Markets and Markups:

A New Empirical Framework and Evidence on Exporters from China

Giancarlo Corsetti
European University Institute and CEPR

Meredith Crowley
University of Cambridge and CEPR

Lu Han*
Bank of Canada and CEPR

Huasheng Song
Zhejiang University

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Abstract

Firms that dominate global trade export to multiple countries and frequently change their foreign destinations. We develop a new empirical framework for analysing markup elasticities to the exchange rate in this environment. The framework embodies a new estimator of these elasticities that controls for endogenous market participation and a new classification of products based on Chinese linguistics to proxy for firms' power in local markets. Applying this framework to Chinese customs data, we document significant pricing-to-market for highly differentiated goods. Measured in the importer's currency, the prices of highly differentiated goods are far more stable than those of less differentiated products.

JEL classification: F31, F41, F14

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

*Corresponding author: Bank of Canada, 234 Wellington Street West, Ottawa, Ontario, Canada, K1A 0G9. Email: hanlulong@gmail.com

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1 Introduction

Firms that export to more than one country account for the lion's share of cross-border trade. Serving multiple markets, these firms face demand conditions and costs shocks that may be specific to an export destination and are inherently time-varying. From the perspective of an exporter, a changing local economic environment systematically creates opportunities to raise profits, or induces the need to contain losses, through destination-specific adjustment of export prices, i.e., by engaging in pricing-to-market (see, e.g., Krugman (1986), Dornbusch (1987), Goldberg and Knetter (1997) and, for a recent reconsideration, Burstein and Gopinath (2014)).[1]

The increasing availability of high-dimensional administrative customs databases has provided a wealth of new insights about the pricing behavior of exporters, stressing that larger, more highly productive firms adjust markups more (see, e.g., Berman, Martin and Mayer (2012), Chatterjee, Dix-Carneiro and Vichyanond (2013), Fitzgerald and Haller (2014), De Loecker et al. (2016), Amiti, Itskhoki and Konings (2014, 2019, 2020)). This literature has broken new ground in documenting significant heterogeneity in markups and markup elasticities across firms by directly employing estimates of the firm's (unobservable) productivity and marginal costs, or by indirectly controlling for unobservables with fixed effects. At the same time, the wealth of information on prices at the firm, product, and market level offers new opportunities for methodological innovations to control for unobservable determinants of pricing, as well as for investigating heterogeneity in pricing behaviour along new dimensions.

In this paper, we build an empirical framework for analyzing the local or destination-specific markup adjustments of multi-destination exporters in administrative datasets that report product exports by firms, and we provide new evidence on pricing behavior of exporters from China. Our contribution is threefold.

On methodological grounds, we contribute an estimator and a new product classification that, together, substantially improve the analysis of pricing-to-market behaviour. 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 firm's unobservable marginal production costs for a product, *while* accounting for endogenous market participation. The approach builds on the seminal work of Knetter (1989), which identifies pricing-to-market from cross-market differences in industry-level average prices in a balanced panel of industry-level export unit values. At the micro level, however, the set of markets in which firms

[1] Pricing-to-market is a standard feature in open macro models, which increasingly feature firm dynamics and competition (see, e.g., Bergin and Feenstra (2001) and Atkeson and Burstein (2008)), vertical interactions of exporters with local producers and distributors (see, e.g., Corsetti and Dedola (2005)), and nominal rigidities in either local or a third-country vehicle currency (Corsetti, Dedola and Leduc (2008), Gopinath (2015) and Gopinath et al. (2020)).

operate in each period (i.e., the firm's product-level "trade pattern") varies endogenously with unobservable changes in production costs and local demand. Any panel of product trade by firms is endogenously unbalanced. Controlling for a firm's time-varying set of destination markets for individual products is necessary to ensure that the estimated markup elasticity is identified.[2]

Our second contribution builds on the observation that the intensity of competition among firms varies not only with local market structure, but also systematically across different types of globally-traded products. We exploit information contained in Chinese customs records—specifically, Chinese linguistic particles that reflect a good's physical attributes and act as measures for numbers of items—to construct a comprehensive, general, and exogenous product classification that distinguishes between goods with high versus low degrees of differentiation. A key advantage of our classification is that it divides the large class of differentiated goods obtained by following the approach of Rauch (1999) into two large subgroups. These subgroups, of high- and low-differentiation products, can then be combined with other criteria (e.g., firm size) and classifications (e.g., functional end-use of a product) to further refine trade data into smaller groups according to the (potential) market power of firms over their products.[3]

Finally, on empirical grounds, we use our TPSFE estimator in conjunction with our new product classification as a refined proxy for market power, to identify markup responses to the exchange rate by exporters from China. Our analysis documents extensive pricing-to-market and significant heterogeneity in pricing behavior across firms and product types, especially after China abandoned the strict peg to the dollar in 2005. Against a 10% appreciation of the renminbi, we find Chinese exporters raise their markups between 1.4% and 3.2% for highly differentiated goods, depending on the firm size and type—large firms and firms with complex corporate structures such as State-Owned or Foreign-Invested Enterprises adjust markups at least twice as much as private firms. Conversely, the estimated markup elasticities for low differentiation products are much lower and typically remain close to zero. This means that exporting firms respond to bilateral currency

[2]Our framework has been specifically developed for application to large, four-dimensional (firm-product-destination-time) unbalanced *customs databases* which cover the universe of firm and product level export records for a country. Recent papers (Berman, Martin and Mayer (2012), Amiti, Itskhoki and Konings (2014), and De Loecker et al. (2016)) have proposed different methodologies aimed at identifying marginal costs and markups, using detailed information on production and costs, including prices and costs of domestic and imported inputs. An advantage of these methodologies over our analysis is that they provide estimates of the overall *level* of markups. An advantage specific to our methodology, however, is a much lower data requirement and a larger range of applicability to standard customs datasets. We obviously see strong complementaries and high potential gains from combining methodologies and cross checking results.

[3]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.

fluctuations by keeping the prices of highly differentiated goods measured in *local currency* far more stable than the prices of less differentiated products; in our study exchange rate pass through into import prices is far lower for more highly differentiated goods.

As an internal check on our framework, we show how our results can be used to estimate the market-specific responsiveness of quantities to currency fluctuations, employing a two-stage procedure. In the first stage, we estimate the predicted changes in relative markups that stem from movements in relative exchange rates using our TPSFE estimator; in the second stage, we regress changes in relative quantities across destinations on the predicted relative markup changes and other aggregate control variables, conditional on firms' product-level trade patterns. Since our estimator differences out common supply factors, the second stage measures the degree to which the quantity supplied responds to shifts in relative profitability across destinations due to changes in relative markups (which, in turn, arise from differences in local factors which shift the relative demand curve). We refer to this measure as the cross market demand elasticity (CMDE). Consistent with our pricing results, we find substantial differences in the cross-market demand elasticities across types of goods and firms. The gap in CMDEs between consumption goods and intermediates is very large, 0.72 vs 2.72. When further disaggregated under our product classification, the gap between estimates opens to a chasm—the CMDE of highly differentiated consumption goods, 0.16, suggests an extreme amount of market segmentation. The CMDE for less differentiated intermediates, 3.84, suggests something much closer to an integrated world market.

Our estimation dataset features the universe of exporters from China and provides annual export data by firm, product, and destination over 2000-2014. This period includes both the last years of the dollar-peg regime (2000-2005) and the early years of the more relaxed managed float (2006-2014). 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.[4] Because exports to the US were subject to two different exchange rate regimes during our sample period, we exclude exports to the US in order to obtain a comparable sample of countries over the full sample period.[5] The final estimation dataset consists of over 200,000 multi-destination exporters, around 8,000 HS08 products, and 152 foreign markets over 15 years.

We close with a model-based analysis of pricing-to-market, providing theoretical guidance on whether and how markup elasticities estimated from large customs databases may be plagued by omitted variable and selection biases, and highlighting the direction of these biases. This last section includes a comparative assessment of fixed effect estimators employed in the literature,

[4]See our online supplementary material SM1.6 for evidence on dollar invoicing.

[5]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.

discussing their performance in the presence of various demand and cost shocks. Overall, an important conclusion is that appropriately specified and sufficiently strict fixed effect estimators, such as our TPSFE estimator, can reduce (and even eliminate) biases due to incomplete information on relevant variables. An exercise comparing results from different estimators on model-simulated data documents that failing to properly account for granular demand and supply shocks can severely bias markup elasticities.

In addition to the contributions referred to above, our paper is also closely related to the literature that examines the effects of extensive margin adjustments of aggregate, product- and firm-level exports on trade elasticities and exchange rate pass through (Chaney (2008, 2014), Helpman, Melitz and Rubinstein (2008), Auer and Chaney (2009), Nakamura and Steinsson (2012), Bas, Mayer and Thoenig (2017) and Fitzgerald and Haller (2018)) as well as studies assessing how Chinese firms respond to changes in foreign trade policy (Khandelwal, Schott and Wei (2013), Crowley, Meng and Song (2018)) and exchange rates (Li, Ma and Xu (2015), Dai and Xu (2017)). Our paper naturally complements the empirical study by Manova and Zhang (2012), who establish a set of stylized facts on exporters from China, highlighting that prices systematically differ across countries, a finding that suggests destination-specific variation in demand and costs may influence firms' price-setting.

The rest of the paper is organized as follows. Section 2 discusses our identification strategy and presents our new TPSFE estimator. Section 3 introduces our product classification and discusses its properties relative to alternative classifications. Section 4 presents the Chinese customs data. Section 5 discusses our empirical results. Section 6 carries out a model-based analysis of biases that potentially plague studies of pricing to market. Section 7 concludes.

2 Identification Strategy: A New Trade Pattern Fixed Effect Estimator

Our identification strategy builds on the insight of Knetter (1989) that, in a panel regression of prices of a product sold by a firm in different destination markets, a time dummy can proxy for the unobserved marginal cost of a product. Hence, the markup elasticity to the exchange rate can be identified from a regression of changes in price residuals across markets on changes in relative exchange rate differences across markets. There are two key advantages to this identification strategy. First, it does not rely on structural assumptions about demand or production functions.[6]

[6] For example, the Goldberg and Hellerstein (2013) approach to estimate the degree of pricing-to-market rests on maintained assumptions about the underlying demand systems. Recent productivity estimation approaches, such as De Loecker et al. (2016), require strong assumptions on the production structure. We discuss in online Appendix OA1.3 how our estimator will achieve the same unbiased estimate of the markup elasticity to exchange rates under

Second, it does not require detailed firm *and* product-level cost information to estimate markups.[7]

However, developing an estimator that applies Knetter's insight to large customs database faces a critical challenge. The set of destination markets served by a firm with a product is volatile:[8] regressing relative prices (of the same firm's product across markets) on relative exchange rates (across markets) while ignoring the endogenous market selection decisions of firms can lead to severe biases. Our methodological contribution is a fixed effects estimator that can reduce and in many cases eliminate such bias. The underlying idea is that a firm's realized selection of markets (its "trade patterns") conveys useful information about the unobservable factors that drive the selection process. By controlling for these patterns, we restrict the variation of unobservables that drive market selection and, effectively, identify the markup elasticity after conditioning upon similar values for unobservable variables.

In this section, we present our estimator, including its basic features, the intuition for how it works, and an easily implementable procedure for use in large, unbalanced micro datasets. We delegate a detailed analysis of the econometric properties of our estimator and all proofs to online Appendix OA1.

2.1 The trade patterns of a firm's product sales: stylized facts

A key feature of international trade data at the level of products sold by firms is that the set of foreign markets reached by an exporting firm changes frequently over time, but specific sets of markets in which the firm sells a given product repeat with some regularity. To introduce concepts that we will use extensively in our study, we present a stylized example in Figure 1. This figure shows different combinations of three markets, A B and C, in which an exporter sells a product over a five-year span. Empty elements indicate that there is no trade in the year. We define the set of markets active at a firm-product level in one period as a *trade pattern*. In our example, the firm has three *unique* trade patterns, A-B, A-C, A-B-C over the course of its five year trade in that product. Notably, however, two of this firm's product-level trade patterns repeat. The pattern A-C repeats in periods 2 and 4; A-B-C repeats in periods 3 and 5.

Using this definition, we can turn to the evidence on trade patterns from the Chinese Customs Database, which is described in detail in Section 4. Table 1 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-

De Loecker et al. (2016)'s structural assumptions.

[7]For example, to estimate *firm and product-level* markups, the De Loecker et al. (2016) approach requires detailed *firm and product-level* balance sheet data which is not available for most countries.

[8]See, e.g., Albornoz et al. (2012), Timoshenko (2015), Araujo, Mion and Ornelas (2016), Fitzgerald, Haller and Yedid-Levi (2016), Ruhl and Willis (2017), Geishecker, Schröder and Sørensen (2019) and Han (2021) for evidence on the variability of firms' product-level trade patterns.

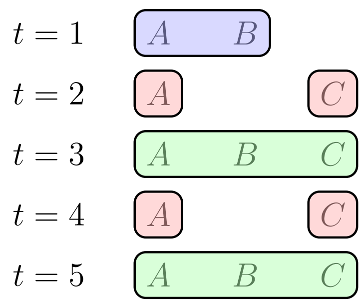

Figure 1: Example of an observed trade pattern

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.

Table 1: Number of Unique Trade Patterns

	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.

2.2 A new estimator explicitly controlling for firm-product level trade patterns

As is well understood, the fundamental reason that omitted variable and selection biases arise is missing information on key variables. Once the variation of these unobservable variables is properly controlled for, both omitted variable and selection biases disappear. In large customs databases with four panel dimensions (i.e., firm$f$, product i, destination d, and time t), fixed effects provide a rich tool to control for unobserved, confounding variables.

However,controlling for variation in unobserved variables that vary along *multiple panel dimensions* is a non-trivial task. The key difficulty is in designing partition matrices that can account for the unbalanced panel structure and eliminate the effect of the unobserved confounding variables.[9] At the core of our identification strategy is the recognition that the time-varying patterns of market participation are informative about economically relevant but unobservable factors that drive exporters' trade strategies. Returning to our example in Figure 1, a plausible hypothesis is that the time-varying unobservables (in demand and production costs) that drive a firm to sell to destinations A and C in periods 2 and 4 are very similar to each other; and that time variation in these unobservables may also drive the firm's choice of destinations A, B and C in period 3 and 5.

Intuitively, by constructing a fixed effect that controls for a destination market d *when it appears as part of a larger trade pattern*, indexed D, one can restrict the comparison of observations to circumstances in which the underlying time-varying unobservables take similar values.[10] This fixed effect restricts the analysis of price and exchange rate variation by comparing observations for a destination conditional on the same (repeated) trade patterns, and thus allows us to construct a difference-in-difference estimator that offers a potentially stronger control in unbalanced panels, compared to alternatives, by effectively limiting the variation of unobserved confounding factors.

Our estimator can address all omitted variable and selection biases that arise from variables varying along the firm-product-destination-trade pattern ($fidD$) and firm-product-time (fit) panel dimensions. Economically, consider the case in which the unobserved marginal cost of a firm's product varies along the fit panel dimensions, while demand conditions across markets facing a firm's product are time invariant, i.e., they vary along the fid panel dimensions. The addition of our trade-pattern fixed effect D to isolate variation along the $fidD$ panel dimension allows

[9] The most relevant reference to our estimator is Wansbeek and Kapteyn (1989), who consider an unbalanced panel with two panel dimensions and two fixed effects. See the appendix for detail on how our estimator improves on and generalizes this contribution, providing a transparent economic interpretation of the different implementation steps.

[10] To be concrete, in our example this implies a set of fixed effects which interact each country with each of its observed trade patterns; this set could be captured by a series of dummies: one for destination A interacted with the trade pattern A-C that takes the value 1 in periods 2 and 4, but 0 in periods 1, 3, and 5; a second dummy for destination A interacted with the trade pattern A-B-C that takes the value of 1 in periods 3 and 5, and a third for destination A interacted with the (non-repeating) trade pattern A-B that is equal to 1 in period 1.

for unobserved firm-product-destination-specific factors that co-move with the trade patterns of the firm-product. For example, changes in economic fundamentals $\mathcal{F}_t$ that have firm-product-destination specific effects can influence the set of destination markets at the firm-product level, resulting in variation along the $fidD$ panel dimensions. These factors can be controlled for by our estimator.

An advantage of our approach is that it can be easily implemented in three steps. Namely, in the first step, for every product in every firm, we strip out the component of the price that is common across the collection of foreign destinations reached in period t. 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:

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

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 RMB); e_{dt} is the bilateral exchange rate defined as the units of RMB per units of destination market currency. All variables are in logs.

Our second step applies firm-product-destination-trade pattern ($fidD$) fixed effects to the residual prices, exchange rates, and other explanatory variables obtained in the first step. 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., $t \in T_{fidD}$:

$$\ddot{x}_{fidt} \equiv \dot{x}_{fidt} - \frac{1}{n^T_{fidD}} \sum_{t \in T_{fidD}} \dot{x}_{fidt} \quad \forall x \in \{p_{fidt}, e_{dt}\} \tag{2}$$

where $\ddot{x}_{fidt}$ 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., $\ddot{e}_{fidt}$, 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 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:

$$\ddot{p}_{fidt} = \beta_0 + \beta_1 \ddot{e}_{fidt} + \ddot{u}_{fidt}. \tag{3}$$

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.[11]

We reiterate that, if the unobserved time varying variable, such as the marginal cost of a firm's product, is not destination-specific, then our estimator gives consistent and unbiased estimates. In this case, due to the unbalanced nature of the panel, applying the second demeaning (i.e., equation (2)) at the firm-product-destination-*trade pattern* level is crucial to get unbiased estimates. To appreciate fully the properties of our estimator, it is worth worth stressing that marginal costs are assumed to be non-destination specific in most studies relying on estimation of productivity and marginal costs—see, e.g., Olley and Pakes (1996), Levinsohn and Petrin (2003), Wooldridge (2009) and De Loecker et al. (2016).[12] Our theoretical and quantitative results suggest that, if the main interest of the analysis is to recover markup elasticities (rather than markup levels), then there is no need to rely on complex productivity and marginal cost estimations, whose feasibility is generally constrained by the availability of data. Applying our proposed estimator is sufficient.

We provide a model-based assessment of our estimator in Section 6, where we also detail the roots and nature of the biases that can arise in analyses of markup elasticities to exchange rates. In conducting our assessment, we examine the general case with unobserved confounding variables varying at all four panel dimensions in a non-separable manner, allowing for firm-product-destination-time specific demand and cost shocks.[13] We will show that our estimator reduces omitted variable and selection biases, outperforming or at least matching existing methods adopted by the pricing-to-market literature.To the best of our knowledge, there is no existing method that can produce unbiased and consistent estimates in this general case without making additional structural assumptions about the process driving the unobserved variables. Therefore, the fact that our estimator can significantly reduce bias in this very challenging setting is already a non-trivial achievement.

[11] 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).

[12] Olley and Pakes (1996), Levinsohn and Petrin (2003) and Wooldridge (2009) estimate firm-level productivity and thus can infer the average marginal cost over all products and destinations at the firm level. De Loecker et al. (2016) estimate the average marginal cost over destinations at the firm-product level. As an exercise, in online Appendix OA1.3, we explore an extension of De Loecker et al. (2016) in which we add a destination dimension to production costs. In the extended framework, under the assumption that the production function is constant returns to scale, we show that our identification strategy recovers an unbiased estimate of the markup elasticity even when the marginal cost varies across destinations (at the firm-product level). Note that the constant return to scale assumption is only needed in the very demanding case when the production function is destination-specific. Under the standard assumptions of De Loecker et al. (2016) where the production function is not destination-specific, our estimator yields unbiased estimates with constant returns to scale (CRS), increasing returns to scale (IRS) and decreasing returns to scale (DRS) production functions.

[13] A variable is separable if it can be decomposed into sub-components that each varies at a smaller panel dimensions. For example, if the unobserved marginal cost $\mathcal{MC}_{fidt}$ varies at all four dimensions but can be decomposed into two components, e.g., $\mathcal{MC}_{fidt} = u_{fit} + u_{fid}$, then we get back to the first case where our estimator produces unbiased and consistent estimates.

2.3 Cross-market demand elasticity

A natural complement to our estimator of the markup elasticity to the exchange rate is an estimator of the quantity adjustment driven by markup adjustments to exchange rate movements. This can be obtained from the following two-step procedure. The first step obtains the predicted relative price changes, $\widehat{\ddot{p}}_{fidt}$, from the TPSFE estimator:

$$\widehat{\ddot{p}}_{fidt} = \widehat{\beta}_0 + \widehat{\beta}_1 \ddot{e}_{fidt} + \ddot{\boldsymbol{x}}'_{fidt}\widehat{\boldsymbol{\beta}}_2. \tag{4}$$

where we have augmented the relative price change specification (3) to include $\boldsymbol{x}$, a set of variables capturing aggregate demand conditions in the destination country.[14] To the extent that twice-demeaning eliminates firm-product-time varying marginal costs of the firm's product, the predicted prices,$\widehat{\ddot{p}}_{fidt}$, capture the relative markup adjustments due to the differential movements of bilateral exchange rates across markets.

The second step consists of regressing the *relative quantity* changes, obtained by demeaning quantity q_{fidt} according to equations (1) and (2), on the predicted *relative markup* changes and other control variables:

$$\ddot{q}_{fidt} = \gamma_0 + \gamma_1 \widehat{\ddot{p}}_{fidt} + \ddot{\boldsymbol{x}}'_{fidt}\boldsymbol{\gamma}_2 + \ddot{v}_{fidt}. \tag{5}$$

where the coefficient γ_1 captures the changes in relative quantities driven by changes in relative markups associated with movements in the exchange rate. Conceptually, the coefficient γ_1 captures the extent to which a firm expects the quantities of its product sold in different markets to change when it adjusts its markups to exchange rate shocks. From the perspective of an exporter, once the marginal cost of the firm-product is properly controlled for, a change in the relative exchange rate is a demand shock: an appreciation of the destination country's currency results in a higher demand for the firm's product, at any given price in the producer's currency. For this reason, with a slight stretch in terminology, we refer to γ_1 as the "Cross-Market Demand Elasticity."[15]

The CMDE estimator has an economically-useful interpretation who value is best appreciated by comparing it to estimates of the relationship between the cross-market adjustments of prices and quantities. This measure is obtained by regressing the twice-demeaned quantities *directly* on

[14] Precisely, we include CPI, real GDP and the import-to-GDP ratio of the destination country in our empirical analysis.

[15] In our online supplementary material SM2, we derive general model free relationships between price and quantity adjustments under demand versus supply shocks. An important takeaway is that the markup and quantity adjustments move in the same direction if the markup adjustment is driven by demand shocks. Intuitively, as predicted by standard oligopolistic competition models, firms tend to absorb part of the shock into their markups. Thus, facing a positive demand shock that increases the potential quantity sold, the firm will increase its markups to maximize its profit. This turns out to be exactly what is implied by our empirical estimates in section 5.2.

twice-demeaned prices (labelled $Cor(\ddot{q}, \ddot{p})$)—that is, without using the the price changes projected on bilateral exchange rates:

$$\ddot{q}_{fidt} = \lambda_0 + \lambda_1 \ddot{p}_{fidt} + \ddot{\boldsymbol{x}}'_{fidt} \boldsymbol{\lambda}_2 + \ddot{v}_{fidt} \tag{6}$$

where λ_1 captures the general correlation between the relative quantity changes and the relative markup changes across markets. We will refer to this as the naïve $Cor(\ddot{q}, \ddot{p})$ estimator.

3 Product Differentiation as a Proxy for Market Power: a New Classification

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 market structure classifications set forth by Rauch (1999), which distinguishes commodities from differentiated goods. 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 quite useful, 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 new product classification that aims to distinguish products by their degree of differentiation. Our new classification splits Rauch's large class of differentiated goods into two groups, high- and low-differentiation goods. The key feature of the Corsetti-Crowley-Han-Song (CCHS) classification is that it exploits linguistics-based information uniquely 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.

3.1 A comprehensive classification based on Chinese linguistics

The core principle underlying our classification is a simple one: traded goods which are discrete items are more differentiated than traded goods which are continuous. The main value-added of our classification consists of 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, we find quantity reported in 36 different measures, many of which exist only in Chinese.[16]

[16]Notably, the linguistic structure of other East Asian languages also requires the use of measure words. In our online supplementary material SM1.4 we explain how Japanese customs declarations integrate indigenous Japanese measure words into the World Customs Organization quantity measurement framework.

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).[17]

The key advantage to using Chinese linguistics to identify if a good is discrete or continuous 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. Specifically, 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.[18] 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 could be endogenous.[19]

To illustrate the variety of measures used in the Chinese Customs Dataset, table 2 reports 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 our online supplementary material SM1.4 for an example of the different Chinese measures words used to quantify closely-related products in our dataset.

The second fact, that quantity must be reported on Chinese Customs forms in indigenous count

[17]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).

[18]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 supplementary material SM1.4 we provide examples of how measure words are used in Chinese grammar.

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

Table 2: 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

Table 3: 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.

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 3.[20]

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.[21]In Table 3, we demonstrate the value-added of our classification system in relation to the leading industry classification set forth by 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 approach are apparent. First, our classification refines the class of differentiated goods in Rauch into two categories—high and low differentiation. From table 3 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 3 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

[20]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 statistics over 2005-2016. See our online supplementary material SM1.4.2 for a discussion of quantity reporting in other customs systems.

[21]See our online supplementary material SM1.4.4 for examples of closely-related HS08 products and the types of measure words they use.

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 3 panel (a)) and 14.8% of export value (table 3 panel (b)) in the Chinese Customs Database in HS08 products that do not uniquely map to a single Rauch category.[22]

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.[23] 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.[24] 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.[25] We will see that all these entries can be exploited

[22]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.

[23]Details regarding the macroeconomic data and information about the Chinese Customs Database are given in our online supplementary material SM1.

[24]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 our online supplementary material SM1.6. We should note upfront that, because our TPSFE estimator differences out the common components across destinations, using prices denominated in dollars with dollar-destination exchange rates versus using prices denominated in renminbi with renminbi-destination exchange rates in the estimation procedure yields exactly the same estimates.

[25]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

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 as opposed to 8,076 8-digit HS codes reported in the database.[26] 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.[27]

Table 4: 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. An overwhelming majority of Chinese exporters serve multiple foreign destinations. A similar pattern has been documented for other 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. Based on our dataset, table 4 presents a breakdown of the proportion of exporting firm, export values, and count of annual

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."

[26]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.

[27]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)).

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.

5 Empirical Results

In this section, we present our empirical estimates of pricing to market. To make our results comparable with leading studies in the literature on exchange rate pass through, we apply all estimators conditional on a price change.[28] Our sample period 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. We will show evidence that exporters' pricing behavior differs across the corresponding subsample periods. Throughout our analysis, to ensure comparability of our estimates across policy regimes, we exclude exports to the US and Hong Kong, and treat eurozone countries as a single economic entity, integrating their trade flows into a single economic region.[29]

[28]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 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 supplementary material SM1.7. 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.

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

5.1 Markup elasticities by product differentiation

We start our analysis by applying our TPSFE estimator to estimate markup elasticities to exchange rates. Three points are worth stressing upfront. First, the estimated markup elasticity would be zero if exporters set the same price (in dollars, RMB or any other international currency) for their product in all destinations—irrespective of whether these prices are sticky or flexible, and of the currency in which they are set. Second, our estimation procedure is robust to the choice of bilateral exchange rates. For example, we get the same estimates from using either the dollar-destination currency or the RMB-destination currency exchange rate as the independent variable. This is because the RMB-dollar exchange rate movement is common across destinations and thus is differenced out from our procedure. Lastly, in all our tables in this section, the last column reports the size of the whole estimation sample (in the same row as the parameter estimates), and the size of the sample that provides identification to the TPSFE estimator (in square brackets [·] in the same row as the standard errors). The identification sample is smaller since it excludes observations corresponding to non-repetitive trade patterns. Because the TPSFE procedure yields identical parameter estimates when applied to either sample,[30] it is important to verify that the (sometimes considerably) smaller identification subsample remains representative of the whole estimation sample—a task we perform in all our exercises, failing to detect noticeable differences.

5.1.1 Baseline results

In table 5, we present results for two exchange rate regimes, as well as breakdowns by the degree of product differentiation. On average, we estimate an average markup elasticity to exchange rates of 5% during the dollar peg period (2000-2005) and of 7% during the managed floating period (2006-2014). The finding that the markup elasticity is rising over time indicates that exporters from China engaged more extensively in price discrimination in the later period, after China abandoned its strict peg to the US dollar.

In both periods, our econometric model detects significant differences in markup elasticities between high and low differentiation goods—validating the usefulness of our linguistics-inspired product classification as a proxy for market power. Starting with the first row, for CCHS high differentiation exports, the markup elasticity is 10%, while for low differentiation goods it is zero. In the period of the managed float of the renminbi (second row), markup elasticities are considerably higher. For high differentiation goods, the markup elasticity rises from 10 to 14%. For low

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

Table 5: Markup elasticities to the exchange rate

	All	HD Goods	LD Goods	n. of obs
2000 − 2005	0.05***	0.10***	0.02	4,279,808
	(0.02)	(0.03)	(0.02)	[1,073,300]
2006 − 2014	0.07***	0.14***	0.04***	19,272,657
	(0.01)	(0.01)	(0.01)	[4,839,333]

Note: Estimates based on specification (3) and 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 *.

differentiation goods, the markup elasticity is smaller, yet becomes significantly positive, at 4%. For these low differentiation goods, pricing-to-market appears to play only a small role after the strict peg is abandoned. It is important to keep in mind that, all else equal, a larger markup adjustment measured in producer's currency implies a smaller change in import prices *measured in the currency of the destination market.* This means that firms exporting more highly differentiated goods kept their prices in local currency more stable against bilateral currency movements relative to firms exporting low differentiation goods.

5.1.2 Combining the CCHS classification with firm and product characteristics

CCHS with firm ownership. The Chinese economy is widely understood to be a hybrid in which competitive, market-oriented private firms operate alongside large, state-owned enterprises (SOEs).[31] Looking at exports, the picture is actually more complex. Quantitatively, export activity is dominated by firms that are wholly foreign owned or are Sino-foreign joint enterprises—the leading types in a group that we label foreign-invested enterprises (FIEs).[32]

A firm's ownership type likely reflects a host of differences including cost structures, available technologies, and the types of products made. First, SOEs and FIEs are believed to have relatively easy access to capital, but are likely to differ in the extent to which they rely on imported intermediates in production. Conversely, private firms are widely seen as facing tighter financing constraints and, relative to FIEs, a lower level of integration with global supply chains. Second, the average size of a firm also differs across these groups; private enterprises are smaller on average, which likely reflects a high rate of entry by young firms. Third, being more integrated in supply chains, FIEs may engage in transfer pricing. In light of these considerations, we might expect

[31] See Hsieh and Song (2015) and Wu (2016) for analyses of the inter-relations of firms and the state in the Chinese economy and Hale and Long (2012) on the importance of inward FDI into China.

[32] Over 2000-2014, about one-half of Chinese export value originated from FIEs. See our online supplementary material SM1.2 for details.

SOEs, FIEs and private firms to endogenously end up producing different products, using different production processes, and possibly targeting different markets. This prompts us to ask whether a firm's registration type contributes to explaining observable differences in markup elasticities.

Evidence on markup elasticities by firm type is presented in table 6, where we focus on the period 2006-2014. Private enterprises stand out for their extremely low markup elasticity of 3% (column 1, row 3). This suggests that these firms follow a pricing strategy that is nearly indistinguishable from setting a single dollar price for their output across destinations. The estimates are much higher for state-owned and foreign-invested enterprises (9% for SOEs and 13% for FIEs), which seems to suggest that these firms hold a high degree of market power which enables them to exploit market segmentation and strategically price-to-market. Although these results may in part capture transfer pricing motivated by profit shfiting practices, at a broad level, the pricing strategies of SOEs and FIEs appear to be very different from those of private enterprises.

Table 6: Markup elasticities by firm registration types ($2006 - 2014$)

Category	All	HD Goods	LD Goods	n. of obs
State-owned Enterprises	0.09***	0.26***	0.03	3,526,943
	(0.02)	(0.04)	(0.02)	[646,352]
Foreign Invested Enterprises	0.13***	0.27***	0.09***	4,990,504
	(0.01)	(0.03)	(0.01)	[1,042,481]
Private Enterprises	0.03***	0.06***	0.02	9,897,091
	(0.01)	(0.01)	(0.01)	[2,996,133]

Note: Estimates based on specification (3) and 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 *.

Product differentiation plays an important role in explaining differences across firm types. The estimated markup elasticity for highly differentiated products sold by SOEs is 26%, while that for low differentiated goods is indistinguishable from zero. Similar, significant differences between highly and less differentiated production are found for FIEs and PEs. These estimates suggest that while FIEs and SOEs have more market power, their ability to segment markets and set destination-specific markups is not unconstrained but crucially depends the type of products they sell.

CCHS with firm size. Our results from table 6 show that market power is best captured by a combination of product *and* firm type. We now consider a measure of firm size at the product-level; a firm's global export revenues for a product.[33] For a given firm-product-year triplet, we

[33]This definition of size differs from that in papers such as Berman, Martin and Mayer (2012) and Amiti, Itskhoki and Konings (2014) which measure firm size as total domestic and foreign revenues for *all* products. The categorization we employ emphasizes that a firm's market power could vary across distinct products.

calculate the firm's global export revenue, summed over all active destinations in that year. We then rank firms within products and years by product-level export revenue, and place them into three equally-sized bins, labelled small, medium and large.[34]

Table 7: Pricing-to-market by exporters' product-level global revenues (2006 − 2014)

Category	All	HD Goods	LD Goods	n. of obs
Small Exporters	0.02**	0.06***	0.01	6,639,830
	(0.01)	(0.02)	(0.01)	[2,646,437]
Medium Exporters	0.07***	0.18***	0.04**	6,519,743
	(0.01)	(0.03)	(0.02)	[1,448,368]
Large Exporters	0.19***	0.32***	0.14***	6,113,084
	(0.02)	(0.04)	(0.03)	[744,528]
All Exporters (size weighted)	0.31***	0.56**	0.21***	19,272,657
	(0.08)	(0.24)	(0.05)	[4,839,333]

Note: Estimates based on specification (3) and 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 first three rows show results separated estimated in each of the firm size bins. The last column shows weighted regression estimates of the full sample using the total trade value of a firm-product pair in all years and destinations as the weight. 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 *.

Exporters' markup elasticities to the bilateral exchange rate increase systematically with their product-level export revenues (table 7 column 1). Regardless of the degree of product differentiation, large exporters appear to command more market power and adjust their markups in response to bilateral exchange rate movements by around 20% on average. In contrast, small exporters adjust markups by a mere 2%, suggesting that their pricing strategies are close to setting a single global price across all destinations.

Further segmenting the sample according to the degree of product differentiation reveals striking heterogeneity in pricing. In response to bilateral exchange rate movements, large firms adjust markups substantially, 32% when exporting highly differentiated products. These firms appear to command a relatively high level of market power even when they sell low differentiation products, with an estimated elasticity of 14%. Thus, the significant price stability in local currency that Chinese exports exhibit on average can be partially understood as a reflection of the fact that large firms (responsible for a large share of trade) let their markups (measured in exporter's currency) absorb the bilateral exchange rate movement between the origin and destination.

[34] Our definition of firm-size categories is at the product-year level. That is, all the firms selling the same product in the year are placed in bins containing the same number of observations. When the number of firms cannot be divided by three, we place more firms in the lower ranked bins. For example, say we have 5 firms selling to 2 destinations each. We put two firms in the "Small" bin, two firms in the "Medium" bin and one firm in the "Large" bin. This is why, in table 7, the number of observations in the "Small" and "Medium" categories is slightly higher than that in the "Large" category.

To gain insights on the degree of incomplete exchange rate pass through due to markup adjustments at the aggregate level, we re-estimate our baseline specification (3) and weight observations by the total trade value of a firm-product pair (in all years and destinations). This specification (the last row of table 7) gives substantially larger markup elasticities and a bigger difference between high (56%) and low (21%) differentiation goods. Therefore, despite the large and multi-destination firms that account for lions share of international trade are in general more responsive to exchange rate changes, substantial differences in the exchange rate pass through across countries can arise due to the different composition of goods imported.

CCHS with UN end-use categories. Firms selling directly to consumers typically engage in branding and advertising campaigns to a much larger extent than firms selling intermediate products. Insofar as producers of consumption goods are successful in making their products less substitutable with other products or product varieties, markets for consumption goods should be less competitive than markets for intermediates. Thus, we may expect destination specific markup elasticities to be higher for consumption goods than for intermediates.

Table 8: Markup Elasticities by BEC Classification (2006 – 2014)

Category	All	HD Goods	LD Goods	n. of obs
Consumption	0.18***	0.29***	0.08***	6,133,394
	(0.01)	(0.02)	(0.02)	[1,759,243]
Intermediate	0.02**	0.03	0.02**	6,288,252
	(0.01)	(0.05)	(0.01)	[1,579,220]

Note: Estimates based on specification (3) and 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 *.

In table 8, we partition our data into four categories by integrating our CCHS classification with the classification of consumption goods and intermediates under the UN's Broad Economic Categories (BEC).[35] We find a clear difference in the markup elasticities for consumption versus intermediate goods; the elasticities of exporters selling consumption goods (0.18) are nearly ten times larger than those of exporters of intermediates (0.02). When we further refine consumption goods into our CCHS product categories, the elasticity of high-differentiation consumption goods becomes strikingly large (0.29).

[35]The UN's BEC classifies all internationally traded goods according to their end-use. The most disaggregated classification available in BEC Rev. 4 maps HS06 products into end-use categories of consumption goods, intermediate inputs, and capital equipment. For our analysis, all HS08 products into the Chinese Customs Database are assigned the end-use of their corresponding HS06 code.

5.2 Cross-market demand elasticity

Thus far, we have presented evidence that some groups of firms exporting from China, particularly larger firms selling highly differentiated goods, discriminate across countries when adjusting their prices in response to bilateral exchange rate changes. Consistent with theory, we may expect them to systematically charge higher markups where, relative to other destinations, bilateral exchange rate movements create more favorable market (i.e., demand) conditions. In this section we show how to use our framework to shed light on this point.

Our point of departure is the observation that, from the vantage point of a firm, for given production costs, changes in the exchange rates act as demand shifters. Thus, to the extent that our TPSFE estimator controls for cost-side factors, the predicted values from a projection of prices on exchange rates using (4) can be interpreted as changes in *relative markups* in response to changes in *relative demand across destinations driven by currency movements*. With this interpretation in mind, an increase in the relative markup charged in a market, raising the revenue per sale accruing to the firm, should be systematically associated with an increase in the relative quantity sold in that market.

Table 9: Cross-Market Demand Elasticities by CCHS Classification

	All		High Differentiation		Low Differentiation		
	(1) $Cor(\ddot{q}, \ddot{p})$	(2) CMDE	(3) $Cor(\ddot{q}, \ddot{p})$	(4) CMDE	(5) $Cor(\ddot{q}, \ddot{p})$	(6) CMDE	n. of obs
$2000 - 2005$	-0.71***	6.18*†	-0.75***	4.07**	-0.68***	19.72†	4,279,808
	(0.01)	(3.18)	(0.01)	(1.72)	(0.01)	(55.14)	[1,073,300]
$2006 - 2014$	-0.70***	1.53***	-0.72***	0.72***	-0.69***	2.72***	19,272,657
	(0.00)	(0.28)	(0.00)	(0.20)	(0.00)	(0.80)	[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 "$Cor(\ddot{q}, \ddot{p})$" column is estimated using specification (6). The CMDE column is estimated based on equations (4) and (5). Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *. † indicates that the t-statistic of the bilateral exchange rate in the first stage is smaller than 2.58.

Our empirical results are shown in table 9, which reports estimated elasticities from applying our CMDE procedure (in column (2), (4) and (6)), as well as using what we dub naïve correlation approach (in columns (1), (3) and (5)). Starting from the latter, the sign of the naïve regression coefficient (of relative quantities on relative prices) is consistently negative. For example, in column (1), a 1% increase in relative prices is statistically associated with a 0.7% *decline* in relative quantities. This is consistent with the idea that the coefficient from the naïve regression simply reflects that firms export relatively less, on average, in markets where they set relatively high prices.

The results are quite different when twice demeaned prices are projected on bilateral exchange rate movements. All of our estimates of CMDEs have positive signs. We interpret the CMDE as a statistical measure capturing how relative quantities move with currency-driven shifts in demand facing a firm for its product(s). In the managed float regime (2006-2014, see row 3 of table 9), the CMDE estimate in column (2) implies a one percent increase in the relative markup (driven by the exchange rate) is associated with 1.53 percent change in the relative quantity across destinations. Table 9 documents sharp differences in CMDE estimates across high and low differentiation goods. Over the same 2006-2014 period, the CMDE estimate is very low (0.72) for high-differentiation goods (row 3, column 4): a one percent increase in the markup charged in a market is associated with a mere 0.72% increase in the export quantities supplied to that market. The estimated CMDE for low-differentiation goods, 2.72%, is instead quite high. Recall that high- and low-differentiation goods feature, respectively, a high and a low markup elasticity—there is more pricing to market in high-differentiation exports. Our evidence thus lends empirical support to the view that firms with market power, such as those exporting high-differentiation products, respond to destination-specific exchange rate movements by adjusting markups substantially while keeping the relative quantity supplied across destinations relatively stable.

Comparing estimates by exchange rate regimes, our results pick up an interesting evolution of Chinese exporters over time. We have seen above that Chinese exporters' engagement in pricing-to-market was modest during the years of the fixed exchange rate regime (with the notable exception of exporters of high differentiation goods). Correspondingly, the CMDE estimates for the period of the fixed exchange rate regime are quite high, ranging from 4.07 to 19.72 for high- and low-differentiation goods. Altogether, these results may suggest that, during the strict peg period, those firms that responded to bilateral exchange rate movements with modest markup adjustments were aggressively pursuing any openings for expanding their market shares abroad.

The pattern highlighted in table 9, that goods and firms for which we estimate a higher relative markup adjustment tend to display a lower CMDE, is confirmed by table 10. From this table, once again, the divide between private firms, on the one hand, and FIEs and SOEs, on the other, is apparent. For private firms, a one percent increase in the relative markup in a market is associated with a 5.23 percent increase in the relative quantity sold in that destination (2.59 for exporters of high differentiation goods, 10.57 for exporters of low-differentiation goods). This is evidence that, on average, private Chinese firms keep their relative markups in check in response to currency movements; they price-to-market less and let relative export quantities move with demand conditions (possibly to gain market share). Relative to private firms, the opposite pattern emerges for SOEs and FIEs. Corresponding to their much higher markup elasticities, the estimated CMDEs are very small and not significantly different from zero (0.34 for SOEs and 0.28 for FIEs).

The evidence in the table underscores the extent and importance of international market segmentation and market power. At one extreme we have SOEs, FIEs and exporters of highly differ-

Table 10: Cross-Market Demand Elasticities by Product and Firm Types (2006 − 2014)

	All		High Differentiation		Low Differentiation		
	(1)	(2)	(3)	(4)	(5)	(6)	
Category	$Cor(\ddot{q},\ddot{p})$	CMDE	$Cor(\ddot{q},\ddot{p})$	CMDE	$Cor(\ddot{q},\ddot{p})$	CMDE	n. of obs
State-owned Enterprises	-0.70***	0.46	-0.67***	0.11	-0.71***	1.26†	3,526,943
	(0.01)	(0.31)	(0.01)	(0.23)	(0.01)	(1.19)	[646,352]
Foreign Invested Enterprises	-0.70***	0.19	-0.70***	0.31	-0.70***	-0.11	4,990,504
	(0.00)	(0.21)	(0.01)	(0.24)	(0.01)	(0.32)	[1,042,481]
Private Enterprises	-0.70***	5.23***	-0.75***	1.99***	-0.67***	16.87†	9,897,091
	(0.00)	(1.88)	(0.00)	(0.72)	(0.00)	(19.58)	[2,996,133]
Small Exporters	-0.65***	3.48**	-0.69***	1.85**	-0.63***	9.93†	6,639,830
	(0.00)	(1.56)	(0.01)	(0.81)	(0.00)	(14.35)	[2,646,437]
Medium Exporters	-0.72***	1.58***	-0.74***	0.51	-0.71***	3.53†	6,519,743
	(0.00)	(0.60)	(0.01)	(0.35)	(0.01)	(2.33)	[1,448,368]
Large Exporters	-0.77***	0.44*	-0.77***	0.06	-0.77***	0.77*	6,113,084
	(0.01)	(0.26)	(0.01)	(0.26)	(0.01)	(0.44)	[744,528]
Consumption	-0.71***	0.47**	-0.77***	0.16	-0.63***	1.68**	6,133,394
	(0.00)	(0.19)	(0.00)	(0.16)	(0.01)	(0.79)	[1,759,243]
Intermediate	-0.71***	3.34**	-0.73***	1.04†	-0.71***	3.84*†	6,288,252
	(0.00)	(1.55)	(0.01)	(1.39)	(0.00)	(1.98)	[1,579,220]

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 "$Cor(\ddot{q},\ddot{p})$" column is estimated using specification (6). The CMDE column is estimated based on equations (4) and (5). Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *. † indicates that the t-statistic of the bilateral exchange rate in the first stage is smaller than 2.58.

entiated consumption goods: the low estimate of quantity substitution across destinations (statistically indistinguishable from zero) suggests that the markets served by these firms and exporters of these goods are highly segmented. At the other extreme, for exporters of low-differentiation intermediates, quantity substitution is quite high (3.84) and markets appear quite integrated.

6 Pricing to Market by Heterogeneous Firms and Products: A Model-based Analysis

In this last section, we rely on a partial equilibrium model to gain insights on when and how a fixed-effect approach to the analysis of pricing to market is effective in addressing the bias arising from omitted variables and market selection. We use simulated data from our model to gauge the performance of alternative fixed-effect estimators in the presence of multiple sources of bias, and discuss how comparing results across estimators may provide informative diagnostics regarding the likely unobservable variables and shocks impacting firms' decisions. Finally, we compare empirical results for the Chinese customs data across a range of widely used fixed-effect estimators.

6.1 Model

As a theoretical reference, we specify a model embedding Kimball (1995) demand, widely used, arguably for its flexibility, in many recent open macro studies.[36] 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.[37] Hence, in the model, at time t a firm f selling the product i makes its pricing and exporting decisions simultaneously, but independently in each destination market d:

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

where P_{fidt} is the border price denominated in the exporter's currency; $\phi_{fidt} \in \{0,1\}$ is an indicator of whether the firm is actively selling in market d in the period; $\mathcal{MC}_{fit}$ is the marginal cost; ζ_i is the exporting cost that the firm needs to pay for each product i sold in a destination market; and $\psi_i(.)$ is a Kimball demand function. This function has four arguments: a markup-irrelevant preference shifter α_{fid} and a markup-relevant demand shifter D_{fidt}; the border price P_{fidt} and the bilateral exchange rate $\mathcal{E}_{dt}$ between the exporting country and the destination country, where an increase in $\mathcal{E}_{dt}$ is a depreciation of the exporting country's currency.

Solving the above problem, we obtain the optimal price charged by a firm for its product in the destination market d at time t as a function of markup-relevant demand and supply shocks, $P^*_{fidt}(D_{fidt}, \mathcal{E}_{dt}, \mathcal{MC}_{fit})$, and the market entry condition, summarized by the selection equation (8) below. Defining the operational profit as the profit achieved at the firm's optimal price P^*_{fidt}:

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

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

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

[36]See Gopinath and Itskhoki (2010), Amiti, Itskhoki and Konings (2019), Gopinath et al. (2020), and Mukhin (2022), etc.

[37]The independent market decisions are usually implied by the assumption of a constant returns to scale production function. As the marginal cost in one destination does not depend on that in another destination, the optimization problem can be solved independently in each market.

We use this model as a reference in the rest of this section, but stress that most of our results are quite general, and can be derived from alternative theoretical frameworks.[38]

6.2 Dissecting biases

Firms make their pricing and exporting decisions based on many pieces of micro information about their (marginal) costs, their potential markets, the competition they are facing in each market, and so on. Granular-level information on all relevant factors is rarely observed by economists. Our stylized model offers theoretically-grounded insights into the biases that can plague estimation of markup elasticities with respect to the exchange rate in large customs databases due to incomplete information.

An important point we stress in our discussion is that, while the unobserved variable needs to be correlated with the bilateral exchange rate to create omitted variable bias, selection bias can arise even when this correlation is zero. What matters is that the unobserved variable enter both the pricing and the profit equations—in our reference model, these would correspond to $P^*_{fidt}(D_{fidt}, \mathcal{E}_{dt}, \mathcal{MC}_{fit})$ and the equation (7).[39] The way in which the variable enters these two equations, in turn, determines the direction of the selection bias.

In table 11, we summarize the direction of biases arising in the estimation of the markup elasticity for five cases, which correspond to different possible relationships between the unobservable variable and other relevant variables. In the top half of the table, we state the assumptions about the relationship between the unobservable and the relevant object – the exchange rate, the optimal price, or the operational profits; in the bottom half of the table we convey the main results about the direction of the bias. A positive or negative sign indicates the assumed sign of correlations between variables and the resulting direction of the bias. A dot indicates zero correlation or no bias. In the first three columns, we focus on selection bias, imposing that the unobservable variable is *not* correlated with the exchange rate. In the last two columns, we consider the more general cases, where omitted variable and selection bias coexist. Column 4 allows for a positive correlation between the exchange rate and the unobservable, while column 5 allows for a negative correlation.

Column 1 of table 11 refers to the equilibrium response to a markup-relevant destination-specific demand shock, e.g., a change in D_{fidt}, that is uncorrelated with exchange rates. This shock may occur, for instance, if the firms' competitors in the destination market unexpectedly raise their

[38]We examine an alternative model developed by Corsetti and Dedola (2005) and used in Berman, Martin and Mayer (2012), where variable markups arise due to the existence of local production or distribution costs. Compared to the Kimball model, the key advantage of the Corsetti and Dedola (2005) setting is that it allows us to derive analytical solutions of the optimal markup and profit functions, and thus make a more transparent statement on the relationship among variables that affect firms' markup and exporting decisions. We report these results in online Appendix OA2.

[39]In the model in online Appendix OA2, these would correspond to equations (OA2-1) and (OA2-4).

Table 11: Direction of the bias caused by an unobserved variable x

	Selection Bias			Selection & OV Bias	
	1	2	3	4	5
Unobservable variable x:	D_{fidt}	α_{fidt}	$\mathcal{MC}_{fit}$	$\mathcal{MC}_{fit}$	$\mathcal{MC}_{fit}$
How does x co-move with:					
– exchange rate, $corr(\Delta \ln x, \Delta \ln \mathcal{E})$	.	.	.	$+$	$-$
– optimal price, $\frac{\partial P^*}{\partial x}$	$+$	.	$+$	$+$	$+$
– operational profit, $\frac{\partial \pi}{\partial x}$	$+$	$+$	$-$	$-$	$-$
Direction of bias					
– omitted variable	.	.	.	$+$	$-$
– selection	$-$	.	$+$	$+$	$+$
Overall bias	$-$	.	$+$	$+$	$+/-$

Note: "." means no correlation or bias. "$+/-$" means the direction of the bias is indeterminant.

prices, which, other things equal, increases the demand for the firm's product. In response to this (demand) shock, it is optimal for the firm to adjust its markup upward (the effect of the unobserved shock on the pricing equation is positive). At the same time, since the firm's operating profit also increases, the firm is more likely to enter and sell in that market.

Although we have restricted shocks to D_{fidt} to be uncorrelated with the exchange rate, this does not rule out the possibility that they are correlated *in the observed transactions*—creating selection bias. To see how, consider the role of the bilateral exchange rate in the pricing and profit functions. It is straightforward that a strong exporting country's currency is associated with lower optimal markups and profits, making the firm less likely to sell in the foreign market.[40] Recall that a low $\mathcal{E}_{dt}$ means the exporting country's currency is strong. Hence, when $\mathcal{E}_{dt}$ is low, the idiosyncratic demand shock D_{fidt} needs to be sufficiently large in order for the firm to start selling in that market, and for the (firm-product-destination-time) transaction to be observed. This creates a negative correlation between $\mathcal{E}_{dt}$ and (the unobserved) D_{fidt} in the *observed* transactions: trade is most likely to occur when $\mathcal{E}_{dt}$ is low and D_{fidt} is large. The result is *downward* selection bias.

In column 2 of table 11, we call attention to an important case, where there is no selection bias even if a variable that drives the firm's exporting decision is omitted from the estimation. Here we consider preference shocks, e.g., a change in α_{fid}, that do not affect optimal pricing. In this case, endogenous selection still makes the exchange rates and the preference shocks correlated in the observed transactions. Yet, there is no selection bias, since the shock does not impinge on the

[40] While the model with Kimball demand does not allow for closed form solutions, in the Online Appendix OA2, we solve an alternative Corsetti and Dedola (2005) model analytically and show how the corresponding elements enter the pricing and profit equations.

optimal markup. The argument can be extended to other variables, such as the entry cost of firms and aggregate demand shifters, that do not directly enter the pricing equation.

In column 3 of table 11, we consider the case of cost shocks uncorrelated with the exchange rate. In contrast to a demand shock, a cost shock enters the pricing and profit equations in opposite directions. An increase in marginal cost raises the firm's optimal price but at the same time reduces its operating profit, making the firm less likely to enter the foreign market. In this case, by the same logic we use in our comments on column 1, even if the unobserved marginal cost shock is uncorrelated with the exchange rate, it will be positively correlated in the observed transactions.[41] The estimated markup elasticity will suffer from an *upward* selection bias.

In the last two columns of table 11 we allow the unobserved variable to be correlated with exchange rates, hence we bring omitted variable bias into the picture. Column 4 is best understood by considering the case of marginal costs of a firm that are positively correlated with exchange rates. Here the omitted variable bias reinforces the selection bias (discussed in column 2), arguably resulting in a large overall bias. In column 5, on the contrary, a negative correlation between the unobservable and the exchange rate means that the omitted variable bias and the selection bias do not go in the same direction. As the selection and the omitted variable biases partly offset each other, the direction of the overall bias depends on which of the two dominates.

6.3 What can be learnt from alternative fixed-effect estimators? An assessment using model-simulated data

Armed with table 11's analysis of bias, we apply fixed effect estimators to model-simulated data and conduct a quantitative comparative assessment of their performance, to draw lessons for interpreting empirical evidence. In this task, we use the specification of the Kimball demand function as in Gopinath and Itskhoki (2010) and Amiti, Itskhoki and Konings (2019):

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

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 competition-relevant demand shocks (i.e., $\mathcal{E}_{dt}$, D_{fidt}). 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 demand shocks.

Simulation setup. We simulate the model for 1,000 firms, 30 destination markets, and 20

[41] When $\mathcal{E}_{dt}$ is low, hence the exporter currency is strong, it takes a large negative idiosyncratic marginal cost shock for the firm to start selling in that market, and the (firm-product-destination-time) transaction to be observed.

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. However, our results are robust to alternative settings of elasticities and shocks.[42]

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

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

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:

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

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. For example, 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} add changes in marginal costs that are uncorrelated with exchange rate movements.

Demand shocks (from the vantage point of the firm) can be of three types:

$$\ln(D_{fidt}) = \begin{cases} 0 & \text{in panel (a): homogenous} \\ \sigma_D \varsigma_{fid} & \text{in panel (b): firm-product-destination-specific} \\ \sigma_D \varsigma_{fid}(\mathcal{F}_t + u_{fidt}) & \text{in panel (c): time-varying} \end{cases} \tag{12}$$

In panel (a), the case of homogenous demand, exchange rate movements are the only reason for the firm to price-to-market, i.e., when $\mathcal{E}_{dt} = 1$, the firm will charge the same markup for its product across all destinations. In panel (b), we allow for unobserved markup-relevant demand drivers. These drivers (captured by ς_{fid}) may reflect (time-invariant) differences in the competitive envi-

[42] We provide additional results on correlated cost shocks in table OA2-2 of online Appendix.

ronment in each destination market. Finally, in panel (c), we allow for firm-product-destination-specific demand to vary over time responding to (i) time-varying factors that drive the exchange rate $\mathcal{F}_t$ and (ii) an idiosyncratic demand shifter u_{fidt}. To appreciate this last experiment, think of changes in economic fundamentals of the origin country that drive the exchange rate changes and at the same time have firm-product-destination-specific effects on the competitiveness of origin firms.

$\mathcal{F}_t, u_{dt}, u_{fit}, u_{fidt}$, 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 $\sigma_D = 0.20$. We give more weight to firm-product specific demand and supply shocks, so that most of the changes of the firms' trade patterns are driven by these unobserved shocks relative to observed bilateral exchange rate changes. 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.

Simulation results. Table 12 reports markup (or price) elasticities obtained from a variety of estimators applied in the literature, together with our new estimator. In all three panels, the simulations allow for exchange rate and firm-product-time-specific cost shocks. The simulations differ in terms of the demand conditions facing by a firm's product in a destination market. Panel (a) imposes homogeneous demand. Panel (b) adds firm-product-destination-specific demand shocks to cost shocks while panel (c) adds firm-product-destination-*time* specific shocks to cost shocks. In each panel, we show the estimates of the markup elasticities for the whole sample of simulated data as well as those for the subsamples of high and low differentiation goods. Consistent with our empirical estimates, we find the goods with a high elasticity of substitution (the low differentiation goods) tend to have a lower markup elasticity than those with low elasticities (the high differentiation goods).

As a benchmark, the last column (8) shows estimates from running an OLS regression using all the *unobserved* variables — an estimator which is obviously not feasible in the data. This regression gives the best linear relationship that an econometrician could obtain without specifying the underlying theoretical model (i.e., equations (7)–(12)).

Focusing on panel (a): column (1) shows the OLS estimates from regressing $\ln(P_{fidt})$ on $\ln(\mathcal{E}_{dt})$. Compared to column (8), these OLS estimates are severely biased. Recall that we calibrated marginal cost to be positively correlated with the bilateral exchange rates. Hence, both omitted variable and selection biases are present and positive (see case 4 of table 11). The two biases reinforce each other and lead to significantly higher estimates than the true markup elasticities in column (8).

Column (2) shows the OLS estimates when, counterfactually, the true marginal cost $\mathcal{MC}_{ift}$ is added as an additional control variable. This column represents the best-case estimates one could obtain following the productivity estimation approach (e.g., De Loecker et al. (2016)). As we can see from Panel (a), this approach will successfully recover the true markup elasticity, but (looking at the other panels) only in the absence of demand shocks.

Column (3) shows estimates obtained by mechanically applying the Knetter (1989) approach. It is worth noting that because the bilateral exchange rate only varies at the destination and time dimensions of the panel and is naturally independent from the unobserved factors varying along the firm and product dimensions, Knetter (1989)'s specification is sufficient to control for firm-product-time varying unobserved marginal costs and gives unbiased estimates if (i) the panel is fully balanced and (ii) the markup elasticity is homogeneous in the estimation sample. When applied to micro data, however, due to the endogenous exporting decisions of firms, the firm and product dimensions of the panel are relevant: the original Knetter (1989) specification is bound to produce significantly biased estimates. As we can see from panel (a), the estimates in column (3) and column (1) exhibit similar biases.

Column (4) shows a setting that originates from Gopinath, Itskhoki and Rigobon (2010) and has been widely used in exchange rate pass through studies. The S-difference (S-diff) specification regresses the cumulated change between the two observed price changes on the corresponding cumulated exchange rate changes, i.e., regressing $\Delta_s \ln(P_{fidt}) = \ln(P_{fid,t}) - \ln(P_{fid,t-s_{fidt}})$ on $\Delta_s \ln(\mathcal{E}_{dt}) = \ln(\mathcal{E}_{d,t}) - \ln(\mathcal{E}_{d,t-s_{fidt}})$ with s_{fidt} counting the periods between the two observed price changes. Our simulations show the S-difference specification produces results that are very similar to the one in column (5) that includes firm-product-destination and time fixed effects.[43] In terms of markup elasticities, the estimates in column (4) and (5) are both upward biased — yet the degree of the bias is much lower compared to the estimates of the OLS and the Knetter specification, in column 1 and 3, respectively.

Column (6) shows the estimates with firm-product-time and destination fixed effects — a setting applied in Amiti, Itskhoki and Konings (2014). This specification successfully uncovers the true markup elasticity when the only shocks hitting firms in the model economy are cost shocks (panel a). Column (7) shows that our TPSFE estimator gives the correct markup elasticities in the HD and LD subsamples. These last two columns, for the TPSFE and best linear estimators, suggest that the TPSFE estimator provides a good estimate of markup elasticities. This is particularly valuable when the productivity estimation approach is infeasible due to a lack of sufficiently accurate information on productivity and marginal cost.

Coming to Panel (b), we now consider the more general case allowing for firm-product-destination demand shocks (ς_{fid}) in addition to cost shocks. As shown in table (11), even if ς_{fid} is uncorrelated

[43] Note that the S-difference estimator is not designed to control for time variation in firm and product-level costs. Indeed, it was designed to estimate the cost-inclusive total exchange rate pass through rather than the markup elasticity. The $fid + t$ fixed effects have been applied in, for example, Berman, Martin and Mayer (2012) and Chatterjee, Dix-Carneiro and Vichyanond (2013).

Table 12: Estimated Markup Elasticity by Different Estimators (based on model simulated data)

Sample	(1) OLS	(2) OLS with $\mathcal{MC}_{fit}$	(3) $d+t$ FE	(4) S-diff	(5) $fid+t$ FE	(6) $fit+d$ FE	(7) TPSFE	(8) Best Linear
Panel (a): firm-product-time cost shocks								
All	1.36	0.17	1.50	0.36	0.35	0.17	0.15	0.17
	(0.02)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HD ($\rho = 4$)	1.51	0.27	1.51	0.46	0.45	0.26	0.27	0.27
	(0.02)	(0.00)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
LD ($\rho = 12$)	1.21	0.09	1.21	0.26	0.26	0.09	0.09	0.09
	(0.02)	(0.00)	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Panel (b): firm-product-time cost shocks + firm-product-destination demand conditions								
All	1.36	0.16	1.53	0.37	0.36	0.14	0.16	0.18
	(0.02)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HD ($\rho = 4$)	1.48	0.24	1.49	0.47	0.46	0.22	0.28	0.28
	(0.02)	(0.00)	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
LD ($\rho = 12$)	1.23	0.08	1.23	0.27	0.27	0.07	0.09	0.09
	(0.03)	(0.00)	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Panel (c): firm-product-time cost shocks + firm-product-destination-time demand shocks								
All	2.24	0.24	0.91	0.31	0.17	0.09	0.13	0.18
	(0.02)	(0.00)	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
HD ($\rho = 4$)	2.11	0.32	0.80	0.40	0.22	0.13	0.28	0.27
	(0.03)	(0.00)	(0.03)	(0.01)	(0.01)	(0.00)	(0.02)	(0.00)
LD ($\rho = 12$)	2.36	0.12	0.86	0.23	0.12	0.05	0.08	0.09
	(0.03)	(0.00)	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)

Note: Estimates and standard errors are calculated based on the average of 10 simulations of each setting.

with exchange rates, it can still cause non-trivial bias due to selection effects. According to case 1 in table (11), when demand shifters have positive effects on both the optimal price and the profit, they will lead to a *downward* bias in the estimates of markup elasticities. In light of this insight, it is no surprise that in the estimates shown in columns (2) and (6) are downward biased: this is because both the productivity estimation approach and the firm-product-time + destination fixed effects approach fail to control for firm-product-destination specific demand conditions. The estimates from the TPSFE estimators in column (7) remain instead close to those in column (8), especially when distinguishing goods by their degree of differentiation.

Panel (c) shows the most challenging case with time-varying firm-product-destination demand conditions and cost shocks. Reassuringly, Column (7) shows that our TPSFE estimator still gives estimates that are close to the true markup elasticities, outperforming the other estimators. Specifically, in this panel the estimates from specification (6) with firm-product-destination and time fixed effects are actually much more biased, reflecting a worsening of the selection bias problem due to the additional time-varying firm-product-destination demand shock. Most interestingly, however, observe that the bias in specification (5) with firm-product-destination and time fixed effects is lower in panel (c) compared to panels (a) and (b). The reason is that the selection bias driven by demand shocks and the omitted variable bias driven by the unobserved cost shocks go in opposite directions and partly offset each other. As already noted, in some special cases, it might even be possible for the two biases to just offset each other. But one cannot count on luck: in general, one bias can dominate, yielding estimates that are far from the true value.

6.4 A comparison of empirical results from fixed-effect estimators

We close our study with a comparative analysis of results from applying alternative fixed-effect estimators to the Chinese customs data. Table 13 reports empirical estimates using our TPSFE estimator (column 1), the $fid + t$ fixed effect estimator (column 2) and the $fit + d$ fixed-effect estimator (column 3). In the upper panel, we focus on high differentiation goods, in the lower panel on low differentiation goods. To save on space we only look at the later period, 2006-2014, and report estimates for relevant subsamples by types of firms and goods.

Looking at Table 13, note that, across the three columns, the estimated markup elasticities are higher for high differentiation goods than for low differentiation goods—consistent with theory. They are also higher for types of firms and goods for which one may expect larger deviations from competitive conditions. Once again, this lends empirical support to the usefulness of our classification and, indirectly, confirms the validity of fixed effects—when appropriately specified—in the estimation of elasticities plagued by missing information.

A comparison of estimates nonetheless prompts two observations. First, the estimates of our

TPSFE estimator (column 1) are in general larger than those of the $fit + d$ fixed effect estimators (column 3), especially for State-Owned Enterprises, Foreign-Invested Enterprises, and high differentiation consumption goods. Second, differences in the estimates using TPSFE versus $fid + t$ fixed effects (column 2) tend to be small for low differentiation goods, and can be either positive or negative depending on the type of the firm and the end-use of the product for high differentiation goods.

Table 13: Estimated Markup Elasticity by Different Estimators (based on Chinese customs data)

Sample	(1) TPSFE	(2) $(fid+t)$ FE	(3) $(fit+d)$ FE	n. of obs
2006-2014, High Differentiation				
State-owned Enterprises	0.26***	0.25***	0.08***	1,617,483
	(0.04)	(0.01)	(0.01)	
Foreign Invested Enterprises	0.27***	0.18***	0.07***	2,267,880
	(0.03)	(0.01)	(0.00)	
Private Enterprises	0.06***	0.11***	0.04***	3,988,833
	(0.01)	(0.00)	(0.00)	
Intermediate Goods	0.03	0.22***	0.03***	580,037
	(0.05)	(0.02)	(0.01)	
Consumption Goods	0.29***	0.23***	0.12***	3,581,291
	(0.02)	(0.01)	(0.00)	
2006-2014, Low Differentiation				
State-owned Enterprises	0.03	0.01	0.01***	1,909,460
	(0.02)	(0.01)	(0.00)	
Foreign Invested Enterprises	0.09***	0.08***	0.05***	2,722,624
	(0.01)	(0.00)	(0.00)	
Private Enterprises	0.02	0.02***	0.03***	5,908,258
	(0.01)	(0.00)	(0.00)	
Intermediate Goods	0.02**	0.02***	0.02***	5,712,115
	(0.01)	(0.00)	(0.00)	
Consumption Goods	0.08***	0.08***	0.05***	2,553,583
	(0.02)	(0.01)	(0.00)	

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.

Furthermore, the theoretical analysis of bias suggests that we can learn about unobserved economic shocks through an inspection of estimates obtained from different estimators. Recall the two key takeaways from our discussion of Table 12. First, there might be unobserved variables which vary along dimensions that are not controlled for by a particular fixed effect specification. For example, the $fid + t$ fixed effects estimator does not control for the average marginal cost of a firm's product in a year; the $fit + d$ fixed effects estimator cannot control for firm-product-destination specific demand conditions. Second, as highlighted by table 11, there are structural restrictions on the direction of the bias an unobserved variable can cause. For example, a markup-relevant demand shock D_{fidt} will result in a *downward* selection bias as it has positive effects on both the optimal price and the operating profit (see case 1 of table 11). Similarly, a shock that changes the marginal cost of the firm will result in an *upward* selection bias (see case 3 of table 11). In light of these theoretical relationships, differences across estimates from various estimators are informative about the underlying unobserved economic shocks. So, in a concluding exercise, we draw on theory to interpret the difference in estimates of the TPSFE and the $fit+d$ fixed effect estimator in terms of underlying large firm-product-destination-specific demand shocks that are time-varying. As discussed in table 11 and shown in our simulations, these shocks would result in a *downward* selection bias, potentially explaining the difference between columns (1) and (3) in the high differentiation good panel. As an indirect validation of this interpretation, one may note that the difference between these columns is small in the LD panel—as firms selling low differentiation goods are likely to face more homogenous demand conditions across markets.

An interpretation of our results stressing the relevance of firm-product-specific cost and demand shocks is also instructive in assessing column (2), referred to as the $fid+t$ fixed effects estimator. On the one hand, the $fid+t$ fixed effects estimator controls for non-time-varying markup-relevant demand shocks. This reduces the *downward* selection bias and brings the estimates from the $fid+t$ fixed effects estimators closer to those of our TPSFE estimator in the absence of other shocks. This is especially true for State-Owned and Foreign-Invested enterprises, as well as for consumption goods, i.e., firms and products that are more prone to firm-product-destination specific shocks. On the other hand, the $fid+t$ fixed effects estimator fails to account for firm-product-time varying marginal costs. To the extent that marginal costs tend to be positively correlated with exchange rates (e.g., due to the rising cost of imported inputs), failing to control for them induces an *upward* bias, as discussed in case 4 of table 11. The fact that the markup elasticity estimated by the $fit+d$ fixed effects estimator is 22% for highly differentiated intermediate goods (row 4 of the upper panel), but reduces to nearly zero when using estimators that control for the cost components (in columns 1 and 3), suggests the presence of relevant unobserved firm-product-specific and time-varying marginal cost shocks in the data.[44]

Overall, an important conclusion from the assessment carried out in this section is that fixed effect estimators, appropriately specified and sufficiently strict, as is our TPSFE estimator, can go a long way to reduce (even eliminate) biases due to incomplete information on relevant variables.

[44]Recall that, if the firm-product-time marginal cost shocks are driving most of the bias, we should observe identical estimates from the TPSFE and $fit+d$ fixed effects estimators while the $fid+t$ fixed effects estimator will be upward biased.

7 Concluding Remarks

We conclude with two observations highlighting the significance of our contributions on methodological and policy grounds. Methodologically, we have shown that at fine levels of disaggregation (i.e., firm-product-destination), appropriately specified fixed effect estimators may actually perform quite well in relation to alternative methods that rely on the direct estimation of productivity and (unobservable) marginal costs at the firm level. The development of productivity- and cost-estimation methods has spawned a number of firm-level studies that have broken important new ground, shedding light on the level and time variation in firms' markups. Yet, applying these methods to our question of interest, concerning the time variation of markups at the product-destination level, gives rise to a key issue. Even if one could obtain the required data for the universe of firms in our sample, information on production inputs would generally be available only at the firm level, not at the firm-product level. In principle, estimates of marginal cost at the firm-product-destination level could still be obtained under a set of maintained assumptions on how inputs are allocated across products and destinations; e.g., by positing that the production functions of single-product, single-destination firms are representative of those of multi-product multi-destination firms. In this paper we have shown that, under the identification assumptions of De Loecker et al. (2016), well-defined fixed effect estimators would also give unbiased estimates of the markup elasticity to exchange rates—and under more general assumptions may perform better. Future research may integrate these different approaches as complementary tools, with application to a wide range of topics including the effects of taxes and tariffs at the international and regional levels.

Concerning policy, the rising importance of China as a global exporter has spawned research into how enhanced competitive pressures worldwide have influenced corporates' 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 people and economists routinely speak of the problem of "the China price," the low price of Chinese merchandise that exporters from other markets and domestic import-competing firms must match if they want to survive. Our contribution is to offer a more detailed and refined account of the nature of competitive pressures originating in China, one that cautions against overplaying the role of exchange rates in the policy debate. Our estimated markup elasticities imply that, for roughly 50% of the value of exports from China, a renminbi appreciation would not yield a uniform impact on Chinese prices. Because of the strategic response of Chinese firms that hold market power, the impact would vary considerably in different destinations and product markets. The effectiveness of a renminbi appreciation in reducing China's competitive pressure globally is far from certain.

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

Giancarlo Corsetti
European University Institute and CEPR

Meredith Crowley
University of Cambridge and CEPR

Lu Han
Bank of Canada and CEPR

Huasheng Song
Zhejiang University

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Contents

OA1 The TPSFE Estimator

OA1.1 Key properties of the TPSFE estimator

As highlighted in section 6 of the paper, the fundamental reason for omitted variable and selection biases to arise is the missing information on 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 fit panel dimension, while the differences in time-invariant demand conditions across markets facing a firm's product vary along 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 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 OA1.1.1 to OA1.1.3 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 OA1.1.4 provides a numerical example to clarify our notation and discussions. Subsection OA1.1.5 generalizes the results to four-dimensional unbalanced panels.

OA1.1.1 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.*

OA1.1.2 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

$$Z \equiv \begin{pmatrix} Z_1, & Z_2 \\ n^{DT} \times n^D & n^{DT} \times n^T \end{pmatrix} \equiv \begin{bmatrix} A_1 & A_1 \iota_{n^D} & & \\ \vdots & & \ddots & \\ A_{n^T} & & & A_{n^T} \iota_{n^D} \end{bmatrix} \tag{OA1-1}$$

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:

$$P \equiv P_2 - \bar{Z}(\bar{Z}'\bar{Z})^{-}\bar{Z}' = (I_{n^{DT}} - \bar{Z}(\bar{Z}'\bar{Z})^{-}\bar{Z}')P_2 \equiv P_1 P_2 \tag{OA1-2}$$

where $P_1 \equiv I_{n^{DT}} - \bar{Z}(\bar{Z}'\bar{Z})^{-}\bar{Z}'$ and the equality of (OA1-2) 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).[1] 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

$$\bar{Z} = P_2 Z_1 = Z_1 - Z_2 \left(Z_2' Z_2\right)^{-1} Z_2' Z_1 \tag{OA1-3}$$

[1] See the numerical example in subsection OA1.1.4.

where Z_1 is a set of destination dummies as defined in (OA1-1) 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.,

$$\begin{aligned} Z_2 \left(Z_2'Z_2\right)^{-1} Z_2' &= \text{diag}\left(\frac{1}{n_1^D} A_1 \iota_{n^D} \iota_{n^D}' A_1', ..., \frac{1}{n_{n^T}^D} A_{n^D} \iota_{n^D} \iota_{n^D}' A_{n^D}'\right) \\ &= \text{diag}\left(\frac{1}{n_1^D} \iota_{n_1^D} \iota_{n_1^D}', ..., \frac{1}{n_{n^T}^D} \iota_{n_{n^T}^D} \iota_{n_{n^T}^D}'\right) \end{aligned} \tag{OA1-4}$$

where the first equality holds by the definition of Z_2 in (OA1-1) 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.,

$$\left(Z_2'Z_2\right)^{-1} = \text{diag}\left(\frac{1}{n_1^D}, \frac{1}{n_2^D}, ..., \frac{1}{n_{n^T}^D}\right); \tag{OA1-5}$$

the second equality in (OA1-3) holds by the definition of the A matrices in (OA1-1). 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

$$Z_2 \left(Z_2'Z_2\right)^{-1} Z_2'Z_1 = \begin{bmatrix} \frac{1}{n_1^D} \iota_{n_1^D} \iota_{n_1^D}' A_1 \\ \vdots \\ \frac{1}{n_{n^T}^D} \iota_{n_{n^T}^D} \iota_{n_{n^T}^D}' A_{n^D} \end{bmatrix} \tag{OA1-6}$$

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.[2]

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 $Z_2 \left(Z_2'Z_2\right)^{-1} Z_2'Z_1$.

OA1.1.3 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 (OA1-3) and (OA1-6)), our estimator applies the trade pattern fixed effect multiplicatively.

[2]See Appendix OA1.1.4 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.[3] Let $\mathcal{TP}$ be the set of unique trade patterns in all years, i.e.,

$$\mathcal{TP} \equiv \{D_1, ..., D_{n^T}\}_{\neq} \tag{OA1-7}$$

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:

$$Z_3 \equiv \begin{bmatrix} B_1 \\ \vdots \\ B_{n^T} \end{bmatrix} \equiv \begin{bmatrix} K_{11} & \cdots & K_{1n^{\mathcal{TP}}} \\ \vdots & \ddots & \vdots \\ K_{n^T 1} & \cdots & K_{n^T n^{\mathcal{TP}}} \end{bmatrix} \tag{OA1-8}$$

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, $\forall x \in \{1, ..., n^T\}, y \in \{1, ..., n^{\mathcal{TP}}\}$,

$$K_{xy} \equiv \begin{cases} I_{n_x^D} & \text{if } D_x = \mathcal{TP}_y \\ \mathbf{0}_{n_x^D \times n_{\mathcal{TP}}^D(y)} & \text{if } D_x \neq \mathcal{TP}_y \end{cases} \tag{OA1-9}$$

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_3P_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.

[3] 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

$$P_3P_2Z_1 = \mathbf{0},$$
$$P_3P_2Z_2 = \mathbf{0},$$
$$P_3P_2Z_3 = \mathbf{0}.$$

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

$$P_3P_2Z_2 = [I_{n^{DT}} - Z_3\left(Z_3'Z_3\right)^{-1}Z_3'][I_{n^{DT}} - Z_2\left(Z_2'Z_2\right)^{-1}Z_2']Z_2 = \mathbf{0}.$$

We prove $P_3P_2Z_1 = \mathbf{0}$ and $P_3P_2Z_3 = \mathbf{0}$ 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:

$$T_3T_2 = T_2T_3. \tag{OA1-10}$$

Second, T_3 projects Z_1 to itself:

$$T_3Z_1 = Z_1. \tag{OA1-11}$$

Given (OA1-10) and (OA1-11), it follows that

$$\begin{aligned}
P_3P_2Z_1 &= [I_{n^{DT}} - T_3][I_{n^{DT}} - T_2]Z_1 \\
&= Z_1 - T_3Z_1 + T_3T_2Z_1 - T_2Z_1 \\
&= T_3T_2Z_1 - T_2Z_1 \\
&= T_2T_3Z_1 - T_2Z_1 \\
&= T_2Z_1 - T_2Z_1 \\
&= \mathbf{0}
\end{aligned}$$

where the second equality is due to (OA1-11); the third equality holds due to the commutativity (OA1-10); the fourth equality applies (OA1-11) one more time. Following the same procedure, it can be shown that $P_3P_2Z_3 = \mathbf{0}$.

We complete our proofs showing that (OA1-10) and (OA1-11) hold.

Proof of (OA1-10):

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:

$$Z_3\left(Z_3'Z_3\right)^{-1}Z_3' = \begin{bmatrix} B_1\left(Z_3'Z_3\right)^{-1}B_1' & \cdots & B_1\left(Z_3'Z_3\right)^{-1}B_{n^T}' \\ \vdots & \ddots & \vdots \\ B_1\left(Z_3'Z_3\right)^{-1}B_{n^T}' & \cdots & B_{n^T}\left(Z_3'Z_3\right)^{-1}B_{n^T}' \end{bmatrix} \tag{OA1-12}$$

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.,

$$\begin{aligned}
\left(Z_3'Z_3\right)^{-1} &= \left(\sum_t B_t'B_t\right)^{-1} \\
&= \begin{bmatrix} \sum_t K_{t1}'K_{t1} & \cdots & \sum_t K_{t1}'K_{tn^{\mathcal{TP}}} \\ \vdots & \ddots & \vdots \\ \sum_t K_{tn^T}'K_{t1} & \cdots & \sum_t K_{tn^{\mathcal{TP}}}'K_{tn^{\mathcal{TP}}} \end{bmatrix}^{-1} \\
&= \begin{bmatrix} r_1^{\mathcal{TP}} I_{n^D_{\mathcal{TP}}(1)} & & \\ & \ddots & \\ & & r_{n^{\mathcal{TP}}}^{\mathcal{TP}} I_{n^D_{\mathcal{TP}}(n^{\mathcal{TP}})} \end{bmatrix}^{-1} \\
&= \operatorname{diag}\left(\frac{1}{r_1^{\mathcal{TP}}} I_{n^D_{\mathcal{TP}}(1)}, ..., \frac{1}{r_{n^{\mathcal{TP}}}^{\mathcal{TP}}} I_{n^D_{\mathcal{TP}}(n^{\mathcal{TP}})}\right)
\end{aligned} \tag{OA1-13}$$

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 (OA1-8) and (OA1-9).

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:

$$B_h\left(Z_3'Z_3\right)^{-1}B_j' = \sum_{z\in\{1,..,n^{\mathcal{TP}}\}} \frac{1}{r_z^{\mathcal{TP}}} K_{hz} I_{n^D_{\mathcal{TP}}(z)} K_{jz}' = \begin{cases} \frac{1}{r_h^{\mathcal{D}}} I_{n_h^D} & \text{if } D_h = D_j \\ \mathbf{0}_{n_h^D \times n_j^D} & \text{if } D_h \neq D_j \end{cases} \tag{OA1-14}$$

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 (OA1-12) and (OA1-4), $Z_3\left(Z_3'Z_3\right)^{-1}Z_3'Z_2\left(Z_2'Z_2\right)^{-1}Z_2'$ 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 (OA1-14), 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

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

□

Proof of (OA1-11):

Proof. From (OA1-12) and the definition of Z_1 in (OA1-1), 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 (OA1-14), we have

$$B_x \left(Z_3'Z_3\right)^{-1} B_y' A_y = \begin{cases} \frac{1}{r_x^D} A_x = \frac{1}{r_y^D} A_y & \text{if } D_x = D_y \\ \mathbf{0}_{n_x^D \times n^D} & \text{if } D_x \neq D_y \end{cases} \tag{OA1-15}$$

With (OA1-15), it follows that

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

$\square$

OA1.1.4 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 discussions 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 OA1-1 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 OA1-1: 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 (OA1-8) and (OA1-9), 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 $5-4\_5$.

$$Z_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad Z_2 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad Z_3 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{OA1-16}$$

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 OA1.1.2, $Z_2\left(Z_2'Z_2\right)^{-1} Z_2'Z_1$ follows a trade pattern structure and $\bar{Z}$ suggests an additive relationship between the destination dummies Z_1 and the trade pattern dummies $Z_2\left(Z_2'Z_2\right)^{-1} Z_2'Z_1$.

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

As we can see from (OA1-17), the projection P does not follow a particular structure. Therefore, our two-step decomposition $P = P_1P_2$ discussed in subsection OA1.1.2 helps to unveil the key economic mechanisms behind the statistical projection.

$$P = \begin{bmatrix} 0.46 & -0.29 & -0.17 & -0.21 & 0.04 & 0.17 & -0.13 & 0.13 & -0.13 & 0.13 \\ -0.29 & 0.46 & -0.17 & 0.04 & -0.21 & 0.17 & 0.13 & -0.13 & 0.13 & -0.13 \\ -0.17 & -0.17 & 0.33 & 0.17 & 0.17 & -0.33 & 0 & 0 & 0 & 0 \\ -0.21 & 0.04 & 0.17 & 0.46 & -0.29 & -0.17 & -0.13 & 0.13 & -0.13 & 0.13 \\ 0.04 & -0.21 & 0.17 & -0.29 & 0.46 & -0.17 & 0.13 & -0.13 & 0.13 & -0.13 \\ 0.17 & 0.17 & -0.33 & -0.17 & -0.17 & 0.33 & 0 & 0 & 0 & 0 \\ -0.13 & 0.13 & 0 & -0.13 & 0.13 & 0 & 0.38 & -0.38 & -0.13 & 0.13 \\ 0.13 & -0.13 & 0 & 0.13 & -0.13 & 0 & -0.38 & 0.38 & 0.13 & -0.13 \\ -0.13 & 0.13 & 0 & -0.13 & 0.13 & 0 & -0.13 & 0.13 & 0.38 & -0.38 \\ 0.13 & -0.13 & 0 & 0.13 & -0.13 & 0 & 0.13 & -0.13 & -0.38 & 0.38 \end{bmatrix} \tag{OA1-17}$$

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 $\widehat{\beta}_1 = 1.000$.

OA1.1.5 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 (OA1-1).

Let n^D_{fi} denote the total number of export destinations by the firm-product and n^D_{fit} $\left(n^D_{fit} \leq n^D_{fi}\right)$ be the number of observed destinations in year t. Let n^T_{fi} denote the maximum number of exporting years and the $n^{DT}_{fi} \equiv \sum_t n^D_{fit}$ be the number of observed transactions by firm-product fi. Let A_{fit} be the $\left(n^D_{fit} \times n^D_{fi}\right)$ matrix obtained from the $(n^D_{fi} \times n^D_{fi})$ 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 (OA1-1) as

$$Z_{fi,1} \equiv \begin{bmatrix} A_{fi1} \\ \vdots \\ A_{fin^T_{fi}} \end{bmatrix}, \quad Z_{fi,2} \equiv \begin{bmatrix} A_{fi1}\iota_{n^D_{fi}} & & \\ & \ddots & \\ & & A_{fin^T_{fi}}\iota_{n^D_{fi}} \end{bmatrix}$$

where $Z_{fi,1}$ is an $n^{DT}_{fi} \times n^D_{fi}$ matrix that gives the dummy structure for the destination fixed effects of firm-product fi and $Z_{fi,2}$ is an $n^{DT}_{fi} \times n^T_{fi}$ 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 (OA1-8) and (OA1-9).

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; $n^{FID} \equiv \sum_{fi} n^D_{fi}$ be the sum of distinct destinations over all firm-products; $n^{FIT} \equiv \sum_{fi} n^T_{fi}$ be the sum of distinct time periods over all firm-products; and $n^{FI\mathcal{DTP}} \equiv \sum_{fi} n^{\mathcal{DTP}}_{fi}$ 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

$$\begin{aligned} Z_3 \left(Z_3' Z_3\right)^{-} Z_3' Z_1 &= \begin{bmatrix} Z_{1,3}\left(Z_{1,3}' Z_{1,3}\right)^{-} Z_{1,3}' Z_{1,1} & & \\ & \ddots & \\ & & Z_{n^{FI},3}\left(Z_{n^{FI},3}' Z_{n^{FI},3}\right)^{-} Z_{n^{FI},3}' Z_{n^{FI},1} \end{bmatrix} \\ &= \begin{bmatrix} Z_{1,1} & & \\ & \ddots & \\ & & Z_{n^{FI},1} \end{bmatrix} = Z_1 \end{aligned} \qquad \text{(OA1-18)}$$

where the first equality uses the property of block diagonal matrices and the the second equality uses the relationship of (OA1-11). Similarly, using the property of block diagonal matrices and the firm-product level relationship (OA1-10), it is straightforward to show the following equations hold:[4]

$$Z_3\left(Z_3'Z_3\right)^{-}Z_3'Z_2\left(Z_2'Z_2\right)^{-1}Z_2' = Z_2\left(Z_2'Z_2\right)^{-1}Z_2'Z_3\left(Z_3'Z_3\right)^{-}Z_3' \tag{OA1-19}$$

$$Z_3\left(Z_3'Z_3\right)^{-}Z_3'Z_2\left(Z_2'Z_2\right)^{-1}Z_2'Z_1 = Z_2\left(Z_2'Z_2\right)^{-1}Z_2'Z_1 \tag{OA1-20}$$

Using (OA1-18), (OA1-19) and (OA1-20), it follows that

$$\begin{aligned}
P_3P_2Z_1 &= [I_{n^{FIDT}} - Z_3\left(Z_3'Z_3\right)^{-}Z_3'][I_{n^{FIDT}} - Z_2\left(Z_2'Z_2\right)^{-1}Z_2']Z_1 \\
&= [I_{n^{FIDT}} - Z_2\left(Z_2'Z_2\right)^{-1}Z_2']Z_1 - Z_3\left(Z_3'Z_3\right)^{-}Z_3'[I_{n^{FIDT}} - Z_2\left(Z_2'Z_2\right)^{-1}Z_2']Z_1 \\
&= [I_{n^{FIDT}} - Z_2\left(Z_2'Z_2\right)^{-1}Z_2']Z_1 - [I_{n^{FIDT}} - Z_2\left(Z_2'Z_2\right)^{-1}Z_2']Z_1 = \mathbf{0}
\end{aligned}$$

and

$$\begin{aligned}
P_3P_2Z_3 &= [I_{n^{FIDT}} - Z_3\left(Z_3'Z_3\right)^{-}Z_3'][I_{n^{FIDT}} - Z_2\left(Z_2'Z_2\right)^{-1}Z_2']Z_3 \\
&= [I_{n^{FIDT}} - Z_3\left(Z_3'Z_3\right)^{-}Z_3']Z_3 - [I_{n^{FIDT}} - Z_3\left(Z_3'Z_3\right)^{-}Z_3']Z_2\left(Z_2'Z_2\right)^{-1}Z_2'Z_3 \\
&= \mathbf{0} - [Z_2\left(Z_2'Z_2\right)^{-1}Z_2'Z_3 - Z_3\left(Z_3'Z_3\right)^{-}Z_3'Z_2\left(Z_2'Z_2\right)^{-1}Z_2'Z_3] = \mathbf{0}
\end{aligned}$$

□

OA1.2 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).[5] 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 set of

[4]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 (OA1-19) and (OA1-20) and can potentially result in substantial biases.

[5]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)).

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:

$$\begin{aligned} p_{dt} &= \boldsymbol{x}_{dt}'\boldsymbol{\beta} + \mathcal{M}_d + \varepsilon_{dt} && \text{(OA1-21)} \\ &= \boldsymbol{x}_{dt}'\boldsymbol{\beta} + \mathcal{M}_d + E(\mathcal{M}_d|\boldsymbol{x}_{dt}, s_{dt}) + E(\varepsilon_{dt}|\boldsymbol{x}_{dt}, s_{dt}) + \nu_{dt} \\ s_{dt} &= \mathbb{1}\{\boldsymbol{w}_{dt}'\boldsymbol{\gamma} + \mathcal{W}_d + u_{dt}\} && \text{(OA1-22)} \end{aligned}$$

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.[6] 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:

$$F(\varepsilon_{d1}, \varepsilon_{d2}, u_{d1}, u_{d2}|\boldsymbol{\vartheta}_d) = F(\varepsilon_{d2}, \varepsilon_{d1}, u_{d2}, u_{d1}|\boldsymbol{\vartheta}_d) \qquad \text{(OA1-23)}$$

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 (OA1-23) states that $(\varepsilon_{d1}, \varepsilon_{d2}, u_{d1}, u_{d2})$ and

[6] 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 (OA1-23):

$$
\begin{aligned}
& E(\varepsilon_{d1}|s_{d1} = 1, s_{d2} = 1|\boldsymbol{\vartheta}_d) \\
\equiv\ & E(\varepsilon_{d1}|u_{d1} < \boldsymbol{w}'_{d1}\boldsymbol{\gamma} + \mathcal{W}_d, u_{d2} < \boldsymbol{w}'_{d2}\boldsymbol{\gamma} + \mathcal{W}_d, \boldsymbol{\vartheta}_d) \\
=\ & E(\varepsilon_{d1}|u_{d1} < \boldsymbol{w}'_{d2}\boldsymbol{\gamma} + \mathcal{W}_d, u_{d2} < \boldsymbol{w}'_{d1}\boldsymbol{\gamma} + \mathcal{W}_d, \boldsymbol{\vartheta}_d) && \text{(OA1-24)} \\
=\ & E(\varepsilon_{d2}|u_{d2} < \boldsymbol{w}'_{d2}\boldsymbol{\gamma} + \mathcal{W}_d, u_{d1} < \boldsymbol{w}'_{d1}\boldsymbol{\gamma} + \mathcal{W}_d, \boldsymbol{\vartheta}_d) && \text{(OA1-25)} \\
\equiv\ & E(\varepsilon_{d2}|s_{d2} = 1, s_{d1} = 1|\boldsymbol{\vartheta}_d)
\end{aligned}
$$

where the first equality (OA1-24) holds because $\boldsymbol{w}'_{d1}\boldsymbol{\gamma} = \boldsymbol{w}'_{d2}\boldsymbol{\gamma}$ and the second equality (OA1-25) holds because of the *conditional exchangeability* condition (OA1-23). 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 (OA1-26) and (OA1-27) as follows:

$$
p_{fidt} = \boldsymbol{x}'_{dt}\boldsymbol{\beta} + \mathcal{M}_{fid} + \mathcal{C}_{fit} + \varepsilon_{fidt} \tag{OA1-26}
$$

$$
s_{fidt} = \mathbb{1}\{\boldsymbol{w}'_{dt}\boldsymbol{\gamma} + \mathcal{W}_{fid} + \mathcal{Q}_{fit} + u_{fidt}\} \tag{OA1-27}
$$

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 (OA1-21) and $\mathcal{Q}_{fit}$ to equation (OA1-22). 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 (OA1-26) and (OA1-27), 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.

OA1.2.1 A two dimensional panel case

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

$$p_{dt} = \boldsymbol{x}'_{dt}\boldsymbol{\beta} + \mathcal{M}_d + \mathcal{C}_t + \varepsilon_{dt} \tag{OA1-28}$$

$$s_{dt} = \mathbb{1}\{u_{dt}\} \tag{OA1-29}$$

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 (OA1-28) 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

$$\ddot{\boldsymbol{x}}_{dt} = \boldsymbol{x}_{dt} - \frac{1}{n_t^D}\sum_{d\in D_t}\boldsymbol{x}_{dt} - \frac{1}{n_{dD}^T}\sum_{t\in T_{dD}}\boldsymbol{x}_{dt} + \frac{1}{n_{dD}^T}\sum_{t\in T_{dD}}\frac{1}{n_t^D}\sum_{d\in D_t}\boldsymbol{x}_{dt} \tag{OA1-30}$$

$$\ddot{\varepsilon}_{dt} = \varepsilon_{dt} - \frac{1}{n_t^D}\sum_{d\in D_t}\varepsilon_{dt} - \frac{1}{n_{dD}^T}\sum_{t\in T_{dD}}\varepsilon_{dt} + \frac{1}{n_{dD}^T}\sum_{t\in T_{dD}}\frac{1}{n_t^D}\sum_{d\in D_t}\varepsilon_{dt}, \tag{OA1-31}$$

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[7]

$$F(\varepsilon_{dD1}, \varepsilon_{dD2}, u_{dD1}, u_{dD2}|\boldsymbol{\vartheta}_{dD}) = F(\varepsilon_{dD2}, \varepsilon_{dD1}, u_{dD2}, u_{dD1}|\boldsymbol{\vartheta}_{dD}), \tag{OA1-33}$$

where we use ε_{dD1} to indicate the first error within the destination-specific trade pattern dD. Given (OA1-33), 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:

$$E\left(\varepsilon_{dDt}|u_{dD1} > 0, u_{dD2} > 0, \boldsymbol{\vartheta}_{dD}\right) = E\left(\varepsilon_{dD\tau}|u_{dD1} > 0, u_{dD2} > 0, \boldsymbol{\vartheta}_{dD}\right) \quad \forall \tau \in T_{dD} \tag{OA1-34}$$

Condition (OA1-33) 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.[8]

OA1.2.2 General setting

We now discuss the general multi-dimensional setting specified in (OA1-26) and (OA1-27). With an additional dimension,[9] we can write the condition for identification as follows:

$$E\left[E\left(\varepsilon_{fidDt}|\mathbf{s}_{fidD}, \boldsymbol{\vartheta}_{fidD}\right)\Big|dt\right] = E\left[E\left(\varepsilon_{fidD\tau}|\mathbf{s}_{fidD}, \boldsymbol{\vartheta}_{fidD}\right)\Big|dt\right] \quad \forall\ \tau \in T_{fidD} \tag{OA1-35}$$

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.

[7] 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:

$$E\left(\varepsilon_{dDt}|u_{dD1} > 0, ..., u_{dDn^T_{dD}} > 0, \vartheta_{dD}\right) = E\left(\varepsilon_{dD\tau}|u_{dD1} > 0, ..., u_{dDn^T_{dD}} > 0, \vartheta_{dD}\right) \quad \forall \tau \in T_{dD} \tag{OA1-32}$$

As will be discussed later, our estimator works under a much weaker condition than (OA1-32) if another panel dimension is available.

[8] The condition for consistency, i.e., $E(s_{dt}\ddot{\boldsymbol{x}}_{dt}\ddot{\varepsilon}_{dt}) = 0$, is satisfied under (OA1-32). 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 (OA1-32), i.e., $E\left(\varepsilon_{dt} - \frac{1}{n^T_{dD}}\sum_{t\in T_{dD}}\varepsilon_{dt}\Big|s_{dD1}, s_{dD2}, s_{dD3}, ..., \vartheta_{dD}\right) = 0$.

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

As can be seen from (OA1-35), we no longer need the error to be zero conditional on the observed pattern ($E\left(\varepsilon_{fidDt}-\varepsilon_{fidD\tau}|\mathbf{s}_{fidD},\boldsymbol{\vartheta}_{fidD}\right)=0$) as in the two dimensional case. Instead, it is sufficient to have the expectation of $E\left(\varepsilon_{fidDt}-\varepsilon_{fidD\tau}|\mathbf{s}_{fidD},\boldsymbol{\vartheta}_{fidD}\right)$ be zero, once it is aggregated at the firm and product dimension. For example, if $E\left(\varepsilon_{fidDt}-\varepsilon_{fidD\tau}|\mathbf{s}_{fidD},\boldsymbol{\vartheta}_{fidD}\right)$ 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 (OA1-35). 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

$$\ddot{\boldsymbol{x}}_{fidt}=\boldsymbol{x}_{dt}-\frac{1}{n^D_{fit}}\sum_{d\in D_{fit}}\boldsymbol{x}_{dt}-\frac{1}{n^T_{fidD}}\sum_{t\in T_{fidD}}\boldsymbol{x}_{dt}+\frac{1}{n^T_{fidD}}\sum_{t\in T_{fidD}}\frac{1}{n^D_{fit}}\sum_{d\in D_{fit}}\boldsymbol{x}_{dt} \tag{OA1-36}$$

$$\ddot{v}_{fidt}=v_{fidt}-\frac{1}{n^D_{fit}}\sum_{d\in D_{fit}}v_{fidt}-\frac{1}{n^T_{fidD}}\sum_{t\in T_{fidD}}v_{fidt}+\frac{1}{n^T_{fidD}}\sum_{t\in T_{fidD}}\frac{1}{n^D_{fit}}\sum_{d\in D_{fit}}v_{fidt}. \tag{OA1-37}$$

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 (OA1-36) and (OA1-37) 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:

$$\frac{1}{n^{FIDT}}\sum_{fidt}\ddot{\varepsilon}_{fidt}\ddot{\boldsymbol{x}}_{fidt}=\frac{1}{n^{FIDT}}\sum_{fidt}(\varepsilon_{fidt}-\varepsilon_{fiDt}-\varepsilon_{fidT}+\varepsilon_{fiDT})\boldsymbol{x}_{dt} \tag{OA1-38}$$

$$=\frac{1}{n^{FIDT}}\sum_{fidt}(\varepsilon_{fidt}-\varepsilon_{fidT})\boldsymbol{x}_{dt}. \tag{OA1-39}$$

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

$$\begin{aligned}
&E(\ddot{\varepsilon}_{fidt}\ddot{\boldsymbol{x}}_{fidt}s_{fidt}) \\
&= E\left[(\varepsilon_{fidt} - \varepsilon_{fidT})\boldsymbol{x}_{dt}s_{fidt}\right] \\
&= E\left\{\boldsymbol{x}_{dt}E\left[E\left(\varepsilon_{fidt} - \varepsilon_{fidT}|\mathbf{s}_{fidD}, \boldsymbol{\vartheta}_{fidD}\right)\Big|dt\right]\right\} \\
&= E\left\{\boldsymbol{x}_{dt}E\left[E\left(\varepsilon_{fidDt} - \frac{1}{n_{fidD}^{T}}\sum_{\tau\in T_{fidD}}\varepsilon_{fidD\tau}|\mathbf{s}_{fidD}, \boldsymbol{\vartheta}_{fidD}\right)\Bigg|dt\right]\right\} \\
&= 0
\end{aligned} \tag{OA1-40}$$

where the first equality follows from using (OA1-39) under our proposed "within transformation"; the second equality from applying the law of iterated expectations; and the last equality from using condition (OA1-35).

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 (OA1-35) 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 (OA1-35) 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.

OA1.3 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 (OA1-35) to be satisfied in this new framework.

OA1.3.1 Structural interpretation of assumptions required by our estimator

We start by writing the production function as follows:

$$Q_{fidt} = F_{fi}(\boldsymbol{V}_{fidt}, \boldsymbol{K}_{fidt})\Omega_{fit}\vartheta_{fid} \tag{OA1-41}$$

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

$$\boldsymbol{s}_{fit} = \{D_{fit}, \boldsymbol{K}_{fit}, \Omega_{fit}, \vartheta_{fid}, \boldsymbol{G}_{fi}, \boldsymbol{r}_{fidt}\} \tag{OA1-42}$$

   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.

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 to changes in relative marginal costs, condition (OA1-35) 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.

OA1.3.2 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.[10]

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

$$\frac{\partial \mathcal{L}_{fit}}{\partial V_{fidt}^{v}} = W_{fit}^{v} - \lambda_{fidt}\Omega_{fit}\vartheta_{fid}\frac{\partial F_{fi}(.)}{\partial V_{fidt}^{v}} = 0, \tag{OA1-43}$$

$$\frac{\partial \mathcal{L}_{fit}}{\partial K_{fidt}^{k}} = R_{fit}^{k} - \lambda_{fidt}\Omega_{fit}\vartheta_{fid}\frac{\partial F_{fi}(.)}{\partial K_{fidt}^{k}} = 0. \tag{OA1-44}$$

Conditions (OA1-43) and (OA1-44) need to hold across inputs and across destinations, which implies the following:

[10] 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.

$$\frac{W^1_{fit}}{W^v_{fit}} = \frac{\frac{\partial F_{fi}(.)}{\partial V^1_{fi1t}}}{\frac{\partial F_{fi}(.)}{\partial V^v_{fi1t}}} = \frac{\frac{\partial F_{fi}(.)}{\partial V^1_{fi2t}}}{\frac{\partial F_{fi}(.)}{\partial V^v_{fi2t}}} = ... = \frac{\frac{\partial F_{fi}(.)}{\partial V^1_{fidt}}}{\frac{\partial F_{fi}(.)}{\partial V^v_{fidt}}} \qquad \forall v = 1, ..., V; \quad d \in D_{fit}, \tag{OA1-45}$$

$$\frac{W^v_{fit}}{R^k_{fit}} = \frac{\frac{\partial F_{fi}(.)}{\partial V^v_{f,i,1,t}}}{\frac{\partial F_{fi}(.)}{\partial K^k_{fi1t}}} = \frac{\frac{\partial F_{fi}(.)}{\partial V^v_{fi2t}}}{\frac{\partial F_{fi}(.)}{\partial K^k_{fi2t}}} = ... = \frac{\frac{\partial F_{fi}(.)}{\partial V^v_{fidt}}}{\frac{\partial F_{fi}(.)}{\partial K^k_{fidt}}} \qquad \forall v, k; \quad d \in D_{fit}. \tag{OA1-46}$$

Note that the production function is assumed to be firm-product specific and constant return to scale. Together with equations (OA1-45) and (OA1-46), these assumptions imply that the allocation of variable inputs is inversely proportional to the ratio of the productivity deflated outputs across destinations, i.e.,

$$\frac{Q_{fidt}}{\Omega_{fit}\vartheta_{fid}} = c \cdot \frac{Q_{fid't}}{\Omega_{fit}\vartheta_{fid'}} \quad \rightarrow \quad c\boldsymbol{V}^*_{fidt} = \boldsymbol{V}^*_{fid't} \quad \text{and} \quad c\boldsymbol{K}^*_{fidt} = \boldsymbol{K}^*_{fid't}. \tag{OA1-47}$$

Utilizing the relationship of (OA1-47) and the assumption that $F_{fi}(.)$ is constant return to scale, it is straightforward to see

$$\frac{\partial F_{fi}(\boldsymbol{V}^*_{fidt}, \boldsymbol{K}^*_{fidt})}{\partial V^v_{fidt}} = \frac{\partial F_{fi}(c\boldsymbol{V}^*_{fidt}, c\boldsymbol{K}^*_{fidt})}{\partial (cV^v_{fidt})} = \frac{\partial F_{fi}(\boldsymbol{V}^*_{fid't}, \boldsymbol{K}^*_{fid't})}{\partial V^v_{fid't}}. \tag{OA1-48}$$

Rearranging (OA1-43) and (OA1-48) yields:

$$\begin{aligned} \lambda_{fidt} &= \left(\frac{\Omega_{fit}\vartheta_{fid}}{W^v_{fit}} \frac{\partial F_{fi}(\boldsymbol{V}^*_{fidt}, \boldsymbol{K}^*_{fidt})}{\partial V^v_{fidt}} \right)^{-1} \\ &= \left(\frac{\Omega_{fit}\vartheta_{fid}}{W^v_{fit}} \frac{\partial F_{fi}(\boldsymbol{V}^*_{fid't}, \boldsymbol{K}^*_{fid't})}{\partial V^v_{fid't}} \right)^{-1}. \end{aligned} \tag{OA1-49}$$

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

$$\frac{\lambda_{fidt}}{\lambda_{fid't}} = \frac{\vartheta_{fid'}}{\vartheta_{fid}} \tag{OA1-50}$$

Although the marginal cost is firm-product-destination specific and time-varying, the relative marginal cost is not. Therefore, condition (OA1-35) is satisfied.

OA1.3.3 An alternative approach

An alternative approach to reconcile our work with De Loecker et al. (2016) consists of directly redefining what a product variety is in their model. Namely, if one redefines a product-destination pair as a variety, i.e., $j = \{i, d\}$, then the original setting and assumptions will go through without any change.

We argue that this approach is not very useful, for two reasons. The first one is practical. De Loecker et al. (2016) define a product variety as a two-digit industry. The need to define a product at the industry level is mainly due to data limitations. If one adopts a more refined product definition, for instance, the estimator by De Loecker et al. (2016) would suffer from a small sample problem—there would not be enough power to estimate. The small sample problem will be much more severe if one defines a product-destination pair as a variety. This is due not only to the smaller number of observations in each cell, but also to the frequent changes in the set of destinations a firm exports a product to.

The second reason is related to conceptual assumptions regarding production functions. De Loecker et al. (2016) rely on the assumption that the production function is the same for single- and multi-product firms. When redefining a product-destination pair as a variety, the identification condition would require the production function to be product-destination specific and invariant along the firm dimension. In the context of our problem, controlling for firm-product level marginal cost is the primary concern. We think that keeping the flexibility of the production function at the product level is extremely valuable.

OA2 Supplementary Model and Simulation Results

In this appendix, we examine markup elasticities estimated using data generated from an alternative model developed by Corsetti and Dedola (2005) and used in Berman et al. (2012), where variable markups arise due to the existence of local production or distribution costs. Compared to the model with Kimball (1995) preference, the key advantage of the Corsetti and Dedola (2005) setting is that it allows us to derive analytical solutions and thus make a more transparent statement about the variables that affect firms' markup and exporting decisions.

The firm's problem is given as follows:

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

$$\psi_i(\alpha_{fidt}, P_{fidt}, \mathcal{E}_{dt}) \equiv \alpha_{fidt} \left(\frac{P_{fidt}}{\mathcal{E}_{dt}} + \chi_i \right)^{-\rho_i}$$

where $\chi_i > 0$ is the local distribution cost denominated in the destination country's currency; $\rho_i > 1$ is the elasticity of substitution across varieties of product i; $\phi_{fidt} \in \{0, 1\}$ is an indicator that equals one if firm f decides to export its product i to destination d at time t; P_{fidt} is the border price denominated in the exporter's currency; $\mathcal{MC}_{fidt}$ denotes the marginal cost; α_{fidt} is a markup-irrelevant demand shifter; $\mathcal{E}_{dt}$ is the bilateral exchange rate with an increase in $\mathcal{E}_{dt}$ meaning a depreciation of the exporting country's currency; and $\psi_i(.)$ gives the demand facing firm f selling product i in destination d in time t.

The firm's optimal price denominated in the exporter's currency is given by:

$$P^*_{fidt} = \frac{\rho_i}{\rho_i - 1}\left(\mathcal{MC}_{fidt} + \frac{\chi_i}{\rho_i}\mathcal{E}_{dt}\right) \tag{OA2-1}$$

Defining the markup as $\mu_{fidt} \equiv P^*_{fidt}/\mathcal{MC}_{fidt}$, the optimal markup adjustment can be written as a function of changes in the exchange rate $\widehat{\mathcal{E}}_{dt}$ and the marginal cost $\widehat{\mathcal{MC}}_{fidt}$ (up to a first-order approximation):

$$\widehat{\mu}_{fidt} = \Gamma_{fidt}\left(\widehat{\mathcal{E}}_{dt} - \widehat{\mathcal{MC}}_{fidt}\right) \tag{OA2-2}$$

with the markup elasticity to exchange rates given by:

$$\Gamma_{fidt} \equiv \frac{\chi_i\mathcal{E}_{dt}}{\rho_i\mathcal{MC}_{fidt} + \chi_i\mathcal{E}_{dt}} \tag{OA2-3}$$

Equations (OA2-2) and (OA2-3) highlight the two key theoretical predictions of the model: (a) the markup elasticity to the exchange rate is *decreasing* in ρ_i, suggesting high differentiation goods tend to have *higher* markup adjustments relative to low differentiation goods; and (b) the markup elasticity is *increasing* in the retail cost ratio, suggesting that more productive firms—with lower marginal costs and larger market shares—tend to make *higher* markup adjustments.

The entry and exit decisions of a firm's product depend crucially on the changes in the operational profit of the firm-product in a destination market:

$$\widehat{\pi}_{fidt} = \widehat{\alpha}_{fidt} + \left(1 + \frac{\rho_i - 1}{1 + \omega_{fidt}}\right)\widehat{\mathcal{E}}_{dt} - \frac{\rho_i - 1}{1 + \omega_{fidt}}\widehat{\mathcal{MC}}_{fidt} \tag{OA2-4}$$

where $\omega_{fidt} \equiv \chi_i\mathcal{E}_{dt}/\mathcal{MC}_{fidt} > 0$ is the retail cost ratio defined as the distribution cost expressed in the producer's currency divided by the marginal cost.

Direction of potential biases. As we discussed in section 6 of the paper, the direction of the selection bias depends on how the variable of interest (i.e., $\mathcal{E}_{dt}$) and the unobserved variable (e.g., $\mathcal{MC}_{fidt}$) enter the pricing and the selection equations. First of all, equations (OA2-1) and (OA2-4) show that the exchange rate $\mathcal{E}_{dt}$ has positive impacts on the optimal price P^*_{fidt} and the operational profit π_{fidt}. Second, we can see from these two equations that a higher marginal cost increases the optimal price of the firm but reduces the operating profit, making the firm less likely to enter a market. These relationships suggest that the unobserved marginal cost will result in an upward selection bias in the estimated markup elasticity to exchange rates. Intuitively, this is because when the exchange rate is unfavourable (i.e., when $\mathcal{E}_{dt}$ is low), the marginal cost $\mathcal{MC}_{fidt}$ needs to be sufficiently low for a firm to find it optimal to export its product to a market. Therefore, selection makes us more likely to observe low (high) marginal cost firms when the exchange rate is low (high), which leads to a *positive* correlation between the unobserved marginal cost and the exchange rate in the *observed* transactions and thus results in an *upward* selection bias.

We have focused on the selection bias in the above discussions. In general, the total bias caused by the unobserved marginal cost will also depend on the correlation between the marginal cost and the exchange rate in the absence of any selection effects. For example, if the marginal cost is positively correlated with exchange rates (e.g., due to a higher cost of imported inputs), then there will be an upward omitted variable bias even if we could observe the optimal price for all firms (including those that do not find it optimal to export). In this case, the omitted variable bias and the selection bias will reinforce each other and result in a significantly larger bias.

Finally, we note that, since preference shocks $\widehat{\alpha}_{fidt}$ do not affect the optimal price of the firm (see equation (OA2-1)), omitting them in the estimation of the markup elasticity to exchange rates will not result in any selection or omitted variable bias. By the same token, since the entry cost ζ_i does not affect the optimal price, changes in the entry cost will not cause any bias.

Simulation setup. We follow the same exchange rate data-generating process as in the paper:

$$\ln(\mathcal{E}_{dt}) = \sigma_{\mathcal{E}}(v_d * \mathcal{F}_t + u_{dt}) \tag{OA2-5}$$

where changes in $\mathcal{E}_{dt}$ are driven by (i) economic fundamentals of the origin country captured by $\mathcal{F}_t$, which can have differential effects in each destination market v_d, and (ii) a noise term u_{dt} that captures exchange rate changes due to financial market fluctuations, for example. $\sigma_{\mathcal{E}}$ controls for the relative size of exchange rate shocks.

The marginal cost $\mathcal{MC}_{fidt} = M_{fidt}/A_{fi}$ is comprised of two terms, where M_{fidt} denotes shocks to the firm's marginal costs due to firm-specific or macro reasons, and A_{fi} is the productivity of the firm-product drawn from a Pareto distribution. In contrast to the simulation setting in our paper, we now allow for firm-product-destination specific cost components and shocks:

$$\ln(M_{fidt}) = \begin{cases} \sigma_M(v_{fi} * \mathcal{F}_t + u_{fit}) & \text{in panel (a)} \\ \sigma_M(v_{fi} * \mathcal{F}_t + u_{fit}) + \sigma_D \varsigma_{fid} & \text{in panel (b)} \\ \sigma_M(v_{fi} * \mathcal{F}_t + u_{fit}) + \sigma_D \varsigma_{fid}(\mathcal{F}_t + u_{fidt}) & \text{in panel (c)} \end{cases} \tag{OA2-6}$$

As we discussed in the paper, the $\sigma_M(v_{fi} * \mathcal{F}_t + u_{fit})$ term in $\ln(M_{fidt})$ captures time-varying firm-product marginal costs that are positively correlated with exchange rates. The setting in panel (b) allows for a firm-product-destination-specific cost component ς_{fid}, whereas the setting in panel (c) permits the firm-product-destination-specific cost component to be time-varying and correlated with the shocks to the economic fundamentals $\mathcal{F}_t$.

Factors $\mathcal{F}_t, u_{dt}, u_{fit}$ and u_{fidt} 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 $\sigma_D = 0.075$ and give more weight to firm-product specific shocks so that most of the changes in the firms' trade patterns are driven by these unobserved shocks rather than by the observed bilateral exchange rate changes. We set the local distribution cost $\chi_i = 0.5$ so that the median distribution margin is around 40-50%, roughly in line with the recent empirical estimates (see, e.g., Berger et al. (2012)). We set the fixed cost of entry ζ_i so that about 20% of firms selling each product export.

Simulation results. Tables OA2-1 and OA2-2 show the estimates under three different marginal cost processes described in (OA2-6) for the Corsetti and Dedola (2005) model discussed above and the Kimball (1995) model in section 6 of the paper, respectively.[11]

We compare the performance of our TPSFE estimator (column 7) along with six alternative approaches (columns 1-6) and the benchmark estimates from an infeasible estimator (column 8). Specifically, column (1) shows the OLS estimates from regressing $\ln(P_{fidt})$ on $\ln(\mathcal{E}_{dt})$. Column (2) shows the estimates that would have been obtained from productivity and marginal cost estimation approaches, where we add the mean marginal cost of a firm's product in a period (i.e., $\overline{\mathcal{MC}}_{fit} \equiv \frac{1}{n^D_{fit}} \sum_{d \in D_{fit}} \mathcal{MC}_{fidt}$) as an additional control variable to the OLS specification in column (1). Column (3) shows the estimates from the original Knetter (1989) approach. Column (4) shows results from the "S-difference" specification of Gopinath et al. (2010). Columns (5) and (6) report estimates using firm-product-destination + time and firm-product-time + destination fixed effects, respectively. Column (7) reports the estimates from our TPSFE estimator. Finally, in the last column (8), we report the benchmark estimates from an infeasible estimator by running an OLS regression which includes *all* the unobserved variables (e.g., the true marginal cost $\mathcal{MC}_{fidt}$) in the specification. This regression gives the best linear relationship that an econometrician could get without specifying the underlying theoretical model.

The key takeaways in panel (a) of the two tables are the same as those we discussed in section 6 of the paper: the marginal cost estimation approach (2) and the fixed effect approaches (6) and (7) give estimates that are very close to the benchmark best linear estimates. Panel (b) of both

[11] Since demand shocks do not result in any bias in the estimation of markup elasticities in Corsetti and Dedola (2005), we also shut down the markup-relevant demand shocks in the simulations of the Kimball model (by setting $\ln(D_{fidt}) = 0$) to make the simulation results of the two models more comparable. We allow for firm-product-destination-specific markup-irrelevant demand shifters α_{fid} in both models.

Table OA2-1: Comparison of Estimators – Corsetti and Dedola (2005)

Sample	(1) OLS	(2) OLS with $\overline{\mathcal{MC}}_{fit}$	(3) $d+t$ FE	(4) S-diff	(5) $fid+t$ FE	(6) $fit+d$ FE	(7) TPSFE	(8) Best Linear
Panel (a): firm-product-time cost shocks								
All	1.30	0.15	1.48	0.31	0.31	0.12	0.12	0.15
	(0.02)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HD ($\rho = 4$)	1.45	0.20	1.45	0.38	0.38	0.17	0.20	0.20
	(0.03)	(0.00)	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
LD ($\rho = 12$)	1.14	0.08	1.14	0.24	0.24	0.07	0.07	0.08
	(0.02)	(0.00)	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Panel (b): firm-product-time cost shocks + firm-product-destination specific cost component								
All	1.29	0.16	1.47	0.31	0.30	0.15	0.12	0.14
	(0.02)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HD ($\rho = 4$)	1.44	0.21	1.44	0.38	0.37	0.19	0.19	0.20
	(0.03)	(0.00)	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
LD ($\rho = 12$)	1.14	0.11	1.14	0.24	0.24	0.10	0.07	0.08
	(0.02)	(0.00)	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Panel (c): firm-product-*destination*-time cost shocks								
All	1.29	0.23	1.46	0.83	0.38	0.23	0.15	0.15
	(0.02)	(0.00)	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
HD ($\rho = 4$)	1.44	0.27	1.42	0.89	0.46	0.26	0.27	0.21
	(0.03)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
LD ($\rho = 12$)	1.14	0.19	1.14	0.77	0.31	0.21	0.10	0.08
	(0.02)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)

Note: Estimates and standard errors are calculated based on the average of 10 simulations of each setting.

Table OA2-2: Comparison of Estimators – Kimball (1995)

Sample	(1) OLS	(2) OLS with $\overline{\mathcal{MC}}_{fit}$	(3) $d+t$ FE	(4) S-diff	(5) $fid+t$ FE	(6) $fit+d$ FE	(7) TPSFE	(8) Best Linear
Panel (a): firm-product-time cost shocks								
All	1.36	0.17	1.50	0.36	0.35	0.17	0.15	0.17
	(0.02)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HD ($\rho = 4$)	1.51	0.27	1.51	0.46	0.45	0.26	0.27	0.27
	(0.02)	(0.00)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
LD ($\rho = 12$)	1.21	0.09	1.21	0.26	0.26	0.09	0.09	0.09
	(0.02)	(0.00)	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Panel (b): firm-product-time cost shocks + firm-product-destination specific cost component								
All	1.34	0.20	1.48	0.35	0.35	0.21	0.16	0.17
	(0.02)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HD ($\rho = 4$)	1.49	0.29	1.49	0.45	0.45	0.29	0.27	0.27
	(0.02)	(0.00)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
LD ($\rho = 12$)	1.20	0.12	1.21	0.26	0.26	0.13	0.09	0.09
	(0.02)	(0.00)	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Panel (c): firm-product-*destination*-time cost shocks								
All	1.35	0.27	1.49	0.86	0.43	0.30	0.17	0.17
	(0.02)	(0.00)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
HD ($\rho = 4$)	1.50	0.35	1.50	0.92	0.53	0.36	0.29	0.27
	(0.02)	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
LD ($\rho = 12$)	1.21	0.21	1.21	0.79	0.33	0.24	0.10	0.09
	(0.02)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)

Note: Estimates and standard errors are calculated based on the average of 10 simulations of each setting.

tables show that, similar to the case of adding firm-product-destination-specific demand conditions discussed in the paper, allowing for firm-product-destination-specific cost components results in biased estimates in specifications (2) and (6). However, a key difference is that the presence of unobserved marginal cost components will result in an upward selection bias (as opposed to a downward bias in the case of markup-relevant demand shocks). As we can see from panel (b) of both tables, the estimates of specifications (2) and (6) tend to be larger than the benchmark estimates in column (8) and the difference in the estimates is larger for low differentiation goods, reflecting that the goods with a high elasticity of substitution are more sensitive to cost changes. Finally, in the very challenging case of exchange rates correlated with firm-product-destination-time cost shocks in panel (c), we see our TPSFE estimator outperforms alternative approaches and gives estimates closer to the benchmark estimates in column (8). This is particularly true for the low differentiation goods that are more sensitive to cost changes.

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Supplementary Data and Replication Materials for "Markets and Markup: A New Empirical Framework and Evidence on Exporters from China"

Giancarlo Corsetti
European University Institute and CEPR

Meredith Crowley
University of Cambridge and CEPR

Lu Han
Bank of Canada and CEPR

Huasheng Song
Zhejiang University

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Contents

SM1 Data

SM1.1 Chinese customs data

China's export growth exploded over 2000-2014 (see table SM1-1). 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 SM1-1: 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

SM1.2 The evolution of exports by private, state-owned and foreign-invested firms in China

In figure SM1-1, 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,

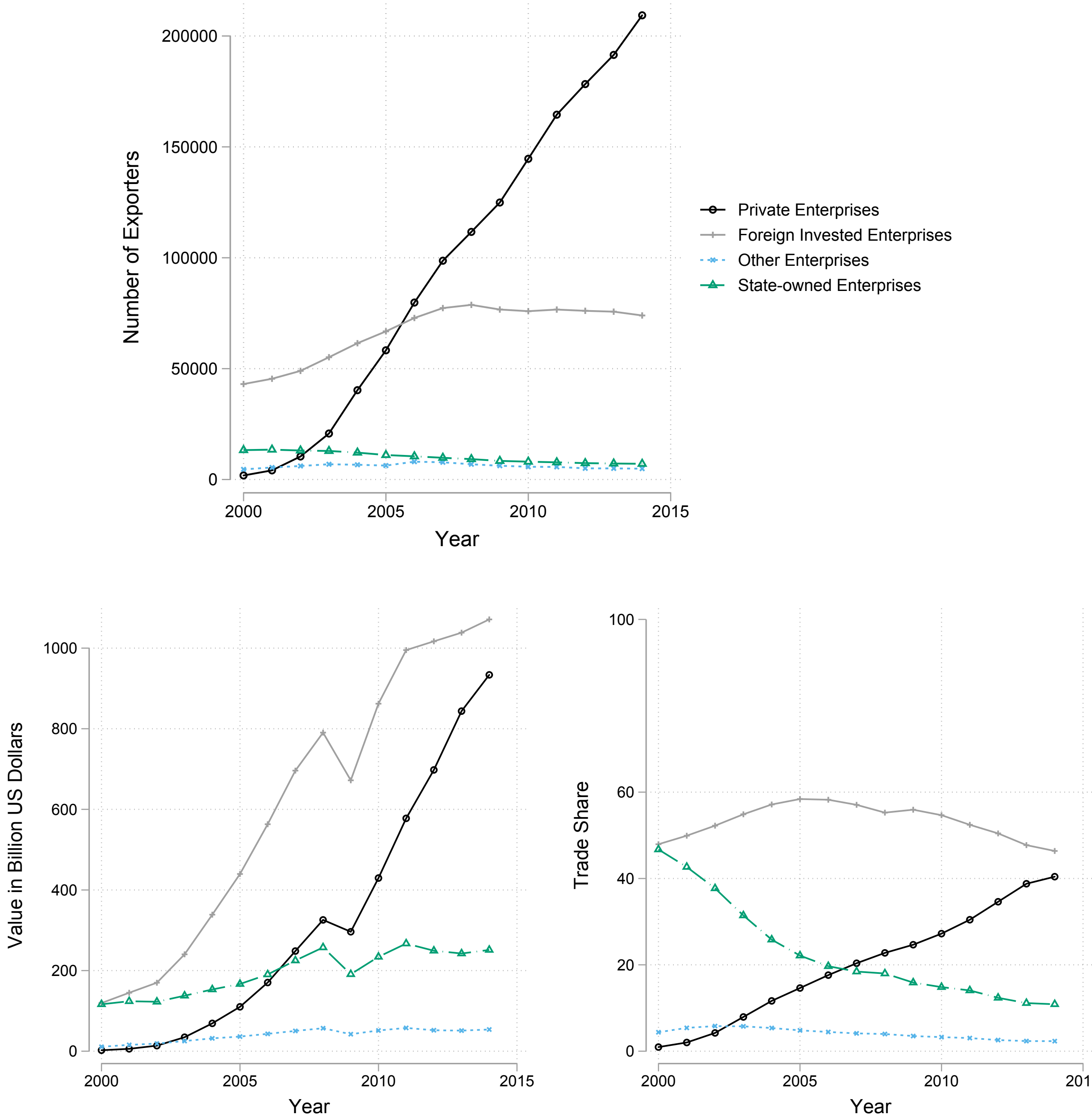


Figure SM1-1: The changing face of Chinese exporters, 2000-2014

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.

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 neglectable 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.[1] 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 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 SM1-1).

The key message from the top panel of figure SM1-1 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 SM1-1). 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.[2]

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 SM1-1). 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

[1]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.

[2]The importance of foreign involvement in Chinese exports has previously been documented by Koopman et al. (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.

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.

SM1.3 Macroeconomic data

Macroeconomic variables on nominal bilateral exchange rates, CPI of all destination countries (normalized so that CPI=100 in 2010 for all series), real GDP in constant 2005 US dollars, and the import to GDP ratio come from the World Bank. We construct the nominal bilateral exchange rate in renminbi per unit of destination currency from China's official exchange rate (rmb per US$) and each destination country's official exchange rate in local currency units per US$ (all series are the yearly average rate). These variables are available for 152 destination countries in our sample. For the 17 eurozone countries which we aggregate into a single economic entity, we use the CPI index, bilateral exchange rate and import-to-GDP ratio for the euro area from the World Bank. We construct a measure of real GDP in local currency for the eurozone using the reported GDP in constant US dollars (2010) variable and the 2010 euro-dollar rate.

In our empirical analysis, we focus on nominal rather than real bilateral exchange rates. Estimation using real exchange rates implicitly imposes a one-to-one linear relationship between each nominal bilateral exchange rate and the ratio of CPI indices (i.e., destination CPI/origin CPI). Real exchange rate series which embed this restriction are highly correlated with nominal exchange rates. Since nominal exchange rate series are significantly more volatile over time than the ratio of CPI indices, movements in the real exchange rate are primarily driven by fluctuations in nominal exchange rates. It is not clear if restricting these two variables with significantly different volatilities into a one-to-one linear relationship is justified in exchange rate pass through studies. Throughout our analysis, we enter nominal bilateral exchange rates and destination CPI index as two separate variables.

In all regressions, we enter variables in logged levels. A problem arising from using logged levels rather than time differences is that nominal series, such as exchange rates and CPI indices, cannot be compared directly across countries. To address this compatibility problem, note that the nominal series can be re-written as a comparable measure plus an unobserved destination specific drift, i.e.,

$$e_{dt}^{nominal} = e_{dt}^{comparable} + \mu_d.$$

Under trade pattern fixed effects, the time-invariant destination-specific drift is absorbed into the fixed effects, which enables us to correctly disentangle the effect of nominal exchange rate fluctuations from destination CPI movements.

SM1.4 Additional information on the CCHS classification

SM1.4.1 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."[3] 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."

SM1.4.2 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

[3]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.

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 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 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.[4]

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`.

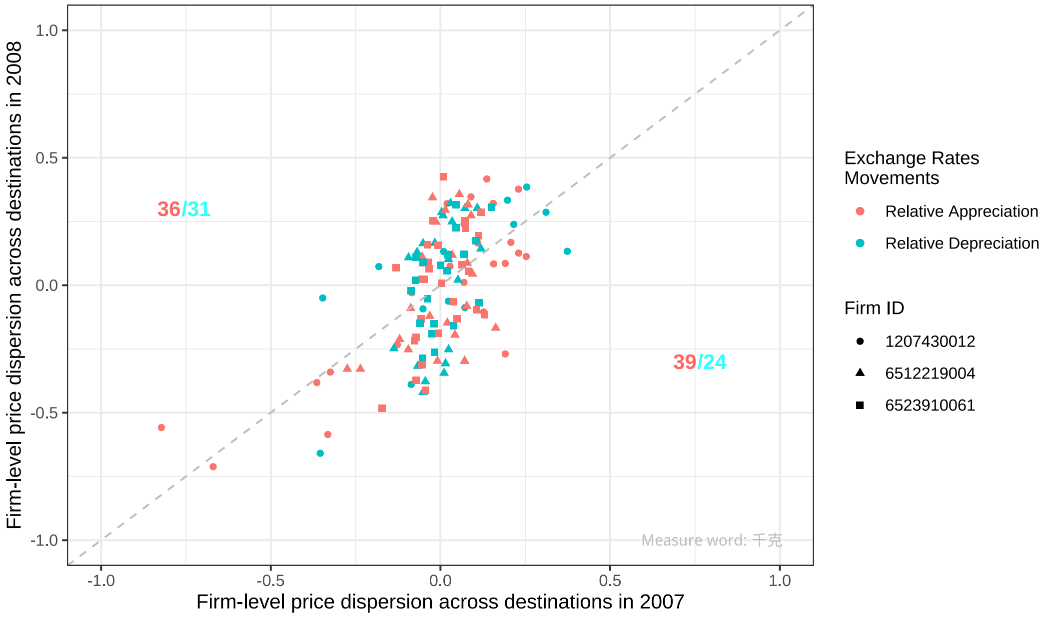
SM1.4.3 The dispersion of prices for high and low differentiation goods: A telling example

To provide intuitive evidence about the relevance of our classification in studies of pricing to market, we offer a case study of price adjustments by firms producing two different products – one low differentiation good and one high differentiation good. We select, respectively, canned tomato paste (measured in kilograms) and wheeled tractors (measured with liàng, 辆).

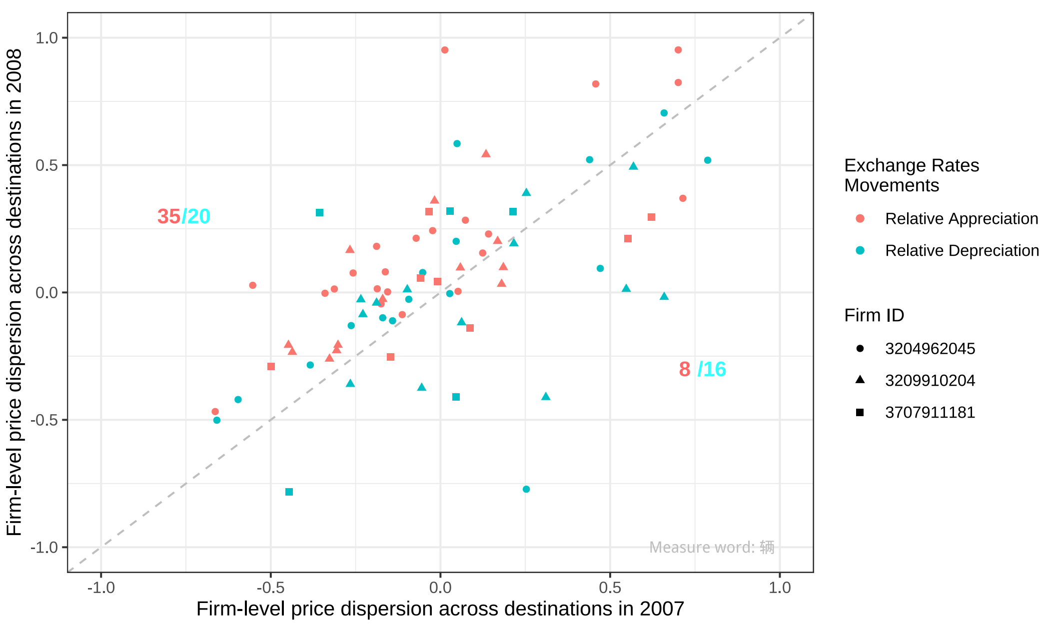
In figure SM1-2, we plot the dispersion of price residuals across destinations for the top three exporters of tomato paste (upper panel) and wheeled tractors (lower panel) in 2007 and 2008. For

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

Figure SM1-2: 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)

Note: Firm-level price dispersion for tomato paste (HS20029010) and wheeled tractors (HS87019011) is calculated as the deviation from the mean log unit value, denominated in RMB, across destinations at the firm-product-year level, i.e., $uv_{ifdt} - \overline{uv}_{ift}$. For this figure, we begin with a balanced panel of firm-product-destination observations for two consecutive years, 2007 and 2008, and plot the observations of residual price dispersion for the top three firms based on the number of observations in the constructed balanced panel. Red observations are for destinations whose currency appreciated relative to the renminbi between 2007 and 2008 while blue observations are for destinations whose currencies depreciated.

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.[5] 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 representing a firm-product-destination triplet 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, first, the relative price residuals for many firm-product-destination triplets, measured in the producer's currency, change from year to year. Second, the low differentiation good, tomato paste, exhibits less dispersion in price residuals across destinations than the high differentiation good, wheeled tractors. Third and 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 differentiation good, tomato paste.

SM1.4.4 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 SM1-2 documents

[5]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).

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-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 code. 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 SM1-2: 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).

SM1.4.5 Integrating the CCHS classification with UN Broad Economic Categories

In table SM1-3, we provide a breakdown of our CCHS classification within the UN's Broad Economic Categories (BEC) of intermediate, consumption and other goods. The majority of intermediate goods are low differentiation and the majority of consumption goods are high differentiation, but all BEC groups include both high differentiation and low differentiation goods.

Table SM1-3: Classification of differentiated goods: CCHS vs. BEC

(a) Share of goods by classification: observation weighted

	Corsetti-Crowley-Han-Song (CCHS)		
	Low Differentiation / (Mass nouns)	High Differentiation / (Count nouns)	
BEC			
Intermediate	29.8	2.7	32.5
Consumption	14.3	20.1	34.4
Other†	15.0	18.1	33.1
	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)	
BEC			
Intermediate	26.0	3.9	29.9
Consumption	8.6	14.0	22.6
Other†	12.6	34.9	47.5
	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. †: The "Other" category refers to capital goods and unclassified products by BEC classification, such as nuclear weapons.

SM1.4.6 Variation in the CCHS classification across industrial sectors

For twenty industrial sectors, Table SM1-4 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 24 count classifiers as high differentiation, while goods measured with 12 mass classifiers

Table SM1-4: 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.

are treated as low differentiation.[6] Column one lists the HS chapters that define the sector. The 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.

[6]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.

SM1.4.7 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 3, 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 SM1-5: 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

SM1.4.8 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 SM1-6.

Table SM1-6: Markup Elasticity by Rauch Classification

Category	All	HD Goods	LD Goods	n. of obs
2000 – 2005				
Differentiated Products	0.06***	0.10***	0.03	3,339,574
	(0.02)	(0.03)	(0.03)	[812,719]
Organized Exchange	0.05	-	0.05	36,656
	(0.07)		(0.07)	[11,945]
Reference Priced	0.06	0.14	0.05	332,678
	(0.06)	(0.16)	(0.07)	[88,809]
2006 – 2014				
Differentiated Products	0.08***	0.14***	0.04***	15,722,023
	(0.01)	(0.01)	(0.01)	[3,927,425]
Organized Exchange	-0.06	-	-0.05	99,373
	(0.06)		(0.06)	[28,086]
Reference Priced	0.05**	0.07	0.05**	1,537,937
	(0.02)	(0.11)	(0.02)	[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 SM1-6 is that the estimated markup elasticity of "differentiated" goods according to the Rauch classification, 8% in the later period, is an average of very different elasticities for high and low differentiation goods, 14% and 4% 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.

SM1.5 Trade pattern statistics by product differentiation

We calculate the trade pattern statistics reported in table 1 separately for high- and low-differentiation goods defined by our CCHS classification. Inspecting Tables SM1-7 and SM1-8, we do not find significant differences in the statistics of market changes for high- and low-differentiation goods in our sample.

Table SM1-7: 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 SM1-8: 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

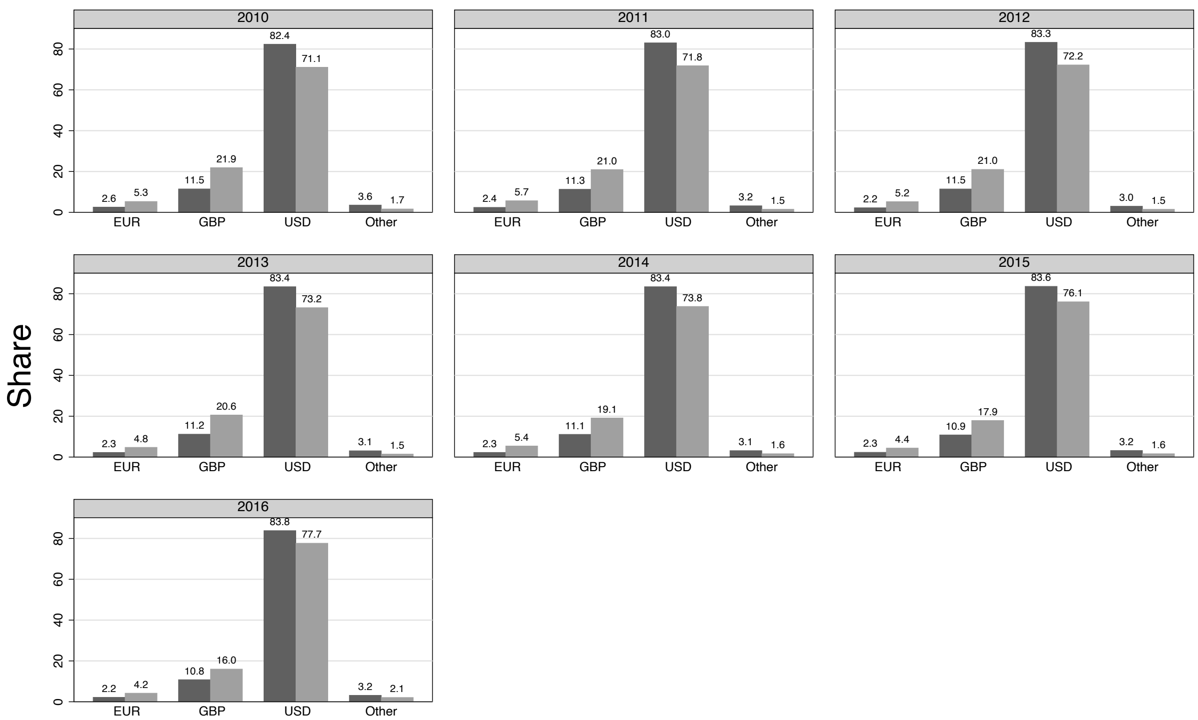
Note: We start from the whole sample of all firms selling *low differentiation* goods and drop firm-product pairs that only exported once in their lifetime. For each firm-product pair, we calculate its total number of exporting years and the number of unique trade patterns in its lifetime and then put 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.

SM1.6 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 as suggestive that Chinese exports to other countries, including those that do not issue vehicle currencies, are likely predominately invoiced in US dollars.

Figure SM1-3: 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.[7] Figure SM1-3 presents the

[7]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.[8] 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."[9] 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.[10] 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

[8] 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 SM1-3.

[9] 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.

[10] 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.

SM1.7 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.

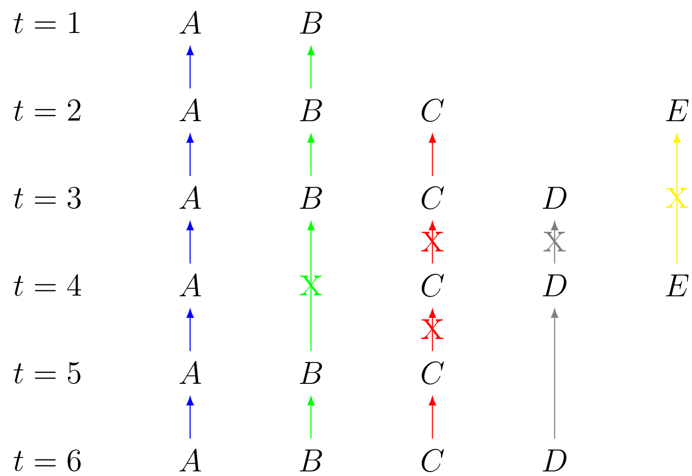
Consider a firm exporting a product to five countries, A through E, over 6 time periods. In the following matrix, $t = 1, 2, 3, ...$ indicates the time period and A, B, C, D, E indicates the country. Empty elements in the matrix indicate that there was no trade.

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

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

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

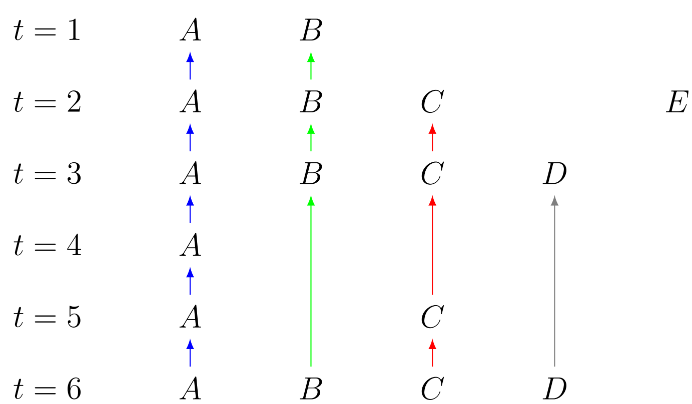
Suppose the pricing currency is the dollar and we want to identify price changes in dollars. First, we compare export prices denominated in dollars over time and at the firm-product-destination level as illustrated in the following figure. Price changes less than 5% are marked with “x”.



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 $|p_{C,5} - p_{C,4}| < 5\%$.[11] 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.

[11]Variables are in logs.

As no prices are sticky, we can stop the iteration.[12] 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 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.

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

SM1.8 Data cleaning process and the number of observations

Table SM1-9: 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 SM1.7
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.)

SM2 General Model-Free Relationships

In this section, we highlight three model-free general relationships. Subsection SM2.1 shows that, regardless of the functional forms of the demand and production functions, a firm's optimal price can always be decomposed into *conceptionally meaningful* marginal cost and markup components. Subsection SM2.2 shows the general relationship between a firm's price and quantity adjustments under supply versus demand shocks. These results are very powerful as they make no assumptions on the underlying market structure. Examples on how to apply these propositions into specific models are available upon request.

SM2.1 The separation of the marginal cost and the markup

We start by deriving a general expression of a firm's profit-maximizing price. Please note that variables in the following derivation are in levels rather than logarithms. Write:

$$\max_p q(p, \psi)p - c[q(p, \psi), \varkappa]. \tag{SM2-1}$$

The firm takes its demand function, $q(p, \psi)$, and cost function, $c[q(p, \psi), \varkappa]$, as given and maximises its profit by choosing its optimal price p. ψ and $\varkappa$ are exogenous demand and supply shifters respectively.

The first order condition of the firm is given by

$$\frac{\partial q(p, \vartheta)}{\partial p} p + q(p, \psi) = \frac{\partial c[q(p, \psi), \varkappa]}{\partial q(p, \psi)} \frac{\partial q(p, \psi)}{\partial p} \tag{SM2-2}$$

From this equation, we can derive the optimal price as

$$p^* = \frac{\vartheta(p^*, \psi)}{\vartheta(p^*, \psi) - 1} mc[q(p^*, \psi), \varkappa]. \tag{SM2-3}$$

where $\vartheta(p, \psi) \equiv -\frac{\partial q(p,\psi)}{\partial p} \frac{p}{q(p,\psi)}$, $mc[q(p, \psi), \varkappa] \equiv \frac{\partial c[q(p,\psi),\varkappa]}{\partial q(p,\psi)}$.

SM2.2 The equilibrium relationship between quantity and price under pure supply versus demand shocks

Proposition 2. *If changes in the equilibrium price and quantity are solely driven by shocks to the supply side, the following expression holds*

$$\frac{d \log(q^*)}{d \log(p^*)} = -\vartheta(p^*, \psi) \tag{SM2-4}$$

Proof.

$$
\begin{aligned}
d\log(q(p^*(\psi,\varkappa),\psi)) =& \frac{1}{q(p^*(\psi,\varkappa),\psi)} dq(p^*(\psi,\varkappa),\psi) \\
=& \frac{1}{q(p^*(\psi,\varkappa),\psi)} \left(\frac{\partial q(p^*(\psi,\varkappa),\psi)}{\partial p^*(\psi,\varkappa)} dp^*(\psi,\varkappa) + \frac{\partial q(p^*(\psi,\varkappa),\psi)}{\partial \psi} d\psi \right) \quad \text{(SM2-5)} \\
d\log(p^*(\psi,\varkappa)) =& \frac{1}{p^*(\psi,\varkappa)} dp^*(\psi,\varkappa) \quad \text{(SM2-6)}
\end{aligned}
$$

Substituting equation (SM2-6) into (SM2-5) and applying the condition $d\psi = 0$ completes the proof. □

Proposition 3. *If changes in the equilibrium price and quantity are solely driven by shocks to the demand side, the following expression holds*

$$
\frac{d\log(q^*)}{d\log(p^*)} = \frac{\varphi_q(p^*,\psi)}{\varphi_p(\psi,\varkappa)} - \vartheta(p^*,\psi) \quad \text{(SM2-7)}
$$

where $\varphi_q(p^*,\psi) \equiv \frac{\partial q(p^*,\psi)}{\partial \psi} \frac{\psi}{q(p^*,\psi)}$ and $\varphi_p(\psi,\varkappa) \equiv \frac{\partial p^*(\psi,\varkappa)}{\partial \psi} \frac{\psi}{p^*(\psi,\varkappa)}$

Proof.

$$
\begin{aligned}
d\log(q(p^*(\psi,\varkappa),\psi)) =& \frac{1}{q(p^*(\psi,\varkappa),\psi)} \left(\frac{\partial q(p^*(\psi,\varkappa),\psi)}{\partial \psi} d\psi + \frac{\partial q(p^*(\psi,\varkappa),\psi)}{\partial p^*(\psi,\varkappa)} dp^*(\psi,\varkappa) \right) \\
=& \left(\varphi_q(p^*,\psi) - \vartheta(p^*,\psi)\varphi_p(\psi,\varkappa)\right) \frac{d\psi}{\psi} \quad \text{(SM2-8)} \\
d\log(p^*(\psi,\varkappa)) =& \frac{1}{p^*(\psi,\varkappa)} dp^*(\psi,\varkappa) \\
=& \frac{1}{p^*(\psi,\varkappa)} \left(\frac{\partial p^*(\psi,\varkappa)}{\partial \psi} d\psi \right) \\
=& \varphi_p(\psi,\varkappa) \frac{d\psi}{\psi} \quad \text{(SM2-9)}
\end{aligned}
$$

□

SM3 Estimating markup elasticities with heterogeneous responses

In this section, we discuss the estimated object captured by the OLS and fixed effect approaches when the markup elasticity is different across firms, products, destinations and time. We highlight two interrelated issues. The first issue arises because linear OLS or fixed effect estimators treat the heterogeneous coefficients as if they were homogeneous. The second issue which arises due to inaccurate first-order log approximations of nonlinear theoretical relationships.

SM3.1 The implicit weight of observations

To introduce this issue, consider the following simple specification:

$$p_{fidt} = \beta_{fidt} e_{dt} + v_{fidt} \tag{SM3-10}$$

where p_{fidt} is the log price and e_{dt} is the log bilateral exchange rate and β_{fidt} as the markup elasticity, which is a function of the bilateral exchange rate as shown in (OA2-2); v_{fidt} is an iid error.

The OLS estimate of β is given by

$$\begin{aligned}
\beta^{OLS} &= \frac{\sum_f \sum_i \sum_d \sum_t (p_{fidt} - \overline{p})(e_{dt} - \overline{e})}{\sum_f \sum_i \sum_d \sum_t (e_{dt} - \overline{e})^2} \\
&= \frac{\sum_f \sum_i \sum_d \sum_t (\beta_{fidt} e_{dt} + v_{fidt})(e_{dt} - \overline{e})}{\sum_f \sum_i \sum_d \sum_t (e_{d,t} - \overline{e})^2} \\
&= \frac{1}{n^F n^I} \sum_f \sum_i \left[\frac{\sum_d \sum_t (\beta_{fidt} e_{dt} + v_{fidt})(e_{dt} - \overline{e})}{\sum_d \sum_t (e_{dt} - \overline{e})^2} \right] \\
&= \frac{1}{n^F n^I} \sum_f \sum_i \left[\frac{\sum_d \sum_t \beta_{fidt} e_{dt} (e_{dt} - \overline{e})}{\sum_d \sum_t (e_{dt} - \overline{e})^2} + \frac{\sum_d \sum_t v_{fidt} (e_{dt} - \overline{e})}{\sum_d \sum_t (e_{dt} - \overline{e})^2} \right] \\
&= \frac{1}{n^F n^I} \sum_f \sum_i \left[\sum_d \sum_t \beta_{fidt} w_{dt} + \frac{\sum_d \sum_t v_{fidt} (e_{dt} - \overline{e})}{\sum_d \sum_t (e_{dt} - \overline{e})^2} \right]
\end{aligned} \tag{SM3-11}$$

where n^F, n^I, n^D, n^T represent the number of firms, products, destinations, and time periods respectively; $w_{dt} \equiv \frac{e_{dt}(e_{dt} - \overline{e})}{\sum_d \sum_t (e_{dt} - \overline{e})^2}$; $\overline{p} \equiv \frac{1}{n^F n^I n^D n^T} \sum_f \sum_i \sum_d \sum_t p_{fidt}$; $\overline{e} \equiv \frac{1}{n^D n^T} \sum_d \sum_t e_{dt}$.[13] Now, the second term in the bracket of (SM3-11) is close to 0 under the assumption of no selection and omitted variable bias. Let's abstract from these biases, and focus on the first term in the bracket.

[13] We have assumed a balanced panel in the discussions of (SM3-11) and (SM3-12) for clarity. We discuss the general case in (SM3-13), (SM3-14) and (SM3-15).

From this term in (SM3-11), it is apparent that, when the markup elasticity is heterogeneous, β^{OLS} is the exchange rate-deviation weighted sum of the β_{fidt}'s.

$$\beta^{OLS} \approx \frac{1}{n^F n^I} \sum_f \sum_i \sum_d \sum_t \beta_{fidt} w_{dt} \neq \frac{1}{n^F n^I n^D n^T} \sum_f \sum_i \sum_d \sum_t \beta_{fidt} \tag{SM3-12}$$

As can be seen from the definition of w_{dt}, the OLS estimator gives a larger weight to high exchange rate values, that is, foreign currency appreciations. The result is different, for instance, from an observation weighted average of the β_{fidt}'s.

In general, with multiple regressors, the weights of an OLS estimator also depend on the variation of other independent variables and the coefficients in front of these variables. The OLS estimates capture

$$\boldsymbol{\beta}^{OLS} \approx (X'X)^{-1}X'(X \circ B) \tag{SM3-13}$$

where X is an $n^{FIDT} \times k$ matrix that stores the values of the k independent variables; B is an $n^{FIDT} \times k$ matrix that stores the heterogeneous coefficients for each of the independent variables; $\circ$ is the Hadamard (element-by-element) product. Similarly, the estimates of a FE estimator and our TPSFE estimator captures

$$\boldsymbol{\beta}^{FE} \approx (X'P'PX)^{-1}X'P'(PX \circ B) \tag{SM3-14}$$

$$\boldsymbol{\beta}^{TPSFE} \approx (X'P_2'P_3'P_3P_2X)^{-1}X'P_2'P_3'(P_3P_2X \circ B) \tag{SM3-15}$$

where P is the projection matrix that is required to perform the conventional FE estimator; P_2 represents a projection matrix that performs a destination demeaning operation and P_3 represents the second demeaning step of the TPSFE estimator at the firm-product-destination-trade pattern level.

For our purposes, there are at least two relevant takeaways from (SM3-13), (SM3-14) and (SM3-15). First, even without the omitted variable and selection biases, the estimated coefficients from the three estimators can differ slightly due to the different weighting matrices applied to the coefficient matrix B. Second, in general, the estimated coefficients for all of the three estimators do not necessarily equal the unweighed average of the coefficients, i.e., $\frac{1}{n^{FIDT}}\iota'_{n^{FIDT}}B$, or any other average that an econometrician may take as the reference benchmark to assess estimation biases. When elasticities are heterogeneous, the assessment of the performance of an estimator may vary with the choice of the benchmark.

SM3.2 Approximation bias

The second issue arises when non-linear relationships are approximated using log-linear equations. In the open marco literature, first order log approximations are widely used to derive theoretical relationships between variables. For example, in equation (OA2-2), we have shown a log linearised equation of the markup response as

$$\widehat{\mu}_{fidt} = \Gamma_{fidt}\left(\widehat{\mathcal{E}}_{dt} - \widehat{\mathcal{MC}}_{fidt}\right)$$

Log-linearisation is obviously convenient here, as the coefficient in front of the exchange rate changes, Γ_{fidt}, directly gives the key parameter of interest, i.e., the markup elasticity to exchange rates. However, as is well known, estimating the relationship using logged variables can lead to a non-trivial bias even if all variables are directly observable and there is no selection bias. Concretely, when we regress the logged markup on the logged exchange rate and the logged marginal cost, we will not in general get the average of the markup elasticity to exchange rates *even after accounting for the weighting issue* analyzed in the previous subsection. A specific bias arises due to the fact that the high order terms of the approximation O_{fidt} are correlated with the variables in the estimation equation (i.e., $\ln(\mathcal{E}_{dt}), \ln(\mathcal{MC}_{fidt})$).

$$\ln(\mu_{fidt}) = \ln(\mu^{Approx}_{fidt}) + O_{fidt} \tag{SM3-16}$$

$$\ln(\mu^{Approx}_{fidt}) \equiv \Gamma_{fidt}\left[\ln(\mathcal{E}_{dt}) - \ln(\mathcal{MC}_{fidt})\right] \tag{SM3-17}$$

To be clear, if we could estimate equation (SM3-17) directly by regressing $\ln(\mu^{Approx}_{fidt})$ on $\ln(\mathcal{E}_{dt})$ and $\ln(\mathcal{MC}_{fidt})$, then the estimates would only reflect the weight problem discussed in the previous subsection—the estimated coefficients would be consistent with the formulae described by (SM3-13), (SM3-14) and (SM3-15). However, the literature usually estimates markup elasticity by regressing $\ln(\mu_{fidt})$ or $\ln(P^*_{fidt})$ on the logged independent variables (e.g., $\ln(\mathcal{E}_{dt})$, $\ln(\mathcal{MC}_{fidt})$). The estimates are bound to suffer from an approximation bias, as the higher order terms O_{fidt} are in general correlated with the first order terms.

Notably, in all of our simulations, the weighting issue and the approximation biases always go in opposite directions and partially offset each other. If we take the unweighted mean of the theoretical markup elasticities as a reference benchmark, the difference between this and our estimated markup elasticities to exchange rates remains reasonably small after splitting the sample into high and low differentiation goods.

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