
\Rightarrow P^f &= \frac{1}{\overline{M}^{cf}}(a-bY\overline{X}-\gamma\overline{\mathcal{D}})
\end{aligned} \tag{B.28}$$

where $\overline{\mathcal{D}}$ and $\overline{M}^{cf}$ are defined above and $\overline{X} = \sum_d X^2_d$.

The expression for the price elasticity for multi-product firms in (B.26) is the same as that for the single product firms in (39) and the expression for the inverse demand function for multi-product firms in (B.28) is the same as that for the single product firms in (40) in the main text. These are outcome of (a) the real output, Y, being a CES aggregate of multiple products and (b) common, destination specific, CIF-FOB margin for all products exported by the firm.

B.2 Markets Characterized by Oligopolistic Competition and Nested CES Demand System

As is common in many studies (e.g., Eslava, Haltiwanger and Urdaneta (2023) (EHU) and HRW), here we assume that demand follows a nested CES utility system. An advantage of nested CES demand is that the price elasticity of demand, as we show in Proposition 3, is independent of price and unobserved demand shifters. This can allow one consistently estimate the output elasticity of quality differentiated material inputs and the ex-post shock using the FOC.

While the assumption of nested CES preference is arguably a stronger restriction, along with oligopolistic competition, it allows for variable markups. When markets are characterized by oligopolistic competition, where the number of firms is finite, firms internalize the effects of their actions on market aggregates. That is actions — setting prices or quantities — by nonatomistic firms also affect the demand shifters, and consequently the price elasticity depends on the firm's share in the total industry revenues.

Before we begin, we list the assumptions made in this section.

Assumption 1 As in EHU and others, consumers derive utility from a nested CES utility function, with a CES layer for firms, indexed j, and another for products, $j\kappa$, within firms. Utility, U, of representative consumer is a CES aggregate of real products, Y_j,

$$U(Y_1, \ldots, Y_j, \ldots, Y_{\mathcal{N}}) = \left[\sum_{j \in \mathcal{F}} (\varphi_j Y_j)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}. \tag{B.29}$$

where $\mathcal{F}$, with $\mathcal{N} = |\mathcal{F}|$, is the set of firms selling their products. The term, φ_j, reflects consumers' relative preference for the real output, Y_j, of the firm j, which, as in (B.1), is given by

$$Y_j = \left[\sum_{\kappa \in \Theta_j} (\varphi_{j\kappa} Y_{j\kappa})^{\frac{\sigma_j - 1}{\sigma_j}} \right]^{\frac{\sigma_j}{\sigma_j - 1}}, \tag{B.30}$$

where the weights, $\varphi_{j\kappa}$, denotes the quality/appeal of the product, $j\kappa$, and Θ_j is the set of products produced by the firm, j. The elasticity of substitution between the outputs of the various firms is denoted by σ, and σ_j is the elasticity of substitution between products, κ, of the firm, j. Also, as it is natural, $\sigma_j > \sigma$.

Assumption 2 As in EHU and others, market structure in all countries is characterized by oligopolistic competitive.

Assumption 3 **Assumption A** and **Assumption B** also hold. According to **Assumption A**, the preference parameters — φ_j in (B.29) and $\varphi_{j\kappa}$ in (B.30), which denote quality — for the products of *a unique firm, j,* are identical in all destinations.

In the rest of this section, except when necessary, we suppress the firm and time subscripts, j and t. Also, the lower case notations are used to denote the logarithm of the respective upper case notations.

Proposition 3 *Under **Assumption A** and **Assumption B** and the assumption that the market shares of a domestic firm in foreign markets are negligible, the inverse of price elasticity of demand for, Y, in (B.30) with respect to the FOB price index,* $P^f = \left[\sum_{\kappa\in\Theta}\left(\frac{P^f_\kappa}{\varphi_\kappa}\right)^{1-\sigma_j}\right]^{\frac{1}{1-\sigma_j}}$ *(see B.3) is*

$$\varepsilon_{PY} = -\frac{1}{\sigma}\left[\sum_{d\neq o}\sum_{\kappa\in\Theta}\mathbb{S}_{\kappa d}(1+M^{cf}_d) + (1-\sum_{d\neq o}\sum_{\kappa\in\Theta}\mathbb{S}_{\kappa d})\frac{1}{(1-MS)}\right], \qquad \text{(B.31)}$$

where $\mathbb{S}_{\kappa d}$ *is the revenue shares of product,* κ*, from the destination, d, in the total revenue of the firm, MS is the market share — firm's share in the total industry revenues — of the firm in the home country, o, and* M^{cf}_d *is the destination, d, specific common CIF-FOB margin for products,* κ*.*

The elasticity, ε_{PY}, consists of three observable terms, (a) $\widetilde{M}^{cf} := \sum\limits_{d\neq o}\sum\limits_{\kappa\in\Theta_j}\mathbb{S}_{\kappa d}(1+M^{cf}_d)$, the aggregate CIF-FOB margin, (b) $S_o := (1-\sum\limits_{d\neq o}\sum\limits_{\kappa\in\Theta}\mathbb{S}_{\kappa d})$, the share of revenue obtained from selling in the home country, o, and (c) the market share, MS, of the firm in the home country. In deriving the elasticity, ε_{PY}, we have assumed that the market share of the firms in foreign market is negligible. This follows the observation in Roberts, Xu, Fan and Zhang (2018), where the market share of the firms in foreign market are found to be very small.

B.2.1 Proof of Proposition 3

The proof of Proposition 3 follows the results in subsection B.1.1, where the demand for the firm's "real" output — a quality weighted CES aggregate of multiple products produced by the firm — in (B.30) followed a non-homothetic preference over "real" outputs of various firms. As in B.1.1, the multi-product firm in the home country, whose demand and elasticity we seek to derive, is denoted by j. The amount of product, $j\kappa$, that it exports to destination, d, is denoted by $Y_{j\kappa d}$. Let the CES aggregate in (B.30) of the quantities, $\{Y_{j\kappa d}\}_{\kappa\in\Theta_j}$, be denoted by Y_{jd}.

For a given Y_{jd} (the amount of "real" output of the firm, j, consumed at destination, d), from (B.3) we know that the demand for product, κ, at destination, d, is given by

$$Y_{j\kappa d} = (\varphi_{j\kappa})^{\sigma_j-1}\left[\frac{P^c_{j\kappa d}}{P^c_{jd}}\right]^{-\sigma_j} Y_{jd}, \text{ where } P^c_{jd} = \left[\sum_{\kappa\in\Theta_j}\left(\frac{P^c_{j\kappa d}}{\varphi_{j\kappa}}\right)^{1-\sigma_j}\right]^{\frac{1}{1-\sigma_j}} \qquad \text{(B.32)}$$

is the CIF price of the "real" output, Y_{jd}. Since the preference for Y_{jd} is given by the utility function in (B.29), we know that the demand for Y_{jd} is given by

$$Y_{jd} = (\varphi_j)^{\sigma-1}\left[\frac{P^c_{jd}}{\mathbb{P}_d}\right]^{-\sigma}\mathbb{Y}_d, \text{ where } \mathbb{P}_d = \left[\left(\frac{P^c_{jd}}{\varphi_j}\right)^{1-\sigma} + \sum_{l\neq j, l\in\mathcal{F}_d}\left(\frac{P_{ld}}{\varphi_l}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}, \quad \text{(B.33)}$$

where $\mathcal{F}_d$, with $\mathcal{N}_d = |\mathcal{F}_d|$, is the set of firms selling their products at destination, d. $\mathbb{Y}_d$ in the above is $\frac{R_d}{\mathbb{P}^c_d}$, where

$$R_d = \sum_{\kappa\in\Theta_j} Y_{j\kappa d}P^c_{j\kappa d} + \sum_{l\neq j, l\in\mathcal{F}_d}\sum_{\kappa\in\Theta_l} Y_{l\kappa d}P_{l\kappa d} \quad \text{(B.34)}$$

is the total expenditure of the consumer at destination, d. Note that in the summations in (B.33) and (B.34), we have use the subscript, l, to denote other firms who sell their produce at destination, d. The price, $P_{l\kappa d}$, could be another CIF price if l happens to be another exporter selling at d. In case l is a firm operating at destination, d, $P_{l\kappa d}$ will be the FOB price of the product, $\kappa \in \Theta_l$.

The above implies that the final demand for firm j's product, κ, at destination, d, is

$$Y_{j\kappa d} = (\varphi_{j\kappa})^{\sigma_j-1}(\varphi_j)^{\sigma-1}\left[\frac{P^c_{j\kappa d}}{P^c_{jd}}\right]^{-\sigma_j}\left[\frac{P^c_{jd}}{\mathbb{P}_d}\right]^{-\sigma}\mathbb{Y}_d. \quad \text{(B.35)}$$

To lighten notations, from here on, unless needed, we drop the script, j.

Given (B.35), the equivalent of (B.17) is given by

$$\sigma\varepsilon^{\kappa'\kappa}_{P^cY,d} = -\frac{d\ln(Y_{\kappa d})}{d\ln(Y_{\kappa' d})} + \Big(\sigma_j - \sigma(1-MS_d)\Big)\sum_{l\in\Theta} S_l\varepsilon^{\kappa' l}_{P^cY,d} \text{ for each } \kappa\in\Theta\ , \quad \text{(B.36)}$$

where MS_d is the market share of the firm, j, at destination, d. To derive the above, we have used Shephard's Lemma according to which $\frac{d\ln(\mathbb{R}_d)}{d\ln(P^c_{jd})} = \frac{d\ln(\mathbb{P}_d)}{d\ln(P^c_{jd})} = MS_d$.

The rest of proof follows the proof in subsection (B.1.1). The equivalent of (B.18) for a nested CES demand system is given by

$$\varepsilon^{\kappa' 1}_{P^cY,d} = -\frac{\varepsilon^{1\kappa'}_Y}{\sigma_j} - \left(\frac{1}{\sigma(1-MS_d)} - \frac{1}{\sigma_j}\right)\sum_{\kappa\in\Theta} S_\kappa\varepsilon^{\kappa\kappa'}_Y$$

$$\vdots$$

$$\varepsilon^{\kappa'\kappa}_{P^cY,d} = -\frac{\varepsilon^{\kappa\kappa'}_Y}{\sigma_j} - \left(\frac{1}{\sigma(1-MS_d)} - \frac{1}{\sigma_j}\right)\sum_{\kappa\in\Theta} S_\kappa\varepsilon^{\kappa\kappa'}_Y$$

$$\vdots$$

$$\varepsilon^{\kappa' K}_{P^cY,d} = -\frac{\varepsilon^{K\kappa'}_Y}{\sigma_j} - \left(\frac{1}{\sigma(1-MS_d)} - \frac{1}{\sigma_j}\right)\sum_{\kappa\in\Theta} S_\kappa\varepsilon^{\kappa\kappa'}_Y, \text{ for any } \kappa'\in\Theta. \quad \text{(B.37)}$$

The equivalent of (B.21) is given by

$$\varepsilon_{PfY} = -\sum_{\kappa\in\Theta} S_\kappa\left(\sum_{d\in\mathfrak{D}} \frac{W_{\kappa d}}{\sigma(1-MS_d)}\right) + \frac{1}{\sigma_j}\sum_{\kappa\in\Theta} S_\kappa\left(\sum_{d\in\mathfrak{D}} W_{\kappa d}\right) - \frac{1}{\sigma_j}\sum_{\kappa\in\Theta} S_\kappa\left(\frac{\sum_{d\in\mathfrak{D}} W_{\kappa d}}{\sum_{\kappa'\in\Theta} S_{\kappa'}\varepsilon_Y^{\kappa'\kappa}}\right). \tag{B.38}$$

The equivalent of (B.24) is given by

$$\varepsilon_{PfY} = -\sum_{\kappa\in\Theta} S_\kappa\left(\sum_{d\in\mathfrak{D}} \frac{W_{\kappa d}}{\sigma(1-MS_d)}\right) \tag{B.39}$$

Since $W_{\kappa d} = s_d \frac{P^c_{\kappa d}}{P^f_{\kappa d}}$ (see (B.22) and (B.23)), where s_d is the destination's d share of revenue in the total revenue, and since the market share of the firms in the foreign destinations is assumed to be negligible, the above reduces to

$$\varepsilon_{PY} = -\frac{1}{\sigma}\left[\widetilde{M}^{cf} + \frac{S_o}{(1-MS)}\right], \tag{B.40}$$

where $\widetilde{M}^{cf} := \sum_{d\neq o}\sum_{\kappa\in\Theta} \mathbb{S}_{\kappa d}(1+M_d^{cf})$ is the aggregate CIF-FOB margin, $S_o := (1 - \sum_{d\neq o}\sum_{\kappa\in\Theta} \mathbb{S}_{\kappa d})$ is the share of revenue obtained from selling in the home country, o, and MS is the market share of the firm in the home country. The term, $\mathbb{S}_{\kappa d} = S_\kappa s_d$, in the above expressions is the revenue shares of product, κ, from the destination, d, in the total revenue of the firm.

B.3 Estimation Method 2: Nonparametric Identification of the TFP impact of exports.

In the following, we discuss estimation of the TFP x on productivity, where, unlike in equation (20) of the main text, we do not restrict the function, $g(\omega_{t-1}, x_{t-1})$, which in equation (6) of the main text governs the evolution of TFP, ω_t. This implies that (28) in main text is written as

$$r_t = \alpha_L l_t + \alpha_K \widetilde{k}_t + \alpha_M \widetilde{m}_t + \beta ms_t + \bar{g}(x_{t-1}, \mathbb{W}_{t-1}) + \eta_t. \tag{B.41}$$

Now, the average partial effect (APE) of changing x at $x = \bar{x}$ by Δx is

$$APE_{x=\bar{x}} := \int \left[\frac{g(\omega_t, \bar{x}+\Delta x) - g(\omega_t, \bar{x})}{\Delta x}\right] dF(\omega_t), \tag{B.42}$$

where the expectation is with respect to unconditional distribution of ω. The APE is difference between the average structural functions (ASF), $\int g(\omega_t, x)dF(\omega_t)$, at $x = \bar{x} + \Delta x$ and $x = \bar{x}$. The notion of ASF is due to Blundell and Powell (2004), who study it in the context of binary response models.

Note that, though suppressed, the function, $g(\omega_t, x)$, includes investment in fixed capital, i_t, as an argument. But we, as in the main text, have suppressed it. So the integration in (B.42) over the joint distribution of ω_t and i_t.

Now, adding and subtracting ϱ_{t+1} in (B.42), we write the APE as

$$\int \left[\frac{g(\omega_t, \bar{x} + \Delta x) - g(\omega_t, \bar{x})}{\Delta x}\right] dF(\omega_t) = \int \left[\frac{(g(\omega_t, \bar{x} + \Delta x) + \varrho_{t+1}) - (g(\omega_t, \bar{x}) + \varrho_{t+1})}{\Delta x}\right] dF(\omega_t, \varrho_{t+1}).$$

To ease notation, from here on, unless necessary, we drop the time script, t. The APE, therefore, is

$$\begin{aligned}
&\int \left[\frac{g(\omega, \bar{x} + \Delta x) - g(\omega, \bar{x})}{\Delta x}\right] dF(\omega) \\
&= \int \left[\frac{(g(\omega, \bar{x} + \Delta x) + \varrho) - (g(\omega, \bar{x}) + \varrho)}{\Delta x}\right] dF(\omega, \varrho) \\
&= \int \left[\frac{(g(\mathbb{Z}, \boldsymbol{\zeta}^{\mathbf{u}}, \bar{x} + \Delta x) + \varrho) - (g(\mathbb{Z}, \boldsymbol{\zeta}^{\mathbf{u}}, \bar{x}) + \varrho)}{\Delta x}\right] dF(\mathbb{Z}, \boldsymbol{\zeta}^{\mathbf{u}}, \varrho) \\
&= \int \int \left[\frac{(g(\mathbb{Z}, \boldsymbol{\zeta}^{\mathbf{u}}, \bar{x} + \Delta x) + \varrho) - (g(\mathbb{Z}, \boldsymbol{\zeta}^{\mathbf{u}}, \bar{x}) + \varrho)}{\Delta x}\right] dF(\mathbb{Z}, \boldsymbol{\zeta}^{\mathbf{u}}, \varrho | ms, \mathbb{W}) dF(ms, \mathbb{W}) \\
&= \int \left[\frac{\tilde{g}(ms, \mathbb{W}, \bar{x} + \Delta x) - \tilde{g}(ms, \mathbb{W}, \bar{x})}{\Delta x}\right] dF(ms, \mathbb{W}) \\
&= \int \left[\frac{\bar{g}(\mathbb{W}, \bar{x} + \Delta x) - \bar{g}(\mathbb{W}, \bar{x})}{\Delta x}\right] dF(\mathbb{W}),
\end{aligned} \tag{B.43}$$

where the second equality follows because ω_t is shown to be a deterministic function of $\{\mathbb{Z}_t, \boldsymbol{\zeta}_t^{\mathbf{u}}\}$. The third is due to the law of iterated expectations, where the conditioning is on $\{ms_{t+1}, \mathbb{W}_t\}$. The fourth equality follows because $\mathbb{Z}_t$ is contained in $\mathbb{W}_t$. The fifth is due to the restriction in (27) according to which $\tilde{g}(ms, .)$ is assumed to be separable in ms. The function, $\bar{g}(\mathbb{W}, \bar{x})$, in (B.43) is obtained by estimating the partially linear model in (B.41).

The APE in (B.43) is point identified if the average structural functions (ASF) in (B.43),

$$\int \bar{g}(\mathbb{W}, \bar{x} + \Delta x) dF(\mathbb{W}) \text{ and } \int \bar{g}(\mathbb{W}, \bar{x}) dF(\mathbb{W}),$$

are point-identified. To point-identify the ASF, it is required that $\bar{g}(\mathbb{W}, \bar{x} + \Delta x)$ and $\bar{g}(\mathbb{W}, \bar{x})$ be evaluated at all values of in the support of the unconditional distribution of $\mathbb{W}$. This requires that the support of the conditional distribution of $\mathbb{W}$, conditional on $\bar{x}$ and $\bar{x} + \Delta x$, be equal to the support of the unconditional distribution of $\mathbb{W}$. This ensures that for any group of firms defined in terms of $\mathbb{W}$, a positive measure of firms experience $\bar{x} + \Delta x$ and $\bar{x}$. This is analogous to the overlap condition in the program evaluation literature, where treatment is discrete.

The support requirement is of concern because $\mathbb{W}$ includes transportation and shipping costs for the exporting firms. And, therefore, if x is, say, export status, conditioning on any particular value of x will restrict the conditional support of $\mathbb{W}$: e.g, transportation costs are zero for the non-exporters and positive for the exporters.[35] The support requirement could be fulfilled if the transportation costs are made inclusive of retail, distribution and domestic transportation costs. This would not restrict the conditional support of $\mathbb{W}$ as non-exporters, too, would be facing positive transportation costs. Although, such data for all destinations might not be easily available.

In the absence of common support, usually bounds on the APE are estimated (see Liu *et al.*, 2024, for a discussion and results on partial identification). This requires a prior knowledge of the upper and lower bounds of $\bar{g}(\mathbb{W}, x)$ for all values of $\{\mathbb{W}, x\}$. Without prior restrictions that place bounds on $\bar{g}(.)$, it is unlikely that bounds on APE can be estimated.

Another option is to estimate average of local average effect (LAR) (Altonji and Matzkin, 2005). LAR averages changes in the conditional response over the conditional distribution of the heterogeneity, $(\boldsymbol{\zeta}_t^{\mathbf{u}}, \varrho_{t+1})$.

$$LAR_{x=\bar{x}} \coloneqq \frac{\partial \bar{g}(\mathbb{W}, \bar{x})}{\partial x}, \tag{B.44}$$

where $\bar{g}(\mathbb{W}, \bar{x})$, as defined in (B.43). For inference, the bootstrap procedure discussed in the main text can be used.

[35] Although, conditional on being an exporter, the APE, e.g., of increasing the export intensity can be computed.

Table 2: Description of Export Related Variables for Estonia

(a) Distribution of Current Export Status against the No. of Years of Exporting

	Consumer Manufacturing		Material Manufacturing		Technological Manufacturing	
	Current Export Status					
	Non-Exporter	Exporter	Non-Exporters	Exporter	Non-Exporter	Exporter
Never Exported	7766	0	10157	0	3685	0
Exported 1 or 2 Years	488	261	798	404	266	115
Exported 3 or 4 Years	55	170	170	284	63	62
Exported 5 or 6 Years	33	106	67	145	20	35
Exported 7 or 8 Years	15	52	11	75	9	12
Exported 9 or 10 Years	3	20	9	38	1	7
Exported 11 Years or More	1	17	0	12	3	4
Total	8361	626	11212	958	4047	235

(b) Summary Statistics of some Export Related Variables

	Consumer Manufacturing				Material Manufacturing				Technological Manufacturing			
	Export Intensity		ln(Export Revenue per Employee)		Export Intensity		ln(Export Revenue per Employee)		Export Intensity		ln(Export Revenue per Employee)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Exported 1 or 2 Years	0.20	0.06	7.97	8.04	0.22	0.09	8.42	8.56	0.14	0.05	7.92	8.09
Exported 3 or 4 Years	0.39	0.27	9.21	9.56	0.38	0.30	9.33	9.82	0.25	0.16	8.55	8.99
Exported 5 or 6 Years	0.48	0.46	9.38	9.80	0.43	0.41	9.59	10.09	0.40	0.30	9.43	9.53
Exported 7 or 8 Years	0.54	0.62	9.56	10.32	0.39	0.37	9.44	9.95	0.39	0.21	9.53	9.47
Exported 9 or 10 Years	0.50	0.57	9.39	9.80	0.45	0.39	9.68	10.25	0.46	0.55	9.62	10.17
Exported 11 Years or More	0.43	0.38	9.38	9.54	0.66	0.90	10.03	10.99	0.56	0.62	10.20	10.24

Note: Number of years of exporting is based on customs data from 2005 to 2019.
The sample of firms used for the table is the same as used for estimation.
Variable Definition: Export intensity is the share of export revenue in the total revenue and logarithm of export revenue per employee is reported.

Table 4: Descriptive Statistics of Variables from the Administrative Data

	ln(Revenue)		ln(Capital)		ln(Materials)		ln(No. of Employees)		Market Share		Share of Materials		Share of Labor	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Consumer Manufacturing														
All Firms	11.38	11.42	10.18	10.05	10.43	10.53	1.23	1.1	0.04	0.01	0.49	0.5	0.3	0.25
Never Exported	11.18	11.22	10.04	9.89	10.17	10.29	1.13	0.92	0.03	0.01	0.48	0.48	0.31	0.26
Exported 1 or 2 Years	12.42	12.5	10.95	10.71	11.69	11.79	1.63	1.61	0.05	0.02	0.57	0.56	0.25	0.21
Exported 3 or 4 Years	12.92	13.03	11.41	11.48	12.13	12.46	2.07	2.08	0.08	0.03	0.53	0.56	0.24	0.18
Exported 5 or 6 Years	12.93	13.11	10.88	11.02	12.12	12.47	2.12	2.2	0.09	0.04	0.49	0.52	0.24	0.19
Exported 7 or 8 Years	13.11	12.96	11.18	11.24	12.3	12.33	2.32	2.3	0.08	0.04	0.48	0.53	0.25	0.25
Exported 9 or 10 Years	13.1	12.92	11.46	11.24	12.18	11.7	2.4	2.77	0.06	0.04	0.44	0.44	0.29	0.3
Exported 11 Years or More	12.35	12.32	10.65	11.01	11.58	11.64	1.94	1.79	0.08	0.02	0.49	0.53	0.36	0.38
Material Manufacturing														
All Firms	11.63	11.71	10.64	10.57	10.84	10.96	1.12	1.1	0.04	0.00	0.52	0.52	0.26	0.2
Never Exported	11.4	11.5	10.49	10.45	10.56	10.72	0.99	0.89	0.03	0.00	0.51	0.51	0.26	0.2
Exported 1 or 2 Years	12.52	12.63	11.44	11.15	11.8	11.81	1.62	1.61	0.07	0.01	0.57	0.56	0.23	0.19
Exported 3 or 4 Years	12.92	13.09	11.31	11.13	12.18	12.3	1.86	1.95	0.09	0.02	0.56	0.56	0.2	0.19
Exported 5 or 6 Years	13.19	13.5	11.28	11.26	12.48	12.83	2.1	2.3	0.09	0.02	0.55	0.56	0.25	0.23
Exported 7 or 8 Years	13.43	13.7	11.63	11.45	12.87	13.06	2.29	2.4	0.13	0.03	0.57	0.58	0.23	0.2
Exported 9 or 10 Years	13.39	13.4	11.63	11.39	12.7	12.63	2.23	2.2	0.08	0.03	0.54	0.57	0.23	0.25
Exported 11 Years or More	13.31	13.37	11.56	11.47	12.42	12.38	2.11	2.4	0.06	0.02	0.45	0.46	0.31	0.3
Technological Manufacturing														
All Firms	11.61	11.73	10.05	10	10.65	10.78	1.06	0.69	0.05	0.01	0.47	0.46	0.31	0.22
Never Exported	11.41	11.51	9.9	9.89	10.39	10.57	0.92	0.69	0.04	0.00	0.46	0.45	0.31	0.22
Exported 1 or 2 Years	12.8	12.95	10.82	10.66	12.01	12.24	1.79	1.95	0.1	0.02	0.52	0.51	0.28	0.21
Exported 3 or 4 Years	12.88	13.07	10.94	10.9	12	12.31	2.06	1.95	0.22	0.07	0.51	0.5	0.27	0.23
Exported 5 or 6 Years	13.05	13.39	11.58	11.95	12.26	12.42	2.04	1.95	0.2	0.08	0.54	0.51	0.27	0.24
Exported 7 or 8 Years	13.74	13.65	11.68	12.25	13.09	13.06	2.55	2.48	0.31	0.18	0.54	0.56	0.25	0.22
Exported 9 or 10 Years	13.74	14.13	11.56	11.97	13.1	13.04	2.68	3.04	0.38	0.32	0.56	0.58	0.25	0.24
Exported 11 Years or More	13.12	12.86	12.42	12.53	12.43	12.39	2.18	1.79	0.17	0.04	0.53	0.52	0.18	0.14

[1] The number of years of exporting is based on customs data from 2005 to 2019, where only those exporters that entered the export markets after 2004 are considered.

[2] The Table uses administrative data from 2005 to 2019.

[3] Market share is the share of the firm's revenue within NACE 5-digit industry Share of materials is the ratio of expenditure on material to the total revenue and the share of labor is the ratio of labor expense to the total revenue.

[4] No. of Firm-years: 8897 in the Consumer Manufacturing, 12168 in the Material Manufacturing, and 4282 in the Technological Manufacturing

Table 5: Output Elasticities and TFP impact of Export Persistence (Data from 2005 to 2019)

	All Manufacturing	Consumer Manufacturing	Material Manufacturing	Technological Manufacturing
Labor	0.253***	0.275***	0.279***	0.559***
	(0.001)	(0.003)	(0.001)	(0.006)
Capital	0.122***	0.118***	0.122***	0.107***
	(0.000)	(0.001)	(0.000)	(0.000)
Materials	0.697***	0.672***	0.638***	0.429***
	(0.001)	(0.003)	(0.002)	(0.005)
Dummy for 1st and 2nd Year of Export	-0.071	-0.051	-0.124	-0.141
	(0.043)	(0.052)	(0.081)	(0.094)
Dummy for 3rd and 4th Year of Export	-0.195	-0.061	-0.181^{+}	-0.419^{+}
	(0.121)	(0.062)	(0.096)	(0.220)
Dummy for 5th and 6th Year of Export	-0.091	-0.026	-0.133	-0.137
	(0.061)	(0.100)	(0.121)	(0.160)
Dummy for 7th and 8th Year of Export	-0.131	-0.019	-0.191	-0.134
	(0.162)	(0.179)	(0.121)	(0.271)
Dummy for 9th and 10th Year of Export	0.121*	0.410*	0.102	0.307
	(0.049)	(0.201)	(0.106)	(0.504)
Dummy for 11th or Higher Year of Export	0.151^{+}	0.308	0.608	-0.901
	(0.078)	(0.186)	(0.321)	(0.905)
No. of Observations	24721	8748	11829	4143

Significance levels : + : 10% : ∗ : 5% ∗∗ : 1% ∗ ∗ ∗ : 0.1%. Standard Error in Parenthesis

Note: Time period for administrative data: 2005 to 2019. The export related variables are based on customs data from 2005 to 2019, where firms that entered the exports market prior to 2005 are dropped.

Table 6: Output Elasticities and TFP impact of Export Persistence (Data from 2009 to 2019)

	All Manufacturing	Consumer Manufacturing	Material Manufacturing	Technological Manufacturing
Labor	0.267***	0.265***	0.272***	0.566***
	(0.001)	(0.003)	(0.002)	(0.007)
Capital	0.122***	0.115***	0.131***	0.095***
	(0.002)	(0.001)	(0.001)	(0.003)
Materials	0.661***	0.682***	0.644***	0.421***
	(0.002)	(0.003)	(0.002)	(0.006)
Dummy for the First Year of Export	-0.035	-0.092	0.035	-0.214
	(0.041)	(0.062)	(0.045)	(0.294)
Dummy for the Second Year of Export	0.071	0.121	0.055	0.026
	(0.036)	(0.071)	(0.081)	(0.201)
Dummy for the Third Year of Export	0.081*	0.129^{+}	0.084	-0.026
	(0.039)	(0.051)	(0.086)	(0.388)
Dummy for the Fourth or Higher Year of Export	0.079^{+}	0.131	-0.058	0.071
	(0.041)	(0.105)	(0.071)	(0.281)
No. of Observations	19625	6991	9235	3394

Significance levels : + : 10% : ∗ : 5% ∗∗ : 1% ∗ ∗ ∗ : 0.1%. Standard Error in Parenthesis

Note: Time period for administrative data: 2009 to 2019. The export related variables are based on customs data from 2009 to 2019; that is, only those exporters that entered in the export markets after the Financial Crisis are considered.

Table 7: Output Elasticities and TFP impact of Export Persistence: Comparison of Estimates From Different Methods

	All Manufacturing	Consumer Manufacturing	Material Manufacturing	Technological Manufacturing	All Manufacturing	Consumer Manufacturing	Material Manufacturing	Technological Manufacturing
	Estimates using the method in this paper.				Estimates using the method in Malikov and Zhao (2023).			
Labor	0.253***	0.275***	0.279***	0.558***	0.7434***	0.7265***	0.7628***	0.7802***
	(0.001)	(0.003)	(0.001)	(0.006)	(0.007)	(0.010)	(0.011)	(0.017)
Capital	0.121***	0.117***	0.125***	0.105***	0.0884***	0.0824***	0.0982***	0.0835***
	(0.004)	(0.001)	(0.003)	(0.000)	(0.004)	(0.005)	(0.005)	(0.009)
Materials	0.699***	0.672***	0.638***	0.429***	0.292***	0.257***	0.351***	0.222***
	(0.001)	(0.003)	(0.002)	(0.005)	(0.003)	(0.006)	(0.004)	(0.007)
No. of Years of Exporting	-0.0511	0.0202	-0.1561*	0.0334	0.1814***	0.2578***	0.1109**	0.1637*
	(0.051)	(0.119)	(0.069)	(0.251)	(0.031)	(0.043)	(0.037)	(0.080)
(No. of Years of Exporting)^2	-0.031	-0.029	0.0271	-0.1109	-0.043**	-0.0724**	0.0005	0.0066
	(0.038)	(0.059)	(0.029)	(0.168)	(0.014)	(0.022)	(0.003)	(0.007)
(No. of Years of Exporting)^3	0.002	0.0014	-0.0021	0.0204	0.004*	0.0074*	-0.0181	-0.061
	(0.002)	(0.008)	(0.006)	(0.033)	(0.002)	(0.003)	(0.020)	(0.045)
(No. of Years of Exporting)^4	-0.0001	0.000	0.000	-0.001	-0.0001+	-0.0003+	0	-0.0002
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
No. of Observations	24721	8748	11829	4143	25297	8956	12077	4264

Significance levels : + : 10% : * : 5% ** : 1% *** : 0.1%. Standard Error in Parenthesis

Note: Time period for administrative data: 2005 to 2019. The export related variables are based on customs data from 2005 to 2019, where firms that entered the export markets prior to 2005 are dropped.

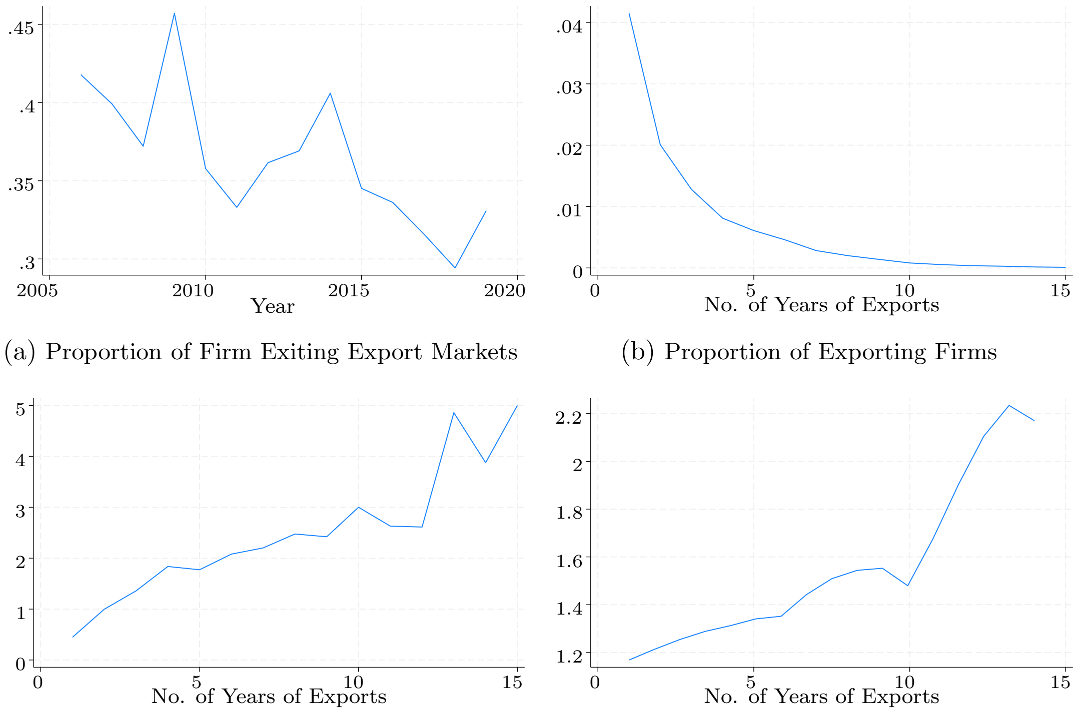
Table 8: Markups and Export Persistence

	All Manufacturing	Consumer Manufacturing	Material Manufacturing	Technological Manufacturing
Dependent Variable: ln(Markups)				
Dummy for Exporting 1 or 2 Years	-0.016 (0.029)	-0.026 (0.047)	0.009 (0.038)	-0.055 (0.093)
Dummy for Exporting 3 or 4 Years	-0.028 (0.045)	-0.077 (0.078)	0.014 (0.056)	-0.013 (0.141)
Dummy for Exporting 5 or 6 Years	-0.075 (0.055)	-0.017 (0.092)	-0.006 (0.067)	-0.423* (0.182)
Dummy for Exporting 7 or 8 Years	-0.087 (0.060)	-0.073 (0.096)	-0.027 (0.075)	-0.307 (0.222)
Dummy for Exporting 9 or 10 Years	-0.078* (0.038)	-0.041 (0.144)	0.046 (0.101)	-0.493* (0.228)
Dummy for Exporting 11 or More Years	-0.230* (0.110)	-0.347** (0.163)	-0.028 (0.120)	-0.291 (0.357)
No. of Observations	25751	8814	12861	4076

Significance levels : + : 10% : * : 5% ** : 1% *** : 0.1%. Standard Error in Parenthesis

Note: (1) The sector specific output elasticities of material inputs used to computing the markups are from Table 5. (2) All estimates use fixed effects regression. (3) All specifications include ln(No. of Employees), ln(Capital), and time and industry Dummies. (4) Time period for administrative data: 2005 to 2019. Number of years of exporting activities is based on customs data from 2005 to 2019.

Figure 3: Exporting Behaviour of Firms



(a) Proportion of Firm Exiting Export Markets

(b) Proportion of Exporting Firms

(c) No. of Destinations

(d) No. of Products

Figure 4: Revenue Productivity, Export Characteristics of the Core Products, Marketing Expense, and Investment in Intangible Assets against Number of Years of Exporting

(a) $\ln\left(\frac{\text{Total Revenue}}{\text{No. of Employees}}\right)$

(b) $\ln\left(\frac{\text{Export Revenue}}{\text{No. of Employees}}\right)$

(c) $\ln\left(\frac{\text{Export Revenue from Core Product}}{\text{No. of Employees}}\right)$

(d) Export Productivity

(e) ln(Price of the Core Product)

(f) $\ln\left(\frac{\text{Marketing Expense}}{\text{No. of Employees}}\right)$

(g) ln(Investment in Intangible Assets)

(h) $\ln\left(\frac{\text{Investment in Intangible Assets}}{\text{No. of Employees}}\right)$

SISUKOKKUVÕTE

Tootmisfunktsiooni hindamine ning püsiva eksportimise tootlikkuse mõju mõõtmine turu ebatäiuslikkuse korral

Käesolevas artiklis pakutakse välja uudne meetod tootmisfunktsiooni hindamiseks ning tootmistegurite kogutootlikkuse ekspordi mõju mõõtmiseks. Seeläbi on uurimuse eesmärgiks arendada metoodikat ekspordist õppimise (inglise keeles, learning by exporting), s.t. ekspordi tootlikkuse mõju, mõõtmiseks. Ekspordist õppimine, s.t. ekspordiga alustamise tõttu kasvanud ettevõtte tootlikkus, viitab erinevatele mehhanismidele, nagu näiteks turundustegevustesse investeerimine, toodete kvaliteedi parandamine, innovatsioon (uuendustegevus) ja välismaa klientidega suhtlemine, mis kõik võivad eksportimisega alustamise korral suurendada eksportiva ettevõtte tootlikkust. Kuigi eksportimisega alustamisel võib olla niisiis positiivne mõju, tuleb seejuures arvesse võtta eksportimise mõju hindadele ning hinnalisandile, s.t. eksportimise positiivset mõju heaolu võib vähendada see, kui eksportöörid saavad küsida kõrgemat hinnalisa, samas võib konkurentsitihedal rahvusvahelisel turul tegutsemine ka hinnalisandit vähendada. Tüüpiliselt uurijate kasutada olevates andmetes ei ole täielikku infot ettevõtte poolt müüdud koguste ja küsitud hindade kohta nii eksportturgudel kui ka siseturule müügi korral, ning eelneva tõttu müügitulude andmete kasutamisest tulenevad väljakutsed motiveerivadki käesolevat uurimustööd.

Mainitud eesmärgi saavutamiseks kirjutame tootmisfunktsiooni osaliselt lineaarse mudelina, kus mitteparameetriline osa, tootlikkuse lähend, sõltub mittevaadeldavatest nõudluse nihutajatest. Tootmisfunktsiooni identifitseerimine põhineb (i) mittejälgitavate nõudluse nihutajate liikumisseaduse postuleerimisel, kusjuures nende dünaamika on endogeenne, ning (ii) tõenäosusjaotusele seatud piirangutest kontrollinaks korrelatsiooni mittevaadeldavate nõudluse nihutajate ning uurijatele huvipakkuvate muutujate (siinkohal nt eksportimise ja tootlikkuse) vahel. Seeläbi tehakse võimalikuks identifitseerida toodangu hinnaelastsused ning tuvastada endogeensete sekkumiste (nt eksportimisega alustamise) mõju tootlikkusele.

Kasutades Eesti töötleva tööstuse sektori ettevõttetasandi andmeid leidsime meie poolt välja pakutud meetodi abil üksnes piiratud tõendusmaterjali ekspordi positiivsest mõjust tootmistegurite kogutootlikkusele, st ekspordi kaudu õppimise kohta. Me omistame sellise nõrga tõendusmaterjali ekspordist õppimise kohta väikestele eksportööridele, kelle Euroopa Liidu sisese ekspordi väärtus on alla 100 tuhande euro, mistõttu nad on uurijatele kasutatavas

tollistatistikale tuginevas andmestikus ekslikult klassifitseeritud mitteeksportijateks. Piiratud tõendusmaterjal näitab samas, et just püsivad (üle mitme aasta) eksportijad suudavad tõenäoliselt parandavad oma tootmistegurite kogutootlikkust tänu eksportimisele. Kuna meil ei olnud võimalik analüüsis täielikult arvesse võtta eksportimist täiendavaid tegevusi, näiteks uuendustegevust (muutusi tooteportfellist või tootmisprotsessides), siis on võimalik, et eksportimise mõju tootmistegurite kogutootlikkusele on suurte ja püsivate eksportijate puhul tingitud kulukatest tootlikkust suurendavatest täiendavatest tegevustest.

Lisaks eelnevatele tulemustele leidsime, et eksportijate hinnalisand on madalam kui mitteeksportijatel, ning see erinevus suureneb koos ekspordi püsivusega (s.t. eksportimise aastate arvuga). Meie tulemused näitavad niisiis efektiivsuse alusel grupeerumist eksportijate seas - ehki madalamate piirkuludega ettevõtted sisenevad raskematele eksporditurgudele, sunnib konkurents neid oma hinnalisasid alandama. Viimast suudavad saavutada kõige paremini püsivad eksportijad, kes juhtumisi kuuluvad ka kõige tootlikumate eksportijate hulka. Samuti näitame, et täiuslikku konkurentsui eeldavaid hindamismeetodeid kasutades saadakse tõenäoliselt väärad tulemused endogeensete sekkumiste (antud juhul eksportimise) mõjust tootmistegurite kogutootlikkusele.