

# Markets and Markups:

## A New Empirical Framework and Evidence on Exporters from China

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### Abstract

Firms that dominate global trade export to multiple countries and frequently change their foreign destinations. We develop an estimator of the destination-specific markup elasticity to the exchange rate that controls for endogenous market selection. To proxy for firms' power in local markets, we introduce a new classification of products based on Chinese linguistics that distinguishes between highly and less differentiated goods. Using Chinese customs data, we show that controlling for selectivity unveils significant pricing-to-market for highly differentiated goods. Measured in the importer's currency, the prices of highly differentiated goods are more stable than those of less differentiated products.

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

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# 1 Introduction

A fundamental feature of international goods markets is that firms exporting to more than one country account for the lion’s share of cross-border trade. Serving multiple markets, these firms face demand conditions, market structures, and policy regimes that differ across locations and are inherently time-varying. Effectively, 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 (Krugman (1986) and Dornbusch (1987)).

Trade globalization has heightened the importance of understanding the many factors that drive a global firm’s pricing strategy. Pricing-to-market is already a standard feature in open macro models, increasingly featuring 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 Casas, Diez, Gopinath and Gourinchas (2017)).<sup>1</sup> The increasing availability of high-dimensional administrative customs databases has provided a wealth of new insights about the pricing behaviour of firms (see, e.g., Berman, Martin and Mayer (2012), Chatterjee, Dix-Carneiro and Vichyanond (2013), Amiti, Itskhoki and Konings (2014), Fitzgerald and Haller (2014), De Loecker, Goldberg, Khandelwal and Pavcnik (2016), Fitzgerald and Haller (2018)). However, there is a sense that research has yet to fully exploit the data in all its dimensions—and in ways that can inform our understanding and modelling of multilateral competition in local and global markets.

In this paper, we build an empirical framework suitable for analyzing the local or *destination-specific* markup adjustments of multi-destination exporters in administrative datasets that report product exports by firms.<sup>2</sup> Applying our framework to exporters from China, we document extensive pricing-to-market, especially for highly differentiated goods. For a 10% appreciation of a destination country’s currency against the renminbi, Chinese exporters raise their markups by 2% for highly differentiated goods, but by only 0.6% for goods characterized by little or no dif-

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<sup>1</sup>Leading questions addressed range from imported inflation and the consequences of large depreciations to efficiency losses from currency misalignments and the design of stabilization policy in an open economy (Engel (2011) and Corsetti, Dedola and Leduc (2018)).

<sup>2</sup>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, Goldberg, Khandelwal and Pavcnik (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 complementarities and high potential gains from combining methodologies and cross checking results.

ferentiation. This implies that exporting firms stabilize the import prices of highly differentiated goods, measured in local currency, far more than they do for less differentiated products. To the extent that firms producing differentiated products are in a better position to segment markets and use their market power, our results are consistent with the idea that pricing-to-market is more pervasive in markets that are more distant from perfect competition.

Our empirical framework introduces two methodological contributions that, when used together, provide a powerful new approach to evaluating pricing-to-market behaviour. The first component of our framework is an estimator that identifies the *destination-specific* markup elasticity to the exchange rate—the *trade pattern sequential fixed effects* (TPSFE) estimator. This markup elasticity is identified by precisely isolating cross-market variation in prices, obtained after removing time-varying factors including a firm’s marginal production costs for a product while accounting for endogenous market participation. The general approach builds on the seminal work by Knetter (1989), which first proposed to net out changes in unobservable marginal costs by using cross-market differences in average prices at the industry level. At the micro level, however, the set of markets in which firms operate each period (i.e., the firm’s product-level “trade pattern”) can and does vary endogenously with unobservable changes in production costs and local demand, which are arguably correlated with changes in bilateral exchange rates. Controlling for the time-varying set of destination markets is essential to ensure that the estimated elasticity is identified. We document that the failure to control for time-varying trade patterns introduces biases into destination-specific markup elasticities that are sizeable both in model simulated data and in administrative customs data from China.

The second component of our empirical framework to identify pricing-to-market begins with 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. Our maintained hypothesis is that producers of highly differentiated consumer goods are better able to segment markets and exercise pricing power in each destination market than producers of undifferentiated intermediates. We introduce a novel product classification of traded goods by their degree of product differentiation, which (under our hypothesis) maps goods into categories of market power. The core idea is a simple one: traded goods whose quantity is recorded in customs data by weight or volume are less differentiated than goods whose quantity is reported in countable units. Chinese customs data provide a unique opportunity to extend this simple idea into an exogenous classification system because the choice to record a product’s quantity in units versus mass is predetermined by Chinese grammar and linguistics. We exploit linguistic information on *measure words* recorded in the Chinese Customs Database to construct the Corsetti-Crowley-Han-Song (CCHS) general product classification for the Harmonized System. Integrating this linguistics-based classification with the UN’s Broad Economic Categories yields even more interesting insights into the extent of

pricing-to-market.

Empirically, we apply our methodology to multi-destination exporters from China using annual export data by firm, product, and destination over 2000-2014.<sup>3</sup> 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.<sup>4</sup> 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.<sup>5</sup> 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 report results from applying our TPSFE estimator conditional on price changes; our results are therefore comparable with recent estimates of exchange rate pass through (ERPT) derived using the approach of [Gopinath, Itskhoki and Rigobon \(2010\)](#) and estimates of markup elasticities by [Fitzgerald and Haller \(2014\)](#).

The empirical application of the TPSFE estimator and the CCHS classification system shows that, on average, firms engage in significant pricing-to-market. Over 2006-2014 (after China gave up the dollar peg), our average estimate of the destination-specific markup elasticity is 20% for high differentiation goods, rising to 33% for consumption goods characterized by high differentiation. Comparing these figures with estimates of exchange rate pass through suggests that, on average, around two-thirds of the price adjustment to the exchange rate for high differentiation goods is due to a destination-specific markup adjustment. Conversely, markup elasticities are small and close to zero for products that we classify as low differentiation—a result that validates the maintained hypothesis behind our linguistics-based product classification.

These findings reveal the inherent value of our new product classification, which improves on the market-structure approach of [Rauch \(1999\)](#) by breaking down Rauch’s large class of differentiated manufactured goods into high and low differentiation subcategories. 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 CCHS linguistics-based classification, about half of this, amounting to 39 percent of Chinese export value, is actually highly differentiated,

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<sup>3</sup>The database consists of monthly records by firm-product-destination for 2000-2006 and annual records by firm-product-destination for 2007-2014. We aggregate the monthly data for 2000-2006 to the annual level in our analysis.

<sup>4</sup>See appendix C.4 for evidence on dollar invoicing.

<sup>5</sup>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.

while 41 percent exhibits low differentiation. A further benefit is that many products which are left unclassified by Rauch can be classified as high or low differentiation goods according to the CCHS system.

The final component of our empirical framework is an analysis of changes in a firm’s destination-specific *quantities of trade*. Having developed an estimator that identifies markup responses in the presence of endogenous entry and exit alongside a product classification framework to proxy for market power, we run an internal check on this framework by turning our attention to export volumes. We show how to estimate the market-specific responsiveness of quantities to currency fluctuations using 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.<sup>6</sup> As 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 within-firm cross market supply elasticity (CMSE).<sup>7</sup>

Under this framework, the difference in the cross-market supply elasticities between consumption goods and intermediates is substantial, 0.72 vs 2.72. When further disaggregated under the CCHS product classification, the gap between estimates opens to a chasm—the CMSE of high differentiation consumption goods, 0.16, suggests an extreme amount of market segmentation. The CMSE for low differentiation intermediates, 3.84, suggests something much closer to an integrated world market. This suggests that our CMSE elasticity provides a measure of market power in a multi-country context that complements the results from empirical studies showing how optimal exchange rate pass through varies with a firm’s market share (Feenstra, Gagnon and Knetter (1996) and Auer and Schoenle (2016)).

We conclude our empirical analysis by exploring the extent to which destination-specific price and quantity elasticities systematically differ across types of firms operating in China. We distinguish among State Owned Enterprises (SOEs), Foreign-Invested Enterprises (FIEs), and private

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<sup>6</sup>The literature investigating quantity responses to exchange rates, e.g. Berman, Martin and Mayer (2012), typically regresses quantities on exchange rates. Apart from the difficulty in controlling for the time-varying marginal cost, such an approach underestimates the heterogeneity in quantity responses across products and firms. Heterogeneity is inherent in the “duality property” of markup responses—a high markup elasticity often originates from a market structure in which a low substitution elasticity across varieties is associated with a low quantity response. The approach conventionally followed in the literature cannot distinguish between these two effects.

<sup>7</sup>This is developed for highly-disaggregated data along the lines of work by Feenstra (1994) and Broda and Weinstein (2006), estimating import demand and export supply elasticities. The elasticity is similar to the cross-destination trade value response to tariffs in Bown and Crowley (2007), but introduces a new identification strategy.

enterprises. Overall, we find a considerably higher degree of markup adjustment as well as a considerably lower degree of exchange rate pass through among SOEs and FIEs relative to private firms. In part, our results may reflect differences in the average size of firms over the sample period and, possibly, profit-shifting practices. Yet, overall, they point to a significantly higher degree of market power among SOEs and FIEs and a substantial divide relative to Chinese private firms.<sup>8</sup>

The rest of the paper is organized as follows. Section 2 presents our empirical framework. Section 3 summarizes the database. Section 4 presents our empirical results. In section 5 we apply our estimator to study pricing by different groups of firms operating in China. Section 6 concludes.

## 2 Empirical Framework

Firms engaged in international trade typically export to multiple foreign destinations – in the administrative data from the Chinese Customs Authority that we use in our study, approximately 97 percent of annual customs transactions and 94 percent of export value in the year 2007 originated from firms exporting to more than one foreign country.<sup>9</sup> Moreover, the set of destination markets—a firm’s trade pattern—is highly variable over time.

By way of example, Table 1 displays the trade pattern for a Chinese private enterprise exporting wheeled tractors over 2007 through 2012. Beginning from a base of selling to both the UK and Australia in 2007, the firm expanded its sales of this product to Canada in 2008, ceased sales to both Australia and Canada in 2010 only to re-enter both of these markets in 2011. In the last year of sales we observe, 2012, the firm has again reduced its global market scope to exclude Canada. This kind of trade pattern is typical of hundreds of thousands of Chinese exporters.<sup>10</sup> Changes in the set of destination markets present fundamental problems to any economist who wants to estimate how prices or markups change in response to exchange rate movements. If market participation is a choice that depends on observed and unobserved economic factors—including unobserved shifts in foreign demand and unobserved changes in production costs, possibly driven by observed changes in tariffs and bilateral exchange rates—how can one obtain an unbiased estimate of a price or markup elasticity to the exchange rate? A way to articulate the same question is to ask, first, which margins of variation are used by a candidate estimator to identify the elasticity of interest? Second, if export participation varies along three margins, i.e., firm, product, and foreign destination, which margins should be used to identify elasticities?

In this section, we introduce an empirical framework designed to evaluate adjustments to

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<sup>8</sup>Differences in the average size across different types of firms, with private firms having much lower export values on average, might simply reflect the high rate of entry of new cohorts of young, private firms.

<sup>9</sup>See table 4.

<sup>10</sup>See Han (2018) for evidence on extensive margin adjustments at the firm-product level and its relationship with exchange rate movements for Chinese exporters.



Table 1: Trade Pattern of a Chinese Exporter (ID 3301962621)  
Selling Wheeled Tractors (HS 87019011)

2007	UK	Australia	
2008	UK	Australia	Canada
2009	UK	Australia	Canada
2010	UK		
2011	UK	Australia	Canada
2012	UK	Australia	

markups for products sold by firms in multiple foreign countries. We begin by discussing our *trade pattern sequential fixed effects* (TPSFE) estimator, developed to study markup adjustment to changes in destination-specific conditions by controlling for unobserved product-level marginal cost within a firm, in an environment with endogenous market selection. As argued above, it is crucial that the estimator is precisely defined with regard to the empirical variation that identifies the markup elasticity. We make efforts to be clear on this point in the analysis to follow and, in section 4.3, carry out a comparison of our estimator against several alternatives that highlights the implications of changing the data dimensions that provide identification.<sup>11</sup>

After introducing the TPSFE, we describe a new classification of Harmonized System products that can serve as a useful proxy for a firm’s ability to segment markets and exercise market power locally. Our classification system draws a distinction between traded goods that are highly differentiated and those with less differentiation. It is especially helpful in proxying for market power within the set of goods which Rauch (1999) classifies is not traded on organized exchanges or through reference price catalogues—i.e., those goods whose price is negotiated. Our estimator and product classification system together enable us to quantify how markup adjustments systematically differ depending on a firm’s market power for individual products.

We complete our empirical framework by developing a metric we dub the *cross-market supply elasticity* (CMSE), which relies on the logic of trade pattern sequential fixed effects, but is implemented to measure how a firm adjusts destination-specific *export volumes* to changes in *relative* market conditions.

Together, the three components of our framework enable us to quantify how markup and trade volume adjustments systematically differ depending on a firm’s market power for individual products, thus providing a comprehensive set of diagnostics for multi-country trade and macro models.

<sup>11</sup>A more technical discussion of the properties of the TPSFE estimator is presented in appendix A.



## 2.1 Estimating a markup elasticity with a large customs database

The question motivating our analysis is how to assess the response of the destination-specific component of the markup for a firm’s product to changes in the bilateral exchange rate,  $e_{dt}$ . Throughout our analysis, we focus on differences in movements of bilateral exchange rates across destination markets as the main source of variation to identify the destination-specific markup elasticity.<sup>12</sup>

We start by writing the observed export price (in logs) of a firm  $f$  selling products  $i$  in destinations  $d$  at time  $t$  as follows:

$$p_{ifdt} = \mu_{ifdt}(e_{dt}) + mc_{ift}(\mathbf{e}_t) \quad (1)$$

$$s_{ifdt} = \mathbb{1}\{\eta_{ifdt}(\mathbf{e}_t) > 0\}. \quad (2)$$

The first line expresses the (log) price as the sum of (1) an unobserved optimal markup,  $\mu_{ifdt}$ , which could be common over all destinations  $d$ , specific to a destination  $d$ , or combine common and destination-specific components, and (2) the unobserved product-level marginal cost within the firm,  $mc_{ift}$ , assumed to be the same for all destinations.<sup>13</sup> Note that in the expression,  $e_{dt}$ —the bilateral exchange rate expressed as  $d$ ’s currency per exporter’s currency—is a demand shifter in destination  $d$ ; while  $\mathbf{e}_t$ —the vector of exchange rates relevant to the firm’s imported inputs—is a marginal cost shifter for the firm  $i$ . The second line accounts for the fact that participation in an export market ( $s_{ifdt}$ ) can vary over time, in response to unobserved changes in local demand conditions for a firm’s product and unobserved changes in product-level marginal cost, both of which could be functions of a vector of bilateral exchange rates.<sup>14</sup>

Intuitively, the problem we address in developing our framework is how to isolate and estimate the responsiveness of the *destination-specific* component of the markup to the bilateral exchange rate when both prices and export participation decisions respond to a variety of unobservable factors.<sup>15</sup> The approach we take recognizes that the four dimensional price,  $p_{ifdt}$ , moves with

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<sup>12</sup>We should stress that our framework is suitable for studying markup and quantity adjustments more generally, that is, conditional on identified economic and policy shocks which vary at the destination and time dimensions.

<sup>13</sup>The marginal cost of production does not need to be identical among varieties sold in different destinations, but is a useful simplifying assumption for illustrating our estimator. We discuss the more general case in which marginal costs vary across destinations and formally derive the identification condition under which our estimator is unbiased in appendix A.

<sup>14</sup>In equation (1), the price, markup and marginal cost are denominated in the exporter’s currency. In practice, when applied to a dataset covering the universe of customs transactions, this price is typically approximated by the unit value, i.e., value of exports/units of quantity. In appendix B.1, we show how the optimal price of a firm under any (static) pricing problem can always be decomposed into a markup component solely explained by the demand elasticity with respect to price and a marginal cost component.

<sup>15</sup>Two major challenges arise when trying to estimate the markup elasticity to the exchange rate: (1) product-level marginal cost is unobserved and is highly likely to be correlated with  $e_{dt}$  directly through imported inputs or indirectly, through general equilibrium effects of the prices of factors of production (Corsetti, Dedola and Leduc

time-varying factors that are unobservable but *common* across the set of destinations served by the firm in each period (denoted  $D_{ift}$ )—these factors determine the (common) marginal cost and a common markup component, charged to all destinations reached in a time period. Our methodological solution consists of sequentially applying controls that reduce these unobservable sources of variation in steps. In the first step, we remove the time-varying unobserved marginal cost and the common component of the markup from the price to isolate price variation *across destinations*. In the second step, we reduce the potential bias associated with endogenous market participation by isolating residual price variation over time *within the same destination and trade pattern* for each product sold by the firm. In the final step, we run an OLS regression using the (residual) variables constructed in the two steps described above.

To elaborate on our framework, in the first step of the sequential procedure, 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:

$$\tilde{x}_{iftD} \equiv x - \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} x \quad \forall x \in \{p_{ift}, e_{dt}, \mathbf{x}_{dt}\} \quad (3)$$

where  $n_{ift}^D$  is the number of active foreign destinations for each product of a firm in year  $t$  and  $D_{ift}$  denotes the set of destinations,  $d$ , in which the firm  $f$  is selling its product  $i$  in period  $t$ ;  $e_{dt}$  is the bilateral exchange rate ( $rmb/d$ ) and  $\mathbf{x}_{dt}$  is a vector of destination-specific macro variables including local CPI and real GDP.

Notably, while operation (3) eliminates the destination-invariant component of each variable, it introduces a new wrinkle. The destination-differencing operation generates a new set of variables, i.e., the destination residuals  $\tilde{x}_{iftD}$ . When the multi-market pattern of participation is not random, but systematic, the variation of these destination residuals will differ along different panel dimensions from that of their corresponding variables in the underlying raw data. To wit: after operation (3), the variability of aggregate variables including  $e_{dt}$  and  $\mathbf{x}_{dt}$  becomes specific to the trade pattern  $D_{ift}$  from which their destination residual forms were constructed. We denote these destination residual forms  $\tilde{e}_{dtD}$  and  $\tilde{\mathbf{x}}_{dtD}$ . The key point is that when market participation is endogenous, the data transformation process in this step introduces a fifth panel dimension to

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(2008)); and (2) the selection of export markets is endogenous, depending on unobserved shifts in foreign demand and unobservable marginal cost, both of which are influenced by the bilateral exchange rate. Appendix A.3 discusses recent papers that derive an estimate of marginal costs and use this to infer the level of the markup. These approaches necessarily require assumptions about the allocation of inputs across the outputs of multi-product firms. Our focus on the *destination-specific* component of the markup allows us to approach the issue of unobserved product-level marginal cost from a different angle.

each observation. Controlling for this fifth dimension, the firm’s product-level trade pattern, will be crucial to identifying the markup elasticity.

This brings us to our second step, which applies firm-product-destination-trade pattern fixed effects to the destination residuals of prices and exchange rates, in order to precisely identify the change in time-varying destination-specific markups. In practice, we difference out this  $\{ifdD\}$  fixed effect by subtracting the mean (over time) of the variables constructed in the first step ( $\tilde{x}_{ifdtD}$ ) conditional upon the variable being observed in a firm-product-destination-trade pattern, i.e.,  $t \in T_{ifdD}$ :

$$\ddot{x}_{ifdtDT} \equiv \tilde{x}_{ifdtD} - \frac{1}{n_{ifdD}^T} \sum_{t \in T_{ifdD}} \tilde{x}_{ifdtD} \quad \forall x \in \{p_{ifdt}, e_{dt}, \mathbf{x}_{dt}\} \quad (4)$$

where  $\ddot{x}_{ifdtDT}$  are the time residuals of the destination residuals, conditional on the firm’s time-varying destination and trade pattern of a product,  $T_{ifdD}$ , and  $n_{ifdD}^T$  is the number of time periods in which a firm’s product is sold in destination  $d$  as part of the trade pattern  $D_{ift}$ .

A simple example illustrates our approach. Consider the trade pattern of a firm exporting a product to three countries, A through C, over 5 time periods. In this figure, empty elements indicate that there was no trade.

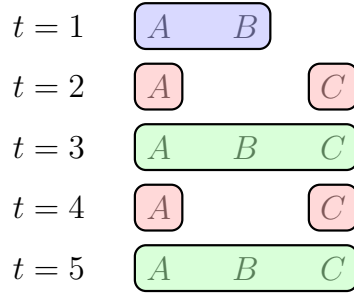


Figure 1: Example of an observed trade pattern

In the context of the example in figure 1, our estimator will exploit the residual (time) variation in the firm’s price in destination A between periods 2 and 4 that remains after differencing out the average destination-demeaned price in periods 2 and 4. This is done by application of a firm-product-destination-trade pattern fixed effect, e.g., a fixed effect for  $\{ifA, AC\}$ , to the destination residuals for country A from periods 2 and 4. In a similar manner, a different time-invariant firm-product-destination-trade pattern fixed effect, which captures the firm’s price in A when it is selling to the trade pattern ABC, e.g., a fixed effect for  $\{ifA, ABC\}$ , is applied to observations on A’s sales in periods 3 and 5. In this second stage, the fixed effect that includes *the firm’s pattern of market participation at the level of a product* precisely controls for time-invariant destination-

specific components of the price (including destination-specific quality) *after* having stripped out time-varying unobservable shifts in the firm’s product-level marginal cost which are captured by the firm’s trade pattern.

At the core of our approach is the idea that the time-varying pattern of market participation is not random, but itself informative about economically important but unobservable factors that drive exporters’ trade strategies. Our key maintained hypothesis is that the time-varying unobservables (in demand and production costs) that drove firm  $f$  to sell product  $i$  in destinations A and C in periods 2 and 4 are very similar to each other. Similarly, the unobservable variation that drove the choice of the set of markets ABC in periods 3 and 5 is likely to be similar. For example, if the firm experienced a cost-reducing productivity shock in periods 3 and 5, this would be a factor behind its expansion into market B which might be an only marginally profitable destination in a typical year. Consistent with this view, controlling for the trade pattern is tantamount to controlling for unobservables that lead firms to serve a given set of markets in a particular time period—an essential step to reduce the bias in the estimated markup elasticity.

Using these twice-differenced variables, in the final step, we run an OLS regression that precisely identifies how the destination-specific markup responds to the bilateral exchange rate, by exploiting cross-destination variation in prices within a firm’s trade pattern at the product level.<sup>16</sup>

$$\ddot{p}_{ifdtDT} = \beta_0 + \beta_1 \ddot{e}_{dtDT} + \ddot{\mathbf{x}}'_{dtDT} \boldsymbol{\beta}_2 + \ddot{v}_{ifdtDT} \quad (5)$$

We refer to the above procedure as the *trade pattern sequential fixed effects* (TPSFE) estimator.  $\beta_1$  is the destination-specific markup elasticity to the exchange rate (DSME). Note that the aggregate variables which normally vary along only two dimensions  $d$  and  $t$  “become” trade pattern ( $D$ ) and time pattern ( $T$ ) specific, i.e.,  $\ddot{e}_{dtDT}$  and  $\ddot{\mathbf{x}}_{dtDT}$ , if the panel of data is unbalanced in a systematic, non-random way.

To compare our estimates of the DSME with measures of the total export price adjustment to exchange rate movements, we construct an export price elasticity estimator which similarly controls for the selection of destination markets. Specifically, we estimate

$$\dot{p}_{ifdtT} = \alpha_0 + \alpha_1 \dot{e}_{dtT} + \dot{\mathbf{x}}'_{dtT} \boldsymbol{\alpha}_2 + \dot{v}_{ifdtT} \quad (6)$$

where  $\alpha_1$  is the export price elasticity to the bilateral exchange rate;<sup>17</sup> and  $\dot{p}_{ifdtT}$ ,  $\dot{e}_{dtT}$ , and  $\dot{\mathbf{x}}'_{dtT}$  are variables demeaned at the firm-product-destination-trade pattern level, i.e., residuals from the

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<sup>16</sup>Because variables are defined conditional on the trade pattern being observed, this is, in practice, an estimation using S-period differences in the variables.

<sup>17</sup> $\alpha_1$  measures 1-ERPT because the export price is denominated in the exporter’s currency.

average over time conditional upon being observed:

$$\hat{x}_{ifdtT} \equiv x - \frac{1}{n_{ifdD}^T} \sum_{t \in T_{ifdD}} x \quad \forall x \in \{p_{ifdt}, e_{dt}, \mathbf{x}_{dt}\} \quad (7)$$

The estimator (6) removes the time-invariant destination-specific markup in levels for each firm-product observation and exploits the residual time variation in the price within the same trade pattern to identify the export price elasticity. The main idea is to control for the effect of market selection when exploiting variation within the same trade pattern to ensure that the results from running (6) are directly comparable with the results from (5). Note that the only (but key) difference between the two estimators is that in (5) we difference out the unobserved time-varying firm-product component from the export price—which contains the common markup and marginal cost across all destinations.

As we always control for the effect of market selection when exploiting variation within the same trade pattern, the results of specifications (5) and (6) are directly comparable.

## 2.2 A new product classification based on Chinese measure words

For the purpose of our analysis, it is important that we identify products for which firms are potentially able to segment markets in order to exploit (local) market power in setting prices. Most studies adopt the industry classifications set forth by Rauch (1999), according to which 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 this system is quite powerful in identifying commodities, a drawback is that the vast majority of manufactured goods end up being classified as differentiated.

We construct a new, finer classification. The core idea is a simple one: traded goods whose quantity is recorded in customs data by weight or volume are less differentiated than goods whose quantity is reported in countable units. In Chinese trade data, we find quantity reported in more than 30 indigenous Chinese units of measure. Because the choice of the *measure word* used to record a product’s quantity is predetermined by Chinese grammar and linguistics, we can exploit this information to construct a general product classification for the Harmonized System.

The Chinese Customs Database reports the universe of China’s exports and imports at the firm and Harmonized System 8-digit (HS08) product level annually from 2000 to 2014. The key variables for our analysis are the export value, the export quantity, and a Chinese-language measure word describing the quantity. The information embedded in the measure word is intrinsically informative about the nature of the good and forms the basis for our classification system. To

wit: linguists sort Chinese measure words into two groups—mass classifiers and count classifiers.<sup>18</sup> Count classifiers are used to measure distinct items while mass classifiers are used to measure things that are naturally measured by weight, volume, length, etc.<sup>19</sup> Our classification criterion is as follows: any good whose quantity is reported with a count classifier is a high differentiation good while goods whose quantity is reported with a mass classifier are low differentiation goods. When integrated with the Rauch system, we indeed verify that commodities traded on organized exchanges are reported with mass classifiers—fully consistent with our view that mass classifiers identify low differentiation products.

For 2008, the dataset reports quantity using 36 different measure words. To illustrate the variety of measures used, table 2 reports a selection of the most common measure words in our dataset, 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 classifiers; the remaining measure words are count 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 associated unique counter that is associated with that type of good. See appendix C.3 for additional information about examples of the Chinese quantity measures in our dataset.

Table 3 demonstrates the value added and power of our classification system in relation to that by Rauch. In the table, we integrate 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 differentiated, reference priced, and organized exchange traded goods. There are two important improvements. 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.

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<sup>18</sup>See Cheng and Sybesma (1998) and Cheng and Sybesma (1999) for a discussion of mass classifiers and count classifiers in Chinese. See Fang, Jiquing and Connelly, Michael (2008), *The Cheng and Tsui Chinese Measure Word Dictionary*, Boston: Cheng and Tsui Publishers, Inc. for translations of hundreds of Chinese measure words into English.

<sup>19</sup>More precisely, 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).

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

	<b>Corsetti-Crowley-Han-Song (CCHS)</b>		
	Low Differentiation / (Mass nouns)	High Differentiation / (Count nouns)	
<b>Rauch (Liberal Version)</b>			
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 <sup>†</sup>	10.5	1.5	12.0
	59.1	40.9	100.0

(b) Share of goods by classification: value weighted

	<b>Corsetti-Crowley-Han-Song (CCHS)</b>		
	Low Differentiation / (Mass nouns)	High Differentiation / (Count nouns)	
<b>Rauch (Liberal Version)</b>			
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 <sup>†</sup>	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. <sup>†</sup>“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.



Second, 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.<sup>20</sup>

A second important benefit of our classification system is that we are able to provide a CCHS classification for *all* HS08 (and HS06) products, including those that cannot be classified under Rauch’s system due to issues with the mapping from HS06 to SITC Rev. 2. This enables us to expand our analysis of market power to include the 12% percent of observations (table 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.<sup>21</sup>

### 2.3 An estimator of firms’ cross-market supply elasticity

We now turn to the flip side of the destination-specific markup adjustment, that is, the adjustment of export quantities across destination markets. We are interested in gaining insight into the relationship between destination-specific quantity and markup adjustments for a firm’s product due to changes in relative demand conditions across destinations.<sup>22</sup>

Towards this goal, we construct the following two-stage estimator. In the first stage, we rely on our TPSFE to obtain predicted prices,  $\widehat{p}_{ifdtDT}$  using specification (5):

$$\widehat{p}_{ifdtDT} = \widehat{\beta}_0 + \widehat{\beta}_1 \ddot{e}_{dtDT} + \ddot{\mathbf{x}}'_{dtDT} \widehat{\beta}_2 \quad (8)$$

In the second stage, we use the predicted prices as explanatory variables in the *relative quantity* regression (9):

$$\ddot{q}_{ifdtDT} = \gamma_0 + \gamma_1 \widehat{p}_{ifdtDT} + \ddot{\mathbf{x}}'_{dtDT} \gamma_2 + \ddot{u}_{ifdtDT} \quad (9)$$

in which  $\ddot{q}_{ifdtDT}$  is the residual quantity sold, that is, demeaned across destinations and time

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<sup>20</sup>The CCHS classification is a general system that can be applied to the customs datasets for other countries. We have constructed a CCHS product classification for the universal 6-digit Harmonized System by categorizing as high (low) differentiation those HS06 categories in which all HS08 products use a count (mass) classifier.

<sup>21</sup>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 1-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.

<sup>22</sup> The question can be addressed in different ways. One option is to regress quantities directly on exchange rates using the same specification as our TPSFE for destination-specific markups, (5). However, the option that we prefer consists of regressing quantities on projections of prices on exchange rates. The two procedures yield very similar results.

according to equations (3) and (4).

Statistically,  $\widehat{\tilde{p}}_{ifdtDT}$  reflects variation in relative prices driven by changes in the relative market condition measure,  $\ddot{e}_{dtDT}$ , while controlling for other aggregate variables. The coefficient  $\gamma_1$  measures the projection of changes in relative quantities on changes in relative prices driven by changes in destination-market conditions.

If cost-side factors are perfectly controlled in (5), then  $\widehat{\tilde{p}}_{ifdtDT}$  can be interpreted as the change in *relative markups denominated in the exporter’s currency in response to changes in* relative demand conditions across destinations.<sup>23</sup> As is well known, holding the relative supply curve fixed, a shift in relative demand induces a movement along the relative supply curve. Heuristically,  $\gamma_1$  could be seen as the slope of the relative supply curve—it captures the cross-market supply elasticity (CMSE) with respect to destination-specific demand changes.

To appreciate the properties of our estimator, we also run a naïve regression of relative quantity changes on relative price changes, including trade pattern fixed effects:

$$\ddot{q}_{ifdtDT} = \lambda_0 + \lambda_1 \ddot{p}_{ifdtDT} + \ddot{\mathbf{x}}'_{dtDT} \boldsymbol{\lambda}_2 + \ddot{u}_{ifdtDT} \quad (10)$$

As shown in section 4, this naïve regression typically results in a significant but negative correlation: a negative  $\lambda_1$  indicates that a higher relative price in one destination is on average associated with a lower relative quantity sold by the firm in that destination. In contrast, our two-stage procedure generates a positive  $\gamma_1$ , suggesting that the relative markups and quantities are positively correlated if changes in markups are driven by (relative) demand changes. See appendix B.2 for an analytic discussion.

### 3 Data

To construct the dataset in this paper, we merge information from two datasets: (1) the Chinese Customs Database which contains the universe of annual import and export records for China from 2000 to 2014 and (2) annual macroeconomic data from the World Bank.<sup>24</sup>

#### 3.1 Chinese Customs Data

The Chinese Customs Database reports detailed annual trade flows (quantities and values) by firm (numerical ID and name) and destination country at the 8-digit Harmonized System product

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<sup>23</sup>The cost-side factors are controlled if the identification condition (30) presented in appendix A is satisfied.

<sup>24</sup>Details regarding the macroeconomic data and further information about the Chinese Customs Database are presented in appendix C.

level.<sup>25</sup> More interestingly, the database contains the Chinese measure word in which quantity is reported, an indicator of the form of commerce for tax and tariff purposes, and a categorization based on the registration type of the exporting firm.<sup>26</sup>

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.<sup>27</sup> Hereafter, we 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 the subtle differences of goods being sold under the same 8-digit HS code. Second, 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.<sup>28</sup>

The Chinese Customs Database reports transactions denominated in US dollars. We calculate the price in the exporter’s currency (renminbi) by multiplying the unit value of dollar transactions with the annual renminbi-dollar rate.<sup>29</sup>

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<sup>25</sup>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.

<sup>26</sup>The form of commerce indicator records the commercial purpose of each trade transaction including “general trade,” “processing imported materials,” and “assembling supplied materials.” Essentially, a firm can produce the same HS08 product under different tax regulations depending on the exact production process used. We simplify different tax treatments into a form of commerce dummy equal to 1 if the transaction is “general trade” and 0 otherwise. The registration type variable contains information on the capital formation of the firm by eight mutually-exclusive categories: state-owned enterprise, Sino-foreign contractual joint venture, Sino-foreign equity joint venture, wholly foreign-owned enterprise, collective enterprise, private enterprise, individual business, and other enterprise. In our analysis, we aggregate the three types of foreign-invested firms, namely wholly foreign-owned enterprises, Sino-foreign contractual joint ventures and Sino-foreign equity joint ventures, into one category dubbed “foreign-invested enterprises.” We group minority categories including collective enterprises, individual businesses and other enterprises into one category and refer to them as “other enterprises.”

<sup>27</sup>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.

<sup>28</sup>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)).

<sup>29</sup>Note 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. 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 Appendix C.4.

### 3.2 “The Happy Few:” Multi-product, multi-destination exporters

Table 4: Multi-product, multi-destination exporters (2007)

		Number of Countries				
		1	2-5	6-10	10+	Total
(a) by Share of Exporters	Number of HS08 Products					
	1	13.5	6.4	1.6	1.2	22.6
	2-5	9.5	16.5	5.8	5.8	37.6
	6-10	2.2	5.5	3.3	4.4	15.3
	10+	2.1	4.7	4.1	13.6	24.6
	Total	27.2	33.1	14.7	25.0	100.0
(b) by Share of Export Values	1	1.2	1.3	0.8	1.3	4.7
	2-5	1.9	4.3	3.3	8.8	18.4
	6-10	0.6	2.2	2.0	8.1	13.0
	10+	1.6	4.0	4.2	54.0	63.9
	Total	5.4	11.9	10.4	72.3	100.0
(c) by Share of Number of Annual Transactions	1	0.4	0.5	0.3	0.6	1.8
	2-5	0.7	2.1	1.7	4.4	9.0
	6-10	0.4	1.5	1.4	4.8	8.1
	10+	1.5	3.9	4.4	71.4	81.2
	Total	3.0	8.0	7.8	81.2	100.0

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

As a starting point, we document that a small fraction of exporters are responsible for most of China’s exports, a pattern that has been previously documented for France by [Mayer, Melitz and Ottaviano \(2014\)](#)). Table 4 presents a breakdown of the proportion of exporters, their corresponding export values, and their corresponding count of annual transactions according to the number of destinations served (columns) and the number of products exported (rows) in 2007. Panel (a) provides a breakdown of the share of exporters while panels (b) and (c) present the corresponding shares of export value and transactions. Overall, we see that around three-quarters of exporters export to more than one destination (row 5 of panel (a) of table 4, 33.1+14.7+25.0); and are responsible for 94.6% of export value (row 5 of panel (b)) and 97% of annual transactions (row 5 of panel (c)). Conversely, we see that transactions by single-destination firms account for a small share of total Chinese export value. In the top left cell of panel (a) of table 4, we observe that 13.5% of exporters sell a single product to a single destination. However, these firms comprised only 1.2% of Chinese export value and 0.4% of export transactions in 2007. The bottom row of

panel (a) shows that slightly more than one quarter of export transactions in 2007 were products exported by a firm to a single destination. However, the last rows of panels (b) and (c) indicate that these single-destination exporters only account for 5.4% of total export value and 3.0% of total annual export transactions.

These statistics highlight two important facts: (1) the identification scheme based on multi-destination exporters uses observations from those firms that are most important to China’s trade and (2) the vast majority of firms are *not* single-product exporters. It is worth stressing that the shares of exporters and export value by count of products and destination markets are relatively stable over the sample period.

## 4 Empirical Results

In this section, we first present our estimates on markup adjustment for the whole sample of Chinese exports. Then we present estimates distinguishing between high and low differentiation goods and extend the analysis to cross-market supply elasticities. In the next section, we analyze firms’ pricing and sales according to their registration type, distinguishing between private and public, as well as domestic and foreign ownership. These results examine not only firm type, but also the product classification within different groups of firms.

To clarify the differences between our estimators and exchange rate pass-through estimators, as a reference benchmark, we report estimates of the export price elasticity to the exchange rate (i.e., the complement of exchange rate pass through), controlling for the firm’s trade pattern (6). This allows us to quantify the relative contribution of the destination-specific markup elasticity (obtained by using our TPSFE estimator) to total export price adjustment.

Furthermore, to make our results comparable with recent leading studies in the literature on exchange rate pass through, we apply the TPSFE estimator *conditional on a price change* in line with the methodology of [Gopinath, Itskhoki and Rigobon \(2010\)](#). 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 renminbi smaller than 5 percent. Thus, our pass-through estimates are based on S-period differences in prices, relative to the change in the exchange rate and other macro variables cumulated over the same S-period. The S-period interval defining a price change can vary within a firm-product-destination triplet and across these triplets. That is, for a single firm-product-destination triplet, we might observe S-period differences of, say, 2, 3, 4 or more years, within the 15 years included in our panel. 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 appendix C.5.<sup>30</sup>

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<sup>30</sup>The main conclusion of our analysis remains the same if we apply our estimator without conditioning on price

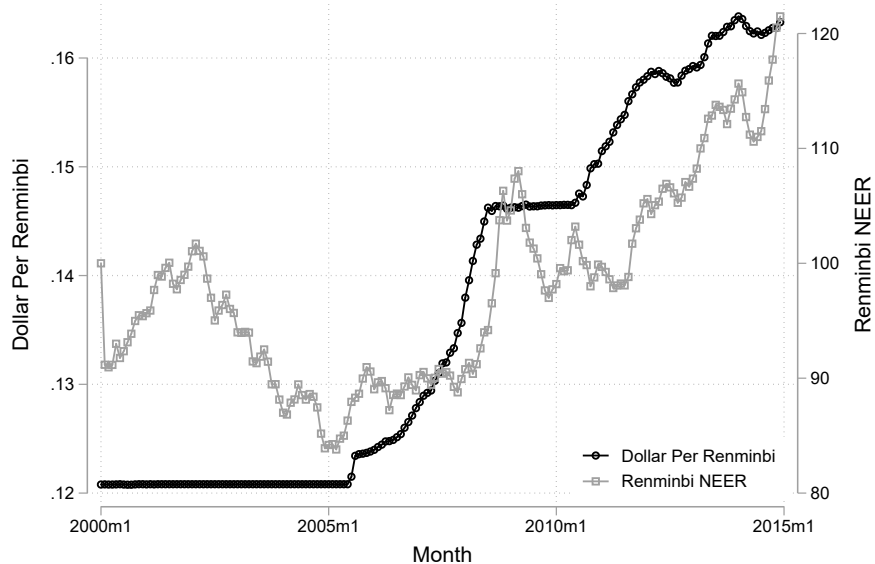


Figure 2: Renminbi Movements 2000-2014

We report results separately for the subsamples corresponding to the two exchange rate regimes pursued by China, the fixed exchange rate regime of 2000-2005 and the managed float regime of the latter period. Figure 2 plots the bilateral movement of the renminbi against the US dollar, as well as China’s nominal effective exchange rate, over our entire sample period. As will be discussed in later sections, there is evidence that exporters’ pricing behavior differs across the two environments. 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.<sup>31</sup>

changes.

<sup>31</sup>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.

## 4.1 Markup adjustment and incomplete pass through

Applying our estimator to Chinese exports, we find that, on average, destination-specific markup adjustments are moderate, of the order of 5 to 10%. Since the degree of exchange rate pass through is relatively high, however, these moderate markup adjustments account for a large share of the incomplete pass through into import prices.

Table 5 reports estimates of the destination-specific markup elasticity (DSME) in columns (3) and (4), together with the export price elasticity to the exchange rate in exporter’s currency (i.e., 1-ERPT) in columns (1) and (2), over the period 2000-2014. To clarify the difference between the two, it is useful to decompose the price adjustment to the exchange rate into three components: (a) a general markup adjustment that is the same across all foreign markets, (b) a destination-specific markup adjustment, and (c) any change in marginal costs. The estimates of the price elasticity to the exchange rate in columns (1) and (2) combine movements in all three components. In particular, the coefficient captures the average of the price elasticity to bilateral exchange rates across all markets. In contrast, our TPSFE estimator in columns (3) and (4) is designed to isolate component (b) – relative price adjustments to relative exchange rate movements across markets. Because our identification condition implies that marginal costs are purged from the estimator, it follows that the *relative price adjustment* is equivalent to the *relative markup adjustment across destinations*, i.e., the destination-specific markup elasticity.

Looking at the first two columns in table 5, we see the elasticity of export prices (in renminbi) to bilateral exchange rates is low during the dollar peg era (column (1)) rising marginally during the managed float (column (2)). Conditional on a price change, the renminbi price of Chinese exports responds to nominal bilateral exchange rate movements by 22% over the 2000-2005 period and 29% over 2006-2014 period. In interpreting these results, recall that we measure export prices in renminbi and bilateral exchange rates as renminbi per unit of foreign currency—a *low coefficient on the export price* elasticity in columns (1) and (2) means a *high pass through into import prices* in foreign (local) currency. Hence, our estimates mean that pass through into import prices in local currency in destination markets is, on average, high and stable over time: it was about 78% in the years of China’s currency peg and essentially the same, 71%, in later years.

The estimates in columns (3) and (4) are quite different from the export price elasticity estimates. Conditional on a price change in renminbi occurring at  $t+s$ , the average destination-specific markup changes by 5% of the cumulated bilateral exchange rate movement between  $t$  and  $t+s$  during the dollar peg period (column 3). After the change in the exchange rate regime, as shown in column (4), the destination-specific markup response rises to 11% of the cumulated movement.

It is important to keep in mind that, everything else equal, the larger the markup adjustment, the lower the change in import prices *in the currency of the destination market*. Our estimate of destination-specific markup adjustment would be zero if exporters set one price for their product



Table 5: Price and Destination-specific Markup Elasticities to Exchange Rates

	Price Elasticity (1-ERPT)		Destination-specific Markup Elasticity (DSME)	
	(1)	(2)	(3)	(4)
	2000-2005	2006-2014	2000-2005	2006-2014
Bilateral nominal exchange rates	0.22*** (0.01)	0.29*** (0.01)	0.05** (0.02)	0.11*** (0.01)
Destination CPI	0.09*** (0.02)	0.72*** (0.01)	0.01 (0.03)	0.01 (0.02)
Destination real GDP	0.33*** (0.03)	0.02 (0.01)	-0.04 (0.05)	-0.06** (0.02)
Import-to-GDP ratio	0.22*** (0.01)	0.33*** (0.01)	-0.02 (0.02)	0.05*** (0.01)
Number of Observations	4,279,808	19,272,657	4,279,808	19,272,657

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 152 destinations excluding Hong Kong and the United States. The “Price Elasticity” and “Destination-specific Markup Elasticity” columns present estimates from specifications (6) and (5) respectively. All results are estimated based on the same estimation sample of filtered price changes following the procedure specified in appendix C.5. The bilateral exchange rate is defined as renminbi per unit of destination currency; an increase means an appreciation of the destination currency. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by \*\*\*, \*\*, and \*.

in all destinations. This would occur irrespective of whether these prices were sticky or move across time and whether they were set in renminbi or dollars. 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.

Comparing the destination-specific markup elasticities with the export price elasticities, note that adjustment of relative markups across destinations accounts for about one-fourth of overall price adjustment in renminbi during the dollar peg period (0.05 divided by 0.22), and for about one-third of it in later period (0.11 divided by 0.29). Thus our results suggest that firms became considerably more active in adjusting their destination-specific markups after China abandoned its strict peg to the US dollar.<sup>32</sup> Plausibly, the differences in markup elasticities we detect across the two time periods reflect more than just the policy reform of switching from a dollar peg to a managed float in China. They may stem from structural changes at the firm and market level, as well as from changes in the frequency and importance of cyclical (policy and technology) shocks at the national and global level that have occurred between the two time periods.<sup>33</sup>

<sup>32</sup>The difference in estimated coefficients on CPI in columns (1) versus (3) and (2) versus (4) arises because the TPSFE estimator removes the global trend in the exporter’s price associated with global CPI movements and isolates the local component.

<sup>33</sup>The price elasticity provides different information relative to estimates of pass through that are made conditional on a specific shock hitting the economy – a point elaborated at length by [Corsetti, Dedola and Leduc \(2008\)](#). To wit:

## 4.2 High versus low differentiation goods

We now examine differences in markup elasticities by degree of product differentiation under the CCHS product classification. To introduce and motivate our product-class analysis, we find it instructive to present a graphical visualization of markup adjustments by firms producing two different products – one low differentiation good and one high differentiation good. As case studies, we select canned tomato paste (measured in kilograms) to represent low differentiation manufactured goods and wheeled tractors (measured with liàng, 辆) to represent high differentiation goods.

In figure 3, we plot the dispersion of markups across destinations for the top three exporters of tomato paste (upper panel) and wheeled tractors (lower panel) in 2007 and 2008. For each annual observation of a sale to a destination, we calculate the deviation of the sales price from its mean across all destinations within the firm-product-year triplet (where sales price is the log unit value in renminbi), i.e.  $uv_{ifdt} - \bar{uv}_{ift}$ , 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.<sup>34</sup> Any observation on the 45 degree line is a product whose relative markup 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 markup 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 markup 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.

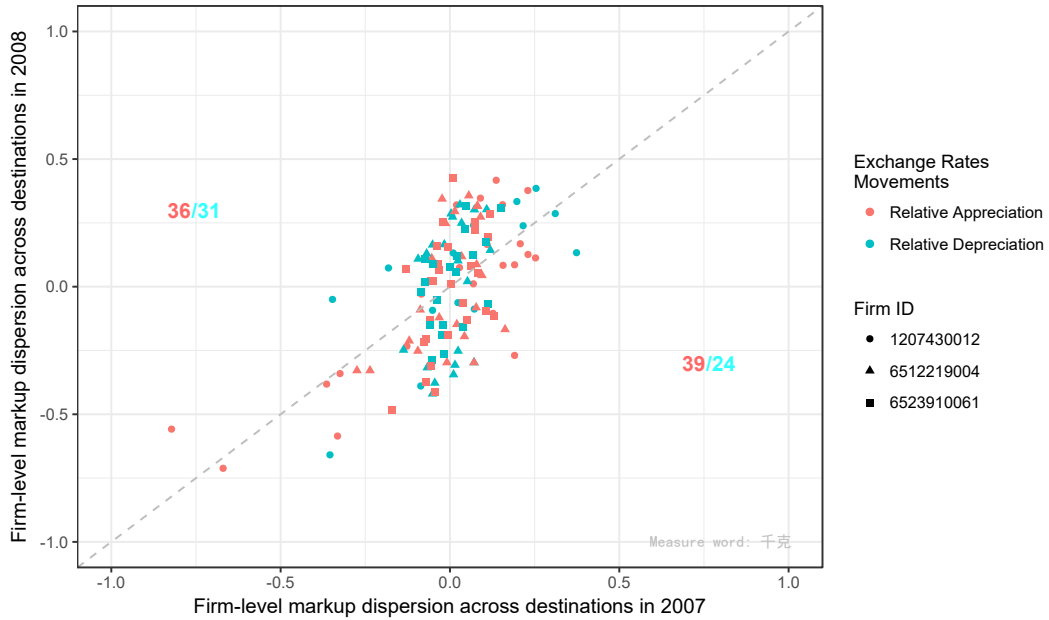
These graphs illustrate three key results. First, the relative markups for many firm-product-destination triplets, measured in the producer’s currency, change from year to year. Second, the

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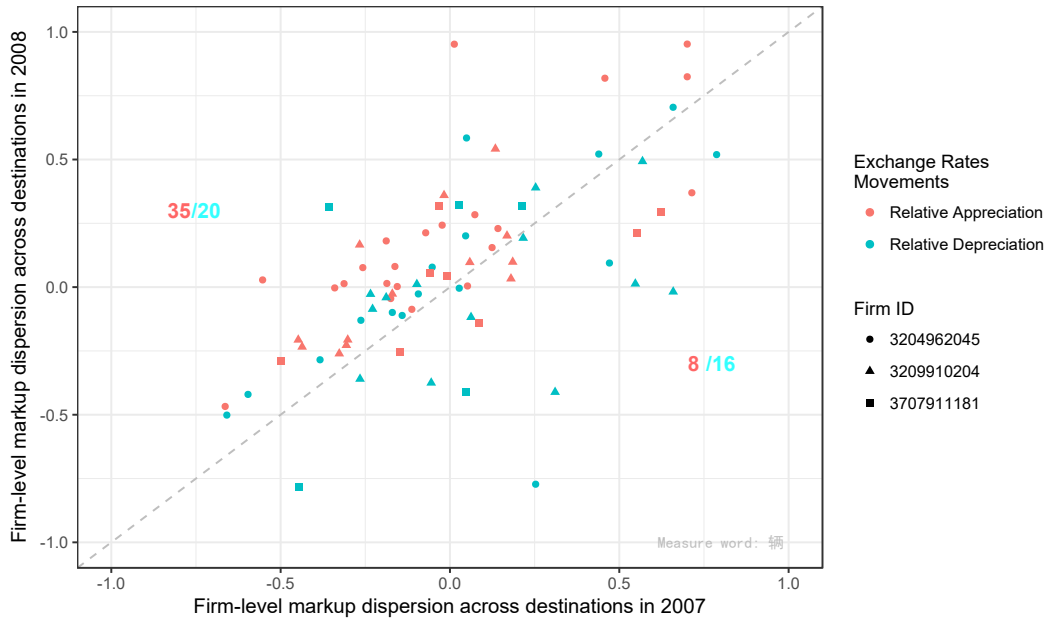
we would expect the price response to exchange rate movements to be quite different if the underlying shock is to productivity as opposed to monetary policy. Estimates of pass through conditional on a shock require methodologies, like VARs, suitable to identifying these shocks in isolation and tracing their effects on the exchange rate, export prices, and markups – see Forbes, Hjortsoe and Nenova (2017).

<sup>34</sup>The magnitude of price dispersion within a year across destinations for wheeled tractors is of the same order of magnitude as that found in European automobile prices in an important study of international market segmentation by Goldberg and Verboven (2001).

Figure 3: Markup 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 markup 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.,  $uv_{ifdt} - \bar{uv}_{ift}$ . 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 markup 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.

low differentiation good, tomato paste, exhibits less dispersion in its markups 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 markups (red dots are denser above the 45 degree line), while depreciation of the destination market currency is associated with a decrease in relative markups. No such clear pattern emerges between relative markup changes and relative currency changes for the low differentiation good, tomato paste.

#### 4.2.1 Markup elasticities using the CCHS product classification

In line with our discussion of the two case studies above, our econometric analysis documents significant differences in both pass through and markup elasticities across high and low differentiation goods—validating the usefulness of our linguistics-inspired product classification as a proxy for market power. That is, we show empirically that more market power enables firms to price-discriminate and keep their prices relatively stable in local currency against bilateral currency movements.

Results are shown in table 6. For comparison, the first two columns of the table reproduce the key results from table 5 of average export price and destination-specific markup elasticities for the universe of Chinese exports. The remaining four columns report results for the subsamples of high and low differentiation goods. The first row refers to the dollar peg period, the second row to the more recent period in the sample. In both subperiods, the renminbi prices and destination-specific markups of high differentiation goods respond more to bilateral exchange rates movements, implying lower ERPT, than low differentiation goods. For low differentiation goods, pricing-to-market actually plays no role during the dollar peg, and only a moderate role after the strict peg is abandoned.

Focusing on the point estimates, during the fixed exchange rate period (row 1), we have already seen that the markup elasticity over all goods is relatively small, 5% (column (2)). The results in the table show that this low average estimate conceals important differences across types of goods. For CCHS high differentiation exports, the average destination-specific markup elasticity is 10%—for low differentiation goods it is zero.

In the period of the managed float of the renminbi (second row of table 6), destination-specific markup elasticities are considerably higher. For high differentiation goods, the export price elasticity rises from 24 to 32% (and exchange rate pass through correspondingly falls to  $1-.32=.68$ ); the destination-specific markup elasticity rises from 10 to 20%. Note that the destination-specific markup adjustment to the exchange rate accounts for two-thirds of the price elasticity ( $0.20/0.32$ ). For low differentiation goods, the markup elasticity is smaller but becomes significantly positive, at 6%. This accounts for about 20% of the adjustment in renminbi prices ( $0.06/0.27$ ).

Table 6: Price and Markup Elasticity by CCHS Classification

	All		High Differentiation		Low Differentiation		n. of obs
	(1) Price	(2) DSME	(3) Price	(4) DSME	(5) Price	(6) DSME	
2000 – 2005	0.22*** (0.01)	0.05** (0.02)	0.24*** (0.02)	0.10*** (0.03)	0.22*** (0.02)	0.01 (0.03)	4,279,808
2006 – 2014	0.29*** (0.01)	0.11*** (0.01)	0.32*** (0.01)	0.20*** (0.02)	0.27*** (0.01)	0.06*** (0.01)	19,272,657

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 152 destinations excluding Hong Kong and the United States. The “Price” and “DSME (Destination-specific Markup Elasticity)” columns present estimates from specifications (6) and (5) respectively. All results are estimated based on the same estimation sample of filtered price changes following the procedure specified in appendix C.5. Destination CPI, real GDP and import-to-GDP ratio controls are included in each regression; related estimates are omitted for conciseness. The bilateral exchange rate is defined as renminbis per unit of destination currency; an increase means an appreciation of the destination currency. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by \*\*\*, \*\*, and \*.

#### 4.2.2 Integrating the CCHS product classification 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.

To gain further insight on how the intensity of market competition can impact pricing by firms, we now 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).<sup>35</sup> These results are reported in Table 7.

Although the DSMEs for both consumption goods and intermediates during the dollar peg period are statistically indistinguishable from zero, when we split each of these end-use categories into high and low differentiation subsamples, significant differences emerge. High-differentiation consumption goods have a sizeable destination-specific markup elasticity of 0.10 (row 1, column (4)) whereas this elasticity is zero (row 1, column (6)) for low-differentiation consumption goods.

Consistent with our results in table 5, after China abandoned the dollar peg, the magnitudes of markup elasticities are higher for both consumption goods and intermediates. Under the managed float, there is a clear difference between the destination specific markup adjustments for

<sup>35</sup> 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.

Table 7: Price and Markup Elasticity by BEC Classification

Category	All		High Differentiation		Low Differentiation		n. of obs
	(1) Price	(2) DSME	(3) Price	(4) DSME	(5) Price	(6) DSME	
2000 – 2005							
Consumption	0.23*** (0.02)	0.04 (0.03)	0.27*** (0.02)	0.10** (0.04)	0.18*** (0.03)	-0.01 (0.04)	1,604,027
Intermediate	0.24*** (0.02)	0.05 (0.04)	0.24*** (0.06)	0.19** (0.09)	0.24*** (0.02)	0.03 (0.04)	1,180,449
2006 – 2014							
Consumption	0.34*** (0.01)	0.21*** (0.02)	0.46*** (0.02)	0.33*** (0.02)	0.17*** (0.02)	0.09*** (0.02)	6,133,394
Intermediate	0.30*** (0.01)	0.05*** (0.02)	0.39*** (0.06)	0.12* (0.07)	0.29*** (0.01)	0.04** (0.02)	6,288,252

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 152 destinations excluding Hong Kong and the United States. The “Price” and “DSME (Destination-specific Markup Elasticity)” columns present estimates from specifications (6) and (5) respectively. All results are estimated based on the same estimation sample of filtered price changes following the procedure specified in appendix C.5. Destination CPI, real GDP and import-to-GDP ratio controls are included in each regression; related estimates are omitted for conciseness. The bilateral exchange rate is defined as renminbis per unit of destination currency; an increase means an appreciation of the destination currency. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by \*\*\*, \*\*, and \*.

consumption goods and intermediates—exporters selling consumption goods (0.21, row 3 column (2)) engage in destination-specific markup changes that are roughly 4 times larger than those selling intermediates (0.05, row 4 column (2)). When we further refine consumption goods into our CCHS product categories, we document a strikingly large destination-specific markup adjustment for high-differentiation consumption goods (0.33, row 3 column (4)).

Our results are informative about the extent to which incomplete exchange rate pass through can be attributed to a destination-specific markup adjustment, as opposed to a markup adjustment that is common across markets and changes in production costs. During the managed float period, the estimated ERPT into import prices in local currency for high differentiation consumption goods is only 54% (corresponding to an export-price elasticity of 0.46). This is far lower than most estimates using micro firm-level data. In our findings, three-quarters of this incomplete ERPT can be attributed to destination-specific markup adjustments (0.33/0.46, row 3, column (4)/column (3)).

For low differentiation intermediates, pass through into import prices is higher, 71% (1-0.29, row 4, column (5)); however, the fraction of the incomplete pass through due to destination-specific markup adjustments is far smaller—about one-eighth (0.04/0.29, row 4, column (6)/column (5)). The same is true for low differentiation consumption goods. For these goods, ERPT is 83% (1-0.17, row 3, column (5)), and the destination-specific markup adjustment explains only about half of the incomplete pass through.

### 4.2.3 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 8.

The most important takeaway from table 8 is that the estimated markup elasticity of “differentiated” goods according to the Rauch classification, 12% in the later period, is an average of very different elasticities for high and low differentiation goods, 20% and 7% respectively. Unsur-



Table 8: Price and Markup Elasticity by Rauch Classification

Category	All		High Differentiation		Low Differentiation		n. of obs
	(1) Price	(2) DSME	(3) Price	(4) DSME	(5) Price	(6) DSME	
2000 – 2005							
Differentiated Products	0.22*** (0.01)	0.07*** (0.02)	0.23*** (0.02)	0.10*** (0.03)	0.20*** (0.02)	0.04 (0.03)	3,339,574
Organized Exchange	0.67*** (0.07)	0.05 (0.09)	-	-	0.69*** (0.07)	0.06 (0.09)	36,656
Reference Priced	0.18*** (0.04)	-0.01 (0.08)	0.08 (0.16)	0.28 (0.22)	0.19*** (0.04)	-0.03 (0.08)	332,678
2006 – 2014							
Differentiated Products	0.26*** (0.01)	0.12*** (0.01)	0.32*** (0.01)	0.20*** (0.02)	0.21*** (0.01)	0.07*** (0.02)	15,722,023
Organized Exchange	1.29*** (0.10)	0.00 (0.09)	-	-	1.29*** (0.10)	0.00 (0.09)	99,373
Reference Priced	0.54*** (0.02)	0.14*** (0.04)	0.16 (0.11)	0.10 (0.18)	0.57*** (0.02)	0.13*** (0.04)	1,537,937

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 152 destinations excluding Hong Kong and the United States. The “Price” and “DSME (Destination-specific Markup Elasticity)” columns present estimates from specifications (6) and (5) respectively. All results are estimated based on the same estimation sample of filtered price changes following the procedure specified in appendix C.5. Destination CPI, real GDP and import-to-GDP ratio controls are included in each regression; related estimates are omitted for conciseness. The bilateral exchange rate is defined as renminbis per unit of destination currency; an increase means an appreciation of the destination currency. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by \*\*\*, \*\*, and \*.

prisingly, our estimates of markup elasticities are zero for goods traded in organized exchanges, which in our classification are treated as low differentiation goods (rows 2 and 5, column (2)). 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. The renminbi price elasticity is correspondingly much higher for this group of goods, relative to differentiated manufactures—it is about 0.7 in the first sample, and even exceeds 1 in the second sample.

For reference-priced goods, the elasticity of renminbi prices is quite high in the second period, but low in the first period—this increase over time matches the pattern we find for the goods traded in organized exchanges. Moreover, 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.<sup>36</sup>

### 4.3 A Comparative Assessment of Estimators

The pricing-to-market and exchange rate pass through literature utilizes a variety of estimators and approaches to identification. In this section, we call attention to a key methodological difference across estimators, the set and sequence of fixed effects implemented in the analysis. We show that the choice of these fixed effects is highly consequential, and document which alternative statistical procedures are equivalent. We start by observing that leading contributions differ in this dimension. Namely, [Berman, Martin and Mayer \(2012\)](#) and [Chatterjee, Dix-Carneiro and Vichyanond \(2013\)](#) applied  $ifd + t$  fixed effects; [Fitzgerald, Haller and Yedid-Levi \(2016\)](#) applied  $ift + d$  fixed effects; [Amiti, Itskhoki and Konings \(2014\)](#) applied  $ift + d$  fixed effects with time differenced variables; [Fitzgerald and Haller \(2018\)](#) applied  $ift + idt$  fixed effects; [Chen and Juvenal \(2016\)](#) applied  $it + fd$  fixed effects.<sup>37</sup> A first point to note is, when using multiple and different fixed effects, the variation in the data that provides identification is not always clear—this problem is inherent in any complex multi-dimensional panel. A second important point to note is that high dimensional fixed effects (HDFE) are often implemented through statistical programs that take an iterative approach to estimating the fixed effects (e.g., [Guimaraes and Portugal \(2011\)](#), [Rios-Avila \(2015\)](#), and [Correia \(2017\)](#)). The way these programs work does not help clarify which dimensions

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<sup>36</sup>The destination-specific markup elasticity for low-differentiation reference priced goods is lower than that for highly differentiated products, but is somewhat higher than for the low-differentiation differentiated products (compare column (6) rows four and six). Note a key difference between differentiated goods and reference-price goods under the low-differentiation heading: in the latter period, the export price elasticity (column 5) is much higher for low-differentiation reference priced goods. While this evidence points to the need for further analysis, we note that our qualitative results do not hinge on including reference-priced goods in the sample.

<sup>37</sup>The fixed effects listed refer to each paper’s main specification equation.

of the data provide identification of the parameters of interest. Finally, as stressed by [Guimaraes and Portugal \(2011\)](#), iterative approaches need to be applied with caution because they may not be consistent due to the importance of the incidental parameters problem in a multi-dimensional panel.

In [table 9](#), we compare our benchmark estimator with seven estimators that are commonly used in the literature. To set the stage for our comparison, we stress from the beginning that all nine estimation procedures in [table 9](#) would produce identical results if the panel of firm-product-destination customs transactions were balanced, i.e., if all firm-product pairs were exported to all destinations in all time periods. Similarly, eight of these nine procedures (1-3 and 5-9) would give identical results if the pattern of missing observations were random.<sup>38</sup>

As shown in [table 9](#), in our sample the nine estimators yield very different values of the markup elasticity.<sup>39</sup> The first column shows the estimates using our benchmark specification of the TPSFE. The second column shows the results from using a variant of our benchmark estimator, where trade-pattern fixed effects rather than firm-product trade pattern fixed effects are implemented in the second step of the estimator.<sup>40</sup> The main difference between the two columns is that our benchmark specification also controls for firm-product-destination specific unobserved variables, such as brand names and firm-product-destination specific preferences. Our preferred specification uses a TPSFE ( $dD$ ) that tightly identifies the parameter of interest from a firm’s sales of a product to the same destination within a trade pattern over time. As apparent from the table, these two specifications give very similar results, except for high differentiation products during 2000-2005.

In contrast, in [column \(3\)](#), we show that the estimates differ sharply when we remove the trade pattern fixed effects, thereby ignoring the endogenous market selection issue. Observe that endogenous selection appears to be empirically relevant: [column \(3\)](#) estimates—which are biased downward in the presence of endogenous selection—are indeed centered around values between 0.01 and 0.03. The estimator without trade pattern fixed effects fails to detect any differences in markup adjustment, not only between the dollar peg and the floating period, but also between high versus low differentiation goods.

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<sup>38</sup>Appendix [A.2](#) presents Monte Carlo evidence.

<sup>39</sup>Each estimating equation in [table 9](#) includes four variables to proxy for changes in local market conditions, namely bilateral exchange rates, local CPI, real GDP in the destination, and the import-to-GDP ratio. Our discussion has emphasized that market selection endogenous to the bilateral exchange rate will introduce bias into the coefficient on the bilateral exchange rate for some specifications. In fact, the estimated coefficient on bilateral exchange rates can be biased if the market selection is endogenous to *any* of these four variables.

<sup>40</sup>As a variation of our benchmark specification, we generate destination-specific trade patterns that are less-specific than the firm-product-destination-and-trade pattern fixed effects in our benchmark. For example, sales by firms to Japan in a year when these firms are selling to Japan, Korea, and Vietnam will be assigned the trade pattern fixed effect associated with “JP-JP-KR-VN.” Similarly, in the same period, firms selling to Korea and Vietnam will be assigned the trade pattern fixed effects for “KR-JP-KR-VN” and “VN-JP-KR-VN,” respectively. Notationally, we denote these destination-specific trade pattern fixed effects as  $\{dD\}$  and the set of firm-product-time triplets satisfying this trade pattern as  $IFT_{dD}$ .

Table 9: Comparison across Estimators

	(1) TPSFE ( <i>ifdD</i> )	(2) TPSFE ( <i>dD</i> )	(3) No Trade Pattern	(4) S-Diff + ( <i>ift</i> )	(5) HDFE ( <i>ifd, t</i> )	(6) HDFE ( <i>ift, d</i> )	(7) Two-step HDFE	(8) HDFE ( <i>ift, ifd</i> )	(9) Two-step HDFE	n. of obs
Destination Demean	Yes	Yes	Yes	No	No	No	Yes	No	Yes	
Time Difference	No	No	No	Yes	No	No	No	No	No	
Fixed Effects	Firm Product Trade Pattern ( <i>ifdD</i> )	Trade Pattern ( <i>dD</i> )	Destination ( <i>d</i> )	<i>ift</i>	<i>ifd + t</i>	<i>ift + d</i>	<i>d + D</i>	<i>ifd + ift</i>	<i>ifd + ifD</i>	
<b>2000-2014</b>										
All Products	0.10*** (0.01)	0.09*** (0.00)	0.02*** (0.00)	0.11*** (0.00)	0.09*** (0.00)	0.06*** (0.00)	0.06*** (0.00)	0.08*** (0.00)	0.08*** (0.00)	23,552,465
High Differentiation	0.18*** (0.02)	0.15*** (0.01)	0.02*** (0.00)	0.14*** (0.00)	0.14*** (0.00)	0.09*** (0.00)	0.09*** (0.00)	0.12*** (0.00)	0.12*** (0.00)	10,185,981
Low Differentiation	0.06*** (0.01)	0.05*** (0.00)	0.03*** (0.00)	0.08*** (0.00)	0.05*** (0.00)	0.04*** (0.00)	0.04*** (0.00)	0.05*** (0.00)	0.05*** (0.00)	13,366,484
<b>2000-2005</b>										
All Products	0.05** (0.02)	0.03*** (0.01)	0.01*** (0.00)	0.07*** (0.01)	0.02*** (0.01)	0.04*** (0.01)	0.04*** (0.00)	0.02*** (0.01)	0.02*** (0.01)	4,279,808
High Differentiation	0.10*** (0.03)	0.04** (0.02)	0.01*** (0.00)	0.10*** (0.01)	0.04*** (0.01)	0.07*** (0.01)	0.07*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	1,922,739
Low Differentiation	0.01 (0.03)	0.01 (0.01)	0.02*** (0.00)	0.05*** (0.01)	0.00 (0.01)	0.01** (0.01)	0.01*** (0.01)	0.00 (0.01)	0.00 (0.01)	2,357,069
<b>2006-2014</b>										
All Products	0.11*** (0.01)	0.12*** (0.01)	0.02*** (0.00)	0.08*** (0.00)	0.11*** (0.00)	0.08*** (0.00)	0.08*** (0.00)	0.09*** (0.00)	0.09*** (0.00)	19,272,657
High Differentiation	0.20*** (0.02)	0.20*** (0.01)	0.01*** (0.00)	0.11*** (0.01)	0.16*** (0.01)	0.11*** (0.00)	0.11*** (0.00)	0.13*** (0.01)	0.13*** (0.01)	8,263,242
Low Differentiation	0.06*** (0.01)	0.08*** (0.01)	0.03*** (0.00)	0.06*** (0.00)	0.07*** (0.00)	0.06*** (0.00)	0.06*** (0.00)	0.07*** (0.00)	0.07*** (0.00)	11,009,415

Note: Each cell reports the estimated destination-specific markup elasticity (DSME) from the estimation method specified on top of each column. Destination CPI, real GDP and import-to-GDP ratio controls are included in all estimation methods; related estimates are omitted for conciseness. Each row indicates a different subsample. Within in a row, all methods are applied based on the same sample. The number of observations in the last column corresponds to Stage 7 of the data cleaning procedure specified in appendix C.5. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by \*\*\*, \*\*, and \*.

A popular specification consists in taking time differences over  $S$ -periods and then adding firm-product-time fixed effects (column (4)). We should stress the inherent fault in this approach. Taking time differences over  $S$ -periods changes the panel dimension along which the unobserved marginal cost varies in an endogenously unbalanced panel. As a result, the estimates are biased even if the unobserved marginal cost is not destination-specific. Column (5) presents estimates from an alternative high-dimensional fixed effect specification. Although specifications (4) and (5) seem very similar to our TPSFE estimator, they give very distinct estimates across time periods and product samples relative to our benchmark estimator (1).

As noted earlier, an important issue in the literature is that the sources of variation that provide identification in multi-dimensional panels can be somewhat obscure. The approach we propose—to control for sets of markets reached by a firm’s product—maps directly into basic and intuitive economics. For this reason, we find it natural to use our procedure to gain insight into the way alternative estimators work. Namely, in columns (6-9), we show that the HDFE iterative estimator is effectively controlling for sets of markets—a property that it is far from obvious from the statistical model. In columns (7) and (9), we implement a two-step procedure that mimics the results of the HDFE iterative approach. In both columns, we start by destination demeaning the data at the firm-product-destination level (the first step of the TPSFE procedure); then, in a second step, we apply  $d+D$  and  $ifd+ifD$  fixed effects using the HDFE estimator, respectively. As apparent from comparing the results in columns (7) and (9) with those in column (3), incorporating the set of destinations  $D$  is key to reducing the bias inherent in failing to control for the endogenous trade pattern. Columns (6) and (7) demonstrate the equivalence between applying  $(ift + d)$  fixed effects using an iterative procedure (column 6), and applying  $(d + D)$  fixed effects (also using an iterative procedure) after demeaning across destinations (column 7). By the same token, the table shows that the  $ift + ifd$  approach in column (8) is equivalent to destination-demeaning the data and then applying  $ifd + ifD$  fixed effects, as in column (9).

Altogether, the evidence in the table lends support to the idea that endogenous market selection is an empirically relevant problem. It is therefore important to use an estimator that takes into account the selection problem of market participation across firms and products. One contribution from our method is to clarify the source(s) of identification of parameters and to document to extent to which different estimators are robust to selection biases when estimating markup elasticities by relying on variation across destinations. We provide a thorough analysis of how our estimator works and why differences across estimators arise in appendix [A](#).

## 4.4 Cross Market Supply Elasticity

We conclude this section by investigating the flip side of the destination-specific markup elasticity to the exchange rate, that is, firms’ cross market supply elasticity. The question we ask is to what extent, in response to exchange rate movements, do firms reallocate their output across markets as they adjust their own markups in different destinations. Table 10 presents the estimates obtained by applying the method developed at the end of section 2.

Table 10: Cross Market Supply Elasticity by CCHS Classification

	All		High Differentiation		Low Differentiation		n. of obs
	(1) $Cor(\dot{q}, \dot{p})$	(2) CMSE	(3) $Cor(\dot{q}, \dot{p})$	(4) CMSE	(5) $Cor(\dot{q}, \dot{p})$	(6) CMSE	
2000 – 2005	-0.71*** (0.01)	6.18*† (3.18)	-0.75*** (0.01)	4.07** (1.72)	-0.68*** (0.01)	19.72† (55.14)	4,279,808
2006 – 2014	-0.70*** (0.00)	1.53*** (0.28)	-0.72*** (0.00)	0.72*** (0.20)	-0.69*** (0.00)	2.72*** (0.80)	19,272,657

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 “ $Cor(\dot{q}, \dot{p})$ ” column is estimated using specification (10). The “CMSE” column is estimated based on equations (8) and (9). 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.

The table reports our estimates of the CMSE together with the results from running a naïve regression of relative quantities on relative prices (labeled  $Cor(\dot{q}, \dot{p})$ ), conditional on trade pattern fixed effects. As shown in columns (1), (3) and (5) of the table, the sign of the naïve regression coefficient is consistently negative. Specifically, in column (1), a 1% increase in relative prices is statistically associated with a 0.7% *decline* in relative quantities. The naïve regression simply reveals that, in equilibrium, firms sell relatively small quantities in markets where they set relatively high prices.<sup>41</sup>

A key finding highlighted by the table is that the results from our CMSE estimator have the opposite sign relative to the results from the naïve regression. Focus on the managed float regime (table 10, row 3). Over the 2006-2014 period, our estimated cross market supply elasticity is positive and equal to 1.53 (row 3, column (2)): 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. In relative terms, firms increase exports to destinations where they increase markups in response to a local currency appreciation.

The difference in the sign of the regression coefficient between the naïve regression and the CMSE is extremely important. The CMSE is designed to isolate the relative quantity adjustments

<sup>41</sup>This could reflect low levels of competition/high market power, in turn pointing to higher barriers to entry or fixed costs as an important component of trade costs.

across destinations *caused* by markup adjustments to exchange rate movements.

To put it in another way, the main idea underlying the development of our statistical procedure consists of exploiting relative movements in bilateral exchange rates to trace shifts in the relative demand across a firm’s markets—by projecting relative prices/markups onto exchange rates. These projections are then used to trace out a firm’s relative “willingness to supply” across markets. A positive slope coefficient from the CMSE estimator confirms that our TPSFE approach is able to isolate the demand-side effects of exchange rate fluctuations.

The second important finding in table 10 consists of the sharp difference in estimated CMSEs across high and low differentiation goods. Over the 2006-2014 period, the estimated CMSE is very low for high differentiation goods, 0.72 (row 3, column 4), consistent with a view that firms exporting high differentiation products respond to destination-specific exchange rate movements by adjusting markups, rather than by letting the foreign-currency price move substantially with the exchange rate (which would effect a larger adjustment in quantities). In contrast, the estimated CMSE for low differentiation goods is quite high: a one percent increase in the relative markup is associated with 2.72% increase in the relative quantity supplied. Altogether, these results underscore important heterogeneity in price-setting and quantity responses between high and low differentiation goods.

We know already that exporters from China engaged in only modest amounts of pricing-to-market during the years of the fixed exchange rate regime in our sample. Indeed, over these years, bilateral exchange rate movements are a quantitatively important predictor of destination-specific markup adjustments only for high differentiation goods—with a sizeable 0.10 markup elasticity (see table 6). For these goods, our estimated CMSE is quite high, 4.07. Altogether, these results suggest that, during the strict peg period, firms responded to bilateral exchange rate movements with modest markup adjustments — instead they aggressively pursued openings for higher profits through large increases in relative quantities, i.e., a 4.07% increase in the relative quantity supplied associated with a one percent increase in the relative markup.

We conclude by providing additional evidence on the extent and importance of international market segmentation and market power. Table 11 reports our CMSE estimates for high and low differentiation goods by Broad Economic Categories. At one extreme we have highly differentiated consumption goods: the very low estimate of quantity substitution across destinations (0.16, statistically indistinguishable from zero) suggests that the markets for these goods are highly segmented. At the other extreme, for low differentiation intermediates, quantity substitution is quite high (3.84) and markets appear quite integrated.



Table 11: Cross Market Supply Elasticity by BEC Classification (2006 – 2014)

Category	All		High Differentiation		Low Differentiation		n. of obs
	(1) $Cor(\dot{q}, \dot{p})$	(2) CMSE	(3) $Cor(\dot{q}, \dot{p})$	(4) CMSE	(5) $Cor(\dot{q}, \dot{p})$	(6) CMSE	
Consumption	-0.71*** (0.00)	0.47** (0.19)	-0.77*** (0.00)	0.16 (0.16)	-0.63*** (0.01)	1.68** (0.79)	6,133,394
Intermediate	-0.71*** (0.00)	3.34** (1.55)	-0.73*** (0.01)	1.04 <sup>†</sup> (1.39)	-0.71*** (0.00)	3.84* <sup>†</sup> (1.98)	6,288,252

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 “ $Cor(\dot{q}, \dot{p})$ ” column is estimated using specification (10). The “CMSE” column is estimated based on equations (8) and (9). Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by \*\*\*, \*\*, and \*. <sup>†</sup> indicates that the t-statistic of the bilateral exchange rate in the first stage is smaller than 2.58.

## 5 Further results by product and firm types

The intense competition that Chinese imports have brought to high income countries has spawned research into how this enhanced competitive pressure has 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 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. In section 4.2, we provided evidence that strategic pricing-to-market and markup adjustments are more prominent in the markets for high differentiation goods, especially consumption goods, while quantitatively less pronounced in the markets for low differentiation manufactured goods with higher degrees of competition. We now dig deeper into the Chinese Customs Database, and examine how to square our results with the evolving identity of Chinese exporters.

The Chinese economy is widely understood to be a hybrid in which competitive, market-oriented private firms operate alongside large, state-owned enterprises (SOEs).<sup>42</sup> 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).

Reflecting their ownership type, firms are likely to have different cost structures and face different demand elasticities. 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,

<sup>42</sup>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.

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 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 pricing, markup adjustments, and cross-destination quantity adjustments.

## 5.1 The evolution of exports by private, state owned and foreign invested firms in China

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

A well-known fact is the extraordinary rate of entry into export activity by private enterprises. This is apparent in the top panel of the figure. From being a small and 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.<sup>43</sup> 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 4).

The key message from the top panel of figure 4 is reinforced by the evidence on export values and shares by different types of firms, shown in the bottom panel. By export value and share of

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<sup>43</sup>At the start of our sample period, export activity was highly regulated in China with most rights to export held by SOEs—only a very limited number of private enterprises were able to export directly. The result of this was that in the earlier years post-2000 private enterprises desiring to export their merchandise exported through SOEs.

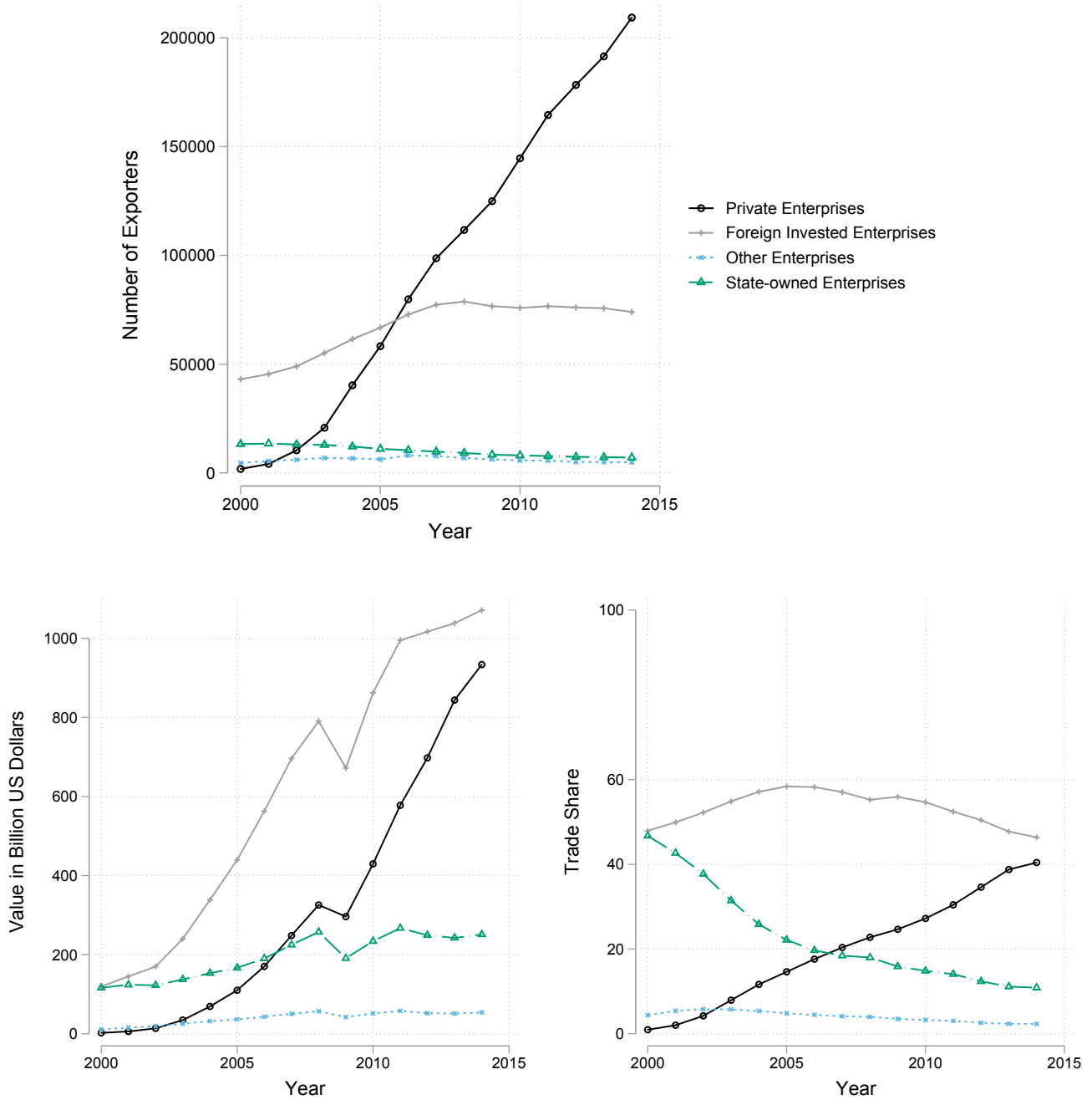


Figure 4: The changing face of Chinese exporters, 2000-2014

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

total exports, the most important single group of exporters from China is that of foreign-invested enterprises. In 2014, the value of their exports was over US \$1 trillion (bottom left panel of figure 4). Over the period, exports from China that originated from firms that are wholly or partially owned by foreigners fluctuated between 45 and 58% of China’s total exports.<sup>44</sup>

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

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

## 5.2 Markup and supply elasticities by firms’ type

Evidence on price, markup and supply elasticities by firm type is presented in table 12, where we focus on the period 2006-2014. In this period, relative to other Chinese exporters, foreign-invested enterprises (FIEs) stand out in that, across destination markets, they make larger adjustments to their renminbi export prices (0.66), have moderately elastic markups (0.24), and have an inelastic within-firm cross market supply elasticity (CMSE) (see table 12, row 2, columns (1), (2) and (4)). The high estimate of the Chinese export price elasticity of 0.66 implies that the ERPT into *import* prices in foreign currency is relatively low (34%), reflecting that these firms are more actively pursuing local currency price stabilization than other groups of firms. Notably, destination-specific markup adjustment accounts for one third (0.24/0.66) of this incomplete pass through into import prices.

Relative to FIEs, the export price response to exchange rates by SOEs is smaller, 0.33 (see row 1, column (1) of table 12), implying a much higher pass through into *import* prices, on average 67%. While SOEs make similar markup adjustments compared to FIEs in absolute terms, the contribution of destination-specific markup adjustment to incomplete pass through is higher (0.21/0.33 versus 0.24/0.66) for SOEs. Like FIEs, SOEs have an extremely low cross market

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<sup>44</sup>The importance of foreign involvement in Chinese exports has previously been documented by [Koopman, Wang and Wei \(2014\)](#). Based on an accounting framework methodology and product-level trade flows, they show that 29.3 percent of Chinese export value comes from foreign, rather than domestic Chinese, value-added. This is not inconsistent with our estimates; our complementary contribution is to document foreign engagement based on *ownership* of exporting firms, rather than through the origin of the value-added content of exported goods.

supply elasticity, 0.19 (row 1, column (4)). This evidence together suggests that both FIEs and SOEs hold a high degree of market power which enables them to exploit market segmentation and strategically price-to-market.

The picture is totally different for private enterprises. On average, these firms adjust their export prices far less than either SOEs or FIEs—by a mere 1.6 percent in response to a 10 percent appreciation (see row 3, column (1) of table 12). Of this, about one-fourth is due to a tiny, yet statistically significant, markup adjustment by destination (0.04/0.16). Pass through into foreign *import* prices is as high as 84 percent. What is truly extraordinary is the within-firm cross market supply elasticity: for private firms, a one percent increase in the relative markup caused by a bilateral exchange rate appreciation leads to a 5.23 percent increase in the relative quantity sold in that destination. This is evidence that, on average, Chinese private firms aggressively chase profit opportunities across destination markets by expanding quantities, but make only small markup adjustments in response to destination-specific currency movements.<sup>45</sup>

The second and third panels of table 12 break down the estimates by firm type, distinguishing between high and low differentiation goods. Two key results stand out. First, within each class of firms, the number of exporters of both high and low differentiation goods is large (see the number of observations for each sample in column (5)): there is no apparent specialization by firm type. This means that the different pricing behavior noted in the top panel of table 12 cannot be attributed to a different typology of goods produced and exported across groups. Second, for each type of firm, results are consistent with our findings in section 4. Markup elasticities are higher for high differentiation goods than for low differentiation goods. Cross market supply elasticities are correspondingly lower for the former and higher for the latter group of goods.

To better appreciate the meaning and potential implications of our results for theory and policy, consider the response of different types of firms and products to an idiosyncratic appreciation of a foreign currency, say, the Mexican peso, relative to the renminbi. For private firms exporting goods with low differentiation, the depreciation of the renminbi leads to relatively high yet not complete pass through into the peso-denominated prices (1-.13 =87 percent, from row 9, column (1) of table 12), but no adjustment in the markup. For private firms exporting high differentiation goods, the exchange rate pass through into peso prices is somewhat lower, about 81% (1-.19, from row 6, column (1)). Yet, markup adjustment is only modestly higher, 10%. Accounting for possibly different cost structures (due, for example, to the higher share of imported intermediate inputs in high differentiation goods), the strategic pricing behavior is quite comparable among private firms, regardless of whether they sell high or low differentiation goods.

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<sup>45</sup>This type of highly responsive substitution of export value ( $p^*q$ ) across markets has also been identified in the context of destination-specific tariff increases and product-level trade flows by [Bown and Crowley \(2006\)](#) and [Bown and Crowley \(2007\)](#). In the trade flow and tariff literature, it is referred to as “trade deflection.” A similar cross-destination supply response of capital flows has been identified by [Giordani, Ruta, Weisfeld and Zhu \(2017\)](#).

Table 12: Pricing Strategies by Firm Registration Types (2006 – 2014)

	(1) Price	(2) DSME	(3) $Cor(\hat{q}, \hat{p})$	(4) CMSE	n. of obs
Full Sample					
State-owned Enterprises	0.33*** (0.02)	0.21*** (0.03)	-0.70*** (0.01)	0.46 (0.31)	3,526,943
Foreign Invested Enterprises	0.66*** (0.02)	0.24*** (0.03)	-0.70*** (0.00)	0.19 (0.21)	4,990,504
Private Enterprises	0.16*** (0.01)	0.04*** (0.01)	-0.70*** (0.00)	5.23*** (1.88)	9,897,091
High Differentiation					
State-owned Enterprises	0.41*** (0.03)	0.41*** (0.05)	-0.67*** (0.01)	0.11 (0.23)	1,617,483
Foreign Invested Enterprises	0.59*** (0.03)	0.33*** (0.04)	-0.70*** (0.01)	0.31 (0.24)	2,267,880
Private Enterprises	0.19*** (0.02)	0.10*** (0.02)	-0.75*** (0.00)	1.99*** (0.72)	3,988,833
Low Differentiation					
State-owned Enterprises	0.28*** (0.02)	0.09** (0.04)	-0.71*** (0.01)	1.26 <sup>†</sup> (1.19)	1,909,460
Foreign Invested Enterprises	0.69*** (0.02)	0.20*** (0.04)	-0.70*** (0.01)	-0.11 (0.32)	2,722,624
Private Enterprises	0.13*** (0.01)	0.01 (0.02)	-0.67*** (0.00)	16.87 <sup>†</sup> (19.58)	5,908,258

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 152 destinations excluding Hong Kong and the United States. The “Price” and “DSME (Destination-specific Markup Elasticity)” columns present estimates from specifications (6) and (5) respectively. The “ $Cor(\hat{q}, \hat{p})$ ” column is estimated using specification (10). The “CMSE” column is estimated based on equations (8) and (9). Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by \*\*\*, \*\*, and \*. <sup>†</sup> indicates that the t-statistic of the bilateral exchange rate in the first stage is smaller than 2.58.

Relative to private firms, for SOEs and FIEs pass through into import prices is considerably lower and markup adjustment is considerably higher. For high differentiation exports from China, ERPT into peso prices is around 50% ( $1 - 0.41 = 59\%$  for SOEs and 41% for FIEs, rows 4 and 5, column (1) of table 12). SOEs and FIEs clearly prefer to raise their markups, by 41% for SOEs and 33% for from FIEs (rows 4 and 5, column (2)), rather than expand sales. The estimated cross-market supply elasticities are indeed very small and not significantly different from zero (0.11 for SOEs and 0.31 for FIEs). A similar picture emerges from our analysis of SOEs and FIEs exporting low differentiation goods, although, not surprisingly, markup adjustment is lower.

Overall, our results provide striking evidence that, on average, SOEs and FIEs exporting from China have significant power in setting prices—they exploit this power by letting their markups increase significantly with a foreign currency appreciation. This points to a strategic decision by firms to exploit market segmentation and keep destination markets separated: averaged over all exported goods, there is virtually no change for SOEs and FIEs in the relative quantity sold in Mexico for a 1% increase in the relative markup. Although these results may in part capture transfer pricing motivated by profit shifting practices, it remains true that the divide relative to Chinese private firms is large: over our sample period, private firms have aggressively pursued local market expansions, rather than exploiting opportunities to raise their prices.

A comment is in order concerning our findings. In comparison to FIEs and SOEs, private enterprises are on average smaller, reflecting the high rate of entry documented at the beginning of this section. Hence, a substantial share of them are likely at an early stage of their life cycle in which growth can be expected to have precedence over the exploitation market power. Interpreting our results from a cross-sectional perspective is likely to overestimate heterogeneity—once they achieve their equilibrium size, private firms may well exercise monopoly power and behave like FIEs and SOEs.<sup>46</sup>

## 6 Conclusions

Understanding how firms adjust prices and quantities to market-specific and international shocks is a classic question into the operation of the global economy. The increasing availability of large, multi-dimensional, administrative datasets of firms has recently enabled researchers to re-examine this classic question in new ways. In this paper, we have proposed a new empirical strategy designed to efficiently exploit administrative data on exporters.

Our first contribution consists of an unbiased estimator of the destination-specific markup elasticity with respect to the exchange rate. Our TPSFE estimator is capable of controlling for a firm’s time-varying marginal cost at the product level, even when the panel of data is endogenously

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<sup>46</sup>We leave to future research a refinement of our analysis along these lines.



unbalanced. Based on these destination-specific markup elasticities, we showed how to derive statistical measures of the corresponding adjustment in export sales across destination markets. While our main motivation in this paper is an analysis of the pricing and quantity response to currency movements, it should be clear that the methodology we developed can be applied to other contexts in which producers sell to multiple markets/buyers and may price discriminate across them in response to a variety of shocks—such as tariffs or VAT changes.

Markup adjustments can be expected to vary with the degree of competition in a market. Our second contribution consists of a new, general classification of Harmonized System products aided by a specific feature of Chinese linguistics and information on traded quantities reported to Chinese Customs Authority. We use a linguistic classification of Chinese measure words, or quantity measures, to classify HS products into high and low differentiation categories and use this to proxy for market power. In conjunction with our TPSFE estimator, this classification allows us to document striking differences in empirical elasticities between high and low differentiation goods. Moreover, it adds value to existing classification systems such as [Rauch \(1999\)](#) and the UN’s Broad Economic Categories.

Our empirical results for the Chinese custom database document significant heterogeneity in how firms adjust markups and quantities to currency movements across categories of goods. We find that firms exporting high differentiation goods from China make moderate but significant destination-specific adjustments to markups in response to movements of bilateral exchange rates—markup adjustments account for up to three quarters of incomplete exchange rate pass through into import prices. In contrast, producers of commodities and low differentiation goods make minuscule or no adjustments. These different elasticities are mirrored (inversely) by cross market adjustments in quantities exported.

Altogether, these results tell us that the nature of the good matters enormously in gauging the extent of international market segmentation and firms’ market power across markets. A high degree of pricing-to-market can be expected for highly differentiated goods, for which the cross-market substitution of quantity by firms is very low. In contrast, firms producing low differentiation intermediates appear more similar to commodity producers in their inconsequential use of destination-specific markup adjustments and their highly elastic cross-market substitution of supply. Relatedly, we find much higher destination-specific markup adjustment among State Owned Enterprises and Foreign-Invested Enterprises (on average larger and endowed with more market power) than among private firms.

Although the focus of this paper is mainly empirical, we should stress that our methodology is motivated and driven by open economy macro theory. While global and local shocks naturally lead firms to reconsider their pricing strategies, their choice sets are not unconstrained, but crucially reflect the extent to which firms have power in local markets and can keep the foreign markets

for their products segmented to minimize arbitrage. Namely, an exporting firm must consider not only the direct effect of changes in the value of its own currency on its own competitiveness, but also the response of foreign rivals to swings in the values of *their* currencies relative to the destination market's—these changes in competitiveness from third countries have key implications for the exporting firm's residual demand and, hence, local pricing power. In this respect, multilateral analyses of markup and quantity elasticities can provide fundamental insights into the effective degree of competition within and across markets, especially if articulated by product and firm characteristics. As a step in this direction, our destination-specific markup elasticity (DSME) and the cross-market supply elasticity (CMSE) together contribute a novel and important diagnostic tool to guide and discipline the development of open-economy models. In a companion paper, we are developing a multi-country model with features drawn from leading contributions in the literature (Corsetti, Crowley and Han 2018). Our results suggest that specific theoretical elements—especially multilateral competition among producers of substitutes and vertical interactions between producers and distributors—are necessary to capture the important aspects of observed behaviour revealed in our elasticities.

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## A The trade pattern sequential fixed effects estimator

Our estimator is designed to address unobserved marginal costs in an environment where firms endogenously select the set of destination markets for their product, i.e., firms' participation in a given market is endogenous. The idea is that the realized selection of markets (the trade patterns) convey useful information about the unobservable factors that drive the selection process. By controlling for these patterns, we restrict the variation of unobservables in the selection equation. In this sense, our approach can be viewed as a variant of the control function approach (e.g., Heckman (1979)) and the first difference approach pursued by Kyriazidou (1997).<sup>47</sup>

To clarify these points, we start by rewriting the problem addressed by Heckman (1979) in his seminal work on selection in cross-sectional data:

$$p_t = \mathbf{x}'_t \boldsymbol{\beta} + \varepsilon_t \tag{11}$$

$$= \mathbf{x}'_t \boldsymbol{\beta} + E(\varepsilon_t | \mathbf{x}_t, s_t) + \nu_t$$

$$s_t = \mathbb{1}\{\mathbf{w}'_t \boldsymbol{\gamma} + u_t\} \tag{12}$$

where  $E(\varepsilon_t | \mathbf{x}_t, s_t)$  is the selection bias and  $\nu_t \equiv [\varepsilon_t - E(\varepsilon_t | \mathbf{x}_t, s_t)]$  is an error term that is uncorrelated with the vector of observed variables  $\mathbf{x}_t$  and the selection bias.  $\mathbf{w}_t$  is a vector of observed variables in the selection equation which can overlap with the elements in  $\mathbf{x}_t$ .  $s_t$  is an indicator variable that equals one if  $p_t$  is observed. As is well known, selection is a problem if  $E(\varepsilon_t | \mathbf{x}_t, s_t) \neq 0$ . The solution of Heckman (1979) is to estimate the function of  $E(\varepsilon_t | \mathbf{x}_t, s_t)$  under some parametric assumptions and then add the predicted value  $\widehat{E(\varepsilon_t | \mathbf{x}_t, s_t)}$  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 in which export market participation is a choice, Kyriazidou (1997)

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<sup>47</sup>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 Verbeek and Nijman (1996), Honoré, Vella and Verbeek (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 and a third 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, Matyas and Wansbeek (2018)). However, they do not discuss the type of selection rules for which their fixed effect estimator is consistent.

studies selection in a two dimensional panel with one fixed effect:

$$p_{dt} = \mathbf{x}'_{dt}\boldsymbol{\beta} + \mathcal{M}_d + \varepsilon_{dt} \quad (13)$$

$$= \mathbf{x}'_{dt}\boldsymbol{\beta} + \mathcal{M}_d + E(\mathcal{M}_d|\mathbf{x}_{dt}, s_{dt}) + E(\varepsilon_{dt}|\mathbf{x}_{dt}, s_{dt}) + \nu_{dt}$$

$$s_{dt} = \mathbb{1}\{\mathbf{w}'_{dt}\boldsymbol{\gamma} + \mathcal{W}_d + u_{dt}\} \quad (14)$$

where  $\mathcal{M}_d$  and  $\mathcal{W}_d$  are unobserved variables varying along the destination  $d$  dimension (i.e. destination fixed effects).  $E(\mathcal{M}_d|\mathbf{x}_{dt}, s_{dt})$  and  $E(\varepsilon_{dt}|\mathbf{x}_{dt}, s_{dt})$  represent the selection biases caused by the unobserved destination-specific heterogeneity and other omitted variables, respectively.  $\nu_{dt} \equiv [\varepsilon_{dt} - E(\varepsilon_{dt}|\mathbf{x}_{dt}, s_{dt}) - E(\mathcal{M}_d|\mathbf{x}_{dt}, s_{dt})]$  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.<sup>48</sup> Kyriazidou (1997) notes that  $E(\mathcal{M}_d|\mathbf{x}_{dt}, s_{dt})$  and  $E(\varepsilon_{dt}|\mathbf{x}_{dt}, s_{dt})$  no longer vary along the time dimension when  $\mathbf{w}'_{d1}\boldsymbol{\gamma} = \mathbf{w}'_{d2}\boldsymbol{\gamma}$  under the following *conditional exchangeability* condition:

$$F(\varepsilon_{d1}, \varepsilon_{d2}, u_{d1}, u_{d2}|\boldsymbol{\psi}_d) = F(\varepsilon_{d2}, \varepsilon_{d1}, u_{d2}, u_{d1}|\boldsymbol{\psi}_d) \quad (15)$$

where  $\boldsymbol{\psi}_d \equiv (\mathbf{x}_{d1}, \mathbf{x}_{d2}, \mathbf{w}_{d1}, \mathbf{w}_{d2}, \mathcal{W}_d, \mathcal{M}_d)$  is a destination specific vector containing information on observed and unobserved variables. Condition (15) states that  $(\varepsilon_{d1}, \varepsilon_{d2}, u_{d1}, u_{d2})$  and  $(\varepsilon_{d2}, \varepsilon_{d1}, u_{d2}, u_{d1})$  are identically distributed conditional on  $\boldsymbol{\psi}_d$ . As noted by Kyriazidou (1997), the main term causing the selection bias,  $E(\varepsilon_{dt}|\mathbf{x}_{dt}, s_{dt})$ , is no longer time-varying when  $\mathbf{w}'_{d1}\boldsymbol{\gamma} = \mathbf{w}'_{d2}\boldsymbol{\gamma}$  under condition (15):

$$E(\varepsilon_{d1}|s_{d1} = 1, s_{d2} = 1|\boldsymbol{\psi}_d)$$

$$\equiv E(\varepsilon_{d1}|u_{d1} < \mathbf{w}'_{d1}\boldsymbol{\gamma} + \mathcal{W}_d, u_{d2} < \mathbf{w}'_{d2}\boldsymbol{\gamma} + \mathcal{W}_d, \boldsymbol{\psi}_d)$$

$$= E(\varepsilon_{d1}|u_{d1} < \mathbf{w}'_{d2}\boldsymbol{\gamma} + \mathcal{W}_d, u_{d2} < \mathbf{w}'_{d1}\boldsymbol{\gamma} + \mathcal{W}_d, \boldsymbol{\psi}_d) \quad (16)$$

$$= E(\varepsilon_{d2}|u_{d2} < \mathbf{w}'_{d2}\boldsymbol{\gamma} + \mathcal{W}_d, u_{d1} < \mathbf{w}'_{d1}\boldsymbol{\gamma} + \mathcal{W}_d, \boldsymbol{\psi}_d) \quad (17)$$

$$\equiv E(\varepsilon_{d2}|s_{d2} = 1, s_{d1} = 1|\boldsymbol{\psi}_d)$$

where the first equality (16) holds because  $\mathbf{w}'_{d1}\boldsymbol{\gamma} = \mathbf{w}'_{d2}\boldsymbol{\gamma}$  and the second equality (17) holds because of the *conditional exchangeability* condition (15). Since the selection bias is no longer time varying, i.e.,  $E(\varepsilon_{d1}|s_{d1} = 1, s_{d2} = 1|\boldsymbol{\psi}_d) = E(\varepsilon_{d2}|s_{d2} = 1, s_{d1} = 1|\boldsymbol{\psi}_d)$ , 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

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<sup>48</sup>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.

for which  $\mathbf{w}'_{d1}\widehat{\boldsymbol{\gamma}} = \mathbf{w}'_{d2}\widehat{\boldsymbol{\gamma}}$ .

Our problem is specified in (18) and (19) below:

$$p_{ifdt} = \mathbf{x}'_{dt}\boldsymbol{\beta} + \mathcal{M}_{ifd} + \mathcal{C}_{ift} + \varepsilon_{ifdt} \quad (18)$$

$$s_{ifdt} = \mathbb{1}\{\mathbf{w}'_{dt}\boldsymbol{\gamma} + \mathcal{W}_{ifd} + \mathcal{Q}_{ift} + u_{ifdt}\} \quad (19)$$

This problem differs from Kyriazidou (1997)'s in two crucial respects. On the one hand, our problem adds unobserved firm-product-time-varying variables  $\mathcal{C}_{ift}$  to equation (13) and  $\mathcal{Q}_{ift}$  to equation (14). In the presence of these time-varying unobserved factors, the *conditional exchangeability* 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. 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.<sup>49</sup>

The method we propose to address the above problem is conceptually close to Kyriazidou (1997). The approach we take however is fundamentally different. If we were to use Kyriazidou (1997)'s approach, all variables driving  $\mathcal{Q}_{ift}$  would need to be observed and controlled for. For our purposes, this is overly difficult because the marginal cost is unobserved and hard to estimate.<sup>50</sup> Indeed, we design 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. The main innovation is to use the realized selection pattern in a panel dimension rather than observed variables in the selection equation to control for selection biases.

Before going through the general problem characterized in equations (18) and (19), we find it useful to start with the discussion of a two-dimensional panel, tracking the choices of a single firm selling one product across a set of endogenous destinations.

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

$$p_{dt} = \mathbf{x}'_{dt}\boldsymbol{\beta} + \mathcal{M}_d + \mathcal{C}_t + \varepsilon_{dt} \quad (20)$$

$$s_{dt} = \mathbb{1}\{u_{dt}\} \quad (21)$$

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  $\mathbf{x}_{dt}$ . 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 (20) to eliminate the

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<sup>49</sup>To wit: many aggregate-level economic indicators, such as exchange rates, vary along the destination and time dimensions, but not at the firm or product dimensions.

<sup>50</sup>See subsection A.3 for a discussion of the difficulties in directly estimating marginal cost.

unobserved destination and time specific factors. More 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,

$$\ddot{p}_{dt} = \ddot{\mathbf{x}}'_{dt} \boldsymbol{\beta} + \ddot{\varepsilon}_{dt} \quad (22)$$

where

$$\ddot{\mathbf{x}}_{dt} = \mathbf{x}_{dt} - \frac{1}{n_t^D} \sum_{d \in D_t} \mathbf{x}_{dt} - \frac{1}{n_{dD}^T} \sum_{t \in T_{dD}} \mathbf{x}_{dt} + \frac{1}{n_{dD}^T} \sum_{t \in T_{dD}} \frac{1}{n_t^D} \sum_{d \in D_t} \mathbf{x}_{dt} \quad (23)$$

$$\ddot{\varepsilon}_{dt} = \varepsilon_{dt} - \frac{1}{n_t^D} \sum_{d \in D_t} \varepsilon_{dt} - \frac{1}{n_{dD}^T} \sum_{t \in T_{dD}} \varepsilon_{dt} + \frac{1}{n_{dD}^T} \sum_{t \in T_{dD}} \frac{1}{n_t^D} \sum_{d \in D_t} \varepsilon_{dt} \quad (24)$$

$D_t$  is the set of destinations the firm serves at time  $t$ ; and  $n_t^D \equiv |D_t|$  is 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 trade pattern emerges. For our proposed approach to work in a two dimensional panel, we need<sup>51</sup>

$$F(\varepsilon_{dD1}, \varepsilon_{dD2}, u_{dD1}, u_{dD2} | \boldsymbol{\psi}_{dD}) = F(\varepsilon_{dD2}, \varepsilon_{dD1}, u_{dD2}, u_{dD1} | \boldsymbol{\psi}_{dD}), \quad (26)$$

where we use  $\varepsilon_{dD1}$  to indicate the first  $\varepsilon$  within the destination-specific trade pattern  $dD$ . We provide an example of the formulation of  $dD$  in table 13. From (26), 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:

$$E(\varepsilon_{dDt} | u_{dD1} > 0, u_{dD2} > 0, \boldsymbol{\psi}_{dD}) = E(\varepsilon_{dD\tau} | u_{dD1} > 0, u_{dD2} > 0, \boldsymbol{\psi}_{dD}) \quad \forall \tau \in T_{dD} \quad (27)$$

Condition (26) can be viewed as a variant 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.,  $\mathbf{w}'_{d1} \boldsymbol{\gamma} = \mathbf{w}'_{d2} \boldsymbol{\gamma}$ ), 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

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<sup>51</sup>Note that Kyriazidou (1997)'s original conditions (and proofs) only cover the case when the number of time periods equal to two. For a more general case with more than two time periods, we impose a condition as follows

$$E(\varepsilon_{dDt} | u_{dD1} > 0, \dots, u_{dDn_{dD}^T} > 0, \boldsymbol{\psi}_{dD}) = E(\varepsilon_{dD\tau} | u_{dD1} > 0, \dots, u_{dDn_{dD}^T} > 0, \boldsymbol{\psi}_{dD}) \quad \forall \tau \in T_{dD} \quad (25)$$

As will be discussed later, our estimator works under a much weaker condition than (25) if another panel dimension is available.

produces unbiased and consistent estimates.<sup>52</sup>

Table 13: An Example of the Indicative Value of Trade Patterns

$d$	$t$	$\mathcal{W}_d$	$\mathcal{Q}_t$	$s_{dt}$	$D_t$	$dD$	$t$	$\mathcal{W}_d$	$\mathcal{Q}_t$	$s_{dt}$	$dD$	$t$	$\mathcal{W}_d$	$\mathcal{Q}_t$	$s_{dDt}$
A	1	1.5	1	1	A-B-C	A- <b>A-B-C</b>	1	1.5	<b>1</b>	1	1	1	1.5	1	1
B	1	0.5	1	1	A-B-C	B- <b>A-B-C</b>	1	0.5	<b>1</b>	1	2	1	0.5	1	1
C	1	-0.5	1	1	A-B-C	C- <b>A-B-C</b>	1	-0.5	<b>1</b>	1	3	1	-0.5	1	1
K	1	-1.5	1	0	A-B-C	K- <b>A-B-C</b>	1	-1.5	<b>1</b>	0	4	1	-1.5	1	0
A	2	1.5	0	1	A-B	A- <b>A-B</b>	2	1.5	<b>0</b>	1	5	2	1.5	0	1
B	2	0.5	0	1	A-B	B- <b>A-B</b>	2	0.5	<b>0</b>	1	6	2	0.5	0	1
C	2	-0.5	0	0	A-B	C- <b>A-B</b>	2	-0.5	<b>0</b>	0	7	2	-0.5	0	0
K	2	-1.5	0	0	A-B	K- <b>A-B</b>	2	-1.5	<b>0</b>	0	8	2	-1.5	0	0
A	3	1.5	1	1	A-B-C	A- <b>A-B-C</b>	3	1.5	<b>1</b>	1	1	3	1.5	1	1
B	3	0.5	1	1	A-B-C	B- <b>A-B-C</b>	3	0.5	<b>1</b>	1	2	3	0.5	1	1
C	3	-0.5	1	1	A-B-C	C- <b>A-B-C</b>	3	-0.5	<b>1</b>	1	3	3	-0.5	1	1
K	3	-1.5	1	0	A-B-C	K- <b>A-B-C</b>	3	-1.5	<b>1</b>	0	4	3	-1.5	1	0
A	4	1.5	0	1	A-B	A- <b>A-B</b>	4	1.5	<b>0</b>	1	5	4	1.5	0	1
B	4	0.5	0	1	A-B	B- <b>A-B</b>	4	0.5	<b>0</b>	1	6	4	0.5	0	1
C	4	-0.5	0	0	A-B	C- <b>A-B</b>	4	-0.5	<b>0</b>	0	7	4	-0.5	0	0
K	4	-1.5	0	0	A-B	K- <b>A-B</b>	4	-1.5	<b>0</b>	0	8	4	-1.5	0	0

Original
Transformed based on the realized trade pattern
Relabelled

As an illustration of how conditioning on the realized trade patterns  $D$  reduces selection bias, consider the numerical example in Table 13. This table reports the realization of trade flows to four destinations ( $d = A, B, C, K$ ) over four time periods ( $t = 1, 2, 3, 4$ ) with  $u_{dt} \equiv \mathcal{W}_d + \mathcal{Q}_t$ , where  $\mathcal{W}_d$  and  $\mathcal{Q}_t$  are destination-specific and time specific variables in the selection process, respectively. The third and fourth columns in each panel in table 13 show the realized values of  $\mathcal{W}_d$  and  $\mathcal{Q}_t$  and the corresponding outcomes,  $s_{dt} = 1$  if the firm exports to destination  $d$  at time  $t$ . Only the dimensional indicator  $d$  and the selection outcome  $s_{dt}$  are observable to the researcher, whereas  $\mathcal{W}_d$  and  $\mathcal{Q}_t$  are unobservable.

The trade pattern  $D_t$  in each period can be constructed based on realized values of the observed selection indicator in each destination, i.e.,  $\{s_{1t}, s_{2t}, s_{3t}, s_{4t}\}$ . The last column of the first panel (“original”) in table 13 shows the constructed trade patterns. In this specific example, there are two unique realized trade patterns, i.e.,  $D_1 = D_3 = \{1, 1, 1, 0\} \equiv$  “A-B-C” and  $D_2 = D_4 = \{1, 1, 0, 0\} \equiv$  “A-B.”

<sup>52</sup>It is straightforward to see the condition for consistency, i.e.,  $E(s_{dt}\ddot{x}_{dt}\ddot{\varepsilon}_{dt}) = 0$ , is satisfied under (25). First, note that  $\frac{1}{n_t^D} \sum_{d \in D_t} \varepsilon_{dt} - \frac{1}{n_{dD}^T} \sum_{t \in T_{dD}} \frac{1}{n_t^D} \sum_{d \in D_t} \varepsilon_{dt} = 0$ . This is because the expression  $\frac{1}{n_t^D} \sum_{d \in D_t} \varepsilon_{dt}$  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 (25), i.e.,  $E\left(\varepsilon_{dt} - \frac{1}{n_{dD}^T} \sum_{t \in T_{dD}} \varepsilon_{dt} \middle| s_{dD1}, s_{dD2}, s_{dD3}, \dots, \psi_{dD}\right) = 0$ .

In this numerical example, by construction, the unobserved time-varying factors are exactly the same for identical trade patterns, i.e.,  $\mathcal{Q}_1 = \mathcal{Q}_3$  and  $\mathcal{Q}_2 = \mathcal{Q}_4$ . Therefore, taking time differences after conditioning on the trade pattern *completely* eliminates the selection bias, i.e., condition (27) is satisfied. The table illustrates the main innovation of our approach: we exploit variation in the dependent and independent variables in the  $dD$  and  $t$  panel dimensions, rather than in the  $d$  and  $t$  panel dimensions by constructing fixed effect estimators conditional on the realized trade patterns. By exploiting variation in trade patterns, we effectively reduce the selection bias caused by unobserved time-varying factors.

In general, however, the underlying time-varying factors in the selection equation need not be restricted to be exactly the same for identical trade patterns. To see why, observe that, given a trade pattern, the range of values that  $\mathcal{Q}_t$  can take is limited. In other words, conditioning on a trade pattern is useful as it pins down the range of variation in  $\mathcal{Q}_t$ ;  $\mathcal{Q}_t$  must take very similar values in those periods where the same pattern emerges:

$$\begin{aligned} \mathcal{W}_d + \mathcal{Q}_t > 0 & \quad \text{if } s_{d,t} = 1 \\ \mathcal{W}_d + \mathcal{Q}_t \leq 0 & \quad \text{if } s_{d,t} = 0 \end{aligned} \tag{28}$$

By way of example, given the realized values of  $\mathcal{W}_d$  specified in table 13, the conditions that  $\mathcal{Q}_t$  needs to satisfy to be in the pattern  $\{1, 1, 1, 0\}$  are:

$$1.5 + \mathcal{Q}_t > 0, \quad 0.5 + \mathcal{Q}_t > 0, \quad -0.5 + \mathcal{Q}_t > 0, \quad -1.5 + \mathcal{Q}_t \leq 0 \tag{29}$$

Since the equations in (29) must be simultaneously satisfied, the range of values  $\mathcal{Q}_t$  can take is  $0.5 < \mathcal{Q}_t \leq 1.5$ . Similarly, we can derive the condition for being in the pattern of  $\{1, 1, 0, 0\}$ , which is  $-0.5 < \mathcal{Q}_t \leq 0.5$ .

Since conditioning on the realized trade pattern restricts the variability of the unobserved  $\mathcal{Q}_t$ , our approach in general reduces the selection bias relative to conventional fixed effect approaches. Admittedly, in a two dimensional panel, the fact that the comparison within the same trade pattern cannot pin down the exact values of  $\mathcal{Q}_t$  may still result in a non-negligible selection bias. This is especially true when both the number of destinations and the number of time periods are small. However, in our context, more panel dimensions are available. Namely, the panel includes many goods produced by many firms making similar choices. As discussed below, under mild conditions the selectivity bias is likely to approach zero as the number of goods and firms increases.

**General Setting:** We now discuss a general multi-dimensional setting specified in (18) and

(19).<sup>53</sup> With an additional dimension,<sup>54</sup> we can write the condition for identification as

$$E \left[ E(\varepsilon_{ifdDt} | \mathbf{s}_{ifdD}, \boldsymbol{\psi}_{ifdD}) \middle| dt \right] = E \left[ E(\varepsilon_{ifdD\tau} | \mathbf{s}_{ifdD}, \boldsymbol{\psi}_{ifdD}) \middle| dt \right] \quad \forall \tau \in T_{ifdD} \quad (30)$$

where  $\mathbf{s}_{ifdD} \equiv (\mathbf{w}'_{d1}\boldsymbol{\gamma} + \mathcal{W}_{ifd} + \mathcal{Q}_{if1} + u_{ifdD1} > 0, \dots, \mathbf{w}'_{dn_{ifdD}^T}\boldsymbol{\gamma} + \mathcal{W}_{ifd} + \mathcal{Q}_{ifn_{ifdD}^T} + u_{ifdDn_{ifdD}^T} > 0)$ ,  $\boldsymbol{\psi}_{ifdD} \equiv (\mathbf{x}_{dD1}, \dots, \mathbf{x}_{dDn_{ifdD}^T}, \mathbf{w}_{dD1}, \dots, \mathbf{w}_{dDn_{ifdD}^T}, \mathcal{W}_{ifd}, \mathcal{M}_{ifd})$  and  $E(\cdot | dt)$  means taking expectation over the firm ( $f$ ) and product ( $i$ ) panel dimensions while keeping destination and time panel dimensions fixed.

As can be seen from (30), we no longer need the error to be zero conditional on the observed pattern ( $E(\varepsilon_{ifdDt} - \varepsilon_{ifdD\tau} | \mathbf{s}_{ifdD}, \boldsymbol{\psi}_{ifdD}) = 0$ ) as in the two dimensional case. Instead, it is sufficient to have the expectation of  $E(\varepsilon_{ifdDt} - \varepsilon_{ifdD\tau} | \mathbf{s}_{ifdD}, \boldsymbol{\psi}_{ifdD})$  to be zero, once it is aggregated at the firm and product dimension. For example, if  $E(\varepsilon_{ifdDt} - \varepsilon_{ifdD\tau} | \mathbf{s}_{ifdD}, \boldsymbol{\psi}_{ifdD})$  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 and consistent estimates under condition (30). Let  $v_{ifdt} \equiv \mathcal{M}_{ifd} + \mathcal{C}_{ift} + \varepsilon_{ifdt}$ . The underlying independent variables and the error term under our estimation approach can be written as

$$\ddot{\mathbf{x}}_{ifdt} = \mathbf{x}_{dt} - \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} \mathbf{x}_{dt} - \frac{1}{n_{ifdD}^T} \sum_{t \in T_{ifdD}} \mathbf{x}_{dt} + \frac{1}{n_{ifdD}^T} \sum_{t \in T_{ifdD}} \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} \mathbf{x}_{dt} \quad (31)$$

$$\ddot{v}_{ifdt} = v_{ifdt} - \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} v_{ifdt} - \frac{1}{n_{ifdD}^T} \sum_{t \in T_{ifdD}} v_{ifdt} + \frac{1}{n_{ifdD}^T} \sum_{t \in T_{ifdD}} \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} v_{ifdt} \quad (32)$$

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.,  $\mathbf{x}_{dt}$  or  $e_{dt}$ .

First, it is straightforward to verify that our estimator controls for firm-product-destination

<sup>53</sup>Note that table 13 represents the observed trade pattern of a particular firm selling a particular product. In the customs data, we observe realized trade patterns of many firm-product pairs.

<sup>54</sup>In the following discussions, we consider firm and product as one combined panel dimension  $if$ .



and firm-product-time fixed effects in the main estimation equation.

$$\begin{aligned}
\ddot{v}_{ifdt} &= \mathcal{M}_{ifd} + \mathcal{C}_{ift} + \varepsilon_{ifdt} - \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} (\mathcal{M}_{ifd} + \mathcal{C}_{ift} + \varepsilon_{ifdt}) \\
&\quad - \frac{1}{n_{ifdD}^T} \sum_{t \in T_{ifdD}} (\mathcal{M}_{ifd} + \mathcal{C}_{ift} + \varepsilon_{ifdt}) + \frac{1}{n_{ifdD}^T} \sum_{t \in T_{ifdD}} \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} (\mathcal{M}_{ifd} + \mathcal{C}_{ift} + \varepsilon_{ifdt}) \\
&= \varepsilon_{ifdt} - \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} (\mathcal{M}_{ifd} + \varepsilon_{ifdt}) - \frac{1}{n_{ifdD}^T} \sum_{t \in T_{ifdD}} (\mathcal{C}_{ift} + \varepsilon_{ifdt}) \\
&\quad + \frac{1}{n_{ifdD}^T} \sum_{t \in T_{ifdD}} \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} (\mathcal{M}_{ifd} + \mathcal{C}_{ift} + \varepsilon_{ifdt}) \\
&= \varepsilon_{ifdt} - \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} \varepsilon_{ifdt} - \frac{1}{n_{ifdD}^T} \sum_{t \in T_{ifdD}} \varepsilon_{ifdt} + \frac{1}{n_{ifdD}^T} \sum_{t \in T_{ifdD}} \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} \varepsilon_{ifdt} \\
&= \ddot{\varepsilon}_{ifdt}
\end{aligned}$$

Second, 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 (31) and (32) in terms of their corresponding variability:

$$\begin{aligned}
\ddot{\mathbf{x}}_{ifdt} &= \mathbf{x}_{dt} - \mathbf{x}_{Dt} - \mathbf{x}_{dT} + \mathbf{x}_{DT} \\
\ddot{v}_{ifdt} &= v_{ifdt} - v_{ifDt} - v_{ifdT} + v_{ifDT} \\
&= \varepsilon_{ifdt} - \varepsilon_{ifDt} - \varepsilon_{ifdT} + \varepsilon_{ifDT} \\
&= \ddot{\varepsilon}_{ifdt}
\end{aligned}$$

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

$$\frac{1}{n^{IFDT}} \sum_{ifdt} \ddot{\varepsilon}_{ifdt} \ddot{\mathbf{x}}_{ifdt} = \frac{1}{n^{IFDT}} \sum_{ifdt} (\varepsilon_{ifdt} - \varepsilon_{ifDt} - \varepsilon_{ifdT} + \varepsilon_{ifDT}) \mathbf{x}_{dt} \quad (33)$$

$$= \frac{1}{n^{IFDT}} \sum_{ifdt} (\varepsilon_{ifdt} - \varepsilon_{ifdT}) \mathbf{x}_{dt} \quad (34)$$

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

$$\begin{aligned}
& E(\ddot{\varepsilon}_{ifdt}\ddot{\mathbf{x}}_{ifdt}s_{ifdt}) \\
&= E[(\varepsilon_{ifdt} - \varepsilon_{ifdT})\mathbf{x}_{dt}s_{ifdt}] \\
&= E\left\{\mathbf{x}_{dt}E\left[E(\varepsilon_{ifdt} - \varepsilon_{ifdT}|\mathbf{s}_{ifdD}, \boldsymbol{\psi}_{ifdD}) \middle| dt\right]\right\} \\
&= E\left\{\mathbf{x}_{dt}E\left[E\left(\varepsilon_{ifdDt} - \frac{1}{n_{ifdD}^T} \sum_{\tau \in T_{ifdD}} \varepsilon_{ifdD\tau} \middle| \mathbf{s}_{ifdD}, \boldsymbol{\psi}_{ifdD}\right) \middle| dt\right]\right\} \\
&= 0
\end{aligned} \tag{35}$$

where the first equality is obtained by using (34) under our proposed “within transformation”; the second equality is obtained by applying the law of iterated expectations; and the last equality is obtained by using condition (30).

Two remarks are useful to understand the implications of our identification condition and place our approach in the literature. First, note that the condition (30) is trivially satisfied if  $\varepsilon$  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  $\mathcal{C}_{ift}$ , 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, Goldberg, Khandelwal and Pavcnik (2016).<sup>55</sup>

Second, an important instance in which condition (30) is satisfied is when the distribution of the

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<sup>55</sup>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, Goldberg, Khandelwal and Pavcnik (2016) estimate the average marginal cost over destinations at the firm-product level. As an exercise, in appendix A.4, we explore an extension of De Loecker, Goldberg, Khandelwal and Pavcnik (2016) in which we add a destination dimension to production costs. We discuss the assumptions that would be required in a structural framework for (30) to be satisfied. Specifically, we allow the functional form of the production function to be firm-product specific with a log-additive productivity term that is firm-product-destination specific. Note that De Loecker, Goldberg, Khandelwal and Pavcnik (2016) would not be identifiable under these assumptions as their identification strategy requires some degree of separability in the functional form in which they have assumed the production function to be product-specific and the Hicks-neutral productivity to be firm-specific. In this extended framework, we show that our identification strategy recovers an unbiased estimate of the markup elasticity even when the marginal cost at the firm-product level varies across destinations, but only if the production function is constant returns to scale. It is only when changes in relative demand across destinations lead to relative changes in quantities (which are associated with changes in destination-specific marginal cost) that condition (30) will be violated. This is only the case if the production function is destination-specific. Under the standard assumptions of De Loecker, Goldberg, Khandelwal and Pavcnik (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.

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  $\varepsilon$  does not automatically lead to a violation of identification.

In what follows, we discuss the identification conditions in estimating markup elasticities using a four dimensional (firm-product-destination-time) customs database. Subsection A.1 presents a general condition for identifying markup elasticity to exchange rates in balanced panels. Subsection A.2 discusses the bias that may arise from unbalanced panels. Subsection A.4 gives a structural interpretation of the required identification condition.

## A.1 Identifying the Markup Elasticity with respect to Exchange Rates in Balanced Panels

To set the stage of our analysis, it is useful to show upfront that the fixed effects imposed by Knetter (1989)—destination and time fixed effects  $(d, t)$ —actually lead to consistent estimates if the panel is balanced, i.e.,  $s_{ifdt} = 1$  for all  $i, f, d, t$ —so that the selection problem is immaterial. Since we have more than two panel dimensions, it is also useful to discuss how fixed effects can be performed using “within estimators”. We establish the following equivalence:

$$\text{A destination } (d) \text{ fixed effect is equivalent to } x_{ifdt} - \sum_i \sum_f \sum_t x_{ifdt} \quad (36)$$

$$\text{A time } (t) \text{ fixed effect is equivalent to } x_{ifdt} - \sum_i \sum_f \sum_d x_{ifdt} \quad (37)$$

These relationships should be distinguished from the following:

$$\text{A firm-product-destination } (ifd) \text{ fixed effect is equivalent to } x_{ifdt} - \sum_t x_{ifdt} \quad (38)$$

$$\text{A firm-product-time } (ift) \text{ fixed effect is equivalent to } x_{ifdt} - \sum_d x_{ifdt} \quad (39)$$

In a balanced panel with  $(d, t)$  fixed effects, we can write the identification condition as follows:

$$\frac{1}{n^I n^F n^D n^T} \sum_i \sum_f \sum_d \sum_t (\tilde{v}_{ifdt} - \frac{1}{n^I n^F n^T} \sum_i \sum_f \sum_t \tilde{v}_{ifdt}) (\tilde{e}_{dt} - \frac{1}{n^T} \sum_t \tilde{e}_{dt}) = 0 \quad (40)$$

where  $n^j$  denotes for the number of indices in dimension  $j \in \{i, f, d, t\}$ ;  $\bar{x}_j$  is defined as the mean of variable  $x$  taken over all dimensions other than  $j$ ; and

$$\begin{aligned} \tilde{v}_{ifdt} - \frac{1}{n^I n^F n^T} \sum_i \sum_f \sum_t \tilde{v}_{ifdt} &= v_{ifdt} - \frac{1}{n^D} \sum_d v_{ifdt} \\ &\quad - \frac{1}{n^I n^F n^T} \sum_i \sum_f \sum_t v_{ifdt} + \frac{1}{n^I n^F n^D n^T} \sum_i \sum_f \sum_d \sum_t v_{ifdt} \\ &\equiv v_{ifdt} - \bar{v}_{ift} - (\bar{v}_d - \bar{v}) \end{aligned}$$

$$\begin{aligned} \tilde{e}_{dt} - \frac{1}{n^T} \sum_t \tilde{e}_{dt} &= e_{dt} - \frac{1}{n^I n^F n^T} \sum_i \sum_f \sum_t e_{dt} \\ &\quad - \frac{1}{n^I n^F n^D} \sum_i \sum_f \sum_d e_{dt} + \frac{1}{n^I n^F n^D n^T} \sum_i \sum_f \sum_d \sum_t e_{dt} \\ &\equiv e_{dt} - \bar{e}_t - (\bar{e}_d - \bar{e}) \end{aligned}$$

Rearranging (40) we get

$$\frac{1}{n^D n^T} \sum_d \sum_t \left[ \frac{1}{n^I n^F} \sum_i \sum_f (v_{ifdt} - \bar{v}_d - \bar{v}_{ift} + \bar{v}) \right] (e_{dt} - \bar{e}_t - \bar{e}_d + \bar{e}) = 0 \quad (41)$$

or equivalently

$$\frac{1}{n^D n^T} \sum_d \sum_t (\bar{v}_{dt} - \bar{v}_d) e_{dt} = 0 \quad (42)$$

An astounding feature of condition (42) is that the firm and product dimensions do not matter. Controlling for aggregate indicators is sufficient to obtain consistent estimates of the markup elasticity to exchange rates. As a corollary, under a balanced panel, all estimators discussed in table 9 would give exactly the same estimates.

The above result, on the irrelevance of the firm and product dimensions, does not necessarily hold when in a unbalanced panel, however, and will generally fail if the market selection is endogenous. As shown below, this means that we need to take into account the patterns of firm and product selection into different destinations over a certain time period.

## A.2 Identifying the Markup Elasticity to Exchange Rates in Unbalanced Panels: Monte Carlo Evidence

In this subsection, we compare our TPSFE estimator to four alternative and closely-related estimation specifications using Monte Carlo simulations. We begin by documenting which specifications return the same estimate as our TPSFE estimator when participation in export markets is random. We then proceed to the case of endogenous selection of markets. We show that, when selection of markets is endogenous, these alternative specifications can produce biased estimates even in the case where the marginal cost component is not destination-specific.

To simplify notation, we suppress the product dimension. We write the optimal price of firm  $f$  in destination  $d$  denominated in the exporter's currency,  $p_{f dt}$ , as a function of the bilateral exchange rate,  $e_{dt}$ , and a collection of unobserved confounding variables captured by  $v_{f dt}$ . We define data generating processes for each of the terms in the price equation,  $e_{dt}$  and  $v_{f dt}$ , as well as the unobserved marginal cost,  $mc_{ft}$ :

$$\begin{aligned}
 p_{f dt} &= \beta e_{dt} + v_{f dt} \\
 e_{dt} &= \mathcal{M}_d + \mathcal{M}_t + \mathcal{M}_d * \mathcal{M}_t \\
 v_{f dt} &= mc_{ft} + \mathcal{I}_1 \mathcal{M}_d + \mathcal{I}_2 \mathcal{M}_d * \mathcal{C}_f + \mathcal{I}_3 \mathcal{M}_{dD} + \epsilon_{f dt} \\
 mc_{ft} &= \mathcal{C}_f + \mathcal{C}_t + \mathcal{C}_f * \mathcal{C}_t \\
 \mathcal{M}_d &\sim N(0, 1) \quad \mathcal{C}_f \sim N(0, 1) \quad \mathcal{M}_t = \mathcal{C}_t \sim N(0, 1) \quad \epsilon_{f dt} \sim N(0, 1)
 \end{aligned} \tag{43}$$

where each of the factors in the data generating processes for  $e_{dt}$ ,  $mc_{ft}$  and  $v_{f dt}$  are drawn from  $N(0, 1)$  distributions. The  $\mathcal{I}$ 's in (43) are indicator variables that take on values of 0 or 1. A specification in which  $\mathcal{I}_1 = 1$  allows for destination-specific demand or cost factors;<sup>56</sup> A specification in which  $\mathcal{I}_2 = 1$  allows firm-destination specific unobserved factors, such as brand name, taste, and distribution cost; a specification in which  $\mathcal{I}_3 = 1$  allows the optimal price to be trade pattern specific.

In this example, the bilateral exchange rate,  $e_{dt}$ , co-moves with firm specific marginal costs,  $mc_{ft}$ , because of the assumption of perfect co-movement between the time-varying factors  $\mathcal{M}_t$  and  $\mathcal{C}_t$ . We simulate panels of price data under three different sets of assumptions about the selection process.

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<sup>56</sup>To capture possible practical difficulties of the estimation problem, we further allow for other unobserved confounding factors that are correlated with the bilateral exchange rate or the marginal cost to affect the optimal price. In our example, we allow difference in prices (denominated in the exporter's currency) across destinations to vary with bilateral exchange rates. In practice, however, nominal series (not only bilateral exchange rates, but also CPI) cannot be directly compared across destinations. Adding the shifter,  $\mathcal{I}_1 = 1$ , mitigates this problem. To see this, note the nominal exchange rate can be treated as the sum of the compatible bilateral exchange rate and an unobserved destination-specific shift, i.e.,  $e_{dt}^{nominal} = e_{dt}^{compatible} + \mu_d$ .

**Case A: Balanced Panel:** For every simulation, we draw a balanced panel with 5000 firms, 10 destinations and 10 time periods, i.e.,  $n^F = 5000, n^D = 10, n^T = 10$ .

**Case B: Randomly Unbalanced Panel:** For the simulated balanced panel of price data, we randomly drop 30% observations.

**Case C: Endogenously Unbalanced Panel:** For the simulated balanced panel of price data, we generate a corresponding unbalanced panel in which the pattern of missing observations is systematically related to the size of the exchange rate and marginal cost shocks. We selectively drop observations from the simulated balanced panel according to the realised values of the exchange rate and marginal cost shocks as follows:

$$p_{fdt} = \begin{cases} \text{missing} & \text{if } \begin{array}{l} \text{the exchange rate shock } (e_{dt} - e_{dt-1}) \text{ is in the bottom 40\% at } t \\ \& \text{the marginal cost shock } (mc_{ft} - mc_{ft-1}) \text{ is in the top 40\% at } t \end{array} \\ \text{observed} & \text{otherwise} \end{cases}$$

This selection rule filters out trade flows from exporters that face a large depreciation of the importer’s currency (a negative shock) and a high positive marginal cost shock at time  $t$ . A depreciation in the destination currency reduces a firm’s profitability as it lowers the price received in the exporter’s currency. A higher marginal cost induces a higher price and thus lowers the demand for the firm’s product. Therefore, both shocks put a negative pressure on a firm’s profitability. As a result, those exporters most exposed to these two shocks may no longer find it optimal to trade. With this selection rule, we drop approximately 16% observations in each period.

In all cases, we set the markup elasticity to exchange rate,  $\beta$ , to 1. This means that the exporter maintains a stable price in the destination currency when there is no change in its marginal cost.

Table 14 presents our results from running six different estimators on the simulated datasets. The first estimator,  $\text{TPSFE}(fdD)$ , is the TPSFE estimator we develop in this paper. The second estimator,  $\text{TPSFE}(dD)$ , is a variant on our estimator in which the fixed effects applied in the second step are destination-trade pattern specific but are not specific to the firm. The next column is the S-difference estimator with firm-time fixed effects, previously discussed in section 4.3. Finally, the last three estimators  $\text{HDFE}(ft, fd)$ ,  $\text{HDFE}(ft, d)$ , and  $\text{HDFE}(fd, t)$  are firm-time + firm-destination, firm-time + destination, and firm-destination + time fixed effects implemented using Correia (2017)’s high dimensional fixed effects program (reghdfe). The first three columns in table 14 ( $\mathcal{I}_1, \mathcal{I}_2, \mathcal{I}_3$ ) indicate the sources of variation that are active in the data generating process of  $v_{fdt}$ . In the first row of each panel, we set all indicator variables to zero so that the price is a function of the exchange rate and marginal cost processes only. In the following rows, we gradually

Table 14: Performance of Estimators

$\mathcal{I}_1$	$\mathcal{I}_2$	$\mathcal{I}_3$	(1) TPSFE ( <i>fdD</i> )	(2) TPSFE ( <i>dD</i> )	(3) S-period Diff + <i>ft</i>	(4) HDFE ( <i>fd, t</i> )	(5) HDFE ( <i>ft, d</i> )	(6) HDFE ( <i>ft, fd</i> )
<b>Balanced Panel</b>								
0	0	0	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)
1	0	0	1.00*** (0.01)	1.00*** (0.01)	1.00*** (0.01)	1.00*** (0.01)	1.00*** (0.01)	1.00*** (0.01)
0	1	0	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)
0	0	1	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)
1	1	1	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)
<b>Random Drops</b>								
0	0	0	1.00*** (0.01)	1.00*** (0.00)	1.18*** (0.00)	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)
1	0	0	1.00*** (0.02)	1.00*** (0.00)	1.24*** (0.00)	1.00*** (0.01)	1.00*** (0.00)	1.00*** (0.00)
0	1	0	0.99*** (0.02)	1.00*** (0.01)	1.14*** (0.00)	1.00*** (0.00)	1.00*** (0.01)	1.00*** (0.00)
0	0	1	1.00*** (0.01)	1.00*** (0.00)	1.13*** (0.00)	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)
1	1	1	0.99*** (0.01)	1.00*** (0.00)	1.17*** (0.00)	1.00*** (0.00)	1.00*** (0.00)	1.00*** (0.00)
<b>Endogenous Selection</b>								
0	0	0	1.00*** (0.00)	1.00*** (0.00)	<b>1.13***</b> (0.00)	<b>1.34***</b> (0.00)	1.00*** (0.00)	1.00*** (0.00)
1	0	0	1.00*** (0.00)	1.00*** (0.00)	<b>1.25***</b> (0.00)	<b>1.30***</b> (0.00)	1.00*** (0.00)	1.00*** (0.00)
0	1	0	1.00*** (0.00)	<b>0.44***</b> (0.00)	<b>1.20***</b> (0.00)	<b>1.32***</b> (0.00)	<b>0.55***</b> (0.00)	1.00*** (0.00)
0	0	1	1.00*** (0.00)	1.00*** (0.00)	<b>1.22***</b> (0.00)	<b>1.35***</b> (0.00)	<b>1.04***</b> (0.00)	<b>1.06***</b> (0.00)
1	1	1	1.00*** (0.00)	<b>0.71***</b> (0.00)	<b>1.24***</b> (0.00)	<b>1.34***</b> (0.00)	<b>0.79***</b> (0.00)	<b>1.04***</b> (0.00)

Note: Estimation results based on a randomly generated sample of 5000 firms, 10 destinations and 10 time periods. Data generating process is specified in the paper.



allow for more complex data generating processes for the residual, allowing the unobserved factors,  $\mathcal{M}_d, \mathcal{M}_d * \mathcal{C}_f, \mathcal{M}_{dD}$ , to shift the optimal price  $p_{fdt}$  as well.

The top panel of table 14 shows that, as long as the panel is balanced, all the estimators return the correct estimate of the true parameter under the data generating processes represented in all five rows.

The second panel in table 14 documents that, if the dataset is randomly unbalanced, all estimators except the S-period time difference estimator, generate the same estimate. We provide a simple decomposition to show why the time differencing approach drives biases even in randomly formulated unbalanced panels. After taking the S-period time difference within a firm and destination (denoted  $\Delta_{s|fd}$ ), we obtain:

$$\Delta_{s|fd}p_{fdt} = \beta\Delta_{s|fd}e_{dt} + \Delta_{s|fd}v_{fdt} \quad (44)$$

where

$$\Delta_{s|fd}e_{dt} = \mathcal{M}_t - \mathcal{M}_{t-s|fd} + \mathcal{M}_d(\mathcal{M}_t - \mathcal{M}_{t-s|fd}) = \mathcal{C}_t - \mathcal{C}_{t-s|fd} + \mathcal{M}_d(\mathcal{C}_t - \mathcal{C}_{t-s|fd}) \quad (45)$$

$$\Delta_{s|fd}v_{fdt} \propto \Delta_{s|fd}mc_{ft} = \mathcal{C}_t - \mathcal{C}_{t-s|fd} + \mathcal{C}_f(\mathcal{C}_t - \mathcal{C}_{t-s|fd}) \quad (46)$$

From the expression for  $\Delta_{s|fd}mc_{ft}$  (46), it can be seen that after S-differencing, the marginal cost term still varies at three dimensions,  $f, d$ , and  $t$ . This variation over three dimensions makes the unobserved marginal cost term uncontrollable. Even the addition of multi-dimensional fixed effects will not be able to control for the unobserved marginal cost after S-differencing. In other words, taking time differences impacts the dimensions along which unobserved variables vary—thus making it impossible to control for them in later stages.

Notably, the bottom panel at table 14 reveals that, if the panel is endogenously unbalanced, only the TPSFE( $fdD$ ) procedure is capable of producing the correct estimate in all specifications. To understand the possible biases that arise due to different combinations of endogenous selection and unobserved confounding factors, we compare the estimates of the various estimators under five different cases.

In the first row of the bottom panel ( $\mathcal{I}_1 = \mathcal{I}_2 = \mathcal{I}_3 = 0$ ), we can see that the HDFE( $fd, t$ ) specification produces biased estimates even without destination-specific unobserved confounding factors, e.g., even if the marginal cost is not destination specific. This is because the endogenous selection changes the data structure and alters the underlying panel dimensions of observed variables (e.g.,  $e_{dt}$ ) and unobserved variables (e.g.,  $mc_{ft}$ ) in a way that is similar to (45) and (46). Since the selection is endogenous to unobserved firm-time specific marginal costs, fixed effect combinations including only time rather than firm-time fixed effects are no longer sufficient to obtain an unbiased estimator. Moving to the second row ( $\mathcal{I}_1 = 1$ ), the existence of destination-specific unobserved

variables tends to offset the bias presented in the estimate obtained from  $\text{HDFE}(ft, fd)$  but exacerbate the bias presented in the estimate obtained from  $\text{S-Diff} + ft$  compared to the estimates in the first row.

In the presence of both firm and destination specific unobserved factors, as shown in row 3 ( $\mathcal{I}_2 = 1$ ), the  $\text{HDFE}(ft, d)$  and  $\text{TPSFE}(dD)$  estimators no longer produce unbiased estimates. This means that the unobserved variables varying along the firm-destination and firm-time panel dimensions (as opposed to the unobserved variables varying along the destination and time panel dimensions) are relevant for identification only in the presence of endogenous selection. Comparing these estimates to the balanced panel and randomly unbalanced panel estimates, we can see that the existence of firm-destination specific factors does not generate biases unless market selection is endogenous.

Finally, in row 4 ( $\mathcal{I}_3 = 1$ ), we can see the  $\text{HDFE}(ft, fd)$  specification gives incorrect estimates if optimal prices depend on the trade pattern of firms. As it should be clear by now, this is the case only if the selection is endogenous. The last row ( $\mathcal{I}_1 = \mathcal{I}_2 = \mathcal{I}_3 = 1$ ) shows that our  $\text{TPSFE}(fdD)$  can recover the correct estimate of the true parameter in a complex environment where multiple types of unobserved confounding variables co-exist with endogenous market participation.

### A.3 Markup Estimation and Pricing-to-Market: A Review of Methods

In constructing consistent estimators of markup elasticities to the exchange rate, there are two major difficulties: (a) the marginal cost is unobserved and is highly likely to be correlated with  $e_{dt}$  directly through imported inputs (see e.g., [Amiti, Itskhoki and Konings \(2014\)](#)) or indirectly, through general equilibrium effects of the prices of factors of production,<sup>57</sup> and (b) the selection of export markets is endogenous, depending on the unobserved marginal costs, but also on the bilateral exchange rates.

One way to address these difficulties is to derive an estimate of marginal costs, and use this to infer (the level of the) markup. This approach requires detailed firm-level information (in addition to the customs dataset). Using balance sheet data, leading contributions have indeed estimated productivity and marginal cost at the firm level [e.g., [Berman, Martin and Mayer \(2012\)](#) and [Amiti, Itskhoki and Konings \(2014\)](#)]. While this development has clearly broken new important ground in firm-level studies, applying this method to our question of interest gives rise to a key issue. Even if we 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

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<sup>57</sup>For example, a positive home productivity shock that lowers the marginal cost of home producers may also cause the home currency to appreciate against its trade partners. See [Corsetti, Dedola and Leduc \(2008\)](#) for a discussion.

level.<sup>58</sup> Without some assumptions on how inputs are allocated across products and destinations, it would be impossible to estimate marginal cost at the firm-product-destination level. For example, the seminal contribution by De Loecker, Goldberg, Khandelwal and Pavcnik (2016) estimates firm-product level marginal costs and markups under the assumption that the production functions of single-product firms are representative of those of multi-product firms.

The approach we follow in this paper has a much lower data requirement, i.e., it relies exclusively on customs data by exploiting variation across destination markets, in the spirit of Knetter (1989). The idea is to impose some restrictions on the variability of unobserved marginal cost. For example, provided that marginal costs are not destination-specific, one can obtain an estimator that controls for changes in the unobservable marginal costs by taking differences of prices across destination markets.

The idea of differencing out marginal costs has been originally pursued by Knetter (1989). But our paper differs from Knetter (1989) in many key respects. An important one is the level of disaggregation. We use micro firm-product-destination level rather than aggregate product-destination level data. One immediate benefit of using disaggregated data is that we obtain a better control for marginal costs—the varieties sold to different destinations are more homogeneous conditional on the same firm selling a product.<sup>59</sup> However, with highly disaggregated data, the extensive margin is much more volatile, raising potential issues in selection bias. Working with highly disaggregated micro data is an advantage, as long as we can properly address the selection problem.

## A.4 Relation to De Loecker, Goldberg, Khandelwal and Pavcnik (2016)

In this subsection, we extend the framework of De Loecker, Goldberg, Khandelwal and Pavcnik (2016) to add a destination dimension, and discuss the structural assumptions that would be required for our main identification condition (30) to be satisfied in this framework.

### A.4.1 Structural Interpretation of Assumptions Required by Our Estimator

We start writing the production function as follows.

$$Q_{fidt} = F_{fi}(\mathbf{V}_{fidt}, \mathbf{K}_{fidt})\Omega_{fit}\Psi_{fid} \quad (47)$$

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<sup>58</sup>We should stress that, in most countries, the mapping between customs databases and industrial-survey data is often incomplete, raising issues of sample selection. In addition, balance sheet data means information is only available at annual frequencies, making it impossible to carry out the analysis at a higher frequency (monthly or quarterly).

<sup>59</sup>To make sure the product-varieties sold to different destinations by the same firm are as comparable as possible, we construct a refined product measure, i.e., a product is defined as a 8-digit HS code + a form of commerce dummy + a CCHS classification dummy. The construction of this measure is further discussed in section 3.

where  $Q_{fidt}$  represents the quantity of exports for product  $i$  from firm  $f$  to destinations  $d$  at time  $t$ ;  $\mathbf{V}_{fidt}$  denotes a vector of variable inputs,  $\{V_{fidt}^1, V_{fidt}^2, \dots, V_{fidt}^v\}$ ;  $\mathbf{K}_{fidt}$  denotes a vector of dynamic inputs; a firm-product pair make decisions on allocating its dynamic inputs across destinations  $D_{fit}$  in each time period,  $\{K_{fidt}^1, K_{fidt}^2, \dots, K_{fidt}^k\}$ . We stress that the above function allows for destination-specific inputs  $\{\mathbf{V}_{fidt}, \mathbf{K}_{fidt}\}$  as well as destination-specific productivity differences,  $\Psi_{fid}$ , 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.  $F_{fi}(\cdot)$  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.  $F_{fi}(\cdot)$  is constant return to scale.
4. Hicks-neutral productivity  $\Omega_{fit}$  is log-additive.
5. The destination specific technology advantage  $\Psi_{fid}$  takes a log-additive form and is not time varying.
6. Input prices  $\mathbf{W}_{fit}$  are firm-product-time specific.
7. The state variables of the firm are

$$\mathbf{s}_{fit} = \{D_{fit}, \mathbf{K}_{fit}, \Omega_{fit}, \Psi_{fid}, \mathbf{G}_{fi}, \mathbf{r}_{fidt}\} \quad (48)$$

where  $\mathbf{G}_{fi}$  includes variables indicating firm and product properties, e.g., firm registration types, product differentiation indicators.  $\mathbf{r}_{fidt}$  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,  $\mathbf{W}_{fit}$ , at time  $t$  as given.

The assumptions 1, 2, 4, 8 are standard in the literature. They are posited by [De Loecker, Goldberg, Khandelwal and Pavcnik \(2016\)](#) but in our version we allow the production function to be firm specific and the Hicks-neutral productivity to be product-specific. Compare 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 (30) 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.

#### A.4.2 The cost minimization problem by firm-product pair

Write the cost function

$$\begin{aligned} \mathcal{L}(\mathbf{V}_{fidt}, \mathbf{K}_{fidt}, \lambda_{fidt}) &= \sum_{v=1}^V W_{fivt}^v \sum_{d \in D_{fivt}} V_{fidt}^v + \sum_{k=1}^K R_{fikt}^k \left( \sum_{d \in D_{fikt}} K_{fidt}^k - K_{fikt}^k \right) \\ &+ \sum_{d \in D_{fidt}} \lambda_{fidt} [Q_{fidt} - F_{fi}(\mathbf{V}_{fidt}, \mathbf{K}_{fidt}) \Omega_{fivit} \Psi_{fid}] \end{aligned}$$

where  $K_{fikt}^k$  is the accumulated capital input  $k$  in the previous period;  $K_{fikt}^k$  stands for the corresponding allocation for destination  $d$ ;  $R_{fikt}^k$  is the implied cost of capital.<sup>60</sup>

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

$$\frac{\partial \mathcal{L}_{fivit}}{\partial V_{fivt}^v} = W_{fivt}^v - \lambda_{fivit} \Omega_{fivit} \Psi_{fid} \frac{\partial F_{fi}(\cdot)}{\partial V_{fivt}^v} = 0 \quad (49)$$

$$\frac{\partial \mathcal{L}_{fivit}}{\partial K_{fikt}^k} = R_{fikt}^k - \lambda_{fivit} \Omega_{fivit} \Psi_{fid} \frac{\partial F_{fi}(\cdot)}{\partial K_{fikt}^k} = 0 \quad (50)$$

Conditions (49) and (50) need to hold across inputs and across destinations, which implies the following:

$$\frac{W_{fivt}^1}{W_{fivt}^v} = \frac{\frac{\partial F_{fi}(\cdot)}{\partial V_{fivt}^1}}{\frac{\partial F_{fi}(\cdot)}{\partial V_{fivt}^v}} = \frac{\frac{\partial F_{fi}(\cdot)}{\partial V_{fivt}^1}}{\frac{\partial F_{fi}(\cdot)}{\partial V_{fivt}^2}} = \dots = \frac{\frac{\partial F_{fi}(\cdot)}{\partial V_{fivt}^1}}{\frac{\partial F_{fi}(\cdot)}{\partial V_{fivt}^v}} \quad \forall v = 1, \dots, V; \quad d \in D_{fivit} \quad (51)$$

<sup>60</sup>The assumption that the production function  $F_{fi}(\cdot)$  is firm-product-specific ensures the implied cost of capital  $R_{fikt}^k$  being not destination-specific.

$$\frac{W_{fit}^v}{R_{fit}^k} = \frac{\frac{\partial F_{fi}(\cdot)}{\partial V_{fi,1,t}^v}}{\frac{\partial F_{fi}(\cdot)}{\partial K_{fi1t}^k}} = \frac{\frac{\partial F_{fi}(\cdot)}{\partial V_{fi2t}^v}}{\frac{\partial F_{fi}(\cdot)}{\partial K_{fi2t}^k}} = \dots = \frac{\frac{\partial F_{fi}(\cdot)}{\partial V_{fidt}^v}}{\frac{\partial F_{fi}(\cdot)}{\partial K_{fidt}^k}} \quad \forall v, k; \quad d \in D_{fit} \quad (52)$$

Note that the production function is assumed to be firm-product specific and constant return to scale. Together with equations (51) and (52), these assumptions imply that the allocation of variable inputs is inversely proportional to the ratio of the productivity deflated outputs across destinations, i.e.,

$$\frac{Q_{fidt}}{\Omega_{fit}\Psi_{fid}} = c \cdot \frac{Q_{fid't}}{\Omega_{fit}\Psi_{fid'}} \quad \rightarrow \quad c\mathbf{V}_{fidt}^* = \mathbf{V}_{fid't}^* \quad \text{and} \quad c\mathbf{K}_{fidt}^* = \mathbf{K}_{fid't}^* \quad (53)$$

Utilizing the relationship of (53) and the assumption that  $F_{fi}(\cdot)$  is constant return to scale, it is straightforward to see

$$\frac{\partial F_{fi}(\mathbf{V}_{fidt}^*, \mathbf{K}_{fidt}^*)}{\partial V_{fidt}^v} = \frac{\partial F_{fi}(c\mathbf{V}_{fidt}^*, c\mathbf{K}_{fidt}^*)}{\partial (cV_{fidt}^v)} = \frac{\partial F_{fi}(\mathbf{V}_{fid't}^*, \mathbf{K}_{fid't}^*)}{\partial V_{fid't}^v}. \quad (54)$$

Rearranging (49) and (54) yields:

$$\begin{aligned} \lambda_{fidt} &= \left( \frac{\Omega_{fit}\Psi_{fid}}{W_{fit}^v} \frac{\partial F_{fi}(\mathbf{V}_{fidt}^*, \mathbf{K}_{fidt}^*)}{\partial V_{fidt}^v} \right)^{-1} \\ &= \left( \frac{\Omega_{fit}\Psi_{fid}}{W_{fit}^v} \frac{\partial F_{fi}(\mathbf{V}_{fid't}^*, \mathbf{K}_{fid't}^*)}{\partial V_{fid't}^v} \right)^{-1} \end{aligned} \quad (55)$$

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

$$\frac{\lambda_{fidt}}{\lambda_{fid't}} = \frac{\Psi_{fid'}}{\Psi_{fid}} \quad (56)$$

Although the marginal cost is firm-product-destination specific and time varying, the relative marginal cost is not. Therefore, condition (30) is satisfied.

#### A.4.3 An alternative approach

An alternative approach to reconcile our work with De Loecker, Goldberg, Khandelwal and Pavcnik (2016) could consist 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, Goldberg, Khandelwal and Pavcnik (2016) define a product variety as a two-digit industry. The need to define a product at industry level is mainly due to data limitations. If one adopts a more refined product definition, for instance, the estimator by De Loecker, Goldberg, Khandelwal and Pavcnik (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, Goldberg, Khandelwal and Pavcnik (2016) relies 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.

## B General Model Free Relationships

### B.1 The separation of marginal cost and markup

We start 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:

$$\max_p q(p, \xi)p - c[q(p, \xi), \zeta] \tag{57}$$

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

The first order condition of the firm is given by

$$\frac{\partial q(p, \xi)}{\partial p} p + q(p, \xi) = \frac{\partial c[q(p, \xi), \zeta]}{\partial q(p, \xi)} \frac{\partial q(p, \xi)}{\partial p} \tag{58}$$

From this equation, we can derive the optimal price as

$$p^* = \frac{\varepsilon(p^*, \xi)}{\varepsilon(p^*, \xi) - 1} mc[q(p^*, \xi), \zeta] \tag{59}$$

where  $\varepsilon(p, \xi) \equiv -\frac{\partial q(p, \xi)}{\partial p} \frac{p}{q(p, \xi)}$ ,  $mc[q(p, \xi), \zeta] \equiv \frac{\partial c[q(p, \xi), \zeta]}{\partial q(p, \xi)}$ .

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

**Proposition 1.** *If changes in the equilibrium price and quantity are solely driven by shocks to the supply side, the following expression holds*

$$\frac{d \log(q^*)}{d \log(p^*)} = -\varepsilon(p^*, \xi) \quad (60)$$

*Proof.*

$$\begin{aligned} d \log(q(p^*(\xi, \zeta), \xi)) &= \frac{1}{q(p^*(\xi, \zeta), \xi)} dq(p^*(\xi, \zeta), \xi) \\ &= \frac{1}{q(p^*(\xi, \zeta), \xi)} \left( \frac{\partial q(p^*(\xi, \zeta), \xi)}{\partial p^*(\xi, \zeta)} dp^*(\xi, \zeta) + \frac{\partial q(p^*(\xi, \zeta), \xi)}{\partial \xi} d\xi \right) \end{aligned} \quad (61)$$

$$d \log(p^*(\xi, \zeta)) = \frac{1}{p^*(\xi, \zeta)} dp^*(\xi, \zeta) \quad (62)$$

Substituting equation (62) into (61) and applying the condition  $d\xi = 0$  completes the proof.  $\square$

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

$$\frac{d \log(q^*)}{d \log(p^*)} = \frac{\varphi_q(p^*, \xi)}{\varphi_p(\xi, \zeta)} - \varepsilon(p^*, \xi) \quad (63)$$

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

*Proof.*

$$\begin{aligned} d \log(q(p^*(\xi, \zeta), \xi)) &= \frac{1}{q(p^*(\xi, \zeta), \xi)} \left( \frac{\partial q(p^*(\xi, \zeta), \xi)}{\partial \xi} d\xi + \frac{\partial q(p^*(\xi, \zeta), \xi)}{\partial p^*(\xi, \zeta)} dp^*(\xi, \zeta) \right) \\ &= (\varphi_q(p^*, \xi) - \varepsilon(p^*, \xi) \varphi_p(\xi, \zeta)) \frac{d\xi}{\xi} \end{aligned} \quad (64)$$

$$\begin{aligned} d \log(p^*(\xi, \zeta)) &= \frac{1}{p^*(\xi, \zeta)} dp^*(\xi, \zeta) \\ &= \frac{1}{p^*(\xi, \zeta)} \left( \frac{\partial p^*(\xi, \zeta)}{\partial \xi} d\xi \right) \\ &= \varphi_p(\xi, \zeta) \frac{d\xi}{\xi} \end{aligned} \quad (65)$$

$\square$



## C Data

### C.1 Chinese Customs Data

China's export growth exploded over 2000-2014 (see table 15). 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 15: 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

### C.2 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.

As discussed previously, taking time differences in an endogenously unbalanced panel tends to make the unobserved marginal cost uncontrollable, potentially introducing bias into the estimates. 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.

### C.3 Additional Information on the CCHS Classification

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.”<sup>61</sup> Both of these objects, ballpoint pens and kitchen knives, are measured with count classifiers (zhī and bǎ, respectively) and are, in our classification, high differentiation goods. In contrast, products reported with mass 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.” While it is possible that our proposed system 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 two 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 undifferentiated masses. Second, the choice of the measure word is predetermined in the minds of Chinese speakers by grammatical rules that have existed for centuries. This choice is clearly exogenous to and predates modern statistical reporting systems.<sup>62</sup>

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 16 documents the intrinsic information content of the measurement units for HS04 product groups 8211 and 8212. The Chinese language descriptions of all of these HS08 products conveys the similarity

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<sup>61</sup>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.

<sup>62</sup>A subtle distinction arises between the statistical reporting of trade data in Japan and China. The Japanese language also requires the use of measure words, aka ‘counters,’ when counting. However, documentation for Japanese trade declarations instructs that the measurement unit “NO” (the English abbreviation for number) should be used for reporting quantity and explains that this Western measure word subsumes 11 Japanese language measure words (個、本、枚、頭、羽、匹、台、両、機、隻、着). These instructions on Japanese Customs declarations validate our approach for China because these 11 Japanese measure words are linguistically similar to Chinese count classifiers. However, because the reporting is based on a Western word, the choice of a measurement unit in Japanese data might not be exogenously driven by the structure of the Japanese language. Thus, there is a reason for basing the classification of goods using linguistic information on Chinese rather than Japanese customs data. We thank Taiji Furusawa, Keiko Ito, and Tomohiko Inui for answering our questions about the use of measure words in Japanese trade data.

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.

Table 16: 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  $\leq 30\text{cm}$ ” (HS60032000), square meters for “Carpets & floor coverings of man-made textile fibres” (HS57019010), and liters for “Beer made from malt” (HS22030000).

### C.3.1 Integrating the CCHS classification with UN Broad Economic Categories

In table 17, 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 17: 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)	
<b>BEC</b>			
Intermediate	29.8	2.7	32.5
Consumption	14.3	20.1	34.4
Other <sup>†</sup>	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)	
<b>BEC</b>			
Intermediate	26.0	3.9	29.9
Consumption	8.6	14.0	22.6
Other <sup>†</sup>	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. <sup>†</sup>: The “Other” category refers to capital goods and unclassified products by BEC classification, such as nuclear weapons.

### C.3.2 Variation in the CCHS classification across industrial sectors

For twenty industrial sectors, Table 18 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 are treated as low differentiation.<sup>63</sup> 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 ap-

<sup>63</sup>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.

Table 18: 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.

parel (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.

### C.3.3 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 19: 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

## C.4 In which currency do exporters from China invoice?

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

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

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.<sup>64</sup>

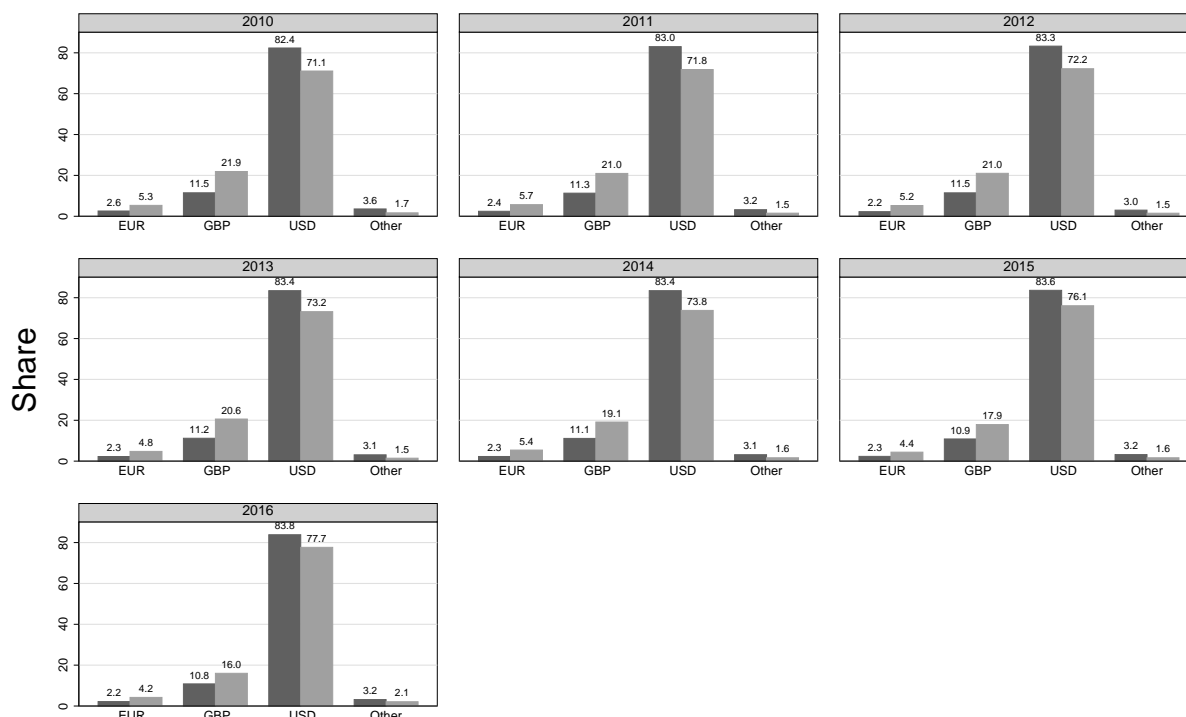
Figure 5 presents the shares of import transactions and import value into the UK from China by invoicing currency.<sup>65</sup> Results are reported for three currencies, the euro (EUR), pound sterling (GBP), and the US dollar (USD). All transactions that use other currencies of invoice, for example, the Swiss franc, Japanese yen or Chinese renminbi, are aggregated into the category “Other.”<sup>66</sup>

<sup>64</sup>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.”

<sup>65</sup> 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 5.

<sup>66</sup> We do not report the number of transactions for which the currency is not reported; the number of transactions

Figure 5: Invoicing currencies for UK imports from China



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

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.<sup>67</sup> 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.

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.

<sup>67</sup>See also Goldberg and Tille (2008) and Goldberg and Tille (2016) who document relatively large shares of exports invoiced in dollars for many countries.



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 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.

## C.5 Price Changes and Trade Pattern Dummies

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.

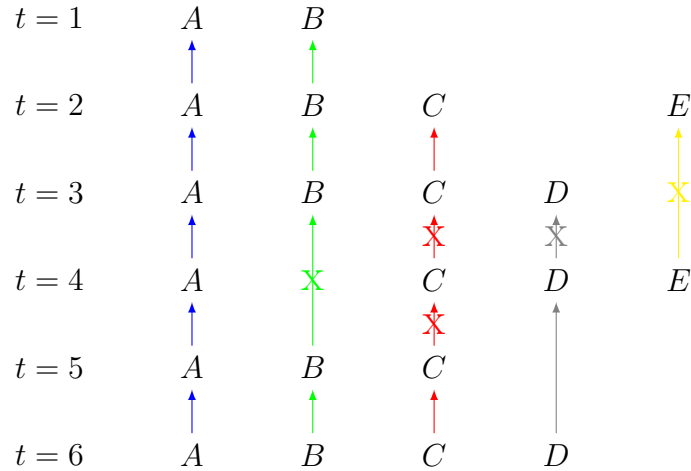
Consider a firm exporting a product to five countries, A through E, over 6 time periods. In the following matrix,  $t = 1, 2, 3, \dots$  indicates the time period and A, B, C, D, E indicates the country. Empty elements in the matrix indicate that there was no trade.

$t = 1$	<i>A</i>	<i>B</i>			
$t = 2$	<i>A</i>	<i>B</i>	<i>C</i>		<i>E</i>
$t = 3$	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	
$t = 4$	<i>A</i>		<i>C</i>	<i>D</i>	<i>E</i>
$t = 5$	<i>A</i>	<i>B</i>	<i>C</i>		
$t = 6$	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	

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

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

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  $|p_{C,5} - p_{C,4}| < 5\%$ .<sup>68</sup> Rather, we repeat the above step using the remaining observations as illustrated below.

<sup>68</sup>Variables are in logs.

$t = 1$	$A$	$B$			
$t = 2$	$\uparrow$ $A$	$\uparrow$ $B$	$\uparrow$ $C$		$E$
$t = 3$	$\uparrow$ $A$	$\uparrow$ $B$	$\uparrow$ $C$	$\uparrow$ $D$	
$t = 4$	$\uparrow$ $A$	$\uparrow$ $B$	$\uparrow$ $C$	$\uparrow$ $D$	
$t = 5$	$\uparrow$ $A$		$\uparrow$ $C$		
$t = 6$	$\uparrow$ $A$	$\uparrow$ $B$	$\uparrow$ $C$	$\uparrow$ $D$	

In this example, we indeed find  $|p_{C,5} - p_{C,3}| > 5\%$  and the remaining pattern is given as follows. As no prices are sticky, we can stop the iteration.<sup>69</sup> 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.

$t = 1$	$A$	$B$		
$t = 2$	$A$	$B$	$C$	
$t = 3$	$A$	$B$	$C$	$D$
$t = 4$	$A$			
$t = 5$	$A$		$C$	
$t = 6$	$A$	$B$	$C$	$D$

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,

<sup>69</sup>In the real dataset, the algorithm often needs to iterate several times before reaching this stage.

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.

## C.6 Data cleaning process and the number of observations

Table 20: Key Statistics for Our Data Cleaning Process

Stage	Observations	Value (Billions US\$)	<i>Number of Unique Values</i>				Firms
			Destinations	Products (HS06)	Products (HS08)	Products (Refined <sup>†</sup> )	
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

<sup>†</sup> 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 [C.5](#)

**Stage 6:** Drop single-destination firm-product-year triplets

**Stage 7:** Drop single-year firm-product-destination triplets

(Our method uses both destination and time variations to identify markup and quantity responses to exchange rate fluctuations. We drop single-year or single-destination observations.)