Markets and Markups:

Evidence on the Rising Market Power of Exporters from China*

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Abstract

We develop an empirical framework that decomposes the export price elasticity to the exchange rate into contributions from markup and marginal cost elasticities. This framework embodies a new estimator of the markup elasticity that controls for marginal costs and endogenous market participation, and a new classification of products based on Chinese linguistics that helps refine the analysis of firms' market power. Using Chinese customs data, we document a two- to three-fold increase in markup elasticities across product and firm types after 2005, indicating exporters from China acquired substantial market power in foreign markets.

JEL classification: F31, F41, F14

Keywords: exchange rate, markup elasticity, pricing-to-market, trade pattern, product classification, differentiated goods, China.

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1 Introduction

The strong decline in exchange rate pass through (ERPT) experienced globally since the 1980s — one of the most striking facts in international economics—has gone hand-in-hand with a rise in market power by firms active in international trade.[1] In the face of currency movements, a firm with sufficient market power may choose to keep the price of its exports stable in a destination country's currency by optimally adjusting its price-cost markup (Dornbusch 1987). Structural interpretations of the fall in exchange rate pass through would naturally link it to the rising importance of pricing-to-market associated with growth in the global trade share of differentiated manufactured goods supplied by imperfectly competitive firms.[2] However, a complementary explanation, in line with structural interpretations, is that the fall in exchange rate pass through could also reflect a higher correlation of costs with the exchange rate. The rise of global production chains and in the share of foreign versus domestic inputs, or shifts in market power for inputs, likely affect the elasticity of costs to the exchange rate.[3] An empirical assessment of market power through an analysis of pricing to market requires first and foremost an appraisal of the incidence of markup adjustment relative to the contribution from a changing cost elasticity to ERPT.[4]

In this paper, we develop an empirical framework to decompose incomplete exchange rate pass-through (ERPT) into the contributions of markups and marginal costs. This framework is suitable for application to large panels of unbalanced administrative customs data. Our approach consists of isolating the contribution of markups by comparing how firms adjust product prices across multiple foreign markets relative to movements in bilateral exchange rates while accounting for the fact that the set of destination markets served by a firm may change over time. We also introduce a classification of markets by the degree of product differentiation, to capture systematic differences in price elasticities across types of goods. Applying this framework to customs transactions data

[1] See, for example, Gust, Leduc and Vigfusson (2010).

[2] Corsetti and Dedola (2005), Goldberg and Campa (2008) and Burstein, Eichenbaum and Rebelo (2007) discuss structural interpretations of ERPT in depth.

[3] See the discussion by Burstein and Gopinath (2014) of the correlation of producers' costs – wages, domestic inputs, and foreign inputs – with the exchange rate. Any of the factors described could lead to a higher correlation of costs with the exchange rate.

[4] A growing body of literature documents a close link between exchange rate pass-through and invoicing currency (see Gopinath, Itskhoki and Rigobon 2010; Barbiero 2020; Bonadio, Fischer and Sauré 2020; Auer, Burstein and Lein 2021; Chen, Chung and Novy 2021; Corsetti, Crowley and Han 2022). The main conclusion from this line of research is that invoicing currencies serve as a reliable proxy for a firm's pricing currency subject to nominal rigidities—firms choose their invoicing currency to implement their desired pricing strategy (Engel 2006). Underlying this literature is the notion that a firm's pricing currency under nominal rigidities (relevant in the short run) depend on how its optimal markup and costs would respond to exchange rate movements under export price flexibility (relevant in the long run). For further discussion on the short- and medium-run determinants of exchange rate pass-through, see Amiti, Itskhoki and Konings (2022). The invoicing currency of Chinese exports is not recorded in our dataset, but the US dollar is widely-held to have been the principal invoicing currency for Chinese exports throughout this period. See Online Appendix OA1.4 for evidence on dollar invoicing.

from China between 2000 and 2014, we document that the significant reduction in ERPT of Chinese exports after 2005, when China switched to a more flexible exchange rate regime, can be almost entirely attributed to larger markup adjustments by Chinese exporters.

We find that the export price elasticity to the bilateral exchange rate (the complement to 1 of ERPT) increased substantially for Chinese exports, from 0.20 in the period 2000-2005 to 0.27 in the period 2006-2014. That is, the prices of exports from China became far more stable in the local currencies of the destination markets across the two periods. Underlying this change, we show that the markup elasticity to bilateral exchange rates, which was low on average (0.06) and close to zero for most products and firms during 2000-2005, nearly tripled (to 0.17) in the second part of our sample. While we find substantial heterogeneity in price and markup elasticities across product and firm subgroups, we show that markup adjustment explains most of the observed change in the price elasticity within each group. Chinese exporters' market power in global markets rose across virtually all products and firms types.

On methodological grounds, our contribution consists of a fixed effects estimator and a product classification. Our estimator of the markup elasticity to the exchange rate—the *trade pattern sequential fixed effects* (TPSFE) estimator—isolates cross-market variation in prices by removing time-varying factors, including the unobservable marginal production costs, for each product sold by a firm across multiple, endogenously chosen, destination markets. The TPSFE builds on the insight by Knetter (1989), that the average price of a product over multiple foreign markets can proxy for unobserved marginal costs; differencing out the average price from individual market prices essentially controls for unobserved marginal costs. Knetter applies his method to industry-level average prices in a balanced panel of industry-level export unit values. At a micro level, however, the panel of product-firm-destination prices is naturally unbalanced, since the set of markets in which firms operate—in our definition, the firm's product-level "trade pattern"—varies each period, reflecting the endogenous response of firms to unobservable changes in production costs and local demand.[5] Our identification strategy consists of conditioning estimation on the same set of destinations for each firm's individual products. Intuitively, conditioning on trade patterns restricts the variation of the unobservable factors that may drive the firm's market participation, thereby eliminating or reducing estimation bias. Mapping the TPSFE to the literature, we show that *variation within trade patterns* is a principle source of identification for the elasticities or parameters of interest in high dimensional fixed effect (HDFE) models.[6] In other words, our *TPSFE* estimator facilitates a deeper understanding of the relevant variation required to obtain identification in empirical models widely used in the literature.

[5] Online Appendix table OA1-6 summarizes the volatile trade patterns of multi-destination Chinese exporters.

[6] As shown in the appendix, statistical high dimensional fixed effect (HDFE) estimators can be mapped into a simple procedure that implicitly uses a variant of the trade pattern fixed effects we propose.

Our second contribution builds on the observation that the intensity of competition among firms varies not only with aspects of market structure, including the size distribution of firms operating in a market, but also with the type of product, that is, the degree of product differentiation and substitutability. We exploit information recorded in Chinese customs data—specifically, Chinese linguistic particles that reflect a good's physical attributes and act as measures for numbers of items—to construct a comprehensive product classification that distinguishes between goods with a high versus low degree of differentiation. A key advantage of our classification consists of breaking down the large class of differentiated goods in Rauch (1999) into two subgroups of comparable size.[7] Combining our classification of high- and low-differentiation products with other criteria that reflect market power, including firm size, allows us to refine trade data into subgroups that facilitate our analysis of the relationship between multiple components of firms' market power and their associated price elasticities.

Applying this framework to Chinese customs data covering around 8,000 HS08 products and 152 foreign markets over 15 years reveals significant heterogeneity in price and markup elasticities to exchange rates across product and firm types.[8] In the early part of our sample (2000-2005), the average markup elasticity was 0.10 for firms selling highly differentiated goods, while it was effectively zero for those selling low-differentiation goods. In the later period (2006-2014), markup elasticities rose to 0.22 and 0.13, for high- and low-differentiation goods, respectively, pointing to a general rise in the market power of Chinese exporters.[9] Comparing markup and price elasticities across the two periods suggests that the markup contribution to the price elasticity rose from about one-third to two-thirds for high-differentiation goods, and from zero to one-half for low-differentiation goods. In other words, most of the change in price elasticities was driven by changes in markup elasticities rather than cost.

Firm size is a classic proxy for market power. Consistent with existing international evidence

[7]As shown in Table 2, applying Rauch (1999)'s categories to the Chinese Customs Database, we find about 80 percent of Chinese export value is classified as differentiated because these products are not traded on organized exchanges or in markets with published reference lists. According to our linguistics-based classification, about half of this, amounting to 39 percent of Chinese export value, is actually highly differentiated, while 41 percent exhibits low differentiation. Furthermore, we find that many products which are left unclassified by Rauch can be classified as high or low differentiation goods according to our classification.

[8]To avoid potential issues raised by changes in the exchange regime influencing the variability of the bilateral exchange rate between the dollar and the renminbi, throughout the analysis we exclude exports to the US. Results including the US are qualitatively similar and available upon request. We omit exports to Hong Kong from our analysis because of the changing importance of its role as an entrepôt over time (see Feenstra and Hanson (2004)). Lastly, we treat the eurozone as a single economic entity and aggregate the trade flows (quantities and prices) to eurozone destinations at the firm-product-year level.

[9]We split out sample around the change in the Chinese exchange rate regime, from the dollar-peg to a more relaxed managed float, in 2005. As discussed in section 5, because the TPSFE estimator differences out all factors that are common across destination markets (including the renminbi-dollar exchange rate), it recovers an accurate markup elasticity from variation across local currency-renminbi exchange rates, that is, independent of the renminbi-dollar exchange rate.

(Atkeson and Burstein (2008); Berman, Martin and Mayer 2012; Amiti, Itskhoki and Konings 2014), we find that larger firms exhibit higher price elasticities to exchange rates than smaller firms (0.60 vs. 0.16, for large vs. small firms over 2006-2014). Using our framework, we show that a similarly large gap characterizes markup elasticities (0.34 vs. 0.09). This implies that the contribution of markup adjustment to the price elasticities for both large and small firms is similar, at slightly above 50%. Moreover, our product classification has explanatory power within each firm-size category: conditional on firm size, we find that price and markup elasticities are significantly higher for firms selling high-differentiation goods.

Behind our headline results lays a significant shift in the composition of Chinese exporters by ownership, captured by firm registration. Between 2000 and 2014, the trade share of private enterprises rose from nearly zero to over 40%, while the trade share of state-owned enterprises dropped from around 50% to just 10%. We find that, relative to other categories of firms, price and markup elasticities are generally smaller for private firms. Yet, even for private firms, we document a considerable increase in the price elasticity from zero in 2000-2005 to 0.13 in 2006-2014, in large part driven by a rise in the markup elasticity from 0 to 0.08 across these two periods. In fact, a substantial increase in price and markup elasticities was observed across all registration types – not only relatively large state-owned and foreign-invested enterprices, but also relatively small private firms – suggesting a broad-based rise in market power for all types of Chinese exporters over time.

We close our analysis by specifying a partial equilibrium model featuring heterogeneous firms and products, variable markups, and endogenous export market participation, calibrated to replicate three empirical patterns we find in the data: (1) the rise in price and markup elasticities in the later period, (2) the increase in the export price elasticity driven primarily by markup adjustments rather than cost components, and (3) the variation in markup elasticities between high- and low-differentiation goods. Based on model-simulated data, we validate our estimation framework, showing that the TPSFE estimator is able to accurately uncover the true price and markup elasticities implied by the model.

Literature. Our paper contributes to two strands of the literature. The first strand is the recent literature studying the rising market power of firms, and its positive implications (De Loecker, Eeckhout and Unger 2020). While we do not directly estimate levels of markups, our estimated markup elasticities to exchange rates suggest the market power of Chinese exporters has increased dramatically over time and is the primary driver of increased import price stablity measured in the local currency of an importing country. In particular, we find a notable increase in the market power of Chinese private enterprises.

The second includes the growing body of research that relies on detailed customs data to study pricing-to-market and incomplete exchange rate pass through. This includes papers emphasising markup adjustments by large firms (Berman, Martin and Mayer 2012; Auer and Schoenle 2016; Fitzgerald and Haller 2014), and cost co-movement with exchange rates, as large exporters are often also large importers (Amiti, Itskhoki and Konings 2014). We contribute to this literature by empirically decomposing the contributions of markup and cost components to incomplete price pass-through and highlighting the importance of product heterogeneity in driving differences in price and markup elasticities.

We stress that our estimates of ERPT and markup elasticities convey different information relative to estimates of ERPT that are made conditional on specific shocks hitting the economy—a point elaborated at length by Corsetti and Dedola (2005). Specifically, we would expect the price response to exchange rate movements to be quite different if the underlying shock is to productivity as opposed to monetary policy. Estimates of ERPT conditional on a shock require methodologies, like VARs, suitable for identifying these shocks in isolation and tracing their effects on the exchange rate, export prices, and markups – see Forbes, Hjortsoe and Nenova (2017). As discussed by Corsetti, Dedola and Leduc (2008), our estimates aim at capturing structural relations among (endogenous) variables, that vary as a complex function of deep parameters.

Finally, our paper is related to the recent papers concerning the trading and pricing behaviour of Chinese exporters (Manova and Zhang 2012, Li, Ma and Xu 2015, Dai and Xu 2017, Crowley, Meng and Song 2018) and their implications (e.g., Amiti et al. 2020 and Jaravel and Sager 2024). Our paper naturally complements the empirical study by Manova and Zhang (2012) that highlights huge variation in firm-product prices across destinations and Li, Ma and Xu (2015) that study the exchange rate pass through of Chinese exporters. Our contribution consists of documenting the change in price and markup elasticities both over time and across products.

The paper is organized as follows. Section 2 explains our identification strategy and introduces our new TPSFE estimator. Section 3 presents our product classification and discusses its properties relative to alternative classifications. Section 4 describes the Chinese customs data. Section 5 discusses our key empirical results. Section 6 documents the changing composition of Chinese exporters and analyses the price and markup elasticities by firm registration type. Section 7 carries out a model-based analysis. Section 8 concludes.

2 An Estimator of Markup Elasticities

In this section, we introduce a decomposition of a product's price response to the exchange rate into markup and cost components, and a fixed effects estimator that disentangles these components empirically. In our study we build on the original insight by Knetter (1989)—that a product's marginal cost can be differenced out by comparing the product's price across different destinations. Knetter's identification strategy is versatile and effective, as recently shown by Fitzgerald and

Haller (2014), who rely on it in their study of Irish firms' pricing in Ireland and the UK. Our approach works out explicitly the theoretical foundations underlying the method and addresses the econometric challenges raised by its generalization to endogenously unbalanced panels.

2.1 A Two-way Decomposition of Export Price elasticities

We start by breaking down the change in the price p_{fidt} charged by firm f selling product i in the destination market d (denominated in the producer's currency), in response to a change in the bilateral exchange rate e_{dt} between the exporting and the destination country, where an increase in e_{dt} is a depreciation of the producer's currency, into three components. These components, in turn, capture the contribution of markups μ_{fidt} and marginal costs mc_{fit} to the price change, as shown in (1):

$$\begin{aligned}\frac{dp_{fidt}}{de_{dt}} &= \frac{\partial\mu_{fidt}}{\partial e_{dt}} + \frac{\partial\mu_{fidt}}{\partial mc_{fit}}\frac{\partial mc_{fit}}{\partial e_{dt}} + \frac{\partial mc_{fit}}{\partial e_{dt}} \\ &= \underbrace{\frac{\partial\mu_{fidt}}{\partial e_{dt}}}_{\text{Markup Contribution}} + \underbrace{\left(1+\frac{\partial\mu_{fidt}}{\partial mc_{fit}}\right)\frac{\partial mc_{fit}}{\partial e_{dt}}}_{\text{Cost Contribution}},\end{aligned} \tag{1}$$

where all variables are in natural logs, so that $\frac{\partial\mu_{fidt}}{\partial e_{dt}}$ is the markup elasticity to exchange rates holding marginal cost fixed, $\frac{\partial mc_{fit}}{\partial e_{dt}}$ captures how the marginal cost of the firm changes with exchange rates (e.g., due to the changing cost of the firm's imported inputs) and $\frac{\partial\mu_{fidt}}{\partial mc_{fit}}\frac{\partial mc_{fit}}{\partial e_{dt}}$ captures the indirect markup adjustments due to the changing level of marginal costs (as a result of the exchange rate movement). The second line in the above expression collects these terms into a markup and a cost-related component. Here, $\frac{dp_{fidt}}{de_{dt}}$ is the (unconditional) export price elasticity to exchange rates—this is one minus the exchange rate pass through into import prices. A higher export price elasticity implies a more stable import price in the local destination currency.[10]

[10] Observe that directly estimating the markup response to exchange rates captures a combination of two effects, i.e., $\frac{\partial\mu_{fidt}}{\partial e_{dt}} + \frac{\partial\mu_{fidt}}{\partial mc_{fit}}\frac{\partial mc_{fit}}{\partial e_{dt}}$, that, while partly offsetting each other, result in a downward-biased estimate of the true markup elasticity (and the corresponding market power of the firm in the destination market). To clarify this point, consider the effects of a foreign exchange rate appreciation (i.e., an increase in e_{dt}). On the one hand, this raises the demand for a given (producer's currency) price p_{fidt}, leading to an increase in the markup, $\frac{\partial\mu_{fidt}}{\partial e_{dt}} > 0$. On the other hand, the foreign appreciation may raise the firm's marginal cost (due to the higher cost of imported inputs), $\frac{\partial mc_{fit}}{\partial e_{dt}} > 0$, which reduces the firm's optimal markup, $\frac{\partial\mu_{fidt}}{\partial mc_{fit}} < 0$. In a standard variable-markup model (as we show in Section 7), $\frac{\partial\mu_{fidt}}{\partial e_{dt}} \approx -\frac{\partial\mu_{fidt}}{\partial mc_{fit}}$. The estimated markup elasticity using this approach is approximately equal to $\frac{\partial\mu_{fidt}}{\partial e_{dt}}\left(1-\frac{\partial mc_{fit}}{\partial e_{dt}}\right)$. In the extreme case where marginal costs perfectly comove with exchange rates, i.e., $\frac{\partial mc_{fit}}{\partial e_{dt}} = 1$, the estimated markup elasticity is zero, regardless of the firm's market power.

2.2 Identification Strategy

In what follows, we propose an empirical approach to identify the markup's contribution to price adjustments to exchange rates, i.e., $\frac{\partial \mu_{fidt}}{\partial e_{dt}}$. To fix ideas, consider a Chinese firm that sells the same product in two markets, Australia and Brazil. Now, conditional on the same firm selling the same product in both markets, the relative export price in the two countries, $p_{AUS,t} - p_{BRA,t}$, would not depend on marginal costs; it only reflects the destination-specific markup in A relative to B.[11] Therefore, by looking at how the relative price change $\Delta(p_{AUS,t} - p_{BRA,t})$ co-moves with the relative change in (bilateral) exchange rates $\Delta(e_{AUS,t} - e_{BRA,t})$, one obtains an estimate of how firms adjust their export price-cost markups across destinations from one period to another due to changes in relative (bilateral) exchange rates. In a setting with multiple markets, one can use the average price and average exchange rate across all markets as the reference or comparison group, and then, reformulate relative changes in terms of deviations from these groups. That is, one can calculate $\Delta(p_{d,t} - \frac{1}{N_d}\sum_d p_{d,t})$ and $\Delta(e_{d,t} - \frac{1}{N^D}\sum_d e_{d,t})$, where d represents a destination market and N^D is the total number of destination markets served by a firm with a product.

A critical requirement for this identification strategy to work is that the marginal costs of the products being sold to different markets are similar. While Knetter (1989)'s original paper applies the method to industry-level data, we apply it to highly granular firm-product level data, which significantly increases the likelihood that the marginal costs underlying the prices in different destination markets are similar. However, in a granular dataset, we face another critical challenge: the set of destination markets to which a firm sells its products varies significantly over time.[12]

To illustrate this problem, Figure 1 shows the trading record of an exporter selling a particular (8-digit) product to three destination markets (A, B, and C) over a five-year span. Empty elements indicate that there is no trade in that year. Defining the set of markets active at a firm-product level in one period as a *trade pattern*, the firm in this example has three *unique* trade patterns: A-B, A-C, A-B-C over the course of its five-year trade in that product. The pattern A-C repeats in periods 2 and 4; A-B-C repeats in periods 3 and 5.

Two questions arise in developing a multiple market application of Knetter (1989)'s strategy. First, can one control for a firm's unobserved marginal costs with the average price across destinations if the set of destinations changes over time? Second, should one be worried about the fact that the market choices may be endogenous to exchange rates and other unobserved variables? In our approach, both questions are addressed by using a simple economic rationale to guide the choice of the relevant comparison group in a multiple market setting: firms choose a set of markets for reasons that may be unobservable to an econometrician.

We start by noting what happens when we apply Knetter's method mechanically, i.e., we differ-

[11] Prices and exchange rates are measured in the same currency and expressed in natural logs.

[12] See Online Appendix table OA1-6 for detailed data about the trade patterns of Chinese exporters.

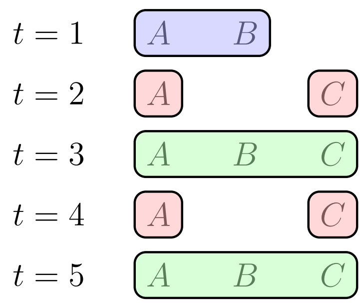

Figure 1: Example of an observed trade pattern

ence out unobserved marginal costs by taking the relative prices within a time period, disregarding the unbalanced nature of the panel. In our example, $\dot{p}_{A,1} \equiv p_{A,1} - \frac{1}{2}(p_{A,1} + p_{B,1})$ removes the common marginal cost between markets A and B in period 1, and $\dot{p}_{A,2} \equiv p_{A,2} - \frac{1}{2}(p_{A,2} + p_{C,2})$ eliminates the common marginal cost between markets A and C in period 2. Across periods, we can similarly define $\dot{e}_{A,1} \equiv e_{A,1} - \frac{1}{2}(e_{A,1} + e_{B,1})$ and $\dot{e}_{A,2} \equiv e_{A,2} - \frac{1}{2}(e_{A,2} + e_{C,2})$. From this example, it should be clear that comparing $\dot{p}_{A,2} - \dot{p}_{A,1}$ with $\dot{e}_{A,2} - \dot{e}_{A,1}$ fails to control for the fact that the comparison group has changed from period 1 to period 2.

To ensure a consistent comparison group, we propose an approach that follows the logic of a simple "difference-in-differences" estimator. The idea is to calculate and compare the relative changes in prices and exchange rates *within the same trade pattern*. Returning to our example, we calculate the relative-price to relative-exchange rate movement in country A between periods 2 and 4 ($\widetilde{\dot{p}}_{A,4} \equiv \dot{p}_{A,4} - \dot{p}_{A,2}$ and $\widetilde{\dot{e}}_{A,4} \equiv \dot{e}_{A,4} - \dot{e}_{A,2}$) and compare it to the corresponding relative-price and relative-exchange rate movement in country C between the same two periods ($\widetilde{\dot{p}}_{C,4} \equiv \dot{p}_{C,4} - \dot{p}_{C,2}$ and $\widetilde{\dot{e}}_{C,4} \equiv \dot{e}_{C,4} - \dot{e}_{C,2}$). Restricting the comparisons within the same trade pattern ensures a like-for-like analysis. The estimator we propose exploits the information in all repeated trade patterns in our dataset – in the example, it will use both the comparisons from data in periods 2 and 4 associated with the A-C trade pattern, and the relative price and relative exchange rate movements in countries A, B, and C between periods 3 and 5, associated with the A-B-C trade pattern, using $\widetilde{\dot{p}}_{A,5}, \widetilde{\dot{p}}_{B,5}, \widetilde{\dot{p}}_{C,5}$ and $\widetilde{\dot{e}}_{A,5}, \widetilde{\dot{e}}_{B,5}, \widetilde{\dot{e}}_{C,5}$.

There is an important reason to use our definition of trade patterns over alternative definitions of the comparison group — such as a group created by extracting a balanced panel by trimming observations or a group that is limited to a subset of markets.[13] At the core of our identification strategy is the recognition that time-varying patterns of market participation are informative about unobservable factors that drive exporters' trade choices. The notion that observed patterns

[13] Note that our approach excludes using information from markets A and C in periods 2 and 3, i.e., using the data $p_{A,2} - \frac{1}{2}(p_{A,2} + p_{C,2})$, $p_{A,3} - \frac{1}{2}(p_{A,3} + p_{C,3})$, $e_{A,2} - \frac{1}{2}(e_{A,2} + e_{C,2})$, and $e_{A,3} - \frac{1}{2}(e_{A,3} + e_{C,3})$?

in an unbalanced panel can be used to address estimation biases has been entertained in earlier econometric studies. For example, Wansbeek and Kapteyn (1989) propose statistical partition matrices that use realized data patterns to eliminate confounding factors in an unbalanced two-dimensional panel. While analytically and conceptually distinct, the introduction of trade pattern fixed effects in our approach shares the same fundamental idea of these earlier studies. We provide a detailed discussion of our estimator in the Online Appendix OA2.[14]

2.3 The Trade Pattern Sequential Fixed Effects TPSFE Estimator

We propose a simple three-step approach to estimating the markup elasticity to exchange rates. For a customs database with four panel dimensions (i.e., firm f, product i, destination d, and time t), the estimator can be implemented as follows.

In the first step, we calculate the destination residual of each dependent and independent variable by subtracting the mean value of each variable (across destinations) over all active destinations for a firm's product in a period:

$$\dot{x}_{fidt} \equiv x - \frac{1}{n^D_{fit}} \sum_{d \in D_{fit}} x \quad \forall x \in \{p_{fidt}, e_{dt}\} \tag{2}$$

where n^D_{fit} is the number of active foreign destinations of firm f selling product i in year t and D_{fit} denotes the set of destinations of this firm-product pair in year t; p is the export price denominated in the producer's currency (i.e., in renminbi); e_{dt} is the bilateral exchange rate defined as the units of renminbi per units of destination market currency. All variables are in logs.

Our second step demeans at the firm-product-destination-trade pattern ($fidD$) level. That is, we subtract the mean of the $\dot{x}_{fidt}$ variables for all time periods associated with the firm-product-destination-trade pattern $fidD$, i.e., $t \in T_{fidD}$:

$$\widetilde{\dot{x}}_{fidt} \equiv \dot{x}_{fidt} - \frac{1}{n^T_{fidD}} \sum_{t' \in T_{fidD}} \dot{x}_{fidt'} \quad \forall x \in \{p_{fidt}, e_{dt}\} \tag{3}$$

where $\widetilde{\dot{x}}_{fidt}$ are the twice-differenced variables. Note that the aggregate variables which normally vary along only two dimensions d and t may "become" firm and product specific, i.e., $\widetilde{\dot{e}}_{fidt}$, due to the unbalancedness of the panel.

Using these twice-differenced variables, in the final step, we run an OLS regression that identifies how markups respond to the bilateral exchange rate; this approach exploits cross-destination

[14] Proofs for the identification condition of the TPSFE estimator using statistical partition matrices (as in Wansbeek and Kapteyn (1989)) are in OA2.1; a discussion of identification following the control function literature (Heckman (1979) and Kyriazidou (1997)) is in OA 2.2; finally, a discussion of identification in light of the contribution on estimating production functions by De Loecker et al. (2016) is in OA2.3

variation in prices within a firm-product's trade pattern as well as intertemporal variation in prices within the same firm-product-destination-trade pattern over time:

$$\widetilde{\dot{p}}_{fidt} = \beta_0 + \beta_1 \widetilde{\dot{e}}_{fidt} + \widetilde{\dot{u}}_{fidt}, \tag{4}$$

where $\widetilde{\dot{u}}_{fidt}$ is the residual term. We refer to the above procedure as the *trade pattern sequential fixed effects* (TPSFE) estimator. β_1 is the markup elasticity to the bilateral exchange rate, i.e., $\frac{\partial \mu_{fidt}}{\partial e_{dt}}$.[15]

A Comparable Price Elasticity Estimator. To conduct our decomposition exercise, we need to relate our estimates of the markup elasticities to comparable estimates of the price elasticities to exchange rates. We specify a suitable estimator for this elasticity by exploiting the intertemporal variations of prices and exchange rates within the same trade pattern, as shown below:

$$\widetilde{p}_{fidt} = \gamma_0 + \gamma_1 \widetilde{e}_{fidt} + \gamma_2 \widetilde{Spell}_{fidt} + \widetilde{u}_{fidt}, \tag{5}$$

where $\widetilde{p}_{fidt}$ and $\widetilde{e}_{fidt}$ are defined as in (3)[16] with $\widetilde{Spell}_{fidt} \equiv t - \frac{1}{n^T_{fidD}} \sum_{t' \in T_{fidD}} t'$ capturing the spell length between two (or more) demeaned price observations.[17] The coefficient γ_1 gives the price elasticity to exchange rates, i.e., $\frac{dp_{fidt}}{de_{dt}}$.

The difference between (5) and (4) is that (5) does not difference out the marginal cost component. As we discuss in Section 7, comparing $\gamma_1^{Est.}$ with $\beta_1^{Est.}$ allows us to quantify the relative contribution of the markup elasticity to the total export price adjustment to exchange rates.

A model-based evaluation of our estimator is presented in Section 7.

2.4 Properties of the TPSFE

Recently, the literature has widely used statistical methods, such as the high-dimensional fixed effects (HDFE) estimator by Correia (2017), and has employed graphical data patterns to iteratively remove confounding factors in fixed-effect specifications.[18] While these statistical approaches are

[15] The standard errors of the estimates can be constructed by applying conventional adjustments to the degrees of freedom, see e.g., Wansbeek and Kapteyn (1989) and Abowd, Kramarz and Margolis (1999).

[16] That is

$$\widetilde{x}_{fidt} \equiv x_{fidt} - \frac{1}{n^T_{fidD}} \sum_{t' \in T_{fidD}} x_{fidt'} \quad \forall x \in \{p_{fidt}, e_{dt}\}.$$

[17] As we discuss in Section 7, the $\widetilde{Spell}_{fidt}$ helps to control for the unobserved time trend in marginal costs and prices when market entry is endogenous. Note that we do not add this control for the markup elasticity estimation as $\widetilde{\dot{Spell}}_{fidt} = 0$ by construction.

[18] Alternative iterative approaches include Guimaraes and Portugal (2011) and Rios-Avila (2015). As Guimaraes and Portugal (2011) points out, these iterative approaches must be applied with caution, as they may not be

powerful, a drawback is that they do not offer an interpretation of the variation used to identify the economic object (e.g., the elasticities) of interest.[19]

Relative to this econometric literature, the TPSFE estimator not only offers a clear *economic* interpretation of such variation; it also provides a key insight into the existing methods. Namely, as discussed in the appendix, we show that the partition and iterative approaches in HDFE estimators are implicitly using the trade pattern information we propose. Propositions 1 and 2 in Online Appendix OA2 formally show that, exploiting the realized trade patterns, iterative approaches can be simplified to two demeaning steps, whether or not the panel is balanced.[20]

3 A Product Classification by Degree of Differentiation

In studying markup elasticities, it is important to identify products for which firms are potentially able to exploit market power in setting prices. Many trade studies employ the product classification set forth by Rauch (1999). In Rauch's classification a product is differentiated if it does not trade on organized exchanges and/or its price is not regularly published in industry sales catalogues. While employed widely by the literature, a drawback of the Rauch classification is that the vast majority of manufactured goods end up being classified as differentiated.

In this section we introduce a product classification that aims to distinguish products by their degree of differentiation. Specifically, it splits Rauch's large class of differentiated goods into two groups, high- and low-differentiation goods. The key feature of our Corsetti-Crowley-Han-Song (CCHS) classification is that it exploits linguistics-based information available in Chinese customs data. This information allows us to create a general, finely defined, and comprehensive system which is applicable internationally to all datasets that use the Harmonized System.[21]

consistent due to the incidental parameters problem in multi-dimensional panels.

[19]To clarify, consider a model that regresses prices on exchange rates using a stringent set of fixed effects in our four-dimensional panel, specifically firm-product-time (fit) and firm-product-destination (fid) fixed effects. When the dataset is large, applying the statistical partition matrices proposed by Wansbeek and Kapteyn (1989) becomes inefficient, if not infeasible. The standard approach is to use iterative procedures to difference out the fid and fit fixed effects. In a balanced panel, this approach is equivalent to a two-step demeaning process, where the first step demeans at the fid level and the second at the fit level (as in the Frisch–Waugh–Lovell theorem). However, in an unbalanced panel, this simple demeaning process is ineffective—the two-step demeaning process used in balanced panels can lead to substantial biases. As a result, current practice often relies on iterative methods (e.g., Correia 2017) that exploit data patterns to sequentially eliminate fixed effects. In complex data structures, this iterative process may require hundreds of iterations to converge. Since each iteration removes small variations of dependent and independent variables, the true variation left for identification remains unclear.

[20]We demonstrate that the fid and fit fixed effects can be decomposed into two steps: first, demeaning the variables at the fit level, and second, applying the fid and trade pattern (D) fixed effects additively. To restate the main result in the appendix: standard fixed-effect approaches can be reformulated as a two-step process, with the second step implicitly applying the trade pattern fixed effect proposed in this paper. Building on this, we combine the two fixed effects used in the second step into a more comprehensive $fidD$ fixed effect, resulting in our TPSFE estimator.

[21]By way of example, Crowley, Han and Prayer (2024) applies our CCHS classification to customs data from

3.1 A Comprehensive Classification Based on Chinese Linguistics

In general, traded goods which are measured in discrete items are more differentiated than traded goods which are measured using continuous metrics. The value added of our classification derives from the way it identifies discrete versus continuous goods. We rely on a feature of Chinese linguistics present in Chinese customs reporting – the use of indigenous Chinese measure words to record quantity for specific HS08 products. In the Chinese Customs Database, quantities are reported in 36 different measures, many of which exist only in Chinese.[22] Linguists categorize Chinese measure words as count/discrete or mass/continuous classifiers; we operationalize this linguistic distinction to categorize each Harmonized System product as highly differentiated (i.e., for discrete goods) or less differentiated (i.e., for continuous goods).[23]

The advantage of using Chinese linguistics to classify goods according to their degree of differentiation arises from the facts that (a) all Chinese nouns have an associated measure word that inherently reflects the noun's *physical attributes* and (b) the Chinese Customs Authority mandates the reporting of quantity for Chinese HS08 products in these measure words. The first fact means that identifying discrete products from Chinese "count classifiers" is arguably more accurate and systematic than alternatives. By way of example, Chinese measure words are more distinctive and more precisely tied to specific nouns by Chinese grammar rules than the eleven units of measure recommended by the World Customs Organization (WCO) are linked to nouns in languages such as English or German.[24] Moreover, because the choice of the *measure word* used to record a product's quantity is predetermined by Chinese grammar and linguistics, we can set aside concerns that the choice of a quantity measure is endogenous.[25]

11 developing countries, documenting differential markup and market share responses to tariff changes for firms selling high- and low-differentiation goods (Table 4). Similarly, Crowley, Han and Son (2024) applies our CCHS classification to UK exporters, documenting the differential evolution of currency choices for firms selling high- and low-differentiation goods following the Brexit referendum (Figure 2).

[22]Notably, the linguistic structure of other East Asian languages also requires the use of measure words. In our Online Appendix OA1.2 we explain how Japanese customs declarations integrate indigenous Japanese measure words into the World Customs Organization quantity measurement framework.

[23]See Cheng and Sybesma (1998, 1999) for a discussion of mass classifiers and count classifiers in Chinese. Cheng and Sybesma (1998) explain: "while massifiers [mass classifiers] *create* a measure for counting, count-classifiers simply *name the unit* in which the entity denoted by the noun it precedes naturally presents itself. This acknowledges the cognitive fact that some things in the world present themselves in such discrete units, while others don't. In languages like English, the cognitive mass-count distinction is grammatically encoded at the level of the noun..., in Chinese the distinction seems to be grammatically encoded at the level of the classifier" (emphasis added).

[24]See Fang, Jiquing and Connelly, Michael (2008), *The Cheng and Tsui Chinese Measure Word Dictionary*, Boston: Cheng and Tsui Publishers, Inc. for a mapping of Chinese nouns to their associated measure words. In our Online Appendix OA1.2 we provide examples of how measure words are used in Chinese grammar.

[25]Since 2011, the WCO has recommended that *net weight* be reported for *all transactions* and supplementary units, such as number of items, be reported for 21.3% of Harmonized System products. However these recommendations are *non-binding*; the adoption and enforcement of this recommendation by a country might be endogenously determined by the value or volume of trade in a product, with high-value products subject to stricter enforcement that counts be reported. The sophistication of a country's border operations and tax authority could also play a

Table 1 illustrates the variety of measures used in the Chinese Customs Dataset, by reporting a selection of the most commonly used measure words, the types of goods that use the measure word, and the percent of export value that is associated with products described by each measure word. In this table, qiān kè (千克) and mǐ, (米) are mass/continuous classifiers; the remaining measure words are count/discrete classifiers. The main point to be drawn from the table is that the nature of the Chinese language means that the reporting of differentiated goods, for example, automobiles, spark plugs and engines, takes place by reporting a number of items and the count classifier that is linguistically-associated with that type of good. All products within an HS08 code use the same measure word. See Online Appendix OA1.2 for an example of the different Chinese measures words used to quantify closely-related products in our dataset.

Table 1: Measure word use in Chinese customs data for exports, 2008

Quantity Measure	Meaning	Types of goods	Percent of export value
qiān kè, 千克	kilogram	grains, chemicals	40.5
tái, 台	machines	engines, pumps, fans	24.7
gè, 个	small items	golf balls, batteries, spark plugs	12.8
jiàn, 件	articles of clothing	shirts, jackets	6.6
shuāng, 双	paired sets	shoes, gloves, snow-skis	2.6
tiáo, 条	tube-like, long items	rubber tyres, trousers	2.5
mǐ, 米	meters	camera film, fabric	2.1
tào, 套	sets	suits of clothes, sets of knives	1.8
liàng, 辆	wheeled vehicles	cars, tractors, bicycles	1.4
sōu, 艘	boats	tankers, cruise ships, sail-boats	1.3
kuài, 块	chunky items	multi-layer circuit boards	0.7

The second fact, that quantity must be reported on Chinese Customs forms in indigenous count units for discrete objects, means that the Chinese Custom system will likely be quite accurate in accounting for discrete items, relative to what can be inferred from the quantity measures actually reported in other customs systems. For example, in Egyptian customs records over 2005-2016, a mere 0.006% of export observations report the discrete unit "pieces" as the unit of quantity. In comparison, the share of Chinese export data that uses a count/discrete measure for reporting quantity is 40.9% of observation-weighted HS08 data and 52.8% of value-weighted HS08 data (see the last rows of panels (a) and (b) in table 2.[26]

role in which measures are reported. See United Nations Statistics Division (2010).

[26] Authors' calculations from EID-Exports-2005-2016 obtained from http://erfdataportal.com. Egypt is a useful comparator in that it had a similar per capital income to China during the midpoint of our sample, 2007, $1667 (Egypt) versus $2693 (China), and it used a similarly large variety of quantity measures, 32, in its export

Table 2: Classification of goods: Integrating the insights from CCHS with Rauch

(a) Share of goods by classification: observation weighted

	Corsetti-Crowley-Han-Song (CCHS)		
	Low Differentiation / (Mass nouns)	High Differentiation / (Count nouns)	
Rauch (Liberal Version)			
Differentiated Products	41.1	38.8	79.8
Reference Priced	6.9	0.7	7.6
Organized Exchange	0.6	0.0	0.6
Unclassified[†]	10.5	1.5	12.0
	59.1	40.9	100.0

(b) Share of goods by classification: value weighted

	Corsetti-Crowley-Han-Song (CCHS)		
	Low Differentiation / (Mass nouns)	High Differentiation / (Count nouns)	
Rauch (Liberal Version)			
Differentiated Products	24.2	47.1	71.3
Reference Priced	9.1	2.8	11.9
Organized Exchange	2.0	0.0	2.0
Unclassified[†]	11.9	2.9	14.8
	47.2	52.8	100.0

Notes: Share measures are calculated based on Chinese exports to all countries including Hong Kong and the United States during periods 2000-2014. [†]"Unclassified" refers to HS08 products that do not uniquely map to differentiated, referenced priced, or organized exchange under the SITC Rev. 2-based classification of Rauch.

3.2 Improvements Relative to the Rauch (1999) Industry Classification

The CCHS linguistics-based product classification can be applied to the universal 6-digit Harmonized System used by all countries by categorizing as high (low) differentiation those HS06 categories in which all HS08 products use a count/discrete (mass continuous) classifier.[27] In Table 2, we demonstrate the value-added of our classification system in relation to Rauch (1999). The table integrates our classification of high versus low differentiation goods with that obtained by mapping HS08 product codes from the Chinese Customs Data to Rauch's original 4 digit SITC Rev. 2 classification of, respectively, differentiated, reference priced, and organized exchange traded goods.

Two advantages of our classification are apparent. First, it refines the large class of differentiated goods in Rauch into two categories—high and low differentiation—of comparable size. From table 2 panel (a), we observe that 79.8 percent of observations in the Chinese Customs Database at the firm-HS08 product level are classified by Rauch as differentiated. Of these, only 48.6 percent (38.8/79.8) use count classifiers and are categorized as high differentiation under the CCHS approach. The picture is similar in panel (b), where observations are value weighted: of the 71.3 percent of the export value classified by Rauch as differentiated, 66.1 percent (47.1/71.3) use count classifiers. Further, table 2 confirms that every good that Rauch categorizes as a commodity (i.e., an organized-exchange traded good) is reported in the Chinese Customs Database with a mass classifier. This conforms with our prior that mass nouns are low differentiation goods and serves as a useful reality check on our approach.

The second advantage is that we are able to provide a CCHS classification for *all* HS08 (and HS06) products, including those that cannot be classified under Rauch's system due to issues with the mapping from HS06 to SITC Rev. 2. This enables us to expand our analysis of market power to include the 12% percent of observations (table 2 panel (a)) and 14.8% of export value (table 2 panel (b)) in the Chinese Customs Database in HS08 products that do not uniquely map to a single Rauch category.[28]

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statistics over 2005-2014. See Online Appendix OA1.2.2 for a discussion of quantity reporting in other customs systems.

[27]See Online Appendix OA1.2.3 for examples of closely-related HS08 products and the types of measure words they use.

[28]To be clear, Rauch provides a classification for each SITC Rev. 2 industry as differentiated, reference priced or organized exchange, but the SITC Rev. 2 industries in his classification are more aggregated than HS06 products. Because the concordance of disaggregated HS06 product codes to (more aggregated) SITC Rev. 2 involves one-to-many or many-to-many mappings for 81 percent of concordance lines, we are only able to classify HS06 products (and even finer HS08 products) into one of the three Rauch groupings if *all* SITC Rev. 2 industries associated with an HS06 product are "differentiated," etc. under Rauch. This one-to-many and many-to-many concordance issue implies that no unique mapping into Rauch's three categories is possible for 12% of observations in the Chinese Customs Database.

3.3 Pricing in High and Low-differentiation Goods Markets: an Illustration

To illustrate the relevance of our classification, we conduct a case study of price adjustments by firms producing two products differing in their degree of differentiation. We select, respectively, canned tomato paste (measured in kilograms) and wheeled tractors (measured with liàng, 辆). In our classification, the former is a low-, the latter is a high-differentiation good.

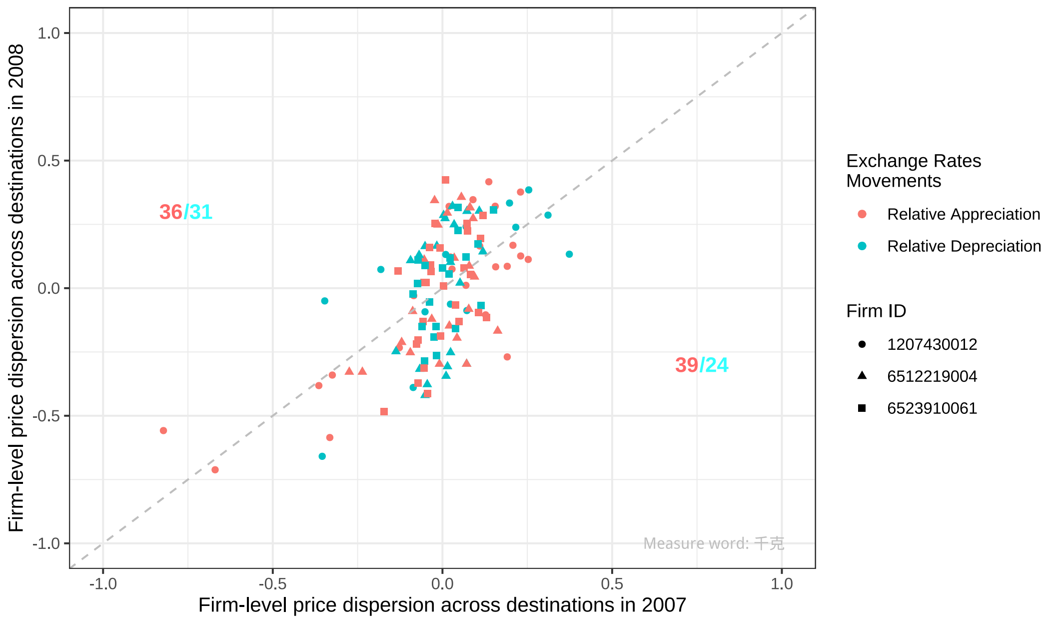
In figure 2, we plot the dispersion of price residuals (from averages) across destinations for the top three exporters of tomato paste (upper panel) and wheeled tractors (lower panel) in 2007 and 2008. For each annual observation of a sale to a destination, we calculate the deviation of the sales price from its mean across all destinations within the firm-product-year triplet (where sales price is the log unit value in renminbi), i.e. $uv_{fidt} - \overline{uv}_{fit}$, and plot these deviations using different shapes (i.e., triangle, square, and circle) for each firm. The x-axis measures positive and negative deviations of the sales price from the mean value in 2007; the y-axis measures the deviations from the mean in 2008.[29] Any observation on the 45 degree line is a product whose relative premium or discount in its destination d did not change between 2007 and 2008. Thus, a point lying on the 45 degree line at 0.2 represents a product that was sold in some destination d at a 20% premium over the firm's mean price in both 2007 and 2008. An observation plotted *above* the 45 degree line depicts a product-destination whose price residual increased between 2007 and 2008 *relative* to the firm's sales of the good in other destinations. Conversely, an observation plotted below the 45 degree line represents a product-destination that saw its relative price fall.

We color-code each point according to whether the destination's currency appreciated or depreciated over 2007-2008 relative to the other destinations the firm was selling to. Red indicates relative appreciation, blue relative depreciation. Above and below the 45 degree line, we report the number of observations marked by red dots, corresponding to bilateral appreciations, in ratio to the number of observations marked by blue dots corresponding to depreciations.

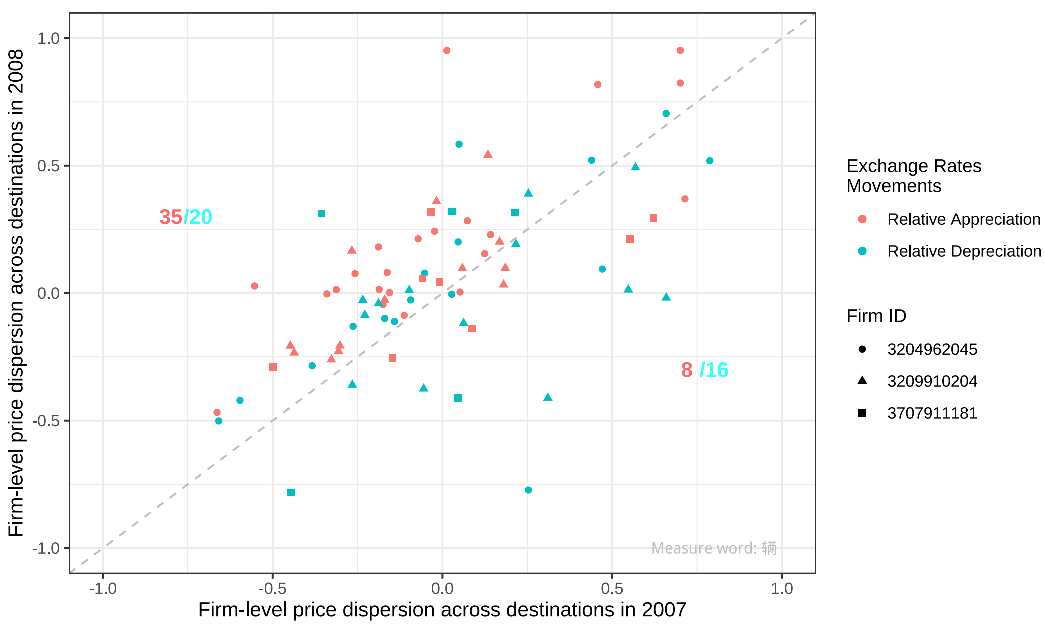
As apparent from these graphs, the relative price residuals for many firm-product-destination triplets, measured in the producer's currency, change from year to year. Yet, the low differentiation good, tomato paste, exhibits less dispersion in price residuals across destinations than the high differentiation good, wheeled tractors. Most importantly, for high differentiation goods, appreciation of the destination market currency relative to the renminbi is associated with an increase in relative price residuals (red dots are denser above the 45 degree line), while depreciation of the destination market currency is associated with a decrease in relative price residuals. No such clear pattern emerges between relative price changes and relative currency changes for the low

[29]The magnitude of price dispersion within a year across destinations for wheeled tractors is of the same order of magnitude as that found in European automobile prices in an important study of international market segmentation by Goldberg and Verboven (2001).

Figure 2: Price dispersion across destinations for top three firms in 2007 and 2008



Example 1: Canned Tomato Paste (a low differentiation product)



Example 2: Wheeled Tractors (a high differentiation product)

differentiation good, tomato paste.

4 Data

Our analysis uses the Chinese Customs Database, the universe of annual import and export records for China from 2000 to 2014 along with annual macroeconomic data from the World Bank.[30] The final estimation dataset consists of over 200,000 multi-destination exporters, around 8,000 HS08 products, and 152 foreign markets over 15 years.

The Chinese Customs Database reports values and quantities of exports in US dollars by firm (numerical ID and name) and foreign destination country at the 8-digit Harmonized System product level over 2000-2014.[31] Chinese exports are thus structured as a panel with four dimensions—firm, product, destination market, and time. However, specific characteristics of the Chinese customs data allow us to obtain a classification of types of products by their differentiation and types of firms by the nature of their commerce. Most notably for our purposes, each observation in the database contains (a) the Chinese measure word in which quantity is reported, (b) an indicator of the form of commerce for tax and tariff purposes, and (c) a categorization based on the registration type of the exporting firm.[32] We will see that all these entries can be exploited to obtain information on the firm's market power in its export markets.

Like other firm-level studies using customs databases, we use unit values as a proxy for prices. However, the rich information on forms of commerce and Chinese measure words enables us to build more refined product-variety categories than prior studies have used. Specifically, we define the product identifier as an 8-digit HS code plus a form of commerce dummy. The application of our product-variety definition generates 14,560 product-variety codes in our final estimation dataset

[30] See Online Appendix OA1 for more details.

[31] The database is available at the monthly frequency during the period 2000-2006 and annual frequency during the period 2007-2014. We aggregate the monthly data for 2000-2006 to the annual level in this study. Because no information on the currency of invoicing is reported in the Chinese Customs Database, we turn to administrative data from Her Majesty's Revenue and Customs (HMRC) in the UK to provide information about the currency of invoicing of Chinese exports to the UK so that we can place our results in context. See Online Appendix OA1.4.

[32] The form of commerce indicator records the commercial purpose of each trade transaction including "general trade," "processing imported materials," and "assembling supplied materials." Essentially, a firm can produce the same HS08 product under different tax regulations depending on the exact production process used. We simplify different tax treatments into a form of commerce dummy equal to 1 if the transaction is "general trade" and 0 otherwise. The registration type variable contains information on the capital formation of the firm by eight mutually-exclusive categories: state-owned enterprise, Sino-foreign contractual joint venture, Sino-foreign equity joint venture, wholly foreign-owned enterprise, collective enterprise, private enterprise, individual business, and other enterprise. In our analysis, we aggregate the three types of foreign-invested firms, namely wholly foreign-owned enterprises, Sino-foreign contractual joint ventures and Sino-foreign equity joint ventures, into one category dubbed "foreign-invested enterprises." We group minority categories including collective enterprises, individual businesses and other enterprises into one category and refer to them as "other enterprises."

as opposed to 8,076 8-digit HS codes reported in the database.[33] Throughout our study, we will use the term "product" to refer to these 14,560 product-varieties. This refined product measure allows us to get a better proxy of prices for two reasons. First, the inclusion of the information on form of commerce helps to distinguish subtle differences of goods being sold under the same 8-digit HS code. Second, as discussed later on in the text, the extensive use of a large number of measure words as quantity reporting units makes unit values in Chinese data conceptually closer to transactions prices than unit values constructed with other national customs datasets.[34]

Table 3: Multi-destination exporters (2007)

	Number of Foreign Destinations				
	1	2-5	6-10	10+	Total
(a) by Share of Exporters	27.2	33.1	14.7	25.0	100.0
(b) by Share of Export Values	5.4	11.9	10.4	72.3	100.0
(c) by Share of Number of Annual Transactions	3.0	8.0	7.8	81.2	100.0

Note: Each cell in the top row is the proportion of exporters in the Chinese customs data in 2007 that fall under the relevant description. The middle and bottom rows present the corresponding proportions for export value and count of annual export transactions, respectively.

Quantitative importance of multi-destination exporters. A general features of granular trade data, that we extensively use in applying our framework, is that a very large share of transactions are conducted by exporters serving multiple foreign destinations. This pattern has been documented for a number of markets, most notably for France by Mayer, Melitz and Ottaviano (2014), suggesting that this is a core feature of foreign market participation by exporting firms. For our dataset, table 3 presents a breakdown of the proportion of exporting firm, export values, and count of annual transactions according to the number of destinations served in 2007. Overall, we see that around three-quarters of exporters reach more than one destination (row a). These firms are responsible for 94.6% of export value (row b) and 97.0% of annual transactions (row c). Conversely, the 27.2% of exporters that sell to a single destination comprised only 5.4% of Chinese export value and 3.0% of export transactions in 2007. While we present a single year snapshot from our dataset in the table, the patterns in year 2007 are by no means special: the shares of exporters, export value, and export transactions by count of destination markets remain relatively stable over our sample period, 2000-2014.

[33] When we clean the data, the number of HS08 products and HS08 product-varieties declines with the number of observations. These numbers refer to products and product-varieties in the final estimation dataset.

[34] Important previous studies have constructed unit values (export value/export quantity) from data in which quantity is measured by weight (Berman, Martin and Mayer (2012)) or in a combination of weights and units (Amiti, Itskhoki and Konings (2014)).

5 Evidence on the Rise in Market Power

The sample period of our study includes an important change in the exchange rate regime pursued by China. In the years 2000-2005, China pursued a fixed exchange rate regime; after that, it switched to a managed float regime. Figure 3 plots the bilateral movement of the renminbi against the US dollar, together with China's nominal effective exchange rate, over our entire sample period. As apparent from the figure, the renminbi has been quite volatile against the currencies of non-US trade partners before and after 2005.

To account for the evolution of elasticities over time, we will report results separately for two subsamples, 2000-2005 vs. 2006-2014, that correspond to the two currency regimes pursued by China relative to the dollar. While different splits are possible, the relaxation of the dollar peg offers a natural break point in the series. To avoid potential issues raised by changes in the exchange rate regime influencing the variability of the bilateral exchange rate between the dollar and the renminbi, throughout the analysis we will exclude exports to the US and Hong Kong.[35]

Prior to the presentation of our results, it is worth clarifying that, since our TPSFE estimator differences out common cost, price, and exchange rate variations across destinations, it also differences out the response to a common third-country exchange rate. To appreciate this point, consider the case in which the optimal markup in a destination responds to both the dollar and the bilateral local exchange rates:

$$\mu_{fidt} = \beta_1 e_{\$,t} + \beta_2 e_{d,t} \tag{6}$$

where $e_{\$,t}$ is the renminbi-dollar exchange rate, and $e_{d,t}$ is the renminbi-destination currency exchange rate. By applying destination demeaning (the first step of our TPSFE), we eliminate the influence of $e_{\$,t}$—since this does not vary across destinations. This features of the TPSFE estimator ensures comparability of our results across the dollar peg and floating exchange rate periods. Note that, by the same property of the TPSFE estimator, our results do not depend on the choice of bilateral exchange rates in our procedure. For instance, we obtain identical estimates whether we use the dollar-destination currency or the renminbi-destination currency exchange rate as the independent variable. Similarly, using prices denominated in dollars together with dollar-destination exchange rates versus using prices denominated in renminbi together with renminbi-destination exchange rates in the estimation procedure yields exactly the same results.

We also call attention to another property of the TPSFE estimator—it explicitly singles out the sample used for identification. For clarity, in all our tables in this section, the last column reports the size of the entire estimation sample (in the same row as the parameter estimates), and the size of the identification sample (in square brackets [·] in the same row as the standard errors). The identification sample is smaller because it excludes observations from non-repetitive

[35] Qualitatively, results do not change if we include exports to the United States and Hong Kong.

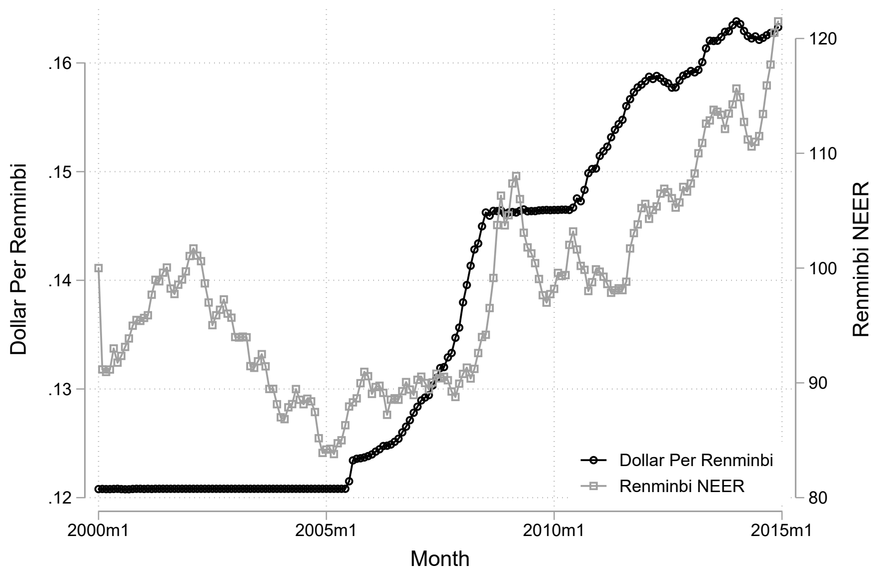


Figure 3: Renminbi Movements 2000-2014

trade patterns. While the TPSFE procedure yields identical parameter estimates when applied to either sample,[36] it is crucial to verify whether the smaller identification subsample is representative of the entire estimation sample. We do so for each estimation we perform.

Throughout the analysis to follow, we will treat eurozone countries as a single economic entity, integrating their trade flows into a single economic region.[37] To make our results comparable with leading studies in the literature on exchange rate pass through, we will apply all estimators conditional on a price change.[38]

[36]This is because, for non-repetitive trade patterns, the demeaning procedure generates zeros for both the dependent and independent variables for observations associated with singleton trade patterns. These zeros do not affect the point estimates of an OLS regression but may generate incorrect standard errors if the true degrees of freedom are not properly adjusted. Fixed effect estimators typically correct for degrees of freedom when estimating standard errors (see, for example, Wansbeek and Kapteyn (1989), p. 346). Therefore, the standard errors we report are based on the size of the *identification sample* rather than the full estimation sample.

[37]We aggregate the export quantity and value at the firm-product-year level for 17 eurozone countries including Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, Netherlands, Portugal, Slovakia, Slovenia and Spain. Latvia and Lithuania joined the eurozone in 2014 and 2015, respectively. We treat them as separate countries throughout our analysis. Our results are robust to the inclusion and exclusion of small countries that adopted the euro in the later period of our sample. We performed two robustness checks. One excludes Slovenia, Cyprus, Malta, Slovakia and Estonia from the eurozone group and treats them as separate individual countries, resulting in an estimation sample of 157 destinations. Another excludes Slovenia, Cyprus, Malta, Slovakia and Estonia from the eurozone group and drops these five countries from our estimation sample, resulting in an estimation sample of 152 destinations. These two alternative estimation samples yield results very similar to our primary estimation sample (152 destinations) which integrates the 17 eurozone countries together.

[38]Specifically, we estimate all parameters *after* applying a data filter to the Chinese export data: for each product-firm-destination combination, we filter out absolute *price changes in dollars* smaller than 5 percent. To be clear, while we condition on price changes in dollars, we regress unit values denominated in renminbi on the bilateral

5.1 Baseline Price and Markup Elasticities

Our baseline estimates of price and markup elasticities are shown in Table 4, categorized by time periods and product differentiation. In the first column, we observe that, across all products and firm sizes, the elasticity of export prices (in renminbi) to bilateral exchange rates, relatively low during the dollar peg era, increases during the managed float period. Specifically, the renminbi price of Chinese exports responds to nominal bilateral exchange rate movements by 20% in the 2000-2005 period and by 27% in the 2006-2014 period. Recall that we measure export prices in renminbi and bilateral exchange rates as renminbi per unit of foreign currency—*a low export price elasticity implies a high pass-through into import prices in foreign (local) currency.* Thus, our estimates suggest that the pass-through into local currency prices in destination markets has become more stable over time: it was around 80% during China's currency peg years, decreasing to 73% in later years.

The second column of Table 4, reveals that markup adjustments play an increasing role in maintaining local price stability across the two periods. Comparing markup elasticities in column (2) with export price elasticities in column (1), we find that markup adjustments account for approximately one-fourth of the overall price adjustment in renminbi during the dollar peg period (0.06 divided by 0.20) and more than half of it in the later period (0.17 divided by 0.27).

Table 4: Price and Markup Elasticities by CCHS Classification

	All		High Differentiation		Low Differentiation		
	Price (1)	Markup (2)	Price (3)	Markup (4)	Price (5)	Markup (6)	n. of obs
2000 – 2005	0.20***	0.06***	0.24***	0.10***	0.17***	0.03	4,279,808
	(0.01)	(0.02)	(0.02)	(0.03)	(0.01)	(0.03)	[1,073,300]
2006 – 2014	0.27***	0.17***	0.33***	0.22***	0.23***	0.13***	19,272,657
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	[4,839,333]

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 152 destinations excluding Hong Kong and the United States. The "Price" and "Markup" columns present estimates from specifications (5) and (4), respectively. The bilateral exchange rate is defined as renminbi per unit of destination currency; an increase indicates an appreciation of the destination currency. Robust standard errors are reported in parentheses. The number of observations in the estimation sample is reported in the last column with the number of observations used for identification reported below it in brackets. Statistical significance at the 1, 5, and 10 percent levels is indicated by ***, **, and *.

renminbi/local currency exchange rate. We provide an example on how the price change filter is constructed and how trade patterns are subsequently formulated based on the price-change-filtered database in our Online Appendix OA1.5. The estimates are similar if we apply our estimator without conditioning on price changes as well as if we filter out absolute price changes in renminbi smaller than 5 percent. This is because our analysis is performed at the annual frequency, a frequency at which most firms adjust their prices so nominal rigidity is less of a concern.

The next four columns of Table 4 highlight significant differences in price and markup elasticities across high- and low-differentiation goods, validating the idea that our product classification captures a dimension of market power. Empirically, we show that the extent to which firms price discriminate varies across types of goods—producers of high differentiation goods are in a better place (i.e., have more market power) to keep their local currency prices stable in the face of bilateral currency movements.

During the dollar peg period, the markup elasticity for high-differentiation goods is 10%, while it is effectively zero for low-differentiation goods. During the renminbi's managed float (second row), markup elasticities increase significantly. For high-differentiation goods, the markup elasticity rises from 10% to 22%. For low-differentiation goods, it becomes significantly positive at 13%. In line with the baseline results, most of the increased price responses are due to more active markup adjustments. For instance, the price elasticity for high-differentiation goods increased by 9 percentage points (from 24% to 33%), which is similar to the increase in markup elasticity (12 percentage points, from 22% to 10%).

5.2 Integrating Product Differentiation with Firm Size

Larger firms tend to have more market power and are more likely to price-to-market (Atkeson and Burstein 2008; Berman, Martin and Mayer 2012; Auer and Schoenle 2016). Larger firms are also more likely to import inputs from abroad, making their marginal costs more sensitive to exchange rate fluctuations (Amiti, Itskhoki and Konings 2014). In this subsection, we contribute to this literature, using our framework, and show that product differentiation continues to have explanatory power when we account for firm size.

We measure firm size at the product level, using global export revenues for a given product.[39] For each firm-product-year triplet, we calculate the firm's global export revenue, summing over all active destinations that year. Firms are ranked within products and years based on their product-level export revenue, and are then placed into three equally sized bins: small, medium, and large. This procedure is conducted separately for the periods 2000-2005 and 2006-2014.[40]

Table 5 shows that, consistent with the previous literature, price elasticities to bilateral exchange rate movements increase systematically with a firm's product-level export revenues, with

[39]This differs from the approach of Berman, Martin and Mayer (2012) and Amiti, Itskhoki and Konings (2014), who measure firm size as total domestic and foreign revenues across all products. Our approach emphasizes that a firm's market power may vary across distinct products.

[40]Our firm-size categories are defined at the product-year level. Firms selling the same product in a given year are grouped into bins containing the same number of observations. When the number of firms cannot be divided evenly by three, more firms are placed in the lower-ranked bins. For instance, if five firms sell to two destinations each, two firms are placed in the "Small" bin, two in the "Medium" bin, and one in the "Large" bin. As a result, the number of observations in the "Small" and "Medium" categories may slightly exceed those in the "Large" category, as shown in Table 5.

Table 5: Pricing-to-market by exporters' product-level global revenues

	All		High Differentiation		Low Differentiation		
Category	Price (1)	Markup (2)	Price (3)	Markup (4)	Price (5)	Markup (6)	n. of obs
2000 – 2005							
Small Exporters	0.19***	0.07*	0.22***	0.09*	0.18***	0.05	1,514,889
	(0.02)	(0.04)	(0.03)	(0.05)	(0.02)	(0.05)	[588,185]
Medium Exporters	0.20***	0.04	0.27***	0.12*	0.15***	-0.01	1,453,618
	(0.03)	(0.04)	(0.04)	(0.07)	(0.03)	(0.05)	[320,476]
Large Exporters	0.24***	0.06	0.29***	0.09	0.20***	0.04	1,311,301
	(0.03)	(0.05)	(0.04)	(0.07)	(0.04)	(0.06)	[164,639]
2006 – 2014							
Small Exporters	0.16***	0.09***	0.21***	0.12***	0.11***	0.07***	6,639,830
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	[2,646,437]
Medium Exporters	0.31***	0.16***	0.39***	0.24***	0.24***	0.11***	6,519,743
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	[1,448,368]
Large Exporters	0.60***	0.34***	0.65***	0.39***	0.55***	0.30***	6,113,084
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	[744,528]

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 152 destinations excluding Hong Kong and the United States. The "Price" and "Markup" columns present estimates from specifications (5) and (4) respectively. The bilateral exchange rate is defined as renminbis per unit of destination currency; an increase means an appreciation of the destination currency. Robust standard errors are reported in parentheses. The number of observations in the estimation sample is reported in the last column with the number of observations used for identification reported below it in brackets.Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

Table 6: Markup contribution to the increase in price elasticity from 2000-2005 to 2006-2014

Category	High Differentiation	Low Differentiation
Medium Exporters	100%	133%
Large Exporters	83%	74%

Note: Statistics are calculated as the change in markup elasticity between 2000-2005 and 2006-2014, divided by the corresponding change in price elasticity over the same periods, based on the estimates in Table 5.

the difference being more pronounced in the post-dollar peg period. Comparing the price and markup elasticities under the dollar peg, we see that the difference in price elasticities across firms' product-level export revenues is primarily driven by the cost channel, as markup elasticities are similar across the firm-product size bins within each product category. However, for high- and low-differentiation goods, differences in price elasticities within each firm-product size bin are largely due to differential markup responses. For example, the price elasticity difference between high- and low-differentiation goods for medium-sized exporters is 0.12 (0.27 - 0.15), which matches the difference in their markup elasticities (0.12 = 0.12 - 0.00). Altogether, our results suggest that, regardless of firm size, Chinese exporters had little market power during 2000-2005, and most of the price responses to exchange rate fluctuations were driven by cost changes.

In the 2006-2014 period, we observe a significant increase in market power among medium and large Chinese exporters, particularly those selling high-differentiation goods. For these large exporters, the markup elasticity increased from 0.09 to 0.39, leading to a substantial rise in local price stability. Comparing price and markup elasticities over time, a key finding is that most of the changes in price elasticities are driven by changes in markup responses, see Table 6.[41] This table highlights that, for medium-sized exporters, markup adjustment explains the entire change in the price elasticity of high-differentiation goods, and more that 100% of the change in the price elasticity of low-differentiation goods.[42] In other words, for medium-sized exporters selling low-differentiation goods, the rise in the markup contribution has more than offset any drop in marginal costs. These results suggest that the rise in local price stability of Chinese exports (implied by the higher export price elasticity) primarily reflects gains in the exporters' market power in local destination markets, rather than from changes in their production structure and/or global sourcing strategies.

6 The Changing Face of Exporters from China

The Chinese economy is generally understood to be a hybrid where competitive, market-oriented private firms coexist alongside large state-owned enterprises (SOEs).[43] However, when it comes to exports, the landscape is more complex. A significant portion of export activity is driven by

[41] It is worth noting that there is no clear theoretical guidance on whether the percentage contribution of the change should be higher for firms selling high-differentiation goods than for those selling low-differentiation goods. From our estimates, we observe that the change in the level (magnitude) of the markup elasticity is generally higher for high-differentiation goods compared to low-differentiation goods. However, if the marginal cost elasticity does not change, we should expect a 100% markup contribution to the change in price elasticity for both types of goods.

[42] Note that the markup contribution can be larger than 100% if the cost contribution is reduced. This is the case for medium-sized exporters selling low-differentiation goods.

[43] See Hsieh and Song (2015) and Wu (2016) for analyses of the interactions between firms and the state in China, and Hale and Long (2012) on the significance of inward FDI into China.

wholly foreign-owned firms or Sino-foreign joint ventures, which dominate the group we classify as foreign-invested enterprises (FIEs).

Due to their ownership structure, firms in China are likely to have varying cost structures and face different demand elasticities. For instance, SOEs and FIEs are generally perceived to have easier access to capital, but they likely differ in their reliance on imported intermediates for production. In contrast, private firms typically face stricter financial constraints and, compared to FIEs, are less integrated into global supply chains. Additionally, the average size of firms varies across these groups, with private firms tending to be smaller, likely due to high rates of entry by young companies. Moreover, since FIEs are often more integrated into supply chains, they may engage in transfer pricing. Given these factors, we expect SOEs, FIEs, and private firms to produce different products, utilize distinct production processes, and potentially target different markets. This raises the question of whether a firm's registration type helps explain observable differences in pricing and markup adjustments.

6.1 The Evolution of Exports by Private, State Owned and Foreign Invested Firms

In figure 4, we lay out some basic facts about the evolution of different types of firms among Chinese exporters. In the Chinese Customs Database, firms report their registration type in one of the following eight categories: state-owned enterprise, Sino-foreign contractual joint venture, Sino-foreign equity joint venture, wholly foreign owned enterprise, collective enterprise, private enterprise, individual business, and "other" enterprise. We combine Sino-foreign contractual joint ventures, Sino-foreign equity joint ventures, and wholly foreign owned enterprises into a single category - foreign invested enterprises (FIEs). Firms with other ownership structures, including collectives, individual businesses, and "other" enterprises, are lumped together under the descriptor "Other" enterprises.

A well-known fact is the extraordinary rate of entry into export activity by private enterprises. This is apparent in the top panel of the figure. From being a small and negligible group in 2000, the number of private enterprises directly exporting goods from China to the rest of the world rose to over 200,000 by 2014.[44] Perhaps less known and understood, however, is the economic weight of a different category of exporters *from* China, the foreign-invested enterprises (FIEs). After a slow and steady rise between 2000 and 2006, their number stabilized at about 75,000 firms—dwarfing the presence of state-owned enterprises (SOEs). Indeed, in spite of the attention paid to them by

[44] At the start of our sample period, export activity was highly regulated in China with most rights to export held by SOEs—only a very limited number of private enterprises were able to export directly. The result of this was that in the earlier years post-2000 private enterprises desiring to export their merchandise exported through SOEs.

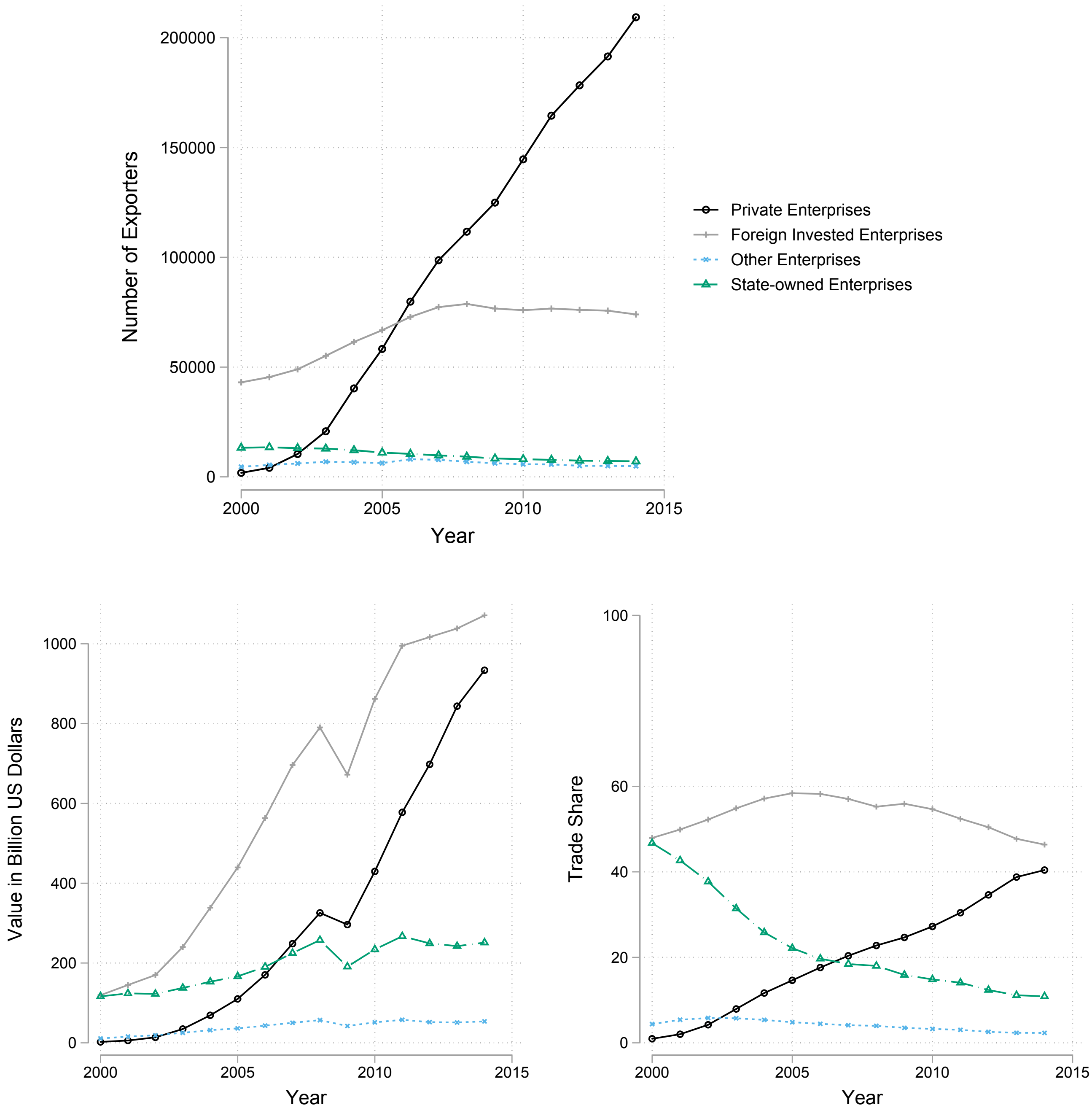


Figure 4: The changing face of Chinese exporters, 2000-2014

Note: Calculations based on the universe of all exporters from the customs database of China. Three types of foreign invested enterprises are reported in our dataset, namely wholly foreign owned enterprises (coded as “4”), sino-foreign joint ventures by jointed equity (coded as “3”) and by contractual arrangements that specify the division of tasks and profits (coded as “2”). The last type is quantitatively small in firm number and trade values.

the media, there were only 10,000 registered SOEs at the start of our sample period. This number gradually fell over time, as successive policy initiatives favored their privatization, or led some of them to exit from foreign markets (top panel, figure 4).

The key message from the top panel of figure 4 is reinforced by the evidence on export values and shares by different types of firms, shown in the bottom panel. By export value and share of total exports, the most important single group of exporters from China is that of foreign-invested enterprises. In 2014, the value of their exports was over US $1 trillion (bottom left panel of figure 4). Over the period, exports from China that originated from firms that are wholly or partially owned by foreigners fluctuated between 45 and 58% of China's total exports.[45]

Conversely, the weight of SOEs, which were essentially at par with FIEs in 2000, declined dramatically from 2000 to 2007 and then settled into a slow and steady negative trend (bottom left panel, figure 4). This is clear evidence that the role of SOEs in foreign trade has been far less dynamic than that of other types of firms. However, the diminishing weight of SOEs in foreign trade has been more than made up by private firms—reflecting both entry of new firms into export markets and privatization of SOEs. By the end of the sample, private firms account for a striking 40% of Chinese exports. We stress nonetheless that this large shift in export shares between SOEs and private firms has not (so far at least) dented the share of exports by FIEs, which has remained quite stable over our sample.

The question is whether, against this evolution in the number of exporters and export shares by ownership, there are significant differences in strategic pricing.

6.2 Integrating Product Differentiation with Firm Ownership

Evidence on price and markup elasticities by firm type is presented in Table 7. For 2000-2005, our estimates reveal that private enterprises exhibit zero price and markup elasticities (columns 1 and 2, row 3), implying that these firms' costs are unaffected by exchange rates, and they lack market power to make destination-specific markup adjustments. For FIEs, prices are more responsive to exchange rate movements, but most of the price responses are driven by cost changes rather than markup adjustments. The only firms displaying significant market power during this period are SOEs, with positive and significant markup adjustments observed for firms selling high-differentiation goods (column 4, row 1).

In the latter period (2006-2014), we observe a notable increase in markup elasticities across all firm types, suggesting that Chinese firms are generally gaining market power in foreign markets.

[45] The importance of foreign involvement in Chinese exports has previously been documented by Koopman, Wang and Wei (2014). Based on an accounting framework methodology and product-level trade flows, they show that 29.3 percent of Chinese export value comes from foreign, rather than domestic Chinese, value-added. This is not inconsistent with our estimates; our complementary contribution is to document foreign engagement based on *ownership* of exporting firms, rather than through the origin of the value-added content of exported goods.

Table 8 shows that changes in markup elasticities are the primary drivers behind the increase in local price stability (reflected in a higher export elasticity), indicating minimal changes in production or sourcing structures. Notably, the markup elasticities of private enterprises increased significantly. Although for private enterprises the change in these elasticities is small compared to that of SOEs and FIEs, the rise in their trade share suggests that these firms are likely the key drivers of the change in aggregate price stability (in foreign currency) for Chinese exports in the latter part of our sample.

Product differentiation plays a critical role in explaining elasticity differences across firm types.In the post-dollar peg period, the estimated markup elasticity for highly differentiated products sold by SOEs is 0.41, compared to just 0.12 for low-differentiation goods. Similarly, the markup elasticity of private enterprises selling high-differentiation goods is nearly twice as large the elasticity of firms selling low-differentiation goods (last row, columns 4 and 6). Comparing price and markup elasticities over time confirms the result that most of the changes in price elasticities are driven by changes in markups also across firm registration types (see Table 8).

Table 7: Markup elasticities by firm registration types

	All		High Differentiation		Low Differentiation		
Category	Price (1)	Markup (2)	Price (3)	Markup (4)	Price (5)	Markup (6)	n. of obs
2000 – 2005							
State-owned Enterprises	0.22***	0.07***	0.26***	0.13***	0.19***	0.03	2,001,357
	(0.01)	(0.03)	(0.02)	(0.04)	(0.02)	(0.04)	[518,272]
Foreign Invested Enterprises	0.21***	0.05	0.24***	0.03	0.19***	0.06	1,144,652
	(0.02)	(0.03)	(0.03)	(0.05)	(0.03)	(0.05)	[266,488]
Private Enterprises	0.01	0.00	0.11*	0.04	-0.06	-0.02	780,901
	(0.04)	(0.06)	(0.06)	(0.09)	(0.05)	(0.09)	[216,157]
2006 – 2014							
State-owned Enterprises	0.32***	0.25***	0.52***	0.41***	0.17***	0.12***	3,526,943
	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	[646,352]
Foreign Invested Enterprises	0.56***	0.31***	0.50***	0.33***	0.59***	0.30***	4,990,504
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	[1,042,481]
Private Enterprises	0.13***	0.08***	0.19***	0.10***	0.10***	0.06***	9,897,091
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	[2,996,133]

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 152 destinations excluding Hong Kong and the United States. The "Price" and "Markup" columns present estimates from specifications (5) and (4) respectively. The bilateral exchange rate is defined as renminbis per unit of destination currency; an increase means an appreciation of the destination currency. Robust standard errors are reported in parentheses. The number of observations in the estimation sample is reported in the last column with the number of observations used for identification reported below it in brackets. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

Table 8: Markup contribution to the increase in price elasticity by firm registration type

Category	High Differentiation	Low Differentiation
State-owned Enterprises	108%	-
Foreign Invested Enterprises	115%	60%
Private Enterprises	75%	50%

Note: Statistics are calculated as the change in markup elasticity between 2000-2005 and 2006-2014, divided by the corresponding change in price elasticity over the same periods, based on the estimates in Table 7.

7 Model-based Analysis

In this section, we specify a partial equilibrium model featuring firm and product heterogeneity, variable markups, and endogenous exporting decisions, in order to obtain a theoretical counterpart to our decomposition of the price elasticity to the exchange rate into its markup and marginal costs components and validate our empirical framework using simulated data from the model.

7.1 Model

We specify a model embedding Kimball (1995) demand, which is widely used due to its flexibility in many recent open macro studies.[46] Departing from a CES demand system, Kimball preferences imply a demand elasticity that is an increasing function of a product's price. Upon a positive cost or exchange rate shock, an increase in the firm's desired price also increases its demand elasticity, resulting in a lower desired markup.

Sharing a conventional assumption with much of the open macro literature, we posit that markets are segmented and each firm makes its pricing and entry decisions independently in each market. Hence, in each period t a firm f selling the product i makes its pricing and exporting decisions simultaneously, but independently in each destination market d:

$$\max_{P_{fidt},\phi_{fidt}\in\{0,1\}} \quad \phi_{fidt}\left[(P_{fidt}-\mathcal{MC}_{fit})\,\psi_i(\alpha_{fid},P_{fidt},\mathcal{E}_{dt})-\zeta_i\right]$$

where $\phi_{fidt}\in\{0,1\}$ is an indicator of whether the firm is actively selling in market d in the period; P_{fidt} is the border price denominated in the exporter's currency; $\mathcal{MC}_{fit}$ is the marginal cost; ζ_i is the cost that the firm needs to pay for each product i sold in a destination market; and $\psi_i(.)$ is

[46] The same setting has been used in various studies, such as Klenow and Willis (2016), Gopinath and Itskhoki (2010), Amiti, Itskhoki and Konings (2019), Gopinath et al. (2020), and Mukhin (2022). Amiti, Itskhoki and Konings (2019) demonstrate that the Kimball demand preference can effectively capture firms' key responses to shocks in a static oligopolistic model (e.g., Atkeson and Burstein 2008) and replicate the key features of data from Belgian firms. Wang and Werning (2022) and Alexander et al. (2024) show that, in a dynamic setting, the differences between firm-level responses and aggregate price dynamics in a dynamic oligopolistic competition model and a well-calibrated Kimball model are small.

a Kimball demand function. This function has three arguments: a markup-irrelevant preference shifter α_{fid}; the border price P_{fidt} and the bilateral exchange rate $\mathcal{E}_{dt}$. The log markup of the firm is defined as the natural log of the border price divided by the marginal cost: $\mu_{fidt} \equiv \ln(P_{fidt}/\mathcal{MC}_{fit})$.

Solving the firm's problem yields the optimal price charged by a firm for its product in the destination market d at time t as a function of exchange rates and price charged, $P^*_{fidt}(\mathcal{E}_{dt}, \mathcal{MC}_{fit})$, and the market entry condition, summarized by the selection equation (8) below. Defining the operating profit as the profit achieved at the firm's optimal price P^*_{fidt}:

$$\pi_{fidt} \equiv \left(P^*_{fidt} - \mathcal{MC}_{fit}\right) \psi_i(\alpha_{fid}, P^*_{fidt}, \mathcal{E}_{dt}), \tag{7}$$

firm f selling product i chooses to enter market d in time t if its operating profit is larger than the entry cost, which gives the selection equation:

$$\phi^*_{fidt} = \begin{cases} 1 \ \ \text{(observed)} & \text{if} \quad \pi_{fidt} \geq \zeta_i \\ 0 \ \ \text{(missing)} & \text{if} \quad \pi_{fidt} < \zeta_i \end{cases} \tag{8}$$

Simulation setup. We specify the Kimball demand function following Gopinath and Itskhoki (2010) and Amiti, Itskhoki and Konings (2019):

$$\psi_i(\alpha_{fid}, P^*_{fidt}, \mathcal{E}_{dt}) \equiv \alpha_{fid} \left[1 - \xi \ln\left(\frac{P_{fidt}}{\mathcal{E}_{dt}}\right)\right]^{\frac{\rho_i}{\xi}} \tag{9}$$

where ρ_i is the elasticity of substitution across varieties of product i sold by firms; and ξ is the super elasticity that governs the extent to which the firm adjusts its markups to shocks (e.g., $\mathcal{E}_{dt}$). When $\xi \to 0$, the model converges to the conventional CES case, where firms charge constant markups $\rho_i/(1-\rho_i)$ and do not respond to destination-specific changes in exchange rates.

We simulate the model for 1,000 firms, 30 destination markets, and 20 years. Each firm sells two products: a high differentiation product ($\rho_i = 4$) and a low differentiation product ($\rho_i = 12$). We choose a super elasticity of $\xi = 1$ for both types of products. This generates results that are well in the range of our empirical estimates—we also verify that our results are robust to alternative sets of elasticities and shocks.

The data-generating process for the exchange rates, marginal costs and demand are as follows. For the exchange rate, we posit:

$$\ln(\mathcal{E}_{dt}) = \sigma_{\mathcal{E}}(v_d \cdot \mathcal{F}_t + u_{dt}), \tag{10}$$

where we normalize the steady-state exchange rates to one. The changes in the bilateral exchange rate are driven by (i) the economic fundamentals of the origin country, captured by $\mathcal{F}_t$, which can have different effects in each destination market v_d, and (ii) a noise term u_{dt} that captures exchange rate changes, for example, due to financial market fluctuations. $\sigma_{\mathcal{E}}$ controls for the relative size of exchange rate shocks. Marginal costs are firm-product specific and time varying:

$$\mathcal{MC}_{fit} = \frac{M_{fit}}{A_{fi}}, \quad \text{with } \ln(M_{fit}) = \sigma_M(v_{fi} \cdot \mathcal{F}_t + u_{fit}) + \sigma_\pi \cdot t, \tag{11}$$

where A_{fi} is the productivity of the firm-product drawn from a Pareto distribution with the parameter that governs the dispersion of productivities set to 5. M_{fit} denotes shocks to the firm's marginal costs due to firm-specific or macro factors. Specifically, the presence of $\mathcal{F}_t$ in equation (11) implies that, in general, the marginal cost is positively correlated with exchange rates. So, when the origin currency depreciates (i.e., when $\mathcal{E}_{dt}$ goes up), imported inputs become more expensive, which drives up the marginal cost of the firm-product. The term v_{fi} allows for the correlation between the exchange rate and the marginal cost to be firm-product specific and u_{fit} adds changes in marginal costs that are uncorrelated with exchange rate movements. Finally, $\sigma_\pi \cdot t$ allows for a time trend in the cost component to account for the fact that the average price level of Chinese exporters has been increasing over time. $\mathcal{F}_t, u_{dt}, u_{fit}$, and $\ln(\alpha_{fid})$ are independently drawn from a standard normal distribution. Firm, product and destination specific effects v_{fi}, v_d and ς_{fid} are drawn from a standard uniform distribution. We set $\sigma_{\mathcal{E}} = 0.02$, $\sigma_M = 0.05$ and $\sigma_\pi = 0.03$. We set the fixed cost of entry ζ_i such that about 20% of firms selling a product domestically are active in the export market.[47]

7.2 Comparing Model vs. Estimated Responses

In this subsection, we decompose the price responses to exchange rates into markup and cost components as shown in equation (1), using simulated data from the model.[48] Table 9 summarizes the estimation results. In the table, columns (1) and (3) report the change in, respectively, the markup and the cost—that sum up to the price response to exchange rates shown in column (6)—, according to the model. These are structural effects, predicted by the model as a function of underlying parameters.[49] Under standard calibrations, prices and costs generally align and

[47] In the latter estimation exercises, we construct a realistic environment that resembles our customs database, where only exporting firms (i.e. $\phi_{fidt} = 1$) are observable in the dataset.

[48] While most variables in this model section are defined in levels, note that the variables in equation (1) are expressed in natural logs for readability, that is: $p_{fidt} = \ln(P_{fidt})$, $e_{dt} = \ln(\mathcal{E}_{dt})$, and $mc_{fit} = \ln(\mathcal{MC}_{fit})$.

[49] The column (1) response is obtained by estimating the markup response to exchange rate changes, controlling for the cost change. Similarly, the column (5) response is obtained by estimating the markup response to marginal cost changes, controlling for exchange rate changes. Specifically, we regress log markups, μ_{fidt}, on log exchange rates, e_{dt}, and log marginal cost, mc_{fit}, taking the coefficient in front of e_{dt} as the partial markup elasticity to exchange rates (controlling for marginal cost), and the coefficient in front of mc_{fit} as the partial markup elasticity to marginal cost (controlling for exchange rates).

contribute positively to the price elasticity. Columns (4) and (5) further decompose these effects, showing how marginal costs respond to exchange rate movements, and in turn how markups respond to marginal cost changes. Note that in the model an appreciation of the foreign currency (an increase in $\mathcal{E}_{dt}$) raises the firm's marginal cost (e.g., due to higher costs of imported inputs) but reduces the optimal markup. This is a common prediction of oligopolistic competition models, where firms with market power only partially pass through their cost shocks. It is also worth noting that, comparing columns (1) and (5), markup adjustments contribute to the price elasticity to the exchange rate via a direct channel and an indirect (marginal cost) channel, that go in opposite directions. It follows that the markup elasticities to exchange rates could be significantly underestimated if the cost channel is not properly controlled for.

Estimation results from applying our empirical framework to simulated data are shown in columns (2) and (7)—using the specifications (4) and (5), respectively. The table shows that our approach can precisely recover the markup and price elasticities in a theoretical environment that relies on standard parameter calibrations *and* accounts for endogenous market participation. Notably, our proposed markup estimator successfully removes the influence of marginal costs. In addition, our price elasticity estimator accurately captures the additional impact of changing marginal costs (column 3), facilitating a decomposition of the relative contributions of the two effects.

In Columns (7) and (8), we compare our price elasticity estimator with a s-period difference estimator that omits our control for the trade-pattern spell $\widetilde{Spell}_{fidt}$ from (5) (e.g., Gopinath, Itskhoki and Rigobon 2010). We find that the estimated price elasticity can be significantly upward biased in the presence of endogenous market selection and a time trend in the cost component ($\sigma_\pi \neq 0$).[50]

These considerations apply to both high- and low-differentiation goods, and when comparing estimates in Table 9, we see that model simulations align with key data features documented in the preceding sections. First, comparing the second and third rows of each panel, we observe that the model successfully explains the higher price and markup elasticities for firms selling high-differentiation goods compared to those selling low differentiation goods. Second, comparing the estimates in panels (a) and (b), the increase in price and markup elasticities of Chinese firms in the latter period can be attributed to higher market power (represented by a higher ξ). Consistent with our empirical estimates, most of the difference in price elasticities between panels (a) and (b) is driven by the markup responses (column 1), while the cost contributions remain relatively constant (column 3).

[50]Setting $\sigma_\pi = 0$ yields similar results to columns (7) and (8). Intuitively, with a time trend in cost and prices ($\sigma_\pi \neq 0$), the magnitude of price changes is a positive function of the time period between two price differences. The additional trade-pattern-spell fixed effect we added to specification (5) controls for the price (and cost) differences driven by the time trend, enabling the recovery of the correct price elasticity.

Table 9: Comparing model versus estimated responses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Markup		Cost			Price		
	$\frac{\partial \mu_{fidt}}{\partial e_{dt}}$ Model	$\frac{\partial \mu_{fidt}}{\partial e_{dt}}$ Est.	$\left(1+\frac{\partial \mu_{fidt}}{\partial mc_{fit}}\right)\frac{\partial mc_{fit}}{\partial e_{dt}}$ Model	$\frac{\partial mc_{fit}}{\partial e_{dt}}$ Model	$\frac{\partial \mu_{fidt}}{\partial mc_{fit}}$ Model	$\frac{dp_{fidt}}{de_{dt}}$ Model =(1)+(3)	$\frac{dp_{fidt}}{de_{dt}}$ Est.	$\frac{dp_{fidt}}{de_{dt}}$ Alt. Est.
(a) Low market power ($\xi = 0.5$)								
All	0.09	0.08	0.29	0.32	-0.08	0.38	0.37	0.55
		(0.00)					(0.02)	(0.01)
HD ($\rho = 4$)	0.15	0.15	0.28	0.33	-0.15	0.43	0.43	0.60
		(0.00)					(0.03)	(0.02)
LD ($\rho = 12$)	0.04	0.04	0.30	0.31	-0.04	0.34	0.34	0.50
		(0.00)					(0.02)	(0.02)
(b) High market power ($\xi = 1.0$)								
All	0.17	0.15	0.27	0.32	-0.15	0.44	0.42	0.58
		(0.00)					(0.02)	(0.01)
HD ($\rho = 4$)	0.26	0.26	0.24	0.32	-0.26	0.50	0.50	0.64
		(0.00)					(0.02)	(0.01)
LD ($\rho = 12$)	0.09	0.09	0.28	0.31	-0.09	0.37	0.37	0.52
		(0.00)					(0.02)	(0.02)

Note: This table compares the true model relationships (marked with "Model") with the estimated responses (marked with "Est."). Panels (a) and (b) show the estimates when the superelasticity of Kimball demand is calibrated to 0.5 and 1.0 respectively – a higher ξ means a higher degree of market power and price complementarity. The "All" column shows pooled regression results, whereas the "HD" and "LD" columns show the results separately estimated for high and low differentiation goods subsamples. Columns (2) and (7) are estimated using specifications (4) and (5), respectively. Column (8) represents an alternative price elasticity estimate from regressing s-period differenced log prices $\Delta_s p_{fidt}$ on s-period differenced log exchange rates $\Delta_s e_{dt}$ where s is the number of years between two observed trade flows at the firm-product-destination level. Estimates and standard errors are calculated based on the average of 100 simulations of each setting.

8 Concluding Remarks

The rising importance of China as a global exporter has prompted extensive research into how increased competitive pressures have influenced corporate decisions to upgrade their product mix Bernard, Jensen and Schott (2006), innovate Bloom, Draca and Van Reenen (2016), lay off workers Autor, Dorn and Hanson (2013), Pierce and Schott (2016), and outsource to lower-wage countries Pierce and Schott (2016). Business leaders and economists frequently refer to the challenge of "the China price"—the low price of Chinese goods that exporters from other countries and domestic import-competing firms must match to remain competitive.

Using detailed customs data, we investigate the changing market power of Chinese firms by estimating their price and markup responses to exchange rate fluctuations. Our findings suggest a notable increase in the local price stability of Chinese exporters, driven by more active adjustments in markups in response to bilateral exchange rate movements. These results imply that an increasing number of Chinese firms have gained market power and are strategically pricing their products across different destinations and markets. With increased market power, Chinese firms may charge higher markups and move away from competing solely on low prices. Consequently, an appreciation of the renminbi may result in relatively stable prices for Chinese products in foreign markets, as exporters have the space to adjust markups optimally to destination market conditions.

Our empirical results nonetheless reveal significant heterogeneity in how firms adjust their markups in response to currency fluctuations across different categories of goods. We find that firms exporting high-differentiation goods from China make moderate but significant markup adjustments in response to bilateral exchange rate movements. In contrast, producers of commodities and low-differentiation goods make minimal or no adjustments. These results, robust to interacting our product classification with firm size and type, suggest that the nature of the goods plays a significant role in determining the extent of market power firms can exercise across markets.

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Online Appendix for "Markets and Markup: A New Empirical Framework and Evidence on Exporters from China"

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Contents

OA1 Data

OA1.1 Chinese customs data

China's export growth exploded over 2000-2014 (see table OA1-1). Statistics from customs data on firms, HS08 products, and firm-products highlight the growth at the extensive margin, including both net entry of firms, and net entry of firm-products. The total number of active exporters almost quintupled over our sample period, from 62,746 in 2000 to 295,309 in 2014. The number of annual transactions at the firm-HS08 product level increased at roughly the same pace as the number of exporters, from about 904 thousand in 2000 to 4.56 million in 2014. The value of total exports measured in dollars increased ten-fold from 2000 to 2014.

Table OA1-1: Chinese exports: firms, products and values, 2000-2014

	HS08 Products	Firms	Firm-HS08 Product Pairs	Observations	Value (billions US$)
2000	6,712	62,746	904,111	1,953,638	249
2001	6,722	68,487	991,015	2,197,705	291
2002	6,892	78,607	1,195,324	2,672,837	325
2003	7,013	95,683	1,475,588	3,328,320	438
2004	7,017	120,567	1,826,966	4,125,819	593
2005	7,125	142,413	2,277,801	5,252,820	753
2006	7,171	171,169	2,907,975	6,312,897	967
2007	7,172	193,567	3,296,238	7,519,615	1,220
2008	7,213	206,529	3,244,484	7,995,266	1,431
2009	7,322	216,219	3,363,610	8,263,509	1,202
2010	7,363	234,366	3,847,708	9,913,754	1,577
2011	7,404	254,617	4,153,534	10,645,699	1,898
2012	7,564	266,842	4,171,770	11,057,899	2,016
2013	7,579	279,428	4,140,897	11,643,683	2,176
2014	7,641	295,309	4,555,912	12,297,195	2,310
2000-2014	10,002	581,141	22,820,644	108,465,375	17,453

OA1.2 Additional information on the CCHS classification

OA1.2.1 The use of measure words in Chinese grammar

To illustrate how measure words encode meaning in Chinese, consider the problem of counting three small objects. Chinese grammar requires the use of a measure word between the number and the noun being counted. Thus, to say "three ballpoint pens," or "three kitchen knives," one would say the English equivalent of "three long-thin-cylindrical-objects [zhī, 支] ballpoint pens" and "three objects-with-a-handle [bǎ, 把] kitchen knives."[1] Both of these objects, ballpoint pens and kitchen knives, are measured with count/discrete classifiers (zhī and bǎ, respectively) and are, in our classification, high differentiation goods. In contrast, products reported with mass/continuous classifiers including kilograms (cereal grains, industrial chemicals), meters (cotton fabric, photographic film), and cubic meters (chemical gases, lumber) are low differentiation goods. Because measure words encode physical features of the object being counted, they allow us to identify when statistical reporting is for a high versus low differentiation good. According to Cheng and Sybesma (1999), "...the distinction between the two types of classifiers is made with explicit reference to two different types of nouns: nouns that come with a built-in semantic partitioning and nouns that do not – that is, count nouns and mass nouns."

OA1.2.2 Comparison to quantity-reporting in other customs systems

While the proposed CCHS classification of goods could lead to some amount of mis-classification because there are some count nouns which exhibit low levels of differentiation and some mass nouns which are quite differentiated, a Chinese-linguistics-based approach to goods classification is still valuable for several reasons. First, nouns with built-in semantic partitioning such as televisions, microscopes and automobiles are high differentiation goods regardless of whether their trade is reported in metric tonnes or units. This is a key advantage of relying on Chinese measure words to classify tradeable goods: measure words clearly identify objects that inherently are semantically partitioned (i.e. are distinct objects), relative to goods that exist as partitionable masses. Second, the use of reported quantity data in other countries' customs systems to identify discrete objects could be less accurate or consistent for a number of reasons discussed below. Finally, the choice of the measure word is predetermined in the minds of Chinese speakers by grammatical rules that have existed for centuries. This choice is clearly exogenous to and predates modern statistical reporting systems.

Like Chinese, Japanese requires the use of measure words between a number word and a noun when counting. Documentation for Japanese trade declarations instructs that the World Customs Organisation (WCO) measurement unit "NO" (the English abbreviation for number of items) subsumes 11 indigenous Japanese measure words used with discrete nouns (個、本、枚、頭、羽、匹、台、両、機、隻、着). We interpret these instructions from Japanese customs declarations as a validation of our approach of using count classifiers in the Chinese Customs Database to identify discrete products in the Harmonized System. However, because the official

[1] English uses measure words; "two dozen eggs" and "a herd of cattle" are two examples. The difference lies in the extent to which unique measure words exist for Chinese nouns and the fact that proper Chinese grammar always requires the use of the appropriate measure word when counting.

measure of discrete items used in Japanese customs data is an English word, we cannot build a linguistics-based classification of discrete and continuous goods directly from measure words in Japanese data. This is one reason why we prefer to build the classification from Chinese rather than Japanese trade data.[2]

Although goods are inherently discrete (e.g., televisions, automobiles) or continuous (e.g., grain, liquid industrial chemicals), in some customs datasets, discrete products might only be reported by net weight rather than by net weight AND countable units, or quantity reporting could be inconsistent. While the WCO has recommended since 2011 that *net weight* be reported for *all transactions* and supplementary units, such as units/pieces, be reported for specific Harmonized System products, these recommendations are *non-binding*. At one end of the spectrum, EU member states follow their own variation of the WCO guidelines and report net weight as well as a supplemental quantity unit for specific CN products. At the other end, administrative customs data for Egyptian exports over 2005-2016 lists 32 distinct measures of quantity with Egyptian statistics reporting only one measure of quantity per transaction, rather than the two, net mass and supplementary unit, recommended by the WCO. Overall, 87% of Egyptian export observations report net mass (net pounds) as the unit of quantity, only 0.006% report "pieces" as the unit of quantity, and the remainder are scattered across official WCO and alternative measures. Authors' calculations from EID-Exports-2005-2016 obtained from `http://erfdataportal.com`.

OA1.2.3 An example of the fine detail in Chinese measure words

To illustrate the variety of count classifiers used for similar objects, note that "Women's or girls' suits of synthetic fibres, knitted or crocheted" (HS61042300) and "Women's or girls' jackets & blazers, of synthetic fibres, knitted or crocheted" (HS61043300) are measured with two distinct Chinese count classifiers, "tào, 套" and "jiàn, 件," respectively. Further, table OA1-2 documents the intrinsic information content of the measurement units for HS04 product groups 8211 and 8212. The Chinese language descriptions of all of these HS08 products conveys the similarity across products; each Chinese description contains the Chinese character 'dao' (刀), which means 'knife' and is a part of longer compound words including table knife and razor. Interestingly, three different Chinese count classifiers, "tào, 套," "bǎ, 把," and "piàn, 片," are used to count sets of knives (HS82111000), knives and razors (HS82119100 - HS82121000), and razor blades (HS82122000), respectively.

Two further points can be drawn from this table. First, this table illustrates that while Chinese customs statistics are reported for eight digits, in many cases, the final two digits of Chinese customs codes are 00, indicating that the eight digit code is identical to the corresponding six-

[2]We thank Taiji Furusawa, Keiko Ito, and Tomohiko Inui for answering our questions about the use of measure words in Japanese trade data.

digit code in the universal Harmonized System. This exemplifies a wider observation that only a single Chinese measure word is used to report quantity for all products in most six-digit HS codes. By extension, Chinese measure words can be used to develop a universal classification for the Harmonized System at the six-digit product level. Second, the discrete noun "knife" or 'dao' (刀) appears in the description of every product reported below. This suggest that it would be theoretically possible to develop a binary classification system of Harmonized System products as discrete versus continuous through the use of natural-language processing software that is trained to recognize discrete nouns in any language. In this light, the use of Chinese measure words to identify discrete nouns can be seen as a shortcut in which the linguistic classification of Chinese measure words replaces the data training step.

Table OA1-2: Examples of count classifiers in the Chinese Customs Database

Quantity Measure	HS08 Code	English Description	Chinese Description
tào, 套	82111000	Sets of assorted knives	成套的刀
bǎ, 把	82119100	Table knives having fixed blades	刃面固定的餐刀
bǎ, 把	82119200	Other knives having fixed blades	其他刃面固定的刀
bǎ, 把	82119300	Pocket & pen knives & other knives with folding blades	可换刃面的刀
bǎ, 把	82121000	Razors	剃刀
piàn, 片	82122000	Safety razor blades, incl razor blade blanks in strips	安全刀片, 包括未分开的刀片条

The most frequently used mass classifier is kilograms. Examples of other mass classifiers include meters for "Knitted or crocheted fabric of cotton, width $\leq$ 30cm" (HS60032000), square meters for "Carpets & floor coverings of man-made textile fibres" (HS57019010), and liters for "Beer made from malt" (HS22030000).

OA1.2.4 Variation in the CCHS classification across industrial sectors

For twenty industrial sectors, Table OA1-3 reports the share of products in each sector that are classified as high differentiation according to the Corsetti, Crowley, Han, and Song (CCHS) classification. For the 36 measure words in our estimation dataset, we categorize goods measured with the 27 count classifiers as high differentiation, while goods measured with 9 mass classifiers are treated as low differentiation.[3] Column one lists the HS chapters that define the sector. The

[3]We thank Prof. Lisa Lai-Shen Cheng for her feedback on our classification of measure words from the Chinese Customs Database into count and mass classifiers. Count classifiers (high differentiation): 个, 百个, 件, 件(套), 副, 只, 台, 块,千块, 千块, 头, 套, 幅, 座, 张, 把, 支, 千支, 条, 枝, 架, 株, 根, 片, 盘, 艘, 辆, 双. The mixed category 件(套)

Table OA1-3: CCHS product classification across sectors

Sector (HS chapters)	Sector's share of total exports	Value share of CCHS high differentiation products within sector
1-5 Live animals; animal products	0.8	4.0
6-14 Vegetable products	1.0	0.6
15 Animal/vegetable fats	0.0	0.0
16-24 Prepared foodstuffs	1.4	0.0
25-27 Mineral products	2.1	0.0
28-38 Products of chemical and allied industries	4.6	0.2
39-40 Plastics/rubber articles	3.4	15.0
41-43 Rawhides/leather articles, furs	1.6	58.6
44-46 Wood and articles of wood	0.8	0.5
47-49 Pulp of wood/other fibrous cellulosic material	0.8	0.0
50-63 Textile and textile articles	13.2	68.4
64-67 Footwear, headgear, etc.	2.9	43.5
68-70 Misc. manufactured articles	1.8	3.2
71 Precious or semiprec. stones	1.4	0.0
72-83 Base metals and articles of base metals	7.7	1.9
84-85 Machinery and mechanical appliances, etc.	42.2	73.1
86-89 Vehicles, aircraft, etc.	4.7	66.1
90-92 Optical, photographic equipment etc.	3.5	79.7
93 Arms and ammunition	0.0	82.5
94-96 Articles of stone, plaster, etc.	6.0	65.0
97 Works of art, antiques	0.1	60.8

Source: Compiled by the authors from exports of Chinese Customs Database, 2000-2014, using the Corsetti, Crowley, Han and Song (CCHS) classification.

second column provides the sector's share in China's total exports over 2000-2014. Quantitatively, important export sectors with large shares of high differentiation goods include optical and photographic equipment (79.7 percent), machinery and mechanical appliances (73.1 percent), textiles and apparel (68.4 percent), vehicles and aircraft (66.1 percent), stone and plaster articles (65.0 percent), leather goods (58.6 percent), and plastics and rubber articles (15.0 percent). The share of high differentiation products across sectors varies widely, but lines up with our prior. Machinery and mechanical appliances and vehicles and aircraft are dominated by CCHS high differentiation goods while virtually all chemicals and base metal products are low differentiation.

is used for HS codes that include items measured as units of clothing (nightgowns) and sets of clothing (pyjamas). Mass classifiers (low differentiation): 米, 平方米, 立方米, 升, 千升, 克拉, 千瓦时, 克, 千克.

OA1.2.5 Applying Rauch's classification to Chinese exports

In order to provide a Rauch classification for HS08 products in the Chinese Customs Database, it was first necessary to concord the SITC Rev. 2 product codes from Rauch's classification to universal HS06 product codes. At the HS06 level, 80% of products map into a unique category – differentiated, reference priced or organized exchange – but 20% of products have no unique mapping and are left unclassified. As noted in table 2, when applied to the universe of Chinese exports at the HS08 level, the 1-to-many and many-to-many concordance issue means approximately 12% of firm-product observations cannot be classified into Rauch categories.

Table OA1-4: Mapping HS06 (2007) products to Rauch categories (Rauch's liberal classification)

	Number of HS06 codes	Percent of HS06 codes
HS06 codes with a unique Rauch classification	4,386	79.98
HS06 codes with multiple Rauch classifications	1,098	20.02
Total	5,484	10.00

OA1.2.6 Integrating the CCHS and Rauch classification systems

According to the Rauch classification system, products traded on organized exchanges are generally regarded as commodities whose prices are expected to fluctuate with global supply and demand. Reference price products are list-price goods: firms producing them compete somewhat directly by supplying at the price published in an industry trade publication. These goods are thought to offer a very limited scope for market power in pricing. Conversely, differentiated goods are defined as goods for which prices are not publicly negotiated—which indicates limited direct competition among firms and greater scope for charging markups. As argued above, our linguistics based classification allows us to refine the Rauch classification by distinguishing differentiated goods using two finer categories, and by classifying goods unclassified under Rauch.

To highlight the contribution of our product-feature-based classification system relative to Rauch (1999)'s market-structure based classification, we now integrate the two in our empirical analysis. Results are shown in table OA1-5.

Table OA1-5: Markup Elasticity by Rauch Classification

	All		High Differentiation		Low Differentiation		
Category	Price	Markup	Price	Markup	Price	Markup	n. of obs
2000 – 2005							
Differentiated Products	0.20***	0.07***	0.24***	0.09***	0.16***	0.04	3,339,574
	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	[812,719]
Organized Exchange	0.55***	0.05	-	-	0.55***	0.05	36,656
	(0.06)	(0.08)			(0.07)	(0.08)	[11,945]
Reference Priced	0.16***	0.08	0.17	0.21	0.16***	0.07	332,678
	(0.04)	(0.07)	(0.15)	(0.19)	(0.04)	(0.07)	[88,809]
2006 – 2014							
Differentiated Products	0.27***	0.17***	0.34***	0.22***	0.19***	0.13***	15,722,023
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	[3,927,425]
Organized Exchange	0.29***	-0.08	-	-	0.29***	-0.07	99,373
	(0.10)	(0.07)			(0.10)	(0.07)	[28,086]
Reference Priced	0.33***	0.13***	0.01	0.10	0.36***	0.14***	1,537,937
	(0.03)	(0.03)	(0.12)	(0.15)	(0.03)	(0.03)	[364,723]

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 152 destinations excluding Hong Kong and the United States. The bilateral exchange rate is defined as RMBs per unit of destination currency; an increase means an appreciation of the destination currency. Robust standard errors are reported in parentheses. The actual number of observations used for identification is reported in the brackets of the last column. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

The most important takeaway from table OA1-5 is that the estimated markup elasticity of "differentiated" goods according to the Rauch classification, 17% in the later period, is an average of very different elasticities for high and low differentiation goods, 22% and 13% respectively. Unsurprisingly, our estimates of markup elasticities are zero for goods traded in organized exchanges, which in our classification are treated as low differentiation goods. Note that for organized exchange-traded goods we can expect prices in renminbi to change with their international market prices, whose movements may be correlated with bilateral exchange rates. For reference-priced goods, consistent with our hypothesis, we find no markup adjustment for the subset of high differentiation goods in this set. Results are less straightforward however for the low-differentiation goods—we find some degree of markup adjustment, although only in the later period.

OA1.3 Evidence on variable trade patterns

Table OA1-6 summarizes the volatility of trade patterns for Chinese exporters. To construct the table, we begin with the universe of firm-product pairs in the Chinese Customs Database over the sample period 2000-2014. We first drop all firm-product pairs that appear only once in the 15 year timespan of our dataset, since there is no time variation associated with these pairs. We next place firm-product pairs into bins according to the total number of years (x) for which sales were observed. In the last row of the table, we report the share of firm-product pairs with observed sales in 2, 3,...,15 years. Firm-product pairs with observed sales in only a few years are the most common: about 60% of firm-product pairs are observed for between two and four years (29.3+17.9+12.0; recall that we exclude single period pairs from the calculation). At the other extreme, only 1.1% of firm-product pairs are observed in every year.

In the columns of the table, for each number of exporting years, we calculate the share of firm-product pairs associated with a specified number of unique trade patterns, y. For example, the firm-product pair in Figure 1 has three unique trade patterns, {A-B, A-C, A-B-C}, over five years of sales abroad. In the table, this firm-product would be included in the cell reporting that 14.1% of firm-product pairs observed for five years have three unique trade patterns. The first row reports the share of firm-product pairs that have perfectly stable trade patterns over the course of their entire export life. At the other extreme, the diagonal elements contain firm-product pairs with extremely volatile trade patterns – these firm-products have a different, non-repeated trade pattern in every year of export life. Most crucially for our purposes, the statistics above the diagonal show that the majority of firm-product pairs have a smaller number of unique trade patterns than their total number of exporting years. This means these firms export a particular product to the same set of destinations for two or more years in their lifetime. For example, consider the firm-product pairs being observed for 5 years: 64.1% (100-35.9%) of them have at least one repeated trade pattern in their exporting life.

Trade pattern by product differentiation. We then calculate the trade pattern statistics for high- and low-differentiation goods defined by our CCHS classification. Inspecting Tables OA1-7 and OA1-8, we do not find significant differences in the statistics of market changes for high- and low-differentiation goods in our sample.

Table OA1-6: Number of Unique Trade Patterns - All Goods

	Total Number of Exporting Years (x)														
Number of Unique Trade Patterns (y)	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Total
1	35.9	26.6	22.4	19.3	16.7	14.0	11.8	10.3	8.8	7.7	6.2	5.5	5.1	4.7	23.4
2	64.1	23.2	16.5	13.0	10.8	9.1	7.7	6.7	6.0	5.4	4.6	4.3	3.8	3.8	28.5
3		50.2	20.3	14.1	11.0	8.9	7.1	6.3	5.4	4.7	3.9	3.5	3.0	3.1	15.0
4			40.8	17.6	12.2	9.3	7.3	6.2	5.1	4.3	3.6	2.9	2.6	2.7	8.9
5				35.9	15.8	11.1	8.3	6.6	5.3	4.5	3.7	2.9	2.7	2.3	6.1
6					33.4	14.9	10.1	7.7	6.2	5.0	3.8	3.0	2.4	2.2	4.5
7						32.7	13.8	9.6	7.3	5.5	4.5	3.7	2.9	2.2	3.5
8							33.9	13.7	9.4	7.0	5.2	4.2	3.3	2.3	2.8
9								33.0	13.5	9.1	6.7	5.0	3.7	2.7	2.0
10									33.3	13.2	8.9	6.8	5.1	3.2	1.6
11										33.6	13.1	9.0	6.5	3.5	1.1
12											35.9	13.7	8.4	5.1	0.9
13												35.6	13.6	7.1	0.6
14													36.9	12.1	0.5
15														42.9	0.5
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Share	29.3	17.9	12.0	9.1	7.3	5.8	5.0	3.7	2.9	2.2	1.6	1.2	0.9	1.1	100.0

Note: The statistics are constructed as follows. We start from the whole sample of all firms and drop firm-product pairs that only exported once in their lifetime. For each firm-product pair, we calculate its total number of exporting years and the number of unique trade patterns in its lifetime and then put it into the relevant cells of the table. The last row "Share" indicates the share of firm-product pairs with the total number of exporting years equal to x. The last column gives the share of firm-product pairs with y number of unique trade patterns.

Table OA1-7: Number of Unique Trade Patterns - High Differentiation Goods

	Total Number of Exporting Years (x)														
Number of Unique Trade Patterns (y)	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Share
1	35.6	26.6	22.1	19.1	16.4	13.9	11.6	10.7	9.3	8.1	6.5	5.7	5.8	5.1	22.8
2	64.4	23.7	16.4	12.9	10.7	8.9	7.6	7.0	6.2	5.5	4.7	4.8	4.5	4.4	27.7
3		49.7	20.3	14.1	10.9	8.8	6.9	6.2	5.3	4.8	3.8	3.8	3.4	3.4	14.6
4			41.2	17.7	12.2	9.2	7.0	6.0	5.1	4.4	3.7	3.2	2.7	3.1	9.1
5				36.2	15.8	11.2	8.3	6.4	5.0	4.4	3.7	3.0	2.7	2.4	6.3
6					34.0	14.7	9.9	7.6	6.1	4.8	3.5	3.0	2.4	2.3	4.7
7						33.3	13.6	9.2	7.1	5.4	4.6	3.6	3.0	2.3	3.7
8							35.1	13.7	9.1	7.0	5.3	4.5	3.3	2.3	3.1
9								33.1	13.3	9.2	6.5	5.0	3.7	2.8	2.2
10									33.5	13.1	9.0	6.8	4.8	3.1	1.7
11										33.2	12.9	9.1	6.0	3.5	1.3
12											35.6	13.6	7.8	5.3	1.0
13												33.9	13.2	6.6	0.7
14													36.5	11.8	0.5
15														41.5	0.5
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Note: We start from the whole sample of all firms selling *high differentiation* goods and drop firm-product pairs that only exported once in their lifetime. For each firm-product pair, we calculate its total number of exporting years and the number of unique trade patterns in its lifetime and then put it into the relevant cells of the table. The last column gives the share of firm-product pairs with y number of unique trade patterns.

Table OA1-8: Number of Unique Trade Patterns - Low Differentiation Goods

	Total Number of Exporting Years (x)														
Number of Unique Trade Patterns (y)	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Share
1	36.1	26.6	22.6	19.5	16.9	14.1	12.0	10.0	8.3	7.3	5.9	5.3	4.4	4.4	23.9
2	63.9	23.0	16.5	13.1	10.9	9.2	7.7	6.5	5.8	5.2	4.4	3.8	3.1	3.3	29.1
3		50.4	20.3	14.1	11.1	8.9	7.2	6.3	5.4	4.6	3.9	3.2	2.7	2.8	15.4
4			40.6	17.6	12.2	9.4	7.4	6.3	5.1	4.3	3.4	2.6	2.6	2.4	8.8
5				35.7	15.9	11.1	8.4	6.7	5.4	4.6	3.8	2.8	2.6	2.3	6.0
6					33.1	15.0	10.2	7.7	6.2	5.2	3.9	3.0	2.4	2.1	4.4
7						32.3	14.0	9.9	7.3	5.6	4.5	3.8	2.8	2.1	3.3
8							33.0	13.7	9.6	7.0	5.2	3.9	3.2	2.3	2.6
9								32.9	13.6	9.0	6.8	5.1	3.7	2.5	1.9
10									33.1	13.2	8.7	6.8	5.3	3.3	1.4
11										33.9	13.2	8.9	6.9	3.5	1.1
12											36.2	13.7	8.9	5.0	0.8
13												37.1	14.0	7.5	0.6
14													37.3	12.4	0.4
15														44.2	0.4
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

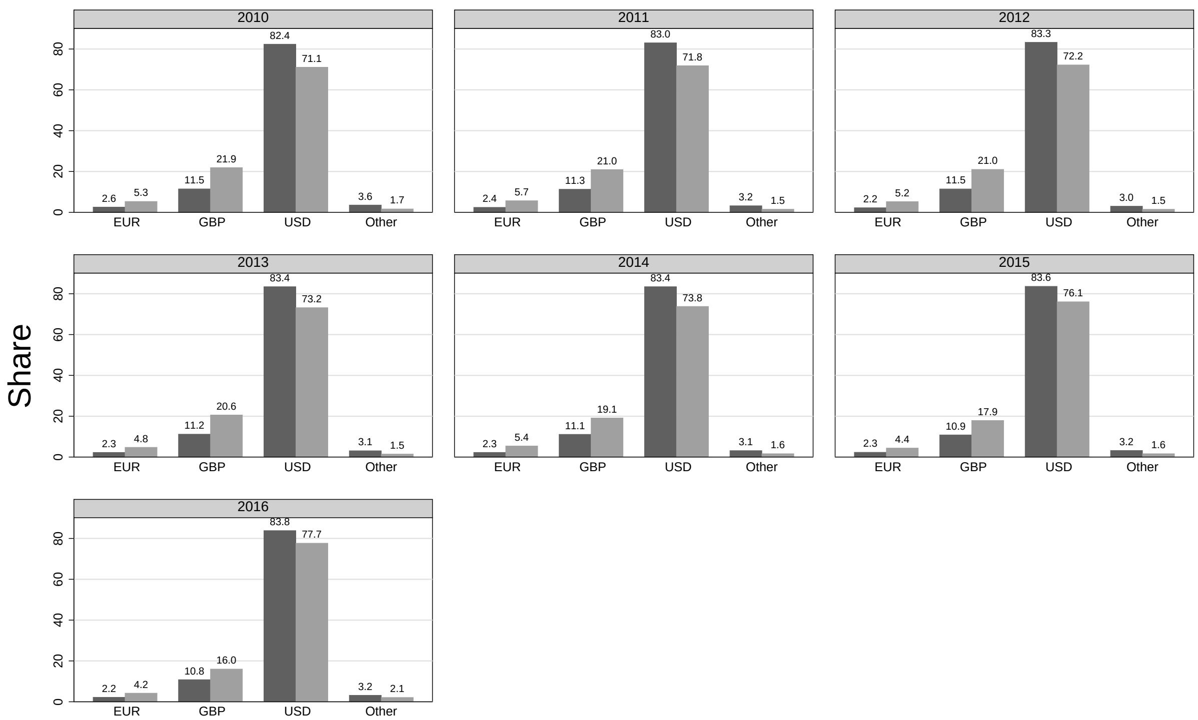
Note: We start from the whole sample of all firms selling *low differentiation* goods and drop firm-product pairs that only exported once in their lifetime. For each firm-product pair, we calculate its total number of exporting years and the number of unique trade patterns in its lifetime and then put it into the relevant cells of the table. The last column gives the share of firm-product pairs with y number of unique trade patterns.

OA1.4 In which currency do exporters from China invoice?

The Chinese Customs Authority reports the value of export shipments in US dollars, but does not provide any information about whether the trade was invoiced in US dollars, renminbi, another vehicle currency or the currency of the destination. We turn to the customs records of Her Majesty's Revenue and Customs (HMRC) in the United Kingdom, one of China's major destination markets, to shed light on this issue.

We interpret the widespread prevalence of dollar invoicing for a country that issues its own vehicle currency, the United Kingdom, as suggestive that Chinese exports to other countries, including those that do not issue vehicle currencies, are likely predominately invoiced in US dollars.

Figure OA1-1: Invoicing currencies for UK imports from China



Black: Share of Transactions; Grey: Share of Trade Value
Source: Calculations based on HMRC administrative datasets.

Since 2010, HMRC has recorded the invoicing currency for the vast majority of import and export transactions between the UK and non-EU trading partners.[4] Figure OA1-1 presents the

[4]The reporting requirements for invoice currency are described in *UK Non-EU Trade by declared currency of Invoice (2016)*, published 25 April 2017. See page 7: "Only data received through the administrative Customs data collection has a currency of invoice declared... For Non-EU import trade, businesses must submit the invoice currency when providing customs declarations. However, 5.0 per cent of Non-EU import trade value [in 2016] did not have a currency... This was accounted for by trade reported through separate systems, such as parcel post and some mineral fuels. For Non-EU export trade, businesses are required to declare invoice currency for declarations with a value greater than £100,000. As a result of this threshold and trade collected separately (reasons outlined above) 10.1 per cent of Non-EU export trade [in 2016] was declared without a currency."

shares of import transactions and import value into the UK from China by invoicing currency.[5] Results are reported for three currencies, the euro (EUR), pound sterling (GBP), and the US dollar (USD). All transactions that use other currencies of invoice, for example, the Swiss franc, Japanese yen or Chinese renminbi, are aggregated into the category "Other."[6] In each graph, the dark bar refers to the share of transactions and the light grey bar refers to the share of import value reported in the relevant currency.

The first point to note is that virtually all of the UK's imports from China are invoiced in one of three major currencies: the pound sterling (GBP), the US dollar (USD), or the euro (EUR). Very little trade is invoiced in any other currency, including the Chinese renminbi.

The second striking point is that the most important currency for Chinese exports to the UK is the US dollar. The dollar's prominence as the invoicing currency of choice for Chinese exports to the UK rose over 2010-2016 with the share of import value growing from 71.1% to 77.7%. The share of transactions invoiced in US dollars was stable at around 83% throughout the 2010-2016 period.[7] Over this same period, the pound's importance as an invoicing currency for imports from China fell. While the share of transactions invoiced in sterling held steady at 10-12% over the period, the share of import value fell from a high of 21.9% in 2010 to a low of 16.0% by 2016. The importance of the euro as an invoicing currency for Chinese exports to Britain was low throughout the 2010-2016 period.

This evidence is relevant to our empirical analysis insofar as a firm that invoices in a vehicle currency, say dollars, also prices its good in that currency. Suppose that the firm sets one single price for its product in dollars: this practice (arguably maximizing the markup relative to global demand) would rule out destination specific adjustment in markups. In this case, our TPSFE estimation should yield insignificant results. The same would be true if firms set different dollar prices across markets (in line with evidence of deviations from the law of one price), but do not adjust them in response to fluctuations in the exchange rate.

This suggests that our TPSFE estimator of markup elasticities can provide evidence on a relevant implication of what Gopinath has dubbed the 'International Price System.' Specifically, our empirical findings can inform us about the possibility of dollar invoicing translating into a 'reference price system' in which firms do not exploit market-specific demand elasticities, but price

[5]To construct this figure, we begin with the universe of UK import transactions for goods originating from China over 2010-2016. Then, we aggregate all transactions within a year that are reported for a firm-CN08product-quantity measure-currency quadruplet to an annual observation for that quadruplet. The variable "quantity measure" records whether a transaction for a CN08 product is reported in kilograms or a supplementary quantity unit like "items" or "pairs." This leaves us with 2.004 million annual transactions which we use to construct figure OA1-1.

[6]We do not report the number of transactions for which the currency is not reported; the number of transactions with no currency reported falls below HMRC Datalab's threshold rule of firms in at least one year and is, for confidentiality reasons, omitted from the figure.

[7]See also Goldberg and Tille (2008) and Goldberg and Tille (2016) who document relatively large shares of exports invoiced in dollars for many countries.

in relation to global demand. If a reference price system dominates, we would expect to observe firms setting one prevailing price in the global market for manufactured goods as they do for commodities.

OA1.5 Price changes and trade patterns

In this subsection, we show how we build our (unbalanced) panel. We will rely on an example to explain how we identify price changes at the firm-product destination level and trade patterns across destinations at the firm-product level in the data.

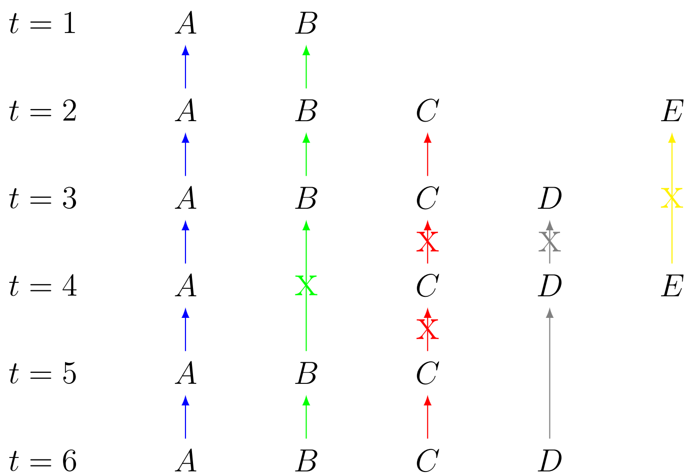
Consider a firm exporting a product to five countries, A through E, over 6 time periods. In the following matrix, $t = 1, 2, 3, ...$ indicates the time period and A, B, C, D, E indicates the country. Empty elements in the matrix indicate that there was no trade.

$$\begin{array}{llllll} t=1 & A & B & & & \\ t=2 & A & B & C & & E \\ t=3 & A & B & C & D & \\ t=4 & A & & C & D & E \\ t=5 & A & B & C & & \\ t=6 & A & B & C & D & \end{array}$$

The following matrix records export prices by destination country and time:

$$\begin{bmatrix} p_{A,1} & p_{B,1} & \cdot & \cdot & \cdot \\ p_{A,2} & p_{B,2} & p_{C,2} & \cdot & p_{E,2} \\ p_{A,3} & p_{B,3} & p_{C,3} & p_{D,3} & \cdot \\ p_{A,4} & \cdot & p_{C,4} & p_{D,4} & p_{E,4} \\ p_{A,5} & p_{B,5} & p_{C,5} & \cdot & \cdot \\ p_{A,6} & p_{B,6} & p_{C,6} & p_{D,6} & \cdot \end{bmatrix}$$

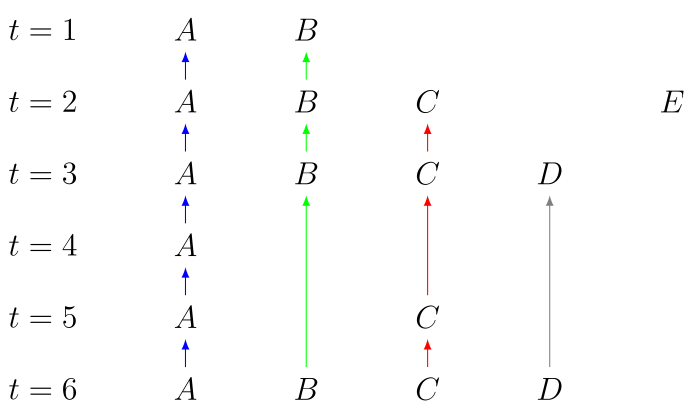
Suppose the pricing currency is the dollar and we want to identify price changes in dollars. First, we compare export prices denominated in dollars over time and at the firm-product-destination level as illustrated in the following figure. Price changes less than 5% are marked with "x".



We then set the batch of individual prices associated with a price changes below $\pm 5\%$ ($p_{B,5}, p_{C,4}, p_{D,4}, p_{E,4}$) to missing. This gives

$$\begin{bmatrix} p_{A,1} & p_{B,1} & . & . & . \\ p_{A,2} & p_{B,2} & p_{C,2} & . & . \\ p_{A,3} & p_{B,3} & p_{C,3} & p_{D,3} & p_{E,3} \\ p_{A,4} & . & . & . & . \\ p_{A,5} & . & p_{C,5} & . & . \\ p_{A,6} & p_{B,6} & p_{C,6} & p_{D,6} & . \end{bmatrix}$$

Note that we did not treat $p_{C,5}$ as missing at this stage. This is because $|p_{C,5} - p_{C,3}|$ could be $> 5\%$ even if both $|p_{C,4} - p_{C,3}| < 5\%$ and $|p_{C,5} - p_{C,4}| < 5\%$.[8] Rather, we repeat the above step using the remaining observations as illustrated below.



In this example, we indeed find $|p_{C,5} - p_{C,3}| > 5\%$ and the remaining pattern is given as follows.

[8]Variables are in logs.

As no prices are sticky, we can stop the iteration.[9] Note that as no price changes can be formulated for the single trade record $p_{E,2}$, this observation is dropped from our sample.

$$\begin{bmatrix} p_{A,1} & p_{B,1} & \cdot & \cdot & \cdot \\ p_{A,2} & p_{B,2} & p_{C,2} & \cdot & \cdot \\ p_{A,3} & p_{B,3} & p_{C,3} & p_{D,3} & \cdot \\ p_{A,4} & \cdot & \cdot & \cdot & \cdot \\ p_{A,5} & \cdot & p_{C,5} & \cdot & \cdot \\ p_{A,6} & p_{B,6} & p_{C,6} & p_{D,6} & \cdot \end{bmatrix}$$

Now we have identified the universe of observations with price changes. The next step is to formulate the trade pattern dummy.

$$\begin{array}{ll} t=1 & A \quad B \\ t=2 & A \quad B \quad C \\ t=3 & \boxed{A \quad B \quad C \quad D} \\ t=4 & A \\ t=5 & A \quad \quad C \\ t=6 & \boxed{A \quad B \quad C \quad D} \end{array}$$

In this example, we find 5 trade patterns, i.e., $A-B$, $A-B-C$, $A-B-C-D$, A, $A-C$, but only one pattern, $A-B-C-D$, which appears at least two times. To compare the change in relative prices across destinations, we require the same trade pattern be observed at least two times in the price-change-filtered dataset. Essentially, by formulating trade pattern fixed effects, we are restricting the comparison within a comparable environment. Firms switch trade patterns for a reason. Restricting the analysis to the same trade pattern also controls for other unobserved demand factors affecting the relative prices.

[9] In the real dataset, the algorithm often needs to iterate several times before reaching this stage.

OA1.6 Data cleaning process and the number of observations

Table OA1-9: Key Statistics for Our Data Cleaning Process

			Number of Unique Values				
Stage	Observations	Value (Billions US$)	Destinations	Products (HS06)	Products (HS08)	Products (Refined†)	Firms
0	108,465,375	17,453	246	5,899	10,002	-	581,141
1	92,308,538	11,553	244	5,880	9,959	-	545,175
2	92,177,750	11,546	243	5,875	9,954	20,472	545,133
3	83,439,493	11,546	227	5,875	9,954	20,472	545,133
4	76,662,842	10,878	155	5,867	9,929	20,334	531,505
5	72,025,441	9,004	155	5,867	9,929	20,334	531,505
6	49,722,707	7,228	155	5,445	9,040	17,232	355,843
7	23,552,465	5,980	152	5,041	8,076	14,560	237,933
8	5,912,633	1,213	152	5,000	7,955	14,111	209,003

† A refined product is defined as 8-digit HS code + a form of commerce dummy. More precisely, this could be described as a variety but we used the term product throughout the paper.

Stage 0: Raw data
Stage 1: Drop exports to the U.S. and Hong Kong
Stage 2: Drop if the destination identifier, product identifier or value of exports is missing; drop duplicated company names
Stage 3: Collapse at the firm-product-destination-year level; integrating 17 eurozone countries into a single economic entity
Stage 4: Drop observations if bilateral exchange rates or destination CPI is missing
Stage 5: Filtering price changes (in logs, denominated in dollar) < 0.05 at the firm-product-destination level following the method described by OA1.5
Stage 6: Drop single-destination firm-product-year triplets
Stage 7: Drop single-year firm-product-destination triplets
Stage 8: Formulating trade pattern; Drop single-year firm-product-trade-pattern triplets
(Finally, we drop "single-year firm-product-trade-pattern triplets." Including these observations will not change the estimates obtained from the TPSFE estimator because they do not provide the within firm, product and destination *intertemporal variation* upon which the estimator relies.)

OA2 The TPSFE Estimator

OA2.1 Key properties of the TPSFE estimator

As highlighted in section 2 of the paper, the fundamental reason why omitted variable and selection biases might arise is missing information for key variables. Once the variation of these missing variables is properly controlled for, both omitted variable and selection biases will disappear. In large customs databases with four panel dimensions (i.e., firm, product, destination and time), fixed effects provide a natural tool to control for unobserved confounding variables.

However, due to endogenous market decisions of firms, correctly controlling for the desired variation of the unobserved variables that vary along multiple panel dimensions is a non-trivial task. The key difficulty is to design partition matrices that can account for the unbalanced panel structure and correctly eliminate the variation of unobserved confounding variables. The most relevant reference to our TPSFE demeaning procedure is Wansbeek and Kapteyn (1989), who consider an unbalanced panel with two panel dimensions and two fixed effects.

The econometrics contribution of our TPSFE estimator is to (a) improve the partition matrices proposed by Wansbeek and Kapteyn (1989), (b) generalize it into a four-dimension unbalanced panel, and (c) apply the method to the estimation of markup elasticities in a large customs database. In particular for (c), thanks to the simplicity and transparency of our method, our TPSFE approach makes it easy to understand the underlying variation that is used to identify the markup elasticity to exchange rates. The approach points to the relevance of including trade patterns of firms' products to controlling for unobserved confounding variables.

Proposition 1. *In an unbalanced panel, our proposed TPSFE procedure eliminates all confounding variables that vary along the $fidD + fit$ panel dimensions.*

We start by introducing Proposition 1, which states that our TPSFE procedure can address all omitted variable and selection biases that are driven by variables varying along the $fidD+fit$ panel dimensions. For example, the unobserved marginal cost of a firm's product varies along the fit panel dimension, while the differences in time-invariant demand conditions across markets facing a firm's product vary along the fid panel dimension. The additional D in $fidD$ further allows for unobserved firm-product-destination-specific factors that co-move with the trade patterns of the firm-product. For example, a change in economic fundamentals $\mathcal{F}_t$ that has firm-product-destination specific effects and influences the choice of the set of destination markets of the firm-product will result in variation along the $fidD$ panel dimension, which can be controlled by our proposed estimator.

We proceed as follows. Subsections OA2.1.1 to OA2.1.3 discuss the key idea and mechanism behind our estimator and compare it to the partition matrices proposed by Wansbeek and Kapteyn

(1989) in a two-dimensional panel. Subsection OA2.1.4 provides a numerical example to clarify our notation and discussion. Subsection OA2.1.5 generalizes the results to four-dimensional unbalanced panels.

OA2.1.1 Identifying the markup elasticity in a two-dimensional unbalanced panel

In this subsection, we discuss the identification of the markup elasticity in a two-dimensional unbalanced panel and introduce two useful lemmas that lay the foundation for the proof of Proposition 1. The idea is that identifying the markup elasticity and controlling for the unobserved confounding variables in a large customs database with four panel dimensions can be thought of as a collection of many smaller firm-product level problems that each have two panel dimensions, i.e., destination (d) and time (t). In those more refined two-dimensional problems, Lemma 1 shows the original partition methods of Wansbeek and Kapteyn (1989) can be decomposed into a two-step procedure with the second step implicitly applying a trade pattern related partition.

Lemma 1. *In a two-dimensional unbalanced panel, factors varying along the d+t panel dimensions can be eliminated using a two-step procedure by which, in the first step, all variables are demeaned across observed destinations within each period and, in the second step, destination (d) and trade pattern (D) fixed effects are applied additively, i.e., $d + D$.*

Building on the insights of Lemma 1, Lemma 2 shows a better estimator can be constructed to deal with more complicated cases, where the unobserved confounding variables vary along the $dD+t$ panel dimensions. The key idea is that, in the second step of the procedure, we can combine the d and D fixed effects interactively instead of additively.

Lemma 2. *In a two-dimensional unbalanced panel, factors varying along the $dD + t$ dimensions can be eliminated in a two-step procedure in which all variables are demeaned across observed destinations within each period in the first stage and destination (d) and trade pattern (D) fixed effects are applied multiplicatively, i.e., dD, in the second stage. This procedure also eliminates all confounding factors that the $d + t$ fixed effects can address.*

OA2.1.2 Proof of Lemma 1

The proof proceeds with two steps. In the first step, we construct a demeaned fixed effect estimator following Wansbeek and Kapteyn (1989). In the second step, we show that the constructed estimator implicitly applies trade pattern fixed effects.

Step 1: Let n_t^D $\left(n_t^D \leq n^D\right)$ be the number of observed destinations for year t. Let $n^{DT} \equiv \sum_t n_t^D$. Let A_t be the $\left(n_t^D \times n^D\right)$ matrix obtained from the $(n^D \times n^D)$ identity matrix from which the rows corresponding to the destinations not observed in year t have been omitted, and consider

$$Z \equiv \left(\begin{array}{cc} Z_1, & Z_2 \\ n^{DT} \times n^D & n^{DT} \times n^T \end{array} \right) \equiv \begin{bmatrix} A_1 & A_1 \iota_{n^D} & & \\ \vdots & & \ddots & \\ A_{n^T} & & & A_{n^T} \iota_{n^D} \end{bmatrix} \tag{OA2-1}$$

where ι_x is a vector of ones with length x, e.g., ι_{n^D} is a vector of ones with length n^D. The matrix Z gives the dummy-variable structure for the incomplete-data model. (For complete data, $Z_1 = \iota_{n^T} \otimes I_{n^D}, Z_2 = I_{n^T} \otimes \iota_{n^D}$.) Define

$$\begin{aligned} P_2 &\equiv I_{n^{DT}} - Z_2 \left(Z_2' Z_2\right)^{-1} Z_2' \\ \bar{Z} &\equiv P_2 Z_1. \end{aligned}$$

Wansbeek and Kapteyn (1989) show P is a projection matrix onto the null-space of Z:

$$P \equiv P_2 - \bar{Z}(\bar{Z}'\bar{Z})^{-}\bar{Z}'$$

where '$-$' stands for a generalized inverse. It follows that, in an unbalanced panel with unobserved confounding variables varying along d and t panel dimensions, unbiased and consistent estimates can be obtained by running an OLS regression with the demeaned data obtained by pre-multiplying the data matrix (Y, X) by the projection matrix P.

Step 2: We now show the projection matrix P can be decomposed into two projection matrices with the second projection matrix applying destination and trade pattern fixed effects in additive terms. We begin by noting that the following relationship holds:

$$P \equiv P_2 - \bar{Z}(\bar{Z}'\bar{Z})^{-}\bar{Z}' = (I_{n^{DT}} - \bar{Z}(\bar{Z}'\bar{Z})^{-}\bar{Z}')P_2 \equiv P_1 P_2 \tag{OA2-2}$$

where $P_1 \equiv I_{n^{DT}} - \bar{Z}(\bar{Z}'\bar{Z})^{-}\bar{Z}'$ and the equality of (OA2-2) uses the fact that P_2 is idempotent (i.e., $P_2 Z_1 = P_2 P_2 Z_1 = P_2 \bar{Z}$). Therefore, applying the projection matrix P to the data matrix (Y, X) is equivalent to first pre-multiplying (Y, X) by the projection matrix P_2, and then pre-multiplying $(P_2 Y, P_2 X)$ by the projection matrix P_1. The projection P_2 applied in the first step is essentially a destination-demean process (the same first step as our TPSFE estimator).[10] The projection P_1 applied in the second step is, by definition, a "demeaning" process at the $\bar{Z}$ level. To see the exact dummy structure based on which the second "demeaning" process is applied, note that $\bar{Z}$ can be rewritten as

$$\bar{Z} = P_2 Z_1 = Z_1 - Z_2 \left(Z_2' Z_2\right)^{-1} Z_2' Z_1 \tag{OA2-3}$$

[10] See the numerical example in subsection OA2.1.4.

where Z_1 is a set of destination dummies as defined in (OA2-1) and $Z_2\left(Z_2'Z_2\right)^{-1}Z_2'Z_1$ is a set of trade pattern dummies.

To see that $Z_2\left(Z_2'Z_2\right)^{-1}Z_2'Z_1$ follows a trade pattern structure, note that $Z_2\left(Z_2'Z_2\right)^{-1}Z_2'$ is a block diagonal matrix with its diagonal blocks equal to a matrix of ones multiplied by (the inverse of) the number of destinations in each period, i.e.,

$$
\begin{aligned}
Z_2\left(Z_2'Z_2\right)^{-1}Z_2' &= \operatorname{diag}\left(\frac{1}{n_1^D}A_1\iota_{n^D}\iota_{n^D}'A_1', ..., \frac{1}{n_{n^T}^D}A_{n^D}\iota_{n^D}\iota_{n^D}'A_{n^D}'\right) \\
&= \operatorname{diag}\left(\frac{1}{n_1^D}\iota_{n_1^D}\iota_{n_1^D}', ..., \frac{1}{n_{n^T}^D}\iota_{n_{n^T}^D}\iota_{n_{n^T}^D}'\right) \qquad \text{(OA2-4)}
\end{aligned}
$$

where the first equality holds by the definition of Z_2 in (OA2-1) and given the fact that $\left(Z_2'Z_2\right)^{-1}$ is a diagonal matrix, with its elements indicating (the inverse of) the number of observed destinations in each period, i.e.,

$$
\left(Z_2'Z_2\right)^{-1} = \operatorname{diag}\left(\frac{1}{n_1^D}, \frac{1}{n_2^D}, ..., \frac{1}{n_{n^T}^D}\right); \qquad \text{(OA2-5)}
$$

the second equality in (OA2-3) holds by the definition of the A matrices in (OA2-1). Pre-multiplying Z_1 by $Z_2\left(Z_2'Z_2\right)^{-1}Z_2'$ and using the definition of Z_1, we have

$$
Z_2\left(Z_2'Z_2\right)^{-1}Z_2'Z_1 = \begin{bmatrix} \frac{1}{n_1^D}\iota_{n_1^D}\iota_{n_1^D}'A_1 \\ \vdots \\ \frac{1}{n_{n^T}^D}\iota_{n_{n^T}^D}\iota_{n_{n^T}^D}'A_{n^D} \end{bmatrix} \qquad \text{(OA2-6)}
$$

where $\iota_{n_t^D}'A_t$ gives the trade pattern in year t and pre-multiplying it by $\iota_{n_t^D}$ repeats the same trade pattern n_t^D times—resulting in the trade pattern matrix for all destinations in period t.[11]

Therefore, the second "demeaning" projection matrix $P_1 \equiv I_{n^{DT}} - \bar{Z}(\bar{Z}'\bar{Z})^{-}\bar{Z}'$ is applied on $\bar{Z}$ that consists of two *additive* parts: (a) the destination dummies Z_1 and (b) the trade pattern dummies $Z_2\left(Z_2'Z_2\right)^{-1}Z_2'Z_1$.

OA2.1.3 Proof of Lemma 2

A key difference between our proposed TPSFE estimator and a conventional fixed effect estimator adding destination and time fixed effects lies in the way the trade patterns are applied in the second step. While the conventional approach applies the destination and trade pattern fixed effects additively (as can be seen from (OA2-3) and (OA2-6)), our estimator applies the trade pattern fixed effect multiplicatively.

[11] See Appendix OA2.1.4 for an numerical example of the matrices.

We start our proof by introducing notation and definitions. Denote the set of exporting destinations in year t as D_t.[12] Let $\mathcal{TP}$ be the set of unique trade patterns in all years, i.e.,

$$\mathcal{TP} \equiv \{D_1, ..., D_{n^T}\}_{\neq} \tag{OA2-7}$$

and $n^{\mathcal{TP}} \equiv |\mathcal{TP}|$ be the number of unique trade patterns. Let $\mathcal{TP}_x$ denote the x'th element of $\mathcal{TP}$. We create destination-specific trade patterns by combining the destinations in a trade pattern with the trade pattern itself, i.e., $\{(d, \mathcal{TP}_x) : d \in \mathcal{TP}_x\}$. Let $\mathcal{DTP}$ be the set of destination-specific trade patterns, i.e.,

$$\mathcal{DTP} \equiv \{(d, \mathcal{TP}_1) : d \in \mathcal{TP}_1, ..., (d, \mathcal{TP}_{n^{\mathcal{TP}}}) : d \in \mathcal{TP}_{n^{\mathcal{TP}}}\}.$$

Let $n^{\mathcal{DTP}} \equiv |\mathcal{DTP}|$ be the number of unique destination-trade pattern pairs observed in the data.

The dummy structure of destination-specific trade patterns is given by the following $(n^{DT} \times n^{\mathcal{DTP}})$ matrix:

$$Z_3 \equiv \begin{bmatrix} B_1 \\ \vdots \\ B_{n^T} \end{bmatrix} \equiv \begin{bmatrix} K_{11} & \cdots & K_{1n^{\mathcal{TP}}} \\ \vdots & \ddots & \vdots \\ K_{n^T 1} & \cdots & K_{n^T n^{\mathcal{TP}}} \end{bmatrix} \tag{OA2-8}$$

where B_t is an $n_t^D \times n^{\mathcal{DTP}}$ matrix indicating the destination-specific trade patterns in period t. Each B_t can be decomposed into $n^{\mathcal{TP}}$ block matrices with its y'th block being equal to an identity matrix if the trade pattern of period t, D_t, is the same as the y'th trade pattern, $\mathcal{TP}_y$, and a matrix of zeros otherwise. That is, $\forall x \in \{1, ..., n^T\}, y \in \{1, ..., n^{\mathcal{TP}}\}$,

$$K_{xy} \equiv \begin{cases} I_{n_x^D} & \text{if } D_x = \mathcal{TP}_y \\ \mathbf{0}_{n_x^D \times n_{\mathcal{TP}}^D(y)} & \text{if } D_x \neq \mathcal{TP}_y \end{cases} \tag{OA2-9}$$

where $I_{n_x^D}$ is an identity matrix of size n_x^D; $\mathbf{0}_{n_x^D \times n_{\mathcal{TP}}^D(y)}$ is a matrix of zeros of size $n_x^D \times n_{\mathcal{TP}}^D(y)$; and $n_{\mathcal{TP}}^D(y) \equiv |\{d : d \in \mathcal{TP}_y\}|$ is the number of destinations in the y'th unique trade pattern $\mathcal{TP}_y$.

Let the projection matrix be $P_3 P_2$, where $P_3 \equiv I_{n^{DT}} - Z_3 \left(Z_3' Z_3\right)^{-1} Z_3'$. The first projection P_2 is the same destination-demean process, whereas the second projection P_3 applies demeaning at the destination-trade pattern level. As discussed in previous sections, the interactive construction of trade pattern fixed effects enables us to handle interactive error terms and reduce the time variation of the unobserved confounding variables.

[12]In a vector form, $\iota_{n_t^D}' A_t$ indicates the set of destinations in year t.

To formally prove Lemma 2, we need to show that

$$\begin{aligned} P_3 P_2 Z_1 &= \mathbf{0}, \\ P_3 P_2 Z_2 &= \mathbf{0}, \\ P_3 P_2 Z_3 &= \mathbf{0}. \end{aligned}$$

We begin by noting that the second relationship holds by definition (of P_2):

$$P_3 P_2 Z_2 = [I_{n^{DT}} - Z_3 \left(Z_3' Z_3\right)^{-1} Z_3'][I_{n^{DT}} - Z_2 \left(Z_2' Z_2\right)^{-1} Z_2']Z_2 = \mathbf{0}.$$

We prove $P_3 P_2 Z_1 = \mathbf{0}$ and $P_3 P_2 Z_3 = \mathbf{0}$ by relying on two relationships that we state here and prove later in the text. First, the two projection matrices $T_3 \equiv Z_3 \left(Z_3' Z_3\right)^{-1} Z_3'$ and $T_2 \equiv Z_2 \left(Z_2' Z_2\right)^{-1} Z_2'$ commute:

$$T_3 T_2 = T_2 T_3. \tag{OA2-10}$$

Second, T_3 projects Z_1 to itself:

$$T_3 Z_1 = Z_1. \tag{OA2-11}$$

Given (OA2-10) and (OA2-11), it follows that

$$\begin{aligned} P_3 P_2 Z_1 &= [I_{n^{DT}} - T_3][I_{n^{DT}} - T_2]Z_1 \\ &= Z_1 - T_3 Z_1 + T_3 T_2 Z_1 - T_2 Z_1 \\ &= T_3 T_2 Z_1 - T_2 Z_1 \\ &= T_2 T_3 Z_1 - T_2 Z_1 \\ &= T_2 Z_1 - T_2 Z_1 \\ &= \mathbf{0} \end{aligned}$$

where the second equality is due to (OA2-11); the third equality holds due to the commutativity (OA2-10); the fourth equality applies (OA2-11) one more time. Following the same procedure, it can be shown that $P_3 P_2 Z_3 = \mathbf{0}$.

We complete our proofs showing that (OA2-10) and (OA2-11) hold.

Proof of (OA2-10):

Proof. We want to prove that the two projection matrices $Z_3 \left(Z_3' Z_3\right)^{-1} Z_3'$ and $Z_2 \left(Z_2' Z_2\right)^{-1} Z_2'$ commute. We do so by proving that the product of these two matrices $Z_3 \left(Z_3' Z_3\right)^{-1} Z_3' Z_2 \left(Z_2' Z_2\right)^{-1} Z_2'$

is symmetric.

$Z_3 \left(Z_3' Z_3\right)^{-1} Z_3'$ can be written as:

$$Z_3 \left(Z_3' Z_3\right)^{-1} Z_3' = \begin{bmatrix} B_1 \left(Z_3' Z_3\right)^{-1} B_1' & \cdots & B_1 \left(Z_3' Z_3\right)^{-1} B_{n^T}' \\ \vdots & \ddots & \vdots \\ B_1 \left(Z_3' Z_3\right)^{-1} B_{n^T}' & \cdots & B_{n^T} \left(Z_3' Z_3\right)^{-1} B_{n^T}' \end{bmatrix} \tag{OA2-12}$$

The blocks of $Z_3 \left(Z_3' Z_3\right)^{-1} Z_3'$ can be further simplified using the following two observations. First, $\left(Z_3' Z_3\right)^{-1}$ is an $n^{\mathcal{DTP}} \times n^{\mathcal{DTP}}$ diagonal matrix with its elements indicating (the reverse of) the number of repetitions for each destination-trade pattern pair, i.e.,

$$\begin{aligned} \left(Z_3' Z_3\right)^{-1} &= \left(\sum_t B_t' B_t\right)^{-1} \\ &= \begin{bmatrix} \sum_t K_{t1}' K_{t1} & \cdots & \sum_t K_{t1}' K_{tn^{\mathcal{TP}}} \\ \vdots & \ddots & \vdots \\ \sum_t K_{tn^T}' K_{t1} & \cdots & \sum_t K_{tn^{\mathcal{TP}}}' K_{tn^{\mathcal{TP}}} \end{bmatrix}^{-1} \\ &= \begin{bmatrix} r_1^{\mathcal{TP}} I_{n^D_{\mathcal{TP}}(1)} & & \\ & \ddots & \\ & & r_{n^{\mathcal{TP}}}^{\mathcal{TP}} I_{n^D_{\mathcal{TP}}(n^{\mathcal{TP}})} \end{bmatrix}^{-1} \\ &= \operatorname{diag}\left(\frac{1}{r_1^{\mathcal{TP}}} I_{n^D_{\mathcal{TP}}(1)}, ..., \frac{1}{r_{n^{\mathcal{TP}}}^{\mathcal{TP}}} I_{n^D_{\mathcal{TP}}(n^{\mathcal{TP}})}\right) \end{aligned} \tag{OA2-13}$$

where $r_z^{\mathcal{TP}} \equiv \left|\{t : D_t = \mathcal{TP}_z\}\right|$ is the number of periods that the trade pattern $\mathcal{TP}_z$ is observed for $z \in \left\{1, ..., n^{\mathcal{TP}}\right\}$. The third equality holds as $K_{th}' K_{tj} = \mathbf{0}\ \forall h \neq j$ and $K_{th}' K_{tj} = I_{n_h^D}\ \forall h = j$ by definitions of (OA2-8) and (OA2-9).

Second, the (h, j) block of $Z_3 \left(Z_3' Z_3\right)^{-1} Z_3'$, i.e., $B_h \left(Z_3' Z_3\right)^{-1} B_j'$, is equal to a matrix of zeros if the trade pattern of period h is different from that of period j and is equal to an identity matrix multiplied by a scalar if the trade pattern of the two periods is the same:

$$B_h \left(Z_3' Z_3\right)^{-1} B_j' = \sum_{z \in \{1,..,n^{\mathcal{TP}}\}} \frac{1}{r_z^{\mathcal{TP}}} K_{hz} I_{n^D_{\mathcal{TP}}(z)} K_{jz}' = \begin{cases} \frac{1}{r_h^{\mathcal{D}}} I_{n_h^D} & \text{if } D_h = D_j \\ \mathbf{0}_{n_h^D \times n_j^D} & \text{if } D_h \neq D_j \end{cases} \tag{OA2-14}$$

where $r_z^{\mathcal{D}} \equiv \left|\{t : D_t = D_z\}\right|$ is the number of periods that the trade pattern D_z is observed.

Finally, from (OA2-12) and (OA2-4), $Z_3 \left(Z_3' Z_3\right)^{-1} Z_3' Z_2 \left(Z_2' Z_2\right)^{-1} Z_2'$ can be decomposed into

$n^T \times n^T$ blocks:

$$\begin{aligned} T &\equiv Z_3 \left(Z_3'Z_3\right)^{-1} Z_3'Z_2 \left(Z_2'Z_2\right)^{-1} Z_2' \\ &= \begin{bmatrix} B_1 \left(Z_3'Z_3\right)^{-1} B_1' \frac{1}{n_1^D} \iota_{n_1^D} \iota_{n_1^D}' & \cdots & B_1 \left(Z_3'Z_3\right)^{-1} B_{n^T}' \frac{1}{n_{n^T}^D} \iota_{n_{n^T}^D} \iota_{n_{n^T}^D}' \\ \vdots & \ddots & \vdots \\ B_1 \left(Z_3'Z_3\right)^{-1} B_{n^T}' \frac{1}{n_1^D} \iota_{n_1^D} \iota_{n_1^D}' & \cdots & B_{n^T} \left(Z_3'Z_3\right)^{-1} B_{n^T}' \frac{1}{n_{n^T}^D} \iota_{n_{n^T}^D} \iota_{n_{n^T}^D}' \end{bmatrix} \end{aligned}$$

where block (x, y) of T is given by

$$T(x, y) = B_x \left(Z_3'Z_3\right)^{-1} B_y' \frac{1}{n_y^D} \iota_{n_y^D} \iota_{n_y^D}'.$$

From (OA2-14), it is straightforward to see that $T(x, y) = T(y, x)'$. That is, if the trade pattern of period x is the same as that of period y, then $T(x, y) = T(y, x)' = \frac{1}{r_x^D n_x^D} \iota_{n_x^D} \iota_{n_x^D}' = \frac{1}{r_y^D n_y^D} \iota_{n_y^D} \iota_{n_y^D}'$; if the trade pattern of period x is different from that of period y, then $T(x, y) = T(y, x)' = \mathbf{0}_{n_x^D \times n_y^D}$.

Now, given that $Z_3 \left(Z_3'Z_3\right)^{-1} Z_3'$, $Z_2 \left(Z_2'Z_2\right)^{-1} Z_2'$, and T are all symmetric, it follows that

$$T = Z_3 \left(Z_3'Z_3\right)^{-1} Z_3'Z_2 \left(Z_2'Z_2\right)^{-1} Z_2' = T' = Z_2 \left(Z_2'Z_2\right)^{-1} Z_2'Z_3 \left(Z_3'Z_3\right)^{-1} Z_3'.$$

$\square$

Proof of (OA2-11):

Proof. From (OA2-12) and the definition of Z_1 in (OA2-1), we can write $T_3 Z_1$ as

$$T_3 Z_1 = \begin{bmatrix} \sum_t B_1 \left(Z_3'Z_3\right)^{-1} B_t' A_t \\ \vdots \\ \sum_t B_{n^T} \left(Z_3'Z_3\right)^{-1} B_t' A_t \end{bmatrix}.$$

Using (OA2-14), we have

$$B_x \left(Z_3'Z_3\right)^{-1} B_y' A_y = \begin{cases} \frac{1}{r_x^D} A_x = \frac{1}{r_y^D} A_y & \text{if } D_x = D_y \\ \mathbf{0}_{n_x^D \times n^D} & \text{if } D_x \neq D_y \end{cases} \tag{OA2-15}$$

With (OA2-15), it follows that

$$T_3 Z_1 = \begin{bmatrix} \sum_{t:D_t=D_1} \frac{1}{r_1^{\mathcal{D}}} A_1 \\ \vdots \\ \sum_{t:D_t=D_{n^T}} \frac{1}{r_{n^T}^{\mathcal{D}}} A_{n^T} \end{bmatrix} = \begin{bmatrix} A_1 \\ \vdots \\ A_{n^T} \end{bmatrix} = Z_1.$$

□

OA2.1.4 A numerical example with projection matrices to visualize differences across estimators

To clarify how the estimator works, we now spell out all the key matrices from the above discussion and provide a numerical example. For illustrative purposes, we use a much simpler data generating process:

$$\begin{aligned} p_{dt} &= \beta_0 + \beta_1 e_{dt} + \beta_2 m_{dt} \\ e_{dt} &= \sigma_e (m_{dt} + u_{dt}) \\ m_{dt} &= \vartheta_d + \epsilon_t + \psi_d * \upsilon_t \end{aligned}$$

with the following reduced form selection rule:

$$p_{dt} = \begin{cases} \text{observed} & \text{if} \quad \gamma_0 + \gamma_1 e_{dt} + \gamma_2 m_{dt} < 0 \\ \text{missing} & \text{if} \quad \gamma_0 + \gamma_1 e_{dt} + \gamma_2 m_{dt} \geq 0 \end{cases}$$

where ϑ_d, ϵ_t, ψ_t, υ_t and u_{dt} are simulated from a standard normal distribution. We set σ_e to be 0.5 such that the bilateral exchange rate shocks are slightly less volatile than the idiosyncratic marginal cost shocks. We set $\beta_1 = \beta_2 = 1$ such that an exchange rate appreciation of the home currency and a positive marginal cost shock increase the border price denominated in the home currency. This also implies a positive omitted variable bias. We set $\gamma_1 = -0.1$ and $\gamma_2 = 1$ such that the selection bias is also positive. The magnitude of γ_1 is set to be smaller than that of γ_2 to reflect the fact that the aggregate shocks (such as bilateral exchange rates) is less detrimental for the firm's entry decisions compared to idiosyncratic factors (such as the unobserved marginal cost). We reduce the number of destinations to 5 and the number of years to 4 to keep the size of the matrices tractable. To keep the example clean, we only allow for two distinct values of the factors affecting the time variation of the unobserved marginal cost (i.e., ϵ_t and υ_t). We set γ_0 such that half of the observations (destination-year pairs) are dropped.

Table OA2-1 shows one particular realization of such a data generating process. The firm exports in all four periods, and its decisions generate two unique trade patterns. In the first two years, the firm exports to destinations 2, 4 and 5. In the last two years, the firm exports only to destinations 4 and 5.

Table OA2-1: Simulated Data

Year	Destination	Trade Pattern	p_{dt}	e_{dt}	m_{dt}	ϵ_t	υ_t
1	2	2_4_5	-0.072	0.155	-0.227	0.843	0.277
1	4	2_4_5	0.178	-0.092	0.270	0.843	0.277
1	5	2_4_5	-1.138	-1.252	0.114	0.843	0.277
2	2	2_4_5	0.455	0.682	-0.227	0.843	0.277
2	4	2_4_5	0.636	0.366	0.270	0.843	0.277
2	5	2_4_5	0.068	-0.046	0.114	0.843	0.277
3	4	4_5	-0.313	0.689	-1.002	-0.191	1.117
3	5	4_5	-0.315	0.071	-0.387	-0.191	1.117
4	4	4_5	-1.099	-0.097	-1.002	-0.191	1.117
4	5	4_5	-0.747	-0.360	-0.387	-0.191	1.117

Z_1 is the matrix that contains the destination dummies. To economize on the matrix size, we only create dummies for destinations that are observed, i.e., we do not create dummies for destinations 1 and 3. For example, the first column of Z_1 reports the observations in which the firm sells to destination 2. From the matrix, we can see that the firm sells to destination 2 two times. Z_2 is the matrix that contains the year dummies. Z_3 gives our proposed destination-specific trade pattern dummies. As defined in (OA2-8) and (OA2-9), it is constructed by interacting the destination dummies with the trade pattern dummies. For example, the first three columns represent the dummy structure for the destinations related to the 2_4_5 trade pattern, i.e., $2-2\_4\_5$, $4-2\_4\_5$ and $5-2\_4\_5$. Similarly, the last two columns represent the dummy structure for the destinations related to the 4_5 trade pattern, i.e., $4-4\_5$ and $5-4\_5$.

$$Z_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad Z_2 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad Z_3 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{OA2-16}$$

From these, we can see clearly that P_2 is a destination demean process.

$$P_2 = \begin{bmatrix} 0.67 & -0.33 & -0.33 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -0.33 & 0.67 & -0.33 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -0.33 & -0.33 & 0.67 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.67 & -0.33 & -0.33 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -0.33 & 0.67 & -0.33 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -0.33 & -0.33 & 0.67 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.50 & -0.50 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -0.50 & 0.50 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.50 & -0.50 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.50 & 0.50 \end{bmatrix}$$

By way of example, for the first observation, $2/3p_{11} - 1/3p_{21} - 1/3p_{31} = p_{11} - \frac{1}{3}(p_{11} + p_{21} + p_{31})$.

As discussed in subsection OA2.1.2, $Z_2\left(Z_2'Z_2\right)^{-1}Z_2'Z_1$ follows a trade pattern structure and $\bar{Z}$ suggests an additive relationship between the destination dummies Z_1 and the trade pattern dummies $Z_2\left(Z_2'Z_2\right)^{-1}Z_2'Z_1$.

$$Z_2\left(Z_2'Z_2\right)^{-1}Z_2'Z_1 = \begin{bmatrix} 0.33 & 0.33 & 0.33 \\ 0.33 & 0.33 & 0.33 \\ 0.33 & 0.33 & 0.33 \\ 0.33 & 0.33 & 0.33 \\ 0.33 & 0.33 & 0.33 \\ 0.33 & 0.33 & 0.33 \\ 0 & 0.50 & 0.50 \\ 0 & 0.50 & 0.50 \\ 0 & 0.50 & 0.50 \\ 0 & 0.50 & 0.50 \end{bmatrix} \quad \bar{Z} = Z_1 - Z_2\left(Z_2'Z_2\right)^{-1}Z_2'Z_1 = \begin{bmatrix} 0.67 & -0.33 & -0.33 \\ -0.33 & 0.67 & -0.33 \\ -0.33 & -0.33 & 0.67 \\ 0.67 & -0.33 & -0.33 \\ -0.33 & 0.67 & -0.33 \\ -0.33 & -0.33 & 0.67 \\ 0 & 0.50 & -0.50 \\ 0 & -0.50 & 0.50 \\ 0 & 0.50 & -0.50 \\ 0 & -0.50 & 0.50 \end{bmatrix}$$

As we can see from (OA2-17), the projection P does not follow a particular structure. Therefore, our two-step decomposition $P = P_1P_2$ discussed in subsection OA2.1.2 helps to reveal the key economic mechanisms behind the statistical projection.

$$P = \begin{bmatrix} 0.46 & -0.29 & -0.17 & -0.21 & 0.04 & 0.17 & -0.13 & 0.13 & -0.13 & 0.13 \\ -0.29 & 0.46 & -0.17 & 0.04 & -0.21 & 0.17 & 0.13 & -0.13 & 0.13 & -0.13 \\ -0.17 & -0.17 & 0.33 & 0.17 & 0.17 & -0.33 & 0 & 0 & 0 & 0 \\ -0.21 & 0.04 & 0.17 & 0.46 & -0.29 & -0.17 & -0.13 & 0.13 & -0.13 & 0.13 \\ 0.04 & -0.21 & 0.17 & -0.29 & 0.46 & -0.17 & 0.13 & -0.13 & 0.13 & -0.13 \\ 0.17 & 0.17 & -0.33 & -0.17 & -0.17 & 0.33 & 0 & 0 & 0 & 0 \\ -0.13 & 0.13 & 0 & -0.13 & 0.13 & 0 & 0.38 & -0.38 & -0.13 & 0.13 \\ 0.13 & -0.13 & 0 & 0.13 & -0.13 & 0 & -0.38 & 0.38 & 0.13 & -0.13 \\ -0.13 & 0.13 & 0 & -0.13 & 0.13 & 0 & -0.13 & 0.13 & 0.38 & -0.38 \\ 0.13 & -0.13 & 0 & 0.13 & -0.13 & 0 & 0.13 & -0.13 & -0.38 & 0.38 \end{bmatrix} \tag{OA2-17}$$

Let $Y = [-0.072, 0.178, -1.138, 0.455, 0.636, 0.068, -0.313, -0.315, -1.099, -0.747]'$ and $X = [0.155, -0.092, -1.252, 0.682, 0.366, -0.046, 0.689, 0.071, -0.097, -0.360]'$. The OLS estimator is given by $(X'X)^{-1}X'Y$, which gives an estimate of $\widehat{\beta}_1 = 0.745$. The estimator applying d and t fixed effects is given by $(X'P'PX)^{-1}X'P'Y$, which gives $\widehat{\beta}_1 = 1.508$. The estimator applying dD

and t fixed effects is given by $(X'P_2'P_3'P_3P_2X)^{-1}X'P_2'P_3'P_3P_2Y$, which gives the calibrated value of $\widehat{\beta}_1 = 1.000$.

OA2.1.5 Identifying markup elasticities in unbalanced panels: adding firm and product dimensions

In this subsection, we introduce firm and product panel dimensions and prove Proposition 1. The key idea is that the data structure of a more complicated customs dataset with four panel dimensions can be viewed as a collection of two dimensional problems presented in (OA2-1).

Let n_{fi}^D denote the total number of export destinations by the firm-product and n_{fit}^D $\left(n_{fit}^D \leq n_{fi}^D\right)$ be the number of observed destinations in year t. Let n_{fi}^T denote the maximum number of exporting years and the $n_{fi}^{DT} \equiv \sum_t n_{fit}^D$ be the number of observed transactions by firm-product fi. Let A_{fit} be the $\left(n_{fit}^D \times n_{fi}^D\right)$ matrix obtained from the $(n_{fi}^D \times n_{fi}^D)$ identity matrix from which, for each firm-product fi, the rows corresponding to the destinations not observed in year t have been omitted. For each firm-product fi, the destination and time fixed effects of the firm-product can be defined analogously to (OA2-1) as

$$Z_{fi,1} \equiv \begin{bmatrix} A_{fi1} \\ \vdots \\ A_{fin_{fi}^T} \end{bmatrix}, \quad Z_{fi,2} \equiv \begin{bmatrix} A_{fi1}\iota_{n_{fi}^D} & & \\ & \ddots & \\ & & A_{fin_{fi}^T}\iota_{n_{fi}^D} \end{bmatrix}$$

where $Z_{fi,1}$ is an $n_{fi}^{DT} \times n_{fi}^D$ matrix that gives the dummy structure for the destination fixed effects of firm-product fi and $Z_{fi,2}$ is an $n_{fi}^{DT} \times n_{fi}^T$ matrix that gives the dummy structure for the year fixed effects of firm-product fi. Similarly, the destination-specific trade pattern dummies of the firm-product, $Z_{fi,3}$, can be defined as in (OA2-8) and (OA2-9).

Let n^{FIDT} be the total number of (non-missing) observations in the dataset; n^{FI} be the total number of distinct firm-products in the dataset; $n^{FID} \equiv \sum_{fi} n_{fi}^D$ be the sum of distinct destinations over all firm-products; $n^{FIT} \equiv \sum_{fi} n_{fi}^T$ be the sum of distinct time periods over all firm-products; and $n^{FI\mathcal{DTP}} \equiv \sum_{fi} n_{fi}^{\mathcal{DTP}}$ be the sum of distinct destination-specific trade patterns over all firm-products. The dummy structure for the full dataset including all firm-products can be constructed as:

$$Z_1 \equiv \begin{bmatrix} Z_{1,1} & & \\ & \ddots & \\ & & Z_{n^{FI},1} \end{bmatrix}, \quad Z_2 \equiv \begin{bmatrix} Z_{1,2} & & \\ & \ddots & \\ & & Z_{n^{FI},2} \end{bmatrix}, \quad Z_3 \equiv \begin{bmatrix} Z_{1,3} & & \\ & \ddots & \\ & & Z_{n^{FI},3} \end{bmatrix}$$

where Z_1 is an $n^{FIDT} \times n^{FID}$ block diagonal matrix representing the dummy structure of firm-product-destination fixed effects; Z_2 is an $n^{FIDT} \times n^{FIT}$ block diagonal matrix representing the dummy structure of firm-product-time fixed effects; and Z_3 is an $n^{FIDT} \times n^{FI\mathcal{DTP}}$ block diagonal matrix representing the dummy structure of firm-product-destination-trade pattern fixed effects. The matrices inside Z_1, Z_2 and Z_3 represent the dummy structure of the corresponding firm-product. For example, the $Z_{1,1}$ and $Z_{n^{FI},1}$ inside Z_1 give the dummy structure of destination fixed effects for the first and the last firm-product in the dataset respectively. Matrices Z_1, Z_2 and Z_3 are block diagonal because all the fixed effects we consider are firm-product specific, under which the elements of $Z_{fi,1}$, $Z_{fi,2}$ and $Z_{fi,3}$ must be zero for the observations associated with the firm-products other than fi.

Proof of Proposition 1:

Proof. Define the two demeaning processes of the TPSFE as

$$P_2 \equiv I_{n^{FIDT}} - Z_2 \left(Z_2' Z_2\right)^{-1} Z_2' \qquad \text{(step 1 of TPSFE)}$$

$$P_3 \equiv I_{n^{FIDT}} - Z_3 \left(Z_3' Z_3\right)^{-} Z_3' \qquad \text{(step 2 of TPSFE)}$$

where $I_{n^{FIDT}}$ is an $n^{FIDT} \times n^{FIDT}$ identity matrix.

We want to show

$$P_3 P_2 Z_1 = \mathbf{0},$$
$$P_3 P_2 Z_2 = \mathbf{0},$$
$$P_3 P_2 Z_3 = \mathbf{0}.$$

First of all, similar to the two-dimensional case, the second equality holds trivially by the design of P_2 (since $[I_{n^{FIDT}} - Z_2 \left(Z_2' Z_2\right)^{-1} Z_2'] Z_2 = \mathbf{0}$). Secondly, block diagonal matrices have a nice property that the multiplication of two conformable block diagonal matrices is equal to the multiplication of the corresponding diagonal blocks of the two matrices. This allows us to apply the key relationships in the two-dimensional panel case to each of the block matrices in Z_1, Z_2 and Z_3. Specifically, we have

$$\begin{aligned} Z_3 \left(Z_3' Z_3\right)^{-} Z_3' Z_1 &= \begin{bmatrix} Z_{1,3} \left(Z_{1,3}' Z_{1,3}\right)^{-} Z_{1,3}' Z_{1,1} & & \\ & \ddots & \\ & & Z_{n^{FI},3} \left(Z_{n^{FI},3}' Z_{n^{FI},3}\right)^{-} Z_{n^{FI},3}' Z_{n^{FI},1} \end{bmatrix} \\ &= \begin{bmatrix} Z_{1,1} & & \\ & \ddots & \\ & & Z_{n^{FI},1} \end{bmatrix} = Z_1 \end{aligned} \qquad \text{(OA2-18)}$$

where the first equality uses the property of block diagonal matrices and the the second equality uses the relationship of (OA2-11). Similarly, using the property of block diagonal matrices and the firm-product level relationship (OA2-10), it is straightforward to show the following equations hold:[13]

$$Z_3 (Z_3' Z_3)^- Z_3' Z_2 (Z_2' Z_2)^{-1} Z_2' = Z_2 (Z_2' Z_2)^{-1} Z_2' Z_3 (Z_3' Z_3)^- Z_3' \tag{OA2-19}$$

$$Z_3 (Z_3' Z_3)^- Z_3' Z_2 (Z_2' Z_2)^{-1} Z_2' Z_1 = Z_2 (Z_2' Z_2)^{-1} Z_2' Z_1 \tag{OA2-20}$$

Using (OA2-18), (OA2-19) and (OA2-20), it follows that

$$\begin{aligned}
P_3 P_2 Z_1 &= [I_{n^{FIDT}} - Z_3 (Z_3' Z_3)^- Z_3'][I_{n^{FIDT}} - Z_2 (Z_2' Z_2)^{-1} Z_2']Z_1 \\
&= [I_{n^{FIDT}} - Z_2 (Z_2' Z_2)^{-1} Z_2']Z_1 - Z_3 (Z_3' Z_3)^- Z_3'[I_{n^{FIDT}} - Z_2 (Z_2' Z_2)^{-1} Z_2']Z_1 \\
&= [I_{n^{FIDT}} - Z_2 (Z_2' Z_2)^{-1} Z_2']Z_1 - [I_{n^{FIDT}} - Z_2 (Z_2' Z_2)^{-1} Z_2']Z_1 = \mathbf{0}
\end{aligned}$$

and

$$\begin{aligned}
P_3 P_2 Z_3 &= [I_{n^{FIDT}} - Z_3 (Z_3' Z_3)^- Z_3'][I_{n^{FIDT}} - Z_2 (Z_2' Z_2)^{-1} Z_2']Z_3 \\
&= [I_{n^{FIDT}} - Z_3 (Z_3' Z_3)^- Z_3']Z_3 - [I_{n^{FIDT}} - Z_3 (Z_3' Z_3)^- Z_3']Z_2 (Z_2' Z_2)^{-1} Z_2' Z_3 \\
&= \mathbf{0} - [Z_2 (Z_2' Z_2)^{-1} Z_2' Z_3 - Z_3 (Z_3' Z_3)^- Z_3' Z_2 (Z_2' Z_2)^{-1} Z_2' Z_3] = \mathbf{0}
\end{aligned}$$

□

OA2.2 The TPSFE estimator in view of the control function approach

In this subsection, we discuss how our approach relates to the classical control function approach (e.g., Heckman (1979)) and the first difference approach pursued by Kyriazidou (1997).[14] We start by rewriting the problem addressed by Heckman (1979) in his seminal work on selection in cross-sectional data. In what follows, think of p_t as the price of a product, and as a function of a

[13] It is worth noting that the modification of the projection matrix in an unbalanced panel needs to be done with extreme caution. A seemingly more general setting can, in lots of cases, result in more (rather than less) bias. Alternative demeaning or partition methods do not necessarily satisfy (OA2-19) and (OA2-20) and can potentially result in substantial biases.

[14] Our estimation approach is related to three strands of the panel data literature. The first strand focuses on estimating the parameter of interest in a panel data model with selection. Existing discussions are restricted to selection equations with one dimensional fixed effects or those that can be combined into one dimensional fixed effects (see recent handbook chapters by Verbeek and Nijman (1996), Honoré et al. (2008) and Matyas (2017) for a complete literature review). The second strand constructs methods of estimating selection equations with unobserved heterogeneity along two dimensions (e.g., Fernández-Val and Weidner (2016) and Charbonneau (2017)). Our approach differs from theirs in that we do not need to estimate the selection equation, but instead, we rely on the realized patterns to formulate a new panel dimension to address the selection problem. A few papers have examined multi-dimensional fixed effects in unbalanced panels (e.g., Wansbeek and Kapteyn (1989) and Balazsi et al. (2018)).

set of controls $\boldsymbol{x}_t'$, observed if the firm decides to enter the market:

$$\begin{aligned}
p_t &= \boldsymbol{x}_t'\boldsymbol{\beta} + \varepsilon_t \\
&= \boldsymbol{x}_t'\boldsymbol{\beta} + E(\varepsilon_t|\boldsymbol{x}_t, s_t) + \nu_t \\
s_t &= \mathbb{1}\{\boldsymbol{w}_t'\boldsymbol{\gamma} + u_t\}
\end{aligned}$$

where s_t is an indicator variable that equals one if p_t is observed; $E(\varepsilon_t|\boldsymbol{x}_t, s_t)$ is the selection bias and $\nu_t \equiv [\varepsilon_t - E(\varepsilon_t|\boldsymbol{x}_t, s_t)]$ is an error term that is uncorrelated with the vector of observed variables $\boldsymbol{x_t}$ and the selection bias. $\boldsymbol{w}_t$ is a vector of observed variables in the selection equation which can overlap with the elements in $\boldsymbol{x}_t$. As is well known, selection bias is a problem if $E(\varepsilon_t|\boldsymbol{x}_t, s_t) \neq 0$. The solution of Heckman (1979) is to estimate the function of $E(\varepsilon_t|\boldsymbol{x}_t, s_t)$ under some parametric assumptions and then add the predicted value $E(\widehat{\varepsilon_t|\boldsymbol{x}_t, s_t})$ as a control variable in the main estimating equation. The essence of this approach is to estimate the parameter of interest conditional on the probability of an observation being observed.

Closer to our problem, where the firm chooses among potential export destination markets, Kyriazidou (1997) studies selection in a two dimensional panel with one fixed effect:

$$\begin{aligned}
p_{dt} &= \boldsymbol{x}_{dt}'\boldsymbol{\beta} + \mathcal{M}_d + \varepsilon_{dt} && \text{(OA2-21)} \\
&= \boldsymbol{x}_{dt}'\boldsymbol{\beta} + \mathcal{M}_d + E(\mathcal{M}_d|\boldsymbol{x}_{dt}, s_{dt}) + E(\varepsilon_{dt}|\boldsymbol{x}_{dt}, s_{dt}) + \nu_{dt} \\
s_{dt} &= \mathbb{1}\{\boldsymbol{w}_{dt}'\boldsymbol{\gamma} + \mathcal{W}_d + u_{dt}\} && \text{(OA2-22)}
\end{aligned}$$

where $\mathcal{M}_d$ and $\mathcal{W}_d$ are unobserved variables varying along the destination d dimension (i.e. destination fixed effects). $E(\mathcal{M}_d|\boldsymbol{x}_{dt}, s_{dt})$ and $E(\varepsilon_{dt}|\boldsymbol{x}_{dt}, s_{dt})$ represent the selection biases caused by the unobserved destination-specific heterogeneity and other omitted variables, respectively. $\nu_{dt} \equiv [\varepsilon_{dt} - E(\varepsilon_{dt}|\boldsymbol{x}_{dt}, s_{dt}) - E(\mathcal{M}_d|\boldsymbol{x}_{dt}, s_{dt})]$ is an error term that is uncorrelated with the observed explanatory variables and the selection biases. p_{dt} denotes the price and s_{dt} is an indicator variable that takes a value of one if the firm exports to destination d in period t and zero otherwise.[15] Kyriazidou (1997) notes that $E(\mathcal{M}_d|\boldsymbol{x}_{dt}, s_{dt})$ and $E(\varepsilon_{dt}|\boldsymbol{x}_{dt}, s_{dt})$ no longer vary along the time dimension when $\boldsymbol{w}_{d1}'\boldsymbol{\gamma} = \boldsymbol{w}_{d2}'\boldsymbol{\gamma}$, i.e., under the following *conditional exchangeability* condition:

$$F(\varepsilon_{d1}, \varepsilon_{d2}, u_{d1}, u_{d2}|\boldsymbol{\vartheta}_d) = F(\varepsilon_{d2}, \varepsilon_{d1}, u_{d2}, u_{d1}|\boldsymbol{\vartheta}_d) \qquad \text{(OA2-23)}$$

where $\boldsymbol{\vartheta}_d \equiv (\boldsymbol{x}_{d1}, \boldsymbol{x}_{d2}, \boldsymbol{w}_{d1}, \boldsymbol{w}_{d2}, \mathcal{W}_d, \mathcal{M}_d)$ is a destination specific vector containing information on observed and unobserved variables. Condition (OA2-23) states that $(\varepsilon_{d1}, \varepsilon_{d2}, u_{d1}, u_{d2})$ and

[15] Kyriazidou (1997) discusses a case in which the number of time periods is small ($n^T = 2$). Therefore, a Heckman (1979) style estimator cannot be applied as it will suffer from the incidental parameters problem due to the limited time dimension.

$(\varepsilon_{d2}, \varepsilon_{d1}, u_{d2}, u_{d1})$ are identically distributed conditional on $\boldsymbol{\vartheta}_d$. As noted by Kyriazidou (1997), the main term causing the selection bias, $E(\varepsilon_{dt}|\boldsymbol{x}_{dt}, s_{dt})$, is no longer time-varying when $\boldsymbol{w}'_{d1}\boldsymbol{\gamma} = \boldsymbol{w}'_{d2}\boldsymbol{\gamma}$ under condition (OA2-23):

$$
\begin{aligned}
& E(\varepsilon_{d1}|s_{d1} = 1, s_{d2} = 1|\boldsymbol{\vartheta}_d) \\
\equiv\ & E(\varepsilon_{d1}|u_{d1} < \boldsymbol{w}'_{d1}\boldsymbol{\gamma} + \mathcal{W}_d, u_{d2} < \boldsymbol{w}'_{d2}\boldsymbol{\gamma} + \mathcal{W}_d, \boldsymbol{\vartheta}_d) \\
=\ & E(\varepsilon_{d1}|u_{d1} < \boldsymbol{w}'_{d2}\boldsymbol{\gamma} + \mathcal{W}_d, u_{d2} < \boldsymbol{w}'_{d1}\boldsymbol{\gamma} + \mathcal{W}_d, \boldsymbol{\vartheta}_d) \qquad \text{(OA2-24)} \\
=\ & E(\varepsilon_{d2}|u_{d2} < \boldsymbol{w}'_{d2}\boldsymbol{\gamma} + \mathcal{W}_d, u_{d1} < \boldsymbol{w}'_{d1}\boldsymbol{\gamma} + \mathcal{W}_d, \boldsymbol{\vartheta}_d) \qquad \text{(OA2-25)} \\
\equiv\ & E(\varepsilon_{d2}|s_{d2} = 1, s_{d1} = 1|\boldsymbol{\vartheta}_d)
\end{aligned}
$$

where the first equality (OA2-24) holds because $\boldsymbol{w}'_{d1}\boldsymbol{\gamma} = \boldsymbol{w}'_{d2}\boldsymbol{\gamma}$ and the second equality (OA2-25) holds because of the *conditional exchangeability* condition (OA2-23). Since the selection bias is no longer time varying, i.e., $E(\varepsilon_{d1}|s_{d1} = 1, s_{d2} = 1|\boldsymbol{\vartheta}_d) = E(\varepsilon_{d2}|s_{d2} = 1, s_{d1} = 1|\boldsymbol{\vartheta}_d)$, it can be absorbed by destination fixed effects. Kyriazidou (1997) proposes a two-step estimator: the first step consistently estimates $\widehat{\boldsymbol{\gamma}}$ and the second step differences out the fixed effect and the selection terms conditional on destinations for which $\boldsymbol{w}'_{d1}\widehat{\boldsymbol{\gamma}} = \boldsymbol{w}'_{d2}\widehat{\boldsymbol{\gamma}}$.

Our problem can be specified in (OA2-26) and (OA2-27) as follows:

$$p_{fidt} = \boldsymbol{x}'_{dt}\boldsymbol{\beta} + \mathcal{M}_{fid} + \mathcal{C}_{fit} + \varepsilon_{fidt} \qquad \text{(OA2-26)}$$

$$s_{fidt} = \mathbb{1}\{\boldsymbol{w}'_{dt}\boldsymbol{\gamma} + \mathcal{W}_{fid} + \mathcal{Q}_{fit} + u_{fidt}\} \qquad \text{(OA2-27)}$$

This problem differs from Kyriazidou (1997)'s in two crucial respects. On the one hand, our problem adds unobserved firm-product-time-varying variables $\mathcal{C}_{fit}$ to equation (OA2-21) and $\mathcal{Q}_{fit}$ to equation (OA2-22). In the presence of these time-varying unobserved factors, the *conditional exchangeablitiy* condition no longer holds. On the other hand, many aggregate-level economic indicators of interest in our study—e.g., exchange rates—vary along the destination and time dimensions, but not at the firm or product dimensions. This is actually helpful. As discussed below, the fact that key variables vary along dimensions that are a subset of the dimensions of the dependent variable facilitates the control of selection biases.

While the method we propose to address the above problem is conceptually close to Kyriazidou (1997), the approach we take is fundamentally different. Specifically, if we were to follow Kyriazidou (1997)'s approach, we would require all variables driving $\mathcal{Q}_{fit}$ to be observed and controlled for. For our purposes, however, this condition cannot be satisfied—if only because the marginal cost is unobserved and cannot be generally estimated at product-firm level. Rather, we need to rely on a method that avoids direct estimation of the selection equation and works in a multi-dimensional panel where more than one fixed effect is present in both the structural equation and the selection equation. Our main innovation is to use the realized selection pattern in a panel dimension, instead of the observed variables in the selection equation, to control for selection biases.

Before analyzing how our method addresses the general problem characterized in equations (OA2-26) and (OA2-27), we find it useful to provide insight by focusing on a two-dimensional panel, tracking the choices of a single firm selling one product across a set of endogenous destinations.

OA2.2.1 A two dimensional panel case

Consider the following for a firms' destination choices with two panel dimensions, destination d and time t:

$$p_{dt} = \boldsymbol{x}'_{dt}\boldsymbol{\beta} + \mathcal{M}_d + \mathcal{C}_t + \varepsilon_{dt} \tag{OA2-28}$$

$$s_{dt} = \mathbb{1}\{u_{dt}\} \tag{OA2-29}$$

where $\mathcal{M}_d$ and $\mathcal{C}_t$ are unobserved destination and time specific factors, respectively, which are potentially correlated with the explanatory variables contained in the vector $\boldsymbol{x}_{dt}$. The price p_{dt} is observed only if s_{dt} equals one or equivalently, if $u_{dt} > 0$.

The first two steps in our approach involve transforming the variables in (OA2-28) to eliminate the unobserved destination and time specific factors. Specifically, in the first step, we demean variables at the time (t) dimension. In the second step, we demean variables at the destination-trade pattern (dD) dimension. After applying these two transformations,

$$\ddot{p}_{dt} = \ddot{\boldsymbol{x}}'_{dt}\boldsymbol{\beta} + \ddot{\varepsilon}_{dt}$$

where

$$\ddot{\boldsymbol{x}}_{dt} = \boldsymbol{x}_{dt} - \frac{1}{n_t^D}\sum_{d\in D_t}\boldsymbol{x}_{dt} - \frac{1}{n_{dD}^T}\sum_{t\in T_{dD}}\boldsymbol{x}_{dt} + \frac{1}{n_{dD}^T}\sum_{t\in T_{dD}}\frac{1}{n_t^D}\sum_{d\in D_t}\boldsymbol{x}_{dt} \tag{OA2-30}$$

$$\ddot{\varepsilon}_{dt} = \varepsilon_{dt} - \frac{1}{n_t^D}\sum_{d\in D_t}\varepsilon_{dt} - \frac{1}{n_{dD}^T}\sum_{t\in T_{dD}}\varepsilon_{dt} + \frac{1}{n_{dD}^T}\sum_{t\in T_{dD}}\frac{1}{n_t^D}\sum_{d\in D_t}\varepsilon_{dt}, \tag{OA2-31}$$

D_t is the set of destinations the firm serves at time t; and $n_t^D \equiv |D_t|$ the number of export destinations at time t. Similarly, T_{dD} denotes the set of time periods in which a destination-specific trade pattern dD is observed, and n_{dD}^T represents the corresponding number of time periods in which the destination-specific trade pattern emerges. For our proposed approach to work in a two dimensional panel, we need[16]

$$F(\varepsilon_{dD1}, \varepsilon_{dD2}, u_{dD1}, u_{dD2}|\boldsymbol{\vartheta}_{dD}) = F(\varepsilon_{dD2}, \varepsilon_{dD1}, u_{dD2}, u_{dD1}|\boldsymbol{\vartheta}_{dD}), \tag{OA2-33}$$

where we use ε_{dD1} to indicate the first error within the destination-specific trade pattern dD. Given (OA2-33), it is straightforward to see that the selection bias can be differenced out over two time periods within a destination-specific trade pattern dD, since the following relationship holds:

$$E\left(\varepsilon_{dDt}|u_{dD1} > 0, u_{dD2} > 0, \boldsymbol{\vartheta}_{dD}\right) = E\left(\varepsilon_{dD\tau}|u_{dD1} > 0, u_{dD2} > 0, \boldsymbol{\vartheta}_{dD}\right) \quad \forall \tau \in T_{dD} \tag{OA2-34}$$

Condition (OA2-33) can be viewed as the analog of the *conditional exchangeability* assumption imposed by Kyriazidou (1997). Instead of controlling for the relationship among the observed variables in the selection process (i.e., $\boldsymbol{w}'_{d1}\boldsymbol{\gamma} = \boldsymbol{w}'_{d2}\boldsymbol{\gamma}$), we control for the realised patterns of selection in a panel dimension (i.e., the pattern of d conditional on t). That is, as long as the distribution of errors is the same for all time periods satisfying a destination-specific trade pattern dD, our approach produces unbiased and consistent estimates.[17]

OA2.2.2 General setting

We now discuss the general multi-dimensional setting specified in (OA2-26) and (OA2-27). With an additional dimension,[18] we can write the condition for identification as follows:

$$E\left[E\left(\varepsilon_{fidDt}|\mathbf{s}_{fidD}, \boldsymbol{\vartheta}_{fidD}\right)\Big|dt\right] = E\left[E\left(\varepsilon_{fidD\tau}|\mathbf{s}_{fidD}, \boldsymbol{\vartheta}_{fidD}\right)\Big|dt\right] \quad \forall\, \tau \in T_{fidD} \tag{OA2-35}$$

where $\mathbf{s}_{fidD} \equiv (\boldsymbol{w}'_{d1}\boldsymbol{\gamma} + \mathcal{W}_{fid} + \mathcal{Q}_{if1} + u_{fidD1} > 0, ..., \boldsymbol{w}'_{dn^T_{fidD}}\boldsymbol{\gamma} + \mathcal{W}_{fid} + \mathcal{Q}_{ifn^T_{fidD}} + u_{fidDn^T_{fidD}} > 0)$, $\boldsymbol{\vartheta}_{fidD} \equiv (\boldsymbol{x}_{dD1}, ..., \boldsymbol{x}_{dDn^T_{fidD}}, \boldsymbol{w}_{dD1}, ..., \boldsymbol{w}_{dDn^T_{fidD}}, \mathcal{W}_{fid}, \mathcal{M}_{fid})$ and $E(.|dt)$ means taking the expectation over the firm (f) and product (i) panel dimensions while keeping the destination and time panel dimensions fixed.

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[16]Note that Kyriazidou (1997)'s original conditions (and proofs) only cover the case when the number of time periods is equal to two. For a more general case with more than two time periods, we impose a condition:

$$E\left(\varepsilon_{dDt}|u_{dD1} > 0, ..., u_{dDn^T_{dD}} > 0, \vartheta_{dD}\right) = E\left(\varepsilon_{dD\tau}|u_{dD1} > 0, ..., u_{dDn^T_{dD}} > 0, \vartheta_{dD}\right) \quad \forall \tau \in T_{dD} \tag{OA2-32}$$

As will be discussed later, our estimator works under a much weaker condition than (OA2-32) if another panel dimension is available.

[17]The condition for consistency, i.e., $E(s_{dt}\ddot{\boldsymbol{x}}_{dt}\ddot{\varepsilon}_{dt}) = 0$, is satisfied under (OA2-32). First, note that $\frac{1}{n^D_t}\sum_{d\in D_t}\varepsilon_{dt} - \frac{1}{n^T_{dD}}\sum_{t\in T_{dD}}\frac{1}{n^D_t}\sum_{d\in D_t}\varepsilon_{dt} = 0$. This is because the expression $\frac{1}{n^D_t}\sum_{d\in D_t}\varepsilon_{dt}$ is moving at the dD dimension only. As there is no variation left after conditioning on the dD dimension, the demeaning process naturally gives zero. Second, demeaning conditional on the same trade pattern is zero under assumption (OA2-32), i.e., $E\left(\varepsilon_{dt} - \frac{1}{n^T_{dD}}\sum_{t\in T_{dD}}\varepsilon_{dt}\Big|s_{dD1}, s_{dD2}, s_{dD3}, ..., \vartheta_{dD}\right) = 0$.

[18]In the following discussions, we consider firm and product as one combined panel dimension fi.

As can be seen from (OA2-35), we no longer need the error to be zero conditional on the observed pattern ($E(\varepsilon_{fidDt} - \varepsilon_{fidD\tau}|\mathbf{s}_{fidD}, \boldsymbol{\vartheta}_{fidD}) = 0$) as in the two dimensional case. Instead, it is sufficient to have the expectation of $E(\varepsilon_{fidDt} - \varepsilon_{fidD\tau}|\mathbf{s}_{fidD}, \boldsymbol{\vartheta}_{fidD})$ be zero, once it is aggregated at the firm and product dimension. For example, if $E(\varepsilon_{fidDt} - \varepsilon_{fidD\tau}|\mathbf{s}_{fidD}, \boldsymbol{\vartheta}_{fidD})$ consists of random errors for each firm and product, the mean of these random errors converges to zero when the number of firm-product pairs increases.

We now show that our proposed approach gives unbiased estimates under condition (OA2-35). Let $v_{fidt} \equiv \mathcal{M}_{fid} + \mathcal{C}_{fit} + \varepsilon_{fidt}$. The underlying independent variables and the error term under our estimation approach can be written as

$$\ddot{\boldsymbol{x}}_{fidt} = \boldsymbol{x}_{dt} - \frac{1}{n^D_{fit}} \sum_{d \in D_{fit}} \boldsymbol{x}_{dt} - \frac{1}{n^T_{fidD}} \sum_{t \in T_{fidD}} \boldsymbol{x}_{dt} + \frac{1}{n^T_{fidD}} \sum_{t \in T_{fidD}} \frac{1}{n^D_{fit}} \sum_{d \in D_{fit}} \boldsymbol{x}_{dt} \tag{OA2-36}$$

$$\ddot{v}_{fidt} = v_{fidt} - \frac{1}{n^D_{fit}} \sum_{d \in D_{fit}} v_{fidt} - \frac{1}{n^T_{fidD}} \sum_{t \in T_{fidD}} v_{fidt} + \frac{1}{n^T_{fidD}} \sum_{t \in T_{fidD}} \frac{1}{n^D_{fit}} \sum_{d \in D_{fit}} v_{fidt}. \tag{OA2-37}$$

The independent variable of interest now varies along four dimensions because it embodies selection that varies across firms and products, even if the variable is specified for only two dimensions, i.e., $\boldsymbol{x}_{dt}$ or e_{dt}.

Note that the exchange rate depends on the firm and product dimensions only through trade and time patterns. To see this, it is useful to rewrite the variables in expressions (OA2-36) and (OA2-37) in terms of their corresponding variability:

$$\begin{aligned}
\ddot{\boldsymbol{x}}_{fidt} &= \boldsymbol{x}_{dt} - \boldsymbol{x}_{Dt} - \boldsymbol{x}_{dT} + \boldsymbol{x}_{DT} \\
\ddot{v}_{fidt} &= v_{fidt} - v_{fiDt} - v_{fidT} + v_{fiDT} \\
&= \varepsilon_{fidt} - \varepsilon_{fiDt} - \varepsilon_{fidT} + \varepsilon_{fiDT} \\
&= \ddot{\varepsilon}_{fidt}.
\end{aligned}$$

Rearranging these expressions, we can show that our main variables of interest $\boldsymbol{x}$ (including exchange rates) in the following expression no longer depend on firm and product dimensions:

$$\frac{1}{n^{FIDT}} \sum_{fidt} \ddot{\varepsilon}_{fidt} \ddot{\boldsymbol{x}}_{fidt} = \frac{1}{n^{FIDT}} \sum_{fidt} (\varepsilon_{fidt} - \varepsilon_{fiDt} - \varepsilon_{fidT} + \varepsilon_{fiDT}) \boldsymbol{x}_{dt} \tag{OA2-38}$$

$$= \frac{1}{n^{FIDT}} \sum_{fidt} (\varepsilon_{fidt} - \varepsilon_{fidT}) \boldsymbol{x}_{dt}. \tag{OA2-39}$$

As a result, the identification condition, $E(\ddot{\varepsilon}_{fidt}\ddot{\boldsymbol{x}}_{fidt}s_{fidt}) = 0$, can be rewritten as

$$
\begin{aligned}
& E(\ddot{\varepsilon}_{fidt}\ddot{\boldsymbol{x}}_{fidt}s_{fidt}) \\
&= E\left[(\varepsilon_{fidt} - \varepsilon_{fidT})\boldsymbol{x}_{dt}s_{fidt}\right] \\
&= E\left\{\boldsymbol{x}_{dt}E\left[E\left(\varepsilon_{fidt} - \varepsilon_{fidT}|\mathbf{s}_{fidD}, \boldsymbol{\vartheta}_{fidD}\right)\Big|dt\right]\right\} \\
&= E\left\{\boldsymbol{x}_{dt}E\left[E\left(\varepsilon_{fidDt} - \frac{1}{n^T_{fidD}}\sum_{\tau\in T_{fidD}}\varepsilon_{fidD\tau}|\mathbf{s}_{fidD}, \boldsymbol{\vartheta}_{fidD}\right)\Big|dt\right]\right\} \\
&= 0
\end{aligned}
\tag{OA2-40}
$$

where the first equality follows from using (OA2-39) under our proposed "within transformation"; the second equality from applying the law of iterated expectations; and the last equality from using condition (OA2-35).

Two remarks are in order to clarify the implications of our identification condition and place our approach in the literature. First, note that the condition (OA2-35) is trivially satisfied if ε is always zero. For example, if goods sold to different destinations by the same firm under the same product category are identical, the marginal cost is only firm-product-time specific and therefore absorbed by $\mathcal{C}_{fit}$, leaving no additional residual term. It is worth stressing that the maintained assumption that marginal costs are non-destination-specific is implicit in studies aimed at estimating productivity (as these do not try to distinguish the marginal cost at the destination level)—see, e.g., Olley and Pakes (1996), Levinsohn and Petrin (2003), Wooldridge (2009) and De Loecker et al. (2016).

Second, an important instance in which condition (OA2-35) is satisfied is when the distribution of the destination-specific component does not change over time, e.g., when the composition of shipments is such that high quality varieties of a product are consistently sold to high-income destinations. From this perspective, the condition clarifies that the existence of destination-specific marginal cost components in ε does not automatically lead to a violation of identification.

OA2.3 The TPSFE estimator relative to De Loecker et al. (2016)

In this subsection, we extend the framework of De Loecker et al. (2016) to add a destination dimension, and discuss the structural assumptions that would be required for our main identification condition (OA2-35) to be satisfied in this new framework. Our empirical approach has been developed for application to large, four-dimensional (firm-product-destination-time) unbalanced customs databases that cover the universe of firm and product-level export records for a country. Recent studies (Berman et al. 2012; Amiti et al. 2014) have identified marginal costs and markups at the firm level using production function estimation approaches. De Loecker et al. (2016) demonstrates that if detailed information on both quantities of outputs and inputs is available, it is possible to estimate firm-product level marginal costs, assuming that the production functions of multi-product firms resemble those of single-product firms. However, Orr et al. (2024) highlights that the approach by De Loecker et al. (2016) tends to generate an unusually large proportion of markups below one, arguing that precisely identifying firm-product markups using production function estimation approaches is challenging, and that only firm-level markups are reliably identifiable. Our method, rather than attempting to recover the level of markups at the firm-product-destination level, estimates *adjustments of markups* at the firm-product-destination level to bilateral exchange rates, while accounting for the endogenous selection of destination markets. A key advantage of our methodology is its lower data requirements and broader applicability to standard customs datasets.

OA2.3.1 Structural interpretation of assumptions required by our estimator

We start by writing the production function as follows:

$$Q_{fidt} = F_{fi}(\boldsymbol{V}_{fidt}, \boldsymbol{K}_{fidt})\Omega_{fit}\vartheta_{fid} \tag{OA2-41}$$

where Q_{fidt} represents the quantity of exports for product i from firm f to destination d at time t; $\boldsymbol{V}_{fidt}$ denotes a vector of variable inputs, $\{V^1_{fidt}, V^2_{fidt}, ..., V^v_{fidt}\}$; $\boldsymbol{K}_{fidt}$ denotes a vector of dynamic inputs; a firm-product pair make decisions on allocating its dynamic inputs across destinations in each time period, $\{K^1_{fidt}, K^2_{fidt}, ..., K^k_{fidt}\}$. We stress that the above function allows for destination-specific inputs $\{\boldsymbol{V}_{fidt}, \boldsymbol{K}_{fidt}\}$ as well as destination-specific productivity differences, ϑ_{fid}, at the firm and product level. In addition, we allow for the production function and Hicks-neutral productivity to be firm-product specific.

Specifically, we posit the following:

1. The production technology is firm-product-specific.

2. $F_{fi}(.)$ is continuous and twice differentiable w.r.t. at least one element of V_{fidt}, and this element of V_{fidt} is a static (i.e., freely adjustable or variable) input in the production of product i.

3. $F_{fi}(.)$ is constant return to scale.

4. Hicks-neutral productivity Ω_{fit} is log-additive.

5. The destination-specific technology advantage ϑ_{fid} takes a log-additive form and is not time varying.

6. Input prices $\boldsymbol{W}_{fit}$ are firm-product-time specific.

7. The state variables of the firm are

$$\boldsymbol{s}_{fit} = \{D_{fit}, \boldsymbol{K}_{fit}, \Omega_{fit}, \vartheta_{fid}, \boldsymbol{G}_{fi}, \boldsymbol{r}_{fidt}\} \tag{OA2-42}$$

   where $\boldsymbol{G}_{fi}$ includes variables indicating firm and product properties, e.g., firm registration types, product differentiation indicators. $\boldsymbol{r}_{fidt}$ collects other observables including variables that track the destination market conditions, such as the bilateral exchange rate and destination CPI.

8. Firms minimize short-run costs taking output quantity, Q_{fidt}, and input prices, $\boldsymbol{W}_{fit}$, at time t as given.

The assumptions 1, 2, 4, 8 are standard in the literature. De Loecker et al. (2016) also posit them, but in our version we allow the production function to be firm specific and the Hicks-neutral productivity to be product-specific. Compared to the conditions assumed in the literature, assumption 5 is a relaxation: it allows for the possibility that (log-additive) productivity be destination-specific. This admits the possibility that a firm has destination-specific marginal costs in producing a product, capturing the idea that different locations might purchase different variants of a product that use, for example, different inputs.

Assumptions 6 and 7 allow prices of inputs to be firm and product specific. These two conditions indicate that firms source inputs at the product level, and then allocate these inputs into production for different destinations. Note that the firm can arrange different quantities of inputs and have different marginal costs across destinations for the same product.

The assumption that is crucial to our identification is that the production technology is constant returns to scale (condition 3). This condition implies that the marginal cost at the firm-product-destination level does not depend on the quantity produced. If changes in relative demand and exports across destinations were systematically associated with changes in relative marginal costs, condition (OA2-35) would be violated. As discussed in the next subsection, looking at the solution to the firms' cost minimization problem, condition 3 ensures that the difference in the marginal costs across destinations only reflects technology differences varying at the destination dimension.

OA2.3.2 The cost minimization problem by firm-product pair

Write the cost function

$$\mathcal{L}(\boldsymbol{V}_{fidt}, \boldsymbol{K}_{fidt}, \lambda_{fidt}) = \sum_{v=1}^{V} W_{fit}^{v} \sum_{d\in D_{fit}} V_{fidt}^{v} + \sum_{k=1}^{K} R_{fit}^{k} \left(\sum_{d\in D_{fit}} K_{fidt}^{k} - K_{fit}^{k} \right) + \sum_{d\in D_{fit}} \lambda_{fidt}[Q_{fidt} - F_{fi}(\boldsymbol{V}_{fidt}, \boldsymbol{K}_{fidt})\Omega_{fit}\vartheta_{fid}]$$

where K_{fit}^{k} is the accumulated capital input k in the previous period; K_{fidt}^{k} stands for the corresponding allocation for destination d; R_{fit}^{k} is the implied cost of capital.[19]

The F.O.C.s of the cost minimization problem are

$$\frac{\partial \mathcal{L}_{fit}}{\partial V_{fidt}^{v}} = W_{fit}^{v} - \lambda_{fidt}\Omega_{fit}\vartheta_{fid}\frac{\partial F_{fi}(.)}{\partial V_{fidt}^{v}} = 0, \tag{OA2-43}$$

$$\frac{\partial \mathcal{L}_{fit}}{\partial K_{fidt}^{k}} = R_{fit}^{k} - \lambda_{fidt}\Omega_{fit}\vartheta_{fid}\frac{\partial F_{fi}(.)}{\partial K_{fidt}^{k}} = 0. \tag{OA2-44}$$

Conditions (OA2-43) and (OA2-44) need to hold across inputs and across destinations, which implies the following:

$$\frac{W_{fit}^{1}}{W_{fit}^{v}} = \frac{\frac{\partial F_{fi}(.)}{\partial V_{fi1t}^{1}}}{\frac{\partial F_{fi}(.)}{\partial V_{fi1t}^{v}}} = \frac{\frac{\partial F_{fi}(.)}{\partial V_{fi2t}^{1}}}{\frac{\partial F_{fi}(.)}{\partial V_{fi2t}^{v}}} = ... = \frac{\frac{\partial F_{fi}(.)}{\partial V_{fidt}^{1}}}{\frac{\partial F_{fi}(.)}{\partial V_{fidt}^{v}}} \qquad \forall v = 1, ..., V; \quad d \in D_{fit}, \tag{OA2-45}$$

$$\frac{W_{fit}^{v}}{R_{fit}^{k}} = \frac{\frac{\partial F_{fi}(.)}{\partial V_{f,i,1,t}^{v}}}{\frac{\partial F_{fi}(.)}{\partial K_{fi1t}^{k}}} = \frac{\frac{\partial F_{fi}(.)}{\partial V_{fi2t}^{v}}}{\frac{\partial F_{fi}(.)}{\partial K_{fi2t}^{k}}} = ... = \frac{\frac{\partial F_{fi}(.)}{\partial V_{fidt}^{v}}}{\frac{\partial F_{fi}(.)}{\partial K_{fidt}^{k}}} \qquad \forall v, k; \quad d \in D_{fit}. \tag{OA2-46}$$

Note that the production function is assumed to be firm-product specific and constant return to scale. Together with equations (OA2-45) and (OA2-46), these assumptions imply that the allocation of variable inputs is inversely proportional to the ratio of the productivity-deflated outputs across destinations, i.e.,

$$\frac{Q_{fidt}}{\Omega_{fit}\vartheta_{fid}} = c \cdot \frac{Q_{fid't}}{\Omega_{fit}\vartheta_{fid'}} \quad \rightarrow \quad c\boldsymbol{V}_{fidt}^{*} = \boldsymbol{V}_{fid't}^{*} \quad \text{and} \quad c\boldsymbol{K}_{fidt}^{*} = \boldsymbol{K}_{fid't}^{*}. \tag{OA2-47}$$

Utilizing the relationship of (OA2-47) and the assumption that $F_{fi}(.)$ is constant return to scale,

[19] The assumption that the production function $F_{fi}(.)$ is firm-product-specific ensures the implied cost of capital R_{fit}^{k} is not destination-specific.

it is straightforward to see

$$\frac{\partial F_{fi}(\boldsymbol{V}^*_{fidt}, \boldsymbol{K}^*_{fidt})}{\partial V^v_{fidt}} = \frac{\partial F_{fi}(c\boldsymbol{V}^*_{fidt}, c\boldsymbol{K}^*_{fidt})}{\partial (cV^v_{fidt})} = \frac{\partial F_{fi}(\boldsymbol{V}^*_{fid't}, \boldsymbol{K}^*_{fid't})}{\partial V^v_{fid't}}. \tag{OA2-48}$$

Rearranging (OA2-43) and (OA2-48) yields:

$$\begin{aligned} \lambda_{fidt} &= \left(\frac{\Omega_{fit}\vartheta_{fid}}{W^v_{fit}} \frac{\partial F_{fi}(\boldsymbol{V}^*_{fidt}, \boldsymbol{K}^*_{fidt})}{\partial V^v_{fidt}} \right)^{-1} \\ &= \left(\frac{\Omega_{fit}\vartheta_{fid}}{W^v_{fit}} \frac{\partial F_{fi}(\boldsymbol{V}^*_{fid't}, \boldsymbol{K}^*_{fid't})}{\partial V^v_{fid't}} \right)^{-1}. \end{aligned} \tag{OA2-49}$$

Therefore, the relative marginal cost across destinations is static, depending on the relative productivity difference across destinations, i.e.,

$$\frac{\lambda_{fidt}}{\lambda_{fid't}} = \frac{\vartheta_{fid'}}{\vartheta_{fid}} \tag{OA2-50}$$

Although the marginal cost is firm-product-destination specific and time-varying, the relative marginal cost is not. Therefore, condition (OA2-35), the identification condition of the TPSFE estimator, is satisfied.

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