Markets and Markups:

A New Empirical Framework and Evidence on Exporters from China

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Abstract

We develop a new empirical framework to analyse destination-specific markup and quantity adjustments to bilateral exchange rates by exporters. The framework offers two methodological innovations. First, we develop an unbiased estimator of the markup elasticity that correctly isolates marginal costs in large unbalanced panels where the set of markets served by firms varies endogenously with currency movements. Second, we exploit Chinese linguistics to process characters recorded in Chinese custom forms to build a novel, general, product classification distinguishing high and low differentiation goods—which we can use to proxy for exporters' market power. Applying this framework to exporters from China over 2000-2014, we document substantial heterogeneity in destination-specific markup elasticities across product classes and firm types. Conditional on a price change, the average markup elasticity for highly differentiated consumption goods is 32%; markup adjustments explain three quarters of incomplete pass through into import prices for these goods. In contrast, the average for low-differentiation intermediates is only 5%, suggesting that pricing for these goods responds to global, rather than local, economic conditions. Markup elasticities are higher for both state-owned and foreign-invested enterprises than for private enterprises, which, on average, pursue aggressively competitive strategies throughout our sample.

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1 Introduction

A fundamental feature of international goods markets is that firms exporting to more than one destination account for the lion's share of cross-border trade. Serving multiple markets, these firms face demand conditions and market structures that differ across locations and are inherently time-varying. Indeed, global and local shocks to fundamentals, as well as country-specific economic policies, bear upon how much competition exporters endure from local and other international producers. Effectively, from the perspective of an exporter, a changing local economic environment systematically creates opportunities to raise profits, or raises the need to contain losses, through destination-specific adjustment of export prices, i.e. by engaging in pricing to market.

Among the many factors motivating pricing to market, currency swings are traditionally singled out as playing a distinctive role (Krugman (1986) and Dornbusch (1987)). Exporters are repeatedly exposed to asymmetric and, possibly, large changes in bilateral exchange rates that raise or lower their competitiveness on cost. While exchange rate movements naturally lead firms to reconsider their pricing strategy, their choice set is not unconstrained, but crucially reflects the extent to which firms have power in local markets and can keep the foreign markets for their products segmented to minimize arbitrage (Corsetti and Dedola (2005)). In this sense, the markup elasticity with respect to the exchange rate—a rigorous measure of exchange rate pass through (Marston (1990))—can provide key insights on the effective degree of competition across markets, especially if this information is articulated by product and firm characteristics.

Although trade globalization has heightened the importance of understanding the scope for and extent of price discrimination, empirical evidence is in short supply. This is an important gap in the literature. Pricing-to-market has become a standard feature in open macro models, increasingly featuring firm dynamics (Atkeson and Burstein (2008)), vertical interactions, and nominal rigidities in either local or a (third-country) vehicle currency (Gopinath (2015) and Casas et al. (2017)).[1] Reliable evidence on destination-specific markup adjustment is vital for analyses of the gains from trade because the level and distribution of these gains vary with the market power of exporters.[2]

In this paper, we build an empirical framework suitable for analyzing destination-specific markup and quantity adjustments to exchange rate movements in large firm-level datasets. On methodological grounds, our contribution is twofold. First, building on the seminal work by Knet-

[1]Leading questions to address 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)).

[2]Recent work by De Loecker et al. (2016), Feenstra and Weinstein (2017) and Feenstra (2018) on welfare gains from trade emphasizes the role of pro-competitive effects of market integration. Beyond comparative advantages, consumer gains potentially stem from (a) a richer set of product varieties, (b) exporters' efficiency, and (c) lower markups. So far, the available empirical evidence is mostly on the first two effects.

ter (1989), we construct an estimator that exploits multiple destination-specific prices of individual products in order to net out unobserved marginal costs. Unlike Knetter's original method, however, our estimator is free of bias even when firms endogenously discontinue or open destination markets in response to exchange rate fluctuations—implying that the panel of observations is endogenously unbalanced.[3] We implement our Trade Pattern Sequential Fixed Effects (henceforth TPSFE) estimator conditional on price changes; our results are therefore fully comparable with recent estimates of exchange rate pass through derived using the approaches of Gopinath, Itskhoki and Rigobon (2010) and Fitzgerald and Haller (2014). We also show how to estimate market-specific responsiveness of *quantities* to currency fluctuations, relying on projections of changes in markups on changes in bilateral exchange rates.

Second, we construct a novel product classification that allows us to proxy for market power using the degree of product differentiation. We do this by drawing on linguistics: specifically, we exploit the information content of "measure words," a specific category of Chinese character that is reported in the Chinese Customs Database. Our classification improves the popular classification by Rauch (1999) in two ways. First, and most importantly, we break down Rauch's large class of differentiated manufactured goods into two similarly-sized groups, distinguishing high- and low-differentiation products. Applying Rauch (1999)'s categories, we find about 80 percent of Chinese exports (observation weighted) are classified as differentiated. According to our Corsetti-Crowley-Han-Song (CCHS) linguistics-based classification, about half of these, amounting to 39 percent of all Chinese exports, are actually highly differentiated, while 41 percent exhibit low differentiation. Second, many products that are left unclassified by Rauch can be classified as high- or low-differentiation goods according to CCHS.

On empirical grounds, we apply our methodology to multi-destination exporters from China using annual data on firm-product-destination exports over 2000-2014.[4] 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). Because the US dollar is widely-held to have been the principal invoicing currency for Chinese exports throughout this period, we exclude exports to the US in order to obtain a comparable sample of countries across the two regimes.[5] After merging available macroeconomic data and eliminating single-destination and single-year exporters, the sample consists of over 200,000 multi-destination exporters, around 8,100 HS08 products, and 154

[3] The estimator is robust to compositional errors, e.g., measurement error due to changes in the mix of varieties within a product sold across destinations over time, under relatively weak assumptions. See appendix C.

[4] 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. In this process, we have treated eurozone countries as a single economic entity and aggregated the trade flows (quantities and prices) to eurozone destinations at the firm-product-year level.

[5] See section 4.2 for evidence on dollar invoicing. We also 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)).

foreign markets over 15 years.

Our main empirical findings are as follows. First, our estimates of the destination-specific markup elasticity for high-differentiation products confirm that, on average, firms engage in significant pricing-to-market. Over 2006-2014 (after China gave up the dollar peg), our average estimate for high differentiation goods is as high as 20%, and peaks at 32% for consumption goods characterized by high differentiation. On average, for high differentiation goods, around two-thirds of a firm's export price adjustment to the exchange rate is due to a markup adjustment. Conversely, our estimates of the markup elasticity are small and close to zero for products that we classify as low-differentiation goods—a result that validates our linguistics-based product classification. For low-differentiation goods, firms appear to charge a common reference price to customers in all destination markets.

Second, we document a small but significant increase in markup elasticities for high differentiation goods after China moved from a dollar-peg regime to a managed float. Interestingly, the average market power of Chinese exporters rose in the second part of our sample, in spite of the extraordinary rise in the number of highly competitive private enterprises directly active in international markets—which by the end of 2014 accounted for 40 percent of China's total exports.

Third, we document substantial heterogeneity in exchange rate pass through into import prices and markup elasticities across firms in China, depending on their ownership type. Notably, exchange rate pass through into import prices is lower for Chinese state-owned enterprises —about 70 percent —than for Chinese-owned private enterprises—about 90 percent. Correspondingly, markup adjustments contribute over 70% of the adjustment of export prices by state-owned enterprises, but only 40% of that by private enterprises.

Our evidence introduces a new angle into the debate on international pricing. Suppose that firms invoicing in a vehicle currency, say dollars, also price their goods in that vehicle currency. An important question is whether these firms would then set one single dollar price for their product—maximizing their profits relative to global demand taken as a whole. Indeed, one possible (extreme) implication of what Gopinath (2015) has dubbed the 'International Price System' is that pricing in dollars overcomes market segmentation and translates into a 'Reference Price System,' by which firms do not exploit market-specific demand elasticities, but price in relation to global demand.[6] If, similar to the case of commodities, there were a single price prevailing globally for a manufactured good sold by an individual firm, we should observe no destination-specific adjustments in markups.

[6] According to Gopinath (2015) the "International Price System" is characterized by two attributes. Firstly, a very large share of international shipments around the globe are invoiced in a few international reserve or vehicle currencies, with the dollar being the dominant currency. Secondly, international prices are stable in their currency of invoicing at a horizon of up to two years. For an analysis of the determinants of the choice of pricing currency, see Devereux, Engel and Storgaard (2004), Bacchetta and Van Wincoop (2005), Engel (2006) and Corsetti and Pesenti (2015).

Regardless of nominal rigidities, our TPSFE estimation would yield insignificant results for both high and low differentiation goods. Note that 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 did not adjust them in response to fluctuations in bilateral exchange rates. Our evidence is clearly at odds with both of these conjectures.

Our core contribution concerns a long-standing issue in the literature on pricing to market and exchange rate pass through, the problem of isolating markup adjustments from marginal cost changes, as the latter are unobservable.[7] In our work, we address this issue by following up on the idea by Knetter (1989) that one could exploit price differentials across destinations and time to control for firm-product marginal cost. We show that, if the trade pattern of firms is fixed (the panel of observations is balanced), the set of destination and time-specific fixed effects (d, t) proposed by Knetter (1989) controls for unobserved firm-product-time varying marginal costs. However, a firm's trade pattern is likely to be endogenous to exchange rate movements, implying that the panel of observations derived from a large firm-product-destination-level dataset is endogenously unbalanced. We show that, in this case, Knetter (1989)'s original identification strategy produces biased results, and the order in which firm, product, destination, and time partitions are applied matters. By virtue of the appropriate partitioning to control for unobserved marginal costs, our TPSFE estimator eliminates the bias. As already mentioned, our estimator can be applied, following Gopinath, Itskhoki and Rigobon (2010), with S-period differences, which enables us to estimate the markup elasticity conditional on price changes.

Following up on our methodology, we also investigate if destination-specific markup adjustments motivated by exchanges rate movements actually translate into differentiated quantity responses across markets. To do so, we propose 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 the firm and product-level trade patterns.[8] As our estimator differences out common supply factors, the second stage measures the degree to which the quantity supplied responds to shifts in relative demand across destinations due to changes in relative markups (which, in turn, arise

[7]See Goldberg and Knetter (1997), Corsetti and Dedola (2005) and Corsetti, Dedola and Leduc (2008) for a discussion. Analysis of exchange rate pass through and deviations from the Law of One Price has been the focus of an extensive literature including Engel and Rogers (1996), Crucini and Shintani (2008), and Cavallo, Neiman and Rigobon (2014).

[8]The conventional approach to investigate the quantity responses to exchange rates, as taken for example by Berman, Martin and Mayer (2012), directly regresses quantities on exchange rates. Apart from the difficulty in controlling the marginal cost, the conventional method would in general underestimate the heterogeneity in quantity responses across products and firms. This arises from the duality property of markup responses – a high markup elasticity often originates from a market structure with low substitutability that is associated with a low quantity response.

from differences in local factors). We refer to this measure as the within-firm cross market supply elasticity (CMSE).[9]

Applying our two stage procedure, the quantitative importance of the difference between the CMSEs of consumption goods (0.54) and intermediates (2.92) is substantial. When further disaggregated under the CCHS product classification, the gap between estimates opens to a chasm – the CMSE of high differentiation consumption goods, 0.23, suggests an extreme amount of market segmentation while that for low differentiation intermediates, 3.27, suggests something much closer to an integrated world market.

We conclude by stressing a qualifying feature of our methodological innovations—they have been 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. A low data requirement in comparison to alternative approaches—necessitating detailed information on production and costs, including prices and costs of domestic and imported inputs—is a key benefit that cannot be over-emphasized.

The rest of the paper is organized as follows. Section 2 presents our empirical identification strategy. Section 3 presents the CCHS product classification. Section 4 summarizes the database. Section 5 discusses our empirical results. In section 6, we describe changes in the landscape of corporate entities operating in China and analyze the markup responses by enterprise type. Section 7 concludes.

2 Empirical Framework

In what follows, we develop an estimator that yields an unbiased measure of the responsiveness of export price markups to bilateral exchange rate movements. Our point of departure is the seminal contribution by Knetter (1989) and Knetter (1993). The main idea is to consider firms selling their product to multiple destinations: by taking the difference of price and exchange rate changes across destination markets, one can obtain an estimator that nets out changes in the unobservable marginal cost.

The original methodology envisioned by Knetter works well in balanced panels in which the pattern of firm-product-destinations repeats identically every period. Indeed, Knetter's original application is to a *balanced* panel of *industry-level* price indices. However, a key problem emerges

[9]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. Our CMSE elasticity potentially provides an alternative measure of market power in a multi-country context that compliments empirical studies characterizing the relationship between market share and optimal exchange rate pass through, e.g., Feenstra, Gagnon and Knetter (1996) and Auer and Schoenle (2016).

when one tries to apply the same estimator to administrative customs datasets that include information on the universe of *firm and product-level export trade records*. A constant trade pattern of firm-product-destinations is highly unlikely to emerge. Bilateral exchange rate movements may well cause a firm to be "priced out" of (or "priced into") some destinations, implying that the panel of observations will be endogenously unbalanced.

In what follows, we first show that, with endogenous shifts in trade patterns, taking price differences across destinations no longer correctly nets out marginal costs that are comparable. Second, building on Han (2017), we introduce an estimator that overcomes this problem— we dub it the "Trade Pattern Sequential Fixed Effects" estimator. Lastly, we show how our empirical analysis of the cross-market *markup elasticity to the exchange rate* can be extended to gain insight into the cross-market *supply elasticity to the markup*.

2.1 A useful decomposition of a firm's export price

In order to place our contribution in the context of the empirical literature, we find it useful to introduce a factor-decomposition of export prices. This builds on the observation that a typical customs database records export flows varying along four dimensions: product, firm, foreign destination and time. Treating these dimensions as factors offers a parsimonious but efficient way to map existing estimators of exchange rate pass through and markup elasticities.

The (logarithm of) the price of firm f selling a good i in destination d in year t, p_{ifdt}, is customarily decomposed into a markup and a marginal cost component:

$$p_{ifdt} = \Gamma_{ifdt} + mc_{ift} \tag{1}$$

where Γ_{ifdt} denotes the firm, product, and destination-specific time-varying markup, and mc_{ift} denotes the marginal cost of product i sold by firm f at time t.[10] Our main idea consists of further decomposing the variation in the markup and marginal cost components into functions of factors that vary along the four key dimensions i, f, d, t. Omitting coefficients (i.e., β_i, etc.) in front of the factors for the sake of expositional clarity, and accounting for all possible combinations among

[10] In appendix D.1, we show 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.

factors, we can write:

$$
\begin{aligned}
\Gamma_{ifdt} \;\; = \;\; & \mathcal{F}_i + \mathcal{F}_f + \mathcal{F}_d + \mathcal{F}_t \\
& + \mathcal{F}_{if} + \mathcal{F}_{id} + \mathcal{F}_{it} + \mathcal{F}_{fd} + \mathcal{F}_{ft} + \mathcal{F}_{dt} \\
& + \mathcal{F}_{fdt} + \mathcal{F}_{idt} + \mathcal{F}_{ift} + \mathcal{F}_{ifd} \\
& + \mathcal{F}_{ifdt} \qquad\qquad (2) \\
mc_{ift} \;\; = \;\; & \mathcal{C}_i + \mathcal{C}_f + \mathcal{C}_t \\
& + \mathcal{C}_{if} + \mathcal{C}_{it} + \mathcal{C}_{ft} \\
& + \mathcal{C}_{ift}
\end{aligned}
$$

This decomposition accounts for both demand and supply-side factors. Demand factors include $\mathcal{F}_d$ and $\mathcal{F}_{id}$, which could be interpreted as destination-specific tastes for all goods and for good i, respectively. Firm-level supply factors include $\mathcal{C}_f$ and $\mathcal{C}_{ft}$. Time-varying factors common to all firms (in our application, GDP growth and CPI inflation in the exporting country, etc.) are captured by $\mathcal{F}_t$. The main object of interest, the bilateral nominal exchange rate between the origin and the destination country d, is accounted for by the factor $\mathcal{F}_{dt}$, which also includes macro variables such as CPI and GDP growth in the destination country d.

The term $\mathcal{C}_{ift}$ captures the time-varying marginal cost at the level of a product within a firm. As is well understood, the fact that this variable is unobservable creates a daunting empirical challenge in analyses of pricing to market.[11] In fact, in the case of multi-product firms, the marginal cost is observable neither to the econometrician, nor to the firm decision makers, because the allocation of some firm-level costs across products is not conceptually well-defined.

[11] The covariance between the unobservable marginal cost, mc_{ift}, and the bilateral exchange rate, $\mathcal{F}_{dt}$, is the key source of bias in ERPT estimates, see the discussion by Corsetti, Dedola and Leduc (2008). The existing literature has relied on various proxies to control for marginal cost—none of which can be considered satisfactory at the product level. To date, the best way of dealing with marginal costs in the exchange rate pass through literature consists of estimating firm-level productivity using balance sheet data [e.g., Berman, Martin and Mayer (2012) and Amiti, Itskhoki and Konings (2014)]. This estimated productivity is arguably a good measure of the average marginal cost for all products in a firm, but it obviously falls short of capturing marginal cost at the product-level. In principle, this method could yield reasonable marginal cost measures for single-product producers/exporters. But this group is not very representative: over 95% of export value is accounted for by multi-product exporters. As multi-product exporters are in general more productive and less likely to be financially constrained, dropping these multi-product exporters will introduce a substantial sample selection bias into the analysis. Morever, since the method relies on balance sheet data, marginal costs can only be estimated at an annual frequency, making it impossible to carry out the analysis at a higher frequency (monthly or quarterly).

2.2 Estimating the markup elasticity in balanced and exogenously unbalanced panels

As shown by Knetter (1989), the problem raised by the fact that marginal costs are unobservable can potentially be addressed by applying d and t fixed effects. If the set of destination markets served by each firm-product pair is constant overtime, it is easy to see that applying d and t fixed effects eliminates unobserved marginal cost components, and the resulting model yields a unbiased estimate of the markup elasticity. One of the remarkable features of Knetter's approach is that it is not necessary to add additional firm and product (i.e., f and i) fixed effects if the panel is balanced—even when information about these dimensions is available in the dataset. As macroeconomic variables only vary along destination and time dimensions, they are naturally orthogonal to unobserved factors changing over firm and product dimensions.

In appendices B.1 and B.2, we show that Knetter's identification strategy can still recover unbiased estimates of the markup elasticity when the set of destination markets served by firms is not constant, provided that changes over time in the deviations of a firm-product's marginal cost from the average marginal cost are *uncorrelated* with changes over time in the deviations of bilateral exchange rates from an average over all destinations. By way of example, if discontinuity in exporting to some markets is random (i.e., the pattern of "missing" trade observations is random), then the Knetter estimator is fine—the panel is "exogenously" unbalanced.

2.3 Estimating the markup elasticity in endogenously unbalanced panels

The key problem in relying on the methodology by Knetter is that panels of highly disaggregated firm-product-destination-time customs data are inherently unbalanced: frequently, the set of destinations served by a firm changes; arguably this occurs endogenously in response to exchange rate movements. Shifts in a firm's trade pattern naturally correspond to the firm's decision to discontinue sales in a market where the currency is too weak for its exports to be 'competitive' (vice versa for entry). This implies that observability of an $ifdt$ price is correlated with the bilateral exchange rate $\mathcal{F}_{dt}$.

If this is the case, the application of a Knetter-style fixed effects estimator is bound to generate an unbalanced panel of residuals, such that residual variation in marginal costs, mc_{ift}, is confounded with residual variation in destination-specific factors that impact the markup, $\mathcal{F}_{dt}$.

To appreciate this problem, let's consider a standard empirical model of nominal exchange rate pass through.[12] Usually, the first step in specifying these models consists of taking a time difference

[12] An advantage of using nominal exchange rates and CPI rather than the real exchange rate is that the nominal variables approach does not implicitly assume a relationship between nominal exchange rates and the relative CPI

of equation (1). Time differencing is motivated by observing that the series of nominal exchange rates or CPI indices cannot be directly compared across countries: the logged time difference, a growth rate, is instead comparable across destinations. However, when the objective of the estimation is to identify the export price markup elasticity, this initial step raises a key issue. Taking time differences changes the dimensions along which unobserved variables vary—making it impossible to control for them in later stages. Specifically, consider an S-period time difference of equation (1) conditional on ifd:

$$\begin{aligned}
\Delta_{s_{|ifd}} p_{ifdt} \quad = \quad & \Delta_{s_{|ifd}} \mathcal{F}_t + \Delta_{s_{|ifd}} \mathcal{C}_t \\
& + \Delta_{s_{|ifd}} \mathcal{F}_{it} + \Delta_{s_{|ifd}} \mathcal{F}_{ft} + \Delta_{s_{|ifd}} \mathcal{F}_{dt} + \Delta_{s_{|ifd}} \mathcal{C}_{it} + \Delta_{s_{|ifd}} \mathcal{C}_{ft} \\
& + \Delta_{s_{|ifd}} \mathcal{F}_{fdt} + \Delta_{s_{|ifd}} \mathcal{F}_{idt} + \Delta_{s_{|ifd}} \mathcal{F}_{ift} + \Delta_{s_{|ifd}} \mathcal{C}_{ift} \\
& + \Delta_{s_{|ifd}} \mathcal{F}_{ifdt}
\end{aligned} \tag{3}$$

where $\Delta_{s_{|j}} x_{j,t} \equiv x_{j,t} - x_{j,t-s} \ \forall j \in \{f, i, f, d, fd, id, if, ifd\}$. Recall that the unobserved cost component $\mathcal{C}_{ift}$ varies along three dimensions in equation (1). Here is the problem: taking the S-period difference within a firm-product-destination introduces a non-zero correlation between changes in the firm-product marginal cost, $\Delta_{s_{|ifd}} \mathcal{C}_{ift}$, and the destination-specific bilateral exchange rate $\Delta_{s_{|ifd}} \mathcal{F}_{dt}$. This is because selection of observations into the unbalanced, time-differenced panel depends on changes in bilateral exchange rates $\mathcal{F}_{dt}$. The change in the price in destination d is only observed when the firm continues to sell the product in d in both periods, t and $t + s$. As already mentioned, this is less likely to occur when the producer's currency has appreciated substantially relative to the local d currency—the producer is endogenously 'priced out' of the market in d. *After* time differencing, introducing firm-product fixed effects to control for marginal cost will be ineffective relative to the goal of identifying the parameter of interest because the two components, cost and the exchange rate, are not orthogonal in time differences.

2.4 Trade Pattern Sequential Fixed Effects (TPSFE)

In the previous subsection we have shown that, because of entry into and exit from destination markets in response to exchange rate movements, applying firm-product-destination fixed effects after taking time differences causes the residual price variation to confound time variation in marginal cost within the firm with intertemporal and cross-destination variation in the firm's markup. An econometrician who relies on the time differencing method ends up comparing apples-to-oranges in residual price variation. Estimates will be biased.

ratio.

We now show that an appropriately developed Knetter-style identification strategy can actually work around the problem, so that it can be applied to endogenously unbalanced panels. The crucial step consists of changing the order in which fixed effects are applied in a high-dimensional panel. The main idea is that, if the primary concern is controlling for unobserved time-varying firm-product marginal costs, $\mathcal{F}_{ift}$, destination fixed effects must be applied *before* the data is partitioned along the time dimension. For this reason, the procedure we propose is best dubbed "trade pattern sequential fixed effects" (TPSFE). We show that the correct sequencing in TPSFE yields unbiased estimates of the price markup adjustment to bilateral exchange rate movements.

To solve the endogenous unbalanced panel problem described in the previous subsection, first, we address the unobserved marginal cost in the first stage of the estimation; this is essential in order to avoid introducing changes in the dimensions along which the unobserved marginal cost varies. Second, we create trade pattern fixed effects, which insure "apples-to-apples" comparisons across sets of firm-product prices in different periods and prevent the bias associated with endogenously changing trading partners.

The TPSFE estimator can be implemented in three steps:

1. Demean each variable in the dataset at the firm-product-time level, so to express each variable as a destination-specific deviation from the mean. This step strips time variation out of the firm's marginal production cost, as well as any global factor that is common across all the destinations a firm serves.

   (a) For each firm-product-time triplet, calculate the mean of each dependent and independent variable over all destinations the firm serves, i.e., calculate:

   $$\frac{1}{n_{ift}^{D}} \sum_{d \in D_{ift}} x_{ifdt} \quad \forall x \in \{p_{ifdt}, e_{dt}, X_{dt}\} \tag{4}$$

   where n_{ift}^{D} is the number of foreign destinations for each firm-product-time triplet.

   (b) Remove the mean over all destinations in order to obtain the residual variation in the variable by destination:

   $$\widetilde{x}_{ifdt,D_{ift}} = x_{ifdt} - \frac{1}{n_{ift}^{D}} \sum_{d \in D_{ift}} x_{ifdt} \quad \forall x \in \{p_{ifdt}, e_{dt}, X_{dt}\} \tag{5}$$

2. Identify the trade pattern for each product sold by a firm in each time period and turn this information into a "trade pattern fixed effect" that incorporates information about the destination associated with each observation as well as the set of all destinations reached by

the firm-product in that period.

For each firm-product-time (f, i, t) triplet:

(a) Collect the set of destinations served:

$$\{d : p_{i'f'dt'} \text{ is observed} : i' = i, f' = f, t' = t\}. \tag{6}$$

(b) Generate a string variable that identifies this set of destinations. For example, VN-KR-JP is attached to a firm f which exports product i to Vietnam, Korea, and Japan in a year t. Notationally, denote this string as D_{ift}.

(c) Create a trade pattern fixed for each $ifdt$ observation by appending the destination country for that observation to the front of its trade pattern string. For example, for the trade pattern fixed effects VN-VN-KR-JP, KR-VN-KR-JP and JP-VN-KR-JP, the first string is associated with a firm's shipment to Vietnam in a year in which the firm sells to Vietnam, Korea and Japan. The second string is associated with that firm's shipment to Korea in the same year, etc. Notationally, denote this trade pattern fixed effect as $TP_{d,D_{ift}}$

3. Run a regression using destination-demeaned variables and the trade pattern fixed effects.

$$\widetilde{p}_{ifdt,D_{ift}} = \kappa_0 + \kappa_1 \widetilde{e}_{dt,D_{ift}} + \widetilde{X}'_{dt,D_{ift}} \kappa_2 + TP_{d,D_{ift}} + \widetilde{u}_{ifdt,D_{ift}} \tag{7}$$

where e_{dt} is the bilateral exchange rate (rmb/d) and X_{dt} is a vector of destination-specific macro variables including local CPI and real GDP.

At this point, it may seem impossible to estimate equation (7) because both the dependent variable, price, and the dummy variable, $TP_{d,D_{ift}}$, vary along four dimensions. However, variation in $TP_{d,D_{ift}}$ is limited and depends on the *count of trade patterns*, D_{ift}, in the dataset. In practice, an exporter's trade pattern, i.e., its chosen set of foreign markets, is not random. As a result, variation in the TPSFE dummy variable, $TP_{d,D_{ift}}$, is much smaller than the total number of observations, making equation (7) identifiable.

The importance of bias in unbalanced panels with selection is obviously a general econometric problem. Indeed, after developing our estimation procedure, we became aware of a related contribution by Correia (2017) who proposes a general high-dimensional fixed effects estimator.[13] However, it is important to stress a subtle but important difference between our approach and Correia's, as a mechanical application of the latter would not work in our context. This is our key result that the

[13] We thank Thierry Mayer for bringing this work to our attention.

order in which firm and product fixed effects are applied matters for the estimation—indeed, the time difference followed by fixed effects is not the only partition procedure that fails to correctly identify the markup response to the exchange rate in an unbalanced panel.[14] Our procedure is explicitly devised to address this problem.

An important and well known issue in the literature is potential biases arising from changes in the composition of products underlying customs unit values or, relatedly, changes in the quality and nature of goods underlying price data within a product code over time.[15] In appendix C, we derive mild assumptions under which the compositional term is a second-order problem, implying only a limited impact on our estimates.

2.5 An estimator of firms' cross-market supply elasticity with respect to the exchange rate (CMSE)

Market power exerted by adjusting markups and prices to exchange rates movements should be detected in destination-specific supply elasticities. We now show how our TPSFE approach to estimating markup elasticities can be used to gain insight on the elasticity of substitution of a firm's output across destination markets. Specifically, we derive a statistical estimator of the degree to which relative price changes in response to relative exchange rate movements map into changes in the quantities of a product exported by a firm across destinations.

The main idea is to estimate the cross-market supply response to "exchange rate-related" changes in relative markups. Namely, based on our TPSFE estimator, we can obtain predicted prices, $\widehat{\widetilde{p}}_{ifdt,D_{ift}}$ using the pricing equation (7):

$$\widehat{\widetilde{p}}_{ifdt,D_{ift}} = \widehat{\kappa}_0 + \widehat{\kappa}_1 \widetilde{e}_{dt,D_{ift}} + \widetilde{X}'_{dt,D_{ift}} \widehat{\kappa}_2 \tag{8}$$

and then use these predicted prices as explanatory variables in the 'quantity' equation (9), speci-

[14] Consider an alternative procedure in which firm-product-destination dummies are added to equation (1). The equation simplifies to:

$$\widetilde{p}_{ifdt} = \widetilde{\mathcal{F}}_t + \widetilde{\mathcal{C}}_t + \widetilde{\mathcal{F}}_{it} + \widetilde{\mathcal{C}}_{it} + \widetilde{\mathcal{F}}_{ft} + \widetilde{\mathcal{C}}_{ft} + \widetilde{\mathcal{F}}_{dt} + \widetilde{\mathcal{F}}_{fdt} + \widetilde{\mathcal{F}}_{idt} + \widetilde{\mathcal{F}}_{ift} + \widetilde{\mathcal{C}}_{ift} + \widetilde{\mathcal{F}}_{ifdt},$$

where $\widetilde{x}_j \equiv x_j - \sum_{t \in T_{ifd}} x_j / n^T_{ifd} \; \forall j \in \{t, it, ft, dt, fdt, idt, ift, ifdt\}$. If the panel dataset is randomly unbalanced, these two distinct partitions, (ift, d) and (ifd, t) give the same results. However, if the pattern of firm participation in foreign markets responds endogenously to bilateral exchange rates and marginal cost shocks, only our procedure correctly recovers the unbiased markup elasticity. We discuss this issue in more detail in appendix B.3.

[15] Although it is natural to think that an 8-digit product or even an inventory control bar code refers to a time-invariant object, it is possible that two or more varieties of different qualities could be subsumed in a single product code.

ficied below

$$\widetilde{q}_{ifdt,D_{ift}} = \gamma_0 + \gamma_1 \widehat{\widetilde{p}}_{dt,D_{ift}} + \widetilde{X}'_{dt,D_{ift}} \gamma_2 + TP_{d,D_{ift}} + \widetilde{v}_{ifdt,D_{ift}} \tag{9}$$

Statistically, $\widehat{\widetilde{p}}_{ifdt,D_{ift}}$ reflects variation in relative prices driven by movements of bilateral relative exchange rates, controlling for other aggregate variables. The coefficient γ_1 measures the projection of changes in relative quantities on changes in exchange-rate-driven relative prices.

As long as cost-side factors are perfectly controlled,[16] $\widehat{\widetilde{p}}_{ifdt,D_{ift}}$ actually measures the change in *relative markups* in response to changes in relative *demand* conditions across destinations. Then, γ_1 captures the cross-market supply elasticity (CMSE) with respect to destination-specific bilateral currency appreciation. Heuristically, holding the supply curve fixed, a shift in relative demand induces movements in quantities along the relative supply curve. In this vein, γ_1 could be seen as the slope of the relative supply curve.

To gain insight into the proposed estimator, we contrast our results with those obtained by running a naïve regression of relative quantity changes on relative prices changes—basically showing the average correlation in the data:

$$\widetilde{q}_{ifdt,D_{ift}} = \lambda_0 + \lambda_1 \widetilde{p}_{dt,D_{ift}} + \widetilde{X}'_{dt,D_{ift}} \lambda_2 + TP_{d,D_{ift}} + \widetilde{v}_{ifdt,D_{ift}} \tag{10}$$

As shown in in sections 5 and 6, this naïve regression typically results in a significant but negative correlation: a negative λ_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 exchange-rate instrumented equation (9) produces a significant, positive correlation: a positive coefficient γ_1 suggests that the relative supply curve is upward sloping within the firm. See appendix D.2 for an analytic discussion.

3 Economics meets linguistics: a general classification of high- and low-differentiation products

For the purpose of our analysis, it is important that we identify products over which firms are potentially able to exploit market power and charge a markup. Most product-level analyses rely on a classification based on the system devised by Rauch: differentiated goods are identified as products that do not trade on open exchanges and/or whose prices are 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

[16]Precisely, in the presence of compositional error, we need condition (44) explained in appendix C.2 to hold.

construct a new classification system at the detailed, HS08 product-level that uses an insight from linguistics to refine the Rauch classification system in the following crucial dimension: differentiated goods are further classified into high differentiation or low differentiation bins. What allows us to achieve this refinement is the information content of "measure words," a specific category of Chinese character that is reported in the Chinese Customs Database.

As further detailed below, 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.[17] 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.[18] Our classification principle 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 all commodities traded on open exchanges are reported with mass classifiers—fully consistent with our view that mass classifiers identify low differentiation products.

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."[19] 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

[17]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.

[18]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).

[19]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.

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.[20]

For 2008, the dataset reports quantity using 36 different measure words. To illustrate the variety of measures used, table 1 reports a selection of measure words, the types of goods that use the measure word, and the 2008 percent of export value that is reported with 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 E.2 for additional examples of the Chinese quantity measures in our data.

For twenty industrial sectors, Table 2 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

[20] 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 (、本、枚、 、羽、匹、台、 、 、 、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.

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

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

treated as low differentiation.[21] Column one lists the HS chapters that define the sector. The second column provides the sector's share in China's total exports over 2000-2014. Quantitatively, important export sectors with large shares of high differentiation goods include optical and photographic equipment (79.7 percent), machinery and mechanical appliances (73.1 percent), textiles and apparel (68.4 percent), vehicles and aircraft (66.1 percent), stone and plaster articles (65.0 percent), leather goods (58.6 percent), and plastics and rubber articles (15.0 percent). The share of high differentiation products across sectors varies widely, but lines up with our priors. 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.

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 HS06 product codes to Rauch's original 4 digit SITC rev. 2 classification of differentiated, reference priced, and open exchange traded goods. The improvement is on at least two dimensions. First, our classification refines the class of differentiated goods in Rauch's. From table 3 panel (a), we observe that 79.8 percent of observations 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) uses count classifiers.[22] Second, every good that

[21] 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.

[22] We have constructed a concordance for all HS06 products as high differentiation or low differentiation by

Table 2: 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.

Table 3: Classification of goods: Integrating the insights from CCHS with Rauch

(a) Share of goods by classification: observation weighted

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

(b) Share of goods by classification: value weighted

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

Notes: Share measures are calculated based on Chinese exports to all countries including Hong Kong and the United States during periods 2000-2014. †: The "Unclassified" category refers to HS08 products that do not uniquely map to the SITC Rev. 2 classification of Rauch.

Rauch categorizes as a commodity (an open-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. Integrating these two systems, we will use the terms "high differentiation" to refer to Rauch differentiated goods that are count nouns and "low differentiation" to refer to Rauch differentiated goods that are mass nouns, commodities, and reference priced goods.

A final, further benefit of our classification system is that we are able to provide a classification for goods that a concordance between HS06 and SITC Rev. 2 leaves unclassified under Rauch's system. Note that around 12% percent of observations in panel (a) (and 14.8% of observations in panel (b)) do not uniquely map to a single Rauch category. They do according to our classification.[23]

In a related paper, we test the performance of our classification by applying it to non-Chinese export data. See Corsetti, Crowley and Han (2018).

4 Data from multi-destination exporters

To construct the dataset in this paper, we merge information from two datasets: (1) the Chinese Customs Database, i.e., the universe of annual import and export records for China from 2000 to 2014 and (2) annual macroeconomic data from the World Bank. Moreover, we turn to administrative data from Her Majesty's Customs and Revenue (HMCR) in the UK to provide information about the currency of invoicing of Chinese exports so that we can place our results in context.

We begin with the Chinese Customs Database that reports detailed trade flows (quantities and values) at the firm-product-destination level. In addition to standard variables, such as the firm ID, an 8-digit HS code, the destination country and year[24], 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.[25]

categorizing as high differentiation those HS06 product groups in which all HS08 products use a count classifier. This means that the CCHS classification of differentiated goods can be applied to the customs datasets for other countries.

[23]The problem that arises is that the concordance of disaggregated HS06 product codes to (more aggregated) SITC Rev.2 involves 1-to-many or many-to-many mappings for 81 percent of concordance lines. Therefore, we cannot identify a unique mapping from HS06 to a Rauch-based SITC rev. 2 classification for 12% of observations in the Chinese Customs Database.

[24]The database is available at monthly frequency during the period 2000-2006 and and annual frequency during the period 2007-2014. We aggregate the monthly data for 2000-2006 to the annual level in this study.

[25]The form of commerce indicator records the commercial purpose of each trade transaction including "general trade," "processing import materials," and "assembling supplied materials," etc. The registration type variable contains information on the capital formation of the firm by 8 categories, namely 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 later analysis, we group three types of foreign invested firms, namely wholly-foreign-owned enterprise, Sino-foreign contractual joint venture and Sino-foreign equity joint venture, into one category and dubbed it as "foreign invested enterprises." We group minority

Like other firm-level studies using customs databases, we use unit values as a proxy for prices. However, the rich information on forms of commerces, 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 + a form of commerce dummy + a CCHS classification dummy.[26] The application of our product-variety definition generates 14,611 product-variety codes as opposed to the roughly 8,100 8-digit HS codes reported in the database. 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.[27] 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.[28]

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.[29]

4.1 The "Happy Few:" Multi-product, multi-destination exporters

The key to identifying price responses to exchange rate movements for our estimator relies on cross-destination market variation in prices. Following Mayer, Melitz and Ottaviano (2014), we use the 2007 cross section of the Chinese Customs Database to document in table 4 that a "happy few" exporters are responsible for most of China's exports. The top panel provides a breakdown of the number of export transactions by the count of products and destinations served by a firm exporting from China. The bottom panel presents the respective shares of export value by firms that differ by exported product count and foreign markets reached. Overall, we see that multi-destination exporters represent almost three-quarters of export transactions (row 5 of the top panel of table 4, 33.1+14.7+25.0) and are responsible for 94.6% of export value (row 5 of the bottom panel of

categories such collective enterprise, individual business and other enterprise into one category and refer to them as "other enterprises."

[26]Firms in the Chinese Customs Database can produce the same product under two or more forms of commerce. Essentially, a good could be produced under different tax regulations depending on the exact production process used. In creating our form of commerce dummy, we generate a dummy variable equal to 1 if the transaction is "general trade" and 0 otherwise. The CCHS classification dummy equals 1 if the product is a high differentiation product and 0 if the product is a low differentiation product.

[27]The primary reason why the number of product-variety exceeds that of HS08 products is due to the addition of the form of commerce dummy.

[28]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 weight and units (Amiti, Itskhoki and Konings (2014)).

[29]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.

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

	No. of Products	Number of Countries 1	2-5	6-10	10+	Total
by Share of Exporters	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
by Share of Exports	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

Note: Each cell in the top panel is the percentage of observations in the Chinese customs data in 2007 that fall under the relevant description. The bottom panel presents the corresponding value of exports.

table 4).[30] 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. The shares of export transactions and export value by count of products and destination markets are relatively stable across years in our sample period. Tables for other years are available in an on-line appendix.

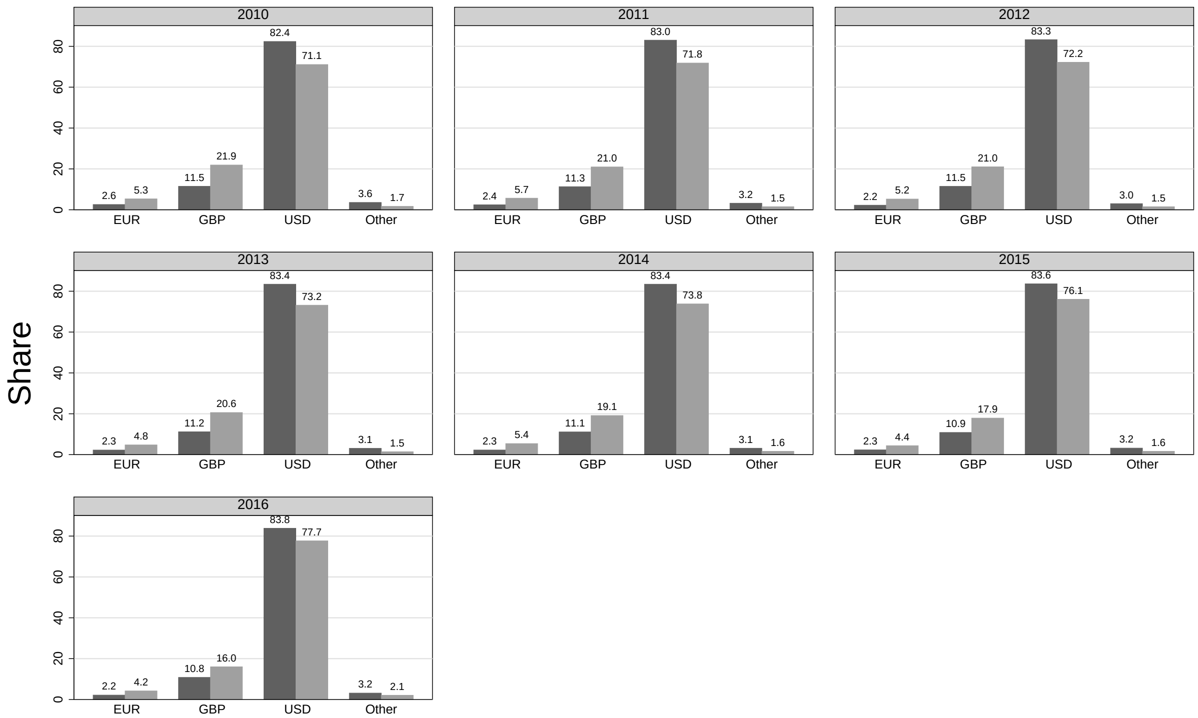
The total number of active exporters increased dramatically over the period from 62,746 in 2000 to 295,310 in 2014. We track the total number of actively traded products by counting unique product-exporter pairs and find this measure increases roughly at the same pace as the number of exporters from about 904 thousand in 2000 to 4.56 million in 2014. The total exported value measured in dollars increased ten-fold from 2000 to 2014. Additional details are provided in the on-line appendix.

4.2 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 originally invoiced in US dollars, renminbi,

[30] 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 the top panel of table 4, we observe that 13.5% of observations on exports in the Chinese Customs Database were articles exported to a single destination by a single product firm. However, these transactions comprised only 1.2% of Chinese export value in 2007. The bottom row of the top panel 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 row of the bottom panel indicates that the value of these transactions by single-destination exporters was only 5.4% of total Chinese exports.

Figure 1: Invoicing currencies for UK imports from China



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

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 to answer this question for one of China's major destination markets. 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.[31]

Figure 1 presents the shares of import transactions and import value into the UK from China by invoicing currency.[32] Results are reported for three currencies, the euro (EUR), pound sterling

[31] 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."

[32] 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

(GBP), and the US dollar (USD). All transactions that use another currency to invoice UK imports from China, for example, the Swiss franc, Japanese yen or Chinese renminbi, are aggregated into the category "Other."[33] 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 2010-2016.[34] Over this same period, the pound's importance as an invoicing currency for imports from China fell. While the share of transactions held steady at 10-12% over the period, the share of import value from China invoiced in sterling 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 2010-2016.

In figure 2 we present information on the currency of invoicing for UK exports to China. Firms are only required to report the currency of invoicing for export transactions whose value exceeds £100,000. Thus, the share of export transactions and value for which no invoicing currency is reported is sizable. In figure 2, these are indicated by "NR." [35]

In almost all years the British pound sterling is the most important currency of invoicing for exports to China, both in transaction and value terms. Interestingly, the sterling does not dominate invoicing of exports entirely; substantial shares of exports are invoiced in US dollars. The euro appears to play a minor role and other currencies, including the Chinese renminbi, are rarely used.

The proportion of Britain's exports for which no currency is reported declines over time. Presumably this is related to an increase in the nominal value of trade transactions such that a greater proportion exceed the £100,000 reporting requirement over time.

This evidence is relevant to our empirical analysis to follow, insofar as a firm that invoices in a vehicle currency, say dollars, also prices its good in that currency. Suppose that the firm sets

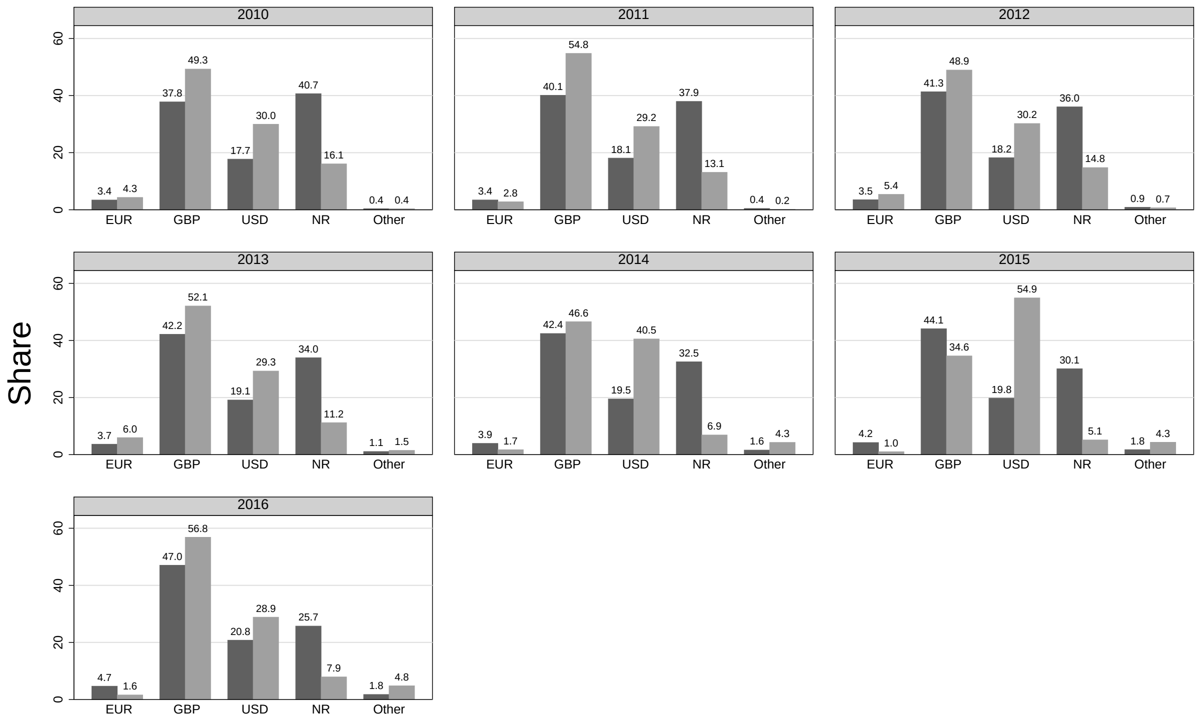
measure-currency quadruplet to an annual observation for that quadruplet. The variable "quantity measure" records whether a transaction for a CN08 product is reported in kilograms or a supplementary quantity unit like "items" or "pairs." This leaves us with 2.004 million annual transactions which we use to construct figure 1.

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

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

[35] To construct figure 2 we follow the same procedure described above for imports. We arrive at approximately 266 thousand annual transactions which we use to construct the figure.

Figure 2: Invoicing currencies for UK exports to China



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

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.

5 Empirical Results

In this and the next section, we present and discuss results obtained by applying our empirical framework to the Chinese Customs Database. We first present our estimates on exchange rate pass through, markup adjustment, and cross-market supply elasticities, then present estimates distinguishing high- and low-differentiation goods, according to our classification, as well as other economic classifications. In the next section, we redo the analysis by grouping firms according to their registration types which indicate public versus private and domestic versus foreign ownership. Our results will unveil significant heterogeneity in pricing strategies across firm and product types.

As explained in section 2, we apply the TPSFE estimator to assess the extent of destination-specific price and markup adjustments, conditional on renminbi price changes. Specifically, we estimate all parameters *after* applying a data filter to the Chinese export data to obtain a panel of *price changes*. For each product-firm-destination combination, we filter out absolute price changes 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 A.

In using conditional on price changes, our results are comparable to evidence on *total* exchange rate pass through into import prices by Gopinath and Rigobon (2008) among others. Indeed, to clarify the difference in methodologies and obtain a reference benchmark, all our tables include estimates of the export price elasticity to the exchange rate (the complement of exchange rate pass through) obtained by following the standard methodology. These estimates allow us to quantify the relative contribution of the markup elasticity (obtained by using our estimator which controls for marginal cost changes) to total export price adjustment.

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 3 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 significantly across the two environments.

In all our estimation samples, we treat eurozone countries as a single economic entity and integrate trade flows to these countries.[36] In addition, we exclude exports to the US and Hong

[36]Specifically, 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

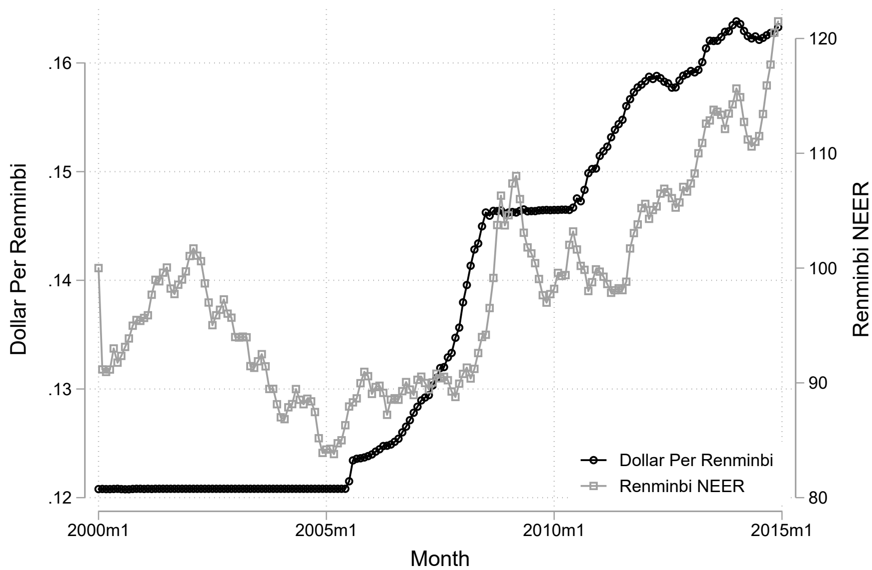


Figure 3: Reminbi Movements During Periods 2000 − 2014

Kong to ensure comparability of our estimates across regimes.

5.1 Markup adjustments and incomplete pass through

We begin by showing two notable results from applying our methodology to the entire sample of exports, without distinguishing goods by their degree of differentiation. First, destination-specific markup adjustments are non-trivial, and account for a non-negligible share of incomplete pass through into import prices. Second, the quantitative importance of markup adjustments increased after China abandoned its strict peg to the dollar in 2005.

Estimation results for the entire sample of exported goods, that is, without distinguishing between high differentiation manufacturing goods and other products, are shown in Table 5. In reading the results in the table, it is important to keep in mind 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 (columns (1) and (2)) means *a high pass through into import prices* in foreign currency.

The first result from the table is that the elasticity of export prices (in renminbi) to bilateral

159 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 154 destinations. These two alternative estimation samples yield very similar results to our primary estimation sample which integrates 17 eurozone countries together.

For macroeconomic series, we use the World Bank reported CPI index, bilateral exchange rates and import-to-GDP ratio for the euro area. We construct a "GDP constant local currency" measure for the eurozone using the reported "GDP constant US dollar (2010)" variable and the 2010 euro-dollar rate.

Table 5: Price and Markup Elasticities to Exchange Rates

	(1) Price Elasticity 2000-2005	(2) Price Elasticity 2006-2014	(3) Markup Elasticity 2000-2005	(4) Markup Elasticity 2006-2014
Bilateral nominal exchange rates	0.23***	0.24***	0.07***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)
Destination CPI	0.09***	0.58***	-0.03*	-0.00
	(0.02)	(0.01)	(0.02)	(0.01)
Destination real GDP	0.41***	0.05***	-0.02	-0.01
	(0.03)	(0.01)	(0.02)	(0.00)
Import-to-GDP ratio	0.22***	0.30***	0.01	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	516,552	3,050,928	1,072,775	4,824,344
FE	No	No	TPSFE	TPSFE
SE	Robust	Robust	Robust	Robust
Con Price Change	Yes	Yes	Yes	Yes

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The "Price Elasticity" columns report estimates regressing S-period accumulated changes in renminbi unit values on S-period accumulated changes in nominal bilateral exchange rates and other macro-level control variables. "Markup Elasticity" columns represent estimates from our TPSFE estimator. Both "Price Elasticity" and "Markup Elasticity" columns are estimated conditional on price changes following the procedure specified in appendix A. 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 *.

exchange rates is low and stable across the two subsamples. On average, conditional on a price change, the renminbi price of Chinese exports responds to nominal bilateral exchange rate movements by 23% over the 2000-2005 period (column 1) and 24% over 2006-2014 period (column 2). These 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 77% in the years of China's currency peg and essentially the same (76%) in later years. Note that the coefficients on real GDP and the import share of GDP, meant to capture the export price response to factors specific to the destination market, have a positive sign, as expected. Also, observe that the destination CPI has a sizeable, positive effect on export prices and that this increases substantially after the renminbi is unpegged from the US dollar.

A shortcoming of the export price elasticity regressions is that they do not isolate markup adjustments from marginal costs changes. This is exactly what our TPSFE estimator accomplishes. In columns (3) and (4), we report our estimated markup elasticities. Conditional on a price change in renminbi occurring at t+s, the average markup changes by 7% of the cumulated bilateral exchange rate movement between t and t+s during the dollar peg period (column 3). After the change in regimes, as shown in column (4), the price markup response rises to 11% of the cumulated movement. These results suggest that, on average, firms became considerably more active in adjusting their destination-specific markups after China abandoned its strict peg to the US dollar.[37]

In interpreting these and the subsequent results, it is useful to reconsider the argument emphasized by Corsetti and Dedola (2005) and Corsetti, Dedola and Leduc (2008) that the pass through coefficient from regression analysis captures the equilibrium comovements of prices, markups and exchange rates resulting from shocks hitting the economy over the observed sample period. Drawing on open macro theory, Corsetti, Dedola and Leduc (2008) further show that the theoretical pass through coefficient can be written out as a function of structural features of the economy, including monopoly power, price rigidities, and vertical interactions among producers and distributors.[38] In light of these analyses, the differences in markup elasticities we detect across our subsamples are likely to reflect more than the policy switch 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 the frequency and importance of cyclical (policy and technology) shocks at the national and global level that have occurred in the two subsamples.[39]

5.2 High-differentiation versus low-differentiation goods

We now turn to our results from disaggregating the sample according to our product classification. To introduce our analysis, we focus on two products as case studies. Our goal is to visualize graphically the relationship between changes in relative markups and movements of relative exchange rates, using our destination-demeaned variables. We select canned tomato paste (measured in kilograms), as representative of low-differentiation manufactured goods according to our CCHS classification, and wheeled tractors (measured with "liang"), as a high-differentiation good. These two cases illustrate well the characteristic features of firm-level pricing that drive our econometric estimates presented below.

In figure 4, we plot data on the dispersion of markups across destinations for the top three

[37] In columns (3) and (4) we also estimate there is a tiny markup adjustment to the idiosyncratic component of local CPI growth over 2000-2005 (column 3) and no change in the later period (column 4). The difference in estimated coefficients on CPI in columns (1) versus (3) and (2) versus (4) arises because our approach removes the global trend in the exporter's price associated with global CPI movements and isolates the local component.

[38] Vertical interactions between producers and distributors are also emphasized by Burstein, Eichenbaum and Rebelo (2005) and Burstein, Eichenbaum and Rebelo (2007) in relation to the transmission of large devaluations into local prices. Variable trade elasticities with markups changing as a function of competition feature in the analysis of Bergin and Feenstra (2001). See Rodnyansky (2018) for an analysis of the general equilibrium effects using microdata from Russia and Japan.

[39] The regression pass through coefficient 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 and Dedola (2005). To wit: the price response to exchange rate movements can be expected 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 identify shocks in isolation and trace their effects on the exchange rate and export prices and markups – see Forbes, Hjortsoe and Nenova (2017).

exporters of tomato paste and wheeled tractors in 2007 and 2008. For each annual observation of a sale, we calculate the deviation of the sales price from its mean across destinations within the firm-product-year triplet (where sales price is the log unit value in renminbi), i.e. $uv_{ifdt} - \overline{uv}_{ift}$, and plot these deviations using different shapes 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.[40] 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, say, 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-destination pair according to whether the destination's currency appreciated or depreciated during 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.

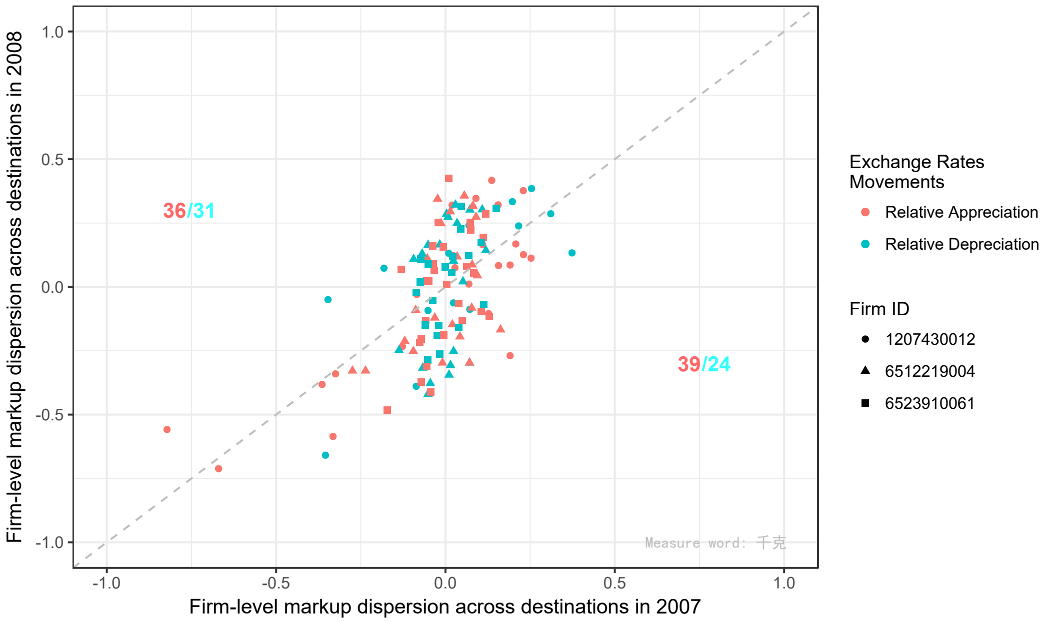
Three important features are captured in these graphs. First, the relative markups for many firm-product-destination triplets, measured in the producer's currency, change from year to year. Second, the low-differentiation good, tomato paste, exhibits less dispersion in its markups across destinations 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.

5.2.1 Markup elasticities using the CCHS product classification

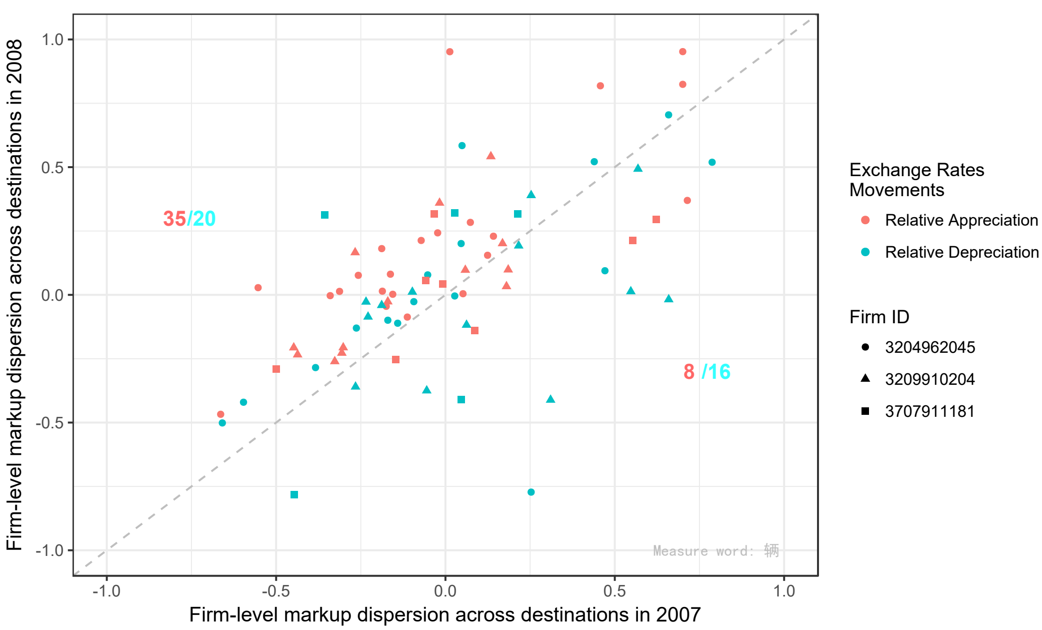
Splitting the sample according to the CCHS product classification, we now document significant differences in both pass through and markup elasticities across high- and low-differentiation goods, in line with our discussion of the two case studies opening this section. Overall, the key message from the table is product differentiation is a good proxy for market power; this validates the

[40] 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 4: 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., $uv_{ifdt} - \overline{uv}_{ift}$. For this figure, we begin with a balanced panel of firm-product-destination observations for two consecutive years, 2007 and 2008, and plot the observations of 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.

usefulness of our linguistics-inspired product classification.

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

Turning to quantitative results, during the fixed exchange rate period (row 1), we have already seen that the markup elasticity over all goods is relatively small, 7% (column (2)). The results in the table show that this low average estimate conceals important differences across types of good. For CCHS high-differentiation exports, the markup elasticity is as high as 14%—for low differentiation goods it is statistically indistinguishable from zero (0.02).

In the period of the managed float of the renminbi (second row of table 6), markup elasticities are considerably higher. For high differentiation goods, the export price elasticity rises from 25 to 32% (and exchange rate pass through correspondingly falls to 1-.32=.68); the markup elasticity rises from 14 to 20%. Note that the 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 one-third of the adjustment in renminbi prices, estimated at 19%.

Table 6: Price and Markup Elasticity by CCHS Classifications

	All		High Differentiation		Low Differentiation		
	Price	Markup	Price	Markup	Price	Markup	n. of obs
2000 – 2005	0.23***	0.07***	0.25***	0.14***	0.22***	0.02	1,076,815
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	
2006 – 2014	0.24***	0.11***	0.32***	0.20***	0.19***	0.06***	4,863,196
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The "Price Elasticity" columns report estimates regressing S-period accumulated changes in renminbi unit values on S-period accumulated changes in nominal bilateral exchange rates and other macro-level control variables. "Markup Elasticity" columns represent estimates from our TPSFE estimator. Both "Price Elasticity" and "Markup Elasticity" columns are estimated conditional on price changes following the procedure specified in appendix A. Destination CPI, real GDP and M/GDP 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 *.

5.2.2 Integrating the CCHS product descriptions 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 consumption goods producers 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 markup elasticities to be higher for consumption goods than for intermediates.

To gain insight on how the intensity of market competition can impact pricing by firms, we now split our data combining our CCHS classification with the classification of consumption goods and intermediates according to the UN's Broad Economic Categories (BEC).[41] Results are shown in Table 7.

In line with our argument above, the price-setting behaviour is quite different across the two types of goods. The estimated markup elasticities are higher for consumption goods than for intermediates, both in the dollar peg years and the managed float period. During the dollar peg era, the markup elasticity is sizeable for consumption goods (0.10, row 1, column (2)), but not statistically significant for intermediate goods (row 2, column (2)). Observe that consistent with our results in table 5, after China abandoned the dollar peg, the magnitude of markup elasticities increases for both consumption goods (0.20, row 3, column (2)) and intermediates (0.05, row 4, column (2)).

Within each end-use category, we can still detect higher markup elasticities for high-differentiation relative to low differentiation goods. During the dollar peg period (top panel of the table), markup elasticities are significantly different from zero only for high-differentiation goods—consumption goods exhibit the largest value (0.17, row 1, column (4)), followed by intermediates (0.14). Under the managed float, markup elasticities are positive and significant for all types of goods, pointing to extensive pricing-to-market. Our estimated elasticity actually peaks for high-differentiation consumption goods (0.32, row 4 column (4)), almost three times the value for high-differentiation intermediates (0.12, row 3 column (6)). The markup elasticities are lower for low-differentiation goods, and quite close for consumption and intermediate goods (0.08 and 0.05, rows 4 and 5, column (4)).

From the evidence in the table, it is apparent that low-differentiation products are sold in more competitive markets. During the dollar peg, nonetheless, the slightly larger markup elasticity of low-differentiation consumption goods (8%) relative to low-differentiation intermediates (5%) lends support to the idea that, even within this group of manufactured goods, at least some firms produc-

[41] 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.

ing consumption goods are successful in acquiring market power—arguably through advertising, branding and other initiatives promoting product recognition among consumers. Furthermore, all groups of products experience a rise markup elasticities with the adoption of the managed float, except for high-differentiation intermediate goods, whose markup elasticities are not statistically different during the peg and the managed float period.

Incomplete exchange rate pass through can be due to either changes in production costs or destination-specific market power. Our estimates can provide crucial insight on this decomposition. During the managed float period, the estimated pass through of exchange rate movements into import prices in local currency for high-differentiation consumption goods is only 56 percent (corresponding to an export-price elasticity of 0.44). This is far lower than most estimates using micro firm-level data. In our findings, three-quarters of the incomplete pass through of exchange rate movements into import prices of high differentiation consumption goods can be attributed to destination-specific markup adjustments (0.32/0.44, row 3, column (4)/column (3)).

For high differentiation intermediates, pass through into import prices is far higher, 66 percent (1-0.34, row 4, column (3)); however, the fraction of the incomplete pass through due to markup adjustments is far smaller – about one-third (0.12/0.34, row 4, column (4)/column (3)). In contrast, low differentiation intermediate inputs are characterised by high exchange rate pass through into import prices, 81 percent (1-0.19, row 4, column (5)); with small markup adjustments explaining only about one-quarter of the incomplete pass through.[42]

[42]The trade policy implications of market power in intermediates characterised by high differentiation or "customisability" are significant; see, e.g., the model by Antràs and Staiger (2012).

Table 7: Price and Markup Elasticity by BEC Classifications

	All		High Differentiation		Low Differentiation		
Category	Price	Markup	Price	Markup	Price	Markup	n. of obs
2000 – 2005							
Consumption	0.25***	0.10***	0.29***	0.17***	0.19***	0.02	426,462
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	
Intermediate	0.23***	0.03	0.22***	0.14***	0.24***	0.01	294,929
	(0.02)	(0.02)	(0.06)	(0.05)	(0.02)	(0.02)	
2006 – 2014							
Consumption	0.33***	0.20***	0.44***	0.32***	0.16***	0.08***	1,756,214
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	
Intermediate	0.21***	0.05***	0.34***	0.12***	0.19***	0.05***	1,593,591
	(0.01)	(0.01)	(0.06)	(0.04)	(0.01)	(0.01)	

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The "Price Elasticity" columns report estimates regressing S-period accumulated changes in renminbi unit values on S-period accumulated changes in nominal bilateral exchange rates and other macro-level control variables. "Markup Elasticity" columns represent estimates from our TPSFE estimator. Both "Price Elasticity" and "Markup Elasticity" columns are estimated conditional on price changes following the procedure specified in appendix A. Destination CPI, real GDP and M/GDP 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 *.

5.2.3 The CCHS and Rauch classification systems compared

According to the Rauch classification system, products traded on open exchanges (OE) are generally regarded as commodities whose prices are expected to fluctuate with global supply and demand. Reference price (RP) products are list-price goods: firms producing them compete somewhat directly by supplying at the price published in some 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 indicate 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 for which there is not enough information about pricing.

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.

Table 8: Price and Markup Elasticity by Rauch Classifications

	All		High Differentiation		Low Differentiation		
Category	Price	Markup	Price	Markup	Price	Markup	n. of obs
2000 − 2005							
Differentiated Products	0.22***	0.09***	0.25***	0.14***	0.20***	0.04**	815,223
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	
Organized Exchange	0.60***	0.02	-	-	0.62***	0.02	11,925
	(0.06)	(0.05)			(0.06)	(0.05)	
Reference Priced	0.23***	0.09**	0.05	0.26**	0.24***	0.08*	88,959
	(0.03)	(0.04)	(0.16)	(0.12)	(0.04)	(0.04)	
2006 − 2014							
Differentiated Products	0.22***	0.12***	0.32***	0.20***	0.14***	0.07***	3,944,681
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	
Organized Exchange	1.02***	-0.05	-	-	1.03***	-0.05	27,235
	(0.07)	(0.05)			(0.07)	(0.05)	
Reference Priced	0.43***	0.11***	0.14	0.16*	0.45***	0.10***	366,974
	(0.02)	(0.02)	(0.10)	(0.09)	(0.02)	(0.02)	

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The "Price Elasticity" columns report estimates regressing S-period accumulated changes in renminbi unit values on S-period accumulated changes in nominal bilateral exchange rates and other macro-level control variables. "Markup Elasticity" columns represent estimates from our TPSFE estimator. Both "Price Elasticity" and "Markup Elasticity" columns are estimated conditional on price changes following the procedure specified in appendix A. Destination CPI, real GDP and M/GDP 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 *.

Not surprisingly, 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)). We nonetheless detect a positive elasticity for goods that are 'reference priced' in Rauch (rows 3 and 6, column (2)). Indeed, even under the Rauch classification (table 8, column (2)), our markup elasticity estimator reveals an increase in market power across the two currency regimes.

The most important takeaway from table 8 is however that the estimated markup elasticity of "differentiated" goods in Rauch is an average of very different elasticities. For higher degrees of product differentiation, firms can exploit their market power and optimally extract rents from different destination markets to a much larger extent than for low-differentiation products.

5.3 The supply response of Chinese exporters

We conclude this section by investigating the flip side of the markup elasticity to exchange rates, that is, firms' cross market supply elasticity. The question we ask is to what extent do firms reallocate their output across markets as they adjust their own markups in different destinations in response to exchange rate movements. Table 9 presents the estimates obtained by applying the method developed at the end of section 2, together with a naïve regression of relative quantities on relative prices, conditional on the trade pattern fixed effects.

Starting from the naïve regression, our estimates show that a 1% increase in relative prices is associated with a 0.7% *decline* in relative quantities (rows 1 and 2, column (1)). The naïve regression simply reveals that, in equilibrium, firms sell relatively small quantities in markets where they set relatively high prices. 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.

The result from the naïve regression contrasts sharply with the results from our CMSE estimator. For the managed float regime, over the 2006-2014 period (table 9, row 2), our estimated cross market supply elasticity is positive and equal to 1.51 (row 2, column (2)): a one percent increase in the relative markup (driven by the exchange rate) is associated with 1.5 percent change in the relative quantity across destinations. The relative quantity increases in destinations where the relative markup has risen in response to a local currency appreciation. The significance of the drastic change in sign when we apply our method cannot be overstated: the CMSE is designed to isolate the relative quantity adjustments across destinations *caused* by markup adjustments to exchange rate movements.

A positive slope coefficient from the CMSE estimator confirms that our TPSFE approach is able to isolate and capture the demand-side effects of exchange rate fluctuations. 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 on exchange rates. These projections are then used to trace out a firm's relative "willingness to supply" across markets.

The most important finding in this table 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, 0.83 (row 2, 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 2.47 percent 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 0.14 markup elasticity (see table 6). For these goods, our estimated CMSE is quite high, 2.57. All together, these results suggest that, during the strict peg period, firms responded to bilateral exchange rate movements with modest markup adjustments— they rather aggressively pursued openings for higher profits through large increases in relative quantities, i.e., a 2.57 percent increase in the relative quantity supplied associated to a 1 percent increase in the relative markup.

Table 9: Cross Market Supply Elasticity by CCHS Classifications

	All		High Differentiation		Low Differentiation		
	Naive Reg.	CMSE	Naive Reg.	CMSE	Naive Reg.	CMSE	n. of obs
2000 – 2005	-0.71***	4.09***	-0.74***	2.57***	-0.68***	†	1,076,815
	(0.00)	(0.82)	(0.00)	(0.49)	(0.00)		
2006 – 2014	-0.70***	1.51***	-0.73***	0.83***	-0.68***	2.47***	4,863,196
	(0.00)	(0.16)	(0.00)	(0.12)	(0.00)	(0.43)	

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The "Naïve Reg" column is estimated using specification (10). The "CMSE" column is estimated based on equations (8) and (9). † indicates that the t-statistic of the bilateral exchange rate in the first stage is smaller than 2.58. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

We conclude with evidence on the importance of international market segmentation and the use of market power. Building upon our analysis of differences in markup elasticities of high and low differentiation goods by Broad Economic Categories, table 10 provides the corresponding CMSEs for these groups of products over 2006-2014. The estimates provide evidence, on the one hand, of an extreme level of market segmentation in which firms exporting highly differentiated consumption goods have very low quantity substitution across markets while, on the other hand, showing a very high level of market integration across destinations for firms which export low differentiation intermediates. In other words, the CMSEs tell us that the nature of the good matters enormously; at one extreme, a high degree of pricing to market exists in products for which cross-market substitution of quantity by firms is very low. At the other extreme, some

Table 10: Cross Market Supply Elasticity by BEC Classification (2006 – 2014)

	All		High Differentiation		Low Differentiation		
Category	Naive Reg.	CMSE	Naive Reg.	CMSE	Naive Reg.	CMSE	n. of obs
Consumption	-0.71***	0.54***	-0.77***	0.23**	-0.63***	1.92***	1,756,214
	(0.00)	(0.11)	(0.00)	(0.09)	(0.00)	(0.59)	
Intermediate	-0.71***	2.92***	-0.74***	1.33	-0.70***	3.27***	1,593,591
	(0.00)	(0.73)	(0.01)	(0.86)	(0.00)	(0.90)	

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The "Naïve Reg" column is estimated using specification (10). The "CMSE" column is estimated based on equations (8) and (9). † indicates that the t-statistic of the bilateral exchange rate in the first stage is smaller than 2.58. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

goods – low differentiation intermediates – appear similar to commodities in their inconsequential use of destination-specific markup adjustments and their highly elastic cross-market substitution of supply.

6 Who exports from China?

The intense competition that Chinese imports have brought to high income countries has spawned research into how this enhanced global 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 markets (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 5.2, 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 so far 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).[43] Looking at exports, the picture is actually more complex. Quantitatively, the dominant role in exports is played by firms that are wholly foreign owned or are Sino-foreign joint enterprises—the leading types in a group

[43] 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.

that we label foreign-invested enterprises (FIEs).

Reflecting their ownership/type, firms are likely to have different cost structures and face different demand elasticities. A popular view of SOEs and FIEs is that they both have relatively easy access to capital, but likely differ in the extent to which they rely on imported intermediates in production. Conversely, private firms are widely seen as facing a tighter financing constraint and, relative to FIEs, a lower level of integration with global supply chains. Moreover, reflecting different rates of entry, the average size of a firm also differs across these groups—with private enterprises being smaller. Last but not least, 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. Our question is whether, due to these factors, observable differences in pricing, markup adjustments and cross-destination quantity adjustments map into firms' registration types.

6.1 The evolution of China's exports by different types of firms

In figure 5, 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.[44] Perhaps less known and understood, however, is the economic weight of a different category of exporters *from* China, the foreign-invested enterprises (FIEs), also highlighted by our figure. 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

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

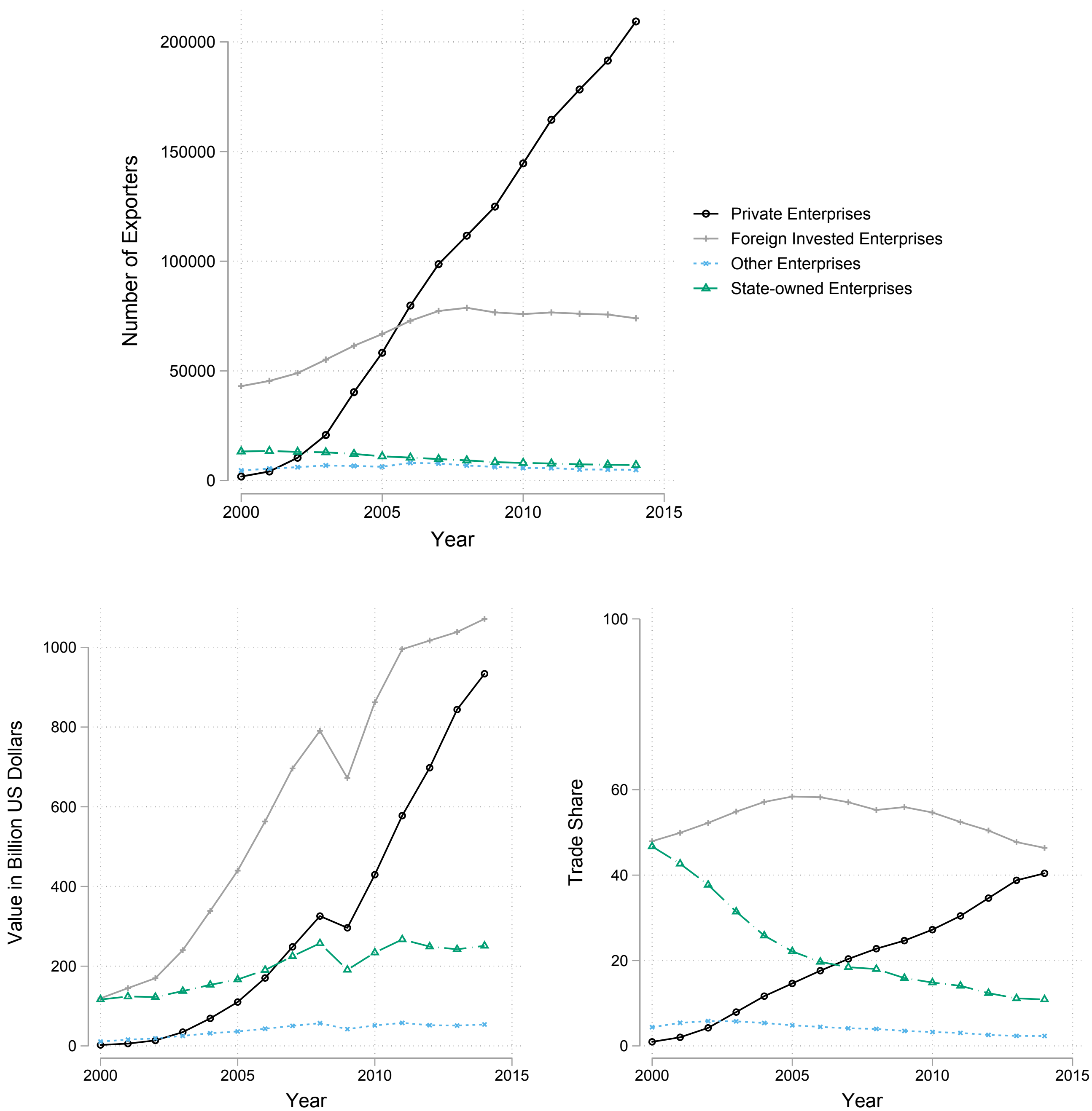


Figure 5: The changing face of Chinese exporters, 2000-2014

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.

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 5).

The key message from the top panel of figure 5 is reinforced by the analysis of export values and shares by different types of firms, shown in the bottom panel. By export value and share of total exports, the most important single group of exporters from China is that of foreign-invested enterprises. In 2014, the value of their exports was over US $1 trillion (bottom left panel of figure 5). Over the period, exports from China that originated from firms that are wholly or partially owned by foreigners fluctuated between 45 and 58% of China's total exports.[45]

Conversely, the weight of SOEs, which were essentially at par with FIEs in 2000, declined dramatically from 2000 to 2007 and then settled into a slow and steady negative trend (bottom left panel, figure 5). 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.

As shown below, against this evolution in the number of exporters and export shares by ownership, there are significant differences in strategic pricing—markup elasticities diverge strikingly across FIEs, SOEs and private firms. We argue that evidence on these differences is key to understanding the dynamic evolution of Chinese enterpreneurs in international markets.

6.2 The market power of Chinese and foreign firms

Evidence on price, markup and supply elasticities by firm type is presented in table 11. 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 (0.49), have moderately elastic markups (0.21), and have an inelastic within-firm cross market supply elasticity (CMSE) (see table 11, row 2, columns (1), (2) and (4)). The high estimate of the Chinese export price elasticity of 0.49 implies that the ERPT into *import* prices in foreign currency is relatively low (51%), reflecting that these firms are more actively pursuing local currency price stabilization than other groups of firms. Notably, markup adjustment accounts for two fifths (0.21/0.49) of this incomplete pass through into import prices,

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

Relative to FIEs, the export price response to exchange rates by SOEs is smaller, 0.32 (see row 1, column (1) of table 11), implying a much higher pass through into *import* prices, as high as 68%. While SOEs make similar markup adjustments compared to FIEs in absolute terms, the share of markup adjustment to incomplete pass through is higher (0.22/0.32 versus 0.21/0.49). Like FIEs, SOEs have an extremely low cross market supply elasticity, 0.47 (row 1, column (4)). This evidence together suggests that both FIEs and SOEs are endowed with 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 percent in response to a 10 percent appreciation (see row 3, column (1) of table 11). Of this, a modest 40 percent is due to a tiny, yet statistically significant, markup adjustment by destination (0.04/0.10). Pass through into foreign *import* prices is as high as 90 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 4.7 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.[46]

The second and third panels of table 11 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 either 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 our comments about the top panel of table 11 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 5. 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-.07 =93 percent, from row 9, column (1) of table 11), and a small (2%) increase in the markup. This small increase in the markup

[46]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 et al. (2017).

Table 11: Pricing Strategies by Firm Registration Types (2006 − 2014)

	Price Elasticity	Markup Elasticity	Naive Reg.	CMSE	n. of obs
Full Sample					
State-owned Enterprises	0.32***	0.22***	-0.70***	0.47***	644,385
	(0.02)	(0.02)	(0.00)	(0.15)	
Foreign Invested Enterprises	0.49***	0.21***	-0.69***	0.22	1,053,734
	(0.01)	(0.02)	(0.00)	(0.14)	
Private Enterprises	0.10***	0.04***	-0.70***	4.72***	3,010,176
	(0.01)	(0.01)	(0.00)	(0.94)	
High Differentiation					
State-owned Enterprises	0.46***	0.39***	-0.69***	0.38***	283,697
	(0.03)	(0.03)	(0.00)	(0.14)	
Foreign Invested Enterprises	0.53***	0.35***	-0.69***	0.09	446,663
	(0.02)	(0.02)	(0.00)	(0.12)	
Private Enterprises	0.16***	0.09***	-0.75***	2.54***	1,153,886
	(0.01)	(0.01)	(0.00)	(0.53)	
Low Differentiation					
State-owned Enterprises	0.24***	0.13***	-0.71***	0.62*	360,688
	(0.02)	(0.02)	(0.00)	(0.35)	
Foreign Invested Enterprises	0.47***	0.14***	-0.69***	0.24	607,071
	(0.02)	(0.02)	(0.00)	(0.28)	
Private Enterprises	0.07***	0.02***	-0.67***	8.42**	1,856,290
	(0.01)	(0.01)	(0.00)	(3.34)	

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The "Naïve Reg" column is estimated using specification (10). Estimation methods for the "Price Elasticity" and "Markup Elasticity" columns are the same as in previous tables. The "Naïve Reg." column is estimated using specification (10). The "CMSE" column is estimated based on equations (8) and (9). † indicates that the t-statistic of the bilateral exchange rate in the first stage is smaller than 2.58. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

accounts for less than one third (0.02/0.07) of the change in export prices. In other words, Chinese private enterprises exporting low differentiation goods respond to an appreciation of the local currency by letting the local-currency price of their products fall and expanding their sales rather aggressively—adjustments to markups are minor. In our estimates, indeed, a 1% increase in the relative markup for the good in Mexico is met with an 8.4% increase in the relative quantity sold by the firm to Mexico (row 9, column (4) of table 11). For private firms exporting high-differentiation goods, the exchange rate pass through into peso prices is somewhat lower, about 84% (1-.16). Yet, markup adjustment is not appreciably higher, 9% instead of 2%. 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.

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-.46 = 54% for SOEs and 47% for FIEs, rows 4 and 5, column (1) of table 11). SOEs and FIEs clearly prefer to raise their markups, by 39% for SOEs and 35% for from FIEs (rows 4 and 5, column (2)), rather than expand sales. The estimated cross-market supply elasticities are indeed very small (0.38 for SOEs and 0.09 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 market power in foreign markets, and exploit that 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 only a 0.47% (SOEs) increase and no change for (FIEs) in the relative quantity sold in Mexico for a 1% increase in the relative markup. Conversely, over our sample period, private firms have aggressively pursued local market expansions.

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.[47]

6.3 Pricing behavior under the dollar-renminbi peg

The results discussed so far suggest that SOEs and FIEs wield substantial market power. Was this also the case in the first part of our sample, when the renminbi was pegged to the US dollar (2000-2005)? An analysis of pricing, markups and the CMSE during this period suggests a different story.

Our evidence for the dollar peg period is shown in Table (12). Across all types of firms in the table, adjustments of export prices to currency movements were modest—ERPT into foreign import prices was as high as 76 percent (1-0.24), 77 percent (1-0.23), and 88 percent (1-0.12) for SOEs, FIEs, and private firms, respectively (rows 1-3, column (1)).

Both FIEs nor SOEs have smaller markup adjustments (rows 2 and 3, column (2)) in response

[47] We leave to future research a refinement of our analysis along these lines.

Table 12: Pricing Strategies by Firm Registration Types (2000 − 2005)

	Price Elasticity	Markup Elasticity	Naive Reg.	CMSE	n. of obs
Full Sample					
State-owned Enterprises	0.24***	0.08***	-0.74***	2.99***	519,674
	(0.02)	(0.02)	(0.00)	(0.81)	
Foreign Invested Enterprises	0.23***	0.05**	-0.59***	7.81**†	268,598
	(0.03)	(0.02)	(0.01)	(3.63)	
Private Enterprises	0.12***	0.09***	-0.76***	2.26**	216,374
	(0.04)	(0.03)	(0.01)	(1.15)	
High Differentiation					
State-owned Enterprises	0.28***	0.15***	-0.77***	1.97***	234,928
	(0.02)	(0.02)	(0.01)	(0.54)	
Foreign Invested Enterprises	0.20***	0.10***	-0.63***	5.82***	123,590
	(0.04)	(0.03)	(0.01)	(2.18)	
Private Enterprises	0.15**	0.14***	-0.82***	1.14	85,859
	(0.06)	(0.04)	(0.01)	(1.08)	
Low Differentiation					
State-owned Enterprises	0.21***	0.03	-0.71***	6.32†	284,746
	(0.02)	(0.02)	(0.01)	(4.93)	
Foreign Invested Enterprises	0.26***	0.01	-0.56***	17.72†	145,008
	(0.03)	(0.03)	(0.01)	(40.86)	
Private Enterprises	0.10**	0.07**	-0.72***	3.56†	130,515
	(0.05)	(0.03)	(0.01)	(2.50)	

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The "Naïve Reg" column is estimated using specification (10). Estimation methods for the "Price Elasticity" and "Markup Elasticity" columns are the same as in previous tables. The "Naïve Reg." column is estimated using specification (10). The "CMSE" column is estimated based on equations (8) and (9). † indicates that the t-statistic of the bilateral exchange rate in the first stage is smaller than 2.58. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

to exchange rates during the dollar peg era. Indeed, these firms appear to have been following a different strategy, namely, aggressively expanding quantity: a 1 percent increase in the relative markup in a destination is associated with a 3 percent increase in the relative quantity for SOEs and a roughly 8 percent increase for FIEs. In contrast to the managed floating period, private firms made significant markup adjustments of 9% (row 3, column (2)), the largest among all groups. We conjecture this is because the sunk cost for private firms to obtain an export license in China was relatively high in early 2000s. With only a limited number of private firms directly engaged in international trade, the level of competition among them was less severe. Consistent with our conjecture, we find a low cross market elasticity (2.26, row 3 column (4)) for this period relative to that during the managed float (4.72, row 3 column (4) in the previous table).

Important insights can be gained by looking at the second and third panels in the table, which break down our estimates by types of goods traded. Comparing SOEs exporting high and low differentiation goods (rows 4 and 7, column (2)), we see that the result in the first panel is entirely due to a significant markup elasticity for high differentiation products. For these products, around one-half of this incomplete pass through is due to markup adjustments (0.15/0.28, from row 4, columns (1) and (2)). For low-differentiation exports by SOEs, we detect no markup adjustment (row 7, column (2)). The story is similar for FIEs: the average markup elasticity is 0.09 across all goods, but this is essentially driven by the high differentiation goods (with an elasticity of 0.10, row 5 column (2)).

One way to interpret this evidence is that, under the peg, exporters from China appear to be operating close to a 'Reference Price System,' whereby firms exploit limited market-specific markup adjustments, but price in relation to global demand, consistent with (but not identical to) with idea of an 'International Price System' heralded by Gopinath (2015). A complementary view is that, in those early years, all Chinese exporters were pursuing aggressive market expansion strategies, exploiting exchange rate movements to expand their sales rather than increase their markups.

In any case, the story of pricing by exporters in the world's second largest economy has changed. The phasing out of the strict peg and adoption of the managed float has coincided with a significant rise in pricing-to-market across all firm and product types—most substantially so for high-differentiation goods exported by SOEs and FIEs.

7 Conclusions

We develop a framework to estimate the export price markup elasticity to bilateral exchange rate movements. We find that firms exporting high differentiation goods from China make destination-specific adjustments to markups in response to movements of bilateral exchange rates and that these adjustments account for up to three quarters of incomplete exchange rate pass through into import prices. In contrast, commodities and low differentiation goods exhibit small or zero markup adjustments.

In conjunction with our new product-classification system, we document heterogeneity in pricing behaviours across high differentiation and low differentiation products, across consumption versus intermediate goods, and across firms with different ownership structures—state-owned enterprises, foreign-invested enterprises, and private enterprises.

Our findings potentially open several new directions of research concerning consumer welfare, the dynamics of the Chinese manufacturing sector, and the international price system. Concerning the analysis of consumer welfare, our results suggest that a refined product classification based on product differentiation works well as a proxy for market power, which impinges on the level and distribution of the welfare gains from trade. By way of example, other things equal, an appreciation of the domestic currency can be expected to lead to higher welfare gains, the larger the share of low-differentiation goods in consumption.

The substantial cross-sectional heterogeneity among Chinese exporters by type we have uncovered contains the seed of important dynamic developments. Relative to FIEs and SOEs, a high entry rate of private enterprises means that the average firm size in this group is likely to be small, and a substantial share of them are likely to be at an early stage of their life cycle. Once they grow large, private firms may well exercise monopoly power and behave like FIEs and SOEs.

Last but not least, a low destination specific markup adjustment by private firms in China appears consistent with what could be dubbed the 'International Reference Price System.' This is a narrower interpretation of Gopinath's 'International Price System' in which firms set only one price—in a vehicle currency— for their product. Perhaps reflecting the relatively small size of their exports (at an early stage of their development), private firms appear to operate by setting dollar prices at a global level, rather than engaging in price discrimination. This average pattern might change again, as private firms grow larger and acquire market power.

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A 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.

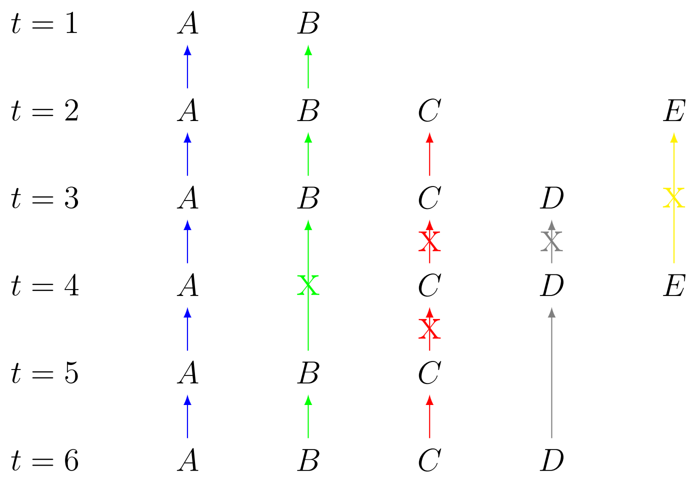
Consider a firm exporting a product to five countries, A through E, over 6 time periods. In the following matrix, rows are time periods and columns are destination countries. Empty elements in the matrix indicate that there was no trade.

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

The following matrix records prices by destination country and time:

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

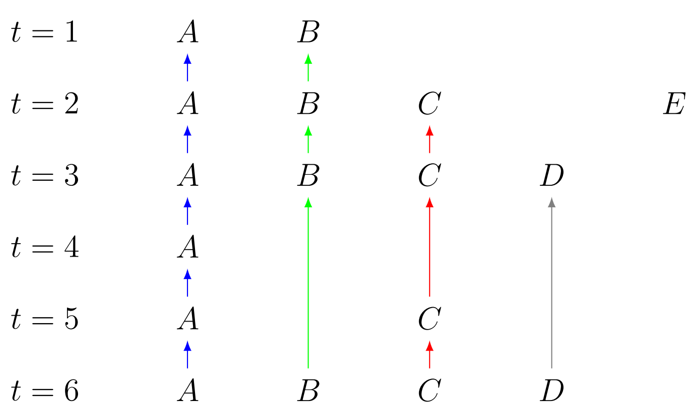
Suppose the pricing currency is the dollar and we want to identify price changes in dollars. First, we compare prices denominated in dollars (vertically) at the firm-product-destination level as illustrated in the following figure. Price changes less than 5% are marked with "x".



We then set the first 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 (i.e., these are the latter of the level price entries used in constructing the change). 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 $|p_{C,5} - p_{C,4}| < 5\%$.[48] Rather, we repeat the above step using the remaining observations as illustrated below.



[48] Variables are in logs.

In this example, we indeed find $|p_{C,5} - p_{C,3}| > 0$ and the remaining pattern is given as follows. As no prices are sticky, we can stop the iteration.[49] Note that as no price changes can be formulated for the single trade record $p_{E,2}$, this observation is dropped from our sample.

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

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

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

In this example, we find 5 trade patterns, i.e., $A - B$, $A - B - C$, $A - B - C - D$, A, $A - C$, but only one pattern, $A - B - C - D$, which appears at least two times. To compare the change in relative prices across destinations, we require the same trade pattern be observed at least two times in the price-change-filtered dataset.[50] In the example presented above, only prices within the trade pattern $A - B - C - D$ will be compared because it is the only unique pattern to appear two times. In the real customs database with hundreds of thousands of firms, each trade pattern typically is associated with many firm-product-time triplets. The destination demeaned (relative) price is first constructed at the firm-product-time level (i.e., this is the first step of in TPSFE estimation procedure) and regressions are then run adding trade pattern fixed effects[51] (i.e., this is the second step of the TPSFE estimator).

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

[50] Essentially, by formulating trade pattern fixed effects, we are restricting the comparison within a comparable environment. Firms switch trade patterns for a reason. Restricting the analysis to the same trade pattern also controls for other unobserved demand factors affecting the relative prices.

[51] To construct trade pattern fixed effect dummies, we prefix the destination country in front of the trade pattern, e.g. $A - A - B - C - D$, $B - A - B - C - D$, $C - A - B - C - D$, $D - A - B - C - D$. Prefixing the destination country code ensures the "destination-trade pattern" comparison of prices and exchange rates.

Year	Country	Value	Price
2001	Germany	7957	.43
	Indonesia	28543	.49
	Italy	2416699	.47
	Thailand	6900	.38
	Vietnam	9391	.49
2002	Indonesia	69241	.48
	Italy	1415535	.54
	Latvia	9302	.53
	Philippines	9126	.52
	South Korea	8908	.48
2003	Germany	47924	.49
	Japan	54450	.36
	Philippines	9126	.52

Table 13: A real data example of changing trade patterns: Exports of tomato paste (HS 20029010) by the firm with identifier 6512910023

B The unbalanced panel problem in estimating the markup elasticity to the exchange rate

In this section, we discuss problems that may arise in estimating markup elasticities using a four dimensional (firm-product-destination-time) customs database. In subsection B.1, we show that Knetter (1989) type (d,t) fixed effects are capable of controlling for the unobserved firm-product specific time-varying marginal cost in a balanced panel. In subsection B.2, we show that the firm-product dimension matters if the panel is endogenously unbalanced. In this case, our procedure can precisely control the unobserved marginal cost and produce unbiased estimates while alternative partitions would generate biased estimates depending on the degree to which the panel is endogenously unbalanced. In subsection B.3, we simulate a numerical example to compare the performance of several commonly used estimating procedures and illustrate the bias that may arise from an endogenously unbalanced panel.

B.1 Balanced panels

We start by proving that the fixed-effect identification strategy of Knetter (1989), applied to firm-level data, does control for firm-product level marginal costs if the panel is balanced.

Starting from (1) and (2), adding (d,t) fixed effects yields:

$$\begin{aligned}
\widetilde{mc}_{ift} &= mc_{ift} - \frac{1}{n^I n^F n^T}\sum_i\sum_f\sum_t mc_{ift} \\
&\quad - \frac{1}{n^I n^F n^D}\sum_i\sum_f\sum_d mc_{ift} + \frac{1}{n^I n^F n^D n^T}\sum_i\sum_f\sum_d\sum_t mc_{ift} \\
&= mc_{ift} - \overline{mc}_t
\end{aligned}$$

$$\begin{aligned}
\widetilde{e}_{dt} &= e_{ift} - \frac{1}{n^I n^F n^T}\sum_i\sum_f\sum_t e_{dt} \\
&\quad - \frac{1}{n^I n^F n^D}\sum_i\sum_f\sum_d e_{dt} + \frac{1}{n^I n^F n^D n^T}\sum_i\sum_f\sum_d\sum_t e_{dt} \\
&= e_{dt} - \overline{e}_d - \overline{e}_t + \overline{e}
\end{aligned}$$

Where n^J denotes for the number of indices in dimension $j \in \{i,f,d,t\}$; $\overline{x}_j$ is defined as the mean of variable x taking over all dimensions other than j.

Since

$$\frac{1}{n^I n^F n^D n^T}\sum_i\sum_f\sum_d\sum_t \widetilde{mc}_{ift}=0 \quad and \quad \frac{1}{n^I n^F n^D n^T}\sum_i\sum_f\sum_d\sum_t \widetilde{e}_{dt}=0,$$

we can write the covariance between bilateral exchange rates and the unobserved marginal cost as

$$\begin{aligned}
&\frac{1}{n^I n^F n^D n^T}\sum_i\sum_f\sum_d\sum_t \widetilde{mc}_{ift}\widetilde{e}_{dt} && (11)\\
&=\frac{1}{n^I n^F n^D n^T}\sum_i\sum_f\sum_d\sum_t \left(mc_{ift}-\overline{mc}_t\right)\left(e_{dt}-\overline{e}_d-\overline{e}_t+\overline{e}\right)\\
&=\frac{1}{n^D n^T}\sum_d\sum_t\left[\frac{1}{n^I n^F}\sum_i\sum_f\left(mc_{ift}-\overline{mc}_t\right)\right]\left(e_{dt}-\overline{e}_d-\overline{e}_t+\overline{e}\right) && (12)\\
&=0
\end{aligned}$$

In a balanced panel, only the average marginal cost matters. An unbiased estimator can be obtained by adding Knetter (1989) type (d,t) fixed effects. No additional firm-product level fixed effects are required.

B.2 The firm-product dimension matters in an unbalanced panel; An incorrect partition may produce biased estimates

In an unbalanced panel, the firm-product dimension partition matters. We show an alternative set of fixed effects, (ifd,t), may change the dimension along which an unobserved variable varies and produce biased estimates.

$$\widetilde{mc}_{ift,T_{ifd}} \equiv mc_{ift}-\frac{1}{n^T_{ifd}}\sum_{t\in T_{ifd}} mc_{ift} \tag{13}$$

$$\widetilde{e}_{dt,T_{ifd}} \equiv e_{dt}-\frac{1}{n^T_{ifd}}\sum_{t\in T_{ifd}} e_{dt} \tag{14}$$

When the panel is unbalanced, the trading periods may differ for each product-firm-destination triplet. Let T_{ifd} be the set of time periods a product-firm-destination triplet exports. The number of trading periods in this set is defined as $n^T_{ifd}\equiv|T_{ifd}|$.

The unbiasedness condition can be written into a similar format as in (11):

$$\frac{1}{n^{IFDT}}\sum_i\sum_f\sum_d\sum_t(\widetilde{mc}_{ift,T_{ifd}}-\frac{1}{n_t^{IFD}}\sum_i\sum_f\sum_d\widetilde{mc}_{ift,T_{ifd}})(\widetilde{e}_{dt,T_{ifd}}-\frac{1}{n_t^{IFD}}\sum_i\sum_f\sum_d\widetilde{e}_{dt,T_{ifd}}) \tag{15}$$

Note that the time demeaning operation makes the unobserved marginal cost vary along four dimensions. As a result, expression (15) may not necessarily be zero depending on the source of unbalanceness. Specifically, the second term in each set of parentheses in expression (15) can be derived as

$$\begin{aligned}
\frac{1}{n_t^{IFD}}\sum_i\sum_f\sum_d\widetilde{mc}_{ift,T_{ift}} &= \frac{1}{n_t^{IFD}}\sum_i\sum_f\sum_d mc_{ift}-\frac{1}{n_t^{IFD}}\sum_i\sum_f\sum_d\frac{1}{n_{ifd}^T}\sum_{t\in T_{ifd}}mc_{ift}\\
&= \overline{mc}_t-\overline{mc}\\
\frac{1}{n_t^{IFD}}\sum_i\sum_f\sum_d\widetilde{e}_{dt,T_{ift}} &= \frac{1}{n_t^{IFD}}\sum_i\sum_f\sum_d e_{dt}-\frac{1}{n_t^{IFD}}\sum_i\sum_f\sum_d\frac{1}{n_{ifd}^T}\sum_{t\in T_{ifd}}e_{dt}\\
&= \overline{e}_t-\overline{e}
\end{aligned}$$

Thus, expression (15) can be rewritten as

$$\frac{1}{n^{IFDT}}\sum_i\sum_f\sum_d\sum_t(mc_{ift}-\overline{mc}_{if,T_{ifd}}-\overline{mc}_t+\overline{mc})(e_{dt}-\overline{e}_{d,T_{ifd}}-\overline{e}_t+\overline{e}) \tag{16}$$

Separating $\overline{mc}_{if,T_{ifd}}$ and $\overline{e}_{d,T_{ifd}}$ from the above expression to simplify this condition gives

$$\begin{aligned}
&\frac{1}{n^{IFDT}}\sum_i\sum_f\sum_d\sum_t(mc_{ift}-\overline{mc}_{if}-\overline{mc}_t+\overline{mc})(e_{dt}-\overline{e}_d-\overline{e}_t+\overline{e})\\
&+\frac{1}{n^{IFDT}}\sum_i\sum_f\sum_d\sum_t(mc_{ift}-\overline{mc}_{if}-\overline{mc}_t+\overline{mc})(e_d-\overline{e}_{d,T_{ifd}})\\
&+\frac{1}{n^{IFDT}}\sum_i\sum_f\sum_d\sum_t(\overline{mc}_{if}-\overline{mc}_{if,T_{ifd}})(e_{dt}-\overline{e}_d-\overline{e}_t+\overline{e})\\
&+\frac{1}{n^{IFDT}}\sum_i\sum_f\sum_d\sum_t(\overline{mc}_{if}-\overline{mc}_{if,T_{ifd}})(\overline{e}_d-\overline{e}_{d,T_{ifd}})
\end{aligned}$$

where $\overline{mc}_{if}\equiv\frac{1}{n_{if}^{DT}}\sum_t\sum_d\overline{mc}_{if,T_{ifd}}$ and $\overline{e}_d\equiv\frac{1}{n_d^{IFT}}\sum_i\sum_f\sum_t\overline{e}_{d,T_{ifd}}$. Note that the first three terms are zero. The last term (17) may or may not be zero depending on the nature of the unbalancedness.

$$\frac{1}{n^{IFDT}}\sum_i\sum_f\sum_d\sum_t(\overline{mc}_{if}-\overline{mc}_{if,T_{ifd}})(\overline{e}_d-\overline{e}_{d,T_{ifd}}) \tag{17}$$

If the unbalanced panel arises from endogenous selection related to marginal cost shocks and exchange rate movements, expression (17) will in general not equal zero.

Similarly, taking time differences conditional on firm-product-destination (f, i, d) triplets can be written as

$$\Delta_{s_{|ifd}} mc_{ift} \equiv mc_{ift} - mc_{ift-s_{|ifd}} \tag{18}$$

$$\Delta_{s_{|ifd}} e_{dt} \equiv e_{dt} - e_{dt-s_{|ifd}} \tag{19}$$

Adding time fixed effects generates

$$\Delta_{s_{|ifd}} mc_{ift} - \frac{1}{n_t^{IFD}}\sum_i\sum_f\sum_d \Delta_{s_{|ifd}} mc_{ift} \tag{20}$$

$$\Delta_{s_{|ifd}} e_{dt} - \frac{1}{n_t^{IFD}}\sum_i\sum_f\sum_d \Delta_{s_{|ifd}} e_{dt} \tag{21}$$

The covariance between S-period time differenced marginal cost and exchange rates with time fixed effects is given by:

$$\frac{1}{n^{IFDT}}\sum_i\sum_f\sum_d\sum_t(\Delta_{s_{|ifd}} mc_{ift} - \frac{1}{n_t^{IFD}}\sum_i\sum_f\sum_d \Delta_{s_{|ifd}} mc_{ift})(\Delta_{s_{|ifd}} e_{dt} - \frac{1}{n_t^{IFD}}\sum_i\sum_f\sum_d \Delta_{s_{|ifd}} e_{dt}) \tag{22}$$

Again, if the endogenous selection is related to the unobserved marginal cost and observed exchange rate movements, expression (22) may not equal zero. We will be more specific regarding this endogenous selection problem in B.3.

We stress here that our our method does not suffer from this problem. As shown in the text, the unobserved firm-product-time varying marginal cost is differenced out in the first stage.

$$\widetilde{mc}_{ift,D_{ift}} \equiv mc_{ift} - \frac{1}{n_{ift}^{D}}\sum_{d\in D_{ift}} mc_{ift} = 0$$

$$\widetilde{e}_{dt,D_{ift}} \equiv e_{dt} - \frac{1}{n_{ift}^{D}}\sum_{d\in D_{ift}} e_{dt}$$

where D_{ift} is the set of destinations to which a firm-product-time triplet exports and the number of destinations in this set is defined as $n^D_{ift} \equiv |D_{ift}|$. It is important to note that $\widetilde{e}_{dt,D_{ift}}$ is not varying at four dimensions, $ifdt$. Rather, the variation is limited to the trade pattern and time space, d, D_{ift}, t. The covariance term is naturally zero, i.e.,

$$\frac{1}{n^{IFDT}} \sum_i \sum_f \sum_d \sum_t \left(\widetilde{mc}_{ift,D_{ift}} - \frac{1}{n_d^{IFT}} \sum_i \sum_f \sum_t \widetilde{mc}_{ift,D_{ift}} \right) \left(\widetilde{e}_{dt} - \frac{1}{n_d^{IFT}} \sum_i \sum_f \sum_t \widetilde{e}_{dt,D_{ift}} \right) = 0 \tag{23}$$

B.3 The bias from endogenously unbalanced panels: a simulation example

To illustrate how an endogenously unbalanced panel would give rise to a problem, we now suppress the product dimension and construct a three dimensional numerical example in which the price p_{fdt} is determined by three components, the markup adjustment in response to bilateral exchange rates, $\beta_1 e_{dt}$, the unobserved marginal cost, $\beta_2 mc_{ft}$, and a residual term, u_{fdt}.

The data generating process is given as follows:

$$\begin{aligned} p_{fdt} &= \beta_1 e_{dt} + \beta_2 mc_{ft} + u_{fdt} \\ e_{dt} &= \mathcal{F}_d + \mathcal{F}_t + \mathcal{F}_d * \mathcal{F}_t \\ mc_{ft} &= \mathcal{C}_f + \mathcal{C}_t + \mathcal{C}_f * \mathcal{C}_t \end{aligned} \tag{24}$$

In this example, bilateral exchange rates, e_{dt}, co-move with firm specific marginal costs, mc_{ft}, through the co-movement between factors $\mathcal{F}_t$ and $\mathcal{C}_t$. The formulation of factors and the residual term is given by (25).

$$\begin{gathered} u_{fdt} = \mathcal{I}_1 \mathcal{C}_f + \mathcal{I}_2 \mathcal{F}_d + \mathcal{I}_3 \mathcal{F}_t + \epsilon_{fdt} \\ \mathcal{F}_d \sim N(0,1) \quad \mathcal{C}_f \sim N(0,1) \quad \mathcal{F}_t = \mathcal{C}_t \sim N(0,1) \quad \epsilon_{fdt} \sim N(0,1) \end{gathered} \tag{25}$$

where $\mathcal{I}$ is an indicator variable that takes values of 0 or 1. For instance, $\mathcal{I}_2$ reflects the cross-destination compatibility problem, i.e., cross-destination comparisons of macro variables such as nominal exchange rates and CPI are meaningless. In each simulation, a balanced panel with 200 firms, 10 destinations and 10 time periods is generated, i.e., $n^F = 200, n^D = 10, n^T = 10$.

For the unbalanced panel experiment, we create missing observations conditional on realised exchange rate and marginal cost shocks in the generated balanced panel, i.e,

$$p_{fdt} = \begin{cases} \text{missing} & if \quad \begin{array}{c} \text{top 20 percentile of exchange rate shocks } (e_{dt} - e_{dt-1}) \text{ at time } t \\ \text{\& top 20 percentile of marginal cost shocks } (mc_{ft} - mc_{ft-1}) \text{ at time } t \end{array} \\ \text{observed} & \qquad\qquad otherwise \end{cases}$$

Our selection rule filters out trade flows from exporters that receive a high positive exchange rate shock and a high positive marginal cost shock at time t. Both shocks induce the price to rise, resulting a lower demand. As a result, the exporter may no longer find it optimal to trade.[52]

Table 14 presents our estimation results. The first column indicates the sources of variation that are active in the data generating process of u_{fdt}. In the first row, by setting all indicator variables to zero, the price is determined by the shocks that drive the exchange rate and marginal cost. In the second row, potential single dimensional distortions could directly impact the price. Both rows (0 0 0) and (1 1 1) show that for a balanced panel, all three estimators return the correct estimate of the true parameter (listed in the last column).

However, in an unbalanced panel, only the TPSFE procedure is capable of producing the correct estimate. S-period differences with time fixed effects shows a significant upward bias while (fd, t) fixed effects generate a significant downward bias. Our simulation suggests that one needs to be careful in applying multiple fixed effects in an unbalanced panel with endogenous choices of trade patterns.

Table 14: Performance of Estimators: Balanced v.s. Unbalanced Panel

	Balanced Panel			Unbalanced Panel			Theoretical
$\mathcal{I}_1$ $\mathcal{I}_2$ $\mathcal{I}_3$	Time Diff	fd, t	TPSFE	Time Diff	fd, t	TPSFE	
0 0 0	1.00***	1.00***	1.00***	1.17***	0.85***	1.00***	1.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	
1 1 1	1.00***	1.00***	1.00***	1.48***	0.84***	1.00***	1.00
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	

Estimates and standard errors are calculated from the average of 100 simulations. Each simulation contains a randomly generated sample of 200 firms, 10 destinations and 10 time periods based on the data generating process specified in the paper. The 'Time Diff' column represents estimates using S-period time differences variables at the frim-destination level adding time fixed effects. The 'fd, t' column represents estimates applying firm-proudct and time fixed effects in the reghdfe estimator. The 'TPSFE' column represents estimates applying our trade pattern sequential fixed effects estimator.

[52] We also allow for other patterns of random drops to make sure the environment we constructed is similar to what we observe from the customs database. In particular, for each firm-year combination, we randomly generate 3 missing values (out of 10) along the destination dimension. We repeat this process for firm-destination combinations, and generating 3 missing values among the remaining observations. The advantage of using two separate processes compared to a random drop at the firm level lies in that the former allows the structure of missing values to differ along time and destination dimensions.

We provide a simple analytical decomposition to show where the difference arises. We first evaluate the "Time Diff" approach where the S-period time difference is taken.

$$\Delta_{s_{|fd}} p_{fdt} = \beta_1 \Delta_{s_{|fd}} e_{dt} + \beta_2 \Delta_{s_{|fd}} mc_{ft} + \Delta_{s_{|fd}} u_{fdt} \tag{26}$$

where

$$\begin{aligned}
\Delta_{s_{|fd}} e_{dt} &= \mathcal{F}_t - \mathcal{F}_{t-s_{|fd}} + \mathcal{F}_d(\mathcal{F}_t - \mathcal{F}_{t-s_{|fd}}) \\
\Delta_{s_{|fd}} mc_{ft} &= \mathcal{C}_t - \mathcal{C}_{t-s_{|fd}} + \mathcal{C}_f(\mathcal{C}_t - \mathcal{C}_{t-s_{|fd}})
\end{aligned}$$

It can be seen clearly that $\Delta_{s_{|fd}} mc_{ft}$ is now varying over all three dimensions (fdt), making the unobserved marginal cost term uncontrollable. Adding additional fixed effect dummies in the later stage will not help to control for the unobserved marginal cost.

Our method deals with the unobserved marginal cost in the first stage. As illustrated in equation (27), the unobserved marginal cost term is controlled by the destination demeaning process.

$$\begin{aligned}
\widetilde{p}_{fdt,D_{ft}} &= \beta_1 \widetilde{e}_{dt,D_{ft}} + \widetilde{u}_{fdt} \\
\widetilde{e}_{dt,D_{ft}} &= e_{dt} - \frac{\sum_{d \in D_{ft}} e_{dt}}{n^D_{ft}} = \widetilde{\mathcal{F}}_{t,D_{ft}}(1 + \mathcal{F}_d)
\end{aligned} \tag{27}$$

C The Problem of Compositional Errors

In this section, we discuss a practical data problem that may arise in using unit values as a proxy for prices in a customs database. We derive the condition under which our estimator is unbiased for the case where the marginal cost is destination specific and changes along all four dimensions. Without loss of generality, we decompose the marginal cost into two components, the common marginal cost component at the firm-product-time level, and a compositional term, ψ_{ifdt}, which stands for deviations from the common component:

$$p_{ifdt} = \Gamma_{ifdt} + mc_{ift} + \psi_{ifdt}$$

As a deviation term, the compositional error must satisfy

$$\frac{1}{n^D_{ift}} \sum_{d \in D_{ift}} \psi_{ifdt} = 0 \ \forall ift \tag{28}$$

Mathematically, equation (28) suggests a multiplicative relationship between factors varying at the destination dimension, $\mathcal{A}_d$, and factors varying at other dimensions, $\mathcal{B}_{ift}$, i.e.,

$$\psi_{ifdt} = \mathcal{A}_d * \mathcal{B}_{ift} \tag{29}$$

with the restriction that $\frac{1}{n^D_{ift}} \sum_{d \in D_{ift}} \mathcal{A}_d = 0 \; \forall ift$.

C.1 Balanced Panels

In a balanced panel, the condition for our estimator to be unbiased is given by:

$$\frac{1}{n^I n^F n^D n^T} \sum_i \sum_f \sum_d \sum_t (\widetilde{\psi}_{ifdt} - \frac{1}{n^I n^F n^T} \sum_i \sum_f \sum_t \widetilde{\psi}_{ifdt})(\widetilde{e}_{dt} - \frac{1}{n^T} \sum_t \widetilde{e}_{dt}) = 0 \tag{30}$$

Where n^J denotes for the number of indices in dimension $j \in \{i, f, d, t\}$; $\widetilde{\psi}_{ifdt} \equiv \psi_{ifdt} - \frac{1}{n^D} \sum_d \psi_{ifdt}$; and $\widetilde{e}_{dt} \equiv e_{dt} - \frac{1}{n^D} \sum_d e_{dt}$. Since exchange rates cannot vary at product and firm dimensions in a balanced panel, we can simplify equation (30) as:

$$\frac{1}{n^D n^T} \sum_d \sum_t \left[\frac{1}{n^I n^F} \sum_i \sum_f \widetilde{\psi}_{ifdt} - \frac{1}{n^I n^F n^T} \sum_i \sum_f \sum_t \widetilde{\psi}_{ifdt} \right] (\widetilde{e}_{dt} - \frac{1}{n^T} \sum_t \widetilde{e}_{dt}) = 0 \tag{31}$$

Throughout our analysis, we define a product as an 8-digit HS code + a form of commerce dummy + a CCHS classification dummy. At the firm-product level, if goods being sold to different destinations are identical for each time period, condition (31) is trivially satisfied as $\psi_{ifdt} = 0 \; \forall ifdt$.

Allowing for compositional errors, expressions in the bracket of equation (31) can be derived as:

$$\frac{1}{n^I n^F} \sum_i \sum_f \widetilde{\psi}_{ifdt} = \frac{1}{n^I n^F} \sum_i \sum_f \psi_{ifdt} - \frac{1}{n^I n^F n^D} \sum_i \sum_f \sum_d \psi_{ifdt} \tag{32}$$

$$\frac{1}{n^I n^F n^T} \sum_i \sum_f \sum_t \widetilde{\psi}_{ifdt} = \frac{1}{n^I n^F n^T} \sum_i \sum_f \sum_t \psi_{ifdt} - \frac{1}{n^I n^F n^D n^T} \sum_i \sum_f \sum_d \sum_t \psi_{ifdt} \tag{33}$$

and equation (31) can be rewritten as

$$\frac{1}{n^D n^T} \sum_d \sum_t (\overline{\psi}_{dt} - \overline{\psi}_t - \overline{\psi}_d + \overline{\psi})(e_{dt} - \overline{e}_t - \overline{e}_d + \overline{e}) = 0 \tag{34}$$

where $\overline{x}_j$ is the mean of variable x taken over all dimensions other than j. The condition states that the deviation from time variation of cross destination deviations of average marginal cost cannot be correlated with the time variation of cross destination deviations of bilateral nominal exchange rates.

There are two simple cases where condition (34) is naturally satisfied: **(a)** the cross destination distribution of composition error does not change over time, i.e., $\overline{\psi}_{dt} = \overline{\psi}_d \; \forall \; t$; **(b)** the intertemporal distribution of composition error does not change over destinations, i.e., $\overline{\psi}_{dt} = \overline{\psi}_t \; \forall \; d$. The former is true, if high quality/cost products are constantly sold to a particular set of destinations, the latter is true if the compositional error is mainly driven by global shocks, e.g., a shock drives global business cycles. In general, satisfying expression (34) would need a much weaker relationship than either (a) or (b).

Notably, we argue that expression (34) can be further simplified using the implicit relationship of the compositional error (29).[53] Therefore, the minimal requirement for an unbiased estimator is given by

$$\frac{1}{n^D} \sum_d \mathcal{A}_d \left[\frac{1}{n^T} \sum_t (\overline{\mathcal{B}}_t - \overline{\mathcal{B}})(e_{dt} - \overline{e}_t) \right] = 0 \tag{35}$$

For a given d, $e_{dt} - \overline{e}_t$ is a variable that varies at the t dimension that represents the destination d's deviation of the mean nominal exchange rate at time t. $\overline{\mathcal{B}}_t - \overline{\mathcal{B}}$ represents the average time demeaned compositional change over firm-products. $\frac{1}{n^T} \sum_t (\overline{\mathcal{B}}_t - \overline{\mathcal{B}})(e_{dt} - \overline{e}_t)$ stands for the time covariance between these two terms. Specifically, condition (35) states that the destination variation of the time covariance between $e_{dt} - \overline{e}_t$ and $\overline{\mathcal{B}}_t - \overline{\mathcal{B}}$ is uncorrelated with the destination variation of $\mathcal{A}_d$.

To be clear, we approximate exchange rates into factors at the first order, i.e,

$$e_{dt} \approx \mathcal{X}_d + \mathcal{Y}_t + \mathcal{X}_d * \mathcal{Y}_t \tag{36}$$

With this approximation, expression (35) can be rewritten as a covariance term at the destination dimension multiplied by a covariance term at the time dimension.

$$\left[\frac{1}{n^D} \sum_d \mathcal{A}_d (\mathcal{X}_d - \overline{\mathcal{X}}) \right] \left[\frac{1}{n^T} \sum_t (\overline{\mathcal{B}}_t - \overline{\mathcal{B}})(\mathcal{Y}_t - \overline{\mathcal{Y}}) \right] = 0 \tag{37}$$

Therefore, the condition requires the empirical covariance between factors in the compositional term and the bilateral exchange rate to be zero either at the d dimension or at the t dimension.

We argue that the term $\frac{1}{n^D} \sum_d \mathcal{A}_d (\mathcal{X}_d - \overline{\mathcal{X}})$ is likely to be zero. The destination factor of bilateral exchange rates, $\mathcal{X}_d$, mainly captures shifts of nominal rates across countries and should be largely uncorrelated with the cross destination distribution of the compositional term, $\mathcal{A}_d$. For example, the fact that South Korean Won was around a thousand units per dollar and British sterling was 0.6-0.8 units per dollar has nothing to do with the composition of products sold to these two countries.

[53] Equation (29) provides additional information helps to pin down the functional form of the compositional term.

C.2 Unbalanced panels

In this subsection, we derive the condition that needs to be satisfied for our estimator to be unbiased in an unbalanced panel.

$$\widetilde{\psi}_{ifdt,D_{ift}} \equiv \psi_{ifdt} - \frac{1}{n_{ift}^{D}} \sum_{d \in D_{ift}} \psi_{ifdt} \tag{38}$$

Similarly, we have

$$\frac{1}{n^{IFDT}} \sum_i \sum_f \sum_d \sum_t (\widetilde{\psi}_{ifdt,D_{ift}} - \frac{1}{n_d^{IFT}} \sum_i \sum_f \sum_t \widetilde{\psi}_{ifdt,D_{ift}})(\widetilde{e}_{dt} - \frac{1}{n_d^{IFT}} \sum_i \sum_f \sum_t \widetilde{e}_{dt,D_{ift}}) = 0 \tag{39}$$

Note that

$$\frac{1}{n_d^{IFT}} \sum_i \sum_f \sum_t \widetilde{\psi}_{ifdt,D_{ift}} = \frac{1}{n_d^{IFT}} \sum_i \sum_f \sum_t \psi_{ifdt} - \frac{1}{n_d^{IFT}} \sum_i \sum_f \sum_t \frac{1}{n_{ift}^{D}} \sum_{d \in D_{ift}} \psi_{ifdt} \tag{40}$$

$$= \overline{\psi}_d - \overline{\psi} \tag{41}$$

Therefore, equation (39) can be simplified into

$$\frac{1}{n^{IFDT}} \sum_i \sum_f \sum_d \sum_t (\psi_{ifdt} - \overline{\psi}_{ift} - \overline{\psi}_d + \overline{\psi})(e_{dt} - \overline{e}_{t,D_{ift}} - \overline{e_d} + \overline{e}) = 0 \tag{42}$$

Note that

$$\frac{1}{n^{IFDT}} \sum_i \sum_f \sum_d \sum_t (\psi_{ifdt} - \overline{\psi}_{ift} - \overline{\psi}_d + \overline{\psi})(\overline{e}_{t,D_{ift}} - \overline{e_t}) = 0 \tag{43}$$

In an unbalanced panel, our approach reduces to the same condition as specified in equation (34).

$$\frac{1}{n^{DT}} \sum_d \sum_t (\overline{\psi}_{dt} - \overline{\psi}_t - \overline{\psi}_d + \overline{\psi})(e_{dt} - \overline{e}_t - \overline{e}_d + \overline{e}) = 0 \tag{44}$$

C.3 Derivation for alternative partitions in an unbalanced panel

The condition of alternative partitions can be simplified to into two terms, the covariance between the compositional error and exchange rates as in equation (44) and the covariance between uncontrolled marginal cost and exchange rates as in equation (23).

$$\widetilde{\psi}_{ifdt,T_{ifd}} = \psi_{ifdt} - \frac{1}{n_{ifd}^{T}} \sum_{d \in T_{ifd}} \psi_{ifdt} \tag{45}$$

$$\widetilde{mc}_{ift,T_{ifd}} = mc_{ift} - \frac{1}{n^T_{ifd}} \sum_{t \in T_{ifd}} mc_{ift} \tag{46}$$

$$\widetilde{e}_{dt,T_{ifd}} \equiv e_{dt} - \frac{1}{n^T_{ifd}} \sum_{t \in T_{ifd}} e_{dt} \tag{47}$$

The condition now involves two terms:

$$\begin{aligned} &\frac{1}{n^{IFDT}} \sum_i \sum_f \sum_d \sum_t (\widetilde{\psi}_{ifdt,T_{ifd}} - \frac{1}{n^{IFD}_t} \sum_i \sum_f \sum_d \widetilde{\psi}_{ifdt,T_{ifd}})(\widetilde{e}_{dt,T_{ifd}} - \frac{1}{n^{IFD}_t} \sum_i \sum_f \sum_d \widetilde{e}_{dt,T_{ifd}}) + \\ &\frac{1}{n^{IFDT}} \sum_i \sum_f \sum_d \sum_t (\widetilde{mc}_{ift,T_{ifd}} - \frac{1}{n^{IFD}_t} \sum_i \sum_f \sum_d \widetilde{mc}_{ift,T_{ifd}})(\widetilde{e}_{dt,T_{ifd}} - \frac{1}{n^{IFD}_t} \sum_i \sum_f \sum_d \widetilde{e}_{dt,T_{ifd}}) = 0 \end{aligned} \tag{48}$$

Therefore, the (ifd, t) fixed effects require the following condition to hold:

$$\begin{aligned} &\frac{1}{n^{DT}} \sum_d \sum_t (\overline{\psi}_{dt} - \overline{\psi}_t - \overline{\psi}_d + \overline{\psi})(e_{dt} - \overline{e}_t - \overline{e}_d + \overline{e}) + \\ &\frac{1}{n^{IFDT}} \sum_i \sum_f \sum_d \sum_t (\overline{mc}_{if} - \overline{mc}_{if,T_{ifd}})(\overline{e}_d - \overline{e}_{d,T_{ifd}}) = 0 \end{aligned} \tag{49}$$

C.4 Numerical Simulations

In this subsection, we expand our numerical example in B.3 and discuss how compositional error would affect our estimates under various scenarios. Specifically, we add ψ_{fdt}, the deviation from the mean marginal cost, to the pricing equation.

We start with the case where components within the compositional term, $\mathcal{A}_d$ and $\mathcal{B}_{ft}$, are random and uncorrelated with factors in e_{dt} and mc_{ft}, i.e.,

$$\begin{aligned} p_{fdt} &= \beta_1 e_{dt} + \beta_2 mc_{ft} + \psi_{fdt} + u_{fdt} \\ e_{dt} &= \mathcal{F}_d + \mathcal{F}_t + \mathcal{F}_d * \mathcal{F}_t \\ mc_{ft} &= \mathcal{C}_f + \mathcal{C}_t + \mathcal{C}_f * \mathcal{C}_t \\ \psi_{fdt} &= \mathcal{A}_d * \mathcal{B}_{ft} \\ \mathcal{A}_d &\sim N(0,1) \quad \mathcal{B}_{ft} \sim N(\mu, \sigma) \end{aligned}$$

In general, we could have set $\psi_{fdt} = \mathcal{A}_d + \mathcal{B}_{ft} + \mathcal{A}_d * \mathcal{B}_{ft}$. However, this would violate equation (28). In addition, we also need the mean of $\mathcal{A}_d$ to be zero to satisfy equation (28). Parameters are set to 1 in the simulation for simplicity, i.e., $\beta_1 = \beta_2 = 1$.

Table 15: Performance of Estimators in the Presence of Compositional Errors – Setup A

	Balanced Panel			Unbalanced Panel			Theoretical
$\mathcal{I}_1$ $\mathcal{I}_2$ $\mathcal{I}_3$	Time Diff	fd,t	TPSFE	Time Diff	fd,t	TPSFE	
$\mu = 0$							
0 0 0	1.00***	1.00***	1.00***	1.18***	0.84***	1.00***	1.00
	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.03)	
1 1 1	1.00***	1.00***	1.00***	1.44***	0.85***	1.00***	1.00
	(0.02)	(0.02)	(0.01)	(0.03)	(0.03)	(0.03)	
$\mu = 0.1$							
0 0 0	1.00***	1.00***	1.00***	1.16***	0.85***	1.00***	1.00
	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.03)	
1 1 1	1.00***	1.00***	1.00***	1.45***	0.85***	1.00***	1.00
	(0.02)	(0.02)	(0.01)	(0.03)	(0.03)	(0.03)	

Estimates and standard errors are calculated from the average of 200 simulations. Each simulation contains a randomly generated sample of 200 firms, 10 destinations and 10 time periods based on the data generating process specified in the paper. The 'Time Diff' column represents estimates using S-period differenced variables at the frim-destination level adding time fixed effects. The 'fd,t' column represents estimates applying firm-proudct and time fixed effects using the reghdfe estimator. The 'TPSFE' column represents estimates applying our trade pattern sequential fixed effects estimator.

Table 15 presents our simulation results. Since the compositional error is random, it will not bias the estimate. In a balanced panel, all three estimators give the correct estimate of 1 with a slight increase in standard errors due to the compositional error. In the unbalanced panel, all three estimators give estimates comparable to table 14, again with a slight increase in standard errors.

Next, we keep $\mathcal{A}_d$ random and uncorrelated with $\mathcal{F}_d$ but set $\mathcal{B}_{ft} = \mu + mc_{ft}$. This setup allows a dependence between the compositional term and firm level factors. For example, the magnitude of the compositional error may depend on the productivity of the firm.

$$
\begin{aligned}
p_{fdt} &= \beta_1 e_{dt} + \beta_2 mc_{ft} + \psi_{fdt} + u_{fdt} \\
e_{dt} &= \mathcal{F}_d + \mathcal{F}_t + \mathcal{F}_d * \mathcal{F}_t \\
mc_{ft} &= \mathcal{C}_f + \mathcal{C}_t + \mathcal{C}_f * \mathcal{C}_t \\
\psi_{fdt} &= \mathcal{A}_d * (\mu + mc_{ft}) \\
\mathcal{A}_d &\sim N(0, 1)
\end{aligned}
$$

Table 16 shows that the firm-level dependence of the compositional error will not generate a bias as long as the destination dimension components of the bilateral exchange rates are uncorrelated with the destination dimension components of the composition error, $\mathcal{A}_d$.

Table 16: Performance of Estimators in the Presence of Compositional Errors – Setup B

$\mathcal{I}_1$ $\mathcal{I}_2$ $\mathcal{I}_3$	Balanced Panel			Unbalanced Panel			Theoretical
	Time Diff	fd, t	TPSFE	Time Diff	fd, t	TPSFE	
$\mu = 0$							
0 0 0	0.96***	0.96***	0.96***	1.15***	0.80***	0.96***	1.00
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	
1 1 1	1.02***	1.02***	1.02***	1.45***	0.88***	1.03***	1.00
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	
$\mu = 0.1$							
0 0 0	0.99***	0.99***	0.99***	1.15***	0.84***	0.99***	1.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	
1 1 1	0.99***	0.99***	0.99***	1.43***	0.84***	0.99***	1.00
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	

Estimates and standard errors are calculated from the average of 200 simulations. Each simulation contains a randomly generated sample of 200 firms, 10 destinations and 10 time periods based on the data generating process specified in the paper. The 'Time Diff' column represents estimates using S-period differenced variables at the frim-destination level adding time fixed effects. The 'fd, t' column represents estimates applying firm-proudct and time fixed effects using the reghdfe estimator. The 'TPSFE' column represents estimates applying our trade pattern sequential fixed effects estimator.

In the next example, we consider the dependence of the destination level factors between bilateral exchange rates and the compositional term, leaving firm level factors uncorrelated. In this setup, for each firm-product-time pair, the compositional error is positively correlated with the bilateral exchange rates at the destination dimension. Simulation results are shown in table 17. Our estimator is still unbiased.

$$
\begin{aligned}
p_{fdt} &= \beta_1 e_{dt} + \beta_2 mc_{ft} + \psi_{fdt} + u_{fdt} \\
e_{dt} &= \mathcal{F}_d + \mathcal{F}_t + \mathcal{F}_d * \mathcal{F}_t \\
mc_{ft} &= \mathcal{C}_f + \mathcal{C}_t + \mathcal{C}_f * \mathcal{C}_t \\
\psi_{fdt} &= \mathcal{F}_d * \mathcal{B}_{ft} \\
\mathcal{F}_d &\sim N(0,1) \quad \mathcal{B}_{ft} \sim N(\mu, \sigma)
\end{aligned}
$$

Table 17: Performance of Estimators in the Presence of Compositional Errors – Setup C

	Balanced Panel			Unbalanced Panel			Theoretical
$\mathcal{I}_1$ $\mathcal{I}_2$ $\mathcal{I}_3$	Time Diff	fd, t	TPSFE	Time Diff	fd, t	TPSFE	
$\mu = 0$							
0 0 0	1.00***	1.00***	1.00***	1.16***	0.86***	1.00***	1.00
	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.03)	
1 1 1	1.00***	1.00***	1.00***	1.44***	0.85***	1.00***	1.00
	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.03)	
$\mu = 0.1$							
0 0 0	1.00***	1.00***	1.00***	1.16***	0.86***	1.01***	1.00
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	
1 1 1	1.00***	1.00***	1.00***	1.40***	0.86***	1.00***	1.00
	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.03)	

Estimates and standard errors are calculated from the average of 200 simulations. Each simulation contains a randomly generated sample of 200 firms, 10 destinations and 10 time periods based on the data generating process specified in the paper. The 'Time Diff' column represents estimates using S-period differenced variables at the frim-destination level adding time fixed effects. The 'fd, t' column represents estimates applying firm-proudct and time fixed effects using the reghdfe estimator. The 'TPSFE' column represents estimates applying our trade pattern sequential fixed effects estimator.

Among all simulations, the only problematic one is the following setup where the destination component of the compositional error is correlated with the destination component of bilateral exchange rates and the firm-time dimension component of the compositional error is correlated with unobserved firm-time factors.

In this case, the bias of the compositional error depends on two parameters, the parameter μ_3 controlling the conditional covariance at the destination dimension $cov_{d|ft}(\psi_{fdt}, e_{dt})$, and the parameter μ_2 controlling conditional covariance at the firm-time dimension $cov_{ft|d}(\psi_{fdt}, mc_{ft})$.

$$
\begin{aligned}
p_{fdt} &= \beta_1 e_{dt} + \beta_2 mc_{ft} + \psi_{fdt} + u_{fdt} \\
e_{dt} &= \mathcal{F}_d + \mathcal{F}_t + \mathcal{F}_d * \mathcal{F}_t \\
mc_{ft} &= \mathcal{C}_f + \mathcal{C}_t + \mathcal{C}_f * \mathcal{C}_t \\
\psi_{fdt} &= \mu_3 \mathcal{F}_d * (\mu_1 + \mu_2 mc_{ft}) \\
\mathcal{F}_d &\sim N(0, 1)
\end{aligned}
$$

Table 18: Performance of Estimators in the Presence of Compositional Errors – Setup D

	Balanced Panel			Unbalanced Panel			Theoretical
μ_1 μ_2 μ_3	Time Diff	fd, t	TPSFE	Time Diff	fd, t	TPSFE	
0 1 1	2.00***	2.00***	2.00***	2.14***	1.85***	1.85***	2.00
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)	
0.1 1 1	1.99***	1.99***	1.99***	2.15***	1.86***	1.85***	2.00
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)	
0.1 0.1 1	1.10***	1.10***	1.10***	1.51***	0.94***	1.08***	1.10
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	
0.1 1 0.1	1.10***	1.10***	1.10***	1.51***	0.95***	1.08***	1.10
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	
0.1 0.1 0.1	1.01***	1.01***	1.01***	1.43***	0.86***	1.00***	1.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	

Estimates and standard errors are calculated from the average of 200 simulations. Each simulation contains a randomly generated sample of 200 firms, 10 destinations and 10 time periods based on the data generating process specified in the paper. The 'Time Diff' column represents estimates using S-period differenced variables at the frim-destination level adding time fixed effects. The 'fd, t' column represents estimates applying firm-proudct and time fixed effects using the reghdfe estimator. The 'TPSFE' column represents estimates applying our trade pattern sequential fixed effects estimator.

Table (18) presents results on five parametrizations. The first row gives the results in the setup where both destination and firm-product covariances are high, i.e., $cov_{d|ft}(\psi_{fdt}, e_{dt}) = 1$ and $cov_{ft|d}(\psi_{fdt}, mc_{ft}) = 1$. In this setting, all three estimators generate upward biased estimates compared to the true markup elasticity $\beta_1 = 1$.[54] Results in the second row show changing values of the mean of the component varying along the firm time dimension, μ_1, will not affect the estimate. As this relationship is generally true in all specifications, we will focus on exploiting variations of μ_2 and μ_3 in rows 3-5. Row 3 presents the case where destination dimension covariance is low but firm-time dimension covariance is high. Row 4 is the reverse of 3. Row 5 presents the case where both covariances are low, $cov_{d|ft}(\psi_{fdt}, e_{dt}) = 0.1$ and $cov_{ft|d}(\psi_{fdt}, mc_{ft}) = 0.1$. Through the last three rows of table 18, we want to show that the compositional term is a second order problem, i.e., the bias will be small if either of these two covariances are small.

We make two comments here. First, the direction of the compositional bias is not always clear. If firms tend to sell high quality (and thus high cost) goods to countries whose currencies appreciate, $cov_{d|ft}(\psi_{fdt}, e_{dt})$ will be positive, leading a positive bias. Alternatively, if the appreciation originates from a foreign productivity shock which making the local firms in the destination more competitive, then exporting firms might choose to sell lower tier products to avoid direct competition; this would result in a negative $cov_{d|ft}(\psi_{fdt}, e_{dt})$ and a negative bias. It is likely forces driving the compositional bias would partly offset each other so that the direction of the bias remains

[54] The theoretical number in the table is calculated based on the statistical relationship imposed by a particular setup. In the case of setup D, the theoretical number is calculated as $\beta_1 + \mu_3 * \mu_2$.

ambiguous. Second, as discussed in C.1, we surmise that a large proportion of destination variation in nominal bilateral exchange rates are driven by nominal differences that can be considered as randomly distributed. This nominal noise in exchange rates would dilute the covariance term, resulting in a small $cov_{d|ft}(\psi_{fdt}, e_{dt})$.

Therefore, with a sufficiently small destination dimension covariance, $cov_{d|ft}(\psi_{fdt}, e_{dt})$, and a reasonable firm-time level covariance, $cov_{ft|d}(\psi_{fdt}, mc_{ft})$, the degree of compositional bias should be small.

D Theoretical Derivations

D.1 Derivation on the separation of marginal cost and markup components

Please note that variables in the following derivation are presented in levels rather than logarithms.

$$\max_p q(p,\xi)p - c[q(p,\xi),\zeta] \tag{50}$$

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. ξ and ζ are exogenous demand and supply function shifters respectively.

The first order condition of the firm is given by

$$\frac{\partial q(p,\xi)}{\partial p}p + q(p,\xi) = \frac{\partial c[q(p,\xi),\zeta]}{\partial q(p,\xi)}\frac{\partial q(p,\xi)}{\partial p} \tag{51}$$

From this equation, we can derive the optimal price as

$$p^* = \frac{\varepsilon(p^*,\xi)}{\varepsilon(p^*,\xi)-1} mc[q(p^*,\xi),\zeta] \tag{52}$$

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

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

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

$$\frac{d\log(q^*)}{d\log(p^*)} = -\varepsilon(p^*,\xi) \tag{53}$$

Proof.

$$\begin{aligned} d\log(q(p^*(\xi,\zeta),\xi)) =& \frac{1}{q(p^*(\xi,\zeta),\xi)} dq(p^*(\xi,\zeta),\xi) \\ =& \frac{1}{q(p^*(\xi,\zeta),\xi)}\left(\frac{\partial q(p^*(\xi,\zeta),\xi)}{\partial p^*(\xi,\zeta)} dp^*(\xi,\zeta) + \frac{\partial q(p^*(\xi,\zeta),\xi)}{\partial \xi} d\xi\right) && (54) \\ d\log(p^*(\xi,\zeta)) =& \frac{1}{p^*(\xi,\zeta)} dp^*(\xi,\zeta) && (55) \end{aligned}$$

Substituting equation 55 into 54 and applying the condition $d\xi = 0$ completes the proof. □

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

$$\frac{d\log(q^*)}{d\log(p^*)} = \frac{\varphi_q(p^*,\xi)}{\varphi_p(\xi,\zeta)} - \varepsilon(p^*,\xi) \tag{56}$$

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.

$$\begin{aligned}
d\log(q(p^*(\xi,\zeta),\xi)) =& \frac{1}{q(p^*(\xi,\zeta),\xi)}\left(\frac{\partial q(p^*(\xi,\zeta),\xi)}{\partial \xi}d\xi + \frac{\partial q(p^*(\xi,\zeta),\xi)}{\partial p^*(\xi,\zeta)}dp^*(\xi,\zeta)\right)\\
=& \left(\varphi_q(p^*,\xi) - \varepsilon(p^*,\xi)\varphi_p(\xi,\zeta)\right)\frac{d\xi}{\xi} \qquad (57)\\
d\log(p^*(\xi,\zeta)) =& \frac{1}{p^*(\xi,\zeta)}dp^*(\xi,\zeta)\\
=& \frac{1}{p^*(\xi,\zeta)}\left(\frac{\partial p^*(\xi,\zeta)}{\partial \xi}d\xi\right)\\
=& \varphi_p(\xi,\zeta)\frac{d\xi}{\xi} \qquad (58)
\end{aligned}$$

□

D.2.1 Two Examples

A. Simple Linear Demand and Constant Marginal Cost

$$\max_p (K-p)(p-c) \tag{59}$$

Optimal quantity and price are given by

$$q^*(K,c) = \frac{K-c}{2} \qquad p^*(K,c) = \frac{K+c}{2} \tag{60}$$

The demand elasticity evaluated at the optimal price is given by

$$\varepsilon(q^*,c) = \frac{K+c}{K-c} \tag{61}$$

If the change is completely driven by the supply shock, dc,

$$dq^*(K,c) = -\frac{1}{2}dc \qquad dp^*(K,c) = \frac{1}{2}dc \tag{62}$$

Therefore,

$$\frac{d\log(q^*(K,c))}{d\log(p^*(K,c))} = \frac{dq^*(K,c)}{dp^*(K,c)}\frac{p^*(K,c)}{q^*(K,c)} = -\frac{K+c}{K-c} = -\varepsilon(q^*,c) \tag{63}$$

If the change is completely driven by the demand shock, dK, we have

$$dq^*(K,c) = \frac{1}{2}dc \qquad dp^*(K,c) = \frac{1}{2}dc \tag{64}$$

and

$$\frac{d\log(q^*(K,c))}{d\log(p^*(K,c))} = \frac{dq^*(K,c)}{dp^*(K,c)}\frac{p^*(K,c)}{q^*(K,c)} = \frac{K+c}{K-c} = \varepsilon(q^*,c) \tag{65}$$

Note that the relationship $\frac{d\log(q^*(K,c))}{d\log(p^*(K,c))} = \varepsilon(q^*,c)$ does not necessarily hold for all demand functions. The general expression is given by

$$\begin{aligned}\frac{d\log(q^*(K,c))}{d\log(p^*(K,c))} &= \frac{\varphi_q(p^*,K)}{\varphi_p(K,c)} - \varepsilon(p^*,c)\\ &= 2\frac{K+c}{K-c} - \frac{K+c}{K-c}\\ &= \varepsilon(q^*,c)\end{aligned} \tag{66}$$

To see this point clearly, we now repeat this exercise with the CES demand function:

B. CES Demand Function and Constant Marginal Cost

$$\max_p \quad (p)^{-\theta}(p-c) \tag{67}$$

For simplicity, we have normalized other factors in the demand function into 1. Optimal quantity and price are given by

$$p^*(\theta,c) = \frac{\theta}{\theta-1}c \quad q^*(p^*,\theta) = (p^*)^{-\theta} \tag{68}$$

The demand elasticity evaluated at the optimal price is given by

$$\varepsilon(\theta) = \theta \tag{69}$$

If the change is completely driven by the supply shock, dc, we have

$$dp^*(\theta,c) = \frac{\theta}{\theta-1}dc \qquad dq^*(p^*,\theta) = -\theta\left(\frac{\theta}{\theta-1}\right)^{-\theta}c^{-\theta-1}dc \tag{70}$$

and

$$\frac{d\log(q^*(\theta,c))}{d\log(p^*(\theta,c))} = -\theta = -\varepsilon \tag{71}$$

If the change is completely driven by the demand shock, $d\theta$, we have

$$dp^*(\theta, c) = \frac{-1}{(\theta-1)^2} d\theta \tag{72}$$

$$\begin{aligned} dq^*(p^*, \theta) &= \frac{\partial q^*(p^*, \theta)}{\partial p^*(\theta, c)} \frac{\partial p^*(\theta, c)}{\partial \theta} - \frac{\partial q^*(p^*, \theta)}{\partial \theta} d\theta &(73) \\ &= -\left(log(p^*) - \frac{1}{\theta - 1}\right) q^*(p^*, \theta) d\theta &(74) \end{aligned}$$

Therefore,

$$\begin{aligned} \frac{d\log(q^*(\theta, c))}{d\log(p^*(\theta, c))} &= \frac{\varphi_q(p^*, \theta)}{\varphi_p(\theta, c)} - \varepsilon(p^*, c) \\ &= log(p^*(\theta, c))\theta(\theta - 1) - \theta \\ &\approx \theta(\theta - 1) log(c) &(75) \end{aligned}$$

E Data Appendix

E.1 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 (constant 2005 US dollars), 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 154 destination countries in our sample.

In our empirical analysis, we focus on nominal rather than real bilateral exchange rates. Estimations using real exchange rates implicitly impose 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 we discussed in previous sections, taking time differences in an endogenously unbalanced panel tends to make the unobserved marginal cost uncontrollable and introduce potential biases. In all our regressions, we enter variables in logged levels. A concern of using logged levels rather than time differences is that nominal series, such as exchange rates and CPI indices, cannot be compared directly across countries. In solving this compatibility problem, it is useful to think of the nominal series as a compatible measure plus an unobserved destination specific drift, i.e.,

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

Due to our trade pattern fixed effects, our proposed approach is robust to this type of destination specific drift, which enables us to correctly disentangle the effect of nominal exchange rate fluctuations from destination CPI movements.

E.2 Additional Information on the CCHS Classification

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, "套" and "件," respectively. Further, table 19 documents the intrinsic information content of the measurement units for HS04 product groups 8211 and 8212. The Chinese language descriptions of all of these HS08 products conveys the similarity across products; each Chinese description contains the Chinese character 'dao' (刀), which means 'knife' and is a part of longer compound words including table knife and razor. Interestingly, three different Chinese count classifiers, "tào, 套," "bǎ, 把," and "piàn, 片," are used to count sets of knives (HS82111000), knives and razors (HS82119100 - HS82121000), and razor blades (HS82122000), respectively.

Table 19: Examples of count classifiers in the Chinese Customs Database

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

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

In table 20, 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 20: Classification of differentiated goods: CCHS vs. BEC

(a) Share of goods by classification: observation weighted

	Corsetti-Crowley-Han-Song (CCHS)		
	Low Differentiation / (Mass nouns)	High Differentiation / (Count nouns)	
BEC			
Intermediate	29.8	2.7	32.5
Consumption	14.3	20.1	34.4
Other†	15.0	18.1	33.1
	59.1	40.9	100.0

(b) Share of goods by classification: value weighted

	Corsetti-Crowley-Han-Song (CCHS)		
	Low Differentiation / (Mass nouns)	High Differentiation / (Count nouns)	
BEC			
Intermediate	26.0	3.9	29.9
Consumption	8.6	14.0	22.6
Other†	12.6	34.9	47.5
	47.2	52.8	100.0

Notes: Share measures are calculated based on Chinese exports to all countries including Hong Kong and the United States during periods 2000-2014. †: The "Other" category refers to capital goods and unclassified products by BEC classification, such as nuclear weapons.